Water &
Environmental Dynamics

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Foreword

Dear Participants,

The ICWRER conference series provides an independent platform for scientists in the fields of hydrology, environmental research, aquatic ecosystem research, water resources research and management. The focus of the 6th conference was set on fostering an integrative understanding of water and the environment. It brought together physical, biological, chemical, statistical, socioeconomic and technical expertise in order to discuss solutions for transient environmental boundary conditions.

The 6th edition of the International Conference on Water Resources and Environment Research (ICWRER) was held in Koblenz, Germany in June 2013. More than 350 participants gathered to discuss current issues with regard to water and sediment.

Five days of intensive discussions on the shores of the Rhine have led us to new scientific insights. We were able to develop a better understanding of practical implications of our work, especially in the face of the major flood that struck Germany during the days of the conference. We also unveiled the boundaries of our understanding and created new momentum for driving science further to implement scientific findings for the benefit of society.

This publication is one of the results of ICWRER VI. We hope that it will remind participants of an inspiring conference. At the same time, we wish to motivate young researchers in water and environment research to challenge what has been added to our general understanding of water and environment.

We are looking forward to meeting you again for the next edition of ICWRER in Japan in 2016.

Johannes Cullmann
Koblenz, February 2014
Table of Content

Climate Change, Research and Adaption Development

Climate change and fresh water sediment

11 In-channel Sand Extraction in River Mungo, Cameroon: Nature Effects and Concerns
Veronica E. Manga · Christopher M. Agyingi · Anatole E. Djieto-Lordon

Abstract
1. Introduction
2. Study area
3. Methodology
4. Results and discussion
5. Conclusion

Hydrological Extremes

Extreme precipitation: how to use past measurements and climate projections for urban hydrologic design?

30 Consideration of uncertainties in measured and projected precipitation time series for use in urban hydrological design
Markus Quirmbach · Thomas Einfalt · Elke Freistühler · Alrun Jasper-Tönnies · Ioannis Papadakis · Markus Jessen

1. Introduction
2. Time series and trend analyses
3. Precipitation analysis from climate projections (CLM regional climate model)
4. Use of climate projection data for urban hydrologic design
5. Use of the climate change signal for urban hydrologic design

43 Rainfall Analysis for the Schoeckelbach Basin (Austria) and Determining its Best-Fit Probability Distribution Model
Majid Galoie · Gerald Zenz · Artemis Motamedi

Abstract
1. Introduction
2. L-moments method
3. Parameter estimation using L-moments method
4. The best-fit probability distribution
5. Statistical Confidence limit

Technological and social adaptation to extreme water hazards

54 A Fundamental Impact Analysis of Prior Release Operation for Flood Management Based on Inflow Prediction at a Multi-Purpose Reservoir
Yohei Amai · Daisuke Nohara · Tomoharu Hori

Abstract
1. Introduction
2. Methodology
3. Case study
4. Conclusions

Management

Water resources modeling, management, and policy

70 Climate change impact assessment on water resources in the Blue Mountains, Australia
Md Mahmudul Haque · Ataur Rahman · Dharma Hagare · Golam Kibria

Abstract
1. Introduction
2. Study area and data
3. Modelling method
4. Model calibration and validation
5. Model Prediction
6. Conclusion
83 Determining the high flood risk regions in a small basin in Austria
Majid Galoie · Gerald Zenz · Artemis Motamedi

Abstract
1. Introduction
2. Rainfall analysis
3. Terrain analysis
4. Loss analysis
5. Rainfall-runoff modeling
6. The high flood risk regions
7. Conclusions

84 Multiple Coincidence of Flood Waves in Complex River Systems
Aleksandra Ilić · Stevan Prohaska

Abstract
1. Introduction
2. Methods
3. Practical application of the model
4. Discussion
5. Conclusion

102 Numerical Modeling of the Effects of artificial Recharge on hydraulic Heads in constant-Density Ground Water Flow to manage the Gaza Coastal Aquifer, South Palestine.
Hasan Sirhan · Manfred Koch

Abstract
1. Introduction
2. Study Area
3. Characteristics of the Gaza Groundwater System
5. Groundwater Flow Model Simulations
6. Sensitivity Analysis
8. Conclusion

147 Modeling the Hydrological Response of Soil and Water Conservation Measures in the Ronquillo Watershed in the Northern Andes of Peru
Joachim Krois · Achim Schulte

Abstract
1. Introduction
2. Material and Methods
3. Results
4. Discussion
5. Conclusions

185 Cumulative sediment curve for an arid zone reservoir: Foum el Kherza (Biskra, Algeria)
Fatima Zohra Tebbi · Hadda Dridi · Gregory L. Morris · Mahdi Kalla

Abstract
1. Introduction
2. Study area
3. Methods
4. Available methods
5. Methodology
6. Results and discussion
7. Final remarks

195 Environmental impact assessment of structural flood mitigation measures in Metro Manila, Philippines using an analytical evidential reasoning approach
Romeo L. Gilbuena, Jr. · Akira Kawamura · Reynaldo R. Medina · Naoko Nakagawa · Hideo Amaguchi

Abstract
1. Introduction
2. EIA by the RIAM technique
3. EIA of SFMM by evidential reasoning approach
4. Results and discussion
5. Conclusion
Catchment water quality management

212 Monitoring and Analyses of impact of the industrial complexes on water quality of the Central Asian Transboundary Rivers
Inom Sh. Normatov · Christian Opp · Parviz I. Normatov

212 Abstract
212 1. Introduction
224 2. Methods
228 3. Conclusion

Hydroinformatics

231 Artificial Neural Network Modeling of the Fractional Transport Rate of Bed-Load in Gravel-Bed Streams
Vasileios Kitsikoudis · Vlassios Hrissanthou

231 Abstract
231 1. Introduction
233 2. Bed-Load Transport in Gravel-Bed Rivers
236 3. Hydraulic Parameters for Bed-Load Quantification
237 4. Study Sites and Available Field Data
241 5. Artificial Neural Networks
245 6. Application and Results
249 7. Conclusions
250 8. Notation

256 Ground water pollution in Central India
Khageshwar Singh Patel · Rakesh Dewangan · Irena Wysocka · Irena Jaron · Laurent Matini

256 Abstract
256 1. Introduction
257 2. Experimental
259 3. Results and discussion
270 4. Conclusion

274 Urbanization impact on rainfall-runoff modeling: an integration of remote sensing and GIS approach
Ghazi A. Al-Rawas

274 Abstract
274 1. Introduction
278 2. Study Area and Methodology
279 3. Results and Discussion
282 4. Conclusion and Recommendations

Modelling, Methods, Mathematics

286 Applying the Log Pearson type 3 distribution for modeling annual inflow to the closed lake
Mikhail Bolgov · Elena Korobkina

286 Abstract
286 1. Introduction
287 2. The main properties of the Log Pearson type 3 distribution
289 3. Method of construction of bivariate probability density function
292 4. Application LP3 to modeling annual inflow to the closed Lake Chany
296 5. Conclusions

298 Pareto – optimal model output correction model selection
Robert Pinzinger · Bastian Klein · Dennis Meissner · Dmytro Lisoniak

298 Abstract
298 1. Introduction
301 2. Time Series Analysis
302 3. Multiobjective Optimization
304 4. The Search Space
307 5. Application
314 6. Summary and Outlook
Flood Frequency Analysis at River Confluences – Univariate vs. Multivariate Extreme Value Statistics
Jens Bender · Thomas Wahl · Christoph Mudersbach · Jürgen Jensen

Abstract
1. Introduction
2. Data
3. Methods
4. Results
5. Conclusion

Statistical methods for detecting changes in mean annual cycle and their application to several runoff series of European rivers
Daniela Jarušková

Abstract
1. Introduction
2. Statistical methods for detecting nonstationarities in mean annual cycle
3. Dimension reduction
4. Results
5. Conclusions

Analysing flood frequencies at the Elbe River – Do recent extreme events affect design levels?
Christoph Mudersbach · Jens Bender · Vitalij Kelln · Jürgen Jensen

Abstract
1. Introduction
2. Data
3. Methods
4. Results
5. Discussion and Conclusions

A comparison of linear and nonlinear regression modelling for forecasting long term urban water demand: A Case Study for Blue Mountains Water Supply System in Australia
Md Mahmudul Haque · Ataur Rahman · Dharma Hagare · Golam Kibria

Abstract
1. Introduction
2. Study area
3. Materials and Methods
4. Model evaluation criteria
5. Result and Discussion
6. Conclusion

Temporal changes in the hydrochemical facies of groundwater quality in two main aquifers in Hanoi, Vietnam
Thuy Thanh Nguyen · Akira Kawamura · Naoko Nakagawa · Hideo Amaguchi · Romeo Gilbuena Jr

Abstract
1. Introduction
2. Study area
3. Data used
4. Results and discussion
5. Conclusion

The Use of Teleconnections for short-term seasonal Climate Prediction in the eastern Seaboard of Thailand
Werapol Bejranonda · Manfred Koch

Abstract
1. Introduction
2. Review of methods and applications of short-term climate prediction
3. Study region and data used
4. Methodology
5. Results and discussion
6. Conclusions
Data assimilation in hydraulics, hydrology and water resources

425\hspace{1em}Uncertainty of the hydraulic and transport model based on the tunnel inflow observation
Ales Balvin · Milan Hokr · Ilona Skarydova · Petr Rálek

Abstract
1. Introduction
2. Observations data
3. Theory and softwares
4. Calibration method
5. Model characteristics
6. Results and discussion
7. Conclusion

Computational methods for optimal management of water resources systems

439\hspace{1em}SWAT – Hydrologic Modeling and Simulation of Inflow to Cascade Reservoirs of the semi-ungaged Omo-Gibe River Basin, Ethiopia
Teshome Seyoum · Manfred Koch

Abstract
1. Introduction
2. Description of the study area
3. Materials and methods
4. SWAT results and discussions
5. Summary and conclusions

Assessment of Climate Change Impact on Water Resources in Serbia

Stevan Prohaska · Vladimir Djuri\'jevi\'c · Aleksandra Ilic · Vanja Vukelic · Vesna Tripkovic

Abstract
1. Introduction
2. Methods
3. Results and discussion
4. Conclusions

Mono- and multi-Model statistical Downscaling of GCM- Climate Predictors for the Upper Blue Nile River Basin, Ethiopia

Netsanet Cherie · Manfred Koch

Abstract
1. Introduction
2. Study region and previous studies
3. Methodology
4. Recent and future climate analysis in the UBNRB
5. Summary of future climate predictions for the UBNRB
6. Conclusions

SWAT-Modeling of the Impact of future Climate Change on the Hydrology and the Water Resources in the Upper Blue Nile River Basin, Ethiopia

Manfred Koch · Netsanet Cherie

Abstract
1. Introduction
2. Study area
3. Methodology
4. Results and discussion
5. Summary and conclusions

New tools for improving water use efficiency in irrigation

560\hspace{1em}Evaluation of field and greenhouse experiments with tomatoes using the aquacrop model as a basis for improving water productivity
Eisa Algharibi · Gerd Schmitz · Franz Lennartz · Niels Schütze · Jens Grundmann · Sebastian Kloss

Abstract
1. Introduction
2. Materials and Methods
3. Results
4. Conclusion
576  Optimal irrigation scheduling for fodder crops under multiple resource constraints in an arid zone environment
Hamed Al-Dhuhli · Gerd H. Schmitz · Franz Lennartz · Niels Schütze · Jens Grundmann · Sebastian Kloss · Marcus Pistorius

Abstract

1. Introduction and Literature Review
2. Experimental Setup, Data and Methods
3. Results
4. Summary and Conclusion

578  Sediment

Addressing the catchment sediment management challenge

588  Polychlorinated biphenyls contamination in pond sediment of central India
Khageshwar Singh Patel · Yogita Nayak · Chin-Chang Hung

Abstract

1. Introduction
2. Experimental
3. Results and discussion
4. Conclusion

582  Modern hydraulics structures for better hydrodynamics and hydromorphology of streams and rivers
Kohji Michioku · Masashi Nanjo · Masanori Haneda · Keichi Kanda · Zuisen Li

Abstract

1. Introduction
2. Modeling of rubble mound structures
3. Application to other rubble mound structures
4. Application of the 2D2L model to vegetated channel hydraulics
5. Concluding remarks

584  Hydrodynamics and hydromorphology of river structures constructed by natural materials
Kohji Michioku · Masashi Nanjo · Masanori Haneda · Keichi Kanda · Zuisen Li

Abstract

1. Introduction
2. Setting
3. Method
4. Results and discussion
5. Conclusions

588  Hydrological Extremes

Extreme precipitation: how to use past measurements and climate projections for urban hydrologic design?

(Addendum, see page 43)

629  Regional depth-duration-frequency curves for Mumbai City
Sherly M A · S. Karmakar · T. Chan · C. Rau

Abstract

1. Introduction
2. Site Description and Methodology
3. Results and Discussion
4. Summary and Conclusions

647  Technological and social adaptation to extreme water hazards

(Addendum, see page 53)

647  Assessment of Flood Hazards and Vulnerability in Cambodian Floodplain
Badri Bhakta Shrestha · Toshio Okazumi · Shigenobu Tanaka · Ai Sugiura · Youngjoo Kwak

Abstract

1. Introduction
2. Methodology for identification of flood hazards and vulnerability
3. Assessment of flood vulnerability indices
4. Results and discussions
5. Conclusions
In-channel Sand Extraction in River Mungo, Cameroon: Nature Effects and Concerns

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Abstract
The River Mungo that drains into the Cameroon Estuary is a major source of sand for the metropolis of Douala, Limbe, Tiko and Muyuka. The present study examines the nature of sand extraction, the associated environmental problems and the regulations that control it. Data on sand mining practices and environmental conditions in the lower reaches of the Mungo River were carried out from three areas of activities namely; Yoke, Missaka and the Mungo Bridge during the period of February – March 2013. Field visits were undertaken to observe sand extraction activities. Product samples were collected and subject to grain size analysis. Current regulations on sand mining and relevant actions to protect the ecosystem were evaluated from consultation of legal texts and interviews with representatives of the relevant agencies and service. Approximately 300,000 tons of sand representing three major product classes is extracted annually. The means of extraction is gradually moving towards semi-mechanised techniques; associated with higher impacts on physical disturbances in noise, turbidity etc. Permit holders are authorized to mine sands anywhere along the river and there is no limit on quantities extracted. Record-keeping by all sectors on the number of permits and quantity of material extracted is absent or erroneous. The study concludes that the current legislation is inadequate in terms of achieving sustainable development mining operations as they do not take into consideration sensitive areas, extraction and deposition rates, and methods of extraction and conflict resolution over other resource users and the distribution of taxes and royalties generated from this activity.

Keywords
Cameroon, sand mining, regulations, extraction techniques, environmental impacts.

1. Introduction
The coastal environment of Cameroon is open to the Atlantic Ocean with a coastline of about 402km (Sayer et al, 1992). This coastline extends from 2° 20’ N at the Equatorial Guinea borders to 4° 40’ N at the Nigerian borders, between Longitudes 8° 151’ E and 9° 30’ E. Two main morphological, dynamic and environmental processes affect this
coastline; erosion of the mountainous slopes of Mt. Cameroon and the deposition of sediments on the continental shelf (Mbuh et al, 2012). The interface between the inland river systems and the shoreline is marked by estuaries that are rimmed with unique mangrove systems (Figure 1). These ecosystems can be disturbed from rapid and unusual changes (natural and anthropogenic) along the coastline that might affect wave and tidal energy. Coastal erosion is probably the most serious environmental problem facing West African coasts today (Hinrichsen, 1990).

In-channel mining of sand is a common practise in many rivers and streams throughout the world. Sand is a valuable resource in the construction industry and in many cases, the application of rudimentary methods of extraction, is a source of employment for many. In many African countries, the combination of a boom in infrastructural development and the need for job creation makes this an attractive development opportunity. Environmental problems occur when the rate of extraction of sand, gravel and other materials exceeds the rate at which natural processes generate these materials. Negative and undesired outcomes include; reduction of water quality and destabilisation of stream bed, channel instability and sedimentation, changes in channel morphology and fluvial processes (Kondolf at al. 1997; Brown et al. 1998; Marchetti, 2002), and the prowess to destroy ecosystem cycles (Ashraf et al, 2011). Some positive effects associated with dredging include the improvement of aquatic habitat (Schloesser et al, 2008), decreased chances of flood damages, improved navigating conditions, more water inputs to rapid economically growing regions and a source of livelihood for the poor.

In tropical regions that are experiencing reduced and episodic rainfall, the immediate and long term impacts can have devastating effects on the sustenance of aquatic ecosystems. In order to minimize these potential negative effects, there is a need for a more sustainable exploitation of these resources. Sustainable sand extraction requires an understanding of the scale and pattern of extraction and potential environmental problems. The impact of dredging on large rivers has received more attention (Lagasse et al. 1980; Lagasse 1986) than gravel mining on small streams.
Sand mining is of immense importance to the Cameroonian economy. Rivers Mungo, Wouri and Dibamba are located in close proximity to the urban growth cycles and are the sites of sand extraction. This paper examines the nature of sand extraction, the associated environmental problems and the status of resource management in the River Mungo. Given that investment climate in Cameroon is characterised by a construction boom which has seen an increase in the number of sand extraction permits issued. The management of the permits and the implementation of regulations and legislations...
designed to limit the negative impacts associated with sand extraction is also the subject of this paper.

2. Study area

2.1. Climatic and oceanic setting

The climate in the region is equatorial, with precipitation depending on altitude. Rainfall always exceeds 1500 mm yr$^{-1}$, reaching 2000 mm yr$^{-1}$ in the western uplands and well over 4000 mm yr$^{-1}$ in the coastal belt, with dramatic variability around Mt Cameroon or Bioko Island. For example, the foot of Mt Cameroon, facing west towards the monsoon, receives an average of 10 mm yr$^{-1}$. So the low salinities of the sea water are partly a result of these exceptional rainfalls (Mahé, 1993).

On the coast of the Gulf of Guinea (from Cap des Palmes to the mouth of the Congo-Zaïre), the Sanaga, with an annual flow of $65.3 \times 10^9$ m$^3$ yr$^{-1}$, is the fourth tributary after the Congo-Zaïre, the Niger and the Ogooué. Due to a prevailing south-westerly swell, most of its waters and their loads are oriented northwards where, at the entrance to the Cameroon Estuary (Figure 2) they meet those of relatively smaller rivers: the Mungo ($9 \times 10^9$ m$^3$ yr$^{-1}$), the Wouri ($16 \times 10^9$ m$^3$ yr$^{-1}$) and the Dibamba ($4 \times 10^9$ m$^3$ yr$^{-1}$) (Nouvclot, 1972; Olivry, 1977). Table 1 is a summary of some characteristics of the rivers draining into the Cameroon Estuary. Suspended particles in these rivers are buffeted by fairly strong tidal flows in the area, which has one of the highest tidal ranges in Western Africa (2 to 3 m at the equinox). Thus, the Bay of Douala acts as a huge estuarine complex, and it is only in the open sea that the main sedimentation of the pelitic fraction and the organic matter associated with it takes place (Giresse and Cahet, 1997).

Table 1: Characteristics of rivers draining into the Cameroon Estuary (Angwe and Gabche, 1997)

<table>
<thead>
<tr>
<th>River</th>
<th>Length (km)</th>
<th>Catchment (Drainage Area)</th>
<th>Sediment yield (kg/yr)</th>
<th>Flow range (Annual mean m$^3$/s)</th>
<th>Total Dissolved Solids (TDS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mungo</td>
<td>150</td>
<td>2,420</td>
<td>-10x109</td>
<td>27-236</td>
<td>78.1</td>
</tr>
<tr>
<td>Wouri</td>
<td>250</td>
<td>82,000</td>
<td>-</td>
<td>49-1,425</td>
<td>43.58</td>
</tr>
<tr>
<td>Dibamba</td>
<td>150</td>
<td>2,400</td>
<td>-</td>
<td>480</td>
<td>28.4</td>
</tr>
</tbody>
</table>
2.1.1. Geological setting

The Cameroon Estuary system evolved during the last marine transgressions of the Tertiary to Early Quaternary period, particularly of the Holocene (which occurred about 10,000 years ago) with drowning of the mouths of coastal rivers along the tropical coastlines. This period witnessed the inundation and submergence of coastal lowlands including estuarine river systems to form the broad embayment into the lagoon system from the Atlantic Ocean.

The Mungo River is 150 km long and has a catchment area of 4,200 square kilometres. The river takes its rise from the Rumpi Hills and is fed by tributaries from Mount Kupe and the Bakossi mountains. The drainage of the Mungo basin is comprised of marine and deltaic deposits laid down during the Tertiary (Mio-Pliocene) system (Dumort, 1968), thus having the same age as the early eruptions in the Mt. Cameroon area. These sedimentary plains are found in the Muyuka, Mbonge and Boa. Soils formed on the older Mio-Pleisocene deposits are sandy clayey with incipient laterite while younger Holocene soils are of mixed textures. The older sedimentary plains are in most places strongly dissected (Malende, Bang Bakundu areas). Typical in these sediments are the large sheets of outcropping laterite duricrust (‘ironcrust’). These occupy somewhat higher positions in the landscape, more resistant as they are to erosion. Residual soil covers on the terraces are rather shallow and contain high amounts of ironstone gravel (laterite rubble). These flat plains are slightly uplifted and tilted towards the sea and are modified by those drainage systems.

River Mungo is navigable south of Mundame for about 100 kilometres as it flows through the coastal plain before entering mangrove swamps, where it splits into numerous small channels that empty into the Cameroon estuary complex. The tidal wave penetrates far up to the estuaries (Morin and Kuete, 1989) travelling upstream by as much as 40km in the case of the Mungo. As a result large intertidal flats and sand banks are exposed at low tide in the estuaries. This not only obstructs boat traffic but together with high freshwater discharge also inflicts a high level of disturbance onto the aquatic ecosystems, intertidal organisms being particularly strongly affected (Gabche et al, 2000).

2.1.2. Mangrove ecosystem

The main estuaries of the Cameroon coast are covered with mangrove ecosystems. The mangrove forest strives best in areas, which, are brackish, swampy, waterlogged, have the influence of tide incursions at least twice daily and in which sedimentary deposition occurs. Deposition occurs either from marine and/or river processes. A change in water levels on a periodic or seasonal basis influences the proliferation or retreat of the forest.
This is because the changes have an influence on the several factors which determine the type of species which abound in the area and also maintains the wetland characteristics of the environment. Factors such as tidal currents and levels, the intensity of the waves, the salinity concentration and the sediment depths have formed and maintained an arrangement or zonation patterns of the species of mangrove forests found in the Cameroon coastal lowlands. This has evolved mainly 3 zonal pattern arrangements of the mangrove species in the Cameroon coastal zone (Asangwe, 1999).

Figure 2  The Cameroon Estuary system

Mangroves have important environmental and ecological values, and provide significant benefits to local and national economies. In addition to their goods and services of: provisioning-food, construction materials; regulatory-water purification and pollution control; providing important carbon sinks; protection of coastal communities from tropical storms; and ecological benefits-breeding and spawning grounds for fish, nesting sites for important migratory birds, and socio-cultural factors, among others (Choudhury, 1997; Hamilton and Snedaker, 1984; Alongi, 2002). The Cameroon estuary mangrove and its adjacent coastal waters play a major role in the Country’s fishery activities; serving as feeding and nursery ground for fish species that account for more than 90% of national fisheries production (CICERO, 2000). Industrial fishing is estimated to be worth FCFA 38.16 billion at current market prices (CICERO, 2000). Artisanal fishing takes place within two nautical miles of the shore, as well as within the mangrove zone. In 1993, the annual
catch was estimated at 65,000 tons, with shrimp accounting for over 15% of the catch. Like most tropical forests, they are being degraded and destroyed globally. About 50% of mangroves were lost in the first half of the 20th century, and the residual 181,390 km² stock continues to be depleted at a rate of about 1% (Spalding et al., 1987; UNEP-WCNC, 2007). Although estimates (Mcleoa and Slam, 2006) indicate that by 2025 mangrove forests in developing countries will have declined by 25%, a recent study shows that this is an underestimate, because about 25% of the mangroves of coastal West-Central Africa have already been lost in the last 25 years (1980-2005), with Cameroon losing about 30% of its mangrove forests (UNEP-WCNC, 2007). Present threats to the mangrove ecosystems in Cameroon include, harvesting of wood for fuel and construction, land conversion for agricultural expansion, and sand mining which is also modifying mangrove ecosystems (Feka and Manzano, 2008).

2.1.3. Coastal development

The majority of the 2.5 million inhabitants of the coastal zone are concentrated in major towns such as Douala, Edea, Limbe, Tiko, and Kribi. In fact, the coastal area has the highest population density in the country, with 132.6 inhabitants per km². Most industrial activities in Cameroon occur along the coastal provincial areas of the South West, Littoral and South provinces. The entire Cameroonian Industrial production accounts for more than 17% of the country’s gross national product (GNP). Out of this entire national percentage, 60% are located along the coastal industrial hub with the city of Douala containing a disproportionately substantial amount of these industries (Angwe and Gabche, 1997). Seventy percent of national industries, including extensive agro-industrial plantations, are also located in the coastal zone CICERO, 2000). The Cameroon Development Corporation has some of its major plantations (rubber, banana and palm) along the coastal area of the Mungo basin. Boh plantation which cultivates banana is a new establishment that runs along the banks of the Mungo for tens of kilometres. Agricultural activities have reduced the amount of land available for other activities; consequently, there is a tendency for land reclamation. This is equally heightened by the expansion from Douala which is rapidly encroaching into the Mungo estuary. Other points of urban expansion including Tiko town and several small fishing communities are located within the mangrove systems that constitute the Cameroon estuary (i.e Mudeka, Misselle, Bwenga etc.). The primary economic activities in these areas are fishing and fish processing and the harvesting of timber from the mangroves. Increasing demands for these products from an ever-expanding population is putting these systems under a lot of stress.
3. Methodology

Data on sand mining practices and environmental conditions in the lower reaches of the Mungo River were carried out from three areas of activities namely; Yoke, Missaka and the Mungo Bridge during the period of February – March 2013. The primary data collection techniques used was participant observation and interviews. Observations were employed in sand extraction sites on the types of materials extracted, techniques and technologies employed in mining and changes in the physical environmental. At each site, data on the characteristics of the river (i.e. depth, width, altitude etc.) were recorded and samples of materials for grain size analysis were collected. At least a 5 kg mass of sample were collected. The samples were air-dried sieved (using a set of sieves and a sieve shaker) and weighed. Data on the intensity of sand extraction considered estimates on the number of persons involved in onsite activities, the number of permits issued and estimates of the quantity of material extracted from the Ministry of Mines, Geology and Technological Development (MINTAD). The current regulations on sand mining and relevant actions to protect the ecosystem was synthesised from consultation of legal texts and interviews with representatives of the Ministry of Mines, Geology and Technological Development and related ministerial agencies.

4. Results and discussion

4.1. River sand extraction

Various types and grades are used for building and road construction. Sand extraction is undertaken from four locations; Yoke, Missaka, Mungo River and Misselle. Table 2 is a summary of the operation sites studied. The sand grains are predominantly quartz with significant fractions of ironstones and kaolinite (Yoke and Missaka).
Table 2: Summary of characteristics of the studied mining sites

<table>
<thead>
<tr>
<th>Property</th>
<th>Yoke (Y)</th>
<th>Missaka (MI)</th>
<th>Mungo Bridge (MB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water depth (m)</td>
<td>15-25</td>
<td>0.5 - 20</td>
<td>5 - 15</td>
</tr>
<tr>
<td>Flood Level (Change)</td>
<td>Decrease</td>
<td>Decrease</td>
<td>Decrease</td>
</tr>
<tr>
<td>Width (m)</td>
<td>120-150</td>
<td>100-120</td>
<td>150-200</td>
</tr>
<tr>
<td>No. of workers</td>
<td>~ 200</td>
<td>~ 150</td>
<td>~ 150</td>
</tr>
<tr>
<td>No. Trucks daily</td>
<td>30-50</td>
<td>100-150</td>
<td>~ 150</td>
</tr>
<tr>
<td>Means of extraction</td>
<td>Artisanal</td>
<td>Artisanal/ Mechanised</td>
<td>Artisanal</td>
</tr>
<tr>
<td>Other activities</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Water based</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Land based</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fishing, Ferry</td>
<td>Fishing, irrigation</td>
<td>Fishing, water supply</td>
<td></td>
</tr>
<tr>
<td>service Farming,</td>
<td>Farming, plantation</td>
<td>Farming</td>
<td></td>
</tr>
<tr>
<td>Fishing, Buea, Limbe</td>
<td>Douala</td>
<td>Douala, Tiko, Limbe</td>
<td></td>
</tr>
<tr>
<td>Market</td>
<td>Muyuka, Buea, Limbe</td>
<td>Douala, Tiko, Limbe</td>
<td></td>
</tr>
</tbody>
</table>

The sands are classified in three categories by the miners; soft (300 μm – 100μm), soft sharp (1mm- 250μm) and sharp sand (4mm – 1mm). However, some sub categories exist in Missaka and Yoke (Figure 3). The uses of the sands are described below:

**Soft sand:** Finer grained-sand referred to as soft or plastering sand is used for the composition of plaster applied to walls and other surfaces.

**Sharp sand:** Coarse-grained sand used in the building structures for the making of building blocks and bricklaying, sharp sand is mixed with cement in a fixed proportion to achieve technically specific strength.

**Soft-sharp sand:** This includes a mixture of sharp and fine-grained sand. It is used for composing reinforced concrete structures i.e. building, pillars, box culverts, pavements etc. Reinforced concrete is a mixture of rock aggregate and sand; this particular grade of sand provides good workability and prevents segregation of other materials.

**Sand for fill and other diverse applications:** Other structures requiring sand of a wide range include sand for the stabilization of clayey earth roads and sand filters for water treatment plants.
Figure 3  Particle size distribution of the various types of sand extracted in the study area.

Building construction particularly in the urban centres exerts the greatest demand on sand (i.e. soft and sharp sand). This is in line with high growth particularly in Douala as construction activities are a part of urban expansion. With an annual effective period of about eight months, and an estimated rate of extraction about 230 to 300 tons per year (see Table 2) the total sand extracted varies from 294,400 – 384,000 tons.

Yoke sands are generally finer, whereas the Missaka sands show the highest diversity which possibly reflects more diverse aquatic niches. This diversity in material can also lead to higher extractive rates and comparably greater negative impacts. Not much statistics on sand extraction is officially reported. Officially, statistics on amounts of sand extracted is recorded at various levels either in progress reports, quarterly declarations and tax receipts on trucks issued by Council. In this study, from field interviews, annual sand extraction is estimated to be between 294,400 and 384,000 tons per year (see Box 1). Tiko and Muyuka located in the Southwest Region and Dibamba in the Littoral Region are councils that benefit from sand extraction in then Mungo. Table 3 shows the revenue returns for the Tiko Council.
Table 3: Amounts of sand extracted in Tiko Council in 2011-2012 (Source: Revenue returns)

<table>
<thead>
<tr>
<th>Year</th>
<th>Period</th>
<th>No. Trucks</th>
<th>Tonnage</th>
</tr>
</thead>
<tbody>
<tr>
<td>2011</td>
<td>January - July</td>
<td>210</td>
<td>2520</td>
</tr>
<tr>
<td></td>
<td>August - December</td>
<td>290</td>
<td>3480</td>
</tr>
<tr>
<td>2012</td>
<td>January - April</td>
<td>2000</td>
<td>24000</td>
</tr>
<tr>
<td></td>
<td>September</td>
<td>100</td>
<td>1200</td>
</tr>
<tr>
<td></td>
<td>October</td>
<td>350</td>
<td>4200</td>
</tr>
<tr>
<td></td>
<td>November</td>
<td>250</td>
<td>3000</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>38400</td>
</tr>
</tbody>
</table>

Permit holders employ sand miners who do the mining and supply the sands. Sand extraction is carried out manually, using rudimentary techniques and local equipment (i.e. wooden canoes, buckets and metallic pans, spades, etc) (Figure 4a). Along the entire length of the study area (in Missaka), only about two operators applied very small dredges and water pumps in their operations (Figures 4b,c). Mining is done during the daytime, all year round with less intensity during the rainy season. Sand extractors using canoes ply the entire waters without limitations, in search of sand deposits; sand is scooped and placed into the canoes which are cruised to the permitted site of the permit holder; unloaded and heaped. It is later uploaded into the trucks of buyers. Of concern here, is the existence of an open-license in which no areas are protected from exploitation.
Figure 4  Extractive methods applied in sand mining: (a) artisanal methods, b and c mechanised methods
4.2. Institutional and legal arrangements for sand extraction

The primary instrument regulating sand extraction is the mining code (law No 1 of 16th April 2001) and its implementing decree (No. 648 of 26th March 2002). This recent mining code undertakes a more integrated approach and is envisaged to include environmental regulations, incorporate community/local participation and provide transparency in terms of quantities extracted and financial revenues. Two main activities are addressed: artisanal and industrial mining. It also identifies two major types of resources; land based-solid materials (i.e. ore minerals, quarry products) and geothermal deposits (i.e. spring waters, mineral and thermo-mineral water). In consultation with officials, while not explicitly stated, sand extraction is considered as artisanal mining. Artisanal mining has the following characteristics:

• All deeds concerning Mining titles shall be recorded in a register referred to as ‘Mining Title Register’.
• Artisanal Mining authorization shall be valid for a period of two (2) years and its renewal is based upon the submission of an annual progress report and the strict compliance with the existing legal provisions and specifications.
• The area under exploitation shall have the shape of a quadrilateral whose sides shall not exceed one hundred (100) metres.
• Mining shall be done at a maximum depth of thirty (30) metres.
• Artisanal Mining authorizations shall submit an annual progress report to the competent Provincial Delegate in charge of Mines, describing their activities especially their output in tons or kilogrammes, the market value of the mineral substances or ores and the number of persons employed.
• Local council officials shall define locally the rate and mode of recovery of council taxes from artisans in accordance with the rules and regulations in force.
• Profit sharing to ensure the benefit of local communities commences with the recovery by the Public Treasury of fees, royalties, taxes on extracted products and ad valorem taxes based on declarations made by the Permit holder. These declarations are forwarded to the Divisional Delegate in charge of Mines.
• Proceeds from the ad valorem tax and tax on the extraction of are based on a formula which attributes financial benefits to the affected communities, the riparian populations, the relevant local council, the control team of the Ministry of Mines and the Public Treasury.
Artisanal mining requires permit holders are required to employ the best known techniques and methods to protect the environment. This effort among other elements includes:

- manage the use of the soil, water, the air as well as energy;
- protect fauna and flora;
- promote or maintain the general health of the population;
- restore damaged soils and sites to adequate stable conditions of safety, fertility and appearance acceptable to the Administrations in charge of Mines and the Environment.

Although these measures do not require an establishment of a formal environmental management plan, specifications defining preventive measures to be undertaken in order to ensure environmental protection shall be put in place in each area covered by one or several artisanal Mining licences. These specifications are conceived by the authorities in charge of the Environment in collaboration with the authorities in charge of Mines.

Related laws include the 1996 law on the environment and the 1998 law on water. Although these laws refer to the protection of resources, no reference has been made to sand mining in any form. Under the 1998 Water Law, the National Water Committee coordinates their actions. The committee is also responsible for proposing actions to the government to assure the conservation, protection and sustainable use of water Resources providing advice on water-related problems. Chaired by the minister in charge of water resources, the National Water Committee includes high-level representatives of major stakeholders involved in water management in Cameroon, including the ministries in charge of finance, public health, environment, land management, urban development and housing, agriculture, livestock and fisheries, commerce and industry, territorial administration and meteorology, as well as associations of mayors and concessionaires of public water and energy services. The National Water Committee was formed by decree in 1985 as a consultative body to coordinate activities in the water sector. It has met only infrequently and never fulfilled its intended role (UN Water/Africa, 2006).

### 4.3. Environmental effects

Sand mining is of immense economic benefit to the local population and the country. It provides employment to many and is a source of revenue to local councils and the nation. However, unsupervised exploitation in face of a growing demand can lead to many long term environmental problems that can affect the future of this resource. Sand mining operation may invoke profound ecological changes that could affect the
entire ecosystem. It can affect local ecology physically, biologically, and chemically. In this section, we present the problems that are inherent in the existing regulations:

**Area of exploitation:** The area covered by permits are carved out at the banks of the river, whereas exploitation takes place anywhere in the river. Measures to limit negative impacts can target sensitive ecological zones (i.e. breeding grounds etc), sand dunes that protects coastal lands from storms and cyclones. Benthic populations are at the greatest disadvantage. They are immobile and hence environmental impacts at local level are most harmful to these populations. During the process of mining, the functional ecosystem, whether natural or disturbed, is destroyed. Sand dune vegetation gets severely affected. Rehabilitation of coastal dunes following mining has been recommended by Lubke et al. (1996). They further suggest that rehabilitation after dune mining results in bare and shifting sand that requires stabilization and management. In the absence of such prohibitions, the result is that such areas are open to exploitation and can subsequently be damaged.

**Quantities of sand exploited:** Although the regulation attempts to quantify the amount of sand extracted, the reasons appear to be solely for calculating taxes and other financial burdens. In some countries, for instance India (Sonak et al, 2006), permit holders are issued passes, as a means of controlling quantities extracted. In Cameroon there is no limit on the amount of sand extracted. It has been shown that, one of the major indicators of environmental problems in sand dredging is the relationship between rates of extraction and the rate at which natural processes generated these materials. Results of this study shows that none of these elements are considered in the regulation; making this area highly vulnerable to over-extraction as many unemployed attempt to fight poverty. Some of the negative consequences of over-extraction includes; changes in stream morphology resulting in the collapse of stream banks and reduced stability of bridges. Of immense importance is the impact of a rise in seal level arising from climate change. Based on climate change prediction models (CICERO, 2000), the effects of inundation will be more important than erosion in the mangroves of the Cameroon estuary, since the zone is largely dominated by muddy coasts. The predicted sea level rise will contribute to an increased efficiency of wave erosion, leading to sediment removal from the upper part of the tidal spectrum and deposition in the lower part. Consequently, the few sandy beaches in the mangrove area could be destroyed. Increased sand extraction increases channel depth and reduces the effects of inundation. The study CICERO (2000) further identified the regulation of sand mining among others as an adaptation strategy to minimise the impact of climate change on mangrove forest ecosystems.
**Extractive methods:** A major tenet of the legislation is that sand extraction is artisanal implying that highly technical equipment is not used. The presence of some dredges and water pumps in a few sites is an indication that there is a move from traditional methods to more mechanised approaches (Figure 4b and c). In this study the output from such installations were higher. Noise, vibration and sediment disturbance from such techniques have a more intensive impact. Turbidity for instance, results due to particles of the mined deposit becoming suspended in the water column. Water turbidity has a variety of impacts, ranging from reducing biological productivity to smothering seabed benthos as the particles settle (Ellis 2001).

**Conflicts:** These operations and the resultant coastal erosion may have an adverse impact on the fishing communities on the coast. The encroachment by miners deprives fisher folk of the space they have used traditionally to land their catch and keep the fishing equipment. A most urgent problem advanced by councils (along the River Mungo) is that associated with the assignment of revenues paid into the Public Treasury. Since there is no specific condition that obligates the permit holder in which administrative unit (i.e. Region) to declare and pay his taxes. Some permit holders especially the high yielding sites make their declarations in the Douala Council; depriving councils where the affected communities are located from a much needed income. These disputes are yet to be resolved. There is a desperate lack of transparency in this sector with regards to the disclosure of amounts extracted. This leads to loss of revenue to the local councils and the government.

**5. Conclusion**

Approximately 300,000 tons of sand is extracted from the River Mungo annually. The method of extraction is gradually moving from more traditional/artisanal to mechanised type. The later is associated with higher disturbance of bottom sediments, increased noise and vibration and the generation of long lasting turbidity. These conditions among other things damage aquatic habitats and benthic organisms; destroy nesting grounds and are sources of psychological stresses in fish and other aquatic organisms. An important factor that determines the environmental sustainability of in-channel sand mining is the balance between extraction and sediment deposition rates. Under the present legislation and permitting system extraction rates are neither known nor are they controlled. Measures to prevent environmental damage should include the following:
• Demarcation of mining zones and clarification of mining concessions in relation to affected populations (i.e. councils to benefit);
• Proper implementation and follow-up of measures of record-keeping as stipulated in the law;
• Promote studies to generate information on the rate of sedimentation.

References


Extreme precipitation: how to use past measurements and climate projections for urban hydrologic design?
1. Introduction

Within the scope of the BMBF (German Federal Ministry of Education and Research) funded project dynaklim (www.dynaklim.de) a substantial effort has been undertaken to analyze potential modifications of precipitation in the Emscher-Lippe region (ELR), see among others Quirmbach et al. (2012) and Freistühler et al. (2012).

Within this project, numerous parameters, key values and time intervals have been investigated in order to obtain a detailed view of the projected climate change and its consequences for hydrology and integrated water management. These investigations include historical measurement data over the time period 1951 – 2010 as well as climate projection data of the regional climate model (RCM) CLM over the time period 1961 – 2100 (Hollweg et al., 2008; Lautenschlager et al., 2009). Two realizations of CLM were available for the project, both based on the A1B emission scenario. Additionally, results of a previous project (ExUS) on trends in precipitation measurement data in North Rhine – Westphalia (NRW) could be used (Einfalt et al., 2011; Quirmbach et al., 2012; Quirmbach et al., 2013) for the time interval 1951 – 2008.

This contribution focuses on the main results from time series and trend analysis, and two methods to provide precipitation data for design tasks which take into account trends of the RCM and their uncertainties. These data are a well founded base to be subsequently used by the different project partners in dynaklim, consisting of engineers, natural scientists, economists and sociologists in their impact models and the definition and interpretation of their adaptation strategies (Merkel et al., 2010; Frehmann et al., 2011).
2. Time series and trend analyses

Developments in time for the parameter precipitation are more complex than future developments for other parameters like temperature. Changes in the yearly precipitation amount and in the yearly distribution of precipitation do not allow for any conclusion for the development of extreme rainfall events. Such events depend on different weather types and thus generation processes which are only in part related to the yearly precipitation amount. Also for extreme events – there is a difference in the data between extremes in the order of once per year and rare extremes – there are differences to be observed in the trends that can be found in the extreme value statistics. For statistical evaluations, it has to be considered that any observed change may be due to several factors, among which are climate change, randomness of the sample and properties of the measurement device. These uncertainties in precipitation statistics based on measured data have to be considered when comparing to trends and statistics from climate projection data.

2.1. Precipitation measurement analysis

In the time interval 1951 – 2010, the measured monthly sums present a shift of the precipitation peak from July and August to September and October. Additionally, an increase of precipitation in the winter months can be observed (Figure 1, left). A comparable development has been observed for the whole region of North Rhine-Westphalia (NRW). This resulted in constant precipitation levels in summer and a substantial increase in the winter months as well as for the yearly sums (Figure 1, right).

Relevant for design in urban hydrology is the development of short and extreme precipitation events. From the measurement data, an increase both in number of events and in average event sum could be observed. Figure 2 illustrates this for the duration of \( D = 60 \text{ min} \), relevant for urban hydrology. Other durations show a similar behavior.
For shorter duration than one hour effects from measurement instruments has to be considered: former technologies were not always able to provide the full temporal resolution of the occurred precipitation (Einfalt et al., 2011).

Small heavy rainfall events with a return period of up to \( T \approx 2 \) a (the classes up to \( N < 40 \text{ mm/d} \)) showed an increase of heavy rainfall events since 1991. On the other hand, no significant trend could be derived for extreme values of rainfall. The randomness of rare heavy rainfall events occurring within one of the samples had a significantly higher influence on the frequency estimation of heavy rainfall events than the climate change signal.

For short time intervals (\( D \leq 1 \text{d} \)) the frequency of heavy rainfall was additionally examined by series of rainfall over threshold and the precipitation amount of heavy rainfall by annual series. Here it became apparent that for all short time intervals, on average both the frequency as well as the precipitation amount of heavy rainfall increased significantly across all 14 time series. Figure 2 shows both the development of the number of heavy rainfall events per year (series of rainfall over threshold) and the development of the mean level of yearly maximum rainfall totals (annual series) for the duration \( D = 60 \text{ min} \).

![Figure 2](image)

Figure 2  (a) Mean number of heavy rainfall events per year for \( D = 60 \text{ min} \) in the ELR  (b) Mean level of yearly maximum rainfall totals for \( D = 60 \text{ min} \) in the ELR

An analysis of daily precipitation sums shows that mainly the number of events increased with a return period up to \( T \approx 2 \) a (Figure 3) corresponding to daily sums up to 40 mm. The frequency of extreme events did not change – even if media want to suggest something else.
As a consequence, no general increase of the statistically determined precipitation amounts (DWA, 2012) can be found in the results of the statistical analysis on basis of the series over threshold (Figure 4). Here, moving time windows of 30 years between 1951-2010 exhibit a higher variation between decades than the resulting differences from a comparison of the earlier (1951–1980) and the later 30 year period (1981–2010), as well as compared to the complete duration. Figure 4 shows that this is valid for short (left) and long time steps (right).

Figure 4  Development of the statistically determined precipitation amounts for the examined return periods $T$ in the ELR; left: duration $D = 60$ min; right: duration $D = 24$ h.

3. Precipitation analysis from climate projections (CLM regional climate model)

Analyzing the regional climate model CLM on monthly values shows for ELR no further shift on monthly sums until the middle of the century (2021–2050) while maintaining a slight increase in the yearly sums. In the second half of the century, the model provides a
shift of summer precipitation into the winter season, while maintaining the yearly sums. The same behavior can be observed with seven other simulations, based on different RCMs and SRES scenarios, all of them fed by ECHAM5 as driver (Figure 5).

Figure 5  Modification of monthly precipitation sums based on the results of seven simulation runs for ELR: left: 2021 – 2050 vs. 1961 – 1990; right: 2071 – 2100 vs. 1961 – 1990

Since the hourly values from CLM have proven to be insufficient to represent short, extreme events, the statistical analysis of CLM relies on daily values only. Based on the results for measurement data and the comparability of trends for short and long duration steps, as discussed in the previous section, the assumption can be made that the trends in daily sums within CLM are approximately representative for future trends of shorter durations.

As a difference to measured data, CLM model data increase also for moderately extreme events, in the order of return periods between $T = 5 \ a - 20 \ a$, according to statistics based on the measured data pool. Because of an increase in number of rare extreme events, the statistically derived precipitation sums are also increasing.

Figure 6 (upper left) shows that the recurrence probability of daily measurement values and CLM1 model data is nearly identical for the time period 1961 – 1990. In this figure, the recurrence interval $n$ ($n = 1/T$) is used instead of the return period $T$. The same evaluation for CLM run 2 however results in a difference of 10 – 20% where the CLM model data are higher (Figure 6, upper right). These values are at the upper limit of the confidence interval for statistical extreme values as defined by KOSTRA-DWD-2000 (DWD, 2005). The confidence interval is depicted by the grey lines. Thus, the extreme values of CLM2 are within the confidence limits i.e. cannot be considered as a change in extreme value statistics.

For the time period 2021 – 2050, the situation is different: here, both CLM model runs provide results beyond the confidence limits (CLM1: Figure 6, lower left; CLM2: Figure 6, lower right). Contributing to the difference are the potential climate change signal, and
the uncertainty of the KOSTRA statistics. A clear statement about the contribution parts of both effects is not possible. For extreme value statistics, a confidence interval of 10 – 20% as function of the return period is normal and due to the inherent uncertainties of the procedure. Only changes beyond this limit can be considered as contribution due to climate change (light blue area in Figure 6, lower left and light red area in Figure 6, lower right).

Figure 6 Comparison of the statistically determined precipitation amounts for varying return frequencies allowing for a tolerance zone for natural precipitation variability, (a) CLM1 (1961 - 1990) vs. measured data (1961 - 1990); (b) CLM2 (1961 - 1990) vs. measured data (1961 - 1990); (c) CLM1 (2021 - 2050) vs. measured data (1961 - 1990); (d) CLM2 (2021 - 2050) vs. measured data (1961 - 1990)

4. Use of climate projection data for urban hydrologic design

Rainfall-runoff modelling for sewer systems and for modelling of natural water courses requires precipitation data with a high spatial and temporal resolution. In its first part, this section presents a method to perform downscaling on CLM model data to achieve a spatial resolution of 1 x 1 km and a temporal resolution of 5 minutes, due to the use of radar data. The resulting time series can be used for continuous long term simulation and for event series simulation.
Some applications have a very high computational demand and therefore cannot use these downscaled data. Here, design storms derived from statistical precipitation analysis can be used. In the second part, this section presents such a pragmatic approach to use the climate change signal to modify a given design storm, as well as the associated uncertainties when using this approach.

4.1. Downscaling of regional climate model data

4.1.1. Method
The basis for the downscaling procedure were corrected and adjusted data from radar Essen (DWD, 1km x 1°, 5 min, DX-product) from Nov 2001 - Nov 2009 (Frerk et al., 2012). In addition, daily classifications into objective weather types for the measurement period of the DWD were used (Bissolli and Dittmann, 2001). Data from the regional climate model CLM, based on the global circulation model ECHAM5, were provided by the Climate Service Center (Lautenschlager et al., 2009): run 1 and run 2 for 1961-2000 (“C20”) and 2001-2100 (scenario A1B). Objective weather types for the ECHAM-CLM data (Krahé et al., 2011) were also employed.

The area used for the downscaling was chosen due to similar orographic conditions and precipitation characteristics and comprises 10 CLM grid points in the Emscher-Lippe Region. For three catchments near Dortmund, Duisburg and Bönen (area size of each catchment: 70-76 km²) high resolution data sets should be produced for the reference period (1961-1990), near and far future (2021-2050, 2071-2100). Trend analysis of CLM precipitation in the region has been done by Freistühler et al. (2012). They found positive future trends for daily and sub daily heavy precipitation.

The presented statistical downscaling procedure combines the analogue method (Zorita and Storch, 1999) with a weather type approach. A schematic overview of the
procedure is given in Figure 7. Daily sums from the CLM model were bias corrected with a quantile mapping method (Piani et al., 2010). To account for the characteristics of the model precipitation as area means, the bias correction was done using radar based areal precipitation for the CLM grid points. In this way, the bias correction differs from the correction based on rain gauge data described by Quirmbach et al. (2012). As RCM values of single grid points do not necessarily reflect the regional mean, probability density functions (PDFs) of 10 neighbouring CLM grid points were determined, and the time series of the grid points covering the selected catchments were modified to match the mean PDF.

The modification of the daily sums was followed by the selection of historical analogues from the period 1 Nov 2001 – 1 Nov 2009. “Similar” days to a model day were selected, defined through the same objective weather type and a similar 24h precipitation sum from the radar data. From the number of historical events satisfying these criteria, one was randomly selected. If no suitable event was found, neighbouring objective weather types were included, and the permitted precipitation difference was increased (to a maximum of 4mm). In order to enlarge the database, a displacement of the radar data within the 10 CLM grid points of the research area was performed.

The selection process was done for each 30 year period. Using the full resolution of the radar data of the selected events, time series for the catchments were generated, constructing data sets with spatial resolution 1kmx1km and time step 5min.

![Figure 8](extreme_precipitation.png)  
*Figure 8*  
*Extreme precipitation (duration 1h, return period 5a) in the reference period from 28 stations and from the downscaling results within the catchments; catchment size is 70-76 km².*
4.1.2. Downscaling results

Extreme precipitation of the high resolution data sets was analyzed. Figure 8 shows results of the extreme precipitation in the reference period (duration 1h, return period 5a) in comparison to observations of 28 quality controlled rain gauge stations in the research area. The downscaling results show a notable variability between the radar pixels within the catchments with a mean standard deviation of ±2.4mm. The absolute mean from the stations (22.7mm) is higher than the mean values of the downscaling results: 19.7mm/ 20.5mm (CLM 1/ CLM 2). This discrepancy can be explained by different characteristics of the radar data (1km² area means), employed for the downscaling, compared to rain gauge measurements (point values). Scheibel et al. (2012) found a similar difference between radar and rain gauge extreme values when analyzing data from 2001-2010 for the Wupper area.

Future extreme precipitation trends are displayed in Figure 9. Trends are mostly positive and range from 5% to +32% compared to the reference period. Mean trends are +18.8%/ +16.4% (CLM 1/ CLM 2) for the near future and +16.4%/ +8.8% for the far future.

The applicability of the high resolution data as input for hydrological models was tested with a model of the Rossbach catchment (Dortmund). Results for the reference period were found to be satisfying in comparison to a model run driven by observations.
5. Use of the climate change signal for urban hydrologic design

This simplified approach makes use of the comparison between measured data and CLM model results for the period 1961 – 1990 for an assessment of the potential bandwidth of future changes of design rainfall. It is taking into account that the changes may result from the climate change signal as well as from the bandwidth of the KOSTRA statistics. For run 1 of the CLM data, the assumption is that there is no clear possibility to separate these two contributions. An increase of values within the confidence interval defined by KOSTRA is considered as being random, whereas values beyond these limits are interpreted as climate change signal (Table 1, line 1).

Since the precipitation values of run 2 of the CLM data is already at the upper limit of the confidence interval for the reference period, all future increases are interpreted as climate change signal (Table 1, line 2). Both runs can therefore be considered to represent the bandwidth of changes which can be obtained from the CLM model runs.

In order to take into account a superposition of a climate trend effect and an unfavourable statistical choice at the upper confidence limit, the “extreme” scenario has been defined: to simulate this effect, the trend from CLM1 data for 2021 – 2050 has been used without taking into account the confidence interval of the extreme value statistics of KOSTRA. Thus, this scenario is a “worst case” scenario, based on the available RCM data (Table 1, line 3).

The opposite extreme scenario is the “zero change” scenario, assuming that the measured precipitation in the time interval 1961 – 1990 was higher than average, and that an increase in precipitation from the climate projection would not be representative. Thus, no change in precipitation statistics would be expected (Table 1, line 4).

Table 4: Projected increase of statistically derived precipitation sums for the near future (2012 – 2050) as compared to the reference period (1961 – 1990)

<table>
<thead>
<tr>
<th>T</th>
<th>1 a</th>
<th>3 a</th>
<th>5 a</th>
<th>20 a</th>
<th>25 a</th>
<th>50 a</th>
<th>100 a</th>
</tr>
</thead>
<tbody>
<tr>
<td>CLM1</td>
<td>9 %</td>
<td>16 %</td>
<td>18 %</td>
<td>15 %</td>
<td>17 %</td>
<td>18 %</td>
<td>14 %</td>
</tr>
<tr>
<td>CLM2</td>
<td>11 %</td>
<td>8 %</td>
<td>8 %</td>
<td>8 %</td>
<td>8 %</td>
<td>7 %</td>
<td>7 %</td>
</tr>
<tr>
<td>Extreme</td>
<td>19 %</td>
<td>26 %</td>
<td>28 %</td>
<td>30 %</td>
<td>32 %</td>
<td>33 %</td>
<td>34 %</td>
</tr>
<tr>
<td>Zero</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>no changes in statistically determined precipitation amounts</td>
</tr>
</tbody>
</table>
In order to produce design rainfall taking into account a potential future trend in extreme precipitation, a factor is applied to the extreme values statistics of the reference period. This factor is given in Table 1 for each of the scenarios and return periods, assuming that there is no further differentiation for different durations. The resulting design storms can be used in impact models to analyze the spectrum of climate change effects to be expected within the plausible bandwidths given by the CLM climate projections and the historical extreme value statistics. To assess the impact of the percent values in Table 1 it should be remembered that an increase of 10% is equivalent to a reduction of the return period by 50%, i.e. an event occurring every 100 years would then statistically occur every 50 years.

Summary
In the scope of dynaklim, application oriented project partners required analysis results on future climate developments and associated design data consistent with the analysis. Extensive analyses of measurement data and climate projection data for the parameters precipitation and temperature provided a solid base for such work. The application oriented project partners could apply the data to their impact models and draw conclusions for the historical time period as well as for the projected time period and assess the associated uncertainties. This yields results which provide information on potential adaptation strategies.

Thus, the extensive analysis of measured and projected climate variables provided the necessary continuous time series and design storms for use in subsequent impact models representing the bandwidth of the trends obtained through the analysis.

References


Rainfall Analysis for the Schoeckelbach Basin (Austria) and Determining its Best-Fit Probability Distribution Model

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Abstract
The aim of this paper is to determine the best-fit probability distribution for the rainfall data in the Schoeckelbach basin which is situated at the northern Graz in Austria. In order to determine the probability of occurrence of any rainfall event, the frequency distribution, which can fit the past characteristics on the magnitude and the probability of occurrence of such rainfalls, should be known. In this paper, in order to find the best-fit probability distribution model, a parameter estimation technique (L-moments method) is used and for goodness of fit test, three methods are used as Chi-Square, Kolmogorov-Smirnov and the root mean square error (RMSE). In this paper, a comparison between four commonly used rainfall frequency distributions are carried out such as Generalized Extreme Value (GEV), Gumbel, Log-Pearson type III (LP III) and 3-parameter Log-normal (LN III). The results are shown that the best-fit probability distribution for the Schoeckelbach basin is Gumble’s distribution. This best-fit probability distribution can be used to determine the Intensity-Duration-Frequency relation (IDF) for the Schoeckelbach basin.

1. Introduction

Rainfall analysis is the first step to determine the rainfall event in many hydrologic design projects. In fact, it is necessary to understand rainfall processes and the significance of the rainfall design data to prepare satisfactory drainage and storm water management projects.

One of the most important parts of a rainfall analysis is Intensity-Duration-Frequency (IDF) analysis. For this reason, the annual extreme data is fitted to a proper probability distribution model in order to estimate rainfall quantities. In order to obtain the best-fit probability distribution model, the parameters for a few commonly used rainfall analysis distributions should be estimated and then the best-fit probability distribution could be selected among these probability distributions. In this paper L-moments method, which was introduced by Hosking (1990), is used.
Also for goodness fit analysis, three methods are used as Chi-Square, Kolmogorov- Smirnov and the root mean square error (RMSE) method. After these analyses, it is possible to choose the best fit probability distribution. This probability distribution model is necessary because the fitted distribution can not only be used to interpolate, but also to extrapolate for finding return periods of extreme values that were not apparent during the relatively short period of observation.

2. L-moments method

L-moments is a linear combination of probability weighted moments [Greenwood et al. 1979] which computed from data values:

\[ b_n = \frac{1}{n} \sum_{i=1}^{n} X_i \]  

\[ b_r = \frac{1}{n(n-1)} \sum_{i=r+1}^{n} \frac{(i-1)(i-2)...(i-r)}{(n-1)(n-2)...(n-r)} X_i \]  

In which \( X_1, X_2, ..., X_n \) are arranged in increasing order and \( n \) is the number of sample data. The first few L-moments are defined as:

\[ L_1 = b_0 \]  

\[ L_2 = 2b_1 - b_0 \]  

\[ L_3 = 6b_2 - 6b_1 + b_0 \]  

\[ L_4 = 20b_3 - 30b_2 + 12b_1 - b_0 \]  

Now by dividing the higher order L-moments by the dispersion measure \( L_2 \), the L-moment ratios can be obtained as follows:

\[ \tau_2 = \frac{L_2}{L_1} \]  

\[ \tau_3 = \frac{L_3}{L_2} \]  

\[ \tau_4 = \frac{L_4}{L_2} \]  

In this paper, daily rainfall data which have been recorded for 66 years were used for the analysis. The annual extreme values are shown in Figure 1.
3. Parameter estimation using L-moments method

In this paper, L-moments method is used to estimate the parameter of four selected distributions as (a) Gumbel, (b) Generalized Extreme Value (GEV), (c) Log-Pearson type III (LP III) and (d) 3-parameter log-normal (LN III) distributions. Table 1 summarizes the distribution parameters. In this Table, $\gamma$ is the location parameter that defines the point where the support set of the distribution begins, $\mu$ is the scale parameter that stretches or shrinks the distribution, $\sigma$ is the shape parameter that affects the shape of the distribution, $R_n$ is the Tr-year return precipitation and $I$ is the Gamma function. The optimized distribution parameters were computed for each distribution and they are shown in Table 2.
Table 1: Distribution parameters using L-moments method.

<table>
<thead>
<tr>
<th>Distribution</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gumbel</td>
<td>( R_{Tr} = \gamma + \mu Y_{Tr} )  \  ( \gamma = L_1 - 0.5772 \mu )  \  ( \mu = \frac{L_2}{\log 2} )  \  ( Y_{Tr} = -\ln \left( -\ln \left( \frac{Tr - 1}{Tr} \right) \right) )</td>
</tr>
<tr>
<td>GEV</td>
<td>( R_{Tr} = \gamma + \frac{\mu}{\sigma} \left( 1 - \left( -\log \left( \frac{Tr - 1}{Tr} \right) \right) \right) )  \  ( \sigma = 7.8590c + 2.9554c^2 )  \  ( c = \frac{2}{3 + \tau_3} \frac{\ln 2}{\ln 3} )  \  ( \mu = \frac{L_3 \sigma}{\left( 1 - 2^{-\sigma} \right) \Gamma \left( 1 + \sigma \right)} )  \  ( \gamma = L_1 - \frac{\mu \left( 1 - \Gamma \left( 1 + \sigma \right) \right)}{\sigma} )</td>
</tr>
<tr>
<td>LP III</td>
<td>( \mu = L_1 )  \  ( \gamma = \frac{2}{\sqrt{\alpha}} \text{sign} (\tau_3) )  \  ( \sigma = \frac{L_2 \Gamma (\alpha) \sqrt{\pi \alpha}}{\Gamma (\alpha + 0.5)} )  \  if ( 0 &lt;</td>
</tr>
<tr>
<td>LN III</td>
<td>Refer to [Yuanfang et al. 2004]</td>
</tr>
</tbody>
</table>
Table 2: The optimized distribution parameters.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>GEV</th>
<th>Gumbel</th>
<th>LP III</th>
<th>LN III</th>
</tr>
</thead>
<tbody>
<tr>
<td>γ</td>
<td>46.044</td>
<td>46.401</td>
<td>2.6549</td>
<td>25.475</td>
</tr>
<tr>
<td>μ</td>
<td>11.473</td>
<td>11.841</td>
<td>0.05616</td>
<td>3.1774</td>
</tr>
<tr>
<td>σ</td>
<td>0.04801</td>
<td>-</td>
<td>22.849</td>
<td>0.55143</td>
</tr>
</tbody>
</table>

In the next step, the goodness of fit tests should be done. The goodness of fit of a statistical model describes how well it fits a set of observations. Measures of goodness of fit typically summarize the discrepancy between the observed values and the values expected under the model in question. Such measures can be used in statistical hypothesis testing such as to test for normality of residuals (RMSE test, [Haan, 2002]), to test whether two samples are drawn from identical distributions (Kolmogorov-Smirnov test, [Seckin et al., 2010]) or whether outcome frequencies follow a specified distribution (Chi-squared test, [Seckin et al., 2010]).

3.1. Chi-Squared test
The Chi-Squared statistic is defined as:

$$\chi^2 = \sum_{i=1}^{k} \left( \frac{O_i - E_i}{E_i} \right)^2$$ \hspace{1cm} (10)

where $O_i$ is the observed frequency for bin $i$, and $E_i$ is the expected frequency for bin $i$ calculated by:

$$E_i = F(x_2) - F(x_1)$$ \hspace{1cm} (11)

where $F$ is the cumulative distribution function of the probability distribution being tested, and $x_1, x_2$ are the limits for bin $i$.

3.2. Kolmogorov-Smirnov test
Assume that there is a random sample $x_1, \ldots, x_n$ from some distribution with cumulative distribution function $F(x)$. The empirical cumulative distribution function is denoted by:

$$F_n(x) = \left[ \frac{N \leq x}{n} \right]$$ \hspace{1cm} (12)

In which $N$ is the number of observations. The Kolmogorov-Smirnov statistic ($D$) is based on the largest vertical difference between the theoretical and the empirical cumulative distribution function:

$$D = \max_{1 \leq i \leq n} \left[ F(x_i) - \frac{i-1}{n}, \frac{i}{n} - F(x_i) \right]$$ \hspace{1cm} (13)
3.3. The Root Mean Square Error (RMSE) test

The RMSE is calculated using the following relation [Haan 2002]:

$$RMSE = \left( \frac{\sum_{i=1}^{n} (R_{Mi} - R_i)^2}{n - m} \right)^{0.5}$$

(14)

In which, $R_{Mi}$ is the modeled rainfall depth (using fitted probability distribution), $R_i$ is the $i^{th}$ observed rainfall depth, $n$ is the number of data and $m$ depends on the number of parameters in the fitted probability distribution (for LP III, LN III and GEV are 3 and for the Gumbel distribution is 2).

4. The best-fit probability distribution

In this paper, these three tests are carried out on the data and the results are shown in Tables 3 and 4.

Table 3: The results of the goodness fit tests.

<table>
<thead>
<tr>
<th>Distribution</th>
<th>Chi-Squared Value</th>
<th>Rank</th>
<th>RMSE Value</th>
<th>Rank</th>
<th>Kolmogorov-S. Value</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gumbel</td>
<td>0.87164</td>
<td>1</td>
<td>2.04</td>
<td>1</td>
<td>0.10534</td>
<td>4</td>
</tr>
<tr>
<td>GEV</td>
<td>2.7235</td>
<td>3</td>
<td>10.22</td>
<td>3</td>
<td>0.09448</td>
<td>2</td>
</tr>
<tr>
<td>LN III</td>
<td>2.9641</td>
<td>4</td>
<td>6.18</td>
<td>2</td>
<td>0.08165</td>
<td>1</td>
</tr>
<tr>
<td>LP III</td>
<td>2.6844</td>
<td>2</td>
<td>14.40</td>
<td>4</td>
<td>0.09764</td>
<td>3</td>
</tr>
</tbody>
</table>

As it can be seen Table 3, the results are a little complicated because the results of the Kolmogorov-Smirnov test are very close to each other for different distributions and their ranks in this test are very different with Chi-Square method and a little with RMSE method. This Table also described that the Gumble distribution is the best-fit distribution in both Chi-Square and RMSE tests. Also, the results of Chi-Square test are shown that the values for LN III, GEV and LP III are much closed whereas the value for Gumbel distribution is very smaller than the others (also in RMSE method).

As a final comparison, the box-plot for sorted observed rainfall and all modeled rainfalls with various distributions are plotted in Figure 2. As this Figure shows, the Gumbel distribution is completely fitted the observed data whereas the LP III is almost far from the observed data especially for the maximum and minimum values in the sorted data. GEV and LN III are almost fitted the observed data but LN III gave the smaller values and
GEV gave greater values. Due to this reason, GEV is better than LN III and finally these distributions are ranked as they are shown in Table 4.

Table 4: The final decision rank.

<table>
<thead>
<tr>
<th>Distribution</th>
<th>Final decision</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gumbel</td>
<td>1</td>
</tr>
<tr>
<td>GEV</td>
<td>2</td>
</tr>
<tr>
<td>LN III</td>
<td>3</td>
</tr>
<tr>
<td>LP III</td>
<td>4</td>
</tr>
</tbody>
</table>

Figure 2 Box-plot for daily observed data and for all distributions.
5. Statistical Confidence limit

A confidence analysis is used in statistical analysis to represent the uncertainty in an estimate of a curve or function based on limited or noisy data. The confidence limits are expressed as follow [Mahdavi 2003]:

\[ X_{Tr,u} = X_{Tr} + S \Delta X \] (15)
\[ X_{Tr,l} = X_{Tr} + S \Delta X \] (16)

in which \( X_{Tr} \) = \( R_{Tr} \) (the Gumbel distribution parameter) and \( \Delta X = \frac{\alpha \sigma}{\sqrt{n}} \).

Also \( \alpha = \sqrt{1+1.3K+1.1K^2} \) where \( S \) is a constant (for 90% confidence \( S=1.645 \)), \( \sigma \) is the standard deviation, \( n \) is the number of data, \( K=\mu \) is the Gumbel parameter and \( X_{Tr,u} \) and \( X_{Tr,l} \) are the upper and lower confidence limits respectively for the return period of \( Tr \).

Based on these equations, a 90% confidence analysis is constructed and the final result is shown in Figure 3. This diagram indicates that the best-fitted probability distribution (Gumbel) is suitable for all observed data and they situated completely between 90% confidence limits.

**Figure 3** Confidence analysis (90%).
Now, this best-fit probability distribution can be used to determine the IDF relation which is necessary in rainfall-runoff modeling of the Schoeckelbach basin.

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References


Hydrological Extremes

Technological and social adaptation to extreme water hazards
A Fundamental Impact Analysis of Prior Release Operation for Flood Management Based on Inflow Prediction at a Multi-Purpose Reservoir

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Abstract

A method for impact analysis of a reservoir’s prior release operations precedential to arrival of floods is developed as a fundamental study in this paper. A Monte Carlo simulation model of a reservoir’s prior release operation coupled with an artificial generation model of inflow predictions is proposed here. The inflow predictions are generated with random errors based on given accuracies of the prediction in order to make it possible to investigate impacts of inflow prediction’s accuracy on the effectiveness of prior release operations. Impacts of prior release operations on flood mitigation and water storage for water utilization are then analyzed and discussed through the proposed simulation model for assumed reservoir operations which are derived from an existing multi-purpose reservoir in Japan.

Keywords

reservoir operation, prior release operation, Monte Carlo simulation, simulated generation of inflow prediction

1. Introduction

Flexible operation of multi-purpose reservoirs is an important issue as it can improve the abilities of the reservoirs without constructing new reservoirs. Prior release operation, which releases storage water from the reservoir in advance of flood situation, is considered as such a flexible and effective way for flood management especially for multi-purpose reservoirs, as it can provide larger empty storage volume during floods while it allows to keep reservoir water level as high as possible for water use purposes except for the case of flood situation. The operation, however, may cause negative impacts for water use purposes by releasing water, which should originally be reserved for water use purposes, when the decision of prior release is made considering hydro-meteorological predictions which have some uncertainty in nature.

Many articles have proposed and discussed advanced reservoir operation methods
for flood control including prior release operation. Hsu and Wei (2007) developed a reservoir real-time operation model for flood control considering precipitation forecast during typhoon invasion. Shimosaka et al. (2009) proposed the flood control method by operating dam gates based on the expected total amount of inflow, which was calculated by the observed rainfall or inflow at the target reservoir catchment. Mitsuishi et al. (2011) verified efficiencies of prior release operation considering rainfall forecast estimated by the Weather Research and Forecasting Model (WRF), which is one of the mesoscale climate models. They showed that introducing prior release operation with rainfall prediction by WRF was capable to yield improvement in flood mitigation although it had some risks in both flood control and water use because of errors contained in the rainfall prediction. Usutani and Nakatsugawa (2010) proposed a method of prior release operation during the snowmelt season based on forecasted cumulative rainfall. Kitada et al. (2010) proposed a flood control method which considers rainfall prediction in addition to the flood control method proposed by Shimosaka et al. (2009) to reflect more foresight on the future inflow to decision making in the flood control operation.

These studies, however, analyzed the impacts by prior release operation considering only actual predictions provided by specific rainfall prediction model. The relationship between accuracies of predictions and the impacts of prior release operation should be analyzed statistically based on many prediction cases generated from the same characteristics of accuracy because the uncertainty which hydro-meteorological predictions have in nature is not able to be analyzed by only a single prediction case. Moreover, the risk and effectiveness for both of water utilization and flood control introduced by prior release operation also depend on the accuracy of referred predictions. Thus, impact analysis of employing prior release operation on the water use purposes should also be carefully and comprehensively conducted in order to design operation rules for more secure and effective prior release operation considering inflow prediction.

This paper, therefore, proposes a Monte Carlo simulation model of prior release operation coupled with an artificial generation model of inflow predictions in order to make it possible to statistically analyze the impacts of prior release operation. The simulation model can generate inflow predictions with random errors based on given accuracies of the prediction so as to enable to investigate impacts of inflow prediction's accuracy on the effectiveness of prior release operations. Impacts of prior release operations considering the inflow prediction on flood mitigation and water storage for water utilization are then analyzed and discussed by use of the proposed simulation model for assumed reservoir operations, which are derived from an existing multi-purpose reservoir in Japan.
2. Methodology

2.1. Outline of the proposed method for impact analysis

In this study, a simulation model of prior release operation coupled with an artificial generation model of inflow predictions with given error characteristics is developed, and impacts of prior release operation on water utilization and flood control are analyzed. As a hydrological prediction, not rainfall but inflow prediction is applied in this study so as to eliminate uncertainty generated by runoff modeling to transform rainfall predictions to inflow predictions.

The flow of the impact analysis method using the simulation model is described as follows (see also Figure 1). First, hourly inflow predictions are artificially generated with one hour time resolution through a certain lead time of the prediction (denoted as L hereafter) by respectively adding errors to the true values of inflow. The errors are randomly generated based on their assumed stochastic characteristics, which can be changed so that the predictions can have various given accuracies. Decision for starting a prior release operation is then made based on generated inflow predictions and operation rules of the target reservoir. If designed criteria to start prior release operation are fulfilled, prior release operation is conducted, otherwise water release for water use purposes is continued as water use operation. The reservoir operation is shifted to the flood control operation if an observed inflow exceeds a value to start the flood control operation. One simulation has finished by carrying out this process through the analysis period (T). Impacts of prior release operation considering inflow predictions with a specific stochastic characteristic relevant to prediction's accuracy can be analyzed by carrying out this simulation for the prescribed simulation times (I) and then analyzing the results of these simulations comprehensively. Furthermore, impacts of prior release operation based on the inflow predictions in various accuracies can be analyzed by conducting these simulations changing the stochastic characteristic of inflow prediction.

2.2. Generation method of artificial inflow predictions

Takeuchi (1990) mentioned two types of method to describe prediction's accuracy. One is a method that defines prediction's accuracy as the difference between predictions and true values (e.g. Lettenmaier, 1984; Datta and Burges, 1984; Sivaarthitkul, 1995). This method can easily describe that accuracy of prediction is getting lower as lead time of prediction is longer. The other is a method that
defines prediction’s accuracy as a degree how a prediction is changed from the one provided at the previous time. This method can describe that the degree of prediction’s change is larger as the accuracy of prediction becomes lower. Because the relationship between prediction lead time and accuracy of prediction is considered to be important in analyzing the efficiencies of prior release operation, the former description is adopted in this paper to model predictions’ accuracy.

Specifically, inflow predictions are generated by adding a value randomly generated as an error, which is assumed to follow a normal distribution with the mean of zero, to the observed value of inflow. Inflow predictions are generated with hourly time resolution for the coming $L$ hours every hourly time step. The AR(1) model (William, 1990) is employed as the generating model of a predicted inflow sequence at each time step in this study, supposing that errors of predictions have the first-order autocorrelation in a sequence of prediction’s errors provided at a time (see also Figure 2). The error of the prediction provided at time step $t$ for $l$ hours ahead $e(t, l)$ is defined by the following equation:

$$e(t, l) = e(t, l-1) \cdot \rho_L(1) + r(t, l) \cdot \sqrt{1 - \rho_L(1)^2} \quad (2 \leq l \leq L, \quad 1 \leq t \leq T)$$

(1)

where $\rho_L(1)$ is auto correlation coefficient of errors in a sequence of the prediction, and $r(t, l)$ is a value generated at random, respectively. The probability distribution followed by $r(t, l)$ is defined as follows:
\[ r(t, l) \in N(0, \{c_e(l) \cdot I_o(t + l)\}^2) \]

where \(c_e(l)\) is a coefficient for describing the relationship between accuracy of prediction and lead time, \(I_o(t+1)\) is the true value at time \((t + 1)\).

Generally, it is considered to get more difficult to predict future hydrological variables as the lead time of the prediction becomes longer. Considering this characteristics in the prediction accuracy, the errors of predictions are supposed to increase as lead time becomes longer, for a fundamental discussion. In order to make discussions as simple as possible, the prediction accuracy is assumed to increase linearly as lead time becomes longer in this study, although some can assume non-linear increase which would be more complicated. The coefficient for representing the above mentioned relationship between accuracy of prediction and lead time \(c_e(l)\) can be defined by the following equation:

\[ c_e(l) = \alpha l \quad (1 \leq l) \]

where \(\alpha\) is a parameter which represents the degree of degradation in prediction accuracy as lead time becomes longer. This expression enables to arbitrarily change the accuracy of generated prediction by changing the value of \(\alpha\). The value of the prediction error generated for the next time step at each time step \(e(t, 1)\) is determined by randomly sampling from the normal distribution \(N(0, \{c_e(1) \cdot I_o(t + 1)\}^2)\). The prediction conducted at time step \(t\) for \(l\) hours ahead \(I_o(t, l)\) is defined by the following equation.

\[ I_o(t, l) = I_o(t + 1) + e(t, l) \]

2.3. Scheme of the prior release operation considering inflow prediction

It is defined in this paper that operation of prior release is determined when a value greater than a criterion given by the operation rule to start the prior release operation (denoted by “flood control inflow” hereafter) is predicted.

Water level of reservoir is lowered to a prescribed elevation as soon as possible by the time flood control operation should start, without exceeding a prescribed flood control inflow as well as a release increase rate, which is prescribed by the operation rule of
the reservoir not to threaten the downstream area with an artificial flood caused by a rapid increase in water release. After completion of lowering elevation by prior release operation, the water level of the reservoir is maintained. If a flood goes over (in other words, if observed inflow becomes lower than flood control inflow after the peak of inflow), all the flood control operations are finished, and reservoir operation is shifted to water use operation.

3. Case study

3.1. Applied reservoir and simulation setting
The proposed simulation model was applied for Kamafusa Reservoir, which is located in the Natori River basin in North East Japan. Specification of Kamafusa Reservoir is shown in Table 1. At Kamafusa reservoir, flood control operation starts when the inflow exceeds the flood control inflow, which is defined as 300m³/s by the operation rules at Kamafusa Reservoir. Water releases at constant rate to the inflow by the time an inflow peak arrives (see also Period (i) shown in Figure 3). The release q_{out} (m³/s) is defined as the following equation:

\[ q_{out} = (q_{in} - 300) \times 0.407 + 300 \]  

(5)

where q_{in} is inflow (m³/s), and maximum of the release q_{out} is defined as 850 m³/s. After the inflow peak arrives, the release is maintained (see also Period (ii) shown in Figure ). The water level is lowered if the water level exceeds the prescribed water level after the flood.

The storage capacity for flood control is fixed as 21,000,000 m³ from July 1st to September 30th (this period is defined as the flood period) as the period is generally the rainy season on the Pacific side of North East Japan where the Kamafusa Reservoir locates.
Table 1: Specification of Kamafusa Reservoir

<table>
<thead>
<tr>
<th>Specification</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total storage capacity</td>
<td>45,300,000 m³</td>
</tr>
<tr>
<td>Active storage capacity</td>
<td>39,300,000 m³</td>
</tr>
<tr>
<td>Flood season (Jul.1st-Sep.30th)</td>
<td></td>
</tr>
<tr>
<td>Dry season (Oct.1st-June.30th)</td>
<td></td>
</tr>
<tr>
<td>Water use capacity</td>
<td>18,300,000 m³</td>
</tr>
<tr>
<td>Flood control capacity</td>
<td>21,000,000 m³</td>
</tr>
<tr>
<td>Designed maximal inflow</td>
<td>1650 m³/s</td>
</tr>
<tr>
<td>Designed release discharge</td>
<td></td>
</tr>
<tr>
<td>Before earthquake</td>
<td>850 m³/s</td>
</tr>
<tr>
<td>After earthquake</td>
<td>600 m³/s</td>
</tr>
<tr>
<td>Maximum release discharge during no flood situation</td>
<td>300 m³/s</td>
</tr>
<tr>
<td>Total release discharge by prior release</td>
<td>2,400,000 m³</td>
</tr>
</tbody>
</table>

Figure 3  Fig. 3.1 Flood control operation at Kamafusa Reservoir

The 2011 off the Pacific coast of Tohoku Earthquake (also known as the 2011 Great East Japan Earthquake), which occurred on March 11th 2011, damaged the facilities or dikes for flood control in the Natori River, which decreased the flood control ability in the lower Natori River. To complement the decreased ability in the lower Natori River, prior release operation was adopted at the Kamafusa Reservoir, which locates at upstream the Natori River.

The prior release operation was designed to conduct within a limit of 300 m³/s: when cumulative rainfall is expected to exceed 50mm for the coming 24 hours, and occurrence of flood is predicted; or when cumulative rainfall is expected to exceed 80 mm. Through
the prior release operation, 2,400,000 m$^3$ of water is released from the storage for water utilization before flood control operation starts so as to prepare empty volume which can allow Kamafusa Reservoir to control more flood water during floods. It was expected that the maximum amount of

![Figure 4](Schematic flow of the prior release operation)

water release can be confined no more than 600 m$^3$/s during floods thanks to this prior release operation.

The operation rules of Kamafusa Reservoir set down that prior release should be conducted: when cumulative rainfall is expected to exceed 50 mm for the coming 24 hours and occurrence of flood is predicted; or when cumulative rainfall is expected to exceed 80 mm. As the simplified conditions corresponding to the original conditions to conduct the prior release operation, it is assumed in this case study that the prior release operation is conducted when a flood control inflow is predicted, so as to eliminate uncertainty produced by runoff modeling to convert estimated rainfall to the inflow prediction. Prior release operation was supposed to be conducted when there was a value greater than 300 m$^3$/s in the predicted inflow sequence for the coming 24 hours (see also Figure 4 for the schematic flow of the prior release operation proposed in this study). It is also supposed in this case study that it takes three hours to confirm the safety at downstream on the river, and to inform conduct of prior release operation to stakeholders (e.g., electric power companies, local governments) both of which are required by the operation rules of Kamafusa Reservoir to complete before the reservoir rapidly increase its water release. Considering the assumption, the prior release operation is defined to start three hours after the condition to conduct the prior release operation is fulfilled.
In this condition, however, whether the decision criteria for prior release operation is fulfilled or not (i.e., whether an inflow more than 300 m$^3$/s is predicted or not) could frequently change as predictions update every hour if the prediction continuously includes no small errors. In this paper, two methods were defined as the operation rule for determining to or not to conduct prior release operation, considering the update of predictions: I) the reservoir operates prior release immediately if an inflow more than 300 m$^3$/s was predicted; and II) the reservoir conducts prior release if inflows more than 300 m$^3$/s were predicted in the prediction sequences respectively provided at three successive hours. On the other hand, two operation methods were defined for operations after switching to prior release operation: i) prior release operation was completed without suspension; and ii) prior release operation was suspended and the water level of the reservoir was maintained, if the predicted inflow sequence provided at three successive hours did not include a value more than 300 m$^3$/s, and the prior release operation was then restarted if inflows more than 300 m$^3$/s were again predicted in three successive prediction sequences.

Prior release operation has impacts on both water utilization and flood control, so the impact evaluation of prior release operation should be considered from these points of view. In this paper, as a fundamental discussion, the evaluation is conducted in terms of physical quantity, which is a reservoir elevation (reservoir storage). About flood control, the impact is evaluated from the point of view whether prior release operation is finished until flood control operation is started or not. About water utilization, the impact is evaluated from the point of view whether the storage for water use purposes is restored after flood control operation or not. The simulation employed eleven historical flood events for the case study, including six large events in which inflows more than the flood control inflow were observed, and five small events in which the peak inflow is between 100 m$^3$/s to the flood control inflow (300 m$^3$/s). These flood cases were assumed to occur in the flood season. On the other hand, the initial storage of the reservoir in each simulation was set to be 18,300,000 m$^3$, which is equal to the maximal storage volume regulated by the operation rule of Kamafusa Reservoir in the flood season. The impacts of the prior release operation on the water use purposes were evaluated by the results of simulations using the five flood events in which the peak inflow is less than the flood control inflow. On the other hand, the impacts on flood control were evaluated by the results of simulations using the six flood events in which the peak inflow is more than the flood control inflow.

The number of simulations was set to be 1000 for each flood event. The initial time of each simulation was set to be 48 hours before the inflow peak arrived at the reservoir.
so as to have a margin before the observed inflow more than the flood control inflow is subject to the prediction. On the other hand, each simulation continued 48 hours after the inflow peak arrived, when the inflow is considered to become lower and stable after the flood. Autocorrelation coefficient of errors at successive lead times $\rho_l(1)$ is supposed to be 0.9 as a fundamental discussion in this case study. The value $\alpha$, which is the coefficient included in $c_i(l)$ in Eq. 6, was supposed to be 0.01, 0.015, 0.02, 0.025 or 0.03 so as to analyze the difference in effects of prior release operations considering inflow predictions with different accuracies.

3.2. Verification of artificial inflow prediction

Verification results about artificial generation of inflow prediction are shown in this section. The results for generation of inflow predictions in the flood event on August 26th, 2005 (the peak inflow is 580 m$^3$/s) were shown here as an example. Mean Error (ME) was introduced to assess the positive and negative deviations of errors, and Mean Absolute Error (MAE) was introduced to assess the volume of errors. ME and MAE of the inflow prediction for $l$ hours ahead at time step $t$, $ME(t, l)$ and $MAE(t, l)$, can be described as follows:

$$ME(t, l) = \frac{1}{l} \sum_{i=1}^{l} e(i, t, l)$$

$$MAE(t, l) = \frac{1}{l} \sum_{i=1}^{l} |e(i, t, l)|$$

where $e(i, t, l)$ is an error for $l$ hours ahead at time step $t$ in simulation time $i$, and $l$ is the total number of simulations (=1000).

Figures 5 and 6 show ME and MAE of the inflow prediction respectively conducted 24 and 12 hours before the inflow peak. It can be seen in Figure 5 that the values of ME seem to separate from 0 in the latter half of lead time. This can be considered because the distribution of generated random numbers is considered to be distorted against prescribed probability distribution. However, the distortion is not considered to have a significant impact on the analysis because their values are around 1% of observation values. This suggests that errors were basically generated as intended.

On the other hand, it can be seen in Figure 6 that MAEs became greater as the value of $\alpha$ became large, and that the MAEs of the 24-hour prediction were larger than those of the 12-hour prediction. It is, therefore, considered that the parameters for accuracy of predictions were successfully defined so that different accuracies of errors could be generated, and that errors are able to be generated larger as lead time is long.
3.3. Impact analysis of prior release operation considering inflow prediction

Three types of rules for prior release operation were considered: 1) prior release operation must be started immediately without suspension if an inflow more than 300 m³/s was predicted; 2) prior release operation was conducted without suspension if an inflow more than 300 m³/s was predicted in the prediction.

Table 3.1 shows the number of simulations, in which prior release operation was conducted, out of simulations using flood cases in which prior release operation was not necessary (five events), for each parameter of prediction accuracy. It can be seen in
Table 2 that a risk to conduct prior release operation unnecessarily was higher as \( \alpha \) was larger. It is considered that there is more possibility to misjudge the necessity to conduct prior release operation as accuracy of prediction decreases especially in operation rule 1), in which the decision for the prior release operation totally depended on predictions. On the other hand, in operation rules 2) and 3), the number of simulations, in which prior release operation was unnecessarily conducted, remarkably decreased. These operation rules are able to lower

Table 2: Number of simulations in which prior release operation was conducted out of those using flood cases in which prior release operation is not necessary (5000 simulations)

<table>
<thead>
<tr>
<th></th>
<th>( \alpha=0.01 )</th>
<th>( \alpha=0.015 )</th>
<th>( \alpha=0.02 )</th>
<th>( \alpha=0.025 )</th>
<th>( \alpha=0.03 )</th>
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</thead>
<tbody>
<tr>
<td>1)</td>
<td>0</td>
<td>37</td>
<td>213</td>
<td>548</td>
<td>903</td>
</tr>
<tr>
<td>2)</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>9</td>
</tr>
<tr>
<td>3)</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>17</td>
</tr>
</tbody>
</table>

Table 3: Number of simulations in which prior release operation was not finished before flood control operation out of those using flood cases in which prior release operation is necessary (6000 simulations)

<table>
<thead>
<tr>
<th></th>
<th>( \alpha=0.01 )</th>
<th>( \alpha=0.015 )</th>
<th>( \alpha=0.02 )</th>
<th>( \alpha=0.025 )</th>
<th>( \alpha=0.03 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1)</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2)</td>
<td>0</td>
<td>0</td>
<td>6</td>
<td>3</td>
<td>5</td>
</tr>
<tr>
<td>3)</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

Figure 7 Time series of reservoir operation in a simulation during the flood event on July 11th in 2002

the risk to conduct prior release operation unnecessarily by decreasing accuracy of predictions.

Table 3 shows the number of simulations, in which prior release operation had not been finished before flood control operation, out of simulations using flood events which peak inflows were more than the flood control inflow. Figure 7 also shows the time series of reservoir operation in a simulation using flood events as an example of simulation results.
With any operation rule of the three, the prior release operation had been finished before the flood control operation started in almost all of the simulations regardless of the values of α, which controlled the accuracy of prediction. It is considered that the decision criteria for prior release operation were easily fulfilled because a prediction of inflow greater than 300 m³/s could be easily generated by the proposed model, which naturally generates both of overestimated and underestimated values in a prediction sequence, in the simulations using the flood events which peak inflows were more than the flood control inflow. In operation rules 2) and 3), there were very few cases in which prior release operation could not be finished before the flood control operation started. It is considered that it takes much time to start prior release operation because of fulfilling the condition in which an inflow more than 300 m³/s was predicted in the prediction sequences respectively provided at three successive hours. It is also considered that it takes much time to finish prior release operation because the prior release operation was suspended.

From these results of simulations about prior release operation at Kamafusa Reservoir, it is considered that the prior release operation considering inflow predictions was safe in terms of flood control, and was danger in terms of water utilization. And it is considered that the accuracy of prediction took some impacts on judgment to conduct prior release operation in simulations using the small scale flood events, in some operation rules. In this study, there was no case that storage for water utilization has been restored after flood because the void capacity yielded by the prior release operation was small, but if the capacity is larger, it may take some impacts on water utilization that prior release operation is conducted unnecessarily. On the other hand, it is suggested that the operation rule of prior release considering predictions provided at successive times as well as those considering suspension have some advantages in water utilization, in that the frequency of misjudged prior release operation can decrease. But it is considered that these operation rules increase danger in flood control, which prior release operation cannot be finished by the prescribed time.

Impacts of prior release operation on water utilization from the point whether the storage for water utilization has been restored after prior release operation could not be evaluated in this study, because the storage for water utilization had been restored at the end of simulation in all simulations. This is because the void capacity by prior release operation was considered to be small comparatively enough to be restored even by small-scale flood events considered in the simulations. There is a possibility that the storage cannot be restored after prior release operation in less scale flood than flood cases in these simulations, but prior release operation itself is thought not to be
conducted in such case even if there are some errors in the predictions because there is little cases prior release operation was conducted in the smallest scale of flood case (the peak inflow is 120 m$^3$/s).

Flood mitigation, that is one of the effects by prior release operation, could not be analyzed because the scales of flood cases in these simulations were small. More large scale of flood needs to be used in the simulations in future.

4. Conclusions

A Monte Carlo simulation model for prior release operation at a reservoir coupled with artificial generation model of inflow predictions was developed in order to make it possible to statistically analyze the impacts of prior release operation. Inflow predictions with random errors based on given accuracies of the prediction were adequately generated with this model so as to enable to investigate impacts of inflow prediction's accuracy on the effectiveness of prior release operations.

The impacts of prior release operations considering inflow predictions on water utilization and flood control at Kamafusa Reservoir were then statistically analyzed by aggregating the results of all the simulations. In this application, it was seen that the conduct of the prior release operation was misjudged more frequently as the accuracy of the prediction became worse for small flood events. It was also suggested that appropriate operation rules for prior release could relax the impact of prediction's accuracy on the performance in the prior release operation while they might slightly increase the danger in flood control. It is supposed that the simulation model developed in this study can provide the reservoir managers with information to design rules for more effective prior release operations by conducting impact analysis of prior release operation like the one in this case study comprehensively.

However, the results in this study are supposed to be a virtual analysis because the generation method of inflow prediction is based on various assumptions in description of prediction errors and hydrological prediction used in operation rules of prior release, as a fundamental discussion. In future, applicability of the generation model of inflow prediction would be verified, such as, by comparing the probability characteristics supposed in this model with the one of actual predictions so that the simulation model can practically analyze the impact of accuracy of prediction on effectiveness of prior release operation.
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Management

Water resources modeling, management, and policy
Climate change impact assessment on water resources in the Blue Mountains, Australia

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1 University of Western Sydney · 2 Sydney Catchment Authority

Abstract
Climate changes, especially its impacts on temperature, precipitation and evaporation, have large effects on water resources. In recent years, water authorities in Australia imposed various water demand management strategies including mandatory water restriction to reduce water demand as the dam storage levels dropped quite low due to the prolonged droughts which affected the country for about 7 years in early 2000s. Since climate change can affect the water resources in many different ways, it is necessary to assess the potential impact of this change on water resources in a reservoir system for effective planning and operation of the reservoir system which are used for urban water supply. This study investigates the climate change impact on future runoff in Katoomba Catchment of the Blue Mountains regions, New South Wales, Australia. Three future climatic scenarios B1 (low), A1B (medium) and A2 (high) have been used in this study to run the model. Downscaled daily rainfall and evaporation data from CSIRO Mk 3 Global Climate Model have been taken as inputs into a continuous rainfall-runoff model namely Australian Water Balance Model (AWBM) to generate runoff sequences under future climatic scenarios. The calibration and verification results indicate that the model performances are quite good (NSE = 0.989; RMSE = 0.48; PBIAS = 4.57%) and it can be used to estimate future runoff for climate change impact studies. The prediction results by the AWBM show that the future runoffs can change by ± 80% under different climatic scenarios during the projection periods (2025-2040) in comparison to the base average annual runoff for the period of 2005-2010.

Keywords
Runoff, Climate change, GCM, Blue Mountains, AWBM, Water balance

1. Introduction
Availability of water resources to provide water in a city is expected to be affected by the potential impact of climate change (i.e. changes in the precipitation patterns and increase in the temperature). The Fourth Assessment of the International Panel on Climate Change reported that global average temperature would increased by 2.3°C
to 6.2°C in this century due to the increased concentration of greenhouse gases in the atmosphere (IPCC, 2008). This increase in temperature will have significant impacts on the rainfall pattern, the magnitude and timing of runoff, the frequency and intensity of floods and droughts (Arnell et al., 2011; Tsanis et al., 2011). These changes in turn will affect the quality and quantity of water availability and influence the existing water supply systems. Ludwig et al. (2011) showed in their review paper on the current state of the art of climate change research for the Mediterranean region that shortages of water resources is happening due to the change in the climatic conditions. From these studies, it is evident that climate change is likely to exacerbate water shortages problem in the world. Therefore, the assessment of the potential impacts of climate change on water resources is crucial for more effective water supply management to secure adequate future water supply.

The potential impact of climate change on runoff can be assessed by the hydrological models driven by regional climate change scenarios downscaled from Global Climate Models (GCM). This approach has become popular in the recent years as daily and monthly runoff characteristics can be estimated directly and other variable of interest can be assessed indirectly (Chiew et al., 2009). In this approach, historical runoff data is used to calibrate the hydrological model first and then future climatic data is taken as the input variables in the model to predict the future runoff scenarios with the calibrated parameters values. Afterwards predicted and historical runoffs are compared with each other to estimate the change in runoff due to the future climatic conditions (Xu, 1999; Chiew and McMahon, 2002). Normally GCMs are used to obtain the future climatic scenarios. However, due to the coarse resolution of the GCMs, the results obtained from these models are not directly considered in the hydrological models. These results are downscaled to catchment-scale climatic variables by different techniques (i.e. statistical downscaling and dynamical downscaling) to use in the hydrological simulation (Fowler et al., 2007).

Australia is one of the driest countries in the world and around 50% to 75% of Australia is located in arid and semi-arid regions. These arid parts of Australia experience less number of rain days in year and mean annual rainfall is relatively low in comparison to mean annual evaporation. Water authorities face challenges to supply adequate water for urban and rural use as water availability is comparatively scarce in these regions. These challenges are compounded by the high inter-annual variability of streamflow and low rainfall-runoff conversion ratio in Australia (Peel et al., 2000). These situations are expected to be aggravated due to the potential impact of climate changes (Vaze et al., 2011). Some studies have already reported some negative impacts on water resources
due to the changing climatic conditions. For example, Vaze et al. (2011) reported 5% to 7% reduction in mean annual runoff under 2030 climatic scenario for Macquarie-Castlereagh region, NSW, Australia. Austin et al. (2010) predicted up to 45% reduction in the wetter/cooler southern catchments and up to 64% in the drier/hotter western and northern catchments of the Murray-Darling Basin under 2070 climatic conditions. Preston and Jones (2008) investigated the future projection of runoff in 238 rivers basins across Australia and found that median changes in runoff by 2030 would be within ±10%.

This study contributes to the existing literature by estimating the potential impact of climate change in the Katoomba catchment that consists of three Cascade dams in the Blue Mountains region, NSW in Australia under three different emission scenarios (i.e. A1B, B1 and A2). Australian Water Balance Model (AWBM) model is used in this study to predict the future runoff under different climatic conditions for the period of 2025 to 2040. AWBM is one of the most widely used hydrological models in Australia (Boughton, 2004). Predicted annual runoffs are compared with the base average annual runoff (2005-2010) to estimate the changes in future runoff.

2. Study area and data

The Blue Mountains catchment consists of three smaller catchments namely, Katoomba, Woodford and Blackheath (Figure 1). Three dams are located in the Katoomba catchment, namely, Lower, Middle and Upper Cascade dams on Cascade Creek. Greaves Creek dam on Greaves Creek and Lake Medlow dam on Adams Creek are located in the Blackheath catchment. Woodford dam at the junction of Bulls Creek and Woodford Creek is located in Woodford catchment (Sydney Catchment Authority, 2013). These dams together with Fish River Scheme supply water to the Blue Mountains Water Supply System which provides water for around 49,000 people in the Blue Mountains region from Mt Victoria to Faulconbridge. Woodford dam is currently decommissioned for supply of water. In this study, Katoomba catchment (total area is 2.811 km²) is taken as the case study area to estimate the climate change impact on future runoff.
The climate of the Blue Mountains is normally moderate than the lower Sydney region. As Mount Victoria is over 1000 meters above Sea Level, the temperature is normally 7°C lower than the coastal Sydney. The average temperature in the Upper Blue Mountains is around 5°C and 18°C in winter (June to August) and summer months (December to February), respectively. The Blue Mountains experience similar rainfall to that of Sydney. The average rainfall in the Upper Blue Mountains is around 1050 mm per year [Bluemountainsaustralia, 2013].

Historical rainfall, evaporation and runoff data for the period of 1987-2005 were collected from Sydney Catchment Authority to calibrate and validate the AWBM model. In this study, climate change impact on runoff was estimated under three future climate scenarios being B1, A1B and A2, which represent low, medium and high future emission scenarios, respectively. Climate projections by CSIRO Mark 3.0 GCM were used in this study. The downscaled climatic data (i.e. rainfall and evaporation) of Katoomba weather station under these three emission scenarios were collected from Sydney Catchment Authority for the period of 2021-2040 to estimate the future runoff.

3. Modelling method

The AWBM is a conceptual rainfall-runoff model which generates runoff in daily time scales from the input data of rainfall and evapotranspiration (Boughton, 2004). AWBM
model consists of three surface moisture stores that allow for partial area runoff generation. Rainfall and evapotranspiration is added and subtracted, respectively to each of the stores at each time steps. The excess from any stores becomes runoff. This runoff is divided between surface runoff and baseflow (Boughton, 2004). The model structure is presented in Figure 2 and the descriptions of the AWBM model parameters are given in Table 1.

![Figure 2](Structure of the AWBM model (Boughton, 2004))

The proportion of the surface runoff and baseflow from the excess is estimated by the baseflow index (BFI), which varies between 0 to 1. This BFI can be estimated from a streamflow record by using any of the established techniques for segregation of flow into surface runoff and baseflow (Chapman, 1999). The recharge of the baseflow and surface runoff store is estimated by the following equations:

\[ \text{Baseflow recharge} = BFI \times \text{Excess} \quad (1) \]
\[ \text{Surface runoff recharge} = (1 - BFI) \times \text{Excess} \quad (2) \]

The daily discharge from the baseflow and surface store into streamflows are estimated by the equations 3 and 4, respectively:

\[ \text{Baseflow discharge} = (1 - K_b) \times BS \quad (3) \]
\[ \text{Surface runoff discharge} = (1 - K_s) \times SS \quad (4) \]
Where \( BS \) and \( SS \) are the amount of moisture in the baseflow and surface store, respectively and, \( Kb \) and \( ks \) are the daily baseflow and surface runoff recession constant, respectively. These recessions constant can be estimated from the streamflow record.

### Table 1: Descriptions of the AWBM model parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>Partial area of smallest store</td>
</tr>
<tr>
<td>A2</td>
<td>Partial area of middle store</td>
</tr>
<tr>
<td>A3</td>
<td>Partial area of largest store</td>
</tr>
<tr>
<td>C1</td>
<td>Surface storage capacity of smallest store</td>
</tr>
<tr>
<td>C2</td>
<td>Surface storage capacity of middle store</td>
</tr>
<tr>
<td>C3</td>
<td>Surface storage capacity of largest store</td>
</tr>
<tr>
<td>BFI</td>
<td>Baseflow index</td>
</tr>
<tr>
<td>Kb</td>
<td>Baseflow recession constant</td>
</tr>
<tr>
<td>Ks</td>
<td>Surface runoff recession constant</td>
</tr>
</tbody>
</table>

The AWBM2002 version has the auto calibration options by which the Model self-calibrates to a data set of daily rainfall, evapotranspiration and runoff. In this auto calibration, fixed pattern of the surface storage capacities and their partial areas are used to disaggregate the average surface storage capacity in the individual values needed to run the model. Average surface storage capacity is determined by matching the total calculated runoff with the total actual runoff. Trial and error adjustment is used to calibrate baseflow parameters to match the calculated daily runoff with the observed daily runoff over the calibration period (Boughton and Chiew, 2007).

### 4. Model calibration and validation

In this study, the AWBM was calibrated against 1987-2002 daily runoff data from the Katoomba catchment using auto calibration option. Model parameters were optimized to maximize the Nash-Sutcliffe efficiency (NSE) of daily runoff. The NSE is a normalized measure (-\( \infty \) to 1), that estimates the relative magnitude of the residual variance compared to the observed data variance (Nash and Sutcliffe, 1970). It can be calculated by the following equation:
Where $O_i$ is the daily observed runoff, $P_i$ is the modelled runoff and $O_{\text{mean}}$ is the mean observed daily runoff.

NSE measures the agreement between all the modelled and observed daily runoff. NSE value equals to 1.0 indicates that all the estimated runoffs are the same as the observed runoffs and NSE <1.0 indicates that modelled results have some degree of disagreement with the observed data.

The NSE value calculated with daily data was found to be 0.994, which indicate the model's ability to estimate the runoff was quite good. Comparison of daily modelled and recorded runoff values over the calibration period is presented in Figure 3, which shows a good agreement between the modelled and observed runoff values. The parameters obtained from the AWBM model calibration for the cascades catchments are given in Table 2.

Figure 3  Comparison of modelled and observed runoff over the calibration period
Table 2: **Calibrated parameter values of the AWBM model**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Modelled Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>0.134</td>
</tr>
<tr>
<td>A2</td>
<td>0.433</td>
</tr>
<tr>
<td>A3</td>
<td>0.433</td>
</tr>
<tr>
<td>C1</td>
<td>3.44</td>
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<tr>
<td>C2</td>
<td>34.152</td>
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<td>C3</td>
<td>68.304</td>
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<td>BFI</td>
<td>0.5</td>
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<tr>
<td>Kb</td>
<td>0.99</td>
</tr>
<tr>
<td>Ks</td>
<td>0.68</td>
</tr>
</tbody>
</table>

The NSE, root mean square error (RMSE) and percent bias (PBIAS) (Gupta et al., 1999) were used to assess the performances of the AWBM. Daily data sets of 2003-2004 were adopted to validate the model. Verification was performed to assess the model’s ability to predict runoff with the calibrated parameter for an independent data period that was not used to calibrate the model. Model verification performance indices are presented in Table 3, which indicates that the calibrated AWBM is capable of estimating runoff with a high degree of accuracy. Comparison of modelled and observed runoff during the verification period is presented in Figure 4, which shows model’s ability to produce a very good result.

Table 3: **AWBM performance for the verification period**

<table>
<thead>
<tr>
<th>Performance Indices</th>
<th>Calculated value</th>
<th>Acceptable Ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td>NSE</td>
<td>0.989</td>
<td>&gt;0.6=Satisfactory, &gt;0.8 = Good (Chiew and McMahon, 1993).</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.48</td>
<td>0 is the ideal value, the smaller the RMSE value the better the model results would be (Shamsudin and Hashim, 2002).</td>
</tr>
<tr>
<td>PBIAS (%)</td>
<td>4.57</td>
<td>25% (Yapo et al., 1996).</td>
</tr>
</tbody>
</table>
5. Model Prediction

The three different climatic scenarios (i.e. A1B, B1 and A2) were used to run the AWBM model to estimate future daily runoff for the period of 2025-2040 for the Katoomba catchment, Blue Mountains, Australia. The optimized model parameters that were estimated during model calibration (Table 2) were used to model the future runoff. Then these estimated daily runoff values were added together to get the monthly and annual predicted runoff. The predicted future runoff values were then compared with the average observed runoff for the period of 2005-2010 to estimate the climate change impact on future runoff. Predicted annual runoff values under three different climatic scenarios are presented in Figure 5. It was found that predicted runoff values were different under climatic scenarios as expected. As can be seen in Figure 5, under A2 and B1 climatic scenarios very low annual flow (i.e. 166 ML for A2 and 466 for B1) might happen at 2035. The year 2040 would be very critical if the climatic scenario A1B would take place. Under A1B climatic scenario, the flow would be around 196 ML in 2040 which is very low as compared to other two scenarios.
Figure 5  Predicted annual runoff values under different climatic conditions during 2025 to 2040

Percentage changes in the annual runoff values of the predicted data with the average observed annual runoff data for the period of (2005-2010) are presented in Table 4. Annual average runoff values for the period of 2005 to 2010 were found to be 1070 ML/year which can be considered as base period runoff. Negative sign in Table 4 indicates that the estimated runoff would be higher than the base annual runoff and the positive sign indicates that estimated runoff would be lower than the base annual runoff. As can be seen in Table 4, estimated runoff would be varied from -83.58% to 84.50% under different climatic conditions, which indicates that there would be remarkable climate change impact on the runoff generations.

Table 4: Percentage changes in the annual runoffs under different climatic conditions in comparison to annual average runoff (2005-2010)

<table>
<thead>
<tr>
<th>Year</th>
<th>A1B</th>
<th>A2</th>
<th>B1</th>
</tr>
</thead>
<tbody>
<tr>
<td>2025</td>
<td>-2.66</td>
<td>68.07</td>
<td>30.77</td>
</tr>
<tr>
<td>2030</td>
<td>44.22</td>
<td>-61.47</td>
<td>54.47</td>
</tr>
<tr>
<td>2035</td>
<td>-83.58</td>
<td>84.50</td>
<td>56.47</td>
</tr>
<tr>
<td>2040</td>
<td>81.65</td>
<td>-28.70</td>
<td>-24.54</td>
</tr>
</tbody>
</table>

From the predicted results, it can be seen that the predicted runoff estimates show a notable variability under different climatic conditions for the same year. For an example, in 2030 the model estimated 84% and 56% reduction under A2 and B1 climatic conditions, respectively whereas the model predicted 83% higher runoff under A1B climatic conditions.
conditions in comparison to the base annual runoff. This indicated that considerable amount of uncertainty exist in the climatic scenarios.

6. Conclusion

In this study, preliminary assessment of climate change impact on future runoff is undertaken by the AWBM rainfall-runoff model in the Katoomba catchment, Blue Mountains, NSW, Australia. The model was calibrated against the observed runoff data for the period of 1987-2002 and the optimized parameter values were used to estimate the future runoff for the period 2025-2040. The future climatic scenarios were obtained by statistically downscaling the projected climatic data from the CSIRO Mk3 Global Climate Model under three different emission scenarios (A1B, A2 and B1). The calibration and verification results indicate that the model performances are quite good and it could be used to estimate future runoff for climate change impact studies.

The predicted results inform that the possibility of occurrence of lower runoff does exist in all the three different climatic scenarios. Very less annual runoff might occur in 2035 under A2 and B1 climatic conditions and in 2040 under A1B climatic conditions in comparison to the observed base annual runoff (2005-2010). The runoffs in 2035 would be around 84% and 56% lower than the base annual runoff under A2 and B1 climatic conditions and in 2040, it would be around 82% lower under A1B conditions. These changes indicate that there would be significant impact on runoff due to the changing climate. However, predicted results are different under different climate conditions and these exhibits a notable variability which indicates the existence of significant uncertainty in the climatic scenarios. Moreover, uncertainty might be present in the hydrological model itself e.g. calibration uncertainty. Therefore, impact of climate change in the Cascades catchments needs to be investigated further adopting different results from different climatic models and using two or more hydrological models.

Acknowledgements

Historical and projected future climatic data (i.e. rainfall and evaporation) were collected from Sydney Catchment Authority (SCA). Moreover, observed runoff data for the Katoomba Catchment were also collected from SCA. The authors express their sincere thanks to Jason Martin and Mahes Maheswaran of Sydney Catchment Authority for their cooperation and assistance during data collection and analysis.
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Determining the high flood risk regions in a small basin in Austria

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Abstract

The purpose of this paper is to forecast the high flood risk regions in the Schoeckelbach basin which is situated at the north part of Graz in Austria. In order to determine the flood risk map, rainfall-runoff modeling should be carried out. Prior to carrying out a rainfall-runoff model, some other analysis should be done such as rainfall analysis, terrain analysis and loss analysis. In this paper, the Intensity-Duration-Frequency (IDF) relation is obtained based on Sherman’s equation and Hec-GeoHMS is used to derive river network of the basin and to delineate sub-basins. Also, to evaluate the amount of losses, the SCS CN method is used. Finally, rainfall-runoff modeling is done using Hec-HMS software and the high flood risk regions are estimated. In order to evaluate the accuracy of the modeling, this model is compared with Natural Hazard Overview and Risk Assessment Austria (HORA) and the results show very good agreement and a successful modeling.

1. Introduction

Floods are one of the most common hazards in many regions of the world. In order to assess the consequences of floods caused by storm events, a rainfall-runoff modeling is required.

For understanding the methodology of rainfall-runoff modeling, one should know about the hydrologic cycle [Raghunath, 2006]. Hydrologic cycle is the water transfer cycle which occurs continuously in nature. The hydrologic cycle is based on the law of conservation of matter which explains that during a given period, the total inflow into a given area must equal the total outflow from the area plus the change in storage. In fact, for a rainfall-runoff modeling (outflow), the amount of inflow (precipitation) and change in storage (loss) should be modeled.

Due to this reasons, the rainfall-runoff modeling includes four different models as follows: 1-Rainfall analysis, 2-Terrain analysis, 3-Loss analysis and 4-Runoff modeling. In this paper, at the first step, the Intensity-Duration-Frequency relation is determined from the observed precipitation data based on Sherman’s equation. To derive the spatial and geomorphologic variations of the model, Hec-GeoHMS is used. In this paper, a
very high resolution DEM (Micro-scale: 1m × 1m) is used in order to obtain the basin characteristic precisely. Since the curve number procedure is a widely used method for estimating direct runoff from rainfall on small to medium-sized basins, in this paper, SCS CN method is used for estimation of rainfall losses. Finally, the rainfall-runoff modeling will be completed using Hec-HMS software and for calibrating the model, some observed data will be used. The high flood risk regions can be then extracted by investigation of discharges, the river cross sections (the stage-discharge relation) and tributaries in the basin.

2. Rainfall analysis

Rainfall analysis is the first step to determine the rainfall event in many hydrologic design projects. One of the most important parts of a rainfall analysis is Intensity-Duration-Frequency (IDF) analysis. In order to evaluate an approximately precise IDF relation, the recorded rainfall data series should be studied for identifying data gaps and also outlying data. After that, annual extremes are extracted from the recorded time series data for each duration and then, the annual extreme data is fit to a probability distribution model in order to estimate rainfall quantities.

In order to obtain the best-fit probability distribution model, first, we can find some significant distributions using skewness test. After that among those distributions, using the Root Mean Square Error (RMSE) method, it is possible to find the best-fit probability distribution model which has the minimum RMSE value. This probability distribution model is necessary because the fitted distribution can not only be used to interpolate, but also to extrapolate to find return periods of extreme values that were not apparent during the relatively short period of observation.

For the Schoeckelbach basin there are two kinds of rainfall data available:

1. Daily rainfall data which have been recorded every day at 7 A.M. for about 66 years (from 01.01.1946 to 30.09.2012).
2. 15-minute rainfall data which have been recorded every 15 minutes for about 8 years (from Sep. 2005 to Oct. 2012).

In order to achieve a precise IDF relation, we should have the observed record of hourly (or other finer resolution) data. For this reason, at first, we extracted 15, 30, 60, 120 and 720 minutes rainfall data from the observed record 15-minute rainfall data and then an IDF relation, which fitted all these data, will be produced. After that, this relation will be
calibrated by the observed record of the daily data.

The RMSE is calculated using the following relation [Haan 2002]:

\[
RMSE = \sqrt{\frac{1}{n-m} \sum_{i=1}^{n} (R_m - R_i)^2}
\]

In which, \(R_m\) is modeled rainfall depth (using fitted probability distribution), \(R_i\) is the \(i\)th observed rainfall depth, \(n\) is number of data and \(m\) is depend on the number of parameters in the fitted probability distribution (for example, for Log-Pearson type III is 3, for 3-parameter log-normal is 3 and for the Gumbel’s distribution is 2). Using this equation indicated that the best-fit probability distribution for the rainfall series of the Schoeckelbach basin is the Gumbel’s distribution \((RMSE_{\text{Gumbel}} = 2.04, \ RMSE_{\text{log-normal 3P}} = 6.18\) and \(RMSE_{\text{log-Pearson III}} = 14.40\)).

The Gumbel’s distribution (also called as Fisher & Tippett or Extreme Value Type I or Double Exponential) is applied in many hydrological events especially for maximum annual series such as floods and rainfall [Loaiciga & Leipnik, 1999]. This distribution has the following form:

\[
x_i = \mu_z + K_{Tr} \sigma_z
\]

where \(x_i\) represent the magnitude of the \(Tr\)-year event, \(\mu_z\) and \(\sigma_z\) are the mean and standard deviation of the annual maximum series respectively, and \(K_{Tr}\) is a frequency factor depending on the return period, \(Tr\). the frequency factor \(K_{Tr}\) is obtained using the relationship (when the number of data is greater than 30):

\[
K_{Tr} = -\frac{\sqrt{6}}{\pi} \left(0.5772 + \ln \left(\ln \left(\frac{Tr}{Tr-1}\right)\right)\right)
\]

0.5772 is the Euler constant (0.5772157). Figure 1 illustrates a comparison between sorted data series and the Gumbel’s distribution model.

![Figure 1 Comparison between sorted data series and the Gumbel's distribution model.](image-url)
In this paper, the Gumbel’s distribution was used to estimate the IDF parameters (Sherman’s Equation) and using a simple graphical method the final results were obtained as follows:

\[ i = \frac{1100T_r^{0.22}}{(t + 10)^{0.879}} \quad T_r \leq 25 \]  
\[ i = \frac{1000T_r^{0.187}}{(t + 10)^{0.88}} \quad T_r > 25 \]  

These two equations will be used in rainfall-runoff modeling of the Schoeckelbach basin.

3. Terrain analysis

The Schoeckelbach basin (33.7 km²) is located at the north part of Graz (the second largest city in Austria). Figure 2 illustrates the Schoeckelbach basin position.

The aim of terrain analysis is to perform an initial analysis of the terrain and to prepare the dataset for further processing. A Digital Elevation Model (DEM) of the study area and its river network are required as input for terrain analysis. In this paper, a very high resolution DEM (micro-scale: 1m × 1m) was used as input for Hec-GeoHMS.

Terrain analysis contains several steps which should be done step by step as follows: DEM reconditioning, Fill sinks, Flow direction, Flow accumulation, Stream network, Stream segmentation, Catchment grid delineation, Catchment polygon processing, Drainage line processing, Drainage point processing, Watershed aggregation, Longest flow path for catchments and Slope. More information can be found in Hec-GeoHMS user’s manual [Hec-GeoHMS user’s manual, 2009]. Figure 3 illustrates the final results as a 3D view.
4. Loss analysis

Rainfall loss refers to that portion of the total rainfall that fails to directly result in storm runoff. Most of the time SCS CN method is used for estimation of rainfall losses. The curve number procedure is a widely used method for estimating direct runoff from rainfall on small to medium-sized basins.

CN can be determined using the hydrologic soil group (HSG), cover type, treatment, hydrologic condition, and antecedent runoff condition (ARC). More information can be found in major hydrology books [Mockus, 1964 and TR55, 1986]. To obtain CN map we need some data as follows: 1-Land use raster data, 2-Soil data and 3-Basin boundary polygon.

Table 1 and 2 indicate the summary information of land use and soil data of the Schoeckelbach basin respectively.
Table 1: *Land use data.*

<table>
<thead>
<tr>
<th>Land use components</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mixed Forest</td>
<td>43.5</td>
</tr>
<tr>
<td>Evergreen Forest</td>
<td>6.2</td>
</tr>
<tr>
<td>Deciduous Forest</td>
<td>3.1</td>
</tr>
<tr>
<td>Low Intensity Residential</td>
<td>9.9</td>
</tr>
<tr>
<td>Urban/Recreational Grasses</td>
<td>0.8</td>
</tr>
<tr>
<td>Pasture (fair)</td>
<td>33.3</td>
</tr>
<tr>
<td>Grasslands</td>
<td>0.5</td>
</tr>
<tr>
<td>Grasslands/Herbaceous</td>
<td>2.7</td>
</tr>
</tbody>
</table>

Table 2: *Soil data.*

<table>
<thead>
<tr>
<th>Soil type</th>
<th>SMU code</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dystric Cambisol (medium)</td>
<td>430001</td>
<td>20.6</td>
</tr>
<tr>
<td>Eutric Cambisol (medium)</td>
<td>430002</td>
<td>5.9</td>
</tr>
<tr>
<td>Rendzic Leptosol (medium)</td>
<td>430007</td>
<td>73.5</td>
</tr>
</tbody>
</table>

Hec-HMS uses the mean CN value for each sub-basin, so, average CN for each sub-basin was calculated as it is shown in *Figure 4.*

![Figure 4](image_url)  
*Final CN map for importing to Hec-HMS.*

5. Rainfall-runoff modeling

In this section, rainfall – runoff modeling for the Schoeckelbach basin was done for 1-day rainfall with return period of 2, 5, 10, 20, 30, 50 and 100 year. In this section a frequency
storm was used in the meteorological model. The intensities for each return period and various durations were computed using IDF relation which was obtained in Section 2.

For calibrating the model, Peak-weighted root mean square error (PWRMSE) method was used. Using a weighting factor, the PWRMSE measure gives greater overall weight to error near the peak discharge [Hec-HMS user’s manual, 2010]:

$$\text{PWRMSE} = \sqrt{\sum_{t=1}^{N} \left( Q_o(t) - Q_M(t) \right)^2 \frac{Q_o(t) + Q_a}{2Q_a}}$$

(6)

$$Q_a = \frac{1}{N} \sum_{t=1}^{N} Q_o(t)$$

(7)

Where $Q_o$ and $Q_M$ are the observed and modeled flow at time $t$ respectively and $Q_a$ is the average observed flow. Figure 5 illustrates the $R^2$ test for the observed and modeled discharges before and after the calibration process.

![Figure 5](image)

**Figure 5**  (right) $R^2$ test for all un-calibrated simulations and (left) $R^2$ test for all calibrated simulations.

6. The high flood risk regions

When a rainfall-runoff modeling is completed, it is possible to evaluate the value of floods in all river tributaries and also sub-basins. Using these data, we can make a flood map and specify the high flood risk regions. This process was done [Galoie & Zenz, 2012] for the Schoeckelbach basin for a 100-year 1-day rainfall-runoff model. Figure 6 illustrates the amount of flood discharges at the river tributaries. The river tributaries also are shown in Figure 7.
As it was predictable, the amounts of flood discharges for the tributaries at northern Schoeckelbach are very small because most of forests are placed at northern Schoeckelbach with high amount of losses and low amount of runoff. The amounts of flood discharges for the tributaries between J155 and outlet are relatively high (greater than 45 m³/sec) (red border in Figure 7).

In order to evaluate the accuracy of model in estimating the high flood regions, this model is compared with Natural Hazard Overview and Risk Assessment Austria (HORA). Figure 8 illustrates the high flood regions in HORA and model in the same scale. As it can be seen in this figure, inundation areas are completely the same.
This Figure shows the accuracy of the model and a successful modeling. These results can be used as a planning tool for flood risk management projects in the area and designing hydraulic structures such as levees, dams, bridges and etc.

7. Conclusions

This paper has described the process of determining high flood risk regions in the Schoeckelbach basin using a numerical rainfall-runoff modeling. For this reason, first, rainfall-runoff modeling of the Schoeckelbach basin was carried out using ArcGIS, Hec-GeoHMS and Hec-HMS. For a precise terrain analysis, a very high resolution DEM (micro-scale: 1m × 1m) was used. For rainfall analysis, two kinds of recorded precipitation (daily rainfall and 15-min rainfall) were used. To evaluate the amount of losses in the basin, SCS CN method was used and finally the runoff modeling was done using Hec-HMS. A comparison between HORA and model was shown that the modeling process was completed successfully. When the rainfall-runoff modeling is completed, it is possible to evaluate the value of floods in all river tributaries and also sub-basins. The results have shown that the most critical regions are placed at southern the basin where the urban area is also located there. These results can be used as a planning tool for flood risk management projects in the area.
Acknowledgments

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References


Multiple Coincidence of Flood Waves in Complex River Systems

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Abstract

The process of flood waves formation in complex river systems, such as the confluence of significant tributaries on the relatively short sector on a main water course, is very complicated, both from the standpoint of flood wave genesis of the mainstream and tributaries, and from the standpoint of selection of design flood flow for the flood control systems in the whole river system. The subject of this paper is to develop a methodology for determining the multiple coincidences of flood waves on the main river and its major tributaries in the complex river systems.

Formed multivariate dependence of main river flood waves and its significant tributaries have the practical significance that can be classified into two categories - primary and secondary. Primary importance is given to:

• Consideration of the genesis of flood waves on the mainstream and major tributaries,
• Forming hydrologic basis for assessing the probabilistic significance of historic and future flooding in complex river systems,
• Giving logistical support to the issue of hydrological real-time forecast for the arrival of the flood wave in complex river systems.

Secondary importance of established multiple coincidence, but not less important, is related to their use in all construction and management designing phases of flood protection systems. Defined multivariate dependences can be used for:

• Providing the basis for cost-effective line flood protection systems designing in zones of interaction between the main river and its major tributaries,
• Assisting in the development of strategies for the construction and reconstruction flood protection systems in the coastal zone of the mutual impact of the main river and its tributaries,
• Creating a basis for reliable and comprehensive assessment of flood risk in complex river systems.

From the point of view of the genesis of flood waves, defined multiple coincidences of various parameters determine flood hydrograph real space where the selected parameters of different probability constellations of occurrence can be found. These
dependencies are very suitable for probabilistic significance evaluation of, both, historical and future flooding. In complex river systems this dependence can be used when issuing real-time forecasts at the outlet of the main river, where forecasted hydrographs are known as the entrance profiles of the main water course and major tributaries.

The developed methodology for defining multiple coincidences of flood waves on the main river and its tributaries is applied to the sector of the Danube River and its main tributaries, the Tisza and the Sava rivers in the territory of Serbia. In particular, a multidimensional probability of coincidence of flood discharges of the Danube River, downstream from Belgrade (h.s. Pančevo) is defined depending on the probability of occurrence of floods on its upstream part (h.s. Bogojevo), Tisza (h.s Senta) and Sava (h.s. Sremska Mitrovica) rivers.

**Keywords:**
flood waves, flood protection systems, multiple coincidence

### 1. Introduction

Obviously, complete flood protection is not possible. There is always a risk that the maximum capacity of the constructed system for flood control will be exceeded, which was dimensioned to design high water even assuming to ignore human effects on the appearance and performance of flooding. Increasing the protection level may require an increase in financial investments. Therefore, the question of the optimal protection level is so important from the standpoint of compliance on investment in the construction and maintenance of the potential damage.

Methodology for establishing design high flow is of great importance in defining the system of flood protection. The classical approach for the assessment of flood risk is to determine the probability with which the flood can overcome the value of considered flood wave parameter that is equivalent to determining the flood return period. At the same time the procedure includes statistical and probabilistic analysis of hydrological data at the nearest hydrological station. This way satisfactory results could be achieved and from an engineering point of view a large number of problems can be solved, especially the problem of flood in the affected territory when there are no river tributaries.

However, when the affected area includes the confluence of more than one tributary, this approach does not provide a reliable estimation of a considered flood wave.
Occurrence of flood waves in two or more neighbouring rivers is typically different, so that the maximum floods do not occur simultaneously. Flood wave in a stream may cause a significant impact on the flow regime to another. In addition, hydrological data are usually collected at hydrological stations located outside the interaction zone between the considered streams, so that the processing of the available data cannot assess the impact of one stream to another. In such circumstances it is particularly important to assess the coincidence of flood waves in the main river and tributaries. If there are a number of important tributaries the problem becomes more complex, it is necessary to perform comprehensive monitoring of hydrological and hydraulic conditions in the region, and to treat random variables as multidimensional, in order to define risk as the most adopted criterion for flood protection system design. Application of the theory of two-dimensional and multi-dimensional random variables used in this paper is an approach that can overcome these problems. This approach provides the ability to determine the probability of simultaneous occurrence of flood events in two or more streams.

2. Methods

Methodology for the multidimensional coincidence of flood waves determination

The probability of simultaneous occurrence of floods on two or more rivers is called "coincidence". It represents the practical application of multivariate probability distribution functions or their conditional probabilities. The simultaneous quantitative characteristics of flood wave hydrographs of the main river, and one or more major tributaries, are considered. In general, these parameters are: peak, volume, duration or lag time between flood wave peaks of the main river and its tributaries. The proposed methodology for the multi-dimensional coincidence of flood waves in complex river systems determination uses the methodology developed for defining the coincidence of flood waves on two neighbouring rivers (Prohaska et al., 1999). "Coincidence" denotes events occurring at the same time and is equal to the probability of simultaneous occurrence of two random variables, $X$ and $Y$, which stand for the considered random variables, flood parameters on neighbouring rivers.

According to the theory of statistics, the two-dimensional probability distribution function of a normally distributed bi-variate random process, $X$ and $Y$, is defined as:
\[ f(x, y) = \frac{1}{2\pi\sigma_x\sigma_y\sqrt{1-\rho^2}} \exp\left\{ -\frac{1}{2\sigma_x^2} (x - \mu_x)^2 - \frac{2\rho (x - \mu_x)(y - \mu_y)}{\sigma_x\sigma_y} + \frac{(y - \mu_y)^2}{\sigma_y^2} \right\} \] (1)

where:

- \( X \) and \( Y \) - random variables (flood characteristics of the main river and the tributary or two nearby profiles of the main river);
- \( x \) and \( y \) - simultaneous realization of the random variables \( X \) and \( Y \), respectively;
- \( \mu_x \) and \( \mu_y \) - expected values of the \( X \) and \( Y \) variables;
- \( \sigma_x \) and \( \sigma_y \) - standard deviations of the \( X \) and \( Y \) variables;
- \( \rho \) - coefficient of correlation between the \( X \) and \( Y \) variables.

For a joint probability density function \( f(x, y) \), the marginal densities, \( f(x, \cdot) \) and \( f(\cdot, y) \), are defined by:

\[ f(x, \cdot) = \int_{y=\infty}^{y=-\infty} f(x, y) \, dy \]
\[ f(\cdot, y) = \int_{x=\infty}^{x=-\infty} f(x, y) \, dx \] (2) (3)

The marginal cumulative probability functions are determined from following Equations 4 and 5 as:

\[ F(x, \cdot) = \int_{t=\infty}^{t=-\infty} f(t, \cdot) \, dt \]
\[ F(\cdot, y) = \int_{z=\infty}^{z=-\infty} f(\cdot, z) \, dz \] (4) (5)

The cumulative probability function \( F(x, y) \), is assessed from:

\[ F(x, y) = P[X \leq x, Y \leq y] = \int_{x=\infty}^{x=-\infty} \int_{y=\infty}^{y=-\infty} f(t, z) \, dt \, dz \] (6)
The exceedance cumulative probability, \( \Phi(x, y) \), can be obtained from the following relation:

\[
\Phi(x, y) = \int_{x}^{\infty} \int_{y}^{\infty} f(t, z) dt \, dz = P[X > x \cap Y > y] = 1 - P[X \cup Y < x \cup y] = 1 - F(x, y) - F(y, x) + F(x, y)
\]  

(7)

The first assumption in following methodology is that the considered variables follow Log-normal distribution function. As it is known the most flood characteristics are not normally distributed, therefore logarithmic transformations are applied like in Equations 8 and 9:

\[
U = \log X
\]  

(8)

\[
W = \log Y
\]  

(9)

The previously described methodology can be tiresome as it involves extensive calculations in three-dimensional space, \( X, Y, \) and \( \rho \). For that reason, a more convenient combination of graphical and analytical methods was implemented (Abramowitz and Stegun, 1972).

Standardized variables, normally distributed, are applied to the model. A well-known procedure can be used to transform non-standard variables into standardized, Equations 10 and 11.

\[
\psi = \frac{u - U}{\sigma_u}
\]  

(10)

\[
\xi = \frac{w - W}{\sigma_w}
\]  

(11)

Based on the above assumption, the variables \( \psi \) and \( \xi \) are normally distributed, with expected values \( \mu_\psi = \mu_\xi = 0 \), and standard deviations \( \sigma_\psi = \sigma_\xi = 0 \). Then the joint probability density function can be defined as (Equation 12):

\[
f(\psi, \xi) = \frac{1}{2\pi\sqrt{1-\rho^2}} \exp \left\{ -\frac{1}{2(1-\rho^2)} \left[ \psi^2 - 2\rho\psi\xi + \xi^2 \right] \right\}
\]  

(12)

The values of the correlation coefficient \( \rho \) should be replaced with \( R \), which can be
estimated from the observed data using a standardized series. After simplifying the notation in Equation 12, the following relation can be established:

\[ \int \int f(\psi, \xi) \, d\psi \, d\xi = 1 - \exp \left\{ -\frac{\lambda^2}{2(1 - \rho^2)} \right\} \]  
(13)

The integral given in Equation 13 over an area \( A \), i.e. the integral over the space \( \psi, \xi \in A \), represents the probability that the realization of events \( \Psi = h \) and \( \xi = k \) will be within the area \( A \) which is encompassed by an ellipse described by the following equation:

\[ \psi^2 - 2\rho\psi\xi + \xi^2 = \lambda^2 \]  
(14)

The symbol \( \lambda \) is related to the constant value of the integral in Equation 13. Consequently, it is related to the variables \( \psi \) and \( \xi \), as well as to the correlation coefficient, \( \rho \). Hence, for each value of \( \lambda = \text{const} \), the probability within the ellipse in Equation 14 can be calculated.

Equation (14) can be rearranged by equating the exponential part of Equation 12 to the exponent of Equation 13, as:

\[ \xi^2 - 2\rho\psi\xi + (\psi^2 - \lambda^2) = 0 \]  
(15)

Any specific value of \( \lambda = \text{const} \) corresponds to an ellipse. Furthermore, any line \( \psi = h \) intersects the ellipse at two different values, \( \xi = k_1 \) and \( \xi = k_2 \).

For any \( \lambda = \text{const} \) corresponding to the required probability, given by Equation 13, by solving Equation 15 two particular coordinates (\( \xi = k_1 \) and \( \xi = k_2 \)) can be obtained, representing the intersection of the ellipse and the line \( \psi = h_0 \). Series of ellipses can be defined by repeating the calculation procedure for several selected values of \( \lambda \), while varying the values of \( \psi = h_0 \). It should be noticed that after each calculation step, an appropriate transformation should be performed in accordance Equation 10 and Equation 11 to obtain non-standardized values of the flood wave parameter instead of standardized logarithmic values.

To overcome difficulties in evaluation of the cumulative distribution function, Abramowitz & Stegun's procedure was implemented. The calculation methodology contains graphical and analytical procedures that define the cumulative probability, \( \Phi(h, k, \rho) \), in terms of the probabilities \( \Phi(h, 0, r) \) and \( \Phi(k, 0, r) \), where instead of the correlation coefficient \( \rho \), the coefficient of correlation \( r \), should be estimated. More specifically, the
probability $\Phi(h,k,\rho)$ can be assessed from Equation 16:

$$
\Phi(h,k,\rho) = \Phi\left(h,0,\left(\frac{ph-k}{\sqrt{h^2 - 2p\rho h + \rho^2}}\right)\right) + \Phi\left(k,0,\left(\frac{pk-h}{\sqrt{k^2 - 2p\rho k + \rho^2}}\right)\right) - \left\{ \begin{array}{ll}
0 & \text{if } h,k \geq 0 \text{ and } h+k \geq 0 \\
\frac{1}{2} & \text{for all other cases}
\end{array} \right. 
$$ (16)

In Equation 16, $(\text{sgn } h)$ and $(\text{sgn } k)$ are equal to 1 when $h$ or $k$, respectively, are greater or equal to zero, while they become -1 when $h$ and $k$ are less than zero.

Further development of the described methodology underlay in the definition of the multiple-coincidence of flood waves in a complex river system that comprised of a main river and two major tributaries, where the influence of lateral inflow is negligible. The flood wave peak was selected as the most adequate representative of the statistical significance of the flood wave. Probability distribution functions of flood wave peaks represent the basis for establishing a multi-dimensional probabilistic dependency of the flood wave probability at the outflow profile as a function of the probabilities of flood waves at all considered inflow profiles of the main river and its tributaries:

$$
P(Q \geq q) = p 
$$ (17)

where

- $P(Q \geq q)$ - probability that the flood peak at all entry/exit profiles will be exceeded;
- $p$ - exceedance probability.

The exceedance probability of a simple coincidence between annual maximum discharges at two entry profiles, $j$ and $k$, is required:

$$
P((Q_j \geq q_j) \cap (Q_k \geq q_k)) = \Theta 
$$ (18)

where

- $P((Q_j \geq q_j) \cap (Q_k \geq q_k))$ exceedance probability of coinciding annual maximum discharges at two considered inflow profiles, $j$ and $k$;
- $\Theta$ exceedance probability.

The procedure for determination of the multiple-coincidence of flood wave peaks in a complex river system was developed for reaches with a main river and two significant tributaries, where the input profile at the main river is $(j)$ and at the tributaries $(k)$ and $(i)$, and the output profile at the main river is $(\text{out})$. 


The first step of approach is to determine the coincidence of maximum annual discharges at the main river outflow profile of the main river and the union of the maximum annual discharges at input profiles of the considered complex river system, or to define the dependency:

$$P((Q_{\text{out}} \geq q_{\text{out}}) \cap (((Q_i \geq q_i)_{p=T}) \cup ((Q_j \geq q_j) \cap (Q_k \geq q_k)))) = \Theta$$  \hspace{1cm} (19)$$

where:

- $Q_{\text{out},p=\theta}$ - peak discharge at the output profile for a fixed probability $p=\theta$;
- $Q_{i,p=T}$ - peak discharge at the i-th input profile for a selected return period $T$;
- $Q_{j,r}$ - peak discharge at the j-th input profile for an arbitrarily selected probability $r$, in accordance with the exceedance probability $P((Q_j \geq q_j) \cap (Q_k \geq q_k))$;
- $Q_{k,z}$ - peak discharge at the k-th input profile for an arbitrarily selected probability $z$, in accordance with the exceedance probability $P((Q_j \geq q_j) \cap (Q_k \geq q_k))$.

Then, for the selected exceedance probability of the outflow hydrograph $\theta$, using Equation 19, the correspondents of the following exceedance probabilities are determined for the arbitrarily selected probability $p$ - $P(Q_{\text{out}} \geq q_{\text{out}})_{p}$ and $P(((Q_i \geq q_i)_{p=T}) \cup ((Q_j \geq q_j) \cap (Q_k \geq q_k)))_{p}$.

Where the variable $((Q_i \geq q_i)_{p=T}) \cup ((Q_j \geq q_j) \cap (Q_k \geq q_k)))_{p}$ represents a conditional value of the flood wave peak at the output profile of the main river $(Q_{\text{out},p=\theta})$, and following condition must be satisfied:

$$((Q_i \geq q_i)_{p=T}) \cup ((Q_j \geq q_j) \cap (Q_k \geq q_k)))_{p} = ((Q_i \geq q_i)_{p=\theta}) + ((Q_j \geq q_j) \cap (Q_k \geq q_k))_{p}$$  \hspace{1cm} (20)$$

At the end, for fixed probability of the outflow hydrograph $\theta$ and the selected return period $T$, the corresponding theoretical flood wave peaks, $Q_{\text{out},p=\theta}$ and $Q_{i,p=T}$, are estimated using Equation 19, or Equation 17. Also, using Equation 18 for one of selected probabilities, $r$ or $z$ (e.g. $r$), using coincidence exceedance probability $P((Q_j \geq q_j) \cap (Q_k \geq q_k)) = q$, theoretical values $Q_{j,r}$ and $Q_{k,z}$ are determined for different combinations of the parameters $r$ and $z$. The results of the determination of “corresponding” probabilities: $p(Q_{\text{out},p=\theta})$, $p(Q_{i,p=T})$, $p(Q_{j,r})$ and $p(Q_{k,z})$, enable the assessment of multi-dimensional dependencies of the probabilities of occurrence of flood waves on the main river and its tributaries:
\[ p(Q_{\text{out},\theta}) = P(p(Q_{i,T}) \cap P(p(Q_{j,r}) \cap p(Q_{k,z}))) \]  
(21)

where:

- \( p(Q_{\text{out},\theta}) \) - exceedance probability of flood-wave peak at the output profile;
- \( p(Q_{i,T}) \) - exceedance probability of flood-wave peak at the input profile, \( i \);
- \( p(Q_{j,r}) \) - exceedance probability of flood-wave peak at the input profile, \( j \);
- \( p(Q_{k,z}) \) - exceedance probability of flood-wave peak at the input profile, \( k \);
- \( P[p(Q_{j,r}) \cap p(Q_{k,z})] \) - exceedance probability of the coincidence of flood wave peaks at input profile, \( j \) and output profile, \( k \).

Such dependencies are established for a number of selected fixed probabilities \( \theta \) at the output profile of a river reach. So far, for known flood wave peaks at the input profiles by Equations from (18) to (21), flood wave peak probabilities at the output profile of the considered river reach can be estimated.

3. Practical application of the model

The methodology developed for the determination of the multiple-coincidence of flood waves on the main river and its tributaries was applied to a reach of the Danube River in Serbia. In this specific case, the multi-dimensional coincidence of flood wave occurrence probability on the Danube River downstream from Belgrade (Gauging Station Pančevo) was established as a function of the probability of occurrence of flood waves on the upstream reach of the Danube (GS Bogojevo), on the Tisza (GS Senta), and on the Sava (GS Sremska Mitrovica) rivers. Schematic presentation of the considered reach is shown on Figure 1.
Maximum annual discharges (peaks) were selected as representative parameters of the flood waves. In establishing the multi-dimensional dependency of flood waves at the designed profiles, it was assumed that the theoretical hydrograph of a certain probability $\theta$ at the output profile of the Danube at GS Pančevó contains flood waves on the Danube River at GS Bogojevo (which probability $p$, or return period $T$ is known) and selected two-dimensional coincidences of flood waves on the Tisza River at GS Senta and on the Sava River at GS Sremska Mitrovica. Using this procedure, the following dependency of the probability of multiple coincidences at the GS profiles was established:

$$p(Q_{out,p=\theta})^{Pan} = P(p(Q_{i,p}=T)^{Bog} \cap P[ p(Q_{j,r})^{Sen} \cap p(Q_{Wk,z})^{Sr.M} ] )$$

(22)

where:

- $p(Q_{out,p=\theta})^{Pan}$ - exceedance probability of annual maximum flood wave peak on the Danube River at the output profile at GS Pančevó;
- $p(Q_{i,p}=T)^{Bog}$ - exceedance probability of annual maximum flood peak at the input profile of the Danube River at GS Bogojevo;
- $p(Q_{j,r})^{Sen}$ - exceedance probability of annual maximum flood peak at the input profile of the Tisza River at GS Senta;
- $p(Q_{Wk,z})^{Sr.M}$ - exceedance probability of annual maximum flood peak at the input profile of the Sava River at GS Sremska Mitrovica;
- $P[ p(Q_{j,r}) \cap p(Q_{Wk,z}) ]$ - exceedance probability of a simple coincidence of annual maximum flood peaks on the Tisza and Sava rivers.
Practical presentation of the assessment of maximum annual flood peaks coincidence on the considered complex reach of the Danube River, for a 100-year return period at the output profile, GS Pančevo, is shown in Table 1. The same procedure was implemented to estimate coinciding peaks of maximum annual discharges of the Danube, the Tisa and the Sava rivers for the following exceedance probabilities: 0.1, 2, 5, 10 and 50% (or, return periods of 1000, 50, 10 and 2 years) at output profile, GS Pančevo.

Using the data shown in Table 1, a graphical presentation of the results of the multiple-coincidence of flood wave peaks on the Danube, the Sava and the Tisza rivers was composed as an example for a 100-year flood wave on the Danube River at GS Pančevo, as shown in Figure 2.

**Figure 2**  Multiple-coincidence of a 100-year flood wave on the Danube River at GS Pančevo as a function of the flood waves probabilities on the Danube, the Tisa and the Sava rivers
Table 1: Coincidence of flood waves in considered complex river system

<table>
<thead>
<tr>
<th>θ (%)</th>
<th>(Q_{out,p}) = θ (%) (m^3/s)</th>
<th>Σ (Q_{out,p} UQ_{SM}) (m^3/s)</th>
<th>p(%)</th>
<th>(Q_{out,p} ∩ Q_{SM}) (m^3/s)</th>
<th>p(%)</th>
<th>Q_{out} (m^3/s)</th>
<th>p(%)</th>
<th>Q_{SM} (m^3/s)</th>
<th>p(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.0</td>
<td>15 206</td>
<td>13 200</td>
<td>4971</td>
<td>0.1</td>
<td>8229</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td>3981</td>
<td></td>
<td></td>
<td>1.0</td>
<td>9219</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td>3683</td>
<td></td>
<td></td>
<td>2.0</td>
<td>9517</td>
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<tr>
<td></td>
<td>2093</td>
<td></td>
<td></td>
<td>50.0</td>
<td>11107</td>
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<td></td>
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<tr>
<td></td>
<td>1499</td>
<td></td>
<td></td>
<td>90.0</td>
<td>11701</td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tbody>
</table>

The corresponding bi-variate coincidence of flood wave peaks on the Danube River at GS Bogojevo and the Sava River at GS Sremska Mitrovica is graphically presented in Figure 3.

The final graphic which shows the probability of exceeding the multiple-coincidence of flood wave peaks at the input profiles of the Danube, the Tisza and the Sava rivers, and the occurrence of flood wave peaks of selected probabilities on the lower Danube at GS Pančevo, is presented in Figure 4.
Figure 3  Bi-variate coincidence of flood waves at input profiles of the Danube and the Sava rivers
4. Discussion

As it is said the significance of the results of the multiple-coincidence estimation can be classified into two groups, primary and secondary.

Primary significance is related to:

- The genesis of flood waves on the Danube River and its main tributaries;
- Establishment of a hydrological basis for an assessment of the probabilistic significance of historic and future floods in the Danube River Basin within the territory of Serbia; and
- Logistical support to the hydrologic real-time forecasts of the occurrence of catastrophic floods on the considered rivers.

The secondary (but not less important) significance, which is not under detail consideration in this paper, of the established multiple-coincidences, is related to their use in all stages
of construction design and management of flood defence systems. The established dependencies may be used to:

- Create groundwork for cost-effective studies of linear flood defence systems in the zone of interaction between the main river and its tributaries;
- Support the development of a construction and reconstruction strategy for flood defence systems in coastal zone of the Danube River and the confluence areas of its main tributaries; and
- Provide background for a more reliable and more comprehensive flood risk assessment.

From the standpoint of the *genesis of flood waves*, the defined curves of the established multiple-coincidences determine the realistic space in which different ranges of flood probabilities on the Danube River and its main tributaries may be found. As an example, *Figure 4* encompasses a wide range of probabilities (from 0.1% to 99%) of flood wave peaks at the input profiles of the Danube River and its main tributaries, the Sava and the Tisza rivers, for a 100-year flood at the output profile of the Danube River. The created probability curves, from 0.1% to 99%, which are parametrically given for the GS Senta on the Tisza River (but may also be provided for any input profile), show the range of possible flood wave peaks at the considered input profiles which characterize a 100-year flood on the Danube River at GS Pančevo. For example, a 100-year flood at this profile, as shown in *Figure 5*, may be caused by multiple-coincidences of the following combinations of input profile peaks:

1. 50-year flood wave on the Danube River at GS Bogojevo, 50-year flood wave on the Tisza River at GS Senta, and 2.2-year flood wave on the Sava River at GS Sremska Mitrovica;
2. 20-year flood wave on the Danube River at GS Bogojevo, 100-year flood wave on the Tisza River at GS Senta, and 30-year flood wave on the Sava River at GS Sremska Mitrovica;
3. 3.7-year flood wave on the Danube River at GS Bogojevo, 50-year flood wave on the Tisza River at GS Senta, and 100-year flood wave on the Sava River at GS Sremska Mitrovica.
The multiple-coincidence graphics are very convenient for assessment of the probabilistic significance of historic floods. For example, Table 2 shows the main indicators of two largest flood waves recorded on the Danube River, according to flood wave peak and corresponding simple probabilities. Flood scenarios in the years during which one of the considered gauging stations recorded the highest flood wave peaks were selected.

Table 2: Highest flood wave peaks recorded on the Danube, the Tisza and the Sava rivers, and their probabilities

<table>
<thead>
<tr>
<th>Year</th>
<th>Bogojevo GS $Q_{\text{max}}$ (m$^3$/s)</th>
<th>Senta GS $Q_{\text{max}}$ (m$^3$/s)</th>
<th>S. Mitrovica GS $Q_{\text{max}}$ (m$^3$/s)</th>
<th>Pančevo GS $Q_{\text{max}}$ (m$^3$/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1965</td>
<td>9250 0.7</td>
<td>2710 17.0</td>
<td>5520 5.0</td>
<td>13909 3.0</td>
</tr>
<tr>
<td>2006</td>
<td>8620 2.8</td>
<td>3720 2.0</td>
<td>4460 32.0</td>
<td>15095 1.0</td>
</tr>
</tbody>
</table>

The data presented above suggest that the greatest flood on the lower Danube recorded in 2006, which flood wave peak return period is 100 years, was caused by coincidence
of 30-year flood wave peak on the upper Danube, 50-year peak on the Tisza River and 3-year peak on the Sava River.

The greatest flood on the upper Danube recorded in 1965, which peak return period is 143 years, in combination with a 20-year flood on the Sava River and a 6-year flood on the Tisza River, caused a 33-year flood on the lower Danube.

The proposed procedure for establishing the probabilistic significance of a certain flood scenario is comprised of the following: based on known flood wave peaks (or their probabilities) at input profiles, specific points are applied to the multiple-coincidence graphic, which correspond to a combination of real peak probabilities at the input profiles. In two analysed cases (years), the points are identified on multiple-coincidence probability curves shown in Figure 6 (1965 and 2006).

As shown in Figure 6 for the 2006 flood, the points with ordinate values $p_{\text{2\%}, \Theta=1\%} = 3\%$ and...
$p_{2\% \theta=0.1\%} = 0.01\%$ correspond to the probability of a flood wave peak on the Tisza River at GS Senta ($p = 2\%$ in 2006). The empirical point with the same ordinate value corresponds to a probability of $p = 2.8\%$, or the probability of the flood wave peak on the Danube River at GS Bogojevo in 2006. A realistic assessment of the probabilistic significance of the 2006 flood scenario is produced by graphical interpolation of ordinate values of the probabilities in Figure 6, as a function of the flood significance $\theta$, as shown in Table 3.

### Table 3: Results of graphical interpolation of the probabilistic significance of selected floods in the Danube River Basin within the territory of Serbia

<table>
<thead>
<tr>
<th></th>
<th>1965</th>
<th></th>
<th></th>
<th>2006</th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Senta</td>
<td>Pančevo</td>
<td></td>
<td>Senta</td>
</tr>
<tr>
<td>$T$ (year)</td>
<td>$p$ (%)</td>
<td>$\theta$ (%)</td>
<td>$\theta$ (%) from plot</td>
<td>$T$ (year)</td>
<td>$p$ (%)</td>
</tr>
<tr>
<td>5.9</td>
<td>17.0</td>
<td>1</td>
<td>4</td>
<td>50</td>
<td>2.0</td>
</tr>
<tr>
<td></td>
<td>0.1</td>
<td>0.02</td>
<td></td>
<td>0.17</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.9</td>
<td>2.8</td>
</tr>
</tbody>
</table>

A cumulative overview of the assessment of the probabilistic significance of the registered floods is presented in Table 4, which shows the probabilities of flood wave peaks and their return periods at the input and output profiles, as well as the assessed probability of the statistical significance of the flood, including return periods.

### Table 4: Results of assessment of statistical significance of considered recorded floods in the Danube River Basin within the territory of Serbia

<table>
<thead>
<tr>
<th>Year of flood</th>
<th>Bogojevo GS $p$ (%)</th>
<th>Senta GS $T$ (year)</th>
<th>Sremska Mitrovica GS $p$ (%)</th>
<th>Pančevo GS $T$ (year)</th>
<th>Statistical significance of flood</th>
<th>$\theta$ (%)</th>
<th>$T$ (year)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1965</td>
<td>0.7</td>
<td>143</td>
<td>17.0</td>
<td>5.9</td>
<td>5.0</td>
<td>33.3</td>
<td>0.17</td>
</tr>
<tr>
<td>2006</td>
<td>2.8</td>
<td>35.7</td>
<td>2.0</td>
<td>50</td>
<td>32.0</td>
<td>1.0</td>
<td>100</td>
</tr>
</tbody>
</table>

Based on the results presented in Table 4, it can be concluded, that the two considered historic flood situations on the Danube River in Serbia have very different statistical significance. The 1965 flood situation comprised of the flood wave peak return periods: 143 years at GS Bogojevo, 50 years at GS Senta, 3.1 years at GS Sremska Mitrovica and 33.3 years at GS Pančevo, has lower probability or higher statistical significance which corresponds to a return period of 588 years.

When real-time flood wave forecasts are issued, the procedure is similar to the assessment of the statistical significance of recorded flood events presented in Table 3.
5. Conclusion

In general, the importance of the results of flood wave coincidence assessment is meaningful.

First, they can be used to assess the statistical significance of different flood hydrograph parameters both on the Danube River and its main tributaries. The practical importance of these results is that if there is no coincidence, then the level of protection of the coastal area in the zone of interaction between the main river and a tributary can be lower than indicated by the conventional one-dimensional approach to the design of the defence system, while providing the same degree of flood protection.

Second, the proposed methodology provides quantitative indicators of the best combinations of the considered random variables from the standpoint of cost-effectiveness and safety of flood defence systems.

Additionally, the methodology can be applied in the case of rivers in lowland, where there is a frequent need to simultaneously protect a large area from flood waves on two or more rivers. Conventional separate flood protection solutions for these rivers are generally costly and often technically infeasible and, as a rule, with the high level of required protection (e.g. in urban areas). The proposed methodology allows an integrated approach to flood protection, considering flood waves coincidence.

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Programme of UNESCO
Numerical Modeling of the Effects of artificial Recharge on hydraulic Heads in constant-Density Ground Water Flow to manage the Gaza Coastal Aquifer, South Palestine.

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Abstract
The coastal aquifers of the Gaza Strip are considered a very important source for water supply and thus very essential for the socio-economic development of the region. High rates of urbanization and increased municipal water demand, as well as extended agricultural activities, have led to an overexploitation of the aquifer, with the consequence, that the groundwater levels have dropped significantly across most of the aquifer area. This has induced sea water intrusion at many sections along the coastal shoreline and led to a deterioration of the groundwater quality, as the chloride concentrations of the freshwater have increased beyond the WHO-endorsed 250 mg/l drinking water standard.

In this context, maintaining the sustainability of the Gaza groundwater system and to forestall imminent future problems, a better understanding of its dynamics is needed. To that avail, numerical groundwater flow modeling is an important task to control ground water level fluctuations as well as for the management of the groundwater resources over the long run. In this paper a coupled three - dimensional groundwater flow and contaminant transport model as implemented in Visual MODFLOW is applied to the Gaza coastal aquifer system. The major purpose of the regional groundwater modeling effort undertaken here is to study the effects of artificial recharge - planned in the Gaza Strip for some time - on the restoration of the groundwater levels on the regional scale.

The groundwater flow simulations of the aquifer system are done in two steps. Firstly, steady-state calibrations with head data for the year 2000 are performed to calibrate the hydraulic conductivity/transmissivity. In the second step monthly data recorded between years 2001-2010 are used to calibrate the storage coefficients and/or the specific yield. However the subsequent sensitivity analysis of the models shows that, the model is more sensitive to the lower than to the upper values of both hydraulic conductivity and recharge.

After successful calibration of the groundwater model, future scenarios of groundwater management strategies for the Gaza aquifer are studied, in order to establish appropriate ground water management policies for the prevention of future aquifer overdraft. To that
avail, the calibrated transient flow model is applied to examine numerous management scenarios within the target period 2011-2040. The first scenario, to be considered the worst one, assumes that there are no new water resources available to recover the sustainability of the aquifer of the Gaza strip. In contrast, in the second scenario artificial recharge of reclamation wastewater is applied as a new water resource option to maintain positive conditions for the aquifer’s water balance and to revamp its depletion.

The results of the first scenario are pessimistic, as they indicate a tremendous decline of the groundwater levels below the mean sea level over time, which will lead to more inland seawater intrusion. On the contrary, the results of the second scenario are more optimistic, as the simulated heads show a slight groundwater mound which rises gradually so that at end of the simulation period in year 2040 the present-day cone of depression will have completely disappeared. This shows that artificial aquifer recharge is a valid option to restore the sustainability of the Gaza coastal aquifer in the long-run.

**Keywords**

Gaza coastal aquifer, groundwater flow modeling, artificial recharge.

**1. Introduction**

Groundwater is the most precious natural resource in the Gaza Strip and it is the only source of water supply for domestic, agricultural, and other uses in the area. Hydrological data reveals that, over the years, the Gaza coastal aquifer has been overexploited from heavy groundwater pumping to meet municipal and agricultural demands, which increased from 136 MCM (million cubic meters) in year 2000 to 174 MCM in year 2010. This increased demand cannot be balanced anymore by natural aquifer replenishment from precipitation. As a result of this over-exploitation, the water levels across most of the coastal aquifer have dropped significantly, with values going up to more than 12 m below the mean sea level in some areas. Such large groundwater level declines have led to increased sea water intrusion and a subsequent deterioration of the freshwater quality, as the chloride concentrations have exceeded the safe drinking threshold value of 250 mg/l recommended by WHO guidelines.
Nowadays, the groundwater situation in the Gaza region has become even more disastrous, so that endeavours to forestall imminent future deficiency problems and to restore and/or maintain the sustainability of the Gaza groundwater system for now and the near future are becoming extremely urgent. Under these circumstances, appropriate groundwater management policies are essential for preventing further aquifer overdraft. Identification of such policies requires first an accurate simulation of the dynamics of the ground water system in response to various hydrological, meteorological, and human impact factors. Numerical modelling is the indispensable tool to achieve this objective.

In the present study the 3D- finite difference (FD) coupled flow and contaminant transport model MODFLOW/MT3D (McDonald and Harbaugh, 1988), as implemented in the Visual MODFLOW-model, is applied to the Gaza coastal aquifer system This modeling package has been chosen because of its easy-to-use interface which has been specifically designed to increase modeling productivity and to decrease the complexities typically associated with building three-dimensional groundwater flow and contaminant transport models.

The main objective of the present paper is then to carry out an integrated numerical resources management analysis for the Gaza coastal aquifer. Thus, once the numerical groundwater flow model has been set-up and calibrated, various groundwater impact scenario schemes for the near future target period 2011-2040 will be simulated, in order to understand the aquifer behaviour, i.e. the variations of the groundwater levels in the long-term. In particular, in order to possibly restore positive conditions of the Gaza aquifer’s water balance and to revamp its depletion, groundwater management scenarios for artificial recharge of groundwater by reclamation wastewater are numerically investigated.

2. Study Area

2.1. Geographic and hydro-climatic situation
Palestine is composed of two-separated areas, the Gaza strip and the West Bank. The Gaza Strip area is located in the south of Palestine at 31°25’N, 34°19’59”E. Its length is 40 km, while its width varies between 6 km in the north to 12 km in the south, comprising a total area of 365 km². The Gaza Strip is physically bounded by the 1948 cease-fire line with Israel in the north and east, by Egypt in the south and by the Mediterranean Sea in the west (Figure 1). Nowadays, with more than 1.65 million inhabitants living in this small area, the Gaza Strip is one of the most densely populated areas in the world (2,638 person/km²), which is bound to increase tremendously in the future, as the annual population growth rate is 3.2% (PCBS, 2000).
The climate of Gaza is a transitional one between an arid tropical climate in the south, with an average annual rainfall of 200 mm/year that increases to 400 mm in the temperate and semi-humid climate of the Mediterranean coast in the north, with mild winters and dry, hot summers (PWA, 2001). Most of the rainfall occurs in the months October to March in the form of thunderstorms and rain showers, but where only a few days during these wet months are actually rainy days. As the potential evaporation in the Gaza Strip is of the order of 1300 mm/yr, it becomes clear that the rejuvenation of water resources in the region is rather low. In fact, groundwater from the coastal aquifer is not only the sole source of fresh water, but the only source of water supply in the region at all.

2.2. Hydrogeology

The coastal aquifer covers an area of about 2000 km² and extends along some 120 km of the Mediterranean coastline from the Gaza Strip in the south, where its width is about 20 km, to Mount Carmel in the north, with of only 3-10 km (Figure 2). Under natural conditions, the groundwater flow in the Gaza Strip is generally directed from east to west towards the Mediterranean sea (Mercado, 1968). This means that part of the recharge of the Gaza section of the groundwater aquifer occurs on the territory of Israel in the east.

The geology of the aquifer system that extends along the coastal plain of the Gaza Strip is of the Pliocene-Pleistocene age consists mainly of marine deposits of sandstone, calcareous siltstone and red loamy soils. With regard to the hydrogeology, the aquifer system can be subdivided near the coast into four separate sub-aquifers, A, B1, B2, and C, which all together form a largely unconfined and confined/unconfined multi-aquifer.
system in the western part of the aquifer area (PEPA, 1996) (Figure 3). Marine clay layers (aquiclude) with a thickness of 20 meters separate these sub-aquifers and extend from the shoreline to about 2-5 km inland.
3. Characteristics of the Gaza Groundwater System

As will be discussed in the later theory section, the differential equation which governs groundwater flow in an aquifer is basically a water balance equation for all in- and outflows into a finite model-domain representation of the aquifer under question. For the 3D-Gaza aquifer domain the relevant water balance components are shown in Figure 4. They will be explained in the following subsections.

3.1. Groundwater recharge

The main water source for recharge in the Gaza Strip area is the precipitation which recharges the aquifer through infiltration and percolation to the sub-surface soil layers. Recharge is generally estimated as a portion of the effective rainfall, i.e. after substraction of losses from evapotranspiration and other surficial water abstractions, and is usually hard to be quantified correctly, as it varies spatially, depending on other factors such as soil type, land use and topography and, not to the least, on the antecedent history of the rainfall itself which affects the soil moisture (e.g. Freeze and Cherry, 1979). In the present application the concept of the recharge coefficient \( C_R \) which is defined as the ratio of the recharge \( R \) to the precipitation \( P \), has been used as a first guess. \( C_R \) depends on the local soil type and varies from \( C_R = 0.25 \) for rather impermeable soils to \( C_R = 0.7 \) for highly permeable soils. Depending on the local soil conditions across the Gaza area, recharge coefficients in this range have been used in the numerical simulations, but have been modified and fine-tuned further during the steady-state calibration of the groundwater flow model.

3.2. Lateral inflow

Lateral subsurface inflow into the Gaza coastal aquifer arises from the Israeli eastern side of the model domain which is congruent with the political border between Gaza and Israel (see Figure 4). The amount of inflow varies each year, as it depends on the head variations at this eastern boundary of the model. Metcalf and Eddy (2000), state the amount of lateral inflow to be within the range of 15-30 M m\(^3\)/y.

Similar to recharge, the exact amount of lateral inflow will be determined during the calibration of the groundwater flow model. Thus, for year 2000 it turns out to be 20 M m\(^3\).
3.3. Return Flows

3.3.1. Irrigation return flow
Following the Gaza Department of Agriculture (GDA), the total amount of annual agricultural abstraction ranges between 80-100 M m³/year. According to Melloul and Collin (1994), the estimated amount of irrigation returns flow is about 20% of the total pumping amount (Ba'lousha, 2005). Knowing that the agricultural groundwater consumption for year 2000 is 85 M m³, this means that 17 M m³ of return flow infiltrates back into the aquifer.

3.3.2. Water system leakage returns flow
Another source of return flow into the aquifer is leakage from the rather poorly maintained water distribution system in the Gaza strip. Most of the water consumed in Gaza comes from the numerous municipal wells which are spread across 98% of the Gaza area. The amount of leakage from the drinking water system is estimated as 16.8 M m³ per year, which correspond to a whopping 30% of the total municipal drinking water production (PWA, 1999).

3.3.3. Wastewater return flow
The amount of leakage from wastewater in the Gaza strip is significant. In this study, the estimated amount of wastewater return flow for year 2000 is 8.5 M m³, and includes leakage from the sewer system network, septic tanks, infiltration at the Wadi Gaza area, and infiltration from the B/Lahia wastewater treatment plant.
3.4. Well abstractions

Abstraction of groundwater by pumping wells is acting as the main internal hydrologic stresses on the Gaza aquifer system. More than 4000 water wells have been dug across the Gaza strip over the recent decades to meet both the domestic and agriculture demand (see Figure 5). As discussed in the introduction, this increasing demand cannot
be balanced anymore by natural replenishment from precipitation and has so led to an overexploitation of the aquifer. The yearly total amount of groundwater abstraction from all of these wells was obtained from the PWA and is shown in Figure 6, from which one may notice that this abstraction has been steadily increasing over the last decade from 136 M m$^3$ in the year 2000 to 174 M m$^3$ in 2010 (PWA, 2010a).


Computer modelling of groundwater flow and transport has become a powerful tool for understanding and analyzing the hydrology of groundwater aquifers and various other aspects of subsurface flow dynamics. Numerous numerical groundwater flow models are nowadays available for that purpose (e.g. Wang and Anderson, 1982; McDonald and Harbaugh, 1988; Anderson and Woessner, 1991; Kresic, 1996). These models usually look for a numerical solution of the fundamental differential equations that describe the physics of flow and transport in a porous subsurface media, after the latter has been put into a conceptual model-form, using available geological and hydro-geological information on the aquifer system. In the following subsections we provide a concise review of the underlying equations governing constant-density groundwater flow as well as the numerical implementation for their solution.

4.1. Groundwater flow equation

The three dimensional movement of groundwater of constant density through a porous media is described by the following parabolic partial differential equation, the so-called groundwater flow equation (McDonald and Harbaugh, 1988):

$$\frac{\partial}{\partial x} \left[ k_{xx} \frac{\partial h}{\partial x} \right] + \frac{\partial}{\partial y} \left[ k_{yy} \frac{\partial h}{\partial y} \right] + \frac{\partial}{\partial z} \left[ k_{zz} \frac{\partial h}{\partial z} \right] - W = S_s \frac{\partial h}{\partial t}$$

where:
- $x$, $y$, and $z$ are the coordinate directions where $z$ is usually aligned with the gravity vector ($L$);
- $h$ is the potentiometric head ($L$);
- $t$ is the time ($T$);
- $k_{xx}$, $k_{yy}$, and $k_{zz}$ are the anisotropic components of the hydraulic conductivity along the $x$, $y$ and $z$ coordinate ($LT^{-1}$), whereby it is assumed that the coordinate system is aligned along the main diagonals of the conductivity-ellipsoid, i.e. the $k$-tensor has been diagonalized.
$W$ is a volumetric flux per unit volume representing sources/sinks of water $[T^{-1}]$.

$S_s$ is the specific storage of the porous media $[L^{-1}]$.

For an isotropic media (assumed in the present application) $k_{xx} = k_{yy} = k_{zz} = k$. Also, for steady-state conditions, the right hand side of Equation 1 is zero, so that Equation 1 reduces to the Poisson equation, or, when, additionally, the source/sink-term $W = 0$, to the Laplace equation.

Once Equation 1 has been solved for the hydraulic head (after specification of appropriate boundary and initial conditions, see below), groundwater flow velocities $v$ can be computed by Darcy’s law:

$$v = -\frac{k}{n} \cdot \text{grad } h$$

where $n$ is the porosity and grad $h$ is the gradient of $h$.

Furthermore, for steady-state conditions streamlines $\Psi$, which are orthogonal to the isolines $h =$ constant, can be computed from an integration of Equation 2.

4.2. Conceptual model

4.2.1. General set-up and discretization

Before the solution of the groundwater Equation 1 can be endeavored, a conceptual model of the aquifer under question must be formulated, using the available geological and hydro-geological data, including the spatial and temporal distribution of sources and sinks in the aquifer. Finally, the boundary- and initial (for the transient model) conditions must be specified. The conceptual model defined in this way for the Gaza coastal aquifer has been set up in the Visual MODFLOW- environment and is shown in Figure 7. This model consists of one unconfined and six confined/unconfined model layers with the vertical grid size based on the hydro-geological and hydraulic properties of the geological stratigraphy. A uniform grid size of 300 m x 300 m in the horizontal plane has been chosen (Figure 8), resulting in 157 rows and 50 columns, and a total cell number of 54,950. Further details on the setup of the conceptual model can be found in Sirhan and Koch (2012).
4.2.2. Boundary conditions

The 3D conceptual model box of the Gaza aquifer is enclosed by boundary surfaces on which appropriate boundary conditions must be imposed, before the numerical solution of the 3D groundwater flow equation can be endeavored. There are two types of boundaries in the conceptual model: Constant head (Dirichlet) boundaries and flux/no-flow (Neumann) boundaries. Dirichlet boundary conditions $h = 0$ are assigned at the western boundary along the coastline of the aquifer, while at the eastern boundary which runs along the Gaza-Israel political border a constant flux of lateral subsurface inflow coming from Israel is assigned. This is done in the model by placing a series of injection wells with some specified recharge rates (whose magnitude will be determined during the calibration process) along this boundary.
Under natural conditions the flow lines are more or less directed from east to west, perpendicular to the coast-line and parallel to a no-flow boundary. Therefore, the remaining vertical boundaries of the model in the north along the Israel border and in the south along the Egypt border are assigned as no-flow boundaries. The same holds for the bottom boundary surface of the model which is also specified as a Neumann no-flow boundary.

Finally, the top boundary surface of the model is specified as a Neumann flux boundary, with the flux representing groundwater recharge by direct surficial infiltration. Figure 9 illustrates again the boundary conditions imposed.

4.2.3. Initial conditions
For the transient groundwater flow simulations that cover a period of 2000-2010, initial conditions for the groundwater heads distributed across the model area must also be set. In the present application these are simulated water levels for year 2000, as obtained during the steady-state calibration of the model.

4.2.4. Hydraulic aquifer parameters
Important hydraulic aquifer parameters assigned to the model in the initial phase of the calibration process have been obtained from pumping tests, which were carried out for different municipal wells as a part of the project of CAMP-2000, under the monitoring of the Palestinian Water Authority (PWA). The results of these aquifer tests indicate that the transmissivity values \( T \) range between 700 and 5,000 m\(^2\)/day, whereas the corresponding values of the hydraulic conductivity \( k \) were estimated to lie in a relatively narrow range of 20-80 m/day, i.e. \( 2.31 \times 10^{-4} - 9.26 \times 10^{-4} \) m/s (PWA, 2000b).
Values for the specific yield for the unconfined aquifer were found to be in the range of 0.15–0.30, while the specific storage for the confined units turned out to be about $10^{-4}$ m$^{-1}$. Table 1 summarizes these initial aquifer hydraulic parameters.

### Table 1: Range of initially assigned hydraulic parameters (PWA, 2000b)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transmissivity (m$^2$/d)</td>
<td>700 - 5000</td>
</tr>
<tr>
<td>Hydraulic conductivity (m/d)</td>
<td>20 - 80</td>
</tr>
<tr>
<td>Specific yield</td>
<td>0.15 – 0.30</td>
</tr>
<tr>
<td>Storativity (m-1)</td>
<td>10-4 - 10-5</td>
</tr>
</tbody>
</table>

5. Groundwater Flow Model Simulations

5.1. Calibration of the groundwater flow model

Calibrations of the groundwater flow models are carried out in order to check that the final model can reasonably well emulate the observed groundwater flow system. Following the usual approach in groundwater flow modeling (e.g. Anderson and Woessner, 1992) both steady-state and transient calibrations of the model are carried out, using as calibration target heads observed on a monthly time-scale in the time-period 2000-2010 at 114 and 50 observation wells, respectively, distributed across the model area.

5.1.1. Steady-state calibration

In the steady-state calibrations, the average observed hydraulic heads for the year 2000 are taken to calibrate the hydraulic conductivity/transmissivity, as well as for getting an estimate of the aquifer's water balance. The calibration of the steady-state model has been done manually by a trial-and-error approach, to find that model which can best mimic the groundwater flow system.

The results of the steady-state calibration runs can be expressed both in terms of a qualitative evaluation and a quantitative assessment. A qualitative picture is obtained from Figure 10, where the observed and calibrated head isolines for the year-2000 steady-state calibration are shown. It is obvious that the calibrated model heads have similar patterns as the observed ones. Therefore, one may conclude that the calibrated steady-state head solution matches the water levels in the target (observed) wells reasonably well.
A more quantitative assessment of the calibration is based on various statistical error estimates (residuals) of the fit of the observed heads by the calibrated model, namely, (1) the mean residual (= - 0.57), (2) the mean absolute residual (=0.83) and, the standard
error of the estimate (=0.08) and (4) the root mean square error (MSE= 1.01). A scatter plot of the calculated versus the observed heads is shown in Figure 11 and which reveals that the model fits the observed groundwater levels rather well, as all points are lying close to the diagonal line, which would represent the ideal match with a correlation coefficient $R = 0.92$.

Table 2 summarizes the various statistical error estimates obtained again, as well as those obtained in the transient simulations to be discussed in the subsequent section.

<table>
<thead>
<tr>
<th>Statistical parameter</th>
<th>steady-state</th>
<th>transient calibration 2001-2008</th>
<th>transient validation 2009-2010</th>
</tr>
</thead>
<tbody>
<tr>
<td>Num. of observation wells</td>
<td>114</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>Min. residual (m)</td>
<td>-0.005</td>
<td>0.007</td>
<td>-0.033</td>
</tr>
<tr>
<td>Max. residual (m)</td>
<td>-3.03</td>
<td>5.639</td>
<td>-2.633</td>
</tr>
<tr>
<td>Mean residual (m)</td>
<td>-0.57</td>
<td>-0.124</td>
<td>0.011</td>
</tr>
<tr>
<td>Mean absolute residual (m)</td>
<td>0.83</td>
<td>0.923</td>
<td>0.906</td>
</tr>
<tr>
<td>Std error of estimate (m)</td>
<td>0.08</td>
<td>0.189</td>
<td>0.164</td>
</tr>
<tr>
<td>Root mean squared error (m)</td>
<td>1.01</td>
<td>1.329</td>
<td>1.146</td>
</tr>
<tr>
<td>Normalized RMS (%)</td>
<td>5.6</td>
<td>5.3</td>
<td>5.743</td>
</tr>
<tr>
<td>Correlation coefficient</td>
<td>0.92</td>
<td>0.923</td>
<td>0.938</td>
</tr>
</tbody>
</table>

5.1.2. Water balance

With reference to the various water-balance components of the Gaza aquifer conceptual model as were shown in Figure 4, Table 3 lists the results of the water budget analysis obtained with the steady-state calibrated model for year 2000.

It should be noted here that the total groundwater abstraction rate assigned to the wells across the region represents the net abstraction for both municipal- and agriculture-uses, i.e. after deducting the return flow which comes from irrigation, sewage infiltration and leakages from water networks (see Section 3.3) from the total abstraction rate. This is done to simplify the modification of the recharge zones assigned to the model and also to decrease the uncertainty coming from assigning the locations of return flow which is not well known.

Table 3 shows that the steady-state water budget for year 2000 is in balance, which provides another evidence of the quality of the steady-state calibration. The table
indicates, in particular, that the pumping well abstraction is balanced only by about 65% from sustainable surface water recharge and upgradient lateral inflow, namely, from Israel, whereas about 35% of the water pumped is coming from intruded seawater from the Mediterranean sea, further accentuating the Gaza groundwater quality problems due to saltwater intrusion.

<table>
<thead>
<tr>
<th>Net Inflows</th>
<th>Quantity (M m³/y)</th>
<th>Percent of Total (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recharge</td>
<td>46.63</td>
<td>43.6</td>
</tr>
<tr>
<td>Lateral inflow</td>
<td>23.43</td>
<td>21.89</td>
</tr>
<tr>
<td>Inflow from Sea</td>
<td>36.98</td>
<td>34.55</td>
</tr>
<tr>
<td>Total</td>
<td>107.04</td>
<td>100</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Net Outflows (M m³/y)</th>
<th>Quantity (M m³/y)</th>
<th>Percent of Total (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wells</td>
<td>106.16</td>
<td>99.18</td>
</tr>
<tr>
<td>Discharge to sea</td>
<td>0.88</td>
<td>0.82</td>
</tr>
<tr>
<td>Total</td>
<td>107.04</td>
<td>100</td>
</tr>
</tbody>
</table>

Net balance = In - Out | % Discrepancy = 0.00

5.1.3. Transient calibrations

In the transient calibration runs, the heads of steady-state calibrated model for year 2000 are used as initial conditions. The total transient simulation period 2001-2010 includes a 8-year-long calibration period 2001-2008 and a 2-year-long validation period 2009-2010. For the latter, the set of calibrated parameter and new stresses are used to simulate observed heads during that time.

The pumping stress period used in the transient simulations is one month (30 days), whereas the pure numerical flow time step is 3 days. Monthly head data of 50 monitoring wells distributed across the model domain has been used as calibration target.

In addition to the aquifer parameters already calibrated in the steady-state model above, such as a the hydraulic conductivity and the porosity, the transient calibration requires the specification of the specific yield \( S_y \) for the unconfined aquifer layers, and of the specific storativity \( S_s \) for the confined layers, as well as of the aquitards. These parameters have been adjusted manually by a trial-and-error during these transient calibration runs until an accepted match between observed and calculated heads has been obtained.
Figure 12 shows the observed and simulated heads, obtained at the end of year 2010 as part of the transient validation process in the validation period 2009-2010. A very good agreement, both in qualitative and quantitative terms, is obtained. Noteworthy here is that the two groundwater head depression cones in the north and south of the Gaza strip are, compared with those obtained for year 2000 (see Figure 10), now, 10 years later, much deeper, which indicates that the groundwater situation has worsened significantly during that time period.

Statistical results of the transient calibration for both the calibration period (2001-2008) and the validation period (2009-2010) are also listed in Table 2, discussed earlier. The values of the various statistical parameters in that table indicate that the transient calibration works equally well for the calibration- and the validation period.

A scatter plot of the simulated versus the observed heads at the end of the validation period (2010) is shown, together with the corresponding statistical measures, in Figure 13. Moreover, Figure 14 illustrates the correlation coefficients $R$, a measure of the goodness
of the fit of the simulated to the observed heads for each month of the calibration time period 2001-2008 and one may note that R lies consistently within the 90-95% range, i.e. the adjustment of the model to the data is consistently good.

Table 4 presents the final calibrated aquifer parameters values found from these calibration runs.
Groundwater flow balance calculations have also been carried out for the transient simulations. These can help to understand the effects of several influential factors, including pumping rate (discharge) and seasonal fluctuations in recharge and storage change. Figure 15 shows the average annual total discharge, recharge and storage change for the aquifer system during the total transient time period 2001-2010. From the figure one may notice that the regional storage change has become permanently negative after 2001, which means that the aquifer has continuously been depleted since that time.

Table 4:  
Calibrated accurate aquifer parameters values for the flow model

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Sub-aquifer</th>
<th>Aquitard</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>$K_{sx}$ (saturated hydraulic conductivity in the x direction)</td>
<td>34 3.94 E-4</td>
<td>0.2 2.3 E-6</td>
<td>m/d m/s</td>
</tr>
<tr>
<td>$K_{sy}$ (saturated hydraulic conductivity in the y direction)</td>
<td>34 3.94 E-4</td>
<td>0.2 2.3 E-6</td>
<td>m/d m/s</td>
</tr>
<tr>
<td>$K_{sz}$ (saturated hydraulic conductivity in the z direction)</td>
<td>3.4 3.94 E-5</td>
<td>0.02 2.3 E-7</td>
<td>m/d m/s</td>
</tr>
<tr>
<td>$S_y$  (Specific yield)</td>
<td>0.18 0.05</td>
<td></td>
<td>-</td>
</tr>
<tr>
<td>$S_s$  (Specific storage)</td>
<td>10-4 10-5</td>
<td></td>
<td>1/m</td>
</tr>
<tr>
<td>$\Phi$ (Effective porosity)</td>
<td>0.25 0.3</td>
<td></td>
<td>-</td>
</tr>
<tr>
<td>$n$ (Total porosity)</td>
<td>0.3 0.45</td>
<td></td>
<td>-</td>
</tr>
</tbody>
</table>

The three panels of Figures 16 show observed and calibrated yearly groundwater levels versus time for both the calibration period 2001-2008 and the validation periods 2009-2010 for wells L57, Pzo36A, and E45, which are located in the south, the middle and the north of Gaza, respectively. These well hydrographs indicate that the observed heads are mimicked well by the simulations, with a discrepancy that in most cases does not exceed 0.5 m.

6. Sensitivity Analysis

A model sensitivity analysis has also been carried out in order to evaluate the effects of uncertainties in various input parameters of the numerical model, such as, for example, the boundary conditions, aquifer parameters and stresses on the output of the calibrated model (e.g. Anderson and Woessner, 1992).
Figure 15  2001-2010 annual simulated discharge, recharge and storage change in the Gaza aquifer.

Figure 16  Observed and calculated heads at wells L57 (south Gaza), Pro36A (middle Gaza) and E45 (north Gaza) for calibration and validation periods
Sensitivity is expressed here by a dimensionless index $SI$, calculated as the ratio between the relative change of model output $\Delta x/x_0$, i.e. $SI = \Delta y/y_0 / \Delta x/x_0$ (e.g. Lenhart et al., 2002; Arlai et al., 2006). The sensitivity tests have been carried out here with the focus on the two input parameters hydraulic conductivity and recharge, which are known in groundwater flow modeling to have significant and often adverse impacts on the simulated heads. During these sensitivity runs the values of these two variables have been changed in +/- 10% increments from the previously determined optimal reference value, whereby the other variable has been kept constant.

**Figure 17** shows that the model is more sensitive to lower values of hydraulic conductivity or recharge than for higher values, as the sensitivity index ($SI$) is higher in the former than in the latter case. This can also be seen from **Figure 18**, where the absolute changes of the various error estimates of model, discussed earlier, namely, the residual mean (RM), the absolute residual mean (ARM) and the root mean square error (RMS) are plotted as a function of the respective percental parameter change. Thus one may note that with increasing hydraulic conductivity or recharge all three calibration measures are decreasing.

**Figure 18** also points out to the well-known problem found also by one of the authors in other groundwater modeling studies (e.g. Arlai et al., 2012; Koch et al., 2012), namely, some amount of trade-off, or ambiguity, in the two varied aquifer parameters hydraulic conductivity and recharge.
conductivity and recharge. That is to say, the effect of increasing the recharge may be partly offset by increasing the hydraulic conductivity, without that a significant change in the simulated heads can be observed. This means, that groundwater calibration alone cannot always substitute for a lack of good and reliable geologic and or hydrological information.


7.1. The need for sustainable aquifer management

Nowadays, because of the disastrous groundwater situation in the Gaza region, there is an urgent need for any action which can restore or, at least, maintain the sustainability of the Gaza groundwater system for now and, more so, for the near future. To that avail, the calibrated groundwater flow model will be employed in this section to simulate the effects of various near-future groundwater management strategies on the Gaza aquifer system, whereby the emphasis will be on the development of particular management policies which may be able to prevent future aquifer overdraft. This is tantamount to the investigation of the long-term safe, or more precisely, the sustainable yield (Miles and Chambet, 1995; Maimone, 2004) of the Gaza aquifer. In addition, new management scenarios that have been proposed to increase this yield, namely, artificial recharge from wastewater, will be investigated numerically.

7.2. The management scenarios investigated

In this section the quantitative and qualitative impacts of two extreme future groundwater management schemes on the groundwater levels for the next 30 years (2011-2040) will be assessed by the calibrated groundwater flow model.

In the first and most pessimistic scenario it is assumed that pumping from the aquifer continues to increase in the near future to meet the rising municipal water demand, as well as the extended agricultural activities, and that there is not further recharge to the aquifer than what is provided by natural precipitation. That is, as possible climate change effects in the region are discarded, the annual natural recharge will be more or less constant during the time-horizon considered.

The second and, hopefully, more optimistic scenario assumes that treated surficial wastewater can be used as a source of additional artificial recharge to the aquifer which, in principle, should not only lead to an increased sustainable yield of the latter, but could, in the best of all cases, revert even some of the adverse present-day conditions in the aquifer.
7.2.1. First Scenario: Increased future pumping

The first model scenario is basically a time-extension of the transient simulation of the previous section up to year 2040, assuming that the groundwater abstraction rate from the aquifer will increase continuously during this time to comply with the population growth and augmenting agricultural needs (as shown in Figure 19) and no new water resources, other than natural rainfall infiltration, are available to recharge the aquifer. This projected abstraction rate is the sum of the increased future domestic water demand due to population growth, assuming an average water consumption of 150 l/person/d, and the assumed agricultural groundwater use. In fact, the latter is expected to decrease from 80 M m$^3$ in year 2010 to 60 M m$^3$ in year 2040; and this for two reasons: firstly, the growth of urban areas, which will invade more and agricultural land and, secondly, that the groundwater water cannot support anymore the future agriculture activities, since most of the crops in the Gaza strip need to be irrigated with fresh water while, as discussed in the introduction, the groundwater has become too saline to be used further for that purpose (Al-Jamal and Al-Yaqubi, 2001).

Groundwater head predictions obtained with this external stress scenario are shown in Figure 20 for the future years 2020, 2030 and 2040. All head isolines indicate negative groundwater levels, i.e. the latter are lying below mean sea level, whereby the depression cones in the north of the Gaza strip go down to -5, -7.6 and -7.6 m (MSL), for years 2020, 2030 and 2040, respectively, but reach even higher values of -13, -14 and -15m (MSL), respectively, in the south.
These results show that the continuously ongoing overexploitation of the aquifer will result, without further sustainable management, in a very negative impact on the aquifer behavior, as the groundwater heads continue to decrease in the future, i.e. the aquifer situation will be far from sustainable, not only from a quantitative, but also from a qualitative point of view, as these lower groundwater levels will accentuate further seawater intrusion, as is further analyzed and discussed by Sirhan (2014).

From the hydraulic heads 3D Darcy flow velocities and, after division by the effective porosity, linear (seepage) velocities for each cell of the finite difference domain grid are computed. These are shown for year 2040 in two EW- cross-sections, one along row 26 in the north, and another one along row 126 in the south of the domain area in the two panels of Figure 21. It is clear from this figure that there is no more discharge of groundwater to the Mediterranean sea, as the velocity vectors are directed inland, with a upward-directed component in the direction of the pre-existing cone of depression, i.e. towards the main well yield, inducing sea water intrusion and a subsequent deterioration of the freshwater quality (Sirhan, 2014). This well field with its large depression cone pulls in water also from the eastern side of the domain, with particularly high velocities, as the infiltration rate in this part of the domain area is low, owing to low permeable to soils here (dark/reddish brown).

Figure 20  Predicted ground water levels for the 1st scenario for the years (a) 2020, (b) 2030, and (c) 2040.
For the south EW- cross section (right panel of Figure 21) the situation is somewhat similar, i.e. the flow velocities indicate the propensity for strong seawater intrusion into the Gaza aquifer.

7.2.2. Second scenario with artificial recharge from wastewater

7.2.2.1. Proposed wastewater artificial recharge design

In this second management scenario treated surficial wastewater will be used as a source of additional, artificial recharge to the aquifer, whereby it is assumed that this wastewater comes the effluent of the main four wastewater treatment plants (WWTP) in the Gaza strip located across the Gaza strip (see Figure 22). In addition to these existing plants, there are plans for three new large-scale WWTP to be built in several stages, starting with primary treatment plus short sea outfalls, supplemented later by tertiary
treatment, plus a reuse of the treated water in order to minimize the risks associated with the release of untreated wastewater into the environment (PWA, 2011). In the long-term could term these WWTP provide additional quantities of water for re-use in agriculture and for artificial recharge. Figure 23 depicts the projection of the future wastewater production in the Gaza strip up to the year 2040.

![Figure 23](image_url)  
*Figure 23  Projection of future wastewater production in the Gaza Strip.*

![Figure 24](image_url)  
*Figure 24  Injection wells inside the depression zones for the 2nd scenario*
7.2.2.2. Numerical implementation of the artificial recharge system

The numerical implementation of the artificial recharge system proposed into the groundwater flow model has been done in the form of two agglomerations of injection wells located above the two groundwater-head depression cones, that have already been established for year 2010 in the south and north of the Gaza strip, respectively (see Figure 10). The locations and extensions of these two well-fields are shown in Figure 24. About 50 injection wells have been used in each of the two well-fields.

In this scenario, the injection of the wastewater through these wells is assumed to start in 2015 and continues until the end of the simulation period in 2040, with the hope to achieve a quasi-stabilization of the groundwater heads at the minimum water level of 0 m above MSL. The artificial recharge rates follow roughly the available production of treated wastewater (see Figure 23), i.e., starts from 50 M m$^3$ for year 2015, increases gradually by an increment of 2 M m$^3$ per year, to reach 100 M m$^3$ at the end of year 2040.

7.2.2.3. Results of the artificial recharge scenario

For this second groundwater management scenario, applying artificial recharge through injection wells, the simulation results hints of some success for achieving the objective intended, namely, the aquifer remediation in the long-term and the restoration of the groundwater levels. In fact, Figure 25 demonstrates that there is a gradual aquifer recovery with time, as the zones of the cones of the depression in the north and the south of the Gaza strip are disappearing more and more for years 2020, 2030 and 2040. Not only that, but the artificial recharge will have induced a groundwater mound in these areas, of up to 2-4 m above MSL by the end of the simulation period in 2040, i.e., the depression cones have converted to ascension cones.

These groundwater mounds will, necessarily, lead to a hydraulic gradient from their summits to the coastline which, in turn, will drive groundwater flow in this direction. This can be clearly seen from Figure 26 - that is to be compared with Figure 21 - which shows the flow velocity vectors in two EW-cross-section in the north and south of the Gaza strip at the end of year 2040. In contrast to the situation of the first management scenario (no artificial recharge, see Figure 21), the flow direction is now reverted in this case, i.e. seawater intrusion is not possible anymore, or will have partly been reverted by that time. However, a definite answer to that regard can only be given after application of a density-dependent flow and transport model, currently under way by the first author, e.g. Sirhan (2014).
The transient evolutions of the groundwater heads, i.e. the development of the groundwater mound in the centers of the north and south pre-existing depressions, relative to their 2015- values, are presented in the two panels of Figure 27. Comparing these values with those existing at the end of the transient simulation time period in 2010 (see Figure 12), one may notice that the break-even time the depression-cones in the north and south have disappeared is around 2025 and 2030, after which time mounding above sea-level will occur.
7.2.3. Comparison of groundwater heads for the two scenarios

EW- cross-sections of the 2040-simulated groundwater heads through the two existing depression cones in the north and the south of the study area and for the two management scenarios discussed are shown in Figure 28. Thus, whereas the curves for each of the two scenarios clearly show the positive effect of the 2nd (artificial recharge) scenario, as the groundwater levels rise more or less steadily with increasing distance from the coastline, unlike for the 1st scenario where the head decreases away from the coastline, until the center of the cone of depression is met, after which it increases again when going towards the eastern border of the model domain.

8. Conclusions

The ongoing depletion of the coastal aquifer in the Gaza strip due to overexploitation has led to a significant decline of the groundwater levels, excessive reductions in yields, and many groundwater wells even going dry. Some of these wells had already to be shut down, due to an increase of the groundwater salinity above the WHO- 250 mg/L drinking standard limit. This significant deterioration of the groundwater quality all across the

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Figure 27 Growth of the groundwater mound at the center of the north (left) and the south (right) pre-existing depressions, relative to the 2015-minimum.

Figure 28 Groundwater water levels along two EW-cross-section in the north (left) and in the south (right) for year 2040 for the two groundwater management scenarios (1st: without; 2nd: with artificial recharge).
Gaza strip indicates that, owing to the decline of the groundwater levels, salt water intrusion from the Mediterranean has become an imminent problem which requires a long-term remediative solution.

This paper has outlined the development of a numerical groundwater flow model for the ultimate purpose of simulating various future groundwater management scenarios that may forestall or remedy the adverse aquifer conditions. To that avail, the 3D finite difference model MODFLOW, as embedded in the VISUAL MODFLOW software environment, has been applied to study and to predict groundwater levels using physically based hydrologic and meteorologic parameters, as well as the anthropic impacts on the groundwater conditions.

The optimal MODFLOW-model for predicting groundwater levels in the Gaza coastal aquifer is developed in two major steps. In the first step, steady-state calibrations for year-2000 observed hydraulic heads have been carried out by adjusting the hydraulic conductivity/transmissivity, as well as the amount of natural recharge. A good agreement between simulated and observed groundwater levels, with a correlation coefficient of \( R=0.92 \), is obtained. In the second step, transient head conditions between years 2001-2010 have been led to calibrate the storage coefficients and the specific yield in transient mode, simulation. Again a good agreement between simulated and observed groundwater levels is achieved for both the calibration period 2001-2008 and the validation period 2009-2010. The head results, as well as those obtained from a water budget analysis, show also that the physical groundwater situation in the region has been continuously deteriorating over the last decade, as groundwater levels have dropped by nearly 10 m in two major pumped areas in northern and southern Gaza.

The subsequent sensitivity analysis of the calibrated groundwater flow model shows that the simulated heads are more sensitive to the lower than to the higher values of both the hydraulic conductivity and recharge. At the same time, some amount of trade-off between these two parameters is found, i.e. they cannot be determined independently in a unique way.

The calibrated groundwater flow model is then used to predict the future groundwater head development in the Gaza strip. To that avail, groundwater level fluctuations within the target period 2011-2040 are examined under two management scenarios schemes. The first (pessimistic) scenario assumes that there are no new water resources available to sustain the aquifer’s yields and that groundwater pumping will continue to increase in parallel with the population growth. Meanwhile, in the second scenario it is assumed that
reclaimed and treated wastewater from sewage plants is available for artificial recharge of the aquifer, in the hope, that this will raise the water levels and revert the now-existing depression cones, as well as the still-ongoing salt water intrusion.

The results obtained with the first management scenario indicate that there will be ongoing negative impacts on the aquifer, since the groundwater levels will continue to decline in the coming thirty years, with particularly high and localized cones of head depression in the north and south of the model. This will lead to an accentuation of the already existing inversion of the direction of groundwater flow from the Mediterranean sea towards inland, i.e. increased seawater intrusion. This phenomenon is further analyzed and discussed in Sirhan (2014).

On the contrary, the head results obtained for the second scenario with artificial groundwater recharge provide evidence for some efficacy of this approach to guarantee the sustainability of the Gaza coastal aquifer up to the end of the target period in year 2040. In fact, this scenario reveals that by about year 2025 the nowadays existing two large depression cones in the north and south of the model area begin to disappear, so that after that time a groundwater mound will even start to build up which, eventually, will induce a hydraulic gradient towards the Mediterranean sea and which, in turn, will lead to groundwater flow in that direction, i.e. there is the chance that the presently existing saltwater intrusion will be reverted to some extent by that time (see Sirhan, 2014, for further details).

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Modeling the Hydrological Response of Soil and Water Conservation Measures in the Ronquillo Watershed in the Northern Andes of Peru

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Abstract
The present study assesses the impact of soil and water conservation (SWC) techniques on the hydrology of the Ronquillo watershed (42 km²) in the northern Andes of Peru. The hydrological model NASIM is applied to evaluate the scenario-based implementation of four different measures of soil and water conservation (terraces, bunds, afforestation, and check dams) with respect to its impact on catchment hydrology. The modeling results indicate that earth works and afforestation significantly affect flow volume, overland flow generation, and high flows. The impact of check dams on the stream flow characteristics of the Ronquillo River is small. Earth works such as terraces and/or bund structures reduce surface runoff by 12–28%; however, flow volume diminishes by 6–14% as well. A loss of water for downstream usage of 1242–1643 m³ha⁻¹y⁻¹ is observed. Afforestation with eucalyptus and pine species reduces surface runoff by 9–11% and flow volume by 6–8%. Water loss due to enhanced interception and evapotranspiration rates of plantations compared to native species or crops amounts to 1062–2586 m³ha⁻¹y⁻¹. On average, high flow discharge is reduced by 2–31%. For a single runoff event of the peak over threshold time series, a maximum reduction of 48% in peakflow is observed. With respect to the appropriateness of SWC practices for water resource management in the Ronquillo watershed, earth works are more recommendable than afforestation because downstream water availability is less affected.

Keywords
hydrological modeling, upscaling, soil and water conservation, Cajamarca, Peru

1. Introduction
In arid and semi-arid regions, water scarcity and land degradation impede poverty alleviation (Cook et al. 2011; Kemp-Benedict et al. 2011) and undermine food security (Falkenmark 1997; FAO 2009; Pimentel 2006; Scherr 1999). Nonetheless, these regions, characterized by rainfed agricultural systems, are thought to play a vital role for food and water security in the future (de Fraiture et al. 2009; Pretty et al. 2003; Rost et al. 2009). However, the productivity of land owners and farmers is frequently impaired owing to
climatic variability (Perez et al. 2010) and biophysical deterioration (Lutz et al. 1994). To cope with climate uncertainty and the unpredictability of the environmental system, a vast number of indigenous practices and adoptive strategies have developed in nearly all semi-arid landscapes around the world (Bruins et al. 1986; Prinz 1996). Many indigenous practices and production systems demonstrated sustainability, as they originated in prehistory and continued in place for long periods of time (Denevan 1995). Although the adaption techniques may differ in design and materials used, each of them best fitting the local environmental setting, the majority of the techniques aim at sustaining and/or improving water availability and thus land productivity.

In the Andean region, for example, estimates suggest that ancient terracing covered an area of over one million hectares (ha), of which 500,000 to 600,000 ha were located in Peru (Denevan 1988, 1995). The antiquity of terracing is unknown, but it may have begun by 500 B.C. and reached its greatest development among the Incas (Matheny and Gurr 1983). As stated by Browman (1987), the principal strategy of former Andean arid land producers has been risk management to guarantee land productivity and food production by water management, frost reduction, erosion control, and soil accumulation (cited in Verbist et al. 2009).

A commonly used term to incorporate the variety of measures is soil and water conservation (SWC) techniques or practices (e.g. Hudson 1987; Unger and Howell 2000). Soil and water conservation techniques (SWCTs) include water harvesting, mechanical structures (e.g. contour bunds, terraces, check dams), soil management and agronomic measures (e.g. cover crops, tillage, mulching, vegetation strips, re-vegetation, and agro-forestry) (Lesschen 2007). A number of studies confirm the potential of SWCTs to enhance infiltration and water productivity (Kahinda et al. 2007; Makurira et al. 2009; Oweis and Hachum 2006; Tian et al. 2003) by simultaneously reducing surface runoff and soil erosion (Al-Seekh and Mohammad 2009; Alegre and Rao 1996; Coker and Flores 1999; Dehn 1995; Hammad et al. 2004). However, the majority of the studies focus on small-scale, on-field and in situ effects of SWCTs (Bazzoffi and Gardin 2011; Inbar and Llerena 2000; Nyssen et al. 2007; Schiettecatte et al. 2005; Verbist et al. 2009). Only a few researchers put emphasis on upscaling the effects of SWCTs on a catchment scale (Andersson et al. 2009; Ngigi 2003; Ngigi et al. 2007; Ouessar et al. 2009) or even more spectacularly on a global scale (Wisser et al. 2010).

However, upscaling of conservation measures is of high interest, as current water resource management and planning approaches, referred to as Integrated Water Resource Management (IWRM) (Hooper 2011), focus on the watershed as an entity,
built up of multi-stakeholder interests and characterized by spatial and temporal interdependencies (Dario Estrada and Posner 2001). Rockström et al. (2010) argue in favor of widening the IWRM approach by integrating the water stored as soil moisture in the root zone, referred to as green water resource, which sustains rainfed agriculture and terrestrial ecosystems. A holistic approach is especially important in arid and semi-arid regions, where water is a scarce commodity and upstream interventions directly affect water availability downstream; such an approach is particularly important in closed and closing basins, where more water is used than is available during some portions of the year (Molle et al. 2010).

The water resources of the Ronquillo River, located in the northern Andes of Peru, are of special interest for the city of Cajamarca, as about one third of the total urban water supply is provided by the discharge of the Ronquillo River (Atkins et al. 2005; EPS SEDACAJ S.A. 2006). The Ronquillo River’s discharge is an integral constituent of the actual and future water supply of the urbanized areas of Cajamarca (EPS SEDACAJ S.A. 2006). However, even today the water demand of the growing city surpasses the water availability during the dry season, so the water supply for end-users is interrupted regularly within the dry season (CES 2010). By 2035 the water demand will double compared to 2005 (EPS SEDACAJ S.A. 2006); thus, issues related to water management and water resource conservation will become even more important in the near future.

In the region of Cajamarca, water scarcity arises owing to the seasonal rainfall distribution (Krois et al. manuscript submitted), the lack of adequate water retarding capacity in the watershed (Krois et al. 2013), and the increasing water demand, related to the ongoing economic development, which is boosted by the fast growing mining industry (Bury 2004, 2005). In contrast to the water shortages during the dry season, the rainy season is characterized by a rainfall excess and correspondingly high runoff events. The negative effect of the pronounced seasonality on water availability is reinforced by the fact that the water retarding capacity of river basins declines owing to a self-reinforcing process in which continued soil erosion causes degradation of the absorptive function of the topsoil, which reduces water infiltration rates and thus enhances the generation of surface runoff, which causes even more soil erosion (Carrillo-Rivera et al. 2008; Martinez-Mena et al. 1998; Römkens et al. 2002). Inappropriate land use and a lack of conservation practices cause land degradation and the deterioration of the hydrological function of a watershed (collection, storage, and discharge). However, land degradation does not have to be an irreversible process and might be mitigated or even reversed by the implementation of resource conservation measures (Kessler and Stroosnijder 2006).
Against the outlined background, the present study assesses the impact of SWCTs on water yield, overland flow generation, and high flows of the Ronquillo River in the northern Andes of Peru by applying a hydrological model approach.

2. Material and Methods

2.1. The Ronquillo watershed

The Ronquillo watershed is located in the northern Andes of Peru (78.53 W–78.63 W / 7.11 S–7.19 S), near the city of Cajamarca (Figure 1). The watershed encompasses an area of 42 km² and an altitudinal range from 2820 m to 3950 m asl. The western catchment border forms the South American Continental Water Divide (SACWD) and thus, the Ronquillo watershed is a headwater basin of the Marañón and Amazon Rivers.

According to the conceptual framework of altitudinal belts of orogens, climate and ecology change with altitude (Blüthgen and Weischet 1980; Stadel 1991). Following the landscape classification scheme of Peru (Pulgar-Vidal 1996), two distinct eco-regions, the Quechua (2300 m–3500 m asl) and the Jalca (3500 m–4000 m asl), emerge within the Ronquillo watershed (Figure 1). The Quechua is characterized by mean temperatures from 11 to 16°C and widespread agricultural activities (wheat, corn, potatoes), whereas grassland is
predominant in the *Jalca*, as cultivation is impaired by lower mean temperatures (7–10°C) and wet atmospheric conditions (Pulgar-Vidal 1996; Sánchez-Vega and Dillon 2006). The *Jalca* is often referred to as a transition zone between the more humid *Páramo* orobiome in the north and the more arid *Puna* orobiome in the south (Luteyn 1992; Molina and Little 1981; Sánchez-Vega et al. 2006; Sánchez-Vega and Dillon 2006). In general, mean annual rainfall is higher in the *Jalca* than in the *Quechua* (ONERN 1975, 1977), which is an important feature in terms of base flow generation and thus water availability during the dry season (Krois et al. 2013). The seasonal march of the Inner Tropical Convergence Zone (ITCZ) results in a seasonal rainfall regime characterized by a rainy season from October to April and a dry season from May to September. Inter- and intra-seasonal variability of rainfall is high, thus resulting in a seasonality index (SI) varying from 0.61 to 0.98, which expresses seasonality as ‘seasonal’ to ‘markedly seasonal with a long dry season’ (Krois et al. manuscript submitted; Walsh and Lawler 1981). However, generalization is difficult as spatial rainfall patterns are related to local topography, rain shadowing effects, and local wind fields (Krois et al. manuscript submitted).

Owing to the different eco-climatological boundary conditions, spatial soil patterns and stream flow characteristics vary significantly within the Ronquillo watershed. The Ronquillo River consists of five major influents (*Figure 1*), only two of which are classified as perennial streams (Krois et al. 2013). The dichotomy in stream flow characteristics is related to the fact that within the Ronquillo watershed, deep, organic-rich Andosols are a major source of base flow generation, although they only occur at higher elevations in the western catchment area (Krois et al. 2013). The dammed lake Mataracocha provides a volume of 123,000 m³ (Chávez-Guzmán 1993); however, its water is used for irrigation purposes, and thus does not contribute to the discharge of the Ronquillo.

### 2.2. The rainfall runoff model NASIM

The impact of SWCTs on the hydrology of the Ronquillo watershed is assessed by applying the rainfall-runoff model NASIM (version 3.7), designed by Hydrotec (Aachen, Germany). The NASIM model system is a conceptual and distributed rainfall-runoff model, developed for the simulation of hydrological processes in natural and urban watersheds (Hydrotec 2009; Reinhardt et al. 2011).

The calculation of the water balance is based on user-defined sub-catchments, which are in addition subdivided into single simulation units. Each of them is determined by the intersection of vector-based digital land use and soil data and characterized by a set of parameters to specify land use (interception capacity, root depth, crop evapotranspiration, surface roughness) and soil characteristics (sequence and thickness of soil layers, pore...
volume, field capacity, wilting point, hydraulic conductivity, maximum rate of infiltration and interflow) (Hydrotec 2009).

In NASIM runoff generation is computed on the basis of the empirical, non-linear infiltration approach of Holtan (1970). Depending on actual soil moisture, surface runoff is generated either as infiltration- or as saturation-excess overland flow. Runoff concentration is simulated from the combination of (1) isochrones, representing the residence time solely based on topography and drainage network characteristics and (2) single linear reservoirs, representing surface runoff, interflow, and baseflow. Finally, the transformation of discharge in the channels is computed according to the Kalinin-Miljukov approach. Flow length, mean gradient, and representative cross sections are assigned to each sub-catchment. The latter are determined by field surveying and parameterized by Strickler roughness ($k_s$). For a more detailed model description, see the NASIM handbook (Hydrotec 2009), Reinhardt (2010) or Rohde (2012).

### 2.3. Data sets used

#### 2.3.1. Meteorological data

The meteorological data of three weather stations are incorporated in the modeling. The Ronquillo rain gauge (78.550 W, 07.159 S) is located close to the southern catchment border at an altitude of 3325 m asl. The rain gauge is maintained by Servicio Nacional de Meteorología e Hidrología del Perú (SENMHI) and its data record is available through the web page of SENMHI (http://www.senamhi.gob.pe/). Two more rain gauges have been installed in 2008 in the course of the research project Conservación del agua y suelo en las cuencas de los ríos Chetillano y Ronquillo en la Sierra norte del Perú (CASCUS). Chamis rain gauge (78.561 W, 07.134 S, 3224 m asl) is located in the north-eastern part of the Ronquillo watershed, whereas Alto Chetilla rain gauge (78.642 W, 07.163 S, 3422 m asl) is located outside the catchment area. Nonetheless, Alto Chetilla rain gauge is integrated in the modeling to account for rainfall dynamics, which originate west of the SACWD (Krois et al. manuscript submitted). All three weather stations provide a temporal resolution of hourly data. A quality control procedure is applied (gross error checking, tolerance test, and internal consistency check) to inspect for continuity and consistency (Aguilar et al. 2003). Missing values are replaced according to the station average method (Paulhus and Kohler 1952). To account for spatial rainfall variability, the meteorological point data are adjusted for each sub-catchment on the basis of the precipitation-elevation relationship, obtained by regression modeling (vertical correction) and the distance from the point of measurement (horizontal correction) as recommended by Verworn (2008). Additionally, each sub-catchment is assigned a temperature and a potential evapotranspiration...
To calculate $ET_p$, the Hargreaves equation is applied (Hargreaves and Samani 1982, 1985; Samani 2000), which is considered to be a robust method (Bakhtiari et al. 2011; Lu et al. 2005). We follow the recommendation given by Droogers and Allen (2002) and apply their modified version of the original equation, which includes a rainfall term (Equation 1).

$$ET_p = 0.0013 \times 0.408 \times RA \times (T_{avg} + 17) \times (TD - 0.0123P)^{0.76}$$  

(1)

where $RA$ is extraterrestrial radiation expressed in MJ m$^{-2}$ d$^{-1}$, $T$ is average daily temperature ($^\circ$C) defined as the average of the daily maximum and daily minimum temperatures, $TD$ ($^\circ$C) is the temperature range, computed as the difference between mean daily maximum and mean daily minimum temperatures, and $P$ is precipitation in mm.

Garcia et al. (2004) compare the Hargreaves method and the Penman-Monteith method, which is recommended by the Food and Agricultural Organization (FAO) as the standard calculation method (Allen et al. 1998). Garcia et al. (2004) report that for the environmental setting of the Bolivian Andes the values obtained by the Hargreaves method are very similar to the values obtained by the Penman-Monteith method.

2.3.2. Stream flow data

Stream flow data are obtained from a piezometer (Orpheus Mini II, OTT Hydrometrie), located at the water intake for drinking water abstraction of the Ronquillo River close to the city of Cajamarca. At the gauging station (2838 m asl, 07.157 S, 78.563 W), water level is recorded in a temporal resolution of 15 minutes. The water level (m) time series is converted into discharge (m$^3$s$^{-1}$) by applying the formula of Poleni (Bretschneider et al. 1993). The water inlet works was constructed in 1942 and is maintained by Cajamarca’s water supplier EPS SEDACAJ S.A. The maximum hydraulic capacity of the facility is reported as 65 ls$^{-1}$ (EPS SEDACAJ S.A. 2006); however, recently the hydraulic capacity has been improved to 90 ls$^{-1}$ (Yanacocha 2013). More details on spatial and temporal stream flow characteristics of the Ronquillo River are given by Krois et al. (manuscript submitted).

2.3.3. Topography and drainage network

Topographical data are provided by a 30-m DEM of the ASTER system. The main channel network and sub-catchments are delineated from the DEM by using the ArcGIS/Arc Hydro Interface (Jenson and Domingue 1988; Maidment 2002). The ASTER DEM serves as the basis for computing watershed limits and stream channels, but also for calculating the residence time and the isochrones. Sub-catchment selection is based on homogeneous criteria with respect to topography, soils, and land use. In sum, 20 sub-catchments with
a mean area of 2.1 km² and mean slopes ranging from 8% to 46% have been identified.

2.3.4. Soils

According to the nomenclature of the World Reference Base for Soil Classification (FAO 2006), the catchment area of Rio Ronquillo consists of six different soil types: Acrisol (4%), Regosol (6%), Phaeozem (8%), Cambisol (11%), Leptosol (25%) and Andosol (46%) (Figure 2a). Information on spatial distribution and physical characteristics of these soils is provided by Landa-E. et al. (1978), ONERN (1975), Poma-Rojas (1989), Poma-Rojas and Alcántara-Boñón (2010), and Poma-Miranda and Poma-Miranda (2001). Poma-Rojas and Alcántara-Boñón (2010) further differentiate the Andosols into Paramo-Andosols and Paramosols. The deep black-colored, organic-rich (7–14 vol.-%) Andosols, are often referred to as 'páramo soils' (Buytaert et al. 2005a; Cabaneiro et al. 2008) and are characterized by a high water storage capacity (Buytaert et al. 2006a; Buytaert et al. 2005b; Célleri and Feyen 2009) and thus are of major relevance for base flow generation (Krois et al. 2013).

The hydraulic soil parameters required for the NASIM model are obtained by literature survey or computed by pedotransfer functions. For model parameterization, each soil type is ascribed a representative soil profile, defined by a sequence and the thickness of soil layers, each characterized by a representative grain size distribution (Landa-E. et al. 1978; ONERN 1975, 1977; Poma-Miranda and Poma-Miranda 2001; Poma-Rojas 1989). The field capacity and wilting point of each soil layer are calculated on the basis of the formulas provided by van Genuchten (1980). The soil parameters of the Andosols have been corrected according to the high organic matter content (AG Boden 1994). The hydraulic conductivity is determined by applying the pedotransfer functions published by Cosby et al. (1984) and Saxton et al. (1986). Pore volume is ascribed to each soil layer according to the soil texture class and packing density (AG Boden 1994). In addition, each soil type is assigned the maximum rate of interflow, which is set to the minimum hydraulic conductivity of a constituent soil layer and the maximum rate of infiltration, which is computed by equation 2, given in the NASIM Handbook (Hydrotec 2009).

\[
Inf_{\text{max}} = -0.0203 \cdot K^{-2} + 3.0669 \cdot K + 3.1821
\]  

where \( Inf_{\text{max}} \) is the maximum infiltration rate expressed in mm h\(^{-1}\) and \( K \) is the hydraulic conductivity in mm h\(^{-1}\).

2.3.5. Vegetation and land use

Land use data are provided by Rohde (2012), who used Quickbird data sets from 2003, 2004, and 2007 to obtain a land use map of the Ronquillo watershed (Figure 2b). The most prominent land cover class is farmland. This class covers 34.6% of the catchment area of 2.1 km² and mean slopes ranging from 8% to 46% have been identified.
area and is concentrated mainly in the middle part of the watershed, where rainfall and temperatures are most favorable for agricultural activities. The most frequently cultivated crops are corn (rye, oat, barley), potatoes and other varieties of Andean tubers (e.g. oca (*Oxalis tuberosa*), ulluco (*Ullucus tuberosus*), mashua (*Tropaeolum tuberosum*)) (Becker and Utermöhlen 1997; Tapia 1997). However, one should note that approximately 40% of farmland lies fallow. In the Andes the fallow agriculture system, associated with subsistence, is widespread and is characterized by a short cropping period of 1–3 years (Lauer 1993) and a subsequent fallow period of 5–10 years (Abreu et al. 2009; Millones 1982) or even up to 20 years (Cabaneiro et al. 2008). Fallow periods perform multiple functions by regenerating soil fertility (Bury 2004), controlling crop diseases and pests (Ortiz 2006), and maintaining areas for extensive grazing and medicinal plant collection (Abadín et al. 2002). In the northern Andean Páramos, this type of agriculture is considered to be ecologically viable (Sarmiento 2000); however, removal of the vegetation cover leaves bare soils, enhances land degradation, and results in higher runoff and erosion rates compared to cultivated fields (Harden 1996; Molina et al. 2007; Poulenard et al. 2001). The second most common land cover class is grassland. This class corresponds to 27.4% of the catchment area and is mainly allocated at highly elevated areas in the *Jalca* orobiome, where agricultural activities are constrained by low temperatures and wet meteorological conditions (Pulgar-Vidal 1996; Sánchez-Vega et al. 2006). The most common plants of the *Jalca* orobiome are angiosperms, pteridophytes, and gymnosperms (Sánchez-Vega and Dillon 2006). Local communities use that area mainly for extensive grazing. Other land use classes are meadows (10%) and shrub lands (7.6%), which are partly used for grazing, scarce vegetation (9.9%), where degraded soils hinder any productive use, and plantations (3.5%), which consist mainly of introduced species such as eucalyptus and pine (van den Abeele 1995). Most common are *Eucalyptus globulus* and *Pinus radiata* (Landa et al. 1975); however, a variety of species has been introduced in order to correspond to the manifold site-specific environmental boundary conditions of the region of Cajamarca (Sánchez-Gómez and Gillis 1982).

The vegetation parameters required for the NASIM model are obtained by literature survey. Crop evapotranspiration coefficients are given by Allen et al. (1998) and Descheemaeker et al. (2011). The interception capacity is either calculated on the basis of leaf area index (LAI) with the equation presented by Hoyningen-Huene (1983) or obtained through additional information given by Burgy and Pomeroy (1958), Domingo et al. (1998), Leuschner (1986) and Valente et al. (1997). Root depth and LAI are obtained from Breuer et al. (2003), who present an extensive review on plant parameter values for modeling purposes. Surface roughness for each land use class is assigned by following the recommendations given by Hydrotec (2009) and LUBW (2002).
2.4. Assessment of model performance

The model performance is assessed by graphical model evaluation techniques such as hydrographs and statistical model evaluation methods. With respect to statistical model evaluation, we follow the guidelines for quantification of accuracy in watershed simulations given by Moriasi et al. (2007). The Nash-Sutcliffe efficiency (NSE) index (Nash and Sutcliffe 1970) and the percent bias (PBIAS) error index (Gupta et al. 1999) are computed. In addition, the ratio of the root mean square error to the standard deviation of measured data (RSR) (Moriasi et al. 2007) is calculated.

The widely applied Nash-Sutcliffe efficiency (NSE) determines the relative magnitude of the residual variance (‘noise’) compared to the measured data variance (‘information’) and ranges between $-\infty$ and 1, with NSE = 1 being the optimal value. Values between 0.0 and 1.0 are generally viewed as acceptable levels of model performance (Moriasi et al. 2007). However, the NSE is overly sensitive to extreme values (Legates and McCabe 1999), so in addition the percent bias (PBIAS) – which measures the average tendency of simulated data to be larger or smaller than their observed counterparts (Gupta et al. 1999) – is applied (Moriasi et al. 2007). The optimal value of PBIAS is 0. Positive values indicate model underestimation bias, and negative values indicate model overestimation bias (Gupta et al. 1999). Finally, the RSR is calculated as the ratio of the root mean square error and standard deviation of measured data (Moriasi et al. 2007). The RSR combines error index statistics with a scaling/normalization factor and varies from the optimal value of 0 to a large positive value. The lower the RSR, the better is the model simulation performance (Moriasi et al. 2007). Equations 3 to 5 show the mathematics of the applied model evaluation statistics (NSE, PBIAS and RSR), and Table 1 shows the general performance ratings for the applied statistics:
\[ NSE = 1 - \frac{\sum_{i=1}^{n} (Y_{i}^{\text{obs}} - Y_{i}^{\text{sim}})^2}{\sum_{i=1}^{n} (Y_{i}^{\text{obs}} - \bar{Y}^{\text{obs}})^2} \] (3)

\[ PBIAS = \left[ \frac{\sum_{i=1}^{n} (Y_{i}^{\text{obs}} - Y_{i}^{\text{sim}}) \cdot (100)}{\sum_{i=1}^{n} (Y_{i}^{\text{obs}})} \right] \] (4)

\[ RSR = \frac{RMSE}{STDEV_{\text{obs}}} = \sqrt{\frac{\sum_{i=1}^{n} (Y_{i}^{\text{obs}} - Y_{i}^{\text{sim}})^2}{\sum_{i=1}^{n} (Y_{i}^{\text{obs}} - \bar{Y}^{\text{obs}})^2}} \] (5)

where \( Y_{i}^{\text{obs}} \) is the ith observation for the constituent being evaluated, \( Y_{i}^{\text{sim}} \) is the ith simulated value for the constituent being evaluated, \( \bar{Y}^{\text{obs}} \) is the mean of observed data for the constituent being evaluated, and \( n \) is the total number of observations.

<table>
<thead>
<tr>
<th>Performance rating</th>
<th>NSE (-)</th>
<th>PBIAS (%)</th>
<th>RSR (-)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very good</td>
<td>0.75 &lt; NSE ≤ 1.00</td>
<td>PBIAS &lt; ±10</td>
<td>0.00 ≤ RSR ≤ 0.50</td>
</tr>
<tr>
<td>Good</td>
<td>0.65 &lt; NSE ≤ 0.75</td>
<td>±10 ≤ PBIAS &lt; ±15</td>
<td>0.50 &lt; RSR ≤ 0.60</td>
</tr>
<tr>
<td>Satisfactory</td>
<td>0.50 &lt; NSE ≤ 0.65</td>
<td>±15 ≤ PBIAS &lt; ±25</td>
<td>0.60 &lt; RSR ≤ 0.70</td>
</tr>
<tr>
<td>Unsatisfactory</td>
<td>NSE ≤ 0.50</td>
<td>PBIAS ≥ ±25</td>
<td>RSR &gt; 0.70</td>
</tr>
</tbody>
</table>

2.5. Scenario development and model modification

The scenario development aims to realize different degrees of implementation of SWCTs and accordingly different scenarios of land use changes. The present study evaluates the impact of four types of SWC measures on the catchment hydrology of the Ronquillo River. These measures are clustered into (A) earth works (terraces and bund systems), (B) afforestation, and (C) the construction of check dams (Table 2). With respect to the hydrological processes concerned, the last differs from the foremost, as check dams are classified as point measures along the river channels, which influence the flood discharge after runoff has already concentrated in the channel. The foremost are assigned as widespread two-dimensional measures in agriculture and forestry that influence runoff generation by decreasing surface runoff and promoting infiltration (Reinhardt et al. 2011).
Table 2: Description of the simulated scenarios.

<table>
<thead>
<tr>
<th>Classification</th>
<th>Type</th>
<th>Description</th>
<th>Scenario</th>
<th>Area (ha)</th>
<th>Area (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Widespread two-dimensional measures in agriculture and forestry</td>
<td>Earth works</td>
<td>Terraces on farmland and fallow</td>
<td>A_T</td>
<td>669</td>
<td>16</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Bunds on farmland and fallow</td>
<td>A_B</td>
<td>506</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Combined bunds and terraces</td>
<td>A_BT</td>
<td>1097</td>
<td>26</td>
</tr>
<tr>
<td>Afforestation</td>
<td></td>
<td>Expansion of existing afforestation areas along an encircling buffer strip of 100 m</td>
<td>B_buffer</td>
<td>649</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Afforestation of areas of scarce vegetation</td>
<td>B_Veg</td>
<td>335</td>
<td>8</td>
</tr>
<tr>
<td>Point measures along the river channels</td>
<td>Check dams</td>
<td>Implementation in all stream channels</td>
<td>C_all</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Implementation in intermittent streams only</td>
<td>C_int</td>
<td>---</td>
<td>---</td>
</tr>
</tbody>
</table>

2.5.1. Earth works (A)

With respect to earth works, the present study focuses on terraces and bund systems. These measures are similar in the sense that both are mechanical structures, characterized by a terrace wall and a bank, or a berm and a basin, respectively. The structures intercept surface runoff, decelerate runoff velocity, encourage infiltration, and act as barriers to water flow (Dorren and Rey 2004; FAO 2000). Additionally, terraces reduce slope steepness by dividing the slope into short sections (Morgan 1986). The terrace and bund design depends on many factors, including slope, soil properties, and rainfall characteristics (Bekele et al. 2009; Critchley and Siegert 1991; FAO 2000; Lesschen 2007).

For scenario development, the potential sites for terraces and bund systems in the Ronquillo basin have been delineated on the basis of a GIS-based multi-criteria evaluation procedure, taking into account several environmental site assessment criteria (meteorology, hydrology, topography, land use, and soil properties), a procedure that is described and discussed in detail in Krois and Schulte (manuscript submitted). However, to secure a realistic approach with respect to an implementation agenda, earth works in the present study are restricted to farmland and fallow land. The earth works scenarios are subdivided into three different representations, each of them accounting for a particular technique and different levels of spatial implementation (Figure 3). Scenario AT represents the implementation of terraces on an area of 669 ha, corresponding to 16% of the catchment area. Scenario AB represents the implementation of bund systems on an area of 509 ha, corresponding to 12%. In addition, both scenarios are combined (ABT). In the case of overlapping areas (approx. 78 ha), in which both conservation measures are rated suitable (Krois and Schulte – manuscript submitted), bund systems have been
preferred over terrace systems, as the construction and maintenance costs of terraces are much higher compared to bund systems (Critchley and Siegert 1991; Dehn 1995; Posthumus 2005). Scenario ABT corresponds to an area of 1097 ha and thus represents 26% of the catchment area.

Earth works measures are parameterized by modifying the model in respect of surface runoff generation and runoff concentration. The surface runoff generation depends on the infiltration process and soil characteristics. To model the encouraging effect of earth works on infiltration, the maximum infiltration rates are modified on the basis of Holtan´s infiltration model (Holtan 1970). Hydrotec (2009) presents a simplified version of Holtan´s equation (Equation 6), where the maximum infiltration rate depends on the soil characteristics (soil depth, pore volume, and field capacity) and on a parameter (av), referred to as 'vegetative parameter' or 'index of surface-connected porosity', which is a function of surface conditions and the density of plant roots (Hydrology Handbook 1996).

\[
Inf_{\text{max}} = av \cdot [SD \cdot (PV - FC)]^{1.4}
\]

where \(Inf_{\text{max}}\) is the maximum infiltration rate (mm h\(^{-1}\)), \(SD\) is the soil depth (m), \(PV\) is the pore volume (mm m\(^{-1}\)), and \(FC\) is the field capacity (mm m\(^{-1}\)). For the computation of encouraged infiltration of bund systems, surface-connected porosity (av) is set to 0.6, and for terraces av is set to 0.8. The chosen values encourage infiltration conditions like those under temporary and permanent sod, respectively (Holtan and Lopez 1971). These conditions are chosen to resemble the high potential of bunds and terraces for reducing surface runoff (Dehn 1995; Inbar and Llerena 2000).

In order to model the impact of earth works on runoff concentration, the surface roughness is adjusted for bunds and terraces. In the NASIM model, each land use class is assigned a Strickler roughness value \((k_v)\). As no roughness values for bunds and terraces are available in the literature, alternatively the Manning’s roughness coefficient \((n)\) is determined by applying a step-wise additive/weighted estimation method (Arcement and Schneider 1989). This method computes the Manning’s roughness coefficient by assessing the surface irregularity, the obstructions to overland flow, the proportion of basal ground cover, and the type and height of the vegetation (Engman 1986; Phillips 1989). After converting into Strickler roughness, values for terraces and bund systems correspond to \(k_v = 3\) and \(k_v = 5\), respectively. In addition to the adjustments of the surface roughness, the DEM is leveled by GIS procedures to account for the reduced slope steepness of the terraces. Therefore contour lines, delineated on the basis of the DEM, are transformed into polygon features and ascribed an altitude, which corresponds
to the arithmetic mean of the upper and lower contour line values. As a result, a stepped terrain morphology is obtained.

2.5.2. Afforestation (B)

With respect to afforestation measures, the present study focuses on plantations of pine and eucalyptus species. The region of Cajamarca is well known for the efforts taken in terms of afforestation during the past decades. In the course of a regional ecosystem recovery initiative, referred to as ‘Poncho Verde’, approximately 45,000 ha of mainly pine (Pinus radiata and Pinus patula) and eucalyptus (Eucalyptus globulus) species have been planted since the mid-1970s (Sánchez-Zevallos 1998; Sánchez-Zevallos 2000). A recent study confirms that in the region of Cajamarca the area of tree plantations replacing the Jalca grasslands increased by approximately 12% per year during the period from 1987 to 2007 (Tovar et al. 2013).

The scenario development of afforestation is based on two underlying hypotheses. The first is that the existing areas of plantations build the nucleus for the computed scenario of forthcoming afforestation. This scenario \( B_{\text{Buffer}} \) is realized by building a spatial buffer of 100 m encircling the existing plantation area derived by remote sensing analysis (Figure 3). The second hypothesis is based on the common idea that afforestation is an appropriate measure for soil conservation and erosion control (Millones 1982). This scenario \( B_{\text{Sveg}} \) is realized by substituting plantations for scarce vegetation, representing mainly degraded areas (Figure 3). The replacement of the land cover classes consequently affects the values of interception capacity, root depth, crop evapotranspiration, and surface roughness.

Although some Eucalyptus species (e.g. Eucalyptus viminalis, Eucalyptus gunnii, Eucalyptus delegatensis, Eucalyptus dalrympleana) are suitable to grow in the Cajamarca region up to 3400 m asl (Sánchez-Gómez and Gillis 1982; van den Abeele 1995), we ascribe all plantations above an elevation of 3300 m asl to pines, as the most common pine species Pinus radiata has its climax in a growth rate between 3100 and 3300 m asl (Villar-C et al. 1982). By contrast, all plantation areas below 3300 m are ascribed to eucalyptus. Scenarios BBuffer and BSveg comprise 649 ha and 335 ha, respectively, which correspond to 15% and 8% of the total catchment area (Figure 3).

To represent the afforestation scenarios in the NASIM model, the pine and the eucalyptus land use classes, characterized by the species-specific parameters of interception capacity, root depth, crop evapotranspiration, and surface roughness, are expanded or replace former land use classes.
2.5.3. Check dams (C)

A check dam is a small, temporary or permanent dam constructed across a channel to lower the speed of concentrated flows. Check dams are classified as a structural erosion prevention and sediment control practice (EPA 1992). In-channel structures such as check dams influence the stream flow in the channel by creating segmented longitudinal profiles and thus altering water depth, flow velocity (Shieh et al. 2007), and sediment dynamics (Boix-Fayos et al. 2008). With respect to hydraulic behaviors, check dams are comparable to step-pool systems, as the longitudinal profile of step-pool reaches resembles a series of check dams (Lenzi 2002).

The initial stage of a check dam is characterized by the retention of sediments and the impounding of floodwater within the check dam. In a later stage, the flow velocity and consequently the sediment transport capacity are reduced upstream owing to the newly formed wider and gentler stream gradient (Xiang-zhou et al. 2004). However, with respect to the control of the sedimentary load, check dams are only a temporary solution, as they fill up rapidly (Boix-Fayos et al. 2008).

For the implementation of check dams in the hydrological model, two scenarios are in development. In scenario \( C_{\text{air}} \), check dams are implemented in all stream channels,
whereas in scenario $C_{int}$ check dams are implemented only in the intermittent stream channel of Manzana and Rosapata River (see Figure 1).

Check dams are parameterized by adjusting the values of river bed roughness. In the NASIM model, the river channels are ascribed $k_{st}$-values to account for different morphological conditions. As check dams resemble the longitudinal profile of step-pool reaches (Lenzi 2002), $k_{st}$ values valid for step-pool systems are used to parameterize river bed roughness in the corresponding river section. Wang and Yu (2007) report Manning’s roughness coefficients for developed step-pools in the range from 0.04 to 0.06, corresponding to Strickler roughness values of $k_{st} = 25–16$. In the present study, a river bed roughness of $k_{st} = 16$ is ascribed to check dams.

3. Results

3.1. Model performance

The model is calibrated on a daily data base for the period from November 1, 2009 to October 31, 2010 (Figure 4). NSE is 0.71 and RSR is 0.54, thus model performance is rated as ‘good’ (see Table 1). PBIAS is 9.04%, which corresponds to a rating of ‘very good’. The modeled dry seasonal recession curve fits the measured data well; however, individual peak flows are misestimated by the model.
The validation period spans the three-year monitoring period from October 1, 2008 to September 30, 2011. The statistical model evaluation for the validation period results in a model performance of $\text{NSE} = 0.57$ and $\text{RSR} = 0.65$. The PBIAS for the validation period is 1.48% and rates as ‘very good’. By aggregating data for weekly, monthly or seasonal time steps, NSE and RSE improve significantly (Table 3). The model is capable of reproducing the seasonal runoff characteristics and cumulative runoff over the three-year monitoring period (Figure 5). The statistical model evaluation supports the assumption that the model is applicable to simulate the hydrological response of the Ronquillo watershed.

The model bias on short time scales is primarily related to the precipitation data input. The accurate measurement and estimation of spatial rainfall distribution in mountainous environments is a nontrivial task (Buytaert et al. 2006b; Rollenbeck and Bendix 2011). As reported by Krois et al. (manuscript submitted), the spatial rainfall pattern is strongly influenced by local topography, and thus the spatial correlation of individual rain gauges is poor. Consequently, the assignment of individual rain gauges to each sub-catchment of the model bears a large uncertainty as regards mimicking the actual spatial rainfall pattern.

**Table 3:** Model performance during the validation period (October 1, 2008 to September 30, 2011) for different time steps.

<table>
<thead>
<tr>
<th>Time step</th>
<th>NSE (-)</th>
<th>PBIAS (%)</th>
<th>RSR (-)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily</td>
<td>0.57</td>
<td>1.48</td>
<td>0.66</td>
</tr>
<tr>
<td>Weekly</td>
<td>0.81</td>
<td>4.35</td>
<td>0.43</td>
</tr>
<tr>
<td>Monthly</td>
<td>0.88</td>
<td>1.47</td>
<td>0.34</td>
</tr>
<tr>
<td>Seasonally</td>
<td>0.94</td>
<td>1.51</td>
<td>0.24</td>
</tr>
</tbody>
</table>
3.2. Hydrometeorology of the Ronquillo watershed - model output

The following summaries of the hydro-meteorological boundary conditions of the Ronquillo watershed are model outputs, characterizing the current state or base line scenario. Mean annual precipitation over the area is 1158 mm. Owing to the seasonal rainfall distribution, about 88% of rainfall occurs during the rainy period from October to April. Mean annual potential evapotranspiration ($ET_p$) is 1023 mm, and mean annual actual evapotranspiration ($ET_a$) amounts to 675 mm. The R-index, defined as the ratio of $ET_a$ to $ET_p$, which is a measure of soil moisture conditions or a measure of plant water supply in relation to plant water demand (Yao 1974), is 0.68 on an annual basis. However, seasonality is well documented in the R-index, as values as low as 0.27 are observed in the dry season and values as high as 0.95 during the rainy season. Mean discharge is 0.350 m$^3$s$^{-1}$, which corresponds to a mean annual runoff depth of 262 mm. Close to 66% of the annual discharge occurs during the rainy season from October to April. The water storage capacity of the watershed totals 86 mm.

The given numbers reflect monthly or annual catchment averages computed by the NASIM hydrological model and thus may differ from the actual measured meteorological point data of the individual rain gauges (Krois et al. manuscript submitted) or the actually measured discharge data of the Ronquillo gauging station (Krois et al. 2013).
3.3. Impact of SWCTs on the catchment hydrology

The impact of SWCTs on the catchment hydrology of the Ronquillo River is assessed by evaluating the cumulative runoff, cumulative overland flow, and peak over threshold (POT) time series of the different scenarios compared to the computed current state. Cumulative runoff is an important feature of watersheds, especially if the discharge of a river is used for water supply. Thus, any resource conservation strategy must ensure that the provisioning of water in the upstream area does not negatively affect the downstream water availability. Overland flow is often related to water erosion. Therefore, a reduction in the overland flow generation mitigates erosion and thus lowers the risk of land degradation. High flows and extreme runoff events are frequently used criteria to characterize the impact of land use changes or to evaluate resource conservation strategies. High flows are characterized by a high river bed erosion and sediment transport capacity. To ensure that nearly independent POTs are selected, the independence criteria proposed by Willems (2009) are applied. The different simulations cover the full three-year investigation period from October 1, 2008 to September 30, 2011 and are thus interpreted as the catchment’s hydrological response to the implementation of SWCTs under the climatic conditions during the investigation period.

3.3.1. Cumulative runoff

The cumulative runoff of the Ronquillo watershed is significantly altered by the implementation of SWC measures. All scenarios representing the implementation of terraces and/or bund systems as well as afforestation result in a reduction of flow volume. The reduced flow volume over the three-year modeling period corresponds to 10.0% (A), 5.7% (A') and 14.0% (A'T) for earth works and to 6.2% (Bbuffer) and 7.9% (Bsvig) for afforestation measures (Figure 6). As expected, the implementation of check dams does not alter flow volume either on an annual or on a seasonal scale (not shown). The reduced flow volume results in a diminution of the mean annual runoff depth of 26, 15, 37, 16 and 21 mm for the scenarios of A, A', A'T, Bsvig and Bbuffer, respectively, corresponding to a stream flow reduction of 35, 20, 49, 22 and 28 ls⁻¹ (Table 4). The diminution of the flow volume corresponds to an enhanced actual evaporation, as the augmenting of areas of plantation, terraces and/or bunds causes the overall interception and transpiration to increase as well.
It is worth noting that there is a seasonal cyclicity in the flow volume reduction. During the rainy period, the diminution is more pronounced than during the dry season (Figure 6). During December to March, the reduction for the different scenarios compared to the current state corresponds to 5.3% ($A_{yr}$) in minimum and 16.2% ($A_{st}$) in maximum. In comparison, during May to September the reduction corresponds to 2.6% and 10.3%, respectively. Seasonality in flow volume reduction arises owing to the cyclicity of actual evaporation, characterized by the interplay of interception and evapotranspiration. During the rainy season, interception accounts for approximately 50% of actual evaporation, whereas interception plays a minor role during the dry season, as evapotranspiration accounts for approximately 80% of actual evaporation (Figure 7). The concurrent forcing of interception and evapotranspiration results in an enhanced evaporation during the rainy season compared to the dry season. For both afforestation scenarios ($B_{buffer}$ and $B_{vkg}$), an enhanced reduction of flow volume is observed during the late dry season (Jun.–Sep.), compared to the earth works scenario. The fast rising limb of the afforestation scenarios in Figure 6 implies that during the dry season afforestation measures put more stress on water resources than do earth works measures.

In terms of effectiveness, which is here defined as the diminution of flow volume per hectare of implemented measures, the most effective scenario is the afforestation of areas with scarce vegetation (2586 m³ha⁻¹y⁻¹), followed by earth works measures (1242–1643 m³ha⁻¹y⁻¹) and the augmenting of afforested areas (1062 m³ha⁻¹y⁻¹) (Table 4). The clear difference among the afforestation scenarios is due to the fact that the net
change of actual evaporation is much higher if areas of scarce vegetation are afforested compared to areas characterized by other types of vegetation cover.

Figure 7  Seasonal reduction in flow volume for different scenarios and fraction of evaporation due to interception.

Table 4:  Reduction in flow volume for the earth works and afforestation scenarios compared to the current computed state in percent, m³, m³ha⁻¹y⁻¹, mmy⁻¹ and ls⁻¹.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>%</th>
<th>m³</th>
<th>m³ha⁻¹y⁻¹</th>
<th>mmy⁻¹</th>
<th>ls⁻¹</th>
</tr>
</thead>
<tbody>
<tr>
<td>A¹</td>
<td>10</td>
<td>3,296,047</td>
<td>1643</td>
<td>26</td>
<td>35</td>
</tr>
<tr>
<td>A₅</td>
<td>5.7</td>
<td>1,883,614</td>
<td>1242</td>
<td>15</td>
<td>20</td>
</tr>
<tr>
<td>A₅T</td>
<td>14.0</td>
<td>4,631,837</td>
<td>1407</td>
<td>37</td>
<td>49</td>
</tr>
<tr>
<td>B_Buffer</td>
<td>6.2</td>
<td>2,067,272</td>
<td>1062</td>
<td>16</td>
<td>22</td>
</tr>
<tr>
<td>BᵥVeg</td>
<td>7.9</td>
<td>2,600,031</td>
<td>2586</td>
<td>21</td>
<td>28</td>
</tr>
</tbody>
</table>

3.3.2. Overland flow
The modeled SWCTs considerably reduce overland flow in the Ronquillo watershed (Figure 8). The impact of earth works on overland flow is more pronounced than the impact of afforestation measures. The combination scenario of bunds and terraces (A₅T) results in a diminution of overland flow of 28.0% compared to the current state. The scenarios A₆ (solely terraces) and A₅ (solely bunds) reduce overland flow by 19.2% and 11.8%, respectively. Afforestation measures lower overland flow by 9.2% (B_Buffer) and 10.8% (BᵥVeg) (Table 5).
In terms of effectiveness, which is here defined as the reduction of overland flow volume per hectare, the most effective measure is the afforestation of areas with scarce vegetation (676 m³ha⁻¹y⁻¹), followed by earth works measures (489–603 m³ha⁻¹y⁻¹) and by the expansion of already existing afforestation areas (297 m³ha⁻¹y⁻¹).

By computing the ratio of the effective reduction of overland flow volume and the effective reduction of flow volume, the resulting coefficient serves as a proxy for efficiency that relates the amount of water being retarded within the watershed and the diminution of overland flow. It follows that the ratio for afforestation scenarios is 3.6–3.8, whereas the ratio for earth works scenarios is 2.6–2.7. In other words, the earth works scenarios reduce overland flow more efficiently because concurrent flow volume does not decrease as strongly as in the afforestation scenarios.

Table 5: Reduction of overland flow volume for the earth works and afforestation scenarios compared to the computed current state in percent, m³, and m³ha⁻¹y⁻¹. The presented ratio is computed by dividing the reduced flow volume per hectare by the reduced overland flow volume per hectare.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>%</th>
<th>m³</th>
<th>m³ha⁻¹y⁻¹</th>
<th>Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>A⁺⁺⁺</td>
<td>19.2</td>
<td>1,209,615</td>
<td>603</td>
<td>2.7</td>
</tr>
<tr>
<td>A⁺</td>
<td>11.8</td>
<td>741,724</td>
<td>489</td>
<td>2.6</td>
</tr>
<tr>
<td>A⁺⁺</td>
<td>28.0</td>
<td>1,767,471</td>
<td>537</td>
<td>2.6</td>
</tr>
<tr>
<td>B_buffer</td>
<td>9.2</td>
<td>578,524</td>
<td>297</td>
<td>3.6</td>
</tr>
<tr>
<td>B_veg</td>
<td>10.8</td>
<td>679,435</td>
<td>676</td>
<td>3.8</td>
</tr>
</tbody>
</table>
3.3.3. High flows

High flows are assessed by plotting the return period of daily maximum discharge for each modeled scenario. On the basis of the independence criteria proposed by Willems (2009), a POT series is constructed to quantify the impact of SWCTs on high flows and to ensure that nearly independent runoff events are selected. Figure 9 shows the return period for the POT series for the different SWCTs, consisting of 43 high flow events. The highest reduction of high flows is observed for earth works, followed by afforestation. The effect of check dams on the return period of maximum daily discharge is small. With respect to the reduction of high flows, the combination of bunds and terraces (ABT) performs best, followed by the scenarios representing terraces (AT), afforestation of scarce vegetation (BSVeg) and bunds (AB), expansion of existing plantations (BBuffer), and check dams (C_wet, C_sm). On average, the high flow events of the POT series are reduced by 31%, 19%, 12%, 12%, 8% and 2%, for the scenarios ABT, AT, B_SVeg, AB, BBuffer and C, respectively (Table 6).

Figure 9  Return period of 43 selected POT high flow events for earth works (upper left), afforestation (upper right), and check dams (lower left).
Table 6: Mean and maximum reduction of high flows for each individual scenario.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>A₁</th>
<th>A₂</th>
<th>A₃</th>
<th>Buffer</th>
<th>BBuffer</th>
<th>Bvég</th>
<th>C_all</th>
<th>Cint</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean reduction (%)</td>
<td>19</td>
<td>12</td>
<td>31</td>
<td>8</td>
<td>12</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Maximum reduction (%)</td>
<td>32</td>
<td>19</td>
<td>48</td>
<td>23</td>
<td>26</td>
<td>5</td>
<td>4</td>
<td>4</td>
</tr>
</tbody>
</table>

The maximum reduction for an individual high flow event of the POT time series varies between 4 and 48%, for the different scenarios. The lowest reduction of high flows is observed for the check dams scenarios. In both scenarios, the average reduction is 2%, and the maximum reduction is 4-5%. The minor impact on high runoff events implies that the natural river roughness of the Ronquillo River is similar to the roughness of check dams, and thus the modeling of check dams does not significantly alter high river flows.

4. Discussion

The present study shows that all modeled scenarios, representing earth works or afforestation, reduce the flow volume of the Ronquillo River by 5.7–14.0%. The diminution of the flow volume is related to enhanced interception and evapotranspiration due to modified land use. The impact of forestry on hydrology has been a matter of long controversy, as site-specific pedological, meteorological and physiological conditions govern the scale of impact on the water balance (Andréassian 2004). However, there is strong evidence that the water consumption of forests is higher than that of short vegetation such as shrub land or grassland (Farley et al. 2005). When grasslands and shrub lands are afforested, annual runoff is reduced on average by 44% and 31%, respectively (Farley et al. 2005). Although the review presented by Farely et al. (2005) does not include an Andean catchment data set, their findings are supported by Buytaert et al. (2007), who found that afforestation of a high Andean watershed with Pinus patula reduces runoff by approximately 50% compared to natural grassland vegetation. Although the present study does not include an extreme scenario such as the afforestation of the whole catchment area, the extrapolation of the reduction in flow volume per hectare obtained for the afforestation scenario BBuffer (1062 m³ha⁻¹y⁻¹) to catchment scale (42km²) reduces the flow volume by approximately 40%, which is very similar to the findings presented by Farley et al. (2005) and Buytaert et al. (2007).

The even higher reduction in flow volume due to the implementation of earth works (1242–1643 m³ha⁻¹y⁻¹) in comparison to the afforestation scenario (B Buffer) is related to the fact that owing to the encouraged infiltration of earth works, more water infiltrates into
the soil column but is consumed instantly by the vegetation. The climatic conditions of the Ronquillo watershed do not favor long-term water storage in soils under agricultural use. The R-index, a proxy for soil moisture conditions (Yao 1974), is ≤ 0.6 for 5 months a year (June–October) and ≤ 0.7 for 7 months a year (June–December). R-index values close to 0.6 can be considered as requiring irrigation for crop growth, and R-index values close to 0.9 can be assumed to be the optimum water requirement (Yao 1974). Consequently, crops benefit from the additional water that infiltrates the soils and accordingly less water contributes to the discharge. However, the diminution of blue water does not have to be considered as an unintentional or even negative finding. As more water is retarded in the watershed and stored in form of soil moisture in the unsaturated zone, referred to as green water flow (Falkenmark and Rockström 2006), more water is available for transpiration and thus for biomass production. Land owners and farmers will benefit from the enhanced biomass production and land productivity. However, Claessens et al. (2010) point out that among groups of terraces the redistribution of water causes spatial heterogeneity in water availability because upslope terraces retain water, resulting in a reduction of run-on for the downslope terraces. Moreover, the adoption of earth works such as terraces depends not only on local water availability but also on economic benefit for the land owners. Increased or more sustainable productivity needs to amortize the investments of construction and maintenance in order to secure longevity of the conservation measure (Antle et al. 2005; Posthumus and De Graaff 2005).

In addition to the reduction in flow volume due to the change in vegetation pattern, a denser canopy cover reduces surface runoff and prevents soil erosion (Durán-Zuazo and Rodríguez-Pleguezuelo 2008). This effect is documented in the modeling results, as surface runoff generation is reduced by 9.2–28.0%. Reduction of overland flow is strongly related to enhanced interception and encouraged infiltration. In the NASIM model, overland flow starts if the rain rate exceeds the infiltration rate or if the soils are saturated. Thus, higher infiltration rates reduce overland flow. However, even before overland flow generation is initiated, the interception capacity interferes with the process by altering the amount of rain that effectively interacts with the soil column. Thus, a different vegetation cover affects overland flow generation as well. This holds true only for low rainfall events, where the interception storage capacity is large enough to significantly reduce the amount of rainfall that interacts with the soil column. For storm events of higher rainfall intensities, interception is secondary, and the maximum soil infiltration capacity becomes more important in reducing overland flow.

The rainfall intensities in the region of Cajamarca are in general low. Romero et al. (2007) report that close to 80% of the rainfall events have an average rainfall intensity lower
than 2.5 mm h\(^{-1}\), and only 4% have an average intensity larger than 7.5 mm h\(^{-1}\). Thus, a modified vegetation pattern may significantly alter the runoff generation process. Moreover, the vegetation cover influences overland flow generation because the specific vegetation-type transpiration rates alter the soil water content and thus govern the probable occurrence of saturation overland flow. The combined effect of the encouraged infiltration and enhanced evapotranspiration and interception becomes evident in the reduction of high flows. On average, the high flow events of the POT series are reduced by 2–31%. The maximum high flow reduction is realized by the scenario that combines terraces and bunds (\(A_{\text{ABT}}\)). For a single runoff event, a maximum reduction of 48% in peakflow is observed. The scale of reduction is in good agreement with the findings of Al-Weshah and El-Khoury (1999), who quantified the peakflow reduction of a combined scenario of afforestation, terracing, and check dams on peakflow for a 50 km\(^2\) catchment in Jordan to be 50–80%. Moreover, plot-scale studies analyzing the effect of terracing on surface runoff generation yield an average reduction in surface runoff of approximately 60% (Hammad et al. 2004), 47% (Hammad et al. 2006), and 41% (Zhang et al. 2008) for terraced plots compared to non-terraced plots.

5. Conclusions

The present study establishes that the implementation of SWC practices such as earth works or afforestation considerably affects the hydrology of the Ronquillo River. In contrast, the impact of check dams on the hydrology of the Ronquillo River is small. With respect to the appropriateness of SWC practices for water resource management in the Ronquillo watershed, it is important to take on-site and off-site effects into account. Positive on-site effects such as the reduction of overland flow or the enhanced water retarding capacity oppose negative off-site effects such as the reduction in water availability for downstream uses such as drinking water supply.

The implementation of terraces and/or bund structures reduces surface runoff by 12–28%; however, flow volume diminishes by 6–14% as well. As more water infiltrates the soils, more water is lost because of an enhanced evapotranspiration. A loss of water for downstream usage of 1242–1643 m\(^3\)ha\(^{-1}\)y\(^{-1}\) is observed. Afforestation with eucalyptus and pine species results in a reduction of surface runoff by 9–11% and of flow volume by 6–8%. Water loss due to enhanced interception and transpiration rates of eucalyptus and pine compared to native species or crops amounts to 1062–2586 m\(^3\)ha\(^{-1}\)y\(^{-1}\). The results show that in the case of afforestation the reduction of 1 m\(^3\) in overland flow is accompanied by a reduction in the flow volume of approximately 3.7 m\(^3\). In contrast,
earth works reduce flow volume by only 2.6–2.7 $m^3$ in order to diminish overland flow by 1 $m^3$. It follows that in closed and closing basins, where water availability does not meet the water demand, at least during some portion of the year, earth works are more recommendable than afforestation in order to reduce overland flow; in addition, they have less impact than afforestation measures on water availability downstream.

Acknowledgments

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Cumulative sediment curve for an arid zone reservoir: foum el kherza (Biskra, Algeria)

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2 Gregory L. Morris Engineering

Abstract
Reservoir sedimentation affects the performance of dams in Algeria from the standpoint of reservoir capacity for storage. Foum El Kherza reservoir near Biskra Town, Algeria, is subject to dredging operation with the intent of recovering 70% of its initial storage capacity of 47 hm³ (million cubic meters). The forecasting of sediment volume trapped in the reservoir is essential to plan the future use of this resource and to sustain irrigation for the palm groves characteristic of the region. However, there are currently no sediment data for predicting sediment inflow based on hydrologic data. Based on earlier study on cumulative sediment rating curve approach using daily inflows, this paper describes an optimization of a cumulative trapped sediment curve for the reservoir based on 44 years of annual water inflows, by using a spreadsheet optimization tool, Microsoft Excel® Solver to calibrate the cumulative sediment load against the cumulative sediment inflow as documented by eight bathymetric surveys since dam construction.

1. Introduction
Most Algerian dams are subject to high rates of silting, losing nearly 1% of their capacity each year [2]. However, gauging sites are few and data may not be reliable or continuously available. Many attempts have been made to estimate sediment yield entering reservoirs in Algeria. Tixeront [11] established a power relationship between the annual erosion rate and the annual runoff depth. Remini and Avenard [7] estimated sedimentation of the Foum El Kherza reservoir as a polynomial function of time. Remini and Hallouche [9] established two relations giving annual sediment inflows as a function of operational time, a power function for Maghreb's reservoirs having a high sedimentation rate and a linear function for those having a low rate. Meddi et al. [5] used data from eighteen Algerian reservoirs to establish a model of annual sediment inflow as a function of two parameters, annual inflows and watershed area. Kassoul et al. [4] developed a classification abacus function model, and Bessenasse et al. [2] applied a bi-dimensional hydraulic model using Saint-Venant equations and convection–diffusion model to predict the evolution of the deposits in Zardezas reservoir.
In the present study the sediment rating relationship is back-estimated from reservoir survey data taken at several points in time, plus water inflow data. Based on earlier study on cumulative sediment rating curve approach using daily inflows [10]. The sediment volume relationship, vs. discharge, is developed by fitting annual Cumulative Trapped Sediment against the available reservoir sedimentation data.

2. Study area

Foum El Kherza reservoir (also known as El Gherza) is located on the Labiod River near the Town of Biskra, Algeria. The reservoir receives approximately 0.60 Mm$^3$ of sediment per year from its 1300 km$^2$ watershed in the southern foothills of Aurès Mountains, which is characterized by a semi-arid to arid climate, sparse vegetative cover, and high relief. Built in 1950, it is one of the oldest reservoirs in Algeria but has lost nearly 75% of its capacity by sedimentation. Considered a national heritage site and because of its importance in preserving the region's traditional date palm groves, a dredging operation is being undertaken to recover 70% of the initial storage capacity of 47 million cubic meters. Knowledge of the time wise variation in sediment inflows can provide information useful to analyse and improve future sediment management options.

Figure 1  Foum El Kherza dam location map.
Table 1: Principal Characteristics of Foum El Kherza dam and its drainage area

<table>
<thead>
<tr>
<th>Labiod catchment</th>
<th>Foum El Kherza reservoir</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area (km$^2$)</td>
<td>1300</td>
</tr>
<tr>
<td>Max altitude (m NGA)</td>
<td>2326</td>
</tr>
<tr>
<td>Min altitude (m NGA)</td>
<td>189</td>
</tr>
<tr>
<td>Concentration time (hours)</td>
<td>16</td>
</tr>
<tr>
<td>Drainage density (km km$^{-2}$)</td>
<td>3.8</td>
</tr>
<tr>
<td>Mean annual rainfall (mm)</td>
<td>230.50</td>
</tr>
<tr>
<td>Mean sediment yield (hm$^3$)</td>
<td>0.6</td>
</tr>
<tr>
<td>Mean annual inflows (hm$^3$)</td>
<td>25.90</td>
</tr>
<tr>
<td>Location</td>
<td>Lat.35°51'08&quot;N</td>
</tr>
<tr>
<td></td>
<td>Long. 5°55'30&quot;E</td>
</tr>
<tr>
<td>Type</td>
<td>Combined Arc-Gravity</td>
</tr>
<tr>
<td>Height (m)</td>
<td>73</td>
</tr>
<tr>
<td>Crest level (m NGA)</td>
<td>203.85</td>
</tr>
<tr>
<td>Initial capacity (hm$^3$)</td>
<td>47</td>
</tr>
<tr>
<td>Impounded in 1950</td>
<td>47</td>
</tr>
<tr>
<td>Actual capacity (hm$^3$)</td>
<td>12.90</td>
</tr>
<tr>
<td>Impounded in 1950</td>
<td>47</td>
</tr>
<tr>
<td>Purpose</td>
<td>Irrigation of 300,000 palms</td>
</tr>
<tr>
<td></td>
<td>Electricity abandoned</td>
</tr>
<tr>
<td>last bathymetric survey</td>
<td>2007</td>
</tr>
</tbody>
</table>

3. Methods

3.1. Data
Annual water inflows computed from a daily reservoir water balance for the period September 1967 to May 2011 were available from the National Agency for Dams and water Transfer (ANBT, Biskra) and are shown in (Figure 2).

![Figure 2](image-url)
Table 2: Descriptive statistics of Annual inflows.

<table>
<thead>
<tr>
<th>Count</th>
<th>$x_{\text{mean}}$ (hm$^3$)</th>
<th>$s_d$ (hm$^3$)</th>
<th>$x_{\text{median}}$ (hm$^3$)</th>
<th>$x_{\text{max}}$ (hm$^3$)</th>
<th>$x_{\text{min}}$ (hm$^3$)</th>
<th>$C_v$</th>
</tr>
</thead>
<tbody>
<tr>
<td>43</td>
<td>25.90</td>
<td>4.23</td>
<td>17.29</td>
<td>135.63</td>
<td>3.150</td>
<td>27.76</td>
</tr>
</tbody>
</table>

Figure 3 shows the cumulative loss of reservoir capacity documented by seven reservoir bathymetric surveys performed in 1967, 1975, 1986, 1993, 2001, 2004 and the last one in 2007 immediately following the first tranche of dredging which removed 4 hm$^3$.

Figure 3  Cumulative storage loss at Foum El Kherza reservoir over time.

4. Available methods


A sediment rating curve (hereafter SRC) is an empirical relationship between the water discharge $Q$ (m$^3$ s$^{-1}$) and the sediment concentration $C$ (kg m$^{-3}$). It is a ‘black box’ type of model not directly related to any physical parameters and having a standard form of:

$$C=aQ^b$$  \hspace{1cm} (1)

Coefficients $a$ and $b$ are empirically determined [1] where $a$ represents the sediment concentration for a discharge of 1.0 m$^3$s$^{-1}$, and $b$ reflect the concentration or load response to changes in discharge.

4.2. Bathymetric survey method

Sediment yield from the watershed can be computed from reservoir deposit volume determined by repeated bathymetric surveys, combined with the deposit mean bulk density estimated by empirical methods or core samples, and correcting for reservoir
trap efficiency. Reservoir resurvey data generally represent a more reliable measure of the long-term basin sediment yield than fluvial gauging stations because they trap sediment from all events and because bed load, which is frequently not measured at fluvial sediment stations, is also completely accounted for [6]. Either by contour or range method, surveys technology has changed significantly over recent decades with the dramatic increase in the speed of data acquisition and computer system processing [12,3]. The main sources of error in reservoir surveys are related to changes in measurement methodology (photogrammetry or topographic maps for pre-impoundment, range line surveys, and computer-assisted contour surveys). Another important source of error is the mean sediment bulk density, which is usually estimated rather than sampled, which varies over the area of the reservoir, and which can change from one survey to the next due to sediment compaction [6].

5. Methodology

5.1. Annual Sediment inflow by rating equation.
Same methodology used in [10] but considering a sediment rating curve relating annual sediment inflows volume to annual water inflows volume entering Foum El Kherza reservoir was constructed and calibrated against the curve of cumulative trapped sediment, and optimized to provide the best fit against the reservoir sedimentation documented by bathymetric surveys of sediment volume. Because the surveys documented the entire trapped sediment load, the rating curve will include both suspended and bed material. The inflowing sediment rating curve was also adjusted to account for reservoir trap efficiency by the Brune curve (which accounts for flood spills), plus sediment removal by flushing, spilling and dredging.

The following procedure was used to fit the best cumulative trapped sediment curve to the available data. First, the 44 years of recorded annual inflows sediment volume \( Q_s \) (hm³) was computed as a power function of annual water inflow \( Q \) (hm³) using following equation.

\[
Q_s = aQ^b
\]  

(2)

This time series was adjusted by volume of sediment released by specific activities, as described below. Further, recorded annual flushed (spilled) volumes.
5.2. Historical sediment inflow time series.
During 43 years of observations six flushing events were reported, typically after each major flood, with the largest flushing volume being that of 2009.

Lacking data on the Water-Sediment ratio for flushing events at Foum El Kherza reservoir, this value was taken as 10, considered as a mean value for Algerian dams [8]. Large spillway overflow events from major floods occurred in 2004, 2005 and 2006. For these events the Water-Sediment volume ratio is taken as 20.

Dredging started in 2006 and 4 Mm3 had been removed prior to undertaking the bathymetric survey in July 2007. The dredged sediments were discharged to basins upstream of the reservoir. The second tranche of the dredging operation had not started at this writing.

The curve of cumulative sediment accumulation adjusted for the sediment removal events as computed above, and plotted as a function of time, adjusting for the sediment removed by the events over all years in the same graph and adding the cumulative sediment volume removed by flushing, spilling and dredging to the volume remaining in the reservoir at each survey date.

5.3. Cumulative Trapped Sediment Curve optimization.
The Cumulative Trapped Sediment curve (CTSC) is obtained by summing annual inflows of sediment overall years Through the Microsoft Excel® Solver's graphical user interface (GUI), we specify cells that contain objective function, constraints and variables and also Solver options which allow advanced features of resolution and accuracy of the result.

Objective function: Maximization of coefficient of determination calculated between cumulative trapped sediment volume and bathymetric survey one at the six correspondent dates (bathymetric survey at 1967 is excluded)

As indicated above, we assume that the power $b$ can take typical values between 1 and 2.

The objective function is a nonlinear function, thus, in Microsoft Excel® Solver’s GUI options the box assume linear model, is leaved unchecked.
6. Results and discussion

By applying this methodology, the optimized SRC obtained from the cumulative trapped sediment one that reflects the observed Foum El Kherza reservoir sedimentation rate is equal to:

\[ Q_s \ (hm^3) = 0.0033Q^{1.63} \ (hm^3) \]  

(3)

Coefficient of determination \( R^2 = 0.96 \)

Performance criteria are tested against the six sedimentation surveys data.

In their study on the same reservoir, Remini and Avenard concluded that reservoir’s sedimentation evolution is the second-degree polynomial function of time and tend towards a stabilization which is not the case as the number of flash floods has increased from 2004 to 2009, with their large sediment loads. Fortunately, sediment spilling was probably more efficient during the 2004 and 2005 floods because the reservoir was already full, plus there were beneficial effects from operation of bottom outlet and dredging. The sediment rating curve approach clearly shows the influence of such events.
Water –Flushed (Spilled) sediment volumes ratios are estimated from observations of Algerian dams, they can be very different from those of Foum El Kherza and even they are probably different from one operation to another. However the considered values are chosen in such a manner to approximate realistic values. Accurate values of these parameters will certainly improve results.

Power $b$ and intercept $a$ are closely correlated coefficients, such optimization problems can have more than one solution, thus, constraints that are derived from the natural learning of the case can help us to keep the closest to reality solution to the problem.

### 7. Final remarks

Cumulative trapped sediment curve as a combination of the sediment rating curve and bathymetric surveys methods constitutes a tool to solve constraints imposed by the lack of gauged data on sediment load. More that it can give more accurate results in forecasting sediment yield than when applying each method separately. A very interesting benefit of this approach is that the sediment yield can be estimated at a small time scale using only water inflows. Thus, highly influential in reservoir operation, updating of the active reservoir capacity is easily done. The adopted approach can be very interesting for several reservoirs if more additional measures from reservoir regarding sediment bulk density, flushed, spilled and dredged Sediment-Water ratios are available.
Acknowledgments
Grateful acknowledgements are addressed specially for Pr. D.E. Walling and to Dr. L. Houichi for fruitful discussions. Special thanks go to Mr A. Khmouli from the National Agency for Dams and water Transfer ANBT (Biskra) for helping us in providing of complementary and valuable data.

References
Management

Integrated multi-disciplinary analysis: A necessity for holistic understanding of water resources management problems
Environmental impact assessment of structural flood mitigation measures in Metro Manila, Philippines using an analytical evidential reasoning approach

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Abstract
The practice of environmental impact assessment (EIA) in the planning processes of infrastructure projects has created significant awareness in many parts of the world on the benefits of environmentally sound and sustainable urban development. In the Philippines, the construction of structural flood mitigation measures (SFMMs) gets high priority from the national government to immediately address the destructive effects of flash floods and inundations in highly urbanized areas, especially in Metro Manila. EIA thus, should be carefully and effectively carried out to maximize the potential benefits that can be derived from SFMMs. An environmental assessment that can be reduced to standardized comparable quantitative values may aid flood managers and decision-makers in planning for effective and environmentally sound structural flood mitigation projects. This study proposes a semi-quantitative approach to EIA using the rapid impact assessment matrix (RIAM) technique, coupled with evidential reasoning approach, to rationally and systematically aggregate the ecological and socio-economic impacts of 4 planned SFMM projects (2 river channel improvements and 2 new open channels) in Metro Manila. Based on the results, the environmental benefits from the river channel improvements and new open channels generally outweigh the likely negative impacts. The utility values also imply that the river channel improvements will yield higher environmental benefits over the 2 new open channels. The results of this study thus, provide valuable insights for the development of environmental impact assessment process for SFMMs in the Philippines.

1. Introduction
Environmental impact assessment is a process undertaken to identify the benefits and harmful impacts of projects, plans, programs or policies on the physical, biological and socio-economic components of the environment (Petts 1999; Wang et al. 2006). The use of appropriate EIA techniques can aid planners and decision-makers in formulating appropriate actions based on informed decisions in light of project urgency and limited resources.
resources, which are common constraints in many developing countries (Shah et al. 2010).

In the Philippines, particularly in Metro Manila, the EIA techniques used for SFMMs are generally descriptive and qualitative in nature (e.g. Department of Public Works and Highways, 1998; City Office of Navotas, 2009), which are basically similar to the ad hoc and checklist methods described by Lohani et al. (1997). Numerous innovations already exist that can address some of the weaknesses of these methods, such as multicriteria/multiattribute decision analysis (McDaniels, 1996; Kim et al., 1998), weighting-scaling checklists (Canter and Sadler, 1997), input-output analysis (Lenzen et al., 2003), life cycle assessment (Tukker, 2000), analytic hierarchical process (Ramanathan, 2001), fuzzy sets approaches (Parashar et al., 1997), and the Rapid Impact Assessment Matrix (RIAM) technique (Pastakia, 1998; Mondal et al., 2009; Al Malek and Mohamed, 2005).

For the SFMM projects in Metro Manila, the authors proposed the use of a modified RIAM technique to reduce the subjectivity and improve the transparency of the EIA process (Gilbuena et al., 2013). This method, however, does not provide the means to measure the overall impact of each project alternative. If an overall impact can be estimated through a quantifiable value, planners and decision-makers may be able to maximize the potential benefits of each project alternative.

![Maps showing the geographical location of Metro Manila, the study area and the planned structural flood mitigation measures indicated by Dike-1, Dike-2, Channel-1 and Channel-2 (Gilbuena et al., 2013).](image-url)
Yang and Sen (1994) developed an evidential reasoning approach that uses a belief structure to model qualitative assessments on the basis of decision theory and the Dempster-Shafer theory of evidence. This method focuses primarily on the uncertainties that are inherent in subjective assessment processes. The evidential reasoning approach, since then, has been used in many multiattribute decision analysis problems in engineering and management (e.g. Yang and Sen, 1994; Sen and Yang, 1995; Wang et al., 1995; Wang, 1997; Yang and Xu, 1998; Yang, 2001; Wang et al., 2006).

A utility-based information transformation technique has been developed in the evidential reasoning approach to provide a systematic procedure to transform various types of information into a unified format, so that both quantitative and qualitative information with uncertainties can be handled in a consistent manner (Yang, 2001). This new evidential reasoning approach has been coupled with the RIAM technique to obtain a unified EIA result in the form of utility values (Wang et al., 2006), which opens a systematic and effective way to compare and rank alternatives. The potential of this approach however, has not been fully explored, especially for its application in the EIA of planned SFMM projects.

This study explores the use of a utility-based recursive evidential reasoning approach, coupled with the RIAM technique, in the EIA of planned SFMM projects. The utility function has been slightly modified to cope with the modified RIAM technique and to estimate the utility values in terms of the utility range [-1 1] to distinctly represent the effects of the aggregated positive and negative impacts. These modifications are intended to improve the outcome of the EIA, but may also find application in other types of projects. The succeeding sections describes the EIA of the 4 SFMMs using the modified RIAM technique; elaborate the recursive evidential reasoning approach; analyze and discuss the results of the impact assessment; and offer some recommendations and conclusions with the aim of improving the practice of EIA for SFMMs in the Philippines.

2. EIA by the RIAM technique

The authors carried out a study that investigated the use of a modified RIAM technique to assess the environmental impacts of 4 planned SFMM projects comprising of 2 dike and 2 new open channels (Gilbuena et al., 2013). The following sub-sections describe the environmental conditions of the study area and the EIA method used.
Table 1: Salient features of the planned structural flood mitigation measures in Metro Manila (Gilbuena et al., 2013).

<table>
<thead>
<tr>
<th>Structural flood mitigation measures</th>
<th>Description of activities</th>
<th>Length (m)</th>
<th>Width (m)</th>
<th>Depth (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dike-1</td>
<td>Raising of masonry wall, installation of ripraps and alteration of river bank configuration at the lower section of the Meycauayan River</td>
<td>4,900</td>
<td>4.0</td>
<td>-</td>
</tr>
<tr>
<td>Dike-2</td>
<td>Raising of riprap dike, installation of new ripraps, and alteration of river bank configuration at the upper section of the Meycauayan River</td>
<td>2,340</td>
<td>4.0</td>
<td>-</td>
</tr>
<tr>
<td>Channel-1</td>
<td>Construction of diversion canal between the Polo River and the Palasan River by excavation</td>
<td>850</td>
<td>9.6</td>
<td>3</td>
</tr>
<tr>
<td>Channel-2</td>
<td>Construction of drainage channel in the lower reaches of the Meycauayan River by excavation</td>
<td>1,650</td>
<td>5.6</td>
<td>2.1</td>
</tr>
</tbody>
</table>

2.1. Environmental Setting

Metro Manila serves as a focal point for the major political and economic activities in the Philippines. Figure 1 shows the geographic location of Metro Manila. At present, the metropolis is comprised of 17 highly urbanized municipalities that has a total population of about 11.76 million (National Statistics Office, 2007). According to the study of the National Statistical Coordination Board (2009), about 30% of the country’s gross domestic product is contributed by Metro Manila. Despite the high economic activities in this region, economic growth and urban development is persistently slow, which according to Page (2000), is partly due to the frequently occurring disasters caused by immense and violent floods that take place during the monsoon and storm periods (from May to October). Recent flood events (Rabonza, 2009) are increasingly devastating, resulting in the loss of many lives and immense damages to agriculture and properties.

This paper focuses on the flood-prone sub-drainage area (approximately 20 km²) that is located at the north-northwest part of Metro Manila (as shown in Figure 1), which is home to approximately 160,000 residents. Its topography is generally characterized by flat and low-lying coastal plains with ground elevation ranging from 0 to 1.5 m above mean sea level. It has a mixed land-use comprised of commercial districts, industrial districts, residential areas and fishponds. The river system has limited aquatic biota due to the poor water quality conditions. Migratory birds that feed on insects, fishes and invertebrates were observed wandering and nesting near the Meycauayan River, while few patches of mangroves exist at the river’s lower section. Most mangrove areas have already been converted to fishponds and settlement areas. Water hyacinths were observed at the approaching upstream of the Meycauayan River. High volume of settlers
is found at and near the left bank of the upper section of the Meycauayan River and along narrow natural waterways. Due to the very poor discharge capacity in this drainage area, floods easily manifest during the rainy seasons, which contributes to the slow economic growth rate of the affected municipalities.

To improve the drainage conditions, 2 river improvement works and 2 open channels were planned by the Department of Public Works and Highways (2001) under the Metro Manila flagship program on flood management. Table 1 shows salient information of the 4 planned SFMM investigated in this study. The locations of these structures are shown in Figure 1. The river improvement works as described in Table 1 involves the construction of masonry walls (Dike-1) and riprap dikes (Dike-2) at the left bank of the lower and upper sections of the Meycauayan River, respectively. These structures will serve as preventive measures from bank overflow, and protection from the scouring effects of turbulent flow against the river’s critical bends and bridge abutments. The open channels consist of a diversion canal (Channel-1) that will discharge excess water from the Polo River to the Palasan River; and a small drainage channel (Channel-2) that will aid in the draining of surface water near the lower section of the Meycauayan River (Figure 1).

2.2. The RIAM technique

The EIA of the 4 SFMMs was carried out by the authors using a modified RIAM technique (Gilbuena et al., 2013). The RIAM technique provides the means for a semi-quantitative evaluation of the environmental factors using a set of standardized assessment criteria. Table 2 shows assessment of Dike-1, Dike-2, Channel-1 and Channel-2 in terms of the 32 environmental components. Figure 2 shows the summary of the RIAM analysis in Table 2. Each of the environmental component falls under one of the 4 environmental categories (Pastakia and Jensen, 1998): Physical/Chemical (PC), Biological/Ecological (BE), Social/Cultural (SC) and Economics/Operational (EO). Each environmental category is divided in terms of project phases (i.e. Preconstruction, Construction and Operation phases), and then further divided into specific environmental components. Details of the RIAM technique are described briefly as follows:

- Assessment criteria are categorized into 2 groups, $A$ and $B$. The $A$ group consists of the Importance Criterion ($A_I$) and Magnitude Criterion ($A_2$), while the $B$ group is composed of the Permanence Criterion ($B_1$), Reversibility Criterion ($B_2$) and Cumulative Criterion ($B_3$). The scale values of $A_I$ and $A_2$ and the impact description of each scale used in this study are described in Gilbuena et al. (2013)
Given the scales determined in each of the assessment criteria, the environmental score ($ES$) was calculated using the formula (Pastakia and Jensen 1998):

$$ES = [A1 \times A2] \times [B1 + B2 + B3]$$

(1)

The environmental score, which ranges from -108 to 108, represents the degree of change that may occur in an environmental component due to the implementation of a project. To define the levels of impact based on the environmental scores, impact bands (or range bands) are assigned to each range of environmental scores denoted by the symbols [-E], [-D], [-C], [-B], [-A], [NC], [NI], [+A], [+B], [+C], [+D] and [+E] as described in Gilbuena et al., 2013.

Figure 2  Histograms for the planned SFMM projects, a) Dike-1, b) Dike-2, c) Channel-1 and d) Channel-2, based on the RIAM analysis in Table 2. The figures show the distribution of the range band counts in terms of environmental categories (PC, BE, SC and EO) and project phases (Pre-construction, Construction and Operation phases).
### Table 2: RIAM analysis of the selected planned structural flood mitigation measures in Metro Manila (Gilbuena et al., 2013) and relative weights of the environmental category and environmental components.

<table>
<thead>
<tr>
<th>Environmental Category, Relative Weight (Wq), 0.25</th>
<th>Code</th>
<th>Item No.</th>
<th>Relative Weight (Wq)</th>
<th>Dike-1</th>
<th>Dike-2</th>
<th>Channel-1</th>
<th>Channel-2</th>
</tr>
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<tr>
<td>Environmental Components</td>
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<td></td>
<td>ES</td>
<td>Range Band</td>
<td>ES</td>
<td>Range Band</td>
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<tr>
<td>Physical/Chemical (PC), 0.25</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Land/soil disturbance due to site clearing</td>
<td>PC-P-1</td>
<td>1</td>
<td>0.1429</td>
<td>0</td>
<td>NC</td>
<td>0</td>
<td>NC</td>
</tr>
<tr>
<td>- Change in landuse</td>
<td>PC-C-1</td>
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<td>0.1429</td>
<td>0</td>
<td>NI</td>
<td>0</td>
<td>NI</td>
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<tr>
<td>- Local geology and soil erosion</td>
<td>PC-C-2</td>
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<td>0.1429</td>
<td>-14</td>
<td>-B</td>
<td>-14</td>
<td>-B</td>
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<tr>
<td>- Drinking water</td>
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<td>0.1429</td>
<td>0</td>
<td>NC</td>
<td>0</td>
<td>NC</td>
</tr>
<tr>
<td>- Erosion and riverbank scouring</td>
<td>PC-C-4</td>
<td>5</td>
<td>0.1429</td>
<td>12</td>
<td>+B</td>
<td>12</td>
<td>+B</td>
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<tr>
<td>- Surface and groundwater hydrology</td>
<td>PC-O-1</td>
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<td>0.1429</td>
<td>-5</td>
<td>-A</td>
<td>-5</td>
<td>-A</td>
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<tr>
<td>- Hydraulic conditions</td>
<td>PC-O-2</td>
<td>7</td>
<td>0.1429</td>
<td>36</td>
<td>+D</td>
<td>36</td>
<td>+D</td>
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<td>Biological/Ecological (BE), 0.25</td>
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<td></td>
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<td>- Aquatic habitat</td>
<td>BE-C-1</td>
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<td>0.125</td>
<td>-10</td>
<td>-B</td>
<td>-10</td>
<td>-B</td>
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<td>- Wildlife and terrestrial impacts</td>
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<td>0.125</td>
<td>-7</td>
<td>-A</td>
<td>-7</td>
<td>-A</td>
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<td>- Riparian and wetlands</td>
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<td>0.125</td>
<td>-10</td>
<td>-B</td>
<td>0</td>
<td>NC</td>
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<td>- Waste generation from construction and excavation</td>
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<td>0.125</td>
<td>-7</td>
<td>-A</td>
<td>-7</td>
<td>-A</td>
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<td>BE-C-5</td>
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<td>- Aquatic habitat</td>
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<td>+A</td>
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<td>+A</td>
<td>6</td>
<td>+A</td>
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<td>- Involuntary Resettlement</td>
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<td>-C</td>
<td>-42</td>
<td>-D</td>
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<td>- Public acceptance</td>
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<td>0</td>
<td>NI</td>
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<tr>
<td>- Air quality</td>
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<td>0.0714</td>
<td>-5</td>
<td>-A</td>
<td>-5</td>
<td>-A</td>
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<tr>
<td>- Noise levels</td>
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<td>0.0714</td>
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<td>- Dependency burden</td>
<td>SC-C-4</td>
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<td>8</td>
<td>+A</td>
<td>8</td>
<td>+A</td>
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<td>- Housing characteristics and utilities</td>
<td>SC-C-5</td>
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<td>0.0714</td>
<td>0</td>
<td>NC</td>
<td>0</td>
<td>NC</td>
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<td>- Health and safety of construction workers</td>
<td>SC-C-6</td>
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<td>0.0714</td>
<td>-4</td>
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<td>-4</td>
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<tr>
<td>- Health and safety of general public</td>
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<td>0.0714</td>
<td>-4</td>
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<td>-A</td>
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<td>- Aesthetic and cultural scenic sites</td>
<td>SC-C-8</td>
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<td>0.0714</td>
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<td>0</td>
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<tr>
<td>- Local planning, coordination and economic growth</td>
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<td>0.0714</td>
<td>4</td>
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<td>4</td>
<td>+A</td>
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<tr>
<td>- Public utilities and infrastructure</td>
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<td>0.0714</td>
<td>-4</td>
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<td>-4</td>
<td>-A</td>
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<tr>
<td>- Natural environmental and health hazards</td>
<td>SC-O-1</td>
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<td>0.0714</td>
<td>30</td>
<td>+C</td>
<td>30</td>
<td>+C</td>
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<tr>
<td>- Urban living conditions</td>
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<td>0.0714</td>
<td>30</td>
<td>+C</td>
<td>30</td>
<td>+C</td>
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<td>Economic/Operational (EO), 0.25</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>0.3333</td>
<td>5</td>
<td>+A</td>
<td>5</td>
<td>+A</td>
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<tr>
<td>- Development potential</td>
<td>EO-O-2</td>
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<td>0.3333</td>
<td>15</td>
<td>+B</td>
<td>15</td>
<td>+B</td>
</tr>
<tr>
<td>- Local revenue and economy</td>
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<td>0.3333</td>
<td>30</td>
<td>+C</td>
<td>30</td>
<td>+C</td>
</tr>
</tbody>
</table>
3. EIA of SFMM by evidential reasoning approach

The evidential reasoning approach provides an effective way to synthesize the information of assessed environmental factors. The process is based on the belief decision matrix and the combination rule of the Dempster-Shafer theory of evidence (Yang, 1994).

An evidential reasoning algorithm was developed by Wang et al., 2006, which can be used to aggregate the assessment results of the basic environmental components in the EIA of planned SFMM project \( p \). The assessment follows a hierarchical process as shown in Figure 3. Based on this figure, the environmental components are first aggregated in each environmental category using the evidential reasoning approach. The assessment results of the environmental categories are then aggregated to determine the overall assessment for each SFMM project. The recursive evidential reasoning algorithm used in this study is briefly described in the following steps:

**Step 1:** Construct the decision matrix \( D_{p,q} (i,n) \), composed of decision elements \( \beta_{p,q,i,n} \) for each \( q \)th environmental category of each \( p \)th SFMM project according to the results of the RIAM analysis, where row \( i \) is the item number of each environmental component of \( q \)th environmental category, and column \( n \) is the identifier of the range band variable \( H_n \) where \( p = 1 \) to \( 4 \), \( i = 1 \) to \( I_{p,q} \) (where \( I_{p,q} = 7, 8, 14 \) and \( 3 \) for \( q = 1, 2, 3 \) and \( 4 \), respectively), and \( H_n = \{ [-E], [-D], [-C], [-B], [-A], [-NC], [-NI], [+A], [+B], [+C], [+D], [+E] \} \) that sequentially corresponds to \( n = 1, 2, 3, \ldots, N \) (where \( N \)). Based on the RIAM analysis in Table 2, \( \beta_{p,q,i,n} \) were determined using the following conditions:

\[
\beta_{p,q,i,n} = 1 \quad \text{if} \quad H_n = H_{n_{(p,q,i)}}
\]

\[
\beta_{p,q,i,n} = 0 \quad \text{if} \quad H_n \neq H_{n_{(p,q,i)}}
\]
where $H_{np}^{i}(p,a,i)$ represents the decision range band by the RIAM analysis of planned SFMM projects.

**Step 2:** Relative weights and are assigned to the $q^{th}$ environmental category and $r^{th}$ environmental component, respectively (as shown in Table 2), with conditions $\sum_{q=1}^{4} w_{p,r}^{q} = 1$ and $\sum_{i=1}^{4} w_{p,a}^{i} = 1$ (Wang et al., 2006). In this study, each environmental category is assumed to be of equal relative importance, thus $w_{p,1} = w_{p,2} = w_{p,3} = w_{p,4} = 1/4$. Similar to Wang et al. (2006), the environmental components have the relative weights: $w_{p,a}^{i} = 1/3$

**Step 3:** Transform the degrees of belief $\beta_{p,q}^{i,n}$ into basic probability mass $m_{p,q}^{i,n}$ and calculate the "unassigned" probability mass $\tilde{m}_{p,q,n}$ (Wang et al., 2006). The probability mass $\tilde{m}_{p,q,n}$ is split into two parts: $\tilde{m}_{p,q}^{i}$ and $\tilde{m}_{p,q,n}^{i}$. The probability mass $\tilde{m}_{p,q,n}^{i}$ is caused by the relative importance of the environmental components, which is the proportion of beliefs that remains to be assigned depending upon how many other environmental components are assessed, while $\tilde{m}_{p,q,n}^{i}$ represents the "incompleteness" (or ignorance) in the assessment (Wang et al., 2006). The probability masses are calculated using the following equations

$$m_{p,q}^{i,n} = w_{p,q}^{i,n}\beta_{p,q}^{i,n}$$

(4)

$$\tilde{m}_{p,q}^{i} = w_{p,q}^{i} \left(1 - \sum_{i=1}^{4} \beta_{p,q}^{i,n}\right)$$

(5)

$$\tilde{m}_{p,q,n}^{i} = 1 - w_{p,q}^{i}$$

(6)

$$\tilde{m}_{p,q,n}^{i} = \tilde{m}_{p,q}^{i} + \tilde{m}_{p,q,n}^{i}$$

(7)

When the RIAM analysis of a SFMM project is complete (i.e. all environmental components are individually assessed), the value $\tilde{m}_{p,q,n}^{i}$ for is zero, thus making $\tilde{m}_{p,q,n}^{i} = \tilde{m}_{p,q,n}^{i}$.

**Step 4:** Construct the decision matrix $D_{p,q}^{i}(q,n)$, whose elements consist of $\beta_{p,q}^{i,n}$ (aggregated in terms of $i$ environmental components). The aggregated decision elements $\beta_{p,q}^{i,n}$ are calculated using the following evidential reasoning algorithm (Wang et al., 2006):

**Step 4.1:** Initial aggregation. Aggregate the first and second probability masses of each environmental category (i.e. $m_{p,q}^{i,n}$ and $m_{p,q}^{i,n}$), where $n_1$ and $n_2$ are the range band identifiers for the first and second environmental components (i.e. $i = 1$ and 2), respectively, by first calculating the normalization factor $K_{p,q}^{i,j}$ of $j^{th}$ the aggregation ($j = 1$) of the environmental components $i$ using Equation 8:
\[ K_{p,q} = \left[1 - \sum_{n=1}^{N} \sum_{n'=1}^{N} m_{p,q,1,n} m_{p,q,2,n'} \right]^{-1} \] (8)

And then calculate the probability masses, \( \mu_{p,q,j,n} \), \( \tilde{\mu}_{p,q,j} \), \( \bar{\mu}_{p,q,j} \), \( \hat{\mu}_{p,q,j} \) at \( j = 1 \) using Equations 9 - 12.

\[
\mu_{p,q,1,n} = K_{p,q,1} \left[ m_{p,q,1,n} m_{p,q,2,n} + m_{p,q,1,n} \tilde{m}_{p,q,2} + m_{p,q,1} \hat{m}_{p,q,2,n} \right] \] (9)

\[
\tilde{\mu}_{p,q,1} = K_{p,q,1} \left[ \tilde{m}_{p,q,1} m_{p,q,2} + \tilde{m}_{p,q,1} \tilde{m}_{p,q,2} + \tilde{m}_{p,q,1} \hat{m}_{p,q,2} \right] \] (10)

\[
\bar{\mu}_{p,q,1} = K_{p,q,1} \left[ \bar{m}_{p,q,1} m_{p,q,2} \right] \] (11)

\[
\hat{\mu}_{p,q,1} = \tilde{\mu}_{p,q,1} + \bar{\mu}_{p,q,1} \] (12)

**Step 4.2: Recursive algorithm for the \( j \)th aggregation of the environmental component \( i \).**

Calculate the normalization factor \( K_{p,q,j} \) and the aggregated probability masses, \( \mu_{p,q,j,n} \), \( \tilde{\mu}_{p,q,j} \), \( \bar{\mu}_{p,q,j} \), \( \hat{\mu}_{p,q,j} \) where \( j = 2 \) to \( J \) and \( J = I_q - 1 \) using the following algorithm.

\[
K_{p,q,j} = \left[1 - \sum_{n=1}^{N} \sum_{n'=1}^{N} \mu_{p,q,j-1,n} \mu_{p,q,j+1,n} \right]^{-1} \] (13)

\*

\[
\mu_{p,q,j,n} = K_{p,q,j} \left[ \mu_{p,q,j-1,n} m_{p,q,j+1,n} + \mu_{p,q,j-1} m_{p,q,j+1,n} + \tilde{\mu}_{p,q,j-1} m_{p,q,j+1,n} \right] \] (14)

\*

\[
\tilde{\mu}_{p,q,j} = K_{p,q,j} \left[ \tilde{\mu}_{p,q,j-1} \bar{m}_{p,q,j+1} + \tilde{\mu}_{p,q,j-1} \bar{m}_{p,q,j+1} + \bar{\mu}_{p,q,j-1} \bar{m}_{p,q,j+1} \right] \] (15)

\*

\[
\bar{\mu}_{p,q,j} = K_{p,q,j} \left[ \bar{\mu}_{p,q,j-1} \bar{m}_{p,q,j+1} \right] \] (16)

\*

\[
\hat{\mu}_{p,q,j} = \tilde{\mu}_{p,q,j} + \bar{\mu}_{p,q,j} \] (17)

Then, calculate the aggregated degree of belief \( \beta_{p,q,n}^i \) of each environmental category from the final aggregated probability masses (i.e. when \( j = J \)) using the following equation.

\[
\beta_{p,q,n}^i = \frac{\mu_{p,q,J,n}}{1 - \bar{\mu}_{p,q,J}} \] (18)
Step 5: Finally, construct the decision vector $D_{p,\cdot}^q(n)$, which consists of the overall decision elements (or overall degree of belief), $\beta_{p,n}^{q,i}$ by aggregating the $q$ environmental categories of the $p^{th}$ SFMM project. The decision elements $\beta_{p,n}^{q,i}$ are calculated using a similar procedure from Steps 1 to 4 by calculating the $j^{th}$ aggregation of the probability masses $\mu_{p,n}^{q,i}$ (aggregated $q$ environmental categories), where $j = 4$ to $J$ aggregations ($J = 3$), using the formula:

$$\beta_{p,n}^{q,i} = \frac{\mu_{p,n}^{q,j}}{1 - \sum_{j} \mu_{p,n}^{q,j}}$$  \hspace{1cm} (19)

Step 6: Calculate the expected utility value $U_p$ of the SFMM project $p$. Figure 4 shows the utility functions used in this study. The expected utility is calculated from the decision vector $D_{p,\cdot}^q(n)$ and utility functions $u(H_n)$ (from Figure 4) as shown in the following equation.

$$U_p = \sum_{n=1}^{N} \beta_{p,n}^{q,i} u(H_n)$$  \hspace{1cm} (19)

where $u(H_n)$ is assumed to be equidistantly distributed in the normalized utility range, such that $u(-E)=-1.00, u(-D)=-0.80, u(-C)=-0.60, u(-B)=-0.40, u(-A)=-0.20, u(0)=0.00, u(+A)=0.20, u(+B)=0.40, u(+C)=0.60, u(+D)=0.80, u(+E)=1.00$

4. Results and discussion

Table 3 shows the degrees of belief $\beta_{p,n}^{q,i}$ determined using Steps 1 to 5 in Section 3 and the expected utility estimated using Equation 18 for Dike-1, Dike2, Channel-1 and Channel-2. These results are similar to the distribution profile in Figure 2, but are not exactly the same. For instance, the range band counts of [-A] in Figure 2 for Dike-1 and Dike-2 are considered the same, while the degree of belief for Dike-2 in Table 4 is slightly higher than in Dike-1. The difference in the distribution profile between Figure 2 and Table 4 can be attributed to the assignment of relative weights $w_{p,n}^{q,i}$ and $w_{p,q,i}$ in the calculation of the probability masses, which contributes to the flexibility of the evidential reasoning approach in terms of defining the relative importance of each environmental component and environmental category in the decision process.

Based on the results in Table 3, the degrees of belief of Dike-1 and Channel-2 are distributed from [-C] to [+C], while Dike-2 and Channel-1 are distributed from [-E] to
[+E]. The domain of the negative range band is dominated by the range band [-A]. This suggests that slight negative change will generally occur for Dike-1, Dike-2, Channel-1 and Channel-2. The domain of the positive range bands, on the other hand, is dominated by [+A] in Dike-1 and Dike-2, while [+B] dominates in Channel-1 and Channel-2. The dominance of [+A] in the dike projects indicates that most of the positive change will only be slightly beneficial, while the [+B] dominance implies that substantial benefits can be obtained from the channelization projects. The distribution of the degrees of belief provides clear insights on the characteristics of the positive and negative domains of the impacts however it is not sufficient to infer the overall characteristics of each SFMM. The overall characteristic of each SFMM, perhaps, can be estimated by determining the expected utility based on the distribution of the degrees of belief. The expected utilities are calculated using Equation 20.

The rightmost column in Table 3 summarizes the expected utility values of each SFMM based on the utility function defined in Section 3. The expected utility of Dike-2 is slightly higher than Dike-1, while Channel-1 is higher than Channel-2. These results imply that Dike-2 is more desirable than Dike-1, while Channel-1 is more desirable than Channel-2. In general the results show that the expected utility of all SFMMs are greater than zero, indicating that the projects are most likely to become beneficial. However, the relatively low expected utility values indicate that the net effect will only be slightly positive. A zero expected utility value would imply that the net environmental effect of a project is the balance between the effects of the positive and negative changes.

Table 3: Aggregated distributed assessment of the 4 planned structural flood mitigation measures in Metro Manila.

<table>
<thead>
<tr>
<th>SFMM</th>
<th>Degree of belief, $p_{ij}$</th>
<th>Expected Utility, $U_p$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>E</td>
<td>D</td>
</tr>
<tr>
<td>Dike-1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Dike-2</td>
<td>0</td>
<td>0.015</td>
</tr>
<tr>
<td>Channel-1</td>
<td>0</td>
<td>0.014</td>
</tr>
<tr>
<td>Channel-2</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

The result of the EIA of the planned SFMM projects using the evidential reasoning approach provides valuable insights with regards to the characteristics of the overall impacts, as well as its distribution in terms of degrees of belief, which can be very useful in the optimization of project environmental benefits. The use of negative utility values in the utility function provided additional insights as to how the negative impacts generally affect the desirability of a SFMM project. It is however recommended to explore other forms of utility functions to further improve the level of environmental assessment and decision analysis. For instance, risk preferences (i.e. risk-aversiveness and risk-seeking) and decision-maker attitudes (i.e. optimistic and pessimistic) can be taken into
consideration to have a more holistic view of the environmental benefits for decision analysis.

5. Conclusion

This study explores the application of an evidential reasoning approach as an extension in the environmental impact assessment process for SFMMs in Metro Manila. The evidential reasoning approach was used to determine the distributed assessment of the environmental categories in terms of the degrees of belief on each assessment grade (range band), and calculated the expected utility of each SFMM. The results showed that Dike-2 is more desirable than Dike-1, while Channel-1 is more desirable than Channel-2. The dike projects are generally more desirable than the channelization projects. The results also showed that the expected utility of all SFMMs are greater than zero, which indicates that the projects are most likely to become environmentally beneficial. However, the relatively low expected utility values imply that the net environmental effects will only be slightly positive. In general, the evidential reasoning approach provides flexibility to the RIAM technique by allowing the assignment of relative weights. The adjustment made on the utility function allowed for a more meaningful interpretation of the utility values in terms of the degrees of belief. This in turn gave the means to calculate the expected utility values in terms of the basic definition of positive and negative impacts. A SFMM project that has a negative expected utility value ($U_p < 0$) would indicate that the negative impacts of the project will outweigh its positive impacts, thus should be avoided or re-evaluated. A positive expected utility value ($U_p > 0$), similarly, would indicate that the positive impacts will outweigh the negative impacts, thus can be pursued or further enhanced for higher positive utility. The combination of the RIAM technique and the evidential reasoning approach thus provides a useful alternative in project assessment, especially when evaluating under the context of environmental sustainability. One important potential application of this new approach is in the optimization of the environmental management plan. The expected utility value can serve as a measure that would help further minimize the potential negative impacts, as well as maximize the positive impacts, of planned SFMM projects. This new approach opens more windows for the improvement of the EIA procedures for planned SFMM projects in the Philippines, but may also find application on other types of EIA studies.
Acknowledgment

This study was carried out as part of the research project, "Solutions for the water-related problems in Asian Metropolitan areas" supported by the Tokyo Metropolitan Government, Japan (represented by A. Kawamura). We would like to thank the Department of Public Works and Highways for supplying the necessary field data from the earlier feasibility studies. We would also like to thank Woodfields Consultants, Inc. for providing the resources and technical expertise during the site verification and field investigations. We are grateful to the reviewers for the corrections and suggestions, which have contributed to marked improvements in the content of our research project.

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Management

Catchment water quality management
Monitoring and Analyses of impact of the industrial complexes on water quality of the Central Asian Transboundary Rivers

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Abstract

It is known that the main waterways of Central Asia are Transboundary and respectively in relationship of the upstream and downstream countries of rivers the question of quantity and quality of waters are dominating. The present article is devoted to more detailed analysis quality of the Zeravshan River waters and formation of floods by essential economic damages and definition of adequate possibility measures for their mitigation. For this purpose meteorological data of Agency of hydrometeorology of Tajikistan, methods of the chemical analysis of waters of the river and statistical data of the Ministry of Emergency Situations of Tajikistan were widely used. In most cases the problem of water quality of the Zeravshan River consider in organic communication with activity of the Anzob Mountain-concentrating Industrial Complex (AMCIC) in Tajikistan. Results of comparison of the analysis of waters have shown about absence of essential pollution of waters of the Zeravshan River by wastewaters of the Anzob mountain-concentrating industrial complex but are changed under the influence of collector drainage water of irrigating basin zone and wastewater of Samarqand, Kattakurgan, Navoi cities of Uzbekistan

1. Introduction

In the Aral Sea Basin on the territory which is located five states, water resources are used basically for irrigation and water-power engineering. These water users demand different modes of regulation of a river drain. In interests of water-power engineering – the greatest development of the electric power and accordingly use large parts of an annual drain of the rivers in winter the cold period of year. For irrigation the greatest volume of water is required in the summer during the vegetative period. Regulation of a river drain is thus carried out by the large reservoirs. Thus all largest hydroelectric power stations are constructed in the countries of a zone of the drain formation - in upstream the rivers Amu Darya and Syr-Darya – in Kyrgyzstan and Tajikistan and the main areas of the irrigated lands are located in states of the downstream of the rivers – Kazakhstan, Turkmenistan and Uzbekistan [8].
The Zeravshan River is the Transboundary Rivers (in Uzbekistan and Tajikistan) by length and basin area of 877 km and 17700 km², accordingly. The average expense of the river waters of 162 m³/sec and originates from the Zeravshansk glacier in mountain knot between Turkestan and Zeravshansk with ridges the River is fed basically with glaciers and snow. Therefore the greatest drain in it is necessary for the summer (July, August) and during the cold period of year Zeravshan bears not enough water. In the summer water in the river muddy, gray-steel color, in the winter pure and transparent. On territories of Republic Uzbekistan near to the Samarkand city the Zeravshan River is divided into two sleeves – Akdarya and Karadarya. Earlier Zeravshan ran into Amu Darya but now loses the waters in desert Kyzyl-Kum, forming two deltas – Karakulsk and Bukhara. The total drain of the Zeravshan River Basin on the periods 1932-1962 and 1962-1991 make is accordingly 146.26 and 145.03 km³ [5].

The water of the Zeravshan river on the Republic Uzbekistan territory is distributed basically on following areas: Samarkand-70.2 % (at irrigated area of 67 %), Navoinsky-13.1 % (at irrigated area of 16 %), Dzhizak-7.4 % (at irrigated area of 8.6 %), Kashkadarinskaja-9.3 of % (at irrigated area of 7.8 %) [1].

From total water intake of the Zeravshan river make is 4834 to the Republic of Tajikistan to come only 253 mln. m³ (5.23 %) [7]. Actual mean of the water volume for irrigation and productivity of agricultural crops in the Zeravshan valley on the period 1980 - 2004 years presented accordingly in Tables 1 and 2.

<table>
<thead>
<tr>
<th>Periods</th>
<th>Sown area</th>
<th>Irrigated lands</th>
<th>Volume of the water for irrigation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1980-1984</td>
<td>29.92</td>
<td>21.28</td>
<td>187.52</td>
</tr>
<tr>
<td>1985-1989</td>
<td>34.30</td>
<td>24.52</td>
<td>185.36</td>
</tr>
<tr>
<td>1990-1994</td>
<td>36.58</td>
<td>26.12</td>
<td>188.36</td>
</tr>
<tr>
<td>1995-1999</td>
<td>38.30</td>
<td>27.40</td>
<td>209.94</td>
</tr>
<tr>
<td>2000-2004</td>
<td>38.28</td>
<td>27.34</td>
<td>181.64</td>
</tr>
</tbody>
</table>
Table 2: Average value of the agriculture crops productivity in Zeravshan valley

<table>
<thead>
<tr>
<th>Periods</th>
<th>grains</th>
<th>potatoes</th>
<th>rice</th>
<th>gardens</th>
<th>maize</th>
<th>vegetables</th>
<th>grapes</th>
</tr>
</thead>
<tbody>
<tr>
<td>1980-1984</td>
<td>1.78</td>
<td>11.52</td>
<td>3.10</td>
<td>4.02</td>
<td>4.04</td>
<td>14.20</td>
<td>8.22</td>
</tr>
<tr>
<td>1990-1994</td>
<td>1.62</td>
<td>11.06</td>
<td>3.20</td>
<td>3.24</td>
<td>3.08</td>
<td>14.70</td>
<td>7.40</td>
</tr>
<tr>
<td>2000-2004</td>
<td>2.12</td>
<td>13.92</td>
<td>4.30</td>
<td>3.60</td>
<td>4.26</td>
<td>18.50</td>
<td>8.72</td>
</tr>
</tbody>
</table>

Tables 1 and 2 are shows that the area of the irrigated lands in the Zeravshan valley though not so big (about 20000 ha) but a tendency of its expansion by the assimilation of foothill territories is observed.

It is necessary to notice that for the Republic of Tajikistan is perspective the energy potential of waterways of the Zeravshan river basin which according to Nurmakhmadov (2007) makes ~ 11.8 Bln. kWt·h. Potential hydropower resources of some inflows of the Zeravshan River present on the Table 3.

Table 3: Potential hydropower resources of some inflows of the Zeravshan River [6]

<table>
<thead>
<tr>
<th>Name</th>
<th>Length, m</th>
<th>Average annual discharge, m³/sec</th>
<th>Average annual power, th. kWt</th>
<th>Average annual production, Mln. kWt·h</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sarmad</td>
<td>22.6</td>
<td>1.52</td>
<td>9.15</td>
<td>80.2</td>
</tr>
<tr>
<td>Artuchdarya</td>
<td>17.14</td>
<td>1.26</td>
<td>8.65</td>
<td>75.8</td>
</tr>
<tr>
<td>Magiandarya</td>
<td>68.4</td>
<td>10.3</td>
<td>76.5</td>
<td>670.0</td>
</tr>
<tr>
<td>Shing</td>
<td>14.2</td>
<td>5.89</td>
<td>20.0</td>
<td>176.0</td>
</tr>
<tr>
<td>Fondarya</td>
<td>24.5</td>
<td>61.1</td>
<td>396.0</td>
<td>3470.0</td>
</tr>
<tr>
<td>Tagobikul</td>
<td>19.8</td>
<td>2.83</td>
<td>17.1</td>
<td>150.0</td>
</tr>
<tr>
<td>Hazorcharsha</td>
<td>12.4</td>
<td>1.70</td>
<td>10.8</td>
<td>94.2</td>
</tr>
<tr>
<td>Pindar</td>
<td>12.3</td>
<td>1.64</td>
<td>12.8</td>
<td>112.0</td>
</tr>
<tr>
<td>Dzijikurut</td>
<td>17.4</td>
<td>1.59</td>
<td>14.9</td>
<td>130.0</td>
</tr>
<tr>
<td>Gaberut</td>
<td>10.1</td>
<td>0.84</td>
<td>4.14</td>
<td>36.3</td>
</tr>
<tr>
<td>Iskandardarya</td>
<td>20.4</td>
<td>21.1</td>
<td>106</td>
<td>927.0</td>
</tr>
<tr>
<td>Saritag</td>
<td>34.0</td>
<td>13.5</td>
<td>68.5</td>
<td>560.0</td>
</tr>
<tr>
<td>Pasrud</td>
<td>28.4</td>
<td>4.68</td>
<td>13.8</td>
<td>121.0</td>
</tr>
<tr>
<td>Turo</td>
<td>12.7</td>
<td>2.07</td>
<td>10.1</td>
<td>94.0</td>
</tr>
<tr>
<td>Yarm</td>
<td>11.1</td>
<td>1.48</td>
<td>11.1</td>
<td>97.2</td>
</tr>
<tr>
<td>Demunora</td>
<td>19.6</td>
<td>3.0</td>
<td>24.1</td>
<td>210.0</td>
</tr>
<tr>
<td>Jindon</td>
<td>18.8</td>
<td>1.61</td>
<td>12.1</td>
<td>105.0</td>
</tr>
</tbody>
</table>
In the presence of such rich energy potential suspended to the Zeravshan River Basin in Sugd area huge deficiency of the electric power is observed - 3-4 Bln. kW·h/year which is covered by import of the electric power from the Republic of Uzbekistan. The intensive grows of the Tajikistan population, presence of the large file of the fertile but not mastered lands suspended to upstream of the Zeravshan River demands principal processing of economic use of the Zeravshan rivers scheme. The mutual combination of interests of upstream and downstream countries of the Zeravshan River is quite achievable by building of the cascade of Hydropower station (HPS) with regulation of the river drain. It causes some discontent of Republic Uzbekistan connected by that realization of programs on development of a hydropower potential of the river by building a number of the water reservoirs leads to deficiency of water in vegetation period of agricultural crops. The cardinal solution of the conflict situation between an irrigation and water-power engineering is the greatest their joint development by building of new HPS with reservoirs. For water-power engineering it means increase in production of cheap and ecological pure energy and for an irrigation – increase of depth of long-term regulation of a drain and water security of already mastered lands, and also possibility of development new. At presence of several HPS with reservoir the top reservoir can work only in power mode, the bottom reservoir of the same volume can regulated a drain up to restoration of its natural regime. Especially it can provide drain regulation in interests of irrigation. At presence not two but many quantities of HPS with reservoirs the situation even more will improve [8].

Thus the analysis of the above-stated material is demonstrated that the solution of a problem of balanced use of two aspects, namely use of a hydroenergy potential of the river Zeravshan with full satisfaction of requirements of agriculture on water demands the deep feasibility report leaves on a plane of bilateral negotiations of the adjoining countries. It seems to us that at the present stage in Global climate change by the most important monitoring and a behavior estimation hydro- and meteorological parameters of a river basin of Zeravshan to climate changes which allows to plan and adapt development and water-power engineering and agriculture taking into account forthcoming values of volume of the river water on immediate prospects is.

The purpose of the present work is monitoring of a current state of water resources and meteorological a condition of the Zeravshan River Basin and an estimation of dynamics of their change for the period 1990 to the present.

One is actual problems of modernity is Global Climate Change and adequate behavior of the each components of ecosystems to this change for the Tajikistan 93% territory which is occupied by mountains and which characterized by availability more 8500 glaciers by
the total area of 8476.2 km\(^2\) or about 6\% of all territory of the Republic of Tajikistan is very important.

### 1.1. Glaciers of the Zeravshan River Basin

**Zeravshan glacier.** The glacier is located on the Zeravshan and Turkestan ridges joints and gives rise to one of the main rivers of the Central Asia – Zeravshan River. It is dendrite glacier by length of 27.8 km, the area 38.7 km\(^2\) and with inflows 132.6 km\(^2\). The tongue of the glacier take place on 2810 m above sea level. Moraines of the Zeravshan glaciers occupy 10 km\(^2\) and with inflows 24 km\(^2\) areas. Observation of the Zeravshan river water discharge are begun from the end of a 19\(^{th}\) Century on the Dupuli Hydropost and since 1927 years are begun detailed observation of the Zeravshan glaciers.

**Rama glacier.** The glacier is located on a southern slope of the Turkestan ridge in upstream of the Zeravshan River in narrow rocky gorge. It is a valley's glacier by length of 8.9 km and the area 22.3 km\(^2\). The end of the tongue of the glacier takes place on 3500 m a. s. l. and is covered by the moraine 3 km\(^2\). As well as all other glaciers of the Zeravshan river basin the Rama glacier recedes.

**Tro Glacier.** The glacier is located on the southern slope of the Turkestan ridge in sources of Zeravshan River. A glacier is valleys by length of 3.0 km and the area 2.2 km\(^2\). The tongues of the glacier take place on 3920 m a. s. l. and buries in a final moraine. Observation of the glacier is begun in 1959 years.

**Dikhadang glacier.** The glacier is located in the Zeravshan River Basin on northern slope of the Zeravshan ridge. The glacier is valleys by length of 2.2 km and the area 2.0 km\(^2\). Dikhadang glacier is covered by a moraine 0.3 km\(^2\). The tongue of the glacier is located on 3600 m a. s. l. Observation of the glacier are begun in 1959 years.

**HGP (Hydrographic party) glacier.** The glacier is located on northern slope of Gissar mountains in the Saritag River Basin running to lake Iskandarkul. Length of a glacier is 1.16 km by the area 0.54 km\(^2\) and average width of 0.47 km. The glacier end lies at height of 3320 m a. s. l. The first observation on a glacier is spent in 1968 and in 1971-1974 periods on a glacier every summer worked complex glaciological expedition. For last 16 years (1990 - 2006 years) a glacier has receded on 35-55 m and annually the average its speed has made about 3 m per year though in the eightieth years of the last century it has made about 8 m annually. Shooting of a cross-section structure has shown that the glacier has not changed almost and recedes only from a final part. Thus, the nearest decade’s disappearance does not threaten glacier HGP (Table 4).
Table 4:  

<table>
<thead>
<tr>
<th>No</th>
<th>Name</th>
<th>Periods</th>
<th>Deviation (m)</th>
<th>Deviation velocity (m/yr)</th>
<th>Note</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Zeravshan</td>
<td>1927-1961</td>
<td>280</td>
<td>65</td>
<td>In the period 1927-1976 years from ice set free the area 1.19 km²</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1961-1976</td>
<td>980</td>
<td>73</td>
<td>In the period 1961-1976 years from ice set free the area 0.93 km²</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1976-1991</td>
<td>1092</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Rama</td>
<td>1929-1948</td>
<td>320</td>
<td>4</td>
<td>From ice set free the area 0.12 km²</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1948-1975</td>
<td>356</td>
<td>9</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>1976-1991</td>
<td></td>
<td>15</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>1989-1991</td>
<td></td>
<td>60</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Tro</td>
<td>1976-1988</td>
<td>18</td>
<td>1-2</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>1988-1990</td>
<td>60</td>
<td>30</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>1990-1991</td>
<td>23</td>
<td>23</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Dikhadang</td>
<td>1977-1991</td>
<td>180</td>
<td>13</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>1990-1991</td>
<td>60</td>
<td>60</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>HGP</td>
<td>1968-1976</td>
<td>18</td>
<td>2.2</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>1982-1990</td>
<td>63</td>
<td>7.9</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>1989-1990</td>
<td>12</td>
<td>12</td>
<td></td>
</tr>
</tbody>
</table>

Table 5:  

Table 5:  

<table>
<thead>
<tr>
<th>Name of Glacier</th>
<th>Reduction</th>
<th>Length (km)</th>
<th>Area (km²)</th>
<th>Volume (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zeravshan</td>
<td></td>
<td>4.0-5.0</td>
<td>25-30</td>
<td>30-35</td>
</tr>
<tr>
<td>Rama</td>
<td></td>
<td>1.5-2.0</td>
<td>3.0-3.5</td>
<td>25-30</td>
</tr>
<tr>
<td>Tro</td>
<td></td>
<td>0.5-1.0</td>
<td>1.0-1.2</td>
<td>30-35</td>
</tr>
<tr>
<td>Dikhadang</td>
<td></td>
<td>1.2-1.5</td>
<td>1.0-1.5</td>
<td>More 50</td>
</tr>
<tr>
<td>HGP</td>
<td>Completely will thaw to 2030 years</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Source: Tajik Hydrometeorology Agency

1.2. Rivers of the Zeravshan River Basin

**Fondarya River.** The Fondarya River is inflow of the left party of the Zeravshan rivers its length it is equal 24.5 km, and the pool of a reservoir is equal to 3230 km². Source Fondarya considers district where incorporate the rivers Jagnob and Iskandardarya. The glaciations area of the Fondarya River concerning to the glaciations of the Matcha river basin is less on six times. Therefore glacial feed of the Fondarya River makes 3 mid-annual feeds and on 8 times less than on the Matcha River. Average long-term discharge of Fondarya River waters 62.2 m³/sec and in same years up to 85.4 m³/sec.
The monthly average charge of weighed deposits of the Fondarya River reaches to 25.8 kg/sec and turbidity to 0.396 kg/m³. This river comes to a year 815 thousand tons of the weighed deposits, i.e. from each square kilometer of the basin of 252 tons of various products washes away in the river Zeravshan.

**Matcha River.** The length of the Matcha River is 200 km and the basin area of 4650 km². This river begins from Zeravshan glacier at height of 2775 m a. s. l. and flows in a direction of the West. The width of the river Matches reaches from 6 m up to 20 m and 70 small rivers run into it and streams which absorb the river.

Initial flood the Matcha Rivers comes the first decade of May. In July all tongues of the Zeravshan glacier are released from seasonal snows and the river passes basically to a glacial feed. The discharge of water of the Matcha River 14.9 m³/sec and the module of a drain (from each square kilometer) is equal to 49.2 l/sec. An average turbidity of the Matcha Rivers in each cubic meter it is equal to 1640 g and yearly from each square kilometer of a river basin 894 tons of the weighed deposits are washed out. Matcha River is hydrocarbonatly. In riverheads НСО₃ ions reaches 50 – 80 mg/l.

**Jagnob River.** The watersheds of the river Jagnob is at height of 3440 m and is formed by merge of two small rivulets which begin from northern slope of Gissar Mountains. These rivulets try from small glaciers. The reservoir of the river Jagnob makes 1650 km². The charge of water in June-July reaches up to 194.2 m³/sec. The average long-term water discharges of the river Jagnob 31.8 m³/sec and the minimal mid-annual charge of water in February-March and equal to 11.28 m³/sec. The average module of the water charge of the Jagnob River is equal 21.2 l/sec. In Jagnob River basin there are 70.8 km² of glaciers. It is established that the river Jagnob takes 29% feeds from underground waters 58% from thawing snows and 13% from glaciers. In each cubic meter of the Jagnob river water have 265 g of the weighed deposit and from each square kilometer the river washes away 187 t of various materials and annual average which to make 308.5 Th. t.

**Pasrud River.** The Pasrud River is one of large inflows of the Fondarya Rivers who joins from the left party near to small town Sarvoda. Length of the Pasrud River is 28.4 km by basins of 371 km². In the river basin there are 22 glaciers by the area 21.6 km². The average annual charge of water of the river makes 4.68 m³/sec. The least charge of water is necessary for February-March (3.32 m³/sec). After merge of the rivers of the Match and Fondarya the river Zeravshan by extent from a source up to border of Republic Uzbekistan on 116 km, but from glacier Zeravshan extent in 316 km is formed. After passage of 56 km, the river Zeravshan accepts from the left party the river Kishtud and
after an interval of 94 km too from the left party other inflow Mogiyan. Other inflows with left and with right the parties incorporating the river Zeravshan is small rivulets which lengths reach 20 km.

*Iskandardarya River.* The river Iskandardarya is the second greater inflow of the river Fondarya, the watershed of the river located at height 2195 m and leaves from Lake Iskandarkul. This river has 21 km length and the area of basin 974 km². The river Iskandardarya proceeds from a southwest direction in a northeast direction between Gissar Mountains from the south and Zeravshan ridge from the north and in near small town Zeravshan-2 jointed to the river Jagnob. Average long-term the charge of water of the Iskandardarya river is equal 18.9 m³/sec but in June and July can reach 111.7 m³/sec. The module a drain of the river in every second is equal to 24.2 liters. Average turbidity of the rivers is equal to 85.4 g/m³ and from each square kilometer of the basin are washed away 64.9 t of various sediments. In the Iskandardarya river basin there are glaciers by the area of 57km².

For creation of the long term scenarios on change of environmental conditions of the Zeravshan River Basin and also for carrying out of operative calculations of hydrological parameters of the river is important the creation of database of mid-annual values of air temperature and precipitation. On Figure 1 mid-annual values of temperature and precipitation of the Zeravshan River Basin according to four main meteorological stations of the basin which basic characteristics are generalized in the Table 6 are presented.

**Table 6:** Main characteristics of meteorological station in Zeravshan River Basin

<table>
<thead>
<tr>
<th>Meteorological station</th>
<th>Absolute high, m</th>
<th>January</th>
<th>July</th>
<th>Average annual temperature</th>
<th>Maximum</th>
<th>Minimum</th>
<th>Annual precipitation, mm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Penjikent</td>
<td>1015</td>
<td>-1.0</td>
<td>25.1</td>
<td>12.2</td>
<td>42</td>
<td>-28</td>
<td>332</td>
</tr>
<tr>
<td>Madrushkat</td>
<td>2254</td>
<td>-5.4</td>
<td>18.4</td>
<td>7.1</td>
<td>34</td>
<td>-30</td>
<td>159</td>
</tr>
<tr>
<td>Dehavz</td>
<td>2564</td>
<td>-7.4</td>
<td>14.9</td>
<td>4.1</td>
<td>30</td>
<td>-33</td>
<td>270</td>
</tr>
<tr>
<td>Anzob</td>
<td>3379</td>
<td>-12.1</td>
<td>9.7</td>
<td>-1.8</td>
<td>24</td>
<td>-36</td>
<td>379</td>
</tr>
</tbody>
</table>
Among all the regions of Tajikistan 93 % of territory which borrow mountains in the Zeravshan River Basin the formation of floods is observed most often (almost 7% of the total across Tajikistan) and their average number in a year reaches 150. More than 300 thousand inhabitants live in the Zeravshan River Basin located in the Ajni and Penjikent regional centers. The local population is affected almost annually with great economic losses (Figure 3 - Figure 4; Table 7).

1.3. Ecological and social - economical estimation of the flood impacts in Zeravshan River Basin

Figure 1  Annual temperature and precipitation change in the Mountain of Zeravshan River Basin according to the date of Meteorological stations: (a) Anzob; (b) Dehavz; (c) Penjikent and (d) Madrushkat

Figure 2  Trends of annual average Zeravshan River runoff (m³/sec) on the date of Dupuli Hydropost
Figure 3  Economical damage of the floods in Penjikent (a) and Ajni (b) district (US Dollars)

Figure 4  Total human victims at flooding in Ajni and Penjikent districts (person) (a) and economical damage in result of floods of 2002-2005 years (b)

Table 7:  Emergency situations connected with the water factor in mountain areas of the Zeravshan Valley (1998 - 2009)

<table>
<thead>
<tr>
<th>Emergency situations</th>
<th>Matcha (Moutain)</th>
<th>Ajni</th>
<th>Penjikent</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total</td>
<td>General material damage, Th. somoni</td>
<td>Total</td>
</tr>
<tr>
<td>Flood</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>mudfloid</td>
<td>3</td>
<td>31.10</td>
<td>9</td>
</tr>
<tr>
<td>Avalanche</td>
<td>2</td>
<td>66.90</td>
<td>3</td>
</tr>
<tr>
<td>Strong thunderous rains</td>
<td>3</td>
<td>31.58</td>
<td>3</td>
</tr>
<tr>
<td>Landslips</td>
<td>2</td>
<td>119.00</td>
<td>15</td>
</tr>
<tr>
<td>Drought</td>
<td>-</td>
<td>-</td>
<td>2</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>248.580</td>
<td>10622.40</td>
</tr>
</tbody>
</table>
1.4. Water quality control of the Zeravshan River

Water quality has become a global issue. Every day, millions of tons of inadequately treated sewage and industrial and agricultural wastes are poured into the world's waters. Every year, lakes, rivers, and deltas take in the equivalent of the weight of the entire human population — nearly 7 billion people — in the form of pollution. Every year, more people die from the consequences of unsafe water than from all forms of violence, including war — and the greatest impacts are on children under the age of five.

From the international level to watershed and community levels, laws on protecting and improving water quality should be adopted and adequately enforced, model pollution-prevention policies disseminated, and guidelines developed for ecosystem water quality. Standard methods to characterize in-stream water quality, international guidelines for ecosystem water quality, and priority areas for remediation need to be addressed globally [11].

Water relations between Central Asia republics during the Soviet Union time were regulated by "Complex Use and Protection of Water Resources Schemes" in Amudarya and Syrdarya basins.

The main purpose of working out basin "Schemes" was to define real volumes situated within the Amudarya and Syrdarya basins and available for using water resources. It was also providing their fair allocation among region republics, meeting all the water users interests.

It should be noticed, that the number of important aspects were not considered and included in "Schemes", for the situation has greatly changed after 1980 (years of the last "Schemes" specification and completion of hydraulic range composition). Mainly it concerns the ecologic acquirements and sanitarian clears thrown into rivers and channels. Overusing basin water in irrigational lands planned as maximum use by "Scheme" resulted in exhausting water resources and appearing new problems. They are:

- deterioration of ecological condition, sometimes leading to ecological disaster in river lowlands of Aral basin.
- great pollution of river water with pesticides, herbicides, other harmful elements and increasing of water mineralization.
The problem of studying the water quality change and development of mechanisms of its control is still actually and concerns not only the separately taken country of Central Asia, but all the states of the region.

For stabilization of an ecological situation in the region a number of measures is offered, for example, by [4]. According to one of them it is necessary to make as a principle the limited water intake with some changes allowing the water users down the river flow to intake the greater water volume in percentage terms. The adoption of this limited water intake system, according to same [4], will allow regulating water intake from the rivers not only in view of irrigated lands, but also in view of water quality, degree of its mineralization.

Nowadays one of the most polluted rivers of Central Asia is Zeravshan River. The capacity of this water is changed under the influence of collector drainage water of irrigating basin zone and wastewater of Samarqand, Kattakurgan, Navoi, and Bukhara cities. Mineralization of water exceeds from origin to estuary from 0.27-0.30g/l to 1.5-1.6g/l.

The most exceed of MC among heavy metals is observed in Cr and Zn. Moreover in Zeravshan river high contain of antimony was found out and its phenol pollution composes 3-7.5 MC, as [2] gives.

Results of reduced chemical analysis of these materials indicate that mineralization of river’s water changes within surveyed area from 0.3 to 2.7 g/1. Down the stream from mountains to Navoi meridian mineralization increases from 0.3 to 1 g/1 and then up to Bukhara oasis it reaches 2.6 g/1. In the same direction the chemical composition of water changes - hydrocarbonate ion decreases and sulphate ion increases. Mineralization level of collector-and-drainage water, broadly used within Bukhara oasis, is higher making 2.5-4 g/1. Lower mineralization (0.6 - 0.7 g/1) occurs in canals water taken from Amudarya River and used for irrigation and partially for potable water supply. According to the results of atomic absorption method the chemical contents of Zeravshan waters is closely related to the collecting points and varies extensively (mg.eqv/%): HCO$_3^-$:15.0-28.0; Cl$: 11.74-27.0; SO$_4^{2-}$: 55.0-69.72; Ca$^{2+}$:27.0-36.79; Mg$^{2+}$:24.0-45.00; Na$^+$+K:28.0-36.82. It was defined that the HCO$_3^-$ content is decreasing and the Cl$^-$ and SO$_4^{2-}$ are generally increasing from Navoi to Bukhara [9].

Now after the statement of Republic Tajikistan about the maximum use of hydropower potential of waterways of the Zeravshan river basin the question of water quality of the river Zeravshan though it existed throughout many years, in new coloring began to rise
from Uzbekistan. Many consider a problem of water quality in organic communication with activity of Anzob mountain-metallurgical industrial complex.

Anzob Mountain-Concentrating Combine (AMCC) the mining enterprise for extraction and enrichment of complex mercury-antimony ores of the Dzhizhikrut deposit. It is located in area Ajni in 13 km of a highway of Dushanbe-Khujand in a right-bank part the rivers Dzhizhikrut which are the left inflow of the river Jagnob (the river Jagnob is the right inflow of the river Fondarya which in turn is the left inflow of the river Zeravshan). The Dzhizhikrut deposit has been opened in 1940 and in 1945-1959 intelligence works were spent and industrial exploitation has begun from 1954. The Dzhizhikrut deposit is located in the ore field area with the same name which are a part of the Zeravshan-Gissar mercury-antimony belt. Since 1966 -1970 reconstruction of industrial complex was spent and for the purpose of prevention of hit of sewage of industrial complex in the river Dzhizhikrut in village of Ravot (8-10 km from industrial complex) on left to river bank Jagnob was are built waste dams (WWD). With 1970 on 1994 a pipeline of sewage functioned normally and since 1994 as a result of heavy rains pipeline pieces has been destroyed. In 2009 the industrial complex has completely restored pipelines and now dams in the complete set and works in the established mode.

2. Methods

For definition influence of the AMCIC on qualities of waters of the river Zeravshan were made sampling of water from the river in two points - on Fondarya and Pete Rivers is located accordingly before and after wastewater dams of AMCIC (Figure 5).

![Figure 5](image-url)
Comparison of results chemical analyses have shown about absence of the factor of pollution of the river Zeravshan by wastewaters of industrial complex. Results of analyses are presented in Tables 7 and 8.

Table 8: Chemical analyses of the Zeravshan river waters from point above WWD

<table>
<thead>
<tr>
<th>Date</th>
<th>T, C</th>
<th>pH</th>
<th>NO₃</th>
<th>NH₄</th>
<th>PO₄</th>
<th>Cr(VI)</th>
<th>Cr(IV)</th>
<th>Hg</th>
<th>Sb</th>
<th>Cd</th>
<th>Zn</th>
</tr>
</thead>
<tbody>
<tr>
<td>06.03.2010</td>
<td>14.4</td>
<td>7.96</td>
<td>30.72</td>
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<td>103.15</td>
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<td>0</td>
<td>0</td>
<td>0.019</td>
</tr>
<tr>
<td>17.04.2010</td>
<td>15.5</td>
<td>8.17</td>
<td>12.10</td>
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<td>146.60</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.017</td>
</tr>
<tr>
<td>22.05.2010</td>
<td>16.2</td>
<td>8.30</td>
<td>11.17</td>
<td>0</td>
<td>112</td>
<td>0.010</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.015</td>
</tr>
<tr>
<td>11.06.2010</td>
<td>16.6</td>
<td>8.19</td>
<td>10.64</td>
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<td>88.1</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.014</td>
</tr>
<tr>
<td>31.07.2010</td>
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<td>7.73</td>
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<td>0.021</td>
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<tr>
<td>12.08.2010</td>
<td>17.4</td>
<td>8.21</td>
<td>4.21</td>
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<td>151.3</td>
<td>0.034</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.019</td>
</tr>
<tr>
<td>06.09.2010</td>
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<td>8.34</td>
<td>22.42</td>
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<td>0.037</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.029</td>
</tr>
</tbody>
</table>

Table 9: Chemical analyses of the Zeravshan river waters sampling from point down WWD

<table>
<thead>
<tr>
<th>Date</th>
<th>T, C</th>
<th>pH</th>
<th>NO₃</th>
<th>NH₄</th>
<th>PO₄</th>
<th>Cr(VI)</th>
<th>Cr(IV)</th>
<th>Hg</th>
<th>Sb</th>
<th>Cd</th>
<th>Zn</th>
</tr>
</thead>
<tbody>
<tr>
<td>06.03.2010</td>
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<td>7.96</td>
<td>27.68</td>
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</tr>
<tr>
<td>17.04.2010</td>
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<td>8.17</td>
<td>11.74</td>
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<td>0.019</td>
</tr>
<tr>
<td>22.05.2010</td>
<td>15.9</td>
<td>8.30</td>
<td>10.95</td>
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<td>110</td>
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<td>0.014</td>
</tr>
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<td>11.06.2010</td>
<td>16.4</td>
<td>8.19</td>
<td>9.74</td>
<td>0</td>
<td>87.4</td>
<td>0.014</td>
<td>0</td>
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<td>0</td>
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<td>0.013</td>
</tr>
<tr>
<td>31.07.2010</td>
<td>16.8</td>
<td>8.29</td>
<td>8.04</td>
<td>0</td>
<td>127</td>
<td>0.025</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.02</td>
</tr>
<tr>
<td>12.08.2010</td>
<td>17.3</td>
<td>8.21</td>
<td>3.34</td>
<td>0</td>
<td>149</td>
<td>0.031</td>
<td>0</td>
<td>0</td>
<td>0</td>
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<td>0.015</td>
</tr>
<tr>
<td>06.09.2010</td>
<td>17.1</td>
<td>8.34</td>
<td>19.3</td>
<td>0</td>
<td>132</td>
<td>0.035</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.025</td>
</tr>
</tbody>
</table>

Figure 6: Content of nitrate, phosphate and ammonium in waters of the Zeravshan River on the Tajikistan and Uzbekistan territory, waters from irrigation channels and drainage collectors in Uzbekistan and tributaries to the Zeravshan River.
From the Tables 7 and 8 and Figure 6 - Figure 8 becomes evident that in waters of the Zeravshan river and its inflows the maintenance, and as a last resort, excess of concentration of heavy metals of maximum permissible concentration isn't observed. The penetrating comprehension of water importance in the region and social responsibility for steady water supply, for example, called immediate reaction of 5 Governments in Central Asia. In February 1992 there was founded Interstate Coordination Water Commission (ICWC). The foundation of ICWC in difficult and unpredictable post-Soviet time enabled the countries of the region to pass painlessly the period of water "anarchy", to ensure equilibrium and consent in the region and has shown strategy of all countries to ensure today and in future mutual understanding and respect in fruitful cooperation.
It gives the ground to hope, that the problem of contamination and ascending of a degree of water arteries mineralization can be solved with the same success by creating (similar ICWC) Interstate Coordination Water Quality Commission (ICWQC). The structure of such organization is presented on the Figure 9.

![Figure 9: Structure of the Interstate Coordination Water Quality Commission](image)

Structural subdividing "The interstate experts" unite the leading technicians in evaluating the quality and composition of waters from all five states of Central Asia.

The main function of this body is to compare the republican experts' information about water composition and to solve disputable questions by carrying out the independent expert appraisals of water quality of Transboundary Rivers. ICWQC Secretary appoints the stuff and sets terms of power of the interstate experts. In Information Center established in each country of Central Asia the water quality control statistics in industrial, agricultural, municipal sectors and hydroposts are gathered, generalized and systematized.
Thus, the data concerning water arteries quality from each country come to Analytical Center of ICWQC.

It should be noted, that after reaching the complete transparency of relative composition and quality of all water arteries in Central Asia the next stage is the development of mechanisms to encourage and take measures to the states polluting water environment. These problems together with other questions should be studied in ICWQC Secretariat for considering at Meeting of Central Asia Heads of Governments.

3. Conclusion

Results of comparison of the analysis of waters have shown about absence of essential pollution of waters of the river by wastewaters of the Anzob mountain-concentrating industrial complex. It can be considered as a special case testifying to reliability only of one dam. In wide aspect and for the purpose of the centralized and timely prevention of pollution of waters creation of the centers on constant control quality of waterways is necessary.

Reference
Management

Hydroinformatics
Artificial Neural Network Modeling of the Fractional Transport Rate of Bed-Load in Gravel-Bed Streams

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1 Department of Civil Engineering, Democritus University of Thrace

Abstract
The present study examines the capabilities of artificial neural networks in modeling the fractional bed-load transport rate in gravel-bed rivers and compares the generated results to those of some of the most popular fractional bed-load formulae. Some of the mechanisms that govern the phenomenon are embedded in the architecture of a custom neural network, which has partially connected neurons between the different layers in order to express the hiding-exposure effects that occur due to the poor sediment sorting on the river bed, in an effort to enlighten the black-box nature of neural networks and create a model that can be used with increased confidence. As network inputs, from several widely used variables, Bagnold's stream power provides the best results. A large dataset from gravel-bed rivers in Idaho (U.S.A.) is used for training the neural network and subsequently testing it with satisfactory results given the complexity of the problem and the inevitable noise inclusion from the field measurements.

1. Introduction
The quantification of bed-load transport rate in gravel-bed rivers is a problem that has drawn a lot of attention, especially from engineers, geomorphologists and river scientists for projects such as river engineering design, habitat maintenance and restoration of river ecosystems, amongst others. The sediment transport problem has not been fully solved yet, and the fact that gravel-bed rivers in nature have poorly sorted sediment, further complicates the problem. In addition to sorting by grain size across and along the streambed surface, gravel-beds tend to also exhibit vertical sorting, wherein the surface of the streambed is coarser than the underlying, subsurface, material. The result is the emergence of hiding-exposure effects (Einstein, 1950; Egiazaroff, 1965) for the former and the formation of the armor layer (Parker and Sutherland, 1990) for the latter case. In his seminal work, Egiazaroff (1965) derived a relation, which is termed hiding function, from consideration of the forces acting on exposed grains on a bed containing a mixture of grain sizes. In Egiazaroff's simple but cogent model, larger grains are harder to move because they are heavier, but on the other hand, they are easier to move because they tend to protrude more into the flow, thus feeling a higher drag. The net result of these
two effects is a modest bias toward lesser mobility for coarser grains (Parker, 2008).

Numerous formulae have been introduced by different researchers based on various concepts to address this problem, but their outputs, generally, are very different and in disagreement with the respective measured data, usually by several orders of magnitude, as it was concluded by several studies (Gomez and Church, 1989; Reid et al, 1996; Almedeij and Diplas, 2003; Bravo-Espinosa et al, 2003; Martin, 2003; Barry et al, 2004). Bed-load transport formulae are founded upon the premise that a specific relation exists between hydraulic variables, sedimentological parameters, and the rate at which bed-load is being transported. Gomez and Church (1989) distinguish four principal approaches to have emerged to the design of bed-load transport formulae, based upon bed shear stress (e.g. DuBoys, 1879), stream discharge (e.g. Schoklitsch, 1934), stochastic functions for sediment movement (e.g. Einstein, 1950), or stream power (e.g. Bagnold, 1980). Most bed-load formulae owe their derivation to a comparatively restricted data base, while their utility has been established on the basis of relatively few field data.

Machine learning techniques may be a solution to problems where the knowledge of the physics is inadequate. In this study, a multilayer feed-forward artificial neural network (ANN) with multiple outputs is utilized, which calculates the fractions of the bed-load transport rate with respect to the sediment size, in order to take into account the hiding factor that emanates from the protrusion of coarse particles into the flow and the sheltering of the fine particles from the coarse ones. An ANN is utilized in this study in an effort to develop a regression model that depends solely on the training data and as a result the user doesn't have to predetermine the degree of the model nonlinearity, as would be the case in the ordinary multiple nonlinear regression. As inputs to the ANN, several combinations of some well known dimensionless variables from fluid mechanics, open channel hydraulics and sediment transport are considered, with Bagnold’s (1966; 1980) stream power being the prevalent, and the results are compared to those of some widely applied bed-load formulae. The results are encouraging, given the complexity of the problem and the inevitable noise inclusion from the field measurements.

The data used in this study originate from selected coarse-bed streams and rivers in Idaho (King et al, 2004) from a series of field campaigns organized by the United States Forest Service and are available on its website. This dataset is one of the largest and most extensive sediment transport regional datasets currently available (Muskatirovic, 2008) and comprises streams with different characteristics, river basins, surface and subsurface sediment size, etc.
2. Bed-Load Transport in Gravel-Bed Rivers

Recking (2010) considers three different transport phases with regard to the armor mobility (Jackson and Beschta, 1982; Ashworth and Ferguson, 1989; Ryan et al, 2002; Bathurst, 2007): As long as the threshold for breakup of the armor layer is not attained, phase 1 is considered with bed-load composed of fine sediments, supplied from upstream or from remobilization of fine sediment deposited from previous transport events in pools and tranquil areas of the bed (Lisle, 1995; Paola and Seal, 1995), and passing over the immobile armor layer. The breakup of the armor layer initiates close to bankfull flow conditions (Ryan et al, 2002) and phase 2 is considered, where coarse grains can participate in transport and the availability of fine sediments from the subsurface is increased (Parker et al, 1982). Finally, phase 3 can also be considered once all sizes are in motion (Parker et al, 1982; Wilcock and McArdell, 1993).

Spatial variability of surface grain size in the field poses a major difficulty in sediment transport calculations. Both Einstein (1950) and Egiazaroff (1965) have noted the hiding phenomenon. In a mixture, finer surface grains typically protrude less into the flow than their coarser neighbors, which shelter them from its mobilizing influence. As a result, finer surface grains in a mixture are less mobile than when they are surrounded exclusively by neighbors of similar size. Likewise, the isolated protrusions offered by coarser surface grains in a mixture render them more mobile than they are in a uniform sediment composed exclusively of the coarser size in question. The transport function depends strongly on grain size through the hiding function and is strongly nonlinear (Wilcock and Crowe, 2003).

The river renders itself able to transport the coarse half of its gravel load at the same rate as its finer half by overrepresenting coarse material on its surface, where it is available for transport (Parker and Klingeman, 1982; Parker and Toro-Escobar, 2002) and thus the mobile-bed armor is formed. Dietrich et al (1989) proposed that the disparity between median grain size of the surface and that of the subsurface or load can arise when the transport rate of sediment exceeds the local supply rate. This imbalance may cause net erosion, but in poorly sorted sediment it may also cause selective erosion and deposition and vertical winnowing to coarsen the bed and raise the critical shear stress. Buffington and Montgomery (1999) further suggest that bed surface texture represents a feedback between rates of both sediment supply and bed-load transport (the latter being a function of surface roughness, excess shear stress, and availability of transportable sediment).
2.1. Fractional Bed-Load Transport

Gravel-bed rivers in nature have poorly sorted sediment and they are characterized by a very wide range of grain sizes. When different particle sizes are in a mixture, it is necessary to quantify the variations in transport rates among particles of different sizes as well as to chart their mutual influences (Muskatirovic, 2008). It has been shown by many researchers (Ashworth and Ferguson, 1989; Parker and Klingeman, 1982; White and Day, 1982; Wilcock and Kenworthy, 2002), using field and laboratory sediment transport data, that the movement of individual particles depends on their relative as well as absolute size. Fractional bed-load transport analysis consists of dividing the bed material distribution into several size ranges, each represented by a particle diameter, \( d_i \), and performing calculations for each fraction for the given hydraulic conditions. Calculations of fractional transport rates also involve the, previously analyzed, hiding function, which accounts for size-dependent differences in the mobility of small and large grains (Andrews, 1994; Parker et al, 1982; Wilcock and Crowe, 2003) and is expressed by a simple ratio of the characteristic diameter of a size fraction to the median diameter of the grain mixture (\( d_i/d_{50} \)).

2.2. Incipience of Motion in Gravel-Bed Rivers

In the field, many events correspond to partial transport, with fine sediments being transported, whereas coarser ones are maintained at rest (Wilcock and McArdell, 1993). In addition, because of hiding effects altering the shear stress acting on fine sediments (Einstein and Chien, 1953; Egiazaroff, 1965), the same flow conditions and the same representative diameter \( d_i \) will not necessarily produce the same transport rate when different sediment size gradations are used (Molinas and Wu, 1998; Recking, 2010). This explains why equations based on the transport threshold of a unique given bed surface diameter usually exhibit poor performance, because they consider that no transport is possible as long as this diameter is at rest, and by doing so, they underestimate low transport rates of fine particles (Barry et al, 2004; Recking, 2010).

Figure 1 shows a modified version of the Shields diagram with the dimensionless shear stress \( \tau_{50}^* \)

\[
\tau_{50}^* = \frac{\tau}{\rho g R d_{50}}
\]

against particle Reynolds number \( Re_{p50} \), which is a surrogate for grain size \( d_{50} \),

\[
Re_{p50} = \frac{\sqrt{R g d_{50} d_{50}}}{\nu}
\]

with data for gravel-bed and sand-bed streams for bankfull flows. In Equations (1) and (2), \( \tau \) is the shear stress, \( \rho \) is the water density, \( g \) is the gravitational acceleration, \( \nu \) is the
water kinematic viscosity, and $R$ denotes the submerged specific gravity of the sediment (nearly 1.65 for the most common natural sediments in rivers).

$$R = \frac{\rho_s}{\rho} - 1$$  \hspace{1cm} (3)

where $\rho_s$ is the sediment density.

There is an obvious deficiency in making predictions based on one single characteristic grain diameter since, as can be seen in Figure 1, even in bankfull flows there are some points based on the median grain diameter that are below the modified Shields curve, despite the fact that in flows of such magnitude, a significant bed-load transport rate is observed.

![Figure 1](image)

**Figure 1**  Dimensionless shear stress based on bankfull flow $\tau_{bf50}^*$ versus particle Reynolds number $Re_{50}$ based on $d_{50}$ for gravel-bed and sand-bed streams (obtained from Parker, 2008)

In this study, a criterion for the initiation of motion has been omitted due to the stochastic nature of the phenomenon caused by turbulence fluctuations. Paintal (1971), in a series of experiments, indicated that a distinct condition for the beginning of movement does not exist. At very low shear stresses, the possibility of movement becomes very small but never equals zero. Lavelle and Mofjeld (1987) argued that under turbulent fluid motion, at a sediment bed, some particle movement must occur at all nonzero time-mean velocities. Nevertheless, the most common criterion for the initiation of motion, especially in field applications, is the one proposed by Shields (1936), modifications of which were proposed by several researchers based on $Re_{50}$. As a result, since the critical shear stress value is obtained from $Re_{50}$, the ANN can make an estimation of the effective portion of the flow that quantifies the sediment transport rate.
3. Hydraulic Parameters for Bed-Load Quantification

Parker and Anderson (1977) and Parker (2008) proposed the following relation to express the transport rate of the bed-load:

\[ q_i^* = T_B \left( \hat{X}_1, \hat{X}_2, \frac{d_i}{d_{50}}, \sigma, Re_{p50}, R \right) \]  

(4)

with \( q_i^* \) denoting a grain-size-specific Einstein number

\[ q_i^* = \frac{q_i}{\sqrt{Rgd_i d_i}} \]  

(5)

where \( q_i \) is the volume transport rate of bed-load per unit width of \( i \)th size range, \( T_B \) is a dimensionless bed-load transport function, \( \hat{X}_1 \) and \( \hat{X}_2 \) are dimensionless parameters closely tied to bed-load, and \( \sigma \) is the arithmetic standard deviation of the stream bed grain size distribution. \( \hat{X}_1 \) and \( \hat{X}_2 \) may contain the parameter \( d_i \) and thus be grain-size-specific.

Researchers such as Fernandez Luque and van Beek (1976) have studied bed-load transport rates for a variety of values of \( R \) and found no discernible independent effect as long as \( R \) is incorporated into the primary dimensionless hydraulic parameters. As a result it is dropped here. There are many possible choices for \( \hat{X}_1 \) and \( \hat{X}_2 \) and several combinations were tested. The best results were obtained with the Reynolds number as \( \hat{X}_1 \) and Bagnold's dimensionless stream power as \( \hat{X}_2 \), which are given in Equations (6) and (9), respectively.

Reynolds number gives a measure of the ratio of inertial forces to viscous forces of the flow

\[ Re = \frac{VD}{v} \]  

(6)

where \( V \) is the mean flow velocity and \( D \) is the mean flow depth.

The power equation appears first to have been applied to sediment transport by Rubey (1933) and later by Velikanov (1955). It was again suggested by Knapp (1938), and was later introduced by Bagnold (1956) in a paper wherein the flowing fluid was regarded as a transporting machine. The available power supply, or time rate of energy supply, to unit length of a stream is the time rate of liberation in kinetic form of the liquid's potential energy as it descends the gravity slope \( S \). Denoting this power by \( \Omega \), Bagnold (1966) derived the formula

\[ \Omega = \rho gQS \]  

(7)
The mean available power supply to the column of fluid over unit bed area, to be denoted by $\omega$, is therefore

$$\omega = \frac{\Omega}{W} = \frac{\rho g QS}{W} = \rho g DSV = \tau V$$ \hspace{0.5cm} (8)

In order to define a dimensionless transport parameter that encapsulates Bagnold’s view of sediment transport as a stream power related phenomenon, Eaton and Church (2011) developed the following formula

$$\omega^* = \frac{\omega}{\rho \left[ g \left( \frac{\rho_s}{\rho} - 1 \right) \right]^{1/2}}$$ \hspace{0.5cm} (9)

The main advantage of using dimensionless stream power to represent the relative flow strength is that $\omega$ can be estimated from measurements of discharge ($Q$), width ($W$) and gradient ($S$) of the stream, whereas estimates of shear stress ($\tau$) require that a flow resistance equation is employed to estimate the water depth. This means that $\omega^*$ can be determined directly from the continuity equation, while it is necessary to invoke a flow resistance equation to relate dimensionless shear stress ($\tau^*$) to discharge, thereby introducing additional uncertainty attached to the chosen flow resistance equation. The necessity to specify a flow resistance equation is particularly problematic in steep, shallow streams where the water surface is strongly influenced by local roughness elements, making it difficult to estimate the mean depth (Eaton and Church, 2011). Gomez and Church (1989) concluded that for the estimation of the magnitude of bed-load transport on the basis of limited hydraulic information, the stream power equations should be used, based on the fact that these equations provide the most straightforward scale correlation.

4. Study Sites and Available Field Data

In an attempt to gain a better understanding of the nature of sediment transport in Idaho gravel-bed streams and rivers, the United States Forest Service in collaboration with other agencies explored the availability of existing sources of suspended and bed-load sediment transport information for streams and rivers within the National Forests of Idaho and in 1994 they initiated a program to measure bed-load and suspended sediment transport and collect supporting site information for selected streams and rivers. The derived dataset constitutes one of the largest and most extensive sediment transport regional datasets currently available (Muskatirovic, 2008). King et al (2004) provide an overview of the study site characteristics and details of the methods used to measure and/or collect the various types of data, whilst the data have already been analyzed in
several papers (Barry et al., 2004; Mueller et al., 2005; Barry et al., 2008; Muskatirovic, 2008; Pitlick et al., 2008; Recking, 2010). Figure 2 shows the location of the study sites in the state of Idaho. All of the study sites used in this paper are within the Snake River Basin, whilst all but one of the study watersheds are within the Northern Rocky Mountain Physiographic Province (Fenneman, 1931); the exception is Rapid River, which is in the Columbia Intermontane Province.

![Figure 2](image)

*Figure 2*  
Location of the study streams and rivers in the state of Idaho, U.S.A.

All streams in the study area are snowmelt dominated and reach peak flows with spring snowmelt runoff, although high flows occasionally occur in fall and winter in association with cyclonic storms or rain-on-snow events. The available discharges cover a wide range of flows, from very low to over bankfull \(Q_{bf}\) flows, as it is shown in Table 1. Gradient was usually calculated as an average over the entire study reach. If a large shift occurred within the reach, gradient was calculated for that portion that typically included the gage location and sediment measurement location. The gradients associated with channel bed elevations, floodplain elevations, and water surface elevations were all used in determining the average gradient for the study reach. Average depth was determined as cross-section area divided by width, whilst average velocity was determined as discharge divided by cross-section area and these variables are given in power relations of water discharge. In developing these power relationships, the data used were collected during the water years of sediment transport measurements and within the range of discharges associated with the sediment transport measurements. Bed-load transport rates were measured with the pressure-difference Helley-Smith bed-load sampler (Helley and
Smith, 1971) at all of the study sites. The standard nozzle has a 3-in (76.2 mm) square entrance and was used in most instances, but at a few sites, the 6-in (152 mm) square entrance model was used during higher flows. The catch bag on the samplers had a 0.25 mm mesh and a sediment-trapping efficiency of 100 percent was assumed for all particle sizes. Table 1 shows the selected rivers that supplied this study with data. The screening of the study sites was done with respect to the simultaneous availability of all the aforementioned variables, the data quality, the availability of both surface and subsurface gradation, whilst from the selected study sites the data measurements prior to 1994 were excluded due to different bed-load sample collection procedures.
<table>
<thead>
<tr>
<th>Rivers</th>
<th>Drainage area (km²)</th>
<th>Data for training</th>
<th>Data for validation</th>
<th>Data for testing</th>
<th>Total data</th>
<th>Slope m/m</th>
<th>d50,sur (mm)</th>
<th>d50,sub (mm)</th>
<th>Date of sampling</th>
<th>Range of discharge m³/s</th>
<th>Q/Q_bf</th>
</tr>
</thead>
<tbody>
<tr>
<td>Big Wood River</td>
<td>356.1</td>
<td>57</td>
<td>19</td>
<td>19</td>
<td>95</td>
<td>0.0091</td>
<td>116.2</td>
<td>26.5</td>
<td>19/05/99 - 21/06/00</td>
<td>6.03 - 29.2</td>
<td>0.28 - 1.33</td>
</tr>
<tr>
<td>Blackmare Creek</td>
<td>46.1</td>
<td>19</td>
<td>7</td>
<td>6</td>
<td>32</td>
<td>0.0299</td>
<td>109</td>
<td>26.2</td>
<td>20/04/93 - 14/06/94</td>
<td>0.37 - 4.70</td>
<td>0.08 - 0.99</td>
</tr>
<tr>
<td>Boise River</td>
<td>2153.8</td>
<td>47</td>
<td>14</td>
<td>16</td>
<td>77</td>
<td>0.0038</td>
<td>70.8</td>
<td>24.6</td>
<td>18/04/94 - 13/06/94</td>
<td>33.70 - 269.9</td>
<td>0.20 - 1.61</td>
</tr>
<tr>
<td>Dollar Creek</td>
<td>42.7</td>
<td>19</td>
<td>8</td>
<td>6</td>
<td>33</td>
<td>0.0146</td>
<td>77.2</td>
<td>23.1</td>
<td>20/04/93 - 14/06/94</td>
<td>0.42 - 6.37</td>
<td>0.06 - 0.99</td>
</tr>
<tr>
<td>Johns Creek</td>
<td>292.7</td>
<td>27</td>
<td>8</td>
<td>10</td>
<td>45</td>
<td>0.0207</td>
<td>199.2</td>
<td>57.7</td>
<td>23/02/95 - 22/08/95</td>
<td>1.88 - 34.26</td>
<td>0.03 - 0.70</td>
</tr>
<tr>
<td>Little Slate Creek</td>
<td>162.1</td>
<td>48</td>
<td>16</td>
<td>16</td>
<td>80</td>
<td>0.0268</td>
<td>221.9</td>
<td>25.6</td>
<td>05/04/94 - 26/10/94</td>
<td>0.53 - 9.85</td>
<td>0.04 - 0.81</td>
</tr>
<tr>
<td>Lochsa River</td>
<td>3054.6</td>
<td>42</td>
<td>14</td>
<td>14</td>
<td>70</td>
<td>0.0023</td>
<td>148.8</td>
<td>27.6</td>
<td>21/04/94 - 14/06/94</td>
<td>110.7 - 495.5</td>
<td>0.25 - 1.11</td>
</tr>
<tr>
<td>Lolo Creek</td>
<td>106.2</td>
<td>39</td>
<td>14</td>
<td>12</td>
<td>65</td>
<td>0.0097</td>
<td>88.3</td>
<td>19.8</td>
<td>29/03/93 - 17/10/95</td>
<td>1.80 - 9.63</td>
<td>0.14 - 0.82</td>
</tr>
<tr>
<td>Main Fork Red River</td>
<td>128.7</td>
<td>45</td>
<td>14</td>
<td>15</td>
<td>74</td>
<td>0.0059</td>
<td>71.5</td>
<td>18.1</td>
<td>06/04/94 - 30/08/94</td>
<td>0.29 - 10.00</td>
<td>0.03 - 1.07</td>
</tr>
<tr>
<td>Rapid River</td>
<td>279.7</td>
<td>57</td>
<td>20</td>
<td>19</td>
<td>96</td>
<td>0.0108</td>
<td>97.2</td>
<td>15.7</td>
<td>02/03/94 - 11/01/95</td>
<td>0.91 - 24.86</td>
<td>0.05 - 1.40</td>
</tr>
<tr>
<td>Salmon River below Yankee Ford</td>
<td>2100.7</td>
<td>35</td>
<td>11</td>
<td>12</td>
<td>58</td>
<td>0.0034</td>
<td>110.3</td>
<td>26.2</td>
<td>06/05/99 - 20/06/00</td>
<td>38.51 - 143.3</td>
<td>0.33 - 1.22</td>
</tr>
<tr>
<td>Salmon River near Obsidian</td>
<td>243.2</td>
<td>30</td>
<td>9</td>
<td>10</td>
<td>49</td>
<td>0.0066</td>
<td>61.8</td>
<td>27.1</td>
<td>25/05/99 - 26/06/99</td>
<td>7.48 - 20.93</td>
<td>0.59 - 1.64</td>
</tr>
<tr>
<td>Selway River</td>
<td>4954.9</td>
<td>39</td>
<td>14</td>
<td>13</td>
<td>66</td>
<td>0.0021</td>
<td>170.7</td>
<td>25.5</td>
<td>21/04/94 - 14/06/94</td>
<td>134.8 - 509.7</td>
<td>0.21 - 0.78</td>
</tr>
<tr>
<td>South Fork Payette River</td>
<td>1163.7</td>
<td>34</td>
<td>11</td>
<td>11</td>
<td>56</td>
<td>0.0040</td>
<td>55.8</td>
<td>21.1</td>
<td>18/04/94 - 13/06/94</td>
<td>20.42 - 122.0</td>
<td>0.24 - 1.42</td>
</tr>
<tr>
<td>South Fork Red River</td>
<td>98.9</td>
<td>51</td>
<td>17</td>
<td>17</td>
<td>85</td>
<td>0.0146</td>
<td>87.6</td>
<td>26.7</td>
<td>05/04/94 - 20/09/94</td>
<td>0.17 - 5.27</td>
<td>0.02 - 0.73</td>
</tr>
<tr>
<td>Squaw Creek (USGS)</td>
<td>185.4</td>
<td>55</td>
<td>18</td>
<td>19</td>
<td>92</td>
<td>0.0100</td>
<td>46.6</td>
<td>30.1</td>
<td>05/05/94 - 03/07/95</td>
<td>0.14 - 7.56</td>
<td>0.03 - 1.48</td>
</tr>
<tr>
<td>Thompson Creek</td>
<td>56.5</td>
<td>49</td>
<td>16</td>
<td>16</td>
<td>81</td>
<td>0.0153</td>
<td>67.1</td>
<td>46.6</td>
<td>06/05/94 - 04/07/95</td>
<td>0.23 - 3.51</td>
<td>0.09 - 1.42</td>
</tr>
<tr>
<td>Trapper Creek</td>
<td>20.8</td>
<td>61</td>
<td>21</td>
<td>20</td>
<td>102</td>
<td>0.0414</td>
<td>66.1</td>
<td>17.1</td>
<td>07/04/94 - 20/09/94</td>
<td>0.05 - 2.31</td>
<td>0.02 - 0.90</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>754</strong></td>
<td><strong>251</strong></td>
<td><strong>251</strong></td>
<td><strong>1256</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*The range of discharge is expressed as a ratio of the 1.5 year return interval discharge, for sites with no field identification of bankfull stage ratio (Q/Q_bf).*
At all sites, the \(d_{50}\) and \(d_{90}\) of the surface material were larger than those of the subsurface material, indicating the presence of a coarser surface armor layer. Sand size material is a major component of the bed-load sediment and at most of the study sites the transport rate of the sand is larger than the rate of any other size class for, almost, every measured discharge. This is in agreement with Leopold's (1992) observation for gravel-bed streams that the largest portion of the bed-load is sand. In common applications, specification of the percentage of a specific grain size fraction in the river bed surface \(F_i\) is a nontrivial matter. Surface grain size can be sampled at low flows, but at higher flows producing substantial transport, bed measurements are prohibitively difficult and dangerous. There is some indication that the surface grain size may vary little with increasing flows in many gravel-bed rivers (Andrews and Erman, 1986; Wilcock, 2001), suggesting that a surface observation at low flow may be used to approximate the bed surface at large flows. Support for this conclusion is found in the relatively small variation in surface grain sizes observed in the experiments of Wilcock et al (2001), which covered a wide range in transport rates. A persistent armor layer does not indicate that the surface grains are immobile. Tracer observations on Sagehen Creek and time-series observations in a recirculating flume (Wilcock and McArdell, 1997) demonstrate that a coarsened bed surface coexists with the transport of all sizes of surface grains (Parker and Klingeman, 1982). The surface actively exchanges grains with the transport while maintaining a coarsened composition, although not all grains may be in motion. A persistent armor layer suggests that the bed surface grain size measured at low flows can be used to make predictions at high flows when the bed is not accessible (Wilcock and DeTemple, 2005; Parker et al, 2007). Nevertheless, in the selected study sites, the data that weren't collected within the year of the bed surface gradation measurements, were discarded.

5. Artificial Neural Networks

ANN is the most widely used machine learning technique. Since abundant information on ANNs is available in the literature (e.g. Haykin, 2009), only a brief description of ANNs is provided, with regard to the methodology applied herein. ANN is a broad term covering a large variety of network architectures and structures. The most common of them, and the one utilized herein, is the multilayer feedforward network. This type of network is a parallel distributed information processing system that consists of the input layer, the hidden layer(s), and the output layer, and the information goes only in a forward direction. Each layer consists of a number of neurons, each one of which is connected with those in the successive layer with synaptic weights that determine the strength
of the connections. The hidden and output layer neurons have an inherent activation function, which accommodates the nonlinear transformation of the input data to the targets.

The training process of an ANN may be viewed as a curve fitting problem and the network itself may be considered simply as a nonlinear input-output mapping, which permits to look on generalization not as a mystical property of the ANN but rather simply as the effect of a good nonlinear interpolation (Haykin, 2009). During supervised training, the input and target paired data are divided into training, validation and test data sets. The network is trained on the training data set until its performance begins to decrease on the validation data set, which signals that generalization has peaked. The test data provide a completely independent assessment of the network generalization. A network that is not sufficiently complex can fail to detect fully the signal in a complicated data set, leading to underfitting. A network that is too complex may fit the noise, not just the signal, leading to overfitting. The goal, in most modeling applications, is to find an optimal balance between model complexity and model applicability by implementing the principle of model parsimony, which states that in a model, the smallest possible number of parameters is employed.

For the ANN application in this study, the computational tool is provided by the MATLAB neural network toolbox (Demuth et al, 2009). Due to the importance of the initial values of the synaptic weights in the search for local minima of the error function, a supplementary MATLAB code was written that determines the most efficient ANN, which is the one that performs best in the validation set, within 200 training executions for each network architecture tested and with random initial weights for every repetition. The training function is the Levenberg-Marquardt back-propagation algorithm (Hagan and Menhaj, 1994), which appears to be the fastest method for training moderate-sized feedforward neural networks. It also has an efficient implementation in MATLAB software, because the solution of the matrix equation is a built-in function, so its attributes become even more pronounced in a MATLAB environment (Demuth et al, 2009). The error function is the mean square error between calculated and observed values and all the neurons in the hidden and output layers have the hyperbolic tangent activation function.

Maier and Dandy (1998) provided a valuable guide on the behavior of back-propagation ANNs under a wide range of operating conditions, although for a particular case study (forecasting salinity in the river Murray). The results obtained indicate that learning rate, momentum, the gain of the transfer function, epoch size and network geometry have a significant impact on training speed, but not on generalization ability. For this reason, the
values of these variables used in this paper are those provided by the MATLAB neural network toolbox by default (Demuth et al, 2009).

5.1. Overview of Partially Connected Artificial Neural Network

The concept of this study is to create a custom ANN, the structure of which has physical meaning and describes the interaction of some generic hydraulic variables with the grain-size-specific ones in an effort to describe the hiding-exposure effects that occur due to the poor sediment sorting on the river bed. By employing such a model, the best results for the fractional bed-load transport rate are obtained and at the same time, the generated ANN model can be used with increased confidence. All the input-output variables are dimensionless in order to obtain dimensional consistency. Figure 3 shows an ANN with this structure, which comprises:

1. One input layer with generic flow variables, namely the Reynolds number $Re$ and the dimensionless stream power $\omega_{50}^*$ with respect to the median diameter $d_{50}$, which are given in Equations (6) and (9), respectively, arithmetic standard deviation $\sigma$ of the bed sediment and a particle Reynolds number $Re_{p50}$, which is given in Equation (2). This input layer is fully connected with one hidden layer that interacts with all the output layers (input layer 1 in Figure 3).

2. $\nu$ input layers with variables describing each size fraction, namely the grain-size-specific version of the dimensionless stream power $\omega_i^*$, the ratio $d_i/d_{50}$ to express the hiding/exposure factor and the mass fraction of surface material in the $i$-th grain size range $F_i$. These input layers are, individually, fully connected with their respective hidden layers (input layers 2 - (1+$\nu$) in Figure 3).

3. $\nu$ output layer neurons, one for each size fraction in terms of a grain-size-specific Einstein number $q_i^*$, which is given in Equation (5). The output neurons are fully connected with some of the hidden layers, according to Figure 3.
The grain size fractions, ideally, would comprise all the grain sizes of the bed gradation; however, this is not feasible since the bed-load samples are much finer than the stream bed material. In addition, zero bed-loads appear erratically for some grain size fractions and hinder the proper training of the ANN, hence some grain size fractions are merged in order to form a more suitable training sample for a data driven technique. As a result, for this study, the grain size fractions considered are three:

1. 8-64 mm
2. 2-8 mm
3. sand size (<2 mm)

The study sites comprise larger particles and boulders as well; however, the incompetence of the flow to move the coarser particles and the small sampling nozzle of the Helley-Smith samplers limit the bed-load samples in this size range. The architecture of Figure 3 provides the interaction of the hiding-exposure phenomena as well as the transport rate of the finer fractions (typically sand) that, sometimes, are not represented in the river bed surface and are supplied from upstream or from remobilization of fine sediment deposited from previous transport events in pools and tranquil areas of the bed (Lisle, 1995; Paola and Seal, 1995), and passing over the immobile armor layer at flows unable to move the larger gravel fractions that make up the framework of the stream bed (Carling, 1989; Emmett, 1976; Jackson and Beschta, 1982).
6. Application and Results

Since the data utilized come from different sites, with different data range and characteristics, the proper usage of ANN dictates the equal representation, in training, validation and testing sets, of all the possible instances. To divide the data into the aforementioned sets, after the completion of the screening procedure the whole dataset was subjected to, the remaining data were placed in their original order and three consecutive paired measurements were picked for the training set followed by one for the validation and one for the testing set. This technique generates a training, validation and testing set with similar statistical distributions, and as a result the ANN can be trained and used with confidence. Table 2 shows some statistical indices of the target values of the ANN three outputs for all the data sets, whilst Table 3 shows the same indices with respect to the total mass bed-load transport rate per unit width, when all the grain size fractions are added, in kg/s/m.

After an extensive trial-and-error procedure, the optimal ANN architecture for the specific problem is depicted in Figure 4, and comprises four neurons in every hidden layer, whilst all the neurons of the hidden as well as the output layers have the hyperbolic tangent activation function. Because of the interaction of different hidden layers in the output neurons, the commonly used linear activation function provides an inadequate network architecture and therefore the hyperbolic tangent activation function is preferred instead.

Figure 4  Optimal ANN architecture used in this study
Table 2: Statistical properties of the training, validation and testing sets for the grain-size-specific Einstein numbers $q_i$ of the ANN outputs

<table>
<thead>
<tr>
<th>Set</th>
<th>Minimum value</th>
<th>Maximum value</th>
<th>Mean value</th>
<th>Standard deviation</th>
<th>Skewness coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>$q_{8--64}$</td>
<td>0</td>
<td>0.0016</td>
<td>2.79×10^{-5}</td>
<td>1.06×10^{-4}</td>
<td>7.689</td>
</tr>
<tr>
<td>$q_{2--8}$</td>
<td>0</td>
<td>8.09×10^{-4}</td>
<td>3.15×10^{-5}</td>
<td>1.12×10^{-4}</td>
<td>4.737</td>
</tr>
<tr>
<td>$q_{sand}$</td>
<td>0</td>
<td>0.0012</td>
<td>3.18×10^{-5}</td>
<td>1.36×10^{-4}</td>
<td>6.648</td>
</tr>
</tbody>
</table>

Table 3: Statistical properties of the training, validation and testing sets for the total bed-load transport rate per unit width (all fractions added) in kg/s/m

<table>
<thead>
<tr>
<th>Set</th>
<th>Minimum value</th>
<th>Maximum value</th>
<th>Mean value</th>
<th>Standard deviation</th>
<th>Skewness coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training Set</td>
<td>0.40×10^{-6}</td>
<td>0.1046</td>
<td>0.0058</td>
<td>0.0131</td>
<td>3.8514</td>
</tr>
<tr>
<td>Validation Set</td>
<td>1.39×10^{-6}</td>
<td>0.0879</td>
<td>0.0058</td>
<td>0.0138</td>
<td>3.4864</td>
</tr>
<tr>
<td>Testing Set</td>
<td>1.38×10^{-6}</td>
<td>0.0961</td>
<td>0.0058</td>
<td>0.0134</td>
<td>4.1894</td>
</tr>
</tbody>
</table>

The best results were obtained with Reynolds number $Re$ as $X_1$, and dimensionless stream power $\omega^*$ as $X_2$, in terms of Equation (4). Nevertheless, other dimensionless variables that were tested, performed, overall, relatively good as well, but they predict poorly the coarser fraction due to the fact that the data contained a lot of zero transport rates in the outputs; as a result, these models were discarded. The ANNs that were based on the surface grain distribution, performed consistently better than the respective models that were based on the subsurface grain distribution. Table 4 shows the performance of the proposed ANN, for all the sets and outputs, in terms of root mean square error (RMSE) and discrepancy ratio (DR). The latter is the percentage of the calculated outputs that lie within a quarter (or a tenth) and four (or ten) times their respective measured value. Figure 5 depicts the scatter plots for each ANN output for the test set with boundaries that show the line of perfect agreement and the aforementioned DRs. The plots of the coarser grain sizes have fewer points due to some zero transport rate values; specifically, the percentage of zero transport values for the 8-64 mm, 2-8 mm, and sand size fraction are 54.70%, 5.49% and 0.00%, respectively, for the entire dataset. Table 5 shows the same evaluation indices with Table 4, but for the total mass bed-load transport rate per unit width (all the fractions added) in terms of kg/s/m, and Figure 6 shows a, similar to the previous, scatter plot, but with respect to the total mass bed-load transport rate per unit width for the test set. Table 6 shows a comparison of the ANN performance, in the
test set, with some commonly used fractional bed-load transport functions with respect to the total mass bed-load transport rate per unit width, from which it can be inferred the superior performance of the ANN in all the evaluation criteria utilized.

![Graphs showing ANN results for different grain sizes](image)

**Figure 5** Scatter plots of measured and calculated bed-load transport rates ($q_i^*$) for every ANN output in the test set.
Table 4: Performance of ANN for all the outputs

<table>
<thead>
<tr>
<th>Set</th>
<th>1/4 &lt;DR&lt; 4 (%)</th>
<th>1/10 &lt;DR&lt; 10 (%)</th>
<th>RMSE (kg/s/m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$q_{mm}$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Training Set</td>
<td>50.30</td>
<td>72.02</td>
<td>0.92×10^{-4}</td>
</tr>
<tr>
<td>Validation Set</td>
<td>48.18</td>
<td>67.27</td>
<td>0.87×10^{-4}</td>
</tr>
<tr>
<td>Testing Set</td>
<td>47.82</td>
<td>73.17</td>
<td>1.19×10^{-4}</td>
</tr>
<tr>
<td>$q_{psand}$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Training Set</td>
<td>44.44</td>
<td>69.90</td>
<td>7.43×10^{-4}</td>
</tr>
<tr>
<td>Validation Set</td>
<td>46.61</td>
<td>68.64</td>
<td>8.72×10^{-4}</td>
</tr>
<tr>
<td>Testing Set</td>
<td>45.58</td>
<td>69.58</td>
<td>8.35×10^{-4}</td>
</tr>
<tr>
<td>$q_{sand}$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Training Set</td>
<td>65.25</td>
<td>84.75</td>
<td>0.0171</td>
</tr>
<tr>
<td>Validation Set</td>
<td>67.33</td>
<td>82.87</td>
<td>0.0163</td>
</tr>
<tr>
<td>Testing Set</td>
<td>63.75</td>
<td>87.25</td>
<td>0.0171</td>
</tr>
</tbody>
</table>

Table 5: Performance of ANN for the total bed-load (all the fractions added)

<table>
<thead>
<tr>
<th>Set</th>
<th>1/4 &lt;DR&lt; 4 (%)</th>
<th>1/10 &lt;DR&lt; 10 (%)</th>
<th>RMSE (kg/s/m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training Set</td>
<td>60.48</td>
<td>81.96</td>
<td>0.0093</td>
</tr>
<tr>
<td>Validation Set</td>
<td>61.35</td>
<td>80.48</td>
<td>0.0100</td>
</tr>
<tr>
<td>Testing Set</td>
<td>59.36</td>
<td>82.47</td>
<td>0.0106</td>
</tr>
</tbody>
</table>

Figure 6 Scatter plot of measured and calculated bed-load transport rates per unit width, in kg/s/m, for the total bed-load (all fractions added) of the test set

The ANN results are relatively good considering that even in a best-case scenario, one should expect that bed-load measurements taken at the same location, at the same discharge will vary by at least an order of magnitude. This is especially true for samples taken at flows near the threshold of motion (Pitlick et al., 2009). Existing data sets indicate that for a given grain size and shear stress, there is at least a threefold range in dimensionless critical shear stress $\tau^*_c$ (Buffington and Montgomery, 1997). Uncertainties in the selection of $\tau^*_c$ can lead to large errors in computed transport rates because
entrainment is a nonlinear function of flow strength and these effects are particularly important in the range of flows slightly above the threshold for motion, where transport rates increase by orders of magnitude for small changes in shear stress. Furthermore, the threshold for entrainment is not the same as the threshold for the maintenance of transport, once a grain is entrained. For example, Fenton and Abbott (1977) demonstrated experimentally that $\tau^*$ diminishes significantly when particles are exposed above the bed rather than hiding within it, as is the case for grains already entrained and in transport, implying that the local sediment transport rate depends on both the ability of the flow to entrain sediment from the bed locally and the supply of already moving grains arriving from elsewhere upstream. The ANN, despite the fact that didn’t have an input denoting a critical value, seems able to handle these mechanisms and derive good results.

Finally, the results of this study partially agree with Gomez and Church (1989) who concluded that none of the selected formulae, in their comparative test, performed consistently well, but they did find that formula calibration increases prediction accuracy and that formulae based upon stream power were the most appropriate, as stream power has a more straightforward correlation with sediment transport than any other parameter.

Table 6: Performance of ANNs and several bed-load transport functions for the 251 paired measurements of the test set for the total bed-load (all the fractions added)

<table>
<thead>
<tr>
<th>Formula</th>
<th>1/4 &lt;DR&lt; 4 (%)</th>
<th>1/10 &lt;DR&lt; 10 (%)</th>
<th>RMSE (kg/s/m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANN</td>
<td>59.36</td>
<td>82.47</td>
<td>0.0106</td>
</tr>
<tr>
<td>Ackers and White (1973)$^a$</td>
<td>27.89</td>
<td>38.25</td>
<td>0.0123</td>
</tr>
<tr>
<td>Ashida and Michiue (1972)</td>
<td>3.19</td>
<td>5.18</td>
<td>2.904</td>
</tr>
<tr>
<td>Parker (1990)$^b$</td>
<td>18.33</td>
<td>27.09</td>
<td>1.285</td>
</tr>
<tr>
<td>Powell et al (2001)$^b$</td>
<td>10.36</td>
<td>18.73</td>
<td>5.015</td>
</tr>
<tr>
<td>Wilcock and Crowe (2003)$^c$</td>
<td>11.95</td>
<td>17.93</td>
<td>3.080</td>
</tr>
</tbody>
</table>

$^a$ Extended with Proffitt and Sutherland’s (1983) hiding function
$^b$ Calculates only the gravel portion of the bed-load (>2 mm)
$^c$ Wilcock and Crowe (2003) formula calculates the bed-material load

7. Conclusions

This study employed an ANN as a regression tool for the quantification of the fractional bed-load transport rate in poorly sorted gravel-bed rivers, based on a function proposed by Parker and Anderson (1977) and Parker (2008). The results showed that ANNs can be an alternative for the calculation of the bed-load transport rate as long as there are
adequate relative data of good quality. The exploited data originate from a large field campaign in the state of Idaho (U.S.A.) and cover a wide range of river flows, slopes, bed material gradations and sediment transport. The models based on the surface grain distribution performed better than those based on the subsurface grain distribution, as expected, and Bagnold’s stream power was the more appropriate variable for the quantification of the phenomenon. The derived model can be applied in the study area and in rivers similar to those the model was trained, for the training data range.

8. Notation

The following symbols are used in this paper:

- \( D \) = mean flow depth (m)
- \( Q \) = water discharge (m\(^3\)/s)
- \( F_i \) = mass fraction of surface material in the \( i \)th grain size range
- \( \text{Re} \) = Reynolds number
- \( \text{Re}_{p_{50}} \) = particle Reynolds number
- \( R \) = submerged specific gravity of the sediment
- \( S \) = energy slope
- \( V \) = mean flow velocity (m/s)
- \( W \) = channel width (m)
- \( d_i \) = characteristic grain diameter (m)
- \( d_{50} \) = median grain diameter (m)
- \( g \) = gravitational acceleration (m/s\(^2\))
- \( q_i \) = volume transport rate of bed-load per unit width of \( i \)th size range (m\(^2\)/s)
- \( q_i^* \) = grain-size-specific Einstein number
- \( \nu \) = kinematic viscosity of water (m\(^2\)/s)
- \( \rho \) = density of water (kg/m\(^3\))
- \( \rho_s \) = density of sediment (kg/m\(^3\))
- \( \sigma \) = arithmetic standard deviation of surface grain size distribution
- \( \tau \) = shear stress [kg/(m\(\cdot\)s\(^2\))]
- \( \tau^* \) = dimensionless shear stress
- \( \tau_c^* \) = critical dimensionless shear stress
- \( \tau_{bf}^* \) = dimensionless shear stress based on bankfull flow conditions
- \( \omega \) = stream power (kg/s\(^3\))
- \( \omega^* \) = dimensionless stream power
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Ground water pollution in Central India

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1 Pt. Ravishankar Shukla University · 2 Central Ground Water Board · 3 Polish Geological Institute · 4 Department of Exact Sciences

Abstract
The most of the natural resourced materials i.e. dolomite, iron pyrite, coal, etc. of the country is reserved in Chhattisgarh state, central India. Several thermal power plants, metal and cement industries are running in this region. The groundwater is seriously deteriorated due to rapid industrialization and urbanization as well overuse of groundwater. In this work, the groundwater contamination in a huge coal burning site of the country, Korba, Chhattisgarh state, central India is described. The concentration of elements: F-, Cl-, NO3-, SO42-, HCO3-, Na+, K+, Mg2+, Ca2+, Al, SiO2, Mn, Fe and Zn was ranged from 1.0 – 12.1, 4.0 – 138, 3.0 – 90, 2.0 – 100, 12 – 476, 4.0 – 165, 0.3 – 23.9, 2.0 – 44, 4.0 – 110, 7.0 – 70, 10.0 – 75, 0.03 – 1.53, 0.5 – 8.2 and 0.01 – 2.03 mg/l with mean value of 4.7±1.0, 31.3±10.7, 25.5±9.6, 20.6±9.3, 124±41, 29±12, 7.9±3.0, 11.5±4.1, 33.2±9.6, 19.7±4.8, 35.1±6.8, 0.50±0.13, 2.8±0.7 and 0.90±0.19 mg/l, respectively in the post monsoon period, 2012. The concentration of other metals: Li, Be, Rb, Co, Ni, Cu, Sn, Sb, Mo, Cd, La, Ce, Pb and U lie in microgram levels. The seasonal and spatial variations, sources and toxicities of the contaminants in the groundwater are discussed.

Keywords
Groundwater, pollution, sources, toxicities, India

1. Introduction

Groundwater is a water located beneath the ground surface in soil pore spaces and in the fractures of lithologic formations. Groundwater makes up ≈ 20% of the world's fresh water supply, which is ≈ 0.61% of the entire world's water, including oceans and permanent ice. Groundwater is an abundant resource for humans, and their overuse cause major problems to the users and to the environment. The most evident problem is a lowering of the water table beyond the reach of existing wells in many countries [1]. A lowered water table causes other problems such as subsidence and saltwater intrusion. Millions of people in the developing world live on groundwater, and water problem has emerged as one of the world's most challenging issues [2]. The quality of available groundwater resources is being increasingly degraded by geogenic and anthropogenic
activities [3]. Asian countries face serious water problems almost everywhere mainly due
to explosive population growth, heavy seasonal rains, massive flooding, decreasing of
water levels, mixing of waste water, etc. [4]. In India, groundwater is used intensively
for drinking, irrigation and industrial purposes. Several land and water-based human
activities are causing pollution of this precious resource [5-6].

This deterioration is more apparent in and around the large urban areas. Inadequately,
untreated industrial and municipal effluents are finding way in the water sources causing
sever contamination beyond repair through conventional means. Water pollution due
to industrial effluents being disposed into streams or other water bodies is common in
industrial canters and industrial units operating from residential areas such as Mumbai,
Delhi, Calcutta, Punjab, Kanpur, etc. [7-9]. Several districts of the country have problems
of high fluoride, iron, nitrate, arsenic, pesticides, etc. [10-25].

In the present study, groundwater contamination in a huge coal burning site of country,
Korba, Chhattisgarh is described.

2. Experimental

2.1. Study area

Korba area, Chhattisgarh, India (22° 21′ 0″ N, 82° 40′ 48″ E) has rich deposits of coal
over ≈ (3.0)×10^3 km. The population of Korba area is ≈ 0.5 million. At least 9 open and
underground coal mines are in operation. A huge amount of coal >10000 MT annually
is consumed by various unit of thermal power plants for generation of ≈ 40000 KW
electricity. The Asia biggest Aluminum Plant is in operation by pouring the effluents in the
environment. The environment of Korba city is polluted with F-, heavy metals, etc. [26]. In
the proposed work, the Korba area was selected for groundwater contamination studies.

2.2. Samples

Twenty eight groundwater samples in duplicate from different sketches of Korba area in
the three seasons: monsoon, pre- and post-monsoon period, 2012 over 1.00 x10^3 km^2
was collected [27], Figure 1. The water sample was divided in two portions. The 1st portion
was used for measurement of physical parameters, carbons and anions. The 2nd portion
was acidified with few drops of ultra pure nitric acid (E. Merck) for analysis of the metals.
2.3. Analysis

The Orion-720 ion meter was used for the measurement of pH, electrical conductivity (EC), total dissolved solid (TDS) and concentration of ions (i.e., F⁻, Cl⁻, SO₄²⁻, Na⁺, K⁺, Mg²⁺ and Ca²⁺). The physical parameters i.e. temperature, pH, electrical conductivity and TDS were measured at the spot. The TISAB-III buffer (prepared by dissolving 300 g sodium citrate, 22 g 1,2-cyclohexanediamine-N,N,N,N-tetraacetic acid and 60 g NaCl in a volume of 1-lit with the de-ionized water with subsequent adjustment of pH value to 5.0 – 5.5) was used for the F⁻ analysis. The Thermo ICP-OES and ICP-MS (Polish Geological Institute, NRI, Central Chemical Laboratory, Warsaw) were employed for analysis of SiO₂, Mn, Fe, Zn, Li, Be, Rb, Co, Ni, Cu, Sn, Sb, Mo, Cd, La, Ce, Pb and U. The organic carbon (OC) and carbonate carbon (CC) were monitored by the thermal method using CHNSO-IRMS Analyzer, SV Instruments Analytica Pvt. Ltd. The hardness and alkalinity value of water were analyzed by titration methods [28]. The Aqachem water quality diagrams software had been utilized for the preparation of Piper diagrams. Multivariate statistical analysis such as factor analysis (FA) and hierarchical cluster analysis (HCA) were employed for the
source apportionment [29-30]. The windows statistical software STATISTICA 7.1 was used for the multivariate statistical calculation.

3. Results and discussion

3.1. Geology and hydrology

The rock of study area has been formed in the archaean to cenozoic age, Figure 2. The archaean to proterozoic age consists of granite gneiss and granitoids, containing enclaves of metasedimentary and meta-igneous suites comprising schists, quartzites, amphibolites and dolomitic marbles [31]. The unclassified metamorphics are composed of quartzites, mica schists, dolomitic marbles, phyllites and biotite chlorite schists (occasionally associated with quartzite bands). However, all these rocks are intruded by metabasic bodies/dykes and quartz and pegmatite veins. Granites occupy by north and south part covering 17% of the study area. The gondwana super group is represented by talchir, karaharbarhi, barakar and kamthi formations. The barakar group covers the major part of the study area. It is composed of medium to coarse grained arkosic sandstone, a few pebble beds, conglomerate and shale with coal seams. Usually the sandstone is feldspathic and ferruginous. More than 82% part of the study area is covered by gondwana rocks.

![Figure 2](image)

The ground water occurs under phreatic, semi-confined and confined conditions. Its movement is controlled by the inter granular pore spaces in the shallow weathered zones.
and joints, fractures and caverns in deeper horizons. Shale beds in gondwana formation act as confining layers and help to form different aquifer system. The water level depth is varied from 3.42 - 11.58 mbgl during pre-monsoon period and from 0.72 - 10.26 mbgl during post monsoon period in the shallow aquifers. The long term (decadal) trend analysis of water level indicated that ≈ 7% and 14% of the wells in pre monsoon and post monsoon showed a significant (20 cm/Yr) falling trend.

3.2. Physical characteristics
The age and depth of 28 tube wells was ranged from 1.0 – 126.0 Yr and 3.9 –18.2 m with mean value of 6.9±0.9 Yr and 10.8±1.1 m, respectively. A slight variation in temperature of the groundwater was recorded from 29.5 – 31.2 °C with mean value of 30.6±0.1 °C. The pH value was varied from 6.5 – 8.2 with mean value of 7.4±0.1. The groundwater was found to be acidic in nature in few locations i.e. Kudurmal, Jamnipali and Bhilai. In turn, the highest pH value was recorded at location: Satnam nagar. Over all, the groundwater of Korba city was found to be generally neutral to slightly alkaline in nature. The EC value of the groundwater was varied from 42 –1515 μS cm⁻¹ with mean value of 379±114 μS cm⁻¹. In study area, low EC value, < 500 µS at 25 °C was observed in the 75% locations. The EC value was well correlated (r = 1.0) with sum of total content of [Cl⁻+NO₃⁻+SO₄²⁻+HCO₃⁻+Na⁺+K⁺]. Similarly, TDS value was ranged from 52 – 1069 mg/l with mean value of 276±79 mg/l. The excellent correlation (r = 1.0) of both values (EC and TDS) was observed.

3.3. Chemical characteristics
The chemical characteristics of 28 groundwater samples collected in the post monsoon period, December 2012 is presented in Tables 1-4. The OC and CC concentration (n = 28) was found relatively higher, ranging from 20 – 5890 and 110 – 7640 mg/l with mean value of 1191±571 and 1155±636 mg/l, respectively. Both carbons was fairly correlated (r = 0.61), indicating origin from same sources. The concentration of F⁻, Cl⁻, NO₃⁻, SO₄²⁻, HCO₃⁻, Na⁺, K⁺, Mg, Ca, Al, SiO₂, Mn, Fe and Zn was ranged from 1.0 – 12.1, 4.0 – 138, 3.0 – 90, 2.0 – 100, 12 – 476, 4.0 – 165, 0.3 – 23.9, 2.0 – 44, 4.0 – 110, 7.0 – 70, 10.0 – 75, 0.03 – 1.53, 0.5 – 8.2 and 0.01 – 2.03 mg/l with mean value of 4.7±1.0, 31.3±10.7, 25.5±9.6, 20.6±9.3, 124±41, 29±12, 7.9±3.0, 11.5±4.1, 33.2±9.6, 19.7±4.8, 35.1±6.8, 0.50±0.13, 2.8±0.7 and 0.90±0.19 mg/l, respectively. Similarly, concentration of other metals: Li, Be, Rb, Co, Ni, Cu, Sn, Sb, Mo, Cd, La, Ce, Pb and U was observed in microgram levels, and ranged from 0.5 – 259, 0.1 – 16.7, 0.2 – 59, 0.2 – 10.5, 2.0 – 34, 1.1 – 142, 0.1 – 9.1, 0.1 – 17.3, 0.1 – 5.0, 0.1 – 0.3, 0.06 – 4.27, 0.05 – 0.78, 0.5 – 27.1 and 0.02 – 10.1 µg/l with mean value of 26±19, 1.3±1.2, 13±5, 2.6±0.9, 7.8±2.5, 12±10, 1.5±0.7, 2.8±1.3, 1.0±0.4, 0.13±0.03, 0.5±0.2, 0.30±0.07, 6.3±2.6 and 1.3±1.0 µg/l, respectively. Among them, the
highest content of CC was observed, may be due to oxidation of the OC. The occurrence trend of 30 elements in the water is: CC > OC >> HCO₃⁻ > SiO₂ > Ca > Cl⁻ > Na⁺ > NO₃⁻ > SO₄²⁻ > Al > Mg > K⁺ > F > Fe > Zn > Mn >> Li > Rb > Cu > Ni > Pb > Sb = Co > Sn > Be = U > Mo > La > Ce > Cd.

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Table 4: Concentration of trace elements in groundwater during post monsoon period, µg/l

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<th>S. No.</th>
<th>Sb</th>
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<th>Cd</th>
<th>La</th>
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<td>0.11</td>
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<td>1.21</td>
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</table>

3.4. Variations

The concentration of elements in groundwater depends upon several factors. The highest concentration of elements: F⁻, Cl⁻, SO₄²⁻, Na⁺, K⁺, Mg²⁺, Ca²⁺, Mn and Fe was observed at location: Kudurmal, mainly due to acidic nature of the groundwater. Similarly, the highest concentration of other elements: HCO₃⁻, Li⁺, Be⁺, Mo, NO₃⁻, Zn⁺, Co⁺, Sb⁺, La, Cu⁺, Sn⁺, Cd⁺, Pb⁺, Rb⁺, Ni, Al, SiO₂, Ce and U was marked at location: Gopalpur, Korba (old BusStand), Gerwaghat, Kosabadi, Dadar, Chhatghat Rampur, Surakachhar Bharotal, Sonpuri, Satnam nagar Risdi and Jamnipali, respectively.

The Kudurmal location was selected for seasonal variation study due to the highest contamination. The elemental concentration variation study was performed in three
seasons: pre monsoon (May, 2012), monsoon (August, 2012) and post monsoon (December, 2012). The pH value of the water was decreased from 6.5 to 5.8 in the monsoon season may be due to percolation of the acidic runoff water. The EC of water was increased enormously (1.5-folds) in the monsoon period. The concentration of 28 elements i.e. F, Cl, NO₃, SO₄²⁻, SiO₂, Li, K, Rb, Cs, Be, Al, Sb, Sn, Cr, Mn, Co, Ni, Cu, Zn, Cd, Mo, Pb, La, Cs and U was increased remarkably in the monsoon period, Figures 3-4. However, the comparable concentration of bedrock metals i.e. Na, Mg and Ca in the three seasons was marked.

Figure 3  Seasonal variation of elements in groundwater
3.5. Type of water

Hydro chemical faces are very useful in the investigation of chemical characterization of water solution in hydrologic system. The Piper diagram was used for water type study [32]. Different types of water exist in aquifer due to groundwater characteristics flow into aquifer system and effect of local recharge. Types of water are interlinked with the geology of the area and distribution of faces with the geological controls. Most of the groundwater is Ca-Mg-HCO$_3$ type with domination of Ca and HCO$_3$ ions, Figure 5. The Ca-Mg-Cl-SO$_4$ type of water exists in few locations: Gewraghat, Surakachhar, Bhilai, Kharmora and Kuchena with domination of Mg, Ca, Cl$^-$ and SO$_4^{2-}$ ions, Figure 5.
3.6. Water quality assessment

The tolerance limit reported for elements i.e. F-, NO$_3^-$, Al, Mg, Ca, Mn, Fe, Ni, Cu, Cd, Pb and U in drinking water is 1.5, 45, 0.1, 30, 75, 0.2, 0.30, 0.10, 0.10, 0.003, 0.01 and 0.015 mg/l [33-34]. The higher concentration of elements i.e. F, Al, Mn and Fe was observed in the all locations, mainly due to discharge of the Aluminum and Thermal power plant effluents into the water. The excessive levels (> 2 mg/l) of OC at all locations were marked. The concentration levels of NO$_3^-$, Mg, Ca and Pb were increased beyond permissible limits in some locations during the post monsoon period. However, they were crossed the permissible limits in the monsoon season. The acidity of the water was increased in the monsoon period at several locations due to percolation of the acidic runoff water. Several cases of public health hazards i.e. fluorosis, hypertension, kidney and heart diseases, asthma, etc. have been observed in this city.

3.7. Cluster analysis

Cluster analysis was performed on the dataset by Ward's method using euclidean distance as similarity in measured variables. The result of cluster analysis is given as a dendrogram (Figure 6) which highlight two groups of tube well water. Group-I (n = 22) is constituted of tube well water represented by the observations O2 – O5, O9 – O15 and O18 – O28. Group-II (n = 6) is formed by the observations O1, O6 – O8, O16 and O17. The two groups is differ each other by the following parameters: age, EC, TDS, OC, CC, F, Fe, NO$_3^-$ and major ions except HCO$_3^-$. These discriminating parameters have the highest median value in group-II, except age and Ca$^{2+}$ in a lesser extent.
3.8. Factor analysis

Nineteen variables were taken in account in this analysis. First the raw data were standardized which gave the mean and variance of the variables equal to zero and one, respectively. The standardization procedure eliminated the influence of different units of measurement, this makes the data dimensionless. In reference to the eigenvalues, five factors were extracted after varimax rotation [35]. The eigenvalues, the percentage of variance and the cumulative percentage of variance associated with each other are summarized in Table 5. Five factors were extracted which explain 83.27% of the total variance.

Table 5: Factor analysis (R-mode) of the parameters in tube well water

<table>
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<tr>
<th>Parameter</th>
<th>Factor-1</th>
<th>Factor-2</th>
<th>Factor-3</th>
<th>Factor-4</th>
<th>Factor-5</th>
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<td>-0.14</td>
<td>-0.30</td>
<td>0.81</td>
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<td>WL</td>
<td>0.35</td>
<td>-0.42</td>
<td>0.17</td>
<td>-0.52</td>
<td>-0.11</td>
</tr>
<tr>
<td>pH</td>
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<td>-0.23</td>
<td>-0.04</td>
<td>-0.25</td>
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<td>EC</td>
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<td>0.26</td>
<td>0.06</td>
<td>0.01</td>
<td>0.03</td>
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<td>TDS</td>
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<td>SO₄²⁻</td>
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<td>NO₃⁻</td>
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<td>SiO₂⁻</td>
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<td>HCO₃⁻</td>
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<td>Na⁺</td>
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### Parameter Factor-1 Factor-2 Factor-3 Factor-4 Factor-5
<table>
<thead>
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<td>Ca²⁺</td>
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<tr>
<td>% Total Variance</td>
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<td>77.20</td>
<td>83.27</td>
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</table>

Significant loading value > 0.70

A 49.58% of the total variance is explained by Factor-1, showing strong positive loadings on EC, TDS, F-, Cl⁻, SO₄²⁻, HCO₃⁻, Na⁺, Mg²⁺ and Ca²⁺. They are related to the mineralization of the groundwater which involve also weathering of gypsum and fluoride bearing minerals such as CaF₂. A 10.93% of the total variance is accounted by factor-2, with strong positive loadings on NO₃⁻ and K⁺, related to coal burning and mining activities. A 8.91% of the total variance is proportionate by OC and CC are strongly related to common sources i.e. microbial and burning oxidation of elemental carbon. A 7.78% of the total variance is explained by factor-4, describing a strong loading on SiO₂. The age factor of tube well is explained by factor-5 with a 6.06% of total variance.

### 3.9. Correlation

The correlation matrix of 14 major elements is summarized in Table 6. Their correlations among themselves are ranged from -0.58 – 1.00. The good correlation of elements i.e. F, Cl⁻, NO₃⁻, SO₄²⁻, HCO₃⁻, Na⁺, K⁺, Mg²⁺, Ca²⁺, Mn and Fe among themselves are achieved, showing origin from similar sources. Whereas, the poor correlation of other three elements i.e. Al, SiO₂ and Zn among themselves are seen, indicating origin from different multiple sources.
4. Conclusion

The whole groundwater of Korba city, Chhattisgarh, India is contaminated with excessive levels of OC, CC, F-, Al, Fe and Mn. The highest degradation of groundwater quality is observed in the monsoon period due to mixing of the runoff water. The multiple sources i.e. coal burning, Aluminum plant effluent, mine leachate, etc. are responsible for the pollution of the water.

Acknowledgement

We are thankful the ICWRER conference organizer, Koblenz and the Alexander von Humboldt Foundation, Bonn for the financial support given to KSP to attend the Water & Environmental Dynamics conference, 3-7 June, 2013, Koblenz, Germany. One of the author, R. Dewangan is thankful to the Regional Director, CGWB, NCCR, Raipur, CG, India for providing research facility.

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Urbanization impact on rainfall-runoff modeling: an integration of remote sensing and GIS approach

Ghazi A. Al-Rawas
Sultan Qaboos University

Abstract
Several studies in the literature have related watershed characteristics to flow discharge, but very few have focused on the impacts of urbanization on stream flow specifically focused in arid regions. Many arid regions such as Oman are experiencing rapid increases in urbanization – primarily occurring in the wadi flood plain. The objective of this study is to determine the surface flow in a selected watershed in Oman through an integration of remote sensing and geographic information system (GIS). Various digital data layers such as satellite imagery, Digital Elevation Model (DEM), land use/land cover maps, and soil map data was used to delineate the necessary physical watershed’s characteristics used in the rainfall-runoff modelling. Soil Conservation Curve Number (SCS) method will be used to determine curve numbers (CN) and runoff flow distribution of the selected watershed. Relationship between the human activities and runoff flow discharge will be investigated. The results are expected to show that human activities (e.g. urban growth) will have a significant impact on the increase of runoff flow. This study is expected to show that remote sensing and GIS integration approach is very helpful for spatial rainfall runoff distribution, especially in the ungauged areas in a watershed. In addition, this study is expected to conclude some recommendations for new regulations and policies that minimize the impact of urbanization on runoff especially in the cases of extreme events that causes flash floods.

Keywords
Flow discharge, urbanization, GIS, Remote Sensing, Curve Number (CN), flash floods.

1. Introduction

Many arid regions such as Oman are experiencing rapid increases in urbanization – primarily occurring in the wadi flood plain. Furthermore, previous studies on arid wadi hydrology show that there is research gap in urbanization and land-use impacts on runoff (Singh 2009; Pilgrim et al. 1988; and Cordery et al. 1983). Huang et al. (2008) investigated the effect of growing watershed imperviousness on hydrograph parameters and peak discharge in Wu-Tu watershed, north of Taiwan. They found that the time to peak of flood
hydrographs for various storms was diminished by 11 to 6 h for various return periods storms of 48 h, whereas peak flow increased from 127 m$^3$/s to 669 m$^3$/s for different storm intensities. Wang et al. (2007) in his study on the effects of land use changes on hydrological processes in an arid region in China stated that due to the continuous expansion of the cultivated land area, the downstream peak flow has decreased by 27-32%. Ferguson and Suckling (1990) found that increasing urbanization in Peachtree Creek, Georgia leads to increase in the total annual flows in wet years and declining runoff in dry years. Others like Galster et al. (2006) studied the effects of urbanization on the discharge–drainage area relationship in east-central Pennsylvania. They found that the impervious surfaces in urban environments decrease infiltration and increase the rate and volume of water delivered to the river. Kang et al. (1998) observed that peak discharge increased and the mean lag time of the On-Cheon Stream watershed in Pusan, Korea, decreased because of urbanization. As the literature shows, much of this knowledge has been accumulating in wetter, humid climates. However, Al-Rawas and Valeo (2010) investigated the relationship between flood flows and watershed characteristics in northern Oman including farming area as an indicator of urbanization. They found that drainage area (DA), Wadi slope (WS), and farms (FR) were the most significant variables among 14 watershed characteristics in flood-peak flow estimation using regression analysis.

Although the SCS (1986) method using the curve number (CN) is widely used for its simplicity, one of its disadvantages is that it does not take into account regional qualities based on geologic and climatic settings. It was originally developed using data from the Midwestern United States (Ponce et al. 1996). Sharma (1987) found that derived CN values for bare crust-forming sandy soils in the Indian arid zone were higher than the values provided by the Soil Conservation Service (SCS) handbook. For example, CN estimated by the SCS method for 0.5% slope is 77, where the actual optimized value was 87. Sharma (1987) stated that using a CN provided by SCS gave under-predicted generated runoff volumes by 47-68% for storms more than 100 mm, and 163-400% for storms less than 25 mm. Descheemaeker et al. (2008) found in their study area of rangelands in semi-arid tropical highlands of northern Ethiopia, that hydrologic soil group was not as important an explanatory factor as land use type for explaining variability in curve numbers. They found that the CN determined for their study is a preferred alternative to the CN handbook. Because of the sensitivity of the SCS method to CN, determining CN values from local studies are more reliable than those taken from CN estimates provided by SCS tables (Hawkins 1993).
The literature shows a relatively poor understanding of hydrological processes in arid regions, and thus, the appropriate application of the SCS method using curve numbers also faces the same difficulties and challenges (Descheemaeker et al. 2008). Shi et al. (2009) in their study in central China found that using the standard SCS method assumptions underestimates large runoff events, and overestimates some of the small events. Others (Ponce and Hawkins 1996; Lim et al. 2006; Mishra and Singh 1999) also found that using modified SCS values (e.g. CN) instead of the standard SCS values could improve runoff predictions. Cooley and Lane (1980) stated that optimized CN values for a Hawaiian watershed are significantly different from the standard tabulated CN values. To use the tabulated CN values, Debo and Reese (2002) suggested that CN should be selected only after a field inspection of the watershed and a review of soil maps.

A study by Nouh (1987) on flood frequency analysis in the southwest region of Saudi Arabia stated that the Rational method produces overestimates of peak flow results compared to the Phi-index and SCS methods when using larger sized drainage basins because of the inaccurate determination of runoff coefficients for the study region (using standard tabulated values). Others like Kang et al. (2009) in his study of design floods in Korea pointed out that the rational method underestimated values as compared to those estimated by the SCS method.

Debo and Reese (2002) summarized that using SCS peak discharge method: (i) the watershed must be hydrologically homogeneous and described by a single CN value; (ii) the watershed can have only one time of concentration derived from the main stream; (iii) the method does not consider hydrologic routing effects; and (iv) the weighted CN can only range between 40 and 98.

1.1. Urbanization Characteristics in Oman
Since 1970, Muscat has experienced a rapid development in its infrastructure. According to the 2003 census conducted by the Oman Ministry of National Economy, the population of Muscat increased from 549,150 in 1993 to 632,073 in 2003 (MNE 2007).

A handful of studies have looked at flooding in Oman wadis. El-Zawahry (2007) stated that urbanization within the very small Wadi Aday sub-catchment may cause relatively high increases in peak flooding, and all urbanized areas in the Wadi Aday watershed would be fully flooded during the 100 year return period flood. Due to the economic growth and the improvements in transportation infrastructure, some other regions in Oman have experienced an expansion in agricultural areas like the Al-Batina coastal region (Harris 2003). After tropical cyclone Gonu hit Muscat on the 5th and 6th of June
2007, the government of Oman decided to install dams in this watershed to protect the main urban centers of Al-Qurm area against flooding (Al-Abri and Magnan 2007).

Many agricultural lots have changed to residential and other commercial and business projects due to economic reasons and booming of oil prices. Unfortunately, this increases the impervious area in Muscat in general and in the Aday watershed - especially in the Al-Qurm residential and commercial area. This increase of impervious surface not only increases the volume of discharge delivered, but also the rate of that delivery (Ferguson and Suckling 1990). Figure 1 is IKONOS high resolution imagery showing agricultural areas that have changed into commercial and business landuses for different parts of Muscat.

Figure 1 shows agricultural land that was completely converted into a commercial land use by 2012. The area became almost completely impervious. In addition, in some other areas the wadi (water channel) became narrower due to the urban exapnsion on the expense of water natural drainage areas. Many other similar practices have occurred, which contribute to the decrease of green lands, a narrowing of the wadi channels, and thus, an increase in the surface runoff in this region. This leads to possible explanations for the recent increases in flash floods in Oman.

The main objectives of this study are: (i) observe changes in an urbanization in flash flood affected areas of Oman; (ii) develop new values for curve numbers for arid regions that may be used in Oman and similar arid regions; and (iii) investigate the impact of this change in urbanization on the surface runoff depth in Wadi Aday watershed in the time period from 1970 to 2003. Since the literature shows a research gap in urbanization and land-use impacts on runoff in wadi hydrology, this study is one of the few applications on the effects of urbanization for this type of area. Moreover, new tables of hydrological
coefficients are created specifically for this type of landform and arid region, which may be used by hydrological engineers in areas with similar arid and urban characteristics.

2. Study Area and Methodology

The selected area for this study was Aday watershed in the northern Oman. The study area is drained northward by wadi Aday through Al-Qurm residential and commercial areas in a watershed that covers an area of 357 km², and finally to the coastal sand plain of Al-Qurm area (MRMEWR 2005) as shown in Figure 2. The mean annual rainfall throughout most regions in Oman is relatively low, less than 100 mm, in the coastal regions, but reaching as much as 350 mm in the mountainous regions with relatively frequency (Al-Rawas 2009).

Geographical Information Systems (GIS) data of land use for the years 1970 to 2003 were used. This data is part of an integration of historical aerial photographs and IKONOS high resolution satellite imagery. The greatest urban expansion occurred from 5.783 km² in 1980 to 13.567 km² in 1990.

Figure 2  Wady Aday Watershed
The methodology of this study consists of computing curve number (CN) tables for the study area based on the soil map; and applying runoff SCS model to explore the effect of urbanization on the surface runoff depth. A Digital Elevation Model (DEM) of 40 m was used to extract the watershed characteristics representing average slope and drainage properties of the watershed.

2.1. Wadi Direct Runoff Depth using SCS Hydrological Curve Number (CN) method

Values of CN were computed for Oman similar to the Soil Conservation Services (SCS, 1986). For residential lot size of 1/8 acre or less (506 m²) with an average of 65% impervious surface, Soil Conservation Services (SCS 1972) curve numbers are computed assuming the runoff from the house and driveway is directed towards the street with a minimum of roof water directed to lawns where additional infiltration may occur. The remaining previous area of 35% (lawns) is considered to be in good pasture condition. In this study area, the remaining previous area is 50% of the lot is mostly covered by interlock which has less infiltration potential than lawns.

Rainfall depth and curve number (CN) which depends on the land use and soil type were used to apply the SCS direct model of runoff computation (Equation 1). An event of one day rainfall ($P$) depth of 80 mm was used in this model for both 1970 and 2003. The SCS method defined the value of the initial abstraction to be approximately equal to 20% of the watershed potential storage, $S$. Based on Brown (2007) finding that for interlock, runoff/rainfall ratio was 0.83 (or $S=0.17P$), and the concrete roof is assumed as 0.95 (Viessman 2002). The curve number for interlock then computed using Equation 2.

\[
Q = \frac{(P - 0.25S)}{P + 0.8S} \quad (P \geq 0.25S) \tag{1}
\]

\[
CN = \frac{25400}{(S + 254)} \tag{2}
\]

Where $P$, total rainfall (mm); $S$, watershed storage (mm); $Q$, actual direct runoff (mm).

3. Results and Discussion

Based on the available soil data used in this study, more than 68% of the watershed is loamy to sandy soil with high variability of percent slopes representing the hydrological soil group C. The soil type in the upstream of Wadi Aday started with loamy and loamy and sandy, and then to a sandy alluvial fan in most of the wadi, followed by extremely gravelly sand in a small part of the wadi. The rest of the wadi is loamy to sandy-loam and
ends with a small portion of clayey-sand in the coast line of Gulf of Oman. Figure 3 shows the spatial urban expansion in the downstream of Wadi Aday watershed. In the period from 1970 to 2003, the results indicate that the urbanization occurred along the wadi itself, and most of the expansion is in the downstream end close to the coast line and specifically in the existing area of Al-Qurm recreational and tourism part facing Oman Sea.

Figure 3  Aday watershed’s urban expansions from 1970 and 2003.
**Figure 3** shows that the urbanized expansion in the Aday watershed is very remarkable, where in 1970 the total urbanized area was less than 2 km² and in 2003 it increased to more than 19 km². The change started after 1970 as mentioned and is commensurate with the economic growth in Oman and improvements in transport infrastructure. The buildings including governmental and residential increased from 1.113 km² in 1980 to 3.189 km² in 1990. In contrast, a declining trend in greenness showed a decrease in agriculture lands by 86% between 1970 and 2003.

A significant increase in the calculated CN for the study area between 1970 and 2003 as depicted in **Figure 4**, which leads to a relative increase in the surface flow. This figure shows very clear that the increase in the CN is associated with the urbanized areas, where most of the area had changed into more impervious surfaces. This explains the effect of urbanization on wadi flow in this study area and the negative impact of human activities by changing the land cover/use as mentioned earlier from agricultural to impervious surfaces. The CN increased overall the area except small area in the northern part (close to the downstream) changes from the range of 85-90 CN in 1970 to 65-70 CN in 2003. This area represents a natural recreational park (Al-Qurm Public Park), which is converted from bare soil area into a green park in the 1980s.

**Figure 4**  
*Change in CN from 1970-2003.*
From Figure 4, the surface runoff was computed for both 1970 and 2003. Using the information of CN's number of cells by the area of one cell (50x50m) in 1970 and 2003 from Figure 4, the number of cells that have at least 40 mm runoff depth was increased from 19162 cells in 1970 to 20035 cells in 2003. Accordingly, the total volume of the discharge was increased from 1916200 m³ in 1970 to 2003500 m³ in 2003 with an increase of 87300 m³. The number of cells which have at least 59 mm depth of rainfall was 174 cells in 1970, and in 2003 increased to 6295 cells. This increment resulted an increase of the runoff volume from 25665 m³ in 1970 to 928512 m³ in 2003. The new computed CN values for the study area were higher than the ones in SCS (1986) created for the USA.

4. Conclusion and Recommendations

This study shows that the increase of urbanization has a significant impact on hydrological curve number (CN) and consequently on the runoff depth in this region. For example, from 1970 to 2003 the weighted curve number CN increased from 76 to 79. Because urbanization responds differently hydrologically than non-urban areas, the manifestation of their effects in runoff parameters will be different as well. This study indicates that the effect of urbanization in this arid study area may not have the same effect as in humid climates. The standard CN values by Soil Conservation Service (SCS) are not valid for an arid region like Oman specifically for the residential areas. Thus, a new CNs computed from this study is recommended for rainfall-runoff modelling.

This study warns that more frequent flash floods could be experienced due to the continuous increase of urbanized area at the expense of greenness areas would lead to higher surface runoff. To avoid this scenario of a decrease in green lands and an increase in surface runoff in Aday watershed, some urgent steps are required to be implemented by the government:

1. stop granting permissions for land use change from agricultural to commercial
2. maintain a balance in the amount of urbanized versus green lands
3. increase the amount of green areas in house lots by increasing public awareness to the impact of impervious surfaces on surface runoff.

The author recommends that greater investigation into infiltration rates and crusting in arid regions be conducted. Detailed data on agricultural areas (e.g. Crop and soil type) be acquired to compute new values of CN specifically for these arid areas. For future efforts, the author recommends that engineers should be recommended to use the new hydrologic curve number (CN) tables that created specifically for the study area. Finally,
the author recommends that immediate and serious efforts should be implemented to stop the continuous rate of urban expansion at the expense of greenness areas in Oman.

References


Modelling, Methods, Mathematics

Statistical tools and methods for water resources research and management
Applying the Log Pearson type 3 distribution for modeling annual inflow to the closed lake

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Abstract

Closed lakes in arid area are fed mainly by rivers annual runoff of which is characterized by high coefficient of variation coupled with very high coefficient of autocorrelation. This feature of river runoff leads to quasi-cyclic fluctuations of lake water level. It was demonstrated that such sequences of annual runoff are described well using Markov model with the Log Pearson Type 3 distribution (LP3) as marginal distribution. The possibility of the probabilistic forecast of the Lake Chany water level on the base of dynamic lake water balance equation and Markov stochastic models of the runoff, precipitation and evaporation is considered in the article.

Keywords

Log Pearson Type 3 distribution; Bivariate distribution; Stochastic modeling; Closed lake, Water level forecast

1. Introduction

In Russian Federation in most cases of hydrological calculations, three parameters Krytskyi and Menkel distribution is recommended by state regulations as a base one. However, the problem of justification of suitable one-dimension probability distribution in hydrology is not settled ones and for all. The purpose of this study was to find fitted distribution for estimation of the annual river runoff time series and then on the base of stochastic model to make a probabilistic forecast of the lake water level.

Stochastic model of the lake water level in the frame of the Markov process approach consists of three main components, namely

1. marginal distribution of the water balance components,
2. bivariate distribution for the simulation of the Markov chain,
3. water balance equation.
The principal two questions are what type of distribution for the water balance components (mainly for the water inflow) and which method of construction of bivariate distribution should be chosen. We proposed to use the Log Pearson Type 3 distribution for estimating of annual discharge series. An attempt was also made to provide a method of construction of bivariate probability density function on the base of bilinear series expansion using orthogonal polynomials. For this case the Log Pearson Type 3 distribution was introduced as weight function. The main usefulness of this approach is that we have bivariate distribution with linear regression equation.

2. The main properties of the Log Pearson type 3 distribution

The random variable \( x \) has a Log Pearson type 3 (LP3) distribution if \( y = \log_a x \) has a Pearson type 3 distribution (which is a gamma distribution when \( C_s = 2C_v \)). In general case, LP3 distribution is derived from the Pearson type 3 distribution by change of variable on the logarithm of this variable. In practice the most commonly used logarithm is the natural logarithm with base \( e \). The density function of the LP3 is defined as:

\[
 f(x; a, b, m) = \frac{1}{\Gamma(b)} x^m \exp[-a(\ln x - m)]
\]

where \( a, b, m \) – scale, shape and location parameters of distribution, \( b > 0 \), \( \Gamma(b) \) – the gamma function. When \( m = 0 \), the gamma type distribution is obtained.

The probability density given in Equation 1 has been investigated in detail [Bobée, 1975; Hoshi and Burges, 1981]. Here we give some properties of the Log Pearson type 3 distribution.

For Distribution 1 relationships between parameters of distribution and moments of logarithms of the observed series are following:

\[
 a = \frac{2}{C_s \sigma_n}, \quad b = \frac{4}{C_s^2}, \quad m = M_{\ln} - \frac{2\sigma_n}{C_s}
\]

where \( M_{\ln}, \sigma_n \) and \( C_s \) – mean, mean square deviation and coefficient of asymmetry of series of natural logarithms of the observed data, respectively. It results from Equation 2 that if coefficient of asymmetry of natural logarithms series goes to zero, the LP3 distribution converges to log normal distribution and parameters cease to exist. LP3
distribution is positively skewed within the interval for the random variable \( e^m \leq x < \infty \) always when \( a > 0 \); negative values of parameter \( a \) corresponds to negative coefficient of asymmetry of logarithmic transformed series of observed data for \( 0 < x \leq e^m \). The range of definition for Function 1 is limited depending on coefficients of asymmetry and variation as follows [Hoshi, Burges, 1981]:

when \( C'_x < C^3_{xx} + 3C'_{xx} \), then \( a < 0 \), \( 0 < x \leq e^m \). (3a)

when \( C'_x \geq C^3_{xx} + 3C'_{xx} \), then \( a > 0 \), \( e^m \leq x \leq \infty \). (3b)

The moments of order \( k \) about the origin are determined by a formula

\[
\beta_k = \int \frac{x^k}{\beta} f(x) \, dx
\]

where \( f(x) \) is the density distribution Function 1. For LP3 distribution moments are expressed as follows

\[
\beta_k = e^m \left( 1 - \frac{k}{a} \right)^{-1}
\]

(5)

And, if \( a < 0 \), moment \( \beta_k \) is always defined, if \( a > 0 \), then moment \( \beta_k \) is defined up to order \( k < a \) [Bobée, 1975].

The moments \( \mu_k \) about the mean are

\[
\mu_k = \sum_{i=0}^{k} C'_x (-1)^i \beta_x \beta_i
\]

(6)

Coefficients of variation and asymmetry may be expressed by

\[
C_x = \frac{\mu_x}{\mu_2}, \quad C_v = \frac{\mu_2}{\mu_1}
\]

(7)

It should be noted, that \( C_x \) and \( C_v \) depend only on parameters \( a, b \) and don't depend on parameter \( m \), and therefore they are expressed in the same way both for the log gamma and the log Pearson type 3 distributions.

To estimate the LP3 distribution parameters \( a, b, m \) we will apply the method of moments
to the observed data and find the logarithms of the first three moments from Equation 5 [Bobée, 1975; Hoshi and Burges, 1981]. Thus, we obtain

\[
\begin{align*}
\ln \beta_1 &= m - b \ln (1 - 1/a) , \\
\ln \beta_2 &= 2m - b \ln (1 - 2/a) , \\
\ln \beta_3 &= 3m - b \ln (1 - 3/a) ,
\end{align*}
\]

(8)

where \( \beta_1, \beta_2, \beta_3 \) – sample moments about the origin. Simple transformations of Equation 8 yield equations for estimation of parameters \( b, m \) and \( a \)

\[
\begin{align*}
b &= \frac{\ln \beta_2 - 2 \ln \beta_1}{2 \ln \left(1 - \frac{1}{a}\right) - \ln \left(1 - \frac{2}{a}\right)} \quad (9) \\
m &= \ln \beta_1 + b \ln \left(1 - \frac{1}{a}\right) \quad (10) \\
\Phi(a) &= \frac{2 \ln (1 - 1/a) - \ln (1 - 2/a)}{3 \ln (1 - 1/a) - \ln (1 - 3/a)} - \frac{\ln \mu_1 - 2 \ln \mu_1}{\ln \mu_3 - 3 \ln \mu_1} = 0 \quad (11)
\end{align*}
\]

3. Method of construction of bivariate probability density function

A common assumption in many hydrological models is that the considered stochastic processes are a Markov processes. It is known that Markov process is fully described by bivariate probability distribution. To construct bivariate distribution of random variables, Bolgov and Sarmanov used technique of the replacing variables for transition from uniformly distributed values of probability to values of variables which have the Pearson type 3 distribution. Then a probability density function (pdf) was presented as the bilinear series Legendre polynomial expansion [Bolgov, Sarmanov, 1996]. Thus, a bivariate pdf with nonlinear regression equation in relation to non-transformed variables is obtained.

However, if random process has very high coefficient of autocorrelation it is very significant to keep linearity of regression equation for two adjacent states of this variable, when simulation or forecasting modeling [Bolgov, Korobkina, 2012]. Sarmanov I.O. proposed to construct the bivariate density using the bilinear series orthonormal polynomials expansion [Sarmanov, Bolgov, 2004]. This method gives possibility to obtain density function which meets a Markov equation and linear regression equation is satisfied for random variables.

As follows from solution of Markov equation, there is a linear correlation between
positive random variables $x$ and $y$, if these variables have a joint probability density function expressed by

$$p(x, y) = p_1(x)p_2(y) \cdot \left[ 1 + \sum_{k=1}^{\infty} R^k p_k(x)p_k(y) \right]$$

(12)

where $p(x, y)$ is bivariate pdf, $p_1(x)$, $p_2(y)$ are marginal density functions, $P_k(x)$ and $P_k(y)$ are orthonormal polynomials, $R$ is the coefficient correlation between variables $x$ and $y$.

Explicit expression for orthonormal polynomials $P_n(x)$ is derived in terms of moments of weighted function [Szegö, 1959], which is a density function of a random variable, and defined as

$$P_n(x) = K_n \begin{bmatrix} \alpha_0 & \alpha_1 & \cdots & \alpha_n \\ \alpha_1 & \alpha_2 & \cdots & \alpha_{n+1} \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_{n-1} & \alpha_n & \cdots & \alpha_{2n-1} \\ 1 & x & \cdots & x^n \end{bmatrix}, \quad K_n = \left( D_{n-1}, D_n \right)^{\frac{1}{2}}, n = 1, 2, \ldots$$

(13)

where $\alpha_n$ is the moment of order $n$ about origin, $D_n$ is expressed as:

$$D_n = \begin{bmatrix} \alpha_0 & \alpha_1 & \alpha_2 & \cdots & \alpha_n \\ \alpha_1 & \alpha_2 & \alpha_3 & \cdots & \alpha_{n+1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \alpha_{n-1} & \alpha_n & \alpha_{n+1} & \cdots & \alpha_{2n-1} \end{bmatrix}$$

(14)

$$D_{n-1} = \begin{bmatrix} \alpha_0 & \alpha_1 & \alpha_2 & \cdots & \alpha_{n-1} \\ \alpha_1 & \alpha_2 & \alpha_3 & \cdots & \alpha_n \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \alpha_{n-1} & \alpha_n & \alpha_{n+1} & \cdots & \alpha_{2(n-1)} \end{bmatrix}$$

The Equation 13 can be written as

$$P_n(x) = K_n \left( A_{n,0} x^n + A_{n,1} x^{n+1} + \cdots + A_{n,2n-2} \right)$$

(15)

where $A_{i,j}$ is corresponding cofactor of the entry in the last row of the determinant in Equation 13. Polynomials $P_n(y)$ are determined by similar way, because of symmetry
considered case.

It should be noted that correlation between random variables $x$ and $y$ determined by **Equation 12** is linear. Conditional expectation of variable $y$ under fixed value of $x$ is expressed

$$\bar{y}(x) = M(y|x) = \int_0^\infty y p(x, y) / p_1(x) \, dy$$

**Equation 16**

Taking into account the equation for the joint density **Equation 12** and the property of orthogonality of polynomials $P_k(y)$, the **Equation 16** can be rewritten as

$$\bar{y}(x) = y_0 + R \frac{(x - \alpha_x)}{\sigma_x} \sigma_y$$

**Equation 17**

where $\sigma_x^2$ and $\sigma_y^2$ are standard deviations of random variables $x$ and $y$, respectively. That confirms linearity of regression function $\bar{y}(x)$.

The moments of order $k$ about the origin of conditional distribution of random variable defined as

$$m_{xk} = \int_0^\infty y^i p(x, y) / p_1(x) \, dy$$

**Equation 18**

Function $y^i$ can be expanded into series by orthonormal polynomials $P_k(y)$ as follows [Sarmanov, 1984]

$$y^i = C_{i1} P_1(y) + C_{i2} P_2(y) + \cdots + C_{ik} P_k(y)$$

**Equation 19**

Multiply both parts of **Equation 19** by $p_1(y) p_k(y)$ and then integrate obtained function over the interval $[0, \infty]$. Thus, using **Equation 15**, one obtains expression for calculation of coefficients of expansion $C_{i,k}$

$$C_{i,k} = K \sum_{j=1}^{IK} A_{ij} \beta_{j,i}$$

**Equation 20**

The substitution of **Equations 19-20** to **18** yields the expression for calculation of moments of order $k$ of condition distribution
So, using orthonormal polynomials with weight function in a form of three parameters distribution, we obtained symmetric bivariate distribution which is satisfied Markov equation and has linear equation of regression Equation 17.

4. Application LP3 to modeling annual inflow to the closed Lake Chany

The closed Lake Chany is of interest to researchers because of its unique water regime with interdecadal quasicyclic fluctuations which has different period long. The Lake Chany is situated in the south of the West Siberia, Russian Federation. It drains an area of 27,340 km² and covers an area about 1500 km². The water surface area of the lake depends on the wet or dry climate cycling, the depth of different parts is varied from 1,4–1,9 to 4,8–8,5 m [Savkin et al, 2005]. Kargat and Chulym rivers are the main tributaries of the Lake Chany.

The Lake Chany is the largest terminal lake in the Ob-Irtysh interfluvial region without drainage. Lake Chany has irregular shape and consists of two main parts, namely, Lake Bolshie Chany including three large pools and Lake Yarkul, and Lake Malye Chany (see Figure 1). All this parts are connected each other by channel and small flow path. The water level of the lake dropped sharply in 1967-68 years and fish kill in the lake was caused by. To rise up the lake level, the largest Yudinsky Pool (its water surface area in 60-ties was 700 km²) was separated from the main part of the lake in 1972 by several dams. In 1974 the spillway was constructed to regulate lake water level at high water. The optimal range of water level was determined from 106,5 to 107,5 m BS. The main purpose of lake level management is to keep optimal water level and salinity from the fisheries, agriculture and hunters points of view.

So, it is very important to develop stochastic models to be able forecast both annual and seasonal variability and manage of the lake level.

Method for stochastic modeling of the level of closed lake Chany was proposed before by authors on the base of the lake water balance equation and Markov stochastic models of fluctuations of the main water balance components – runoff, precipitation and evaporation [Bolgov and Korobkina, 2012].

Simulation of synthetic series of water balance components of the Lake Chany was
carried out on the base of joint (two-dimensional) distribution of random variables. Here we suppose that time series of the total annual inflow of Chulym and Kargat rivers distributed as Log Pearson 3 type, and precipitation and evaporation as three-parameters distribution of Kritskyi and Menkel. A bivariate probability density function was constructed by bilinear expansion in orthogonal polynomials series as described above, and then pdf was used to simulate annual inflow to Lake Chany. For this case the LP3 distribution was introduced as weight function.

Figure 1  *Lake Chany watershed.*

The substantial feature of river runoff of Chulym and Kargat rivers is very high value of coefficient of variation. Statistical parameters of annual runoff time series were estimated by method of moments and then parameters of Log Pearson distribution were found from **Formulae 9-11.** Thus, mean \( \bar{X} = 12 \, \text{m}^3/\text{s} \), coefficient of variation \( C_v = 0.93 \) and ratio of coefficients asymmetry and variation \( C_s/C_v = 1.9 \), and distribution parameters \( a = -3.17 \), \( b = 10.7 \), \( m = 2.93 \). Sampling statistical parameters of annual time series of the main components of the lake water balance presented in **Table 1.**

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Runoff, m³/s</td>
<td>Mean</td>
</tr>
<tr>
<td>12.6</td>
<td>0.93</td>
</tr>
<tr>
<td>Precipitation, mm</td>
<td>342</td>
</tr>
<tr>
<td>Evaporation, mm</td>
<td>541</td>
</tr>
<tr>
<td>Water level (1934-1972), m BS</td>
<td>106.2</td>
</tr>
<tr>
<td>Water level (1973-2006), m BS</td>
<td>106.18</td>
</tr>
</tbody>
</table>
Comparison of two stochastic models of runoff of the Chulym and Kargat rivers with linear (LP3 distribution) and nonlinear (Kritskyi and Menkel distribution) regression between adjacent values of random variables was carried out. It was revealed that they are both well fitted to empirical distribution function (Figure 2). But it appears that application of LP3 distribution as marginal distribution is more suitable for simulating of synthetic time series annual because of much more saving computational algorithm as compared with using of Kritskyi and Menkel distribution.

A number of probabilistic forecasts of the Lake Chany water level have been obtained for hypothetical scenarios of the water management within the lake watershed. Water level in the lake is controlled by spillway, several regimes of operation of which have been considered in the model for managing Lake Chany at high water level. Figure 3 demonstrates cumulative distribution function (separately for Yudinsky Pool and Lake Chany) for six scenarios of water use within the lake basin (Table 2).

The result of calculations demonstrated that operation of spillway leads to a marked reduction in mean annual values of the lake water level in the range of low probability events (2-3% or less). However, the operation of the spillway (discharges of water through spillway from the Lake to the Yudinsky Pool) does not give stabilization of the lake level.
fluctuations in a narrow range of values. To stabilize the lake level, the water transfer from other watershed(s) as well as reconstruction of the existing hydraulic facilities (first of all, spillway) have to be considered.

Table 2: Water management scenarios in the Lake Chany watershed for the water level forecasting

<table>
<thead>
<tr>
<th>No</th>
<th>Management activities</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Outflow regulator (orifice, spillway...)</td>
<td>crest level is 107.5 m</td>
</tr>
<tr>
<td>2</td>
<td>Outflow regulator (orifice, spillway...)</td>
<td>crest level is 106.5 m</td>
</tr>
<tr>
<td>3</td>
<td>Withdrawal</td>
<td>5% from the mean annual inflow to the lake</td>
</tr>
<tr>
<td>4</td>
<td>Withdrawal</td>
<td>10% from the mean annual inflow to the lake</td>
</tr>
<tr>
<td>5</td>
<td>Water transfer from other river basins</td>
<td>5 m³/s (if water level in the lake is less than 107.0 m BS level)</td>
</tr>
<tr>
<td>6</td>
<td>Water transfer from other river basins</td>
<td>10 m³/s (if water level in the lake is less than 107.0 m BS level)</td>
</tr>
</tbody>
</table>

Figure 3  Cumulative distribution function for the six scenarios of water management within the Lake Chany watershed.
5. Conclusions

A bivariate probability density function constructed as bilinear series expansion using orthogonal polynomials in the form of explicit definition through the moments of weight function have been proposed to simulate annual inflow to Lake Chany. For this case the Log Pearson Type 3 distribution was introduced as weight function. It appears that application of LP3 distribution as marginal distribution is useful because of much more saving computational algorithm are created as compared with using of Kritskyi and Menkel distribution.

The probabilistic forecast of the Lake Chany water level on the base of dynamic lake water balance equation and Markov stochastic models of the runoff, precipitation and evaporation was carried out. Further attempt should be made to evaluate possibility of effective lake water level managing.

Acknowledgments
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References

Pareto – optimal model output correction model selection

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Abstract

Ideas from the field of mathematical optimization will be employed in order to gain a new view on model output correction. We will compare several kinds of models with regard to their performance considering model output correction multidimensionally. Decision problems we were confronted with will be discussed, as well as the quality and shortcomings of the models our research resulted in. We will point out in what direction future research might head and what behavior is to be considered bad when it comes to model output correction modeling. Furthermore, we will point out, that one metric of model performance performs poorly with respect to our problem.

1. Introduction

The German Federal Institute of Hydrology (BfG) provides – among many other services – waterlevel forecasts for the German Federal Waterways. Among these waterways are the rivers Rhine and Danube which both belong to the most heavily used waterways in Europe. For this reason, waterlevel forecasts for these rivers are of great interest for the European economy. Also, accurate waterlevel forecasts may aid as a warning system that will help informing the local authorities to take measures against floods in advance so that lives of people and their property are protected against the hazardous effects of floods.

In order to be able to forecast the water-level of the German Federal Water-ways, the BfG operates a hydrological model – the HBV model [6] – coupled to a hydraulic model – the SOBEK model – by the FEWS-framework at the River Rhine. This combination of models and solvers compute future water levels, but a great caveat of forecasting is, that one is always confronted with a great deal of uncertainty (confer [7]).

This uncertainty has multiple causes: besides the input uncertainty of current and future weather conditions and the unknown - and therefore uncertain - initial conditions, a major source of uncertainty is the forecasting model itself. Hydrological and hydraulic models are only mathematical abstractions of the reality and the estimation of the model parameters is uncertain. Also, errors may arise from the mathematical schemes that are
used to compute within these models, since most numerical algorithms are either very general schemes whose accuracy is of very low order, or their accuracy is of high order, but they are so specialized that they work only with certain kinds of problems and fail with all the other problems.

In order to reduce the influence of the model error in forecasting, a variety of schemes has been developed and tested by the scientific community. But in general, there only exist rules of thumb which aid the forecaster when it comes to choosing the best model. We will interpret the question of how to select forecast error-correction models as a multiobjective optimization problem, and therefore, we will use ideas from multiobjective optimization in order to legitimize our choice of models, because there exist many metrics that measure the quality of a numerical approximation scheme, but when it comes to selecting a good numerical scheme, most times one relies on just one metric. Also, in many instances, researchers only consider a few numerical models, and thereby limit themselves and the choices they can make.

In Section 2, we will give the reader a short introduction to time series analysis. Section 3 will be devoted to multiobjective optimization and the concept of domination. The search space of the optimization problem and the implementation of domination in this setting will be presented in Section 4. In Section 5, the scheme of multiobjective optimization will be applied to the problem of model forecast error-correction. We will summarize our experience and give the reader an outlook as to where future research might be heading in Section 6.

2. Time Series Analysis

Even though time series analysis is a vast field of scientific research, we limit ourselves in this section to only consider these aspects that were of importance during the work that resulted in this paper.

2.1. Autoregressive Models

Autoregressive models (AR) are linear models that formulate the idea that the future of a given quantity is a linear extrapolation of that quantity’s past [1]:

\[ y_t = \delta + \sum_{i=1}^\infty \alpha_i y_{t-i} + \varepsilon_t \]  \hspace{1cm} (1)
where \( y_t \) is the variable in question at time point \( t \), the \( \alpha \) are weights that weigh the influence of different time steps, and \( \varepsilon_t \) is a random shock that influences \( y \) at time point \( t \). \( \delta \) is a variable that reflects that the long-time mean of \( y_t \) is non-zero. In the above formula, we call \( n \) the order of the model.

### 2.2. ARIMA Models

ARIMA models [1] are an extension to AR models. The difference between an AR and an ARIMA model is, that the ARIMA model extends the AR model by so called Moving Average terms [1].

\[
zt + \delta + \sum_{i=1}^{n} \alpha_i z_{t-i} = \sum_{i=1}^{m} \beta_i \varepsilon_{t-i}
\]

(2)

where \( z_t \) is a possibly differentiated version of the variable which is used to describe the time series, \( \beta_i \) are the weights that weigh the influence of the random shocks \( \varepsilon_t \). By “differentiated version of the variable”, we mean the following: let \( y_t \) be the variable that is monitored. Then \( z_t \) is the first derivative of \( y_t \) if

\[
z_t = y_t - y_{t-1}
\]

(3)

Obviously, we can achieve higher orders of differentiation by iterating the scheme we pointed out in Equation 3. Usually, one differentiates a time series using the scheme from Formula 3 in order to remove polynomial trends from the data.

### 2.3. VARX Models

Furthermore, in this study, we consider VARX models which were trained upon the wavelet decomposition of a time series. Since we are only considering the wavelet decomposition using the Haar wavelet, we may summarize the wavelet decomposition the following way: let \( h = (0.5, 0.5) \) be the discrete low pass filter, and let the signal be \( s_0(t) = y_t \) where \( y_t \) is the original time series. Now let

\[
s_{-1}(t) = \sum_{l=0}^{k} h(l)s(k + 2l)
\]

\[
d(k) = s_{-1}(k) - s(k)
\]

\[
y_t = s_k(t) + \sum_{i=1}^{m} d_i(t)
\]

(4)

Then, we can interprete \( s_k \) as a smoothed version of the original time series, and \( d_i \) as the difference between two consecutive scales of smoothing, the so called details.
Since these $d_i$ are the difference between two different scales of smoothing $s_j$, these $d_i$ only contain temporal dynamics which last longer than $2^i - 1$ time steps. Therefore a wavelet decomposition of a time series results in a set of time series with different lengths of the minimal dynamic which is contained in these resulting time series.

VARX models are multidimensional AR models with an exogeneous input. Following the notation from [3], we may write a VARX model as

\[
x_{i,t} = \phi x_i + \gamma u_i + \varepsilon_i \\
y_i = A x_i + B u_i + \tilde{\varepsilon}_i
\]  

(5)

$x_i$ is an unobserved state vector that is rendered by matrix $\phi$ and by the exogeneous input vector $\gamma$, where $u_i$ is the exogeneous input vector and $\gamma$ is a matrix of appropriate dimension. $\varepsilon_i$ is a vector of random shocks. This means, that the observed vector $y_i$ is rendered by the unobserved vector $A x_i$, the observed exogeneous input vector $Bu_i$, and the random shock vector $\tilde{\varepsilon}_i$. In our case, $y_i$ is the vector of the wavelet decomposed measurement signal, $A x_i$ is the vector of the difference between $y_i$ and $Bu_i$, and $u_i$ is the vector of the wavelet decomposed simulation result. This scheme allows to create a multidimensional time series model for the different components of the wavelet decomposition of the observed variable using the wavelet decomposed time series of the simulation data and a vector that models the difference between these two time series vectors.

3. Multiobjective Optimization

Mathematical optimization is a vast field and study upon the solution of optimization problems accompanies the research of mathematics throughout its history.

In the case of multiobjective optimization, one does not attempt to optimize one single objective function, but rather one tries to optimize several objective functions simultaneously. Depending on the nature of the optimization problem, these different objective functions might be competing. This means that an improvement of one objective function worsens another objective function.

There exist several approaches to solve multiobjective optimization problems: when the set of possible solutions is small enough, one usually computes all possible solutions and evaluates these. If the search space is too big, one usually applies randomized
algorithms like genetic algorithms [4], particle swarms [5] or evolutionary algorithms [4]. All these schemes have in common, that solutions are created, and that these solutions are evaluated according to the objective functions.

In order to compare these solutions multidimensionally, the concept of Pareto optimality was introduced: if solution $A$ outperforms solution $B$ in every single objective function, then solution $B$ is called “dominated” by solution $A$. If solution $B$ is dominated by another solution, we know that knowing solution $B$ is of no value for finding optimal solutions, and therefore we can ignore all dominated solutions. All solutions that are not dominated are part of the Pareto front. Hence, the Pareto front formulates the tradeoff between the competing objectives of the optimization problem at hand.

That is why we create several solutions, compare them, and then remove the dominated solutions from the set of possible solutions.

4. The Search Space

In Section 2, we introduced the reader to basic time series analysis and in Section 3, a short introduction to multiobjective optimization was given. In this section, we want to combine our knowledge gained from the previous sections in order to create a toolbox that enables us to select the "best" output correction model.

4.1. Of Models and Errors

Models can only approximate reality. Since we know this, we have to develop metrics that are able to evaluate how well a model performs.

The most basic error metric is the Mean Absolute Error (MAE). This metric evaluates the distance between the measured reality and the model output. Let $o_i$ be a measurement and let $s_i$ be the corresponding simulation, then we can write the MAE as

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |o_i - s_i|$$

Some kind of relative of the MAE is the Maximum Absolute Error (MaxAE). Whereas the MAE considers the distance between all observations and their corresponding simulations, the MaxAE focuses solely on the maximal distance between simulation and measurement:
\[ \text{MaxAE} = \max_i |o_i - s_i| \]  

(7)

In the case of MAE and MaxAE, we want to minimize the metric.

A somewhat more elaborate metric is the Nash Sutcliffe Model Efficiency Coefficient (NSE). The NSE compares the squared distance between observation and simulation with the squared distance between observation and the mean of the observation:

\[ \text{NSE} = 1 - \frac{\sum_{i=1}^{n} (o_i - s_i)^2}{\sum_{i=1}^{n} (o_i - \mu)^2} \]  

(8)

where \( \mu \) is the mean of the observations. Since both, nominator and denominator are always positive, the NSE cannot produce values greater than 1. This results in the fact, that a good model has a NSE of approximately 1, whereas a bad model has a NSE lesser than 1. This means, that the NSE of a good model tends to be great, whereas the MAE and the MaxAE of a good model tend to be small.

Another metric of how well a model performs is the variance (\( V \)) between the observations and the simulations: if a model approximates reality well, there should be small differences between measurement and simulation, and therefore, the variance between both should be small:

\[ V = \frac{1}{n-1} \sum_{i=1}^{n} ((o_i - \mu_o) - (s_i - \mu_s))^2 \]  

(9)

In Formula 9, \( \mu_o \) is the mean of the observations and \( \mu_s \) is the mean of the simulations. The problem with variance as an error metric is, that the variance only considers how much the simulations and the observations deviate from the mean of the difference between these two.

If the difference of the means of simulation and observation is not zero, the model produces a non-negligible error, because the model either tends to overestimate or to underestimate. This error is measured by the bias (\( B \)), where we take the difference of the means of the observations and the simulations. Since we do not differentiate between over- and underestimation, we take the absolute value:
One final metric we would like to mention is the Pearson correlation \( r \) between the observations and the simulations. Since we want our simulation model to react properly, we will prefer models whose correlation has an absolute value close to 1, since these models have a strong linear relationship to the observations. Yet we have to stress, that the Pearson correlation only measures linear dependencies, and therefore that the Pearson correlation is not able to capture nonlinear relationships. But since the models we introduced in Section 2 are linear models, a metric that captures linear dependency is sufficient.

\[
r = \left| \text{Corr}(o,s) \right| \quad (11)
\]

If we consider our search for optimal models as an optimization problem, we can use all these 6 metrics as objective functions. Obviously, we want to minimize the \( \text{MAE} \), the \( \text{MaxAE} \), \( B \) and \( V \), and we want to maximize \( \text{NSE} \) and \( r \).

### 4.2. Configurations

Since some of the metrics we introduced above are nonlinear and since we have no a priori knowledge on the relationship between different configurations of the time series models and their behavior with respect to the metrics from above, we have to rely on search procedures for solving the optimization problem of finding the best model. Due to reasons of simplicity, we perform the necessary computations using the statistical programming language GNU R (confer [8]).

Our procedure will be the following: instead of fitting one single model to a set of data, we will differentiate between different configurations. We will pick one configuration and use a rolling temporal calibration window and fit an individual model to every calibration window according to the model configuration. In the case of AR models, we will differentiate between the order of the AR models and the length of the calibration window. We will vary the length of the calibration window because there are good reasons for short and for long calibration windows: if we use short calibration windows, the model will learn the most current dynamics in the data set and therefore adapt better to these current dynamics than if we used a longer calibration period, where the most current dynamics in the data set are not as prominent as they are in a short calibration period. On the other hand, measurement errors are of much greater influence in a short
calibration period because of the shortness of the data set, whereas in the case of a long calibration period, measurement errors will be statistically less important. We will also try different orders for the AR models. AR models with low order have in theory inferior capability to adapt the dynamics in a data set whereas models with high order may be prone to overfitting. Therefore, in the case of AR models, the configurations will differ with respect to the length of the training period and the order of the AR Model.

In the case of ARIMA models, we will limit ourselves to only considering different lengths of the calibration period. For each of the rolling temporal calibration windows, we will have the best model with respect to the AIC selected by the function "auto.arima" from the GNU R package "forecast" (confer [9]).

In the case of the VARX models, we will consider different numbers of scales of the wavelet decomposition, different lengths of the calibration period, and we will also consider hard and soft thresholding. In the case of hard thresholding, a threshold is introduced, and all data that are absolutely smaller than the threshold are set to zero. In the case of soft thresholding, all data are corrected by multiplication with that threshold. Using different numbers of scales results in a different filtering of the data set: the more scales are used for the wavelet decomposition, the more dynamics of the data set are extracted. Again, if we use too many scales, our VARX model will be prone to overfitting, if we use too few scales, we might miss important dynamics.

The observation and simulation data that were used for the wavelet decomposition were normal quantile transformed. For this, we used a sample of those data and created for each data set an interpolation function. Let $d$ be a datum, let $v$ be the result of the mapping, $P$ the cumulative density function that maps the probability that a datum is smaller than $d$ and $\Phi$ the standard normal distribution. Then

$$v = \Phi^{-1}(P(d))$$

4.3. The Search Space

In the case of AR models, we will vary the length of the calibration period between 192 and 8600 hours using steps of 1680 hours. We will vary the order of the models between 3 and 50.

In the case of the ARIMA models, we will only vary the length of the calibration period. We will vary those lengths as in the case of the AR models. "auto.arima" [9] is set up to consider at most 5 AR terms and at most 5 MA terms. The selection of the models is done
using the AIC. Therefore, "auto.arima" considers every single model of the 36 possible combinations of the AR and MA terms. Since we wanted to keep the computational effort for the AR models and the ARIMA models comparable, we limited the search space of "auto.arima" to at most 5 AR and at most 5 MA terms.

In the case of the VARX models, we will vary the length of the calibration period as in the case of the AR models. We also will vary the number of scales of the wavelet decomposition between 4 and 13 wherever it is possible, because for being able to use a scale $j$ we need at least $2^j - 1$ data points. As mentioned before, we will also vary between hard and soft thresholding.

Therefore our search space will contain AR models with varying length of calibration window and varying order, ARIMA models with varying length of calibration window, and VARX models with varying length of calibration window, varying number of scales and varying thresholding. Since we do not know the response surface of this search space, we will perform a complete search: we will consider every possible model that can be constructed based on the properties defined above, and have these models evaluated according to the metrics we introduced in the beginning of this section.

4.4. Domination
Since we will consider six different metrics we have to have some kind of idea how we can formulate domination. Specifically, we will apply our models to learning the difference between measured runoff and the forecasts made by the HBV model [6]. Therefore, for every forecast date in the validation data a forecast of the systematic error of the HBV model for the first 175 hours after the forecast date will be made for every configuration considered. We will evaluate the error metrics for every single time step in the forecast horizon, i.e., we will evaluate the $MAE$, the $MaxAE$, the $NSE$, the $V$, the $B$ and the $r$ for every single hour of the 175 hours forecast horizon.

We decide whether a given model $A$ or model $B$ performs better with respect to metric $X$ the following way:
In the formulae above, \( A \ trm{dominates} B \) denotes that model \( A \) dominates model \( B \) with respect to metric \( X \). For the computation of the score \( s \) we test for every time step of the forecast horizon, whether the value \( a_i \) or \( b_i \) is greater, where \( a_i \) is the performance value of model \( A \) with respect to metric \( X \) at forecast date \( i \). Since we want to maximize the values of \( NSE \) and \( r \), but minimize the values of \( MAE \), \( MaxAE \), \( B \) and \( V \), we introduce the projection \( m(x) \) that differentiates between those metrics, that we want to maximize, i.e. \( NSE \) and \( r \), and those, that we want to minimize. This condenses to the following idea: \( A \) dominates \( B \) according to metric \( X \) if \( A \) outperforms \( B \) with respect to metric \( X \) in more time steps of the forecast horizon than \( B \) outperforms \( A \).

In line of thought, model \( B \) is dominated if there exists at least one model \( A \), so that \( A \ trm{dominates} B \) for all metrics considered. All models, that are not dominated, are part of the Pareto front.

5. Application

We will apply the thoughts from above to three gauges, Maxau at the river Rhine, Grolsheim at the river Nahe and Trier at the river Moselle. We chose these stations since the river Rhine is the most important waterway of Germany, and the rivers measured at these gauges all influence the river Rhine. Also, these gauges represent catchments of different size, different anthropological influence and also different sizes of their runoffs. The catchment of the gauge Maxau is 50196 km\(^2\) big and the MQ is 1253 m\(^3\)/s. The river Rhine near Maxau is influenced by barrages upstream of Maxau. The catchment of the gauge Grolsheim is 4013 km\(^2\) big and the MQ is 30.5 m\(^3\)/s. Amongst the three stations Grolsheim is the one least influenced by human impact. As a natural impact floods in the river Rhine may cause backwater effects in the river Nahe which is measured at Grolsheim. The gauge at Trier is heavily influenced by man because of the numerous weirs along the Moselle River. The size of the catchment of Trier is 23857 km\(^2\) and the MQ is 280 m\(^3\)/s.
For each gauge, we used a data set of 3 years of measurements and simulation results. Since we wanted to develop a system whose results might be applicable in the operational forecasting service of the Federal Institute of Hydrology, we simulated for every day in our data set forecasts starting at 6 a.m.. These forecasts were evaluated using the six metrics introduced above. We then used the ideas from above in order to distinguish the dominated models from the non-dominated models. For every gauge, we produced two plots: one plot that contains the results for all models that were part of the Pareto front, and one plot, that only contains those models that performed best with respect to at least one metric. In all of the following plots the black line corresponds to the performance of the uncorrected HBV model in continuous simulation mode. Since the HBV model is used by the BfG to make predictions, we use the uncorrected model in order to evaluate what improvements of the quality of the forecasts are achieved by applying the different models from the Pareto front.
In Figure 2 we see the performance of all models in the Pareto front coloured from red to blue. Since we were simulating use case behavior where we made only one forecast per day, the quality of the forecasts made by the HBV model has a daily cycle. This daily cycle might be explained, for example, by anthropogenic or physical processes that influence the runoff but which are not modeled by the HBV model appropriately. In this Pareto front, we clearly see the tradeoff between different metrics: if we preferred a model with a high NSE score, we would prefer the red models. But exactly these red models perform poorly considering MAE and V. We also notice, that applying models from the Pareto front only can help improving the performance of the HBV model with respect to the error metric bias.
In Figure 3 we clearly see the tradeoff with respect to different metrics. In this plot, we selected for every metric the best model, and again, we see that the red model performs best with respect to $\text{MAE}$ but worst with respect to $B$. The brown model performs best with respect to $B$ but worst with respect to $\text{NSE}$.

In Figure 4 we again see a tradeoff with respect to different metrics. In Maxau, the blue models perform best with respect to $\text{MAE}$ but worst with respect to $\text{NSE}$. This tradeoff is also depicted in Figure 5.

In Figure 6 we notice, that for the Trier data set all members of the Pareto front performed almost identically. This is also depicted in Figure 7.

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Figure 3  The best models for Grolsheim
Figure 4  The Pareto front for Maxau

Figure 5  The best models for Maxau
Figure 6  The Pareto front for Trier

Figure 7  The best models for Trier
In Figure 4 we notice that one model performs very bad considering the $MaxAE$. If we take a look at that data set, we notice, that this huge error is produced by the forecast in Figure 8. In this picture, black depicts the observations, blue depicts the output of the HBV model, and red depicts the error-correction that is proposed with respect to the criterion of Pareto optimality. We notice, that the error-correction works almost perfectly right in the beginning of the forecast, but after that, the correction does not match the rise in the observations. Also the correction exhibits some kind of swingy behavior which would result in predictions that do not look and feel natural. We would like to point the reader to the fact, that models like this may be part of the Pareto front, unless one develops a metric that punishes swingy behavior.

Furthermore, we notice that this model only performs in the first few time steps significantly worse than the others with respect to the $MaxAE$. After the first 50 hours, this model performs, with respect to the $MaxAE$, better than most of the blue models. According to our formulation of domination (Equation 13) bad behavior that is limited to a short period is better than bad behavior for a long period of time. This is why the model in question can not be dominated by the blue models. Also, if we take a look at the bias, we clearly notice, that all of the blue models are outperformed by the red models, and therefore that faulty model (with respect to the $MaxAE$) can not be dominated by the blue models with respect to the bias. From this, we conclude, that $MaxAE$ is a bad error metric, because it punishes models for their worst behavior. If we imagine the extreme case of a model performing perfectly for all but one cases, and miserably in that remaining one case, we would imagine a model that would perform miserably with respect to $MaxAE$ whereas its miserable behavior is limited to just one single case. Due to these considerations, we will omit all metrics that simply consider the maximum bad behavior in future research.
6. Summary and Outlook

In this paper, we examined the problem of finding model output-correction models in a strictly linear and multidimensional perspective. We found out, that there are data sets, for which we cannot determine a single best correction model, but where we rather have to accept a tradeoff between different error metrics. This means that we have to formulate what tradeoff we are willing to make. We also have to consider, what metrics are of great importance, and what metrics are of minor importance.

We found out, that there might be solutions to our problem which appear to be good if we consider the metrics at hand alone, but which might behave undesirably if we have a closer look at the data (confer Figure 8). Therefore, we have to develop metrics that punish unnatural behavior of our error correction models.

Figure 8  One example for erroneous swingy behavior
We also limited ourselves to the examination of linear models alone, whereas we could delve into nonlinear output-correction models.

Furthermore, we did not incorporate any external knowledge like weather time series.

Thus, our future line of research will be:
1. develop a metric that punishes undesirable behavior
2. explore nonlinear models
3. incorporate external information

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8. R Core Team (2013). R: A Language and Environment for Statistical Computing
Flood Frequency Analysis at River Confluences – Univariate vs. Multivariate Extreme Value Statistics

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Abstract

In this study we analyze the combined flood probability at a confluence using different statistic procedures. The study is exemplarily carried out at the confluence of the rivers Ilz and Wolfsteiner Ohe in Germany, where long time series of the hourly discharge are available at both rivers upstream of the confluence as well as downstream. On the one hand we perform a univariate statistical flood frequency analysis upstream and downstream of the confluence as it is applied commonly at major German rivers. The aim is to determine the statistical relevant inflow of the tributary for several given design discharges at the main stream. On the other hand we perform a bivariate statistical analysis using Archimedean copula functions at both streams upstream of the confluence. Comparing the results highlights the limited capability of the univariate approach to determine the statistical relevant inflows from the tributary. In particular for higher return period discharges at the main stream, the resulting inflows from the tributary differ from the results of the bivariate statistical analysis.

1. Introduction

Design discharges at rivers are required for many engineering purposes, e.g. numerical inundation modeling, design of flood protection structures, etc. As an alternative to rainfall-runoff modeling, a broad variety of univariate statistical methods are available to determine the design discharges (e.g. HQ100) along rivers based on recorded discharge data (see e.g. Rao and Hamed, 2000). However, gauge data upstream of a confluence does not provide information on the statistical relevant inflow from the tributary. Especially for flow modeling along a river the inflow boundary conditions of tributaries are of great interest. Not at least because inflows affect the water levels downstream of the confluence and can cause hydraulic effects, like turbulences and tailbacks. In Germany only few approaches exist to estimate the statistical relevant discharge boundary conditions at a tributary for a given design flood at the main stream and vice versa. One of those approaches is the so called "Confluence Formula" (German: Mündungsformel). Today, the Confluence Formula is a widely used approach to estimate the discharge conditions at river confluences in Germany. The formula was developed by the Federal Department
of Environment of the state Baden-Wuerttemberg on basis of gauge records at a single confluence of two rivers. Due to the lack of available methods, however, the Confluence Formula is often applied to other ungauged rivers neglecting different topographical and hydrological boundary conditions of the catchments.

Several studies have been carried out considering the bivariate nature of this concern. Morris and Calise (1987) estimated the joint flood probability at a tributary, which is influenced by the water level in the main stream. They used bivariate density functions to describe the dependence between the water level in the main stream and the tributary.

Raynal and Salas (1987) were the first who used the bivariate General Extreme Value (bGEV) distribution in the context of joint flood risk at the confluence of the rivers Bear and Dry Creek in California, USA. They compared four approaches to estimate the total discharge downstream of a confluence: (i) with the sum of the recorded discharges, (ii) under the assumption of a perfect linear dependence (i.e. correlation of one) between the main stream and tributary discharges, (iii) under assumption of independence (correlation of zero) between the discharges, and (iv) with the use of the bGEV considering a correlation of $r = 0.86$. They suggested that the correlation coefficient was a suitable measure to describe the dependence and they proposed the application of the bivariate Normal distribution function for estimating the joint probability of floods at confluences.

Over the last years copula functions have been used for several multivariate hydrological analyses. They were applied for rainfall frequency analysis (e.g. De Michele and Salvadori, 2003, Grimaldi and Serinaldi, 2006, Zhang and Singh, 2007), flood frequency analysis considering peak flow and flood volume (e.g. Favre et al., 2004, Zhang and Singh, 2006, Karmakar and Simonovic, 2009), drought frequency analysis (e.g. Shiau, 2006, Kao and Govindaraju, 2010, Song and Singh, 2010a, b), storm surge modelling (e.g. Wahl et al., 2012), and for several other multivariate problems.

For flood risk analyses at river confluences copulas were already used by Wang et al. (2009). They presented a copula-based algorithm to determine the joint probability at a river confluence using copulas of the Archimedean family. Using Monte-Carlo simulations they determined the joint probability of a concurrent occurrence of flood events in both streams.

NCHRP (2010) first presented a general approach to estimate the joint flood risk at ungauged rivers for the design of road drainage structures. The study was based on 83 homogeneous distributed gauge pairs throughout the USA. Basically three multivariate
methods were applied: bivariate distribution functions, copula functions and the total probability method. For the generalization of the results from individual gauge pairs they used the ratio of the confluent catchments.

Chen et al (2012) used 4-dimensional Copula functions to model the coincident risk of concurrent occurring flood magnitudes and dates at confluences. Case studies were the upper Yangtze River in China and the Colorado River in the United States.

At German major rivers, where a dense network of discharge gauges exists, this bivariate issue is however still reduced to a univariate problem. This allows the application of common extreme value models to the data sets from all gauges along the stream. The difference between two design discharges derived by two neighbored gauges is then considered as the statistical relevant discharge of all tributaries between the gauges. If there is more than one tributary between two gauges the inflow of the individual tributaries is weighted according to the catchment sizes (BfG, 2009).

In the present study we conduct two analyses of the joint flood occurrence at a gauged river confluence in Germany. First, the simplified univariate approach is applied as it is done at the German major rivers. In a second step we use Archimedean copula functions to determine the joint flood risk. The main intention of this study is to compare the results of both approaches to determine their capability of assessing the joint flood risk at the confluence.

2. Data

2.1. General

This study is exemplarily carried out at the confluence of the river Ilz and its tributary Wolfsteiner Ohe in Bavaria, Germany. Hourly discharge data are available at river Ilz some 2.2 km upstream (gauge Schrottenbaumühle) as well as 3.6 km downstream (gauge Kalteneck) of the confluence. The river Wolfsteiner Ohe has a gauge (Fürsteneck) approx. 2.0 km upstream the confluence with the river Ilz (see Figure 1). All time series were provided by the Federal Environment Authority of Bavaria and cover the period from 1972 to 2011, i.e. 40-yr long time series without gaps or discontinuities are available for the analyses.
River Ilz drains at gauge Schrottenbaumühle a total area of 364 km² upstream of the confluence, whereas river Wolfsteiner Ohe contributes at gauge Fürsteneck an almost equal drainage area of 370 km². The mean discharge at gauge Schrottenbaumühle amounts to $MQ_s = 7.6 \text{ m}^3/\text{s}$ with a standard deviation of $s_s = 7.7 \text{ m}^3/\text{s}$. At gauge Fürsteneck and gauge Kalteneck the mean discharges and the standard deviations amount to $MQ_F = 8.5 \text{ m}^3/\text{s}$, $s_F = 8.0 \text{ m}^3/\text{s}$, and $MQ_K = 16.6 \text{ m}^3/\text{s}$, $s_K = 16.3 \text{ m}^3/\text{s}$, respectively. The highest discharges at all three gauges were observed on 21st December 1993 with $HHQ_s = 208.1 \text{ m}^3/\text{s}$ at gauge Schrottenbaumühle and $HHQ_F = 192.4 \text{ m}^3/\text{s}$ at gauge Fürsteneck which in turn resulted in a maximum discharge at gauge Kalteneck of $HHQ_K = 416.9 \text{ m}^3/\text{s}$. Although the highest measured flood peaks occurred at the same day, thorough investigations show that 13 of the total 40 annual maximum flood peaks at rivers Ilz and Wolfsteiner Ohe did not occur concurrently within a time frame of ±7 days.

2.2. Measurement Inaccuracies

A general problem in flood frequency analysis based on discharge data sets is related to inaccuracies of the measurements. In particular during extreme events the extrapolated water level-discharge function (discharge curve) often leads to large errors since discharge curves are calibrated on measurements during low or medium runoffs (Maidment, 1992). In the case at hand considerable discrepancies between the sum of the gauge data upstream and the gauge data downstream of the confluence can be found, especially during flood events. Although no information is available on incorrect operation of any of the gauges, these discrepancies would affect the results of the statistical analysis. For that reason and by having the exemplary nature of this study in mind, the discharge data at gauge Kalteneck is replaced by a synthetic time series derived by the sum of the discharges observed at the two gauges located upstream:

$$Q(t)_{Kalteneck\ syn} = Q(t)_{Schrottenbaumühle} + Q(t)_{Fürsteneck}$$

(1)
3. Methods

3.1. Simplified univariate Approach

The univariate approach only uses the discharge time series at the main stream, up- and downstream of the confluence, which are in this case the gauges Schrottenbaumühle and Kalteneck (synthetic). A common univariate flood frequency analysis is carried out for both time series using extreme value distribution functions. The annual maximum discharges (AMAX) of the hydrological years (in Germany from 1 November until 30 October) is considered as the relevant flood indicator. For catchments smaller than 50,000 km², as it is the case here, Svensson et al. (2005) suggested considering a minimum time interval of five days as independence criterion in order to separate consecutive flood events.

In a next step, univariate distribution functions are fitted to the AMAX series of the gauges at the main river upstream and downstream of the confluence. Although the General Extreme Value distribution (GEV) is often being treated as one of the main distribution functions for extreme value analyses (e.g. Coles, 2001), other distribution functions are additionally fitted to the data set. The most appropriate distribution function is identified by the minimum root mean square error (RMSE) of the empirical distribution and the parametric distribution function. The distribution parameters are estimated with the maximum likelihood approach (e.g. Rao and Hamed, 2000) and the plotting positions are derived by following the approach proposed by Gringorten (1963). Further Information about flood frequency analyses can be found e.g. in Rao and Hamed (2000).

Next, all relevant quantiles of the parametric distribution functions are determined. In this study we focus on the common quantiles in flood frequency analyses for the non-exceedance probabilities of \( P = 0.5, 0.8, 0.9, 0.95, 0.98 \) and \( 0.99 \) with the corresponding annual return periods of \( T = 2, 5, 10, 20, 50 \) and \( 100 \) years. Since higher return periods then these are usually of minor interest for design purposes, they are not considered in this study. The difference of the downstream quantiles and the upstream quantiles are treated as the statistical relevant inflow of the tributary for a given flood event at the main stream with an annual return period of \( T \).

3.2. Bivariate Approach using Copula Functions

3.2.1. Theoretical Background

Copulas are flexible joint distributions for modeling the dependence structure of two or even more random variables. First mentioned by Sklar (1959), the joint behavior of two (or
more) random variables $X$ and $Y$ with continuous marginal distributions $u = F_X(x) = P(X \leq x)$ and $v = F_Y(y) = P(Y \leq y)$ can be described uniquely by an associated dependence function or copula-function $C$. In the bivariate case, the relationship between all $(u, v) \in [0,1]^2$ can be written as

$$F_{x,y}(x,y) = C[F_X(x), F_Y(y)] = C(u,v) \quad (2)$$

where $F_{x,y}(x,y)$ is the joint cumulative distribution function (cdf) of the random variables $X$ and $Y$.

A copula function with a strictly monotonically decreasing generator function $\phi: [0,1] \rightarrow [0,\infty]$ with $\phi(1) = 0$ belongs to the Archimedean Copula family. The general form of one-parametric Archimedean copulas is

$$C_\theta(u,v) = \phi^{-1}[\phi(u) + \phi(v)] \quad (3)$$

where $\theta$ denotes the copula parameter. In this study three Archimedean copulas, namely the Clayton, Frank, and Gumbel copulas are considered. They are relatively easy to construct, flexible and capable to cover the full range of tail dependencies. The Clayton copula has lower tail dependence, while the Frank copula has no tail dependence and the Gumbel copula has strong upper tail dependence (Schölzl and Friedrichs, 2008). The copula parameters are estimated based on the inversion of Kendall’s $\tau$. This is possible as there exists an expression for $\tau$ as a function of $\theta$ for Archimedean copulas (see Table 1).
Table 1: Archimedean copula functions considered for the present study and their generator functions, ranges for the copula parameters $\theta$ and functional relationship to Kendall’s $\tau$.

<table>
<thead>
<tr>
<th>Copula function $C_{\theta}$</th>
<th>Generator $\phi(t)$**</th>
<th>Range of $\theta$</th>
<th>Functional relationship of $\theta$ to $\tau$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clayton or Cook-Johnson</td>
<td>$u^{-\theta} + v^{-\theta} - 1$</td>
<td>$[0, \infty)$</td>
<td>$\frac{\theta}{\theta + 2}$</td>
</tr>
<tr>
<td>Frank</td>
<td>$-\frac{1}{\theta} \ln \left[ 1 + \frac{(e^{-u\theta} - 1)(e^{-v\theta} - 1)}{e^{-\theta} - 1} \right]$</td>
<td>$(-\infty, \infty) \setminus {0}$</td>
<td>$1 - \frac{4}{\theta} \left[ 1 - D_1(\theta) \right]^*$</td>
</tr>
<tr>
<td>Gumbel or Gumbel-Hougaard</td>
<td>$\exp \left{ - \left[ (-\ln u)^\theta + (-\ln v)^\theta \right]^\frac{1}{\theta} \right}$</td>
<td>$[1, \infty)$</td>
<td>$1 - 3^{-1}$</td>
</tr>
</tbody>
</table>

$* 1.$ Debye Function $D_1(\theta) = \int_0^\infty \frac{t}{\theta e^t - 1} dt$

$** t = u$ or $t = v$

Further important features of copulas and information about the theoretical background can be found e.g. in Nelsen (1999), who provided a detailed introduction to the subject.

4. Results

4.1. The univariate approach

In the univariate case we fitted distribution functions to the AMAX series of gauges Schrottenbaummühle and the synthetic gauge Kalteneck. In both cases the GEV distribution provides the best fit. Figure 2 shows the result from fitting the GEV including the upper and lower 95% confidence levels.
Figure 2  Fitted GEV distributions to AMAX series of gauge Schrottenbaummühle upstream of the confluence (A) and the synthetic gauge Kalteneck downstream of the confluence (B) including the upper and lower 95% confidence levels.

Table 2 shows the numeric quantiles of both fitted distributions. It can be seen that the analyzed quantiles of the downstream located synthetic gauge Kalteneck varies between 151.1 m³/s and 390.7 m³/s for $P = 0.5$ ($T = 2 \, a$) and $0.99$ ($T = 100 \, a$), respectively. At gauge Schrottenbaummühle the values vary between 80.6 m³/s and 214.7 m³/s for the same quantiles.

<table>
<thead>
<tr>
<th>$P$</th>
<th>0.5</th>
<th>0.8</th>
<th>0.9</th>
<th>0.95</th>
<th>0.98</th>
<th>0.99</th>
<th>[-]</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T$</td>
<td>2</td>
<td>5</td>
<td>10</td>
<td>20</td>
<td>50</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>$HQ_T$ - Kalteneck (syn.)</td>
<td>151.1</td>
<td>207.8</td>
<td>248.2</td>
<td>289.1</td>
<td>345.6</td>
<td>390.7</td>
<td></td>
</tr>
<tr>
<td>$HQ_T$ - Schrottenbaumm.</td>
<td>80.6</td>
<td>111.1</td>
<td>133.3</td>
<td>156.2</td>
<td>188.3</td>
<td>214.5</td>
<td></td>
</tr>
<tr>
<td>Difference</td>
<td>70.5</td>
<td>96.7</td>
<td>114.9</td>
<td>132.9</td>
<td>157.3</td>
<td>176.2</td>
<td></td>
</tr>
</tbody>
</table>
The difference of the same quantiles is than treated as the statistical relevant inflow of river Wolfsteiner Ohe for the corresponding flood events at river Ilz. These values range between $Q = 70.5$ m$^3$/s ($P = 0.5$, $T = 2$ a) and $Q = 176.2$ m$^3$/s ($P = 0.99$, $T = 100$ a).

4.2. The bivariate approach using Copulas

In contrast to the univariate approach, the time series of gauge Kalteneck does not play a role in the bivariate analysis. In this case, only the discharge series of both gauges upstream of the confluence are considered (gauges Schrottenbaumühle and Fürsteneck). Before choosing a suitable copula type, the marginal distributions need to be fitted. Here, in turn, the question arises which data should be modeled. In many bivariate statistical investigations mostly the AMAX series of both variables are modeled, e.g. the annual maximum peak flow series and the annual maximum flood volume series, despite considering possible different background of their genesis and physical relations.

Here, we model the AMAX series of the main stream at gauge Schrottenbaumühle together with the concurrent flows of the tributary at gauge Fürsteneck. The fact that 13 of the total 41 annual maxima values did not occur within a time frame of ±7 days confirms that this procedure is reasonable. For the sake of minimizing the randomness of the concurrent discharges, we consider the maximum discharge at gauge Fürsteneck within a time frame of ±7 days with reference to the occurrence time of the AMAX values at gauge Schrottenbaumühle. We already showed that the GEV fits the AMAX series at gauge Schrottenbaumühle best (see Figure 2). For the gauge Fürsteneck, the 2-parametric Weibull distribution provides the best fit (see Figure 3).

![Figure 3](image)

*Figure 3* Fitted 2-parametric Weibull distribution to concurrent discharge values at gauge Fürsteneck with reference to the occurrence of the AMAX values at gauge Schrottenbaumühle
In order to choose the most appropriate Archimedean copula function, we applied the Bayesian method for copula selection as suggested by Huard et al. (2005). The Gumbel copula appears to be the best model to describe the dependence structure between the AMAX values at gauge Schrottenbaummühle and the concurrent discharges at gauge Fürsteneck. With a given value of Kendall’s $\tau = 0.567$ the copula parameter $\theta$ can be calculated using the functional relationship of $\tau$ and the Gumbel copula parameter as outlined in Table 1 to $\theta = 2.3077$. The results from fitting the Gumbel copula (with the above mentioned marginal distributions) to the data set are illustrated in Figure 4.

![Figure 4](image)

**Figure 4** Isolines of equal return periods derived by the bivariate analysis compared with the results of the univariate approach.

The black crosses in Figure 4 show the observed AMAX values at gauge Schrottenbaummühle and the concurrent discharges at gauge Fürsteneck. The grey dots are 10,000 synthetic values derived from the fitted copula and the marginal distribution functions giving an optical impression of the goodness of the fit. The black lines illustrate the bivariate isolines of equal quantiles or return periods, respectively. Here, the bivariate return period of a certain quantile is defined as the inverse value of the non-exceedance probability. Other approaches defining the return period in multivariate cases can be found in Gräler et al. (2013).

For comparison purposes the blue crosses illustrate the results of the univariate method as described in section 5.1. It can be seen, that for small return periods (up to $T = 20 \text{ a}$), the probabilities of the concurrent flows (on the ordinate) of both approaches agree well. However, the values for higher return periods, i.e. $T = 50$ and $100 \text{ a}$, deviate by up to $20 \text{ m}^3/\text{s}$ ($12.5\%$). This might be caused by the use of the Weibull distribution in
the bivariate case and the GEV in the univariate case; both distributions have different curvatures in the range of higher return periods (see Figures 2A and 3).

Although the statistically relevant inflows of the tributary derived with the univariate approach generally correspond with the results using copulas, the return periods of the univariate discharge combinations are higher as compared to the bivariate approach. This is highlighted in Figure 4 by the fact that the results from the univariate analysis lie generally in the upper right of the isolines from the bivariate analysis. The discharge with a return period of $T = 10 \text{ a}$ in the univariate case would be classified, despite almost equal marginal values, as an event with a return period of $T" = 15 \text{ a}$ in the bivariate case (considering the above mentioned definition of bivariate return period). Using the univariate approach assumes independent variables which is not valid in this case where the modeled variables have a rank correlation of $\tau = 0.567$.

5. Conclusion

The main objective of this study was to compare the results from univariate and bivariate statistical extreme value analysis at a river confluence. The application of both methods to a case study in Germany with long discharge time series at both confluent rivers shows that the simplified univariate approach is capable to determine the statistical relevant discharges of the tributary given design discharges for the return periods of $T = 2, 5, 10$ and $20 \text{ years}$ at the main stream (i.e. the results of the univariate and bivariate approach are similar). However, significant differences are found for higher return periods, i.e. $T = 50$ and $100 \text{ a}$. Whether this result is transferable to other confluences, in particular to major rivers, will be further investigated. Moreover, classifying the results of the univariate approach according to bivariate probabilities shows that the return periods are generally overestimated. This is due to the fact that using univariate approaches does not allow for modeling the dependence structure of the two variables.

References


Statistical methods for detecting changes in mean annual cycle and their application to several runoff series of European rivers

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Abstract
Statistical methods for detecting change(s) in seasonal behavior of climatological and hydrological time series are suggested. Changepoint detection analysis is based on testing a statistical hypothesis of stationarity of a mean of random vectors, where the analyzed vectors are certain linear combinations of daily measurements corresponding to one calendar year. More precisely, all annual cycles are approximated by a finite Fourier series or by a principal-components approximation and stationarity of their parameters is studied using three types of test statistics. The methods are applied to runoffs (measured in several stations) of three European rivers — the Danube, the Rhine and the Elbe.

1. Introduction

An impact of "global warming" on hydrological variables is often discussed in papers on climate change, see Milly et al (2005), Wetherald (2010), Irmak et al (2012), among others. Many papers present a prediction of discharge and its stochastic characteristics for large European rivers using climatological and hydrological models, see, e.g., Middelkoop et al (2001), Nohara et al (2006) or Gudmundsson et al (2012). Far fewer papers are devoted to statistical inference on changes of historical runoffs. They usually analyze trends in series of annual or monthly means, see, e.g., Pekárková et al (2003) or Dai et al (2009). However, "global warming" may not only be a cause of trends in annual means but it may also affect the seasonal behavior of runoffs series. In some papers it was shown that in snowmelt-dominated basins the change consisted in a shift of peak time, see, e.g., Stewart et al (2005). Changes in seasonal behavior using statistical inference were also analyzed by Ye H. (2004).

The goal of our paper is to suggest statistical procedures that enable detection of non-stationarities in the mean annual cycle. In the classical literature on the changepoint analysis, i.e., in the book by Csörgő and Horváth (1997), the reader may find many useful statistical methods that may be applied to finding changes in time series. Problems encountered when applying changepoint methods to temperature and discharge series
are presented in Jarušková (1997). The paper by Reeves et al (2006) compares and categorizes some of the methods suitable for application in climatology and hydrology. Our paper deals with one specific changepoint problem that is not treated in Reeves et al (2006), i.e., detecting changes in seasonal behavior of the series of daily mean values. We proceed as follows. First, we approximate annual cycles by a Fourier series or using a principal-component approximation, and then we look for a change in mean of the newly introduced vectors of parameters. As we seek a change in relatively many parameters, we recommend application of the proposed methods to the series that cover a time span of 100 years or longer. We would like to point out that in addition to being suggested for detection of a sudden change, the changepoint methods are able to detect even more complex types of changes.

We applied the proposed methods to several Danube, Rhine and Elbe series. The goal of statistical analysis was not to get overall results on changes of seasonal behavior of these three rivers. For such a purpose we would have to analyze the series in many more profiles. Rather, we gained experience in how to tune up the parameters of the methods when we wish to analyze the stationarity of the European rivers, and we showed that the statistical methods using daily means perform better than those based on monthly means.

We hope that better statistical methods may help us in understanding the on-going processes connected with global warming.

2. Statistical methods for detecting nonstationarities in mean annual cycle

For a decision on stationarity of the mean annual cycle, monthly or daily averages may be applied. In both cases the data set consists of \(n\) vectors, where \(n\) denotes the number of years in which the measurements were taken. If we study stationarity of the annual cycle using monthly averages, the data are realizations of vectors \(X_i = (X_{i,1},...,X_{i,12})^T, i = 1,...,n\), which are twelve-dimensional; \(X_{i,1}, i = 1,...,n\), represent January averages, \(X_{i,2}, i = 1,...,n\), represent February averages, etc. If we use daily averages for the same purpose, then the data are realizations of vectors \(X_i = (X_{i,1},...,X_{i,365})^T, i = 1,...,n\), which have 365 components because the averages of the 29th of February are usually omitted. (In the text \(a^T\) denotes a transposed vector to vector \(a\).)

We assume that vectors \(X_1,...,X_n\) are independent random vectors with possibly correlated
components. In practice this assumption may not be satisfied, as the last components of each preceding year is correlated with the first components of the next year. However, this dependence between two subsequent years is not strong and does not substantially influence the obtained results.

The aim of statistical inference is to decide whether the vectors of mean values \( \mu_i = (\mu_{i,1}, \ldots, \mu_{i,p})^T, \ i = 1, \ldots, n \) (\( p = 12 \) or \( p = 365 \)) of vectors \( X_i, i = 1, \ldots, n \), remain unchanged. If this is true, we estimate the overall mean vector \( \mu = \frac{1}{n} \sum_{j=1}^{n} X_{i,j} \), \( j = 1, \ldots, p \). Let us suppose that the covariance matrix \( \Sigma = \sigma_{ll} \) of the components of vectors \( X_i, i = 1, \ldots, n \) does not change during measurements. Then we may use, for testing equality of all mean vectors \( \mu_1 = \cdots = \mu_n \), a two-sample test statistic

\[
\chi^2(k) = \frac{k(n-k)}{n^2} (\overline{X}(k) - \overline{X}^*(n-k)) \Sigma^{-1} (\overline{X}(k) - \overline{X}^*(n-k))
\]

where \( \overline{X}(k) = (\overline{X}_1(k), \ldots, \overline{X}_p(k))^T \) is a vector of averages over the first \( k \) years, while \( \overline{X}^*(n-k) = (\overline{X}_1^*(n-k), \ldots, \overline{X}_p^*(n-k))^T \) is a vector of averages over the last \( (n-k) \) years. The matrix \( \Sigma^{-1} \) is an inverse to the matrix \( \Sigma = \sigma_{ll} \) with elements \( \hat{\sigma}_{ij} = \sum (X_{i,j} - \overline{X}_j)(X_{i,j} - \overline{X}_j) / n \). For more detail, see Anderson (1984). For a large \( n \), supposing that \( k/n \to \epsilon \in (0,1) \), the test statistic \( \chi^2(k) \) has approximately \( \chi^2 \) distribution with \( p \) degrees of freedom. Choosing a significance level \( \alpha \), the null hypothesis of stationarity is rejected when \( \chi^2(k) \) is larger than \((1 - \alpha) \times 100\% \) quantile of \( \chi^2 \) distribution with \( p \) degrees of freedom.

A natural question may arise: how to choose the value of \( k \). The test procedure using \( \chi^2(k) \) is most powerful when \( \mu_1 = \cdots = \mu_k \neq \mu_{k+1} = \cdots = \mu_n \). Here, \( k \) is called a change point. If we do not know where the change point \( k \) may be, we can calculate the test statistics \( \{\chi^2(k)\} \) for all possible values \( 1 \leq k < n \) with the hope that at least one of these statistics will be large. Test statistics expressed as certain functions of the sequence \( \{\chi^2(k)\} \) attaining a large value if at least one of the statistics \( \{\chi^2(k)\} \) large are natural candidates for testing the existence of a change in the case of an unknown change point. The test statistics most frequently applied in the changepoint detection analysis are the following:

\[
T = \max_{\beta = k: 1 \leq k \leq n} \chi^2(k), \quad (1)
\]

\[
TW = \max_{1 \leq k \leq n} \frac{k(n-k)}{n^2} \chi^2(k), \quad (2)
\]

\[
MW = \frac{1}{n} \sum_{k=1}^{n} \frac{k(n-k)}{n^2} \chi^2(k). \quad (3)
\]
(The value of parameter $\beta$ is usually set to a small positive number. In our case we have chosen $\beta = 0.05$.) The presented test statistics were suggested by Csörgő and Horváth (1997) and later applied by Horváth and Kokoszka (1999), among others.

The statistics $T$, $TW$ and $MW$ attain a large value when a sudden change exists in the analyzed mean vector. However, they may also attain a relatively large value when there are several change points, or even when coordinates of the mean vectors $\mu_i, i = 1, \ldots, n$, are monotonous functions of time index $i$.

Csörgő and Horváth (1997) showed that, under the null hypothesis of stationarity, the test statistics $T$, $TW$ and $MW$ have asymptotic distributions (as $n$ grows towards infinity) but these distributions are too complex to provide us with an exact limit critical values. Fortunately, another way exists for obtaining approximate critical values of $T$, $TW$ and $MW$ which is based on permutation principle. The permutation principle is applied as follows: rows of the original data matrix, where every row corresponds to one year, are repeatedly randomly permuted. The value of the considered test statistic is computed for any random permutation. In this way a large set of values is obtained that can be used for computing an empirical distribution function of the test statistic. For significance level $\alpha$, the $(1 - \alpha) \times 100\%$ empirical quantile can serve as an approximate $\alpha \times 100\%$ critical value and the empirical distribution function may be also used for estimating $p$-values of the test. Antoch and Hušková (2001) have shown that, for a large value of $n$, critical values obtained by the permutation principle are close to the asymptotic critical values.

3. Dimension reduction

For a decision on changes of the mean annual cycle, monthly averages may be used. This approach was applied by Horváth and Kokoszka (1999) or Jarušková (2010) to statistical inference on stationarity of temperature series. It seems obvious that a statistical analysis based on daily averages should provide us with more accurate results than an analysis based only on monthly averages. On the other hand, any estimate of the mean of a vector with 365 components is certainly bad unless the number of observed vectors is very large. As series of daily mean runoffs are usually shorter than 200 years, a direct application of statistical methods described above is not reasonable. For such series we may use an approach that is often applied in multivariate statistical analysis. It is based on replacing the original observed vectors of daily measurements by some vectors with fewer coordinates. The new coordinates are suitably chosen linear combinations of the original vectors' components. Clearly, if changes in the mean of the new vectors are
detected then changes exist in the mean of the original vectors as well.

### 3.1. Fourier series approximation

For a chosen \( l \) we consider the \( l \) smallest Fourier frequencies \( \{2\pi r / 365\} , \ r = 1, \ldots , l \). We replace the vectors of daily measurements \( X_i , i = 1, \ldots , n \), with the \( L = (2l + 1) \) dimensional vectors \( Y_i = (m_{i,1}, \hat{A}_1, \ldots , \hat{A}_l, \hat{B}_1, \ldots , \hat{B}_l)^T \), \( i = 1, \ldots , n \), whose components are the least square estimates of the Fourier coefficients \( m_{i,1}, \hat{A}_1, \ldots , \hat{A}_l, \hat{B}_1, \ldots , \hat{B}_l \) in the Fourier expansion:

\[
m_{i,j} = m_i + \sum_{r=1}^{l} A_j(r) \cos \frac{2\pi j r}{365} + B_j(r) \sin \frac{2\pi j r}{365} , \quad j = 1, \ldots , 365
\]

Indeed, \( \hat{m}_i = (1 / 365) \sum_{j=1}^{365} X_{i,j} \) and \( \hat{A}_j(r) = (2 / 365) \sum_{j=1}^{365} X_{i,j} \cos \frac{2\pi j r}{365} \), \( \hat{B}_j(r) = (2 / 365) \sum_{j=1}^{365} X_{i,j} \sin \frac{2\pi j r}{365} \), \( r = 1, \ldots , l \) are linear combinations of the daily means in the \( i \)th year. The test described above is applied to detection of change(s) in the mean of the Fourier coefficients.

The method works well if we may expect that, for \( i = 1, \ldots , n \), the mean vectors \( \text{EX}_i = (\mu_{i,1}, \ldots , \mu_{i,365})^T \) may be relatively well approximated by vectors \( (m_{i,1}, \ldots , m_{i,365})^T \). This may be true as the annual cycle of discharges is a result of the Earth's rotation around the Sun. Therefore, we may assume that the mean vectors are periodic functions of the time index \( j \) in the sense that \( \mu_{i,1} \) and \( \mu_{i,365} \) are close. Moreover, we may assume that the mean vectors vary slowly with a small number of "peaks and valleys". The number \( l \) of the Fourier frequencies has to be chosen subjectively. According to our experience, it is usually sufficient to take \( 1 \leq l \leq 3 \) for the change point analysis of the mean annual cycle of the European rivers.

### 3.2. Principal-components approximation

In the method of principal-components approximation we replace the vectors of daily measurements \( X_i , i = 1, \ldots , n \), by vectors whose components are linear combinations of the components of \( X_i \) with the largest variances. More precisely, let \( \hat{u}_1, \ldots , \hat{u}_k \) be eigenvectors corresponding to the \( K \) largest eigenvalues \( \hat{\lambda}_1, \ldots , \hat{\lambda}_K \) of the estimated variance-covariance matrix \( \hat{\Sigma} \); then we replace vectors \( \{X_i\} \) by vectors \( \{Y_i\} \), where

\[
Y_i = (\hat{u}_1^T X_i, \ldots , \hat{u}_k^T X_i)^T , \text{ and we look for a change in the mean of these new vectors.}
\]

We may ask why the method of principle components works quite well for the changepoint detection. If a relatively large change exists in the mean of some linear combinations of daily measurements, then its sample variance is large. Thus it has a big chance to be included in the set of \( K \) linear combinations with the largest variances. For a more detailed explanation see Aston and Kirch (2012). The number \( K \) of considered linear
combinations has to be chosen subjectively. In our experience it is usually sufficient to choose $6 \leq K \leq 12$.

### 3.3. Comparison of dimension reduction techniques and test statistics

For decisions on stationarity of the mean annual cycle we proposed to apply statistical hypotheses testing. As the series of daily discharge averages are usually not very long, it is not reasonable to look for a change in the mean of the daily average vectors. We suggested two techniques for dimension reduction – the Fourier series approximation and the principal-components approximation, which can be compared with the method based on monthly averages. Moreover, we suggested three test statistics – $T$, $TW$ and $MW$. The question may arise which of the suggested dimension reduction techniques and which of the suggested test statistics is better for purposes of detection of change(s) in the mean annual cycle.

Table 1 shows results of tests for runoffs of the Danube River at Bratislava in the period 1901-2009. It presents the values of the test statistics together with the corresponding $p$-values (in parentheses) that were obtained by the permutation method using 5 000 random permutations. The rows correspond to the three applied test statistics $T$, $TW$ and $MW$, while the columns correspond to the different reduction techniques. As we require approximately the same number of parameters for all three methods, we have chosen $l = 5$ and $l = 6$ for the Fourier series approximation method and $K = 12$ for the principal components approximation method, but we have already mentioned that we usually obtain smaller $p$-values for $1 \leq l \leq 3$, resp. $6 \leq K \leq 12$.

<table>
<thead>
<tr>
<th>statistic</th>
<th>mont. av.</th>
<th>6 freq.</th>
<th>5 freq.</th>
<th>12 eig.v.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T$</td>
<td>23.65 (38) (0.30)</td>
<td>28.93 (32) (0.04)</td>
<td>25.31 (22) (0.12)</td>
<td>25.17 (37) (0.16)</td>
</tr>
<tr>
<td>$TW$</td>
<td>5.37 (38) (0.14)</td>
<td>6.43 (38) (0.03)</td>
<td>5.62 (38) (0.06)</td>
<td>5.71 (32) (0.08)</td>
</tr>
<tr>
<td>$MW$</td>
<td>2.96 (0.05)</td>
<td>3.23 (0.02)</td>
<td>2.97 (0.03)</td>
<td>3.11 (0.03)</td>
</tr>
</tbody>
</table>

Features similar to those observed in Table 1 may be seen in many studied series. The tests for detecting changes in the mean annual cycle analyzing the means of the Fourier series approximations’ parameters, or those of the principal-components approximations, are
more suitable than the tests based on monthly averages. The method of the Fourier series approximation and the method of principal-components approximation often result in similar decisions on stationarity even though the $p$-values of the Fourier series approximation method are sometimes smaller. It is well-known that the test based on the test statistic $T$ has more power to detect a sudden change in mean vectors if the change point is either at the beginning or at the end of the series, while the test based on the test statistic $TW$ has more power when a change occurs in the middle of the series. The test based on the statistic $MW$ performs better if there are more changes in the mean annual cycle or if the type of change is more complex, e.g., the studied means are monotone functions of the time index $i$.

4. Results

We studied stationarity of the annual cycle for three long European rivers – the Danube, the Rhine, and the Elbe in several of their profiles, and stationarity of the annual cycle of some of their tributaries in one profile. The data, i.e., the daily mean runoffs were provided by The Global Runoff Data Center, 56068 Koblenz, Germany and by The Slovak Hydrometeorological Institute. As is well known, the statistical tests are based on a kind of "signal-to-noise" ratio, i.e., they compare a difference between mean values and their variability. This difference is more apparent if a larger data set is available. Therefore, we mostly describe results for series that cover a time span of 100 years or longer.

4.1. The Danube

The Danube River is the second longest European river. Its vast drainage includes a variety of natural conditions that affect its regime. The upper Danube collects its water from the Alps and other mountain areas. In the lower basin all Alpine traits disappear completely from the river regime and the runoff maximum occurs in April. We investigated the annual cycle of the Danube River in the following profiles: Hofkirchen (GE 1900-2009), Bratislava (SL 1901-2009), Nagymaros (HU 1930-1999), Mohacs (HU 1930-1999), Orsova (RO 1840-1990), Zimnicea (RO 1931-2009), and of the Inn River in the profile Wasserburg (GE 1827-2009) and its tributary, Salzach, in the profile Burghausen (GE 1827-2009). In all stations the annual cycle is clearly seasonal, typically with only one peak. In Wasserburg and Burghausen the maximum is attained in the period from June to the first half of July, in Hochkirchen and Bratislava in the period from the second half of May to the first half of July, in Nagymaros and Mohacs in the period from July to the first half of September, and in Orsova and Zimnicea in the period from April to the first half of June.
We performed statistical analysis of stationarity of the annual cycle for the series longer than 100 years, i.e., Burghausen, Wasserburg, Hofkirchen, Bratislava and Orsova. Before analyzing the daily mean discharge series, we also studied stationarity of the annual mean series with the help of the same statistical hypotheses testing procedures \((p = 1)\) as described in Section 2. The Burghausen series was the only one where the changepoint test statistics \(T, TW\) and \(MW\) applied to the annual means were significant at the significance level of \(\alpha = 0.01\). It was also the only one where a significant decreasing linear trend in the series of annual means was discovered. For all other stations, neither a test for a changepoint detection nor a test for a linear trend rejected the hypothesis of the annual mean series' stationarity.

For the Burghausen and Wasserburg discharge series, using the method of the Fourier series approximation with \(l = 1, 2, 3\) as well as using the method of principal-components approximation with \(6 \leq K \leq 12\) provided \(p\)-values of all test statistics smaller than 0.01. Therefore, the hypothesis of stationarity of the mean annual cycle was clearly rejected.

The Hofkirchen station is the only one among the three studied Danube stations where the stationarity of the annual cycle was not rejected at the significance level of 0.05. However, the \(p\)-values are mostly between 0.05 and 0.3. For \(l = 3\) the \(p\)-values of the statistic \(T\) is 0.12, while it is 0.08 for the statistic \(TW\), and 0.16 for the statistic \(MW\).

For the Bratislava discharge series, using the method of Fourier series approximation with \(l = 1, 2, 3\) provided \(p\)-values smaller than 0.01. Using the method of principal-components approximation with \(6 \leq K \leq 12\) all \(p\)-values of the statistic \(MW\) are less than or equal to 0.02, while all \(p\)-values of the statistics \(TW\) are less than or equal to 0.05, and all \(p\)-values of the statistic \(T\) are less than or equal to 0.09. The hypothesis of stationarity of the mean annual cycle was rejected by most test statistics.

For the Orsova series, using the method of the Fourier series approximation with \(l = 1, 2, 3\) provided \(p\)-values of all test statistics smaller than 0.03. Especially for \(l = 1\) they are all smaller than 0.01. In the method of principal components with \(7 \leq K \leq 12\), all \(p\)-values are smaller than 0.05 with only one exception. The hypothesis of stationarity of the mean annual cycle was clearly rejected.

The obtained results may be compared to the results obtained when the testing procedure for detecting changes in the mean annual cycle is based on monthly averages, see Table 2.
Table 2: Values of the test statistics $T$, $TW$ and $MW$ with the corresponding $p$–values (in parentheses) based on monthly averages for the analyzed series.

<table>
<thead>
<tr>
<th></th>
<th>$T$</th>
<th>$TW$</th>
<th>$MW$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hochkirchen</td>
<td>20.62 (0.54)</td>
<td>4.70 (0.27)</td>
<td>2.23 (0.35)</td>
</tr>
<tr>
<td>Bratislava</td>
<td>23.65 (0.28)</td>
<td>5.37 (0.14)</td>
<td>2.96 (0.05)</td>
</tr>
<tr>
<td>Orsova</td>
<td>32.30 (0.02)</td>
<td>7.00 (0.01)</td>
<td>2.68 (0.12)</td>
</tr>
<tr>
<td>Wasserburg</td>
<td>98.50 (0.00)</td>
<td>16.52 (0.00)</td>
<td>7.74 (0.00)</td>
</tr>
<tr>
<td>Burghausen</td>
<td>46.78 (0.00)</td>
<td>11.63 (0.00)</td>
<td>6.69 (0.00)</td>
</tr>
</tbody>
</table>

Figures 1 through 4 represent two smoothed mean annual cycles of the Wasserburg (Inn), Hochkirchen (Danube), Bratislava (Danube) and Orsova (Danube) series. The x–axis represents calendar days in a year, the y–axis represents discharge in $m^3/s$. The series were split into two parts – before 1941 and after 1941. (We have chosen the year 1941 for the split as the statistics $T$ and $TW$ often attained its maximum either at this time point or close to it.) Both of these mean annual cycles were smoothed by a Gaussian filter with $h = 10$. A similar type of change can be seen in all three series, an increase of daily discharges in the period February-April and a decrease of daily discharges in the period August-October.

Figure 1 Wasserburg (Inn) – smooth mean annual cycle before 1941 (dashed line) and after 1941 (full line)

Figure 2 Hochkirchen (Danube) – smooth mean annual cycle before 1941 (dashed line) and after 1941 (full line).
4.2. The Rhine

The Rhine River is the longest German river. The upper Rhine has a characteristic Alpine regime. Below Basel, the Rhine tributaries change its regime so that the Köln and Rees series contain two runoff peaks. We analyzed its mean annual cycle in three profiles: Basel (1869-1995), Köln (1817-2009), and Rees (1815-2009), as well as the mean annual cycles of three Rhine tributaries: the Neckar in Plochingen (1915-2010), the Main in Würzburg (1824-2010) and the Mosel in Cochen (1900-2009). All stations are situated in Germany. The annual cycle of the Basel series, the Plochingen series, the Cochen series and the Würzburg series have a "sine" character with one "peak of maxima" and one "valley of minima." However, these peaks and valleys appear in different periods of the year. Maximal daily discharges of the Basel series are attained in the period June through the first half of August and minimal discharges in the period December - February. Maximal discharges of the Plochingen series are attained in April through the first half of June and minimal discharges in the period October - December. Maximal discharges of the Cochen series are attained in the period March - May and minimal discharges in September-November. Maximal discharges of the Würzburg series are attained in January - March and minimal discharges in July - September. Interestingly, the mean annual cycles of the Köln and Rees series look very similar to each other with two "peaks of maxima". The first one, which is higher and broader, appears in January - March, the second one, which is smaller and narrower, appears in June - the first part of July. Minimal daily discharges are attained in September - October.

Before analyzing stationarity of the mean annual cycle, we investigated stationarity of the annual mean series with the help of the described tests for changepoint analysis as well as the test for existence of a linear trend. Except for the Würzburg series, none of
considered tests applied to the series of the annual means rejected the null hypothesis of stationarity. The Würzburg annual mean discharges started to increase around 1960 and this change is significant using all changepoint test statistics as well as the test statistic for a linear trend.

Similar to for the Danube discharge series, statistical inference on stationarity of the annual cycle has only been performed for series that covered more than 100 years.

For the Basel series, using the method of Fourier series approximation with \( l = 1 \) provides \( p \)-values of the test statistics \( T \), \( TW \) and \( MW \) smaller than 0.01 and for \( l = 2, 3 \) \( p \)-values of the test statistics \( T \) and \( MW \) smaller than 0.05, while the test statistic \( TW \) is smaller than 0.17. Using the method of principal-components approximation with \( 3 \leq K \leq 11 \) the \( p \)-values of all statistics \( T \), \( TW \) and \( MW \) are smaller than 0.05. We conclude that a change in the mean annual cycle has been clearly detected.

For the Köln and Rees series, using the method of Fourier series approximation with \( 1 \leq l \leq 3 \) provided \( p \)-values of all test statistics smaller than 0.05. For the Köln series, using the principal components with \( 5 \leq K \leq 7 \) provided \( p \)-values of the test statistics \( T \) and \( TW \) smaller than 0.05, while for \( 8 \leq K \leq 12 \) they are all less than 0.12. For the Rees station, using the method of principal components approximation with \( 8 \leq K \leq 12 \) the \( p \)-values of all statistics \( T \) and \( MW \) are smaller than 0.05 and the \( p \)-values of the statistic \( TW \) are smaller than 0.16. We conclude again that a change in the mean annual cycle has been detected.

For the Würzburg (Main) and Cochem (Mosel) series the null hypothesis of stationarity of the mean annual cycle was not rejected at a significance level of \( \alpha = 0.1 \).

The obtained results may again be compared to the results of the testing procedure for detecting changes in the mean annual cycle based on the monthly averages, see Table 3.
Table 3: Values of the test statistics $T$, $TW$ and $MW$ with the corresponding $p$-values (in parentheses) based on the monthly averages for the analyzed series.

<table>
<thead>
<tr>
<th></th>
<th>$T$</th>
<th>$TW$</th>
<th>$MW$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basel</td>
<td>25.68 (0.14)</td>
<td>5.81 (0.06)</td>
<td>3.07 (0.04)</td>
</tr>
<tr>
<td>Köln</td>
<td>27.66 (0.12)</td>
<td>4.73 (0.30)</td>
<td>2.44 (0.20)</td>
</tr>
<tr>
<td>Rees</td>
<td>29.48 (0.06)</td>
<td>5.17 (0.19)</td>
<td>2.71 (0.10)</td>
</tr>
<tr>
<td>Cochem</td>
<td>20.24 (0.57)</td>
<td>4.34 (0.38)</td>
<td>2.27 (0.33)</td>
</tr>
<tr>
<td>Würzburg</td>
<td>29.80 (0.07)</td>
<td>4.66 (0.31)</td>
<td>2.20 (0.36)</td>
</tr>
</tbody>
</table>

Figure 5 Basel (Rhine) – smooth mean annual cycle before 1941 (dashed line) and after 1941 (full line).

Figure 6 Köln (Rhine) – smooth mean annual cycle before 1941 (dashed line) and after 1941 (full line).

Figure 7 Rees (Rhine) – smooth mean annual cycle before 1941 (dashed line) and after 1941 (full line).

Figure 8 Würzburg (Main) – smooth mean annual cycle before 1941 (dashed line) and after 1941 (full line).
Figures 5 through 8 show two smoothed mean annual cycles corresponding to the period before 1941 (dashed line) and after 1941 (full line). The Gaussian filter with $h = 10$ was again applied for smoothing. We see that the daily mean discharges measured in the Basel station increased in December-May and decreased in August-October. The mean annual cycles of the Köln and Rees series have a completely different character from the Basel but the daily mean discharges also increased in the period December-May and decreased in August-November. These observations are completely in agreement with conclusions of the research carried out by the International Commission for the Hydrology of the Rhine basin. Here the results were obtained by several water balance models; for more details, see Middelkoop et al (2001).

4.3. The Elbe

We analyzed the mean annual cycles in four profiles – Děčín (1888-2007), Wittenberg (1900-2009), Barby (1900-2009), Neu Darchau (1875-2008).

Before analyzing stationarity of the discharge annual cycle we investigated stationarity of the annual mean series with the help of the described tests for changepoint analysis as well as a test for the existence of a linear trend. None of the considered tests applied to the annual mean discharge series rejected the null hypothesis of stationarity.

The mean annual cycles of all analyzed Elbe stations look very similar to each other. They have a "sine" form with one relatively narrow "peak of maxima" in the period from the second half of March through the first half of April and a broad "valley of minima" that extends roughly from July until November. None of the applied test statistics has rejected the null hypothesis of stationarity of the mean annual cycle for any of the four studied series.

5. Conclusions

We suggested three test statistics for testing a change in the mean of random vectors. The studied vectors were parameters of the Fourier series approximation or components in the principal-components approximation. For an analysis of nonstationarities in seasonal behavior of European rivers we recommend to choose $1 \leq \ell \leq 3$ for the first method and $6 \leq K \leq 12$ for the second method. We applied the proposed procedures to several time series of daily mean runoffs for the Danube, the Rhine, the Elbe and their tributaries. Despite a complete different ideas of the tests the results are practically in
mutual agreement in all cases, although the test based on the series of monthly means is slightly less sensitive to different departures from the mean annual cycle's stationarity.

We rejected the null hypothesis of stationarity for Bratislava (Danube), Orsova (Danube), Wasserburg (Inn) and Burghausen (Salzach) while we did not reject it for the Hofkirchen (Danube) series. Further, we rejected the null hypothesis of stationarity for all analyzed Rhine series – Basel, Köln and Rees, but we did not reject it for its tributary series – Cochen (Mosel), Würzburg (Main). Furthermore, we did not reject the stationarity of annual cycle for any Elbe series.

The suggested methods are not able to indicate main features of non-stationary behavior of seasonal cycle. However, for all runoff series where stationarity was rejected, the change consisted in an increase of winter discharge and decrease of late summer - early autumn discharge. To illustrate an increase of winter discharges Table 4 and Table 5 present medians, lower and upper quartiles of average discharges in the first 100 days of calendar years before and after the year 1941 for the Danube river and its tributaries and the Rhine river and its tributaries. For many series we could see a shift of the peak runoff. In the last years it appeared earlier than in the past. Table 6 and Table 7 presents medians of time locations (days) of the peak run-offs before the year 1941 and after it.

It seems plausible that the detected changes are results of "global warming." Although it is difficult to exclusively associate all detected changes in seasonal behavior of runoffs with climate changes, because they may also be partially explained by dam and reservoir regulations and use of water in agriculture, industry and by households, we have observed a similar behavior for other European rivers as well.

The aim of our paper was to suggest methods for detecting changes of run-offs series. We have seen that in some cases changes in seasonal behavior are already clearly detectable when statistical inference is based on daily mean values. According to our opinion it is important to compare results of statistical analysis with outputs of theoretical hydrological and climatological models to improve prognostic reliability.
**Table 4:** Medians, lower quartiles Q25 and upper quartiles Q75 of average discharges in the first 100 days of calendar years before 1941 and after it for the Danube river and its tributaries.

<table>
<thead>
<tr>
<th>Location</th>
<th>Median - 1941</th>
<th>Median 1942</th>
<th>Q25 - 1941</th>
<th>Q25 1942</th>
<th>Q75 - 1941</th>
<th>Q75 1942</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hochkirchen</td>
<td>540</td>
<td>553</td>
<td>440</td>
<td>443</td>
<td>648</td>
<td>666</td>
</tr>
<tr>
<td>Bratislava</td>
<td>1713</td>
<td>1905</td>
<td>1464</td>
<td>1637</td>
<td>1942</td>
<td>2164</td>
</tr>
<tr>
<td>Orsova</td>
<td>5588</td>
<td>6197</td>
<td>4382</td>
<td>5158</td>
<td>6559</td>
<td>6816</td>
</tr>
<tr>
<td>Wasserburg</td>
<td>167</td>
<td>190</td>
<td>145</td>
<td>165</td>
<td>183</td>
<td>225</td>
</tr>
<tr>
<td>Burghausen</td>
<td>137</td>
<td>164</td>
<td>114</td>
<td>144</td>
<td>167</td>
<td>191</td>
</tr>
</tbody>
</table>

**Table 5:** Medians, lower quartiles Q25 and upper quartiles Q75 of average discharges in the first 100 days of calendar years before 1941 and after it for the Rhine river.

<table>
<thead>
<tr>
<th>Location</th>
<th>Median - 1941</th>
<th>Median 1942</th>
<th>Q25 - 1941</th>
<th>Q25 1942</th>
<th>Q75 - 1941</th>
<th>Q75 1942</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basel</td>
<td>744</td>
<td>811</td>
<td>602</td>
<td>740</td>
<td>882</td>
<td>945</td>
</tr>
<tr>
<td>Köln</td>
<td>2291</td>
<td>2539</td>
<td>1955</td>
<td>2033</td>
<td>2729</td>
<td>3095</td>
</tr>
<tr>
<td>Rees</td>
<td>2542</td>
<td>2794</td>
<td>2147</td>
<td>2231</td>
<td>2999</td>
<td>3401</td>
</tr>
</tbody>
</table>

**Table 6:** Medians of time locations of peak run-offs before the year 1941 and after it for the Danube river and its tributaries.

<table>
<thead>
<tr>
<th></th>
<th>Hochkirchen.</th>
<th>Bratislava</th>
<th>Orsova</th>
<th>Wasserburg</th>
<th>Burghausen</th>
</tr>
</thead>
<tbody>
<tr>
<td>1941</td>
<td>191</td>
<td>164</td>
<td>127</td>
<td>184</td>
<td>172</td>
</tr>
<tr>
<td>1942</td>
<td>165</td>
<td>159</td>
<td>119</td>
<td>180</td>
<td>171</td>
</tr>
</tbody>
</table>

**Table 7:** Medians of time locations of peak run-offs before the year 1941 and after it for the Rhine river.

<table>
<thead>
<tr>
<th></th>
<th>Basel</th>
<th>Köln</th>
<th>Rees</th>
</tr>
</thead>
<tbody>
<tr>
<td>1941</td>
<td>187</td>
<td>78</td>
<td>72</td>
</tr>
<tr>
<td>1942</td>
<td>174</td>
<td>75</td>
<td>60</td>
</tr>
</tbody>
</table>
Acknowledgements
The work of the author was supported by grant GAČR 201/09/0755.

References


Analysing flood frequencies at the Elbe River – Do recent extreme events affect design levels?

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Abstract
Within this investigation, we focused on a detailed analyses of the discharge data of the gauge Neu Darchau (Elbe River), which is the most downstream discharge gauge of the Elbe River before it becomes an estuary. We followed the questions, if the discharge characteristics of the Elbe River have changed over the last decades and how much the design discharges (i.e. HQ100) are affected by the latest extreme events in 2002, 2006, and 2011. Hence, we conducted (i) trend estimations for different flood indicators, (ii) trend and seasonality analysis of flood frequencies and (iii) an assessment of time-dependencies of flood risk by using extreme value statistics with both block maxima and peak-over-threshold approaches. Trends for winter floods do show slightly downwards trends, whereas the summer floods remain constantly. However, none of these trends (only one exception) are statistically significant. The time-dependent characteristic of the extreme value statistics (i.e. HQ100) considering the main flood indicators is not significantly affected by the extreme events in 2002, 2006, and 2011.

1. Introduction

During the last decades several severe floods occurred in different river basins in Germany (e.g. 1993 and 1995 Rhine; 1997 Odra; 1999, 2001 and 2006 Danube, 2002, 2006 and 2011 Elbe) (Petrow and Merz, 2009). In a public perception there seems to be a trend to more frequent hydrological extreme events resulting in a rising flood hazard.

Within this investigation, we focus on detailed analyses of the discharge data of the gauge Neu Darchau (Elbe River). The gauge Neu Darchau is the most downstream discharge gauge of the Elbe River before it becomes an estuary (Fig. 1). The gauge is considered as a benchmark for the total discharge of the Elbe River (WSA Lauenburg, 2012). Thus, the discharge statistics of this gauge is of special importance for all designing purposes downstream this location.
For the determination of design discharges, traditionally a stationary behaviour of the flood regime is assumed and has to be assured. The severe flood events on 23 August 2002 ($Q_{\text{Neu Darchau}} = 3410$ m$^3$/s), 9 April 2006 ($Q_{\text{Neu Darchau}} = 3590$ m$^3$/s), and 23 January 2011 ($Q_{\text{Neu Darchau}} = 3593$ m$^3$/s) may lead to the assumption, that more frequent extreme events are likely or at least a period with a clustering of floods occurs. While the floods in 2006 and 2011 occurred within the typical flood period (December – May), the 2002 flood occurred in summer and is rated as the highest summer flood within the observational records.

Thus, the questions arise if the discharge characteristics of the Elbe River have changed over the last decades and how much the design discharges (i.e. the 100-yr return discharge) are affected by the latest extreme events in 2002, 2006, and 2011?

Many recent studies focussed on trend estimations in flood magnitude, frequency and seasonality of European or German rivers (e.g. Mudelsee et al., 2003; Mudelsee, 2004; Petrow et al., 2009; Petrow and Merz, 2009; Beurton and Thieken, 2009; Stahl et al., 2010; Bormann et al., 2011). Mudelsee et al. (2003) investigated discharge data sets from the Elbe and Odra River for the past 80 to 150 years. For the Elbe River (gauge Dresden), they found a decreasing trend in winter floods, while summer floods do not show any significant trend.
Mudelsee (2004) analysed extreme floods in central Europe (namely the Elbe and Odra River) over the past 500 years. In this context he focused on so-called Vb-cyclones, which are responsible for heavy rainfall events in central Europe, especially in the summer period. Based on the used data sets he finds for both the Elbe and Odra River significantly decreasing trends in winter flood risk and no significant trends in summer flood risk during the twentieth century.

Petrow und Merz (2009) investigated flood time series for 145 discharge gauges in Germany in the period of 1952 to 2002. For trend estimates, they studied eight flood indicators such as annual maximum daily mean discharge, seasonal annual maximum daily mean discharge for winter and summer season, peak-over-threshold magnitude and others. The locations of the gauges are more or less equally distributed over Germany. The individual names of gauges are not listed in their paper, but looking at the plotted maps it is obvious, that the gauge Neu Darchau was one of the analysed sites. For most flood indicators they found no significant trends for the gauge Neu Darchau as for most gauges in the north-eastern region of Germany, while a considerable fraction of basins in other German locations show upward trends. Analysing at the seasonal behaviour, they found larger changes for winter periods compared to summer periods.

Petrow et al. (2009) analysed the impact of changes in the frequency and persistence of circulation patterns on flood hazards in Germany. For their study, they used discharge data from 122 mesoscale catchments covering a period of 52 years (1951 to 2002). The individual gauges are not listed in their paper, but focusing on the displayed map therein reveals that only one gauge in the middle Elbe region was investigated (not Neu Darchau). As a result, they found significant flood trends at the 10% significance level for a large number of catchments. For easterly regions, where the middle Elbe belongs to, increasing trends for the winter period and decreasing trends for the summer period were found.

Beurton and Thieken (2009) investigated the seasonal distribution of annual maximum floods at 481 gauge stations across Germany. As a result, they created a map with three regions representing homogeneous flood regimes. The Elbe River belongs to the so called cluster B, which covers most parts of Germany. This flood regime is characterized by spring and winter floods. In comparison to Cluster A (mainly westerly regions of Germany), the maximum in December is shifted to March. However, winter is the most important season for flooding.
In a recent study Stahl et al. (2010) investigated discharge trends from 441 small catchments in 15 countries across Europe. Small catchments are defined as areas not exceeding an area of 1000 km². Thus, no data sets from the middle or lower Elbe River were used. The investigated catchments in the easterly regions show negative trends in annual discharges and positive trends for the winter season.

Bormann et al. (2011) conducted a spatial analysis of German discharge and flood stage data. They used 78 gauges and most of the data sets do not show any significant trends in any of the considered flood parameters. Looking more into detail, non-uniform trends along the Elbe River were detected. The gauge Dresden shows a decreasing trend in the annual maximum discharge of -3.9 m³/s/a from 1852 to 2005. The downstream located gauge of Wittenberg shows an increasing trend of 11.96 m³/s/a from 1950 to 2003, whereas the gauge of Neu Darchau does not exhibit any significant trend from 1874 to 2005. However, the authors emphasize the strong dependence of the trend on the underlying record length.

Interannual and decadal oscillations as well as correlations between discharge, precipitation and other meteorological forcings (e.g. NAO) in the Elbe River basin are investigated more in detail in recent years (e.g. Markovic, 2006; Kropp and Schellnhuber, 2011). In analysing different Elbe River discharge time series from gauge Dresden to the downstream gauge Neu Darchau, Markovic (2006) identified statistically significant low frequency oscillations with periods of 7.1 yrs and 10-14 yrs occurring additionally to the seasonal cycle, indicating the occurrence of extended dry and wet cycles. In Kropp and Schellnhuber (2011), numerous authors addressed longterm correlations in hydro-meteorological variables showing that many discharge records in Europe and Germany are characterized by such effects.

With respect to trends in discharge time series, there are much more publications available on a European or worldwide scale, which are not mentioned here. For a brief literature review see e.g. Svensson et al., 2006.

In order to answer the above mentioned questions with respect to the gauge Neu Darchau, we conduct the following:

- trend estimations for different flood indicators as the annual maximum daily mean discharge (AMF), annual winter maximum daily discharge (AWMF), the annual summer maximum daily mean discharge (ASMF), and the annual peak-over-threshold series with different thresholds
• trend and seasonality analysis of flood frequencies
• assessment of time-dependent flood frequencies by using extreme value statistics with both, the block maxima (Generalized Extreme Value distribution, GEV) and the peak-over-threshold (Generalized Pareto distribution, GPD) approach.

2. Data

2.1. Daily mean discharge data
For this study, discharge data from the gauge Neu Darchau at Elbe location 536.4 km (Fig. 1) were obtained from the Water and Shipping Office Lauenburg (WSA Lauenburg), which is the official gauge operator. The records comprise daily mean discharge values from 1 November 1874 to 31 October 2011 (hydrological year in Germany: 1 November to 31 October), resulting in a time series covering 136 years without any gaps. The discharge measurements operate regularly since 1874 without any discontinuities. Since 1 November 1997 data with a resolution in time of 15 minutes are available. Prior to that, several measurements per day (not equally distributed) are the basis for the daily mean discharge data. Since the catchment size amounts to 131,950 km², these daily measurements are also suitable to compute representative daily mean discharge data.

The most extreme flood in the official data set is on 25 March 1888 with HHQ = 4400 m³/s. Since it was a severe winter flood, it is known that during this event river icing occurred in the Elbe River which significantly influenced the flood stage measurement at gauge Neu Darchau (WSA Lauenburg, 2012). Hence, the dedicated discharge of 4400 m³/s is also affected by river icing. For this flood event the WSA Lauenburg also provides a corrected peak discharge of 2310 m³/s on 24 March 1888 instead of 4400 m³/s on 25 March 1888 (Rölver, 2012), which allows for the incorrect flood stage measurement. Although the corrected discharge is not officially fixed, we decided to use this corrected value instead of the original value, since the original –and obviously incorrect– value would significantly affect the extreme value statistics. Figure 2 illustrates the corrected daily mean discharge series at gauge Neu Darchau from 1875 to 2011.
2.2. Flood indicators

Eight flood indicators were analysed in this study using both, the block maxima and the peak-over-threshold approach. The most common flood indicator in flood trend studies is the annual maximum discharge, i.e. the largest daily mean discharge that occurs in each hydrological year. This flood indicator is labelled as AMF. In addition to the AMF, seasonal maximum time series were computed, where summer and winter periods are distinguished. The summer period covers 1 May to 31 October while the winter period covers 1 November to 30 April. These flood indicators are hereafter referred to as ASMF (annual summer maximum flood) and AWF (annual winter maximum flood).

The annual maxima approach has extensively been used in the past (Acero et al., 2011). However, it can be a wasteful method if further data of extremes are available (Coles, 2001). Conversely, if no extreme flood occurs within a year, the maximum value will still be selected. To overcome these shortcomings, some alternative approaches came up in hydrological statistics. The most prominent methods are the r-largest approach (e.g. Smith, 1986; Coles, 2001) and the peak-over-threshold (POT) approach (e.g. Leadbetter, 1991; Bayliss and Jones, 1993; Coles, 2001).

In the r-largest approach, not only the annual maximum values \( r = 1 \) are considered in the sample, but e.g. the two \( r = 2 \) or three \( r = 3 \) largest annual values. The advantages and disadvantages of this method are obvious. Given a year with several extreme floods, using the r-largest method extends the data basis by including more of the available information concerning extreme discharge events. In contrast, if a year has no major
floods, using the r-largest approach still considers the r-largest events of this year within the sample.

Discharge datasets can exhibit dependencies that are related to the same event that caused these floods. By creating a sample of the r-largest values per year, one has to ensure independence of the selected events, which means that the events should have a certain distance in time (declustering time). Following Svensson et al. (2005), we use a declustering time of 20 days, since the catchment area of the gauge Neu Darchau is >100,000 km². In this study we compute the annual r-largest samples considering the r = 2 and r = 3 largest events per year, hereafter referred to as AMFr2 and AMFr3.

The POT approach (also known as partial duration series) provides a more flexible representation of floods compared to the AMF approach, since it accounts for stochastically and unequally distributed occurrences of floods. A POT sample is created using all values exceeding a predefined threshold. The main advantage of the POT approach is therefore the consideration of all severe floods within a flood intensive year, while years with no extreme events are neglected. Thus, a POT time series captures more information concerning the entire flood characteristics of a river than using AMF. The key challenge of the POT approach, however, is the threshold selection, since statistical methods (e.g. extreme value distribution) may react very sensitive to different thresholds. Selecting suitable thresholds is therefore a complex task representing the main difficulty associated with the POT approach (Lang et al., 1999). Additionally, the independence of the individual events has to be assured as well.

Lang et al. (1999) reviewed some threshold selection techniques. An important factor in the threshold selection is the mean number N of events per year. They recommend that there should be at least a mean number of floods of N = 2 or 3 per year. A common threshold selection criteria is to use a standard frequency factor f, so that the threshold can be estimated from the daily mean discharge series Q by:

\[ u = \mu_Q + f \cdot \sigma_Q \]

where \( \mu_Q \) and \( \sigma_Q \) are the mean and standard deviation of the daily mean discharge series \( Q \), respectively. Rosbjerg and Madsen (1992) prefer to use a standard frequency factor of \( f = 3 \), but take care for the condition \( N > 2 \).

For daily mean discharge data of gauge Neu Darchau, Table 1 shows a compilation of a range of standard frequency factors, thresholds and the resulting mean number of floods.
per year. One can see, that the standard frequency factor $f = 3$ violates the condition $N > 2$, thus we do not consider this factor anymore. The standard frequency factors $f = 0.67$, $f = 1.00$ and $f = 1.20$ lead to a mean number of floods per year of $N = 3$, $N = 2.3$ and $N = 2$, respectively. These seem to be suitable factors. For the sake of comparison with AMF, we also choose $f = 2.10$, since it results in a mean number of 1 flood per year.

Resumed, we compiled POT series using the standard frequency factors $f = 0.67$, 1.00, and 2.10 named as POT-0.67, POT-1.00 and POT-2.10. Note that POT-0.67 is not equal to AMFr3 and POT-2.10 is not equal to AMF although the mean number of events per year is the same.

Table 1: Compilation of thresholds, standard frequency factors and the resulting mean number of floods per year at gauge Neu Darchau based on daily mean discharge data

<table>
<thead>
<tr>
<th>Standard frequency factor</th>
<th>Threshold U</th>
<th>Mean number of floods per year</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.67</td>
<td>1009 m³/s</td>
<td>3</td>
</tr>
<tr>
<td>1.00</td>
<td>1154 m³/s</td>
<td>2.3</td>
</tr>
<tr>
<td>1.20</td>
<td>1244 m³/s</td>
<td>2</td>
</tr>
<tr>
<td>2.00</td>
<td>1599 m³/s</td>
<td>1.1</td>
</tr>
<tr>
<td>2.10</td>
<td>1644 m³/s</td>
<td>1</td>
</tr>
<tr>
<td>3.00</td>
<td>2044 m³/s</td>
<td>0.5</td>
</tr>
</tbody>
</table>

3. Methods

For trend estimation we used linear regression models with an ordinary least square estimation technique. The significance of the trends was tested using the Mann-Kendall test (Kendall, 1955). Nowadays, the Generalized Extreme Value distribution (GEV) and the Generalized Pareto distribution (GPD) have established as the main distribution functions for extreme value statistics (e.g. Coles, 2001; Arns et al., under review). A series of block maxima is described by the GEV which is defined as

$$GEV = \exp \left\{ - \left[ 1 + \frac{z - \mu}{\sigma} \right]^{-\frac{1}{\xi}} \right\}$$

with the location parameter $\mu$, the scale parameter $\sigma$, the shape parameter $\xi$ and the block maxima values considered, denoted as $z$. This formula combines the Gumbel, Fréchet and Weibull families into one single family. Each family has a location $\mu$ and a scale parameter $\sigma$ while the Fréchet and the Weibull families additionally have a shape parameter $\xi$ (Coles, 2001).
The use of POT methods is based on the GPD. The GPD encompasses a number of common extreme functions (Hawkes et al., 2008) and is defined as

\[
GPD(y) = \left[ 1 + \frac{\xi y}{\sigma} \right]^{\frac{1}{\xi}}
\]

with

\[
\hat{\sigma} = \sigma + \xi (u - \mu)
\]

with the location parameter \(\mu\), the scale parameter \(\sigma\), the shape parameter \(\xi\) and threshold value \(u\) (Coles, 2001).

The parameter estimation method in this paper is maximum likelihood estimation (MLE) for all model parameters (Smith, 1986; Hosking and Wallis, 1997; Davison and Smith, 1990). The MLE is a general and flexible method to estimate the unknown parameters of a distribution (Coles, 2001). However, according to Katz et al. (2002), the performance of MLE can be extremely erratic for small samples \((n \leq 25)\), especially when estimating extreme quantiles of the GEV distribution.

4. Results

4.1. Trends of daily mean discharge and seasonality

Figure 2 shows the adjusted (see Sect. 2) daily mean discharge time series from 1 November 1874 to 31 October 2011 of gauge Neu Darchau. Even if the latest extreme events in 2002, 2006, and 2011 are very noticeable, the time series reveals that extreme floods already occurred in a comparable magnitude in former years. The overall mean of the daily mean discharge from 1875 to 2011 (hydrological years) amounts to \(MQ = 709\ m^3/s\) with a standard deviation of \(\sigma = 445\ m^3/s\). The linear trend with a standard error is \(-0.003 \pm 0.05\ m^3/s/yr\), which is a non-significant trend at the 95% confidence level. In addition, we fitted a non-linear function to the time series, using locally weighted scatterplot smoothing (LOWESS). The applied LOWESS function fits simple models to localized subsets of the data using linear least-squares fitting and a first-degree polynomial (Cleveland, 1981). The LOWESS results with a filter span of 10 years illustrate, that the series can be intersected into two periods. A first one from 1875 to about 1920, where a rather small variance exists, followed by a period up to the end with higher magnitudes. Interannual or decadal variations in discharges may be explained to a
certain extend by the North Atlantic Oscillation (NAO) (Villarini et al., 2011; Kingston et al., 2006; Pociask-Karteczka 2006).

In order to analyse more in detail the periodicity of the discharge data, we performed a frequency analysis using a Fast-Fourier-Transformation (FFT). The results highlight an annual cycle with an amplitude of about 259 m$^3$/s. Furthermore, the FFT results point to a semi-annual cycle (77 m$^3$/s), a 5-year cycle (90 m$^3$/s) as well as a 10-year cycle (82 m$^3$/s). The latter may be linked to North-Atlantic-Oscillation (NAO) (Markovic, 2006). In summary, discharge variations on an interannual and interdecadal scale seem to be usual for the Elbe River (Ionita, 2009).

For analysing the annual cycle we calculated the mean values of each month from 1875 to 2011. Maximum discharge values occur in March and April, with mean values of $MQ_{\text{March}} = 1100$ m$^3$/s and $MQ_{\text{April}} = 1117$ m$^3$/s. The minimum value appears in September with $MQ_{\text{September}} = 444$ m$^3$/s. The standard deviation varies between 82 m$^3$/s (November) and 208 m$^3$/s (March). The winter season is therefore the most important season for the genesis of floods. Trend estimates with standard errors were performed for each month and the significance is tested at a 95% confidence level using the Mann-Kendall test. The results indicate that there is only little evidence for general changes with time. Except for the month May, no significant trends could be found at the 95% confidence level.

Since the cumulative annual discharge at the gauge Neu Darchau is an important proxy for the Elbe inflow into the North Sea, we calculated these cumulative annual discharge values based on the daily mean discharge data. Figure 3 illustrates the corresponding time series and results reveal that there is no significant long term trend, but a strong interdecadal variability. During the last decades a period with an increasing number of years with high annual flows is suggested. The maximum value occurred in 1941 and amounts to 328 mm/yr (i.e. 43,279.6 Mio. m$^3$/yr); the minimum was in 1934 with 90.6 mm/yr (i.e. 11,954.7 Mio. m$^3$/yr). Hence, there is no strong evidence, that the recent extreme events (2002, 2006, 2011) significantly influence the annual flows of the Elbe River.
4.2. Trends in flood indicators

With regard to the time-dependent behaviour of the different flood indicators, we applied trend tests to six samples derived using the flood indicators AMF, AMFr2, AWMF, ASMF, POT-0.67, and POT-1.00. The results are displayed in Fig. 4. Considering the AMF and AMFr2 series, there are negative trends of \( \text{AMF/AMFr2} = -0.5 \pm 1.6 \text{ m}^3/\text{s/yr} \).

The winter flood time series (AWMF) shows a quite similar trend compared to the AMF with \( \text{AWMF} = -0.5 \pm 1.6 \text{ m}^3/\text{s/yr} \), which is a result of the AMF time series being dominated by winter floods. The ASMF time series remains rather constantly in time with a trend of \( \text{ASMF} = 0.1 \pm 1.1 \text{ m}^3/\text{s/yr} \). It is worth to mention, that the flood in 2002 represents the most severe summer flood in the time series, which underlines the relevance of the 2002 event for flood risk management issues. The differences in the computed trends for winter (downward) and summer (no trend) confirm former studies, which found comparable results (Mudelsee et al., 2003; Mudelsee, 2004; Bormann et al., 2011). Taking a closer look to the POT time series, it is apparent from the trend analyses that there are slightly increasing trends with \( \text{POT-0.67} = 1.0 \pm 0.7 \text{ m}^3/\text{s/yr} \) (i.e. 3 floods per year in mean) and \( \text{POT-1.00} = 0.4 \pm 0.8 \text{ m}^3/\text{s/yr} \) (i.e. 2.3 floods per year in mean). It is important to mention, that –with the exception of the POT-0.67 trend– none of the computed trends can be assessed as being significant at the 95% confidence level.
4.3. Changes in flood risk

As introduced in Sect. 1 we tried to clarify, if the extreme floods in 2002, 2006, and 2011 events will affect extreme value statistics and if common design values for engineering tasks (i.e. HQ100) have changed over the last decades. Time-dependent changes in extreme value statistics can be investigated using a non-stationary extreme value statistics approach (e.g. Mendez et al., 2007; Mudersbach and Jensen, 2010). However, since the time series of the daily mean discharge and the considered flood indicators do not show any obvious non-stationary characteristics with respect to the trend estimates, here we use a quasi non-stationary extreme value approach in order to analyse the influence of single extreme events on the extreme value statistics. The quasi non-stationary approach is based on common stationary extreme value distributions (i.e. GEV and GPD) and a stepwise analysis of different time series lengths. Firstly, stationary extreme value statistics are computed for a time period from 1875 to 1950. Afterwards, the time series is extended step by step by one year until the entire time series from 1875 to 2011 is analysed. This procedure reflects the real situation in statistical or engineering practice, where design values have to be steadily verified due to new data. Regarding the different POT time series, the thresholds change with time and thus, for each time span a slightly modified time series may result. In terms of the AMF, AMFr2, AMFr3, AWMF, and ASMF the time series are simply extended by adding a new year.
Figure 5 illustrates the results of the extreme value analysis. The black thick lines represent the time-dependent behaviour of the 100-yr return levels \(HQ_{100}\) for each time span. This means, the first value plotted at the year 1950 is the \(HQ_{100}\) value resulting from extreme value analyses using the time series from 1875 to 1950. The next value, plotted at 1951, results from the time series 1875 to 1951 and so on. The red lines display the 95% confidence levels in each case.

Results from analysing the \(POT-0.67\) time series with the \(GPD\) show a decreasing development of the \(HQ_{100}\) from 1950 to about 1970 and a more or less stable characteristic with only slight variations between 3920 m\(^3\)/s and 4010 m\(^3\)/s until 2011. With respect to the extreme events in 2002, 2006, and 2011 there are increases of the \(HQ_{100}\) of 40 to 50 m\(^3\)/s, respectively. However, these changes are not extraordinary large and are not unusual with respect to the entire time series. Assessing the results of the \(POT-1.00\) series, there is generally a comparable behaviour to the \(POT-0.67\) series, but showing lesser variations and a small offset in the \(HQ_{100}\), which results in \(HQ_{100}\) values of about 3880 m\(^3\)/s for the last decades. The changes due to the mentioned three extreme events are between 30 to 40 m\(^3\)/s (increase). The \(POT-2.10\) series reveals \(HQ_{100}\) values in the range of 3750 m\(^3\)/s for the last decades, and shows a smaller decreasing trend from 1950 to about 1970 in comparison to \(POT-0.67\) and \(POT-1.00\). Changes due to the recent flood events vary between 0 to 15 m\(^3\)/s. The \(AMF\) series exhibits a larger decreasing trend from 1950 to about 1970 and a slightly increasing tendency from 1970 to the end. In 2002, 2006, and 2011 jumps of approximately 50 to 60 m\(^3\)/s appear, but these jumps are not unusual assessing the behaviour of the entire time series. The flood indicators \(AMFr_2\) and \(AMFr_3\) do show a quite similar characteristic to the \(AMF\), whereas the decreasing trend from 1950 to about 1970 is more distinctive. It is also remarkable, that these two flood indicators have an offset of about 300 m\(^3\)/s in comparison to the \(AMF\).

Focusing on the winter floods (\(AWMF\)), it can be seen that there is a big similarity with the \(AMF\) analyses, which is mainly caused by the fact, that the \(AMF\) series is dominated by winter events. In contrast, the statistics of the summer floods (\(ASMF\)) show a different behaviour from the other flood indicators. From 1950 to about 1970 an increasing flood risk can be observed, followed by a more or less constant development until 2001. In 2002, a sudden jump of about 200 m\(^3\)/s occurs, which is due to the extraordinary summer flood in 2002. This analysis clearly highlights the effect of a single extreme event on the extreme values statistics. However, the \(ASMF\) series is of minor importance for designing tasks because of the rather low summer floods, which result in \(HQ_{100}\) values of about 3100 m\(^3\)/s for the last decade.
In summary, it can be stated, using the here applied quasi non-stationary extreme value approach, that the time dependent behaviour of return discharges of the main flood indicators is not significantly affected by the extreme events in 2002, 2006, and 2011.

Figure 5 Time-dependent 100-yr return levels of discharge (thick black line) at gauge Neu Darchau from 1950 to 2011 using different flood indicators derived by extreme value statistics. The red lines refer to the 95% confidence levels.

5. Discussion and Conclusions

The main objective of this paper was to answer the questions, if the discharge characteristics of the Elbe River have changed over the last decades and how much the design discharges (i.e. \textit{HQ100}) are affected by the latest extreme events in 2002, 2006, and 2011. The results found from the trend analyses revealed no clear evidences for an increasing flood risk. Moreover, the trends for \textit{AWMF} show a slight downwards trend, whereas the \textit{ASMF} remains constantly. However, none of these trends (with only one exception) were statistically significant. These results point out, that the time series of the gauge Neu Darchau is stationary and less affected by climate change or effects due to river training along the Elbe River. This basically confirms the findings from (Mudelsee, 2004) who analysed extreme floods in central Europe. However, a recent publication (Busch et al., 2012) investigated the influence of large dams on flood discharges in the
Elbe River catchment. They found that the peak discharge of flood events can be reduced due to dam regulation from \(359 \text{ m}^3/\text{s}\) up to \(757 \text{ m}^3/\text{s}\) at gauge Dresden and from \(183 \text{ m}^3/\text{s}\) to \(616 \text{ m}^3/\text{s}\) at the gauge Wittenberge (approximately 80 km upstream the gauge Neu Darchau). As we did not separate anthropogenic (e.g. river engineering/training) and climate change effects on the discharge data in our analyses, no quantitative statements regarding the interactions of these effects can be made.

One key finding is that the time dependent behaviour of the extreme value statistics of the main flood indicators is not significantly affected by the extreme events in 2002, 2006, and 2011. Only the summer flood indicator ASMF shows a significant dependency linked to the 2002 event. However, the results obtained within this investigation for the gauge Neu Darchau are not unrestricted transferable to more upstream located gauges (e.g. Dresden) due to differences in the catchment size, runoff concentration time and specific discharge.

Nevertheless, the stability of \(T_{2\text{yr}}\) return discharges strongly depend on the analysed record length. The shorter the analysed time series, the larger the variability and the uncertainty of return discharge estimates. Merz et al. (2011) discussed this topic with respect to the return period of the 2002 flood at the Elbe River gauge Dresden. This phenomenon is also present in this study. Due to the long record from 1875 to 2011 (i.e. 137 years) a resilient time series is available and results from the quasi non-stationary extreme value analysis indicate (Fig. 5), that from about 1970 onwards the return discharges are more or less constant.

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References


A comparison of linear and nonlinear regression modelling for forecasting long term urban water demand: A Case Study for Blue Mountains Water Supply System in Australia

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Abstract
Prediction of long term water demand is necessary to assess the future adequacy of water resources, to attain an efficient allocation of water supplies among competing water users and to ensure long-term water sustainability. In order to predict future water demand and assess the effects of future climate and other factors on water demand, suitable mathematical models are needed. The study compares a multiple linear and nonlinear regression model to forecast monthly water demand in the Blue Mountains Water Supply System, Australia. The performance of the developed models are assessed through the relative error (RE), the coefficient of determination ($R^2$), the percent bias (PBIAS) and the accuracy factor ($Af$), computed from the observed and model predicted water demand values. The RE, $R^2$, PBIAS, $Af$, values are found to be 0.46%, 0.88, 2.07% and 1.04, respectively for multiple linear regression model and 2.49%, 0.30, -20.79% and 1.21, respectively for multiple nonlinear regression model. The results of the study show that the developed multiple linear regression model is capable of predicting water demand more accurately than multiple nonlinear regression model.

1. Introduction

Urban water demand modelling plays an important role in efficient planning, design and development of water supply systems. In order to ensure reliable water supply to the residents of a city, an accurate estimate of future water demand is necessary. This estimate can help in planning a cost effective and reliable infrastructure expansion, developing alternative water supply sources and incorporating water demand management programs [House-Peters & Chang, 2011]. Mathematical models can be developed to estimate future water demand under changing climate, population growth and conservation measures. Therefore, development of a suitable water demand forecasts model is essential to have the prediction of future water demand. Water demand forecasting can be classified into two types, i.e. short term and long term forecasting [House-Peters & Chang, 2011; Nasseri et al., 2011]. Short term forecasting is required for operation of reservoirs and pumping stations, and maintenance of a water
supply system [Jain et al., 2001]. On the other hand, long term forecasting is essential for planning and design of system expansion and future resilience analysis [Bougadis et al., 2005].

In literature, many approaches have been proposed to forecast short and long term urban water demands. Froukh [2001] mentioned that time extrapolation, disaggregate end-uses, single coefficient method and multiple coefficient method are suitable for long term forecasting. In contrast, time series models (e.g. Box Jenkins and ARIMA), memory-based learning technique, probabilistic method and artificial neural networks models are suitable for short term forecasting. Babel et al. [2007] also mentioned that domestic water demand can be forecasted by time extrapolation methods, single coefficient requirement methods, multiple coefficient requirement models, multiple coefficient demand models and disaggregated water use forecast models. Qi & Chang [2011] have grouped the existing forecasting approaches into five categories, which are the regression analysis, the time series analysis, the artificial intelligence approach (e.g. Artificial Neural Networks, fuzzy logic and agent based models), the hybrid and the Monte Carlo simulation approaches.


In respect to multiple linear regression analysis of urban water demand, there has been rather limited research on multiple nonlinear regression modelling. Examples include Adamowski et al. [2012] and Yasar et al. [2012]. Adamowski et al. [2012] used
polynomial functions to develop multiple nonlinear regression equations using observed data for forecasting domestic water demand in Montreal, Canada. Yasar et al. [2012] assumed a general form of nonlinear equation for forecasting water demand, which was the multiplication of all the independent variables with a power relationship for the dependent variable.

In this study, a linear and a nonlinear multiple regression models were developed for forecasting long term residential water demand using the demographic, socio-economic and climatic variables as predictor variables. Firstly, a simple regression analysis was carried out for each of the predictor variables (with the dependent variable) to find out a suitable relationship (i.e. water demand). Thereafter, the nonlinear multiple regression functions were defined using the identified dependent-independent relationships. The developed multiple linear and nonlinear regression models were applied to the water supply systems for modelling of the single dwelling residential water demand in the Blue Mountains regions, Australia. The obtained results were compared for both the multiple linear and nonlinear regression models. Finally, the performances of the developed linear and nonlinear multiple regression models were evaluated using a number of statistical performance indices such as relative error, the coefficient of determination, the percent bias and the accuracy factor.

2. Study area

The Blue Mountains region (Figure 1) of New South Wales, Australia is selected as the study area. The Blue Mountains Water Supply System provides water to around 48,000 population from Faulconbridge to Mount Victoria, which are considered as Upper and Middle Blue Mountains area [Sydney Catchment Authority, 2009]. Cascades and Greaves Creek delivery systems together make up the Blue Mountains Water Supply system which provides water to the twelve reservoir zones, namely, Mount Victoria, Blackheath, Catalina, Katoomba, Yosemite, Wentworth Falls, Bodington, Bullaburra, Lawson, Woodford, Linden, and Faulconbridge.
The climate of the Blue Mountains is normally moderate than the lower Sydney region. As Mount Victoria is over 1000 meters above Sea Level, the temperature is normally 7°C lower than the coastal Sydney. The average temperature in the Upper Blue Mountains is around 5°C and 18°C in winter (June to August) and summer months (December to February), respectively. The Blue Mountains experience similar rainfall to that of Sydney. The average rainfall in the Upper Blue Mountains is around 1050 mm per year [Bluemountainsaustralia, 2013].

3. Materials and Methods

3.1. Data context
Data on per dwelling monthly metered water consumption which has been considered as dependent variable in the linear and nonlinear regression models were obtained from
Sydney Water for the period of January 1997 to September 2011 for the study area. Data on water usage price and water conservation savings (WCS) were also obtained from Sydney Water for the same period. In this study, WCS refers to the water savings from the implemented water demand management programs in Blue Mountains, such as rainwater tank, WaterFix (installation of new showerheads, flow restrictions and minor leak repairs undertaken by a licensed plumber), DIY (Do-It-Yourself) kits (self installed flow restrictors), water efficient washing machines and toilets [Sydney Water, 2010]. Data on water restriction savings (WRS) due to imposed water restriction in the Blue Mountains Water Supply System during the drought period (2003-2009) were estimated from the water consumption data. Temperature and rainfall data were obtained from Sydney Catchment Authority for the period of January 1997 to September 2011 for the study area. The available data (1997-2011) was divided into two data sets, model development set (January 97 to June 09) and validation set (July 09 to September 11).

3.2. Multiple linear regression analysis

Multiple linear regression (MLR) analysis examines the relationship between several independent variables and a dependent variable. In MLR, the relationship between the dependent variable and the independent variables are assumed to be linear. The following represents a multiple linear regression equation [Montgomery et al., 2001]:

\[ Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k \]  

(1)

where \( \alpha \) is the model intercept are the regression coefficients, and \( \beta_i \) is the number of independent variables.

In this study, three forms of MLR were adopted to model the single dwelling residential water demand which were Raw-Data (i.e. no transformation of the variables), Semi-Log (i.e. transformation of the dependent variable in the logarithmic form), and Log-Log (i.e. transformation of the dependent and independent variables in the logarithmic form). Based on the models performance, the semi-log model was finally selected to undertake the MLR analysis. The finally adopted MLR equation has the following form:

\[ \ln(Y) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 \]  

(2)
Where \( Y \) = per dwelling water consumption in a month (kL/dwelling/month), \( X_1 \) = total monthly rainfall in mm, \( X_2 \) = monthly mean maximum temperature (in °C), \( X_3 \) = water usage price in AUD/kL, \( X_4 \) = water conservation savings in kL/dwelling/month, and \( X_5 \) = water restriction savings in kL/dwelling/month.

The regression coefficients were estimated using Minitab software [Minitab, 2010].

### 3.3. Multiple nonlinear regression analysis

In the multiple nonlinear regression (MNLR) analysis, the relationship between the dependent and the independent variables are assumed to be nonlinear. Nonlinear regression can estimate a model using random relationship between dependent and independent variables. In this study, a series of simple regression analysis between the dependent and the independent variables were conducted first. Thereafter, the multiple nonlinear regression equation was developed to model the single dwelling residential water demand using the identified relationship during simple regression analysis. Linear, power, quadratic, cubic, logarithmic and exponential functions were used to identify the best relationship. Results of the simple regression analysis between the dependent variable and the independent variables are presented in Table 1.

**Table 1:** Correlation coefficients of the simple regression analysis between the dependent and the independent variables

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Linear</th>
<th>Logarithmic</th>
<th>Quadratic</th>
<th>Cubic</th>
<th>Power</th>
<th>Exponential</th>
</tr>
</thead>
<tbody>
<tr>
<td>( X_1 )</td>
<td>0.024</td>
<td>0.029</td>
<td>0.028</td>
<td>0.028</td>
<td>0.027</td>
<td>0.024</td>
</tr>
<tr>
<td>( X_2 )</td>
<td>0.086</td>
<td>0.083</td>
<td>0.086</td>
<td>0.086</td>
<td>0.08</td>
<td>0.082</td>
</tr>
<tr>
<td>( X_3 )</td>
<td>0.38</td>
<td>0.39</td>
<td>0.41</td>
<td>0.42</td>
<td>0.46</td>
<td>0.44</td>
</tr>
<tr>
<td>( X_4 )</td>
<td>0.46</td>
<td>*</td>
<td>0.46</td>
<td>0.53</td>
<td>*</td>
<td>0.52</td>
</tr>
<tr>
<td>( X_5 )</td>
<td>0.61</td>
<td>*</td>
<td>0.61</td>
<td>0.61</td>
<td>*</td>
<td>0.68</td>
</tr>
</tbody>
</table>

*Logarithmic and power models cannot be calculated due to existence of zero values.

Based on the results presented in Table 1, logarithmic, linear, power, cubic and exponential models are more suitable for \( X_1, X_2, X_3, X_4 \) and \( X_5 \) variables, respectively (as marked in bold in Table 1). Finally, the following multiple nonlinear equation form was adopted for the prediction of water demand.

\[
Y = \alpha + \beta_1 \ln(X_1) + \beta_2 X_2 + \beta_3 X_3^2 + \beta_4 X_4 + \beta_5 X_4^2 + \beta_6 X_4^3 + \beta_7 X_5 + \beta_8 \exp^{\beta_9 \times X_5} \quad (3)
\]

The regression coefficients for nonlinear regression analysis were obtained using Minitab software [Minitab, 2010].
4. Model evaluation criteria

The performances of the developed MLR and MNLR models were compared using four statistical performance indices, namely the relative error (RE), the coefficient of determination ($R^2$), the percent bias (PBIAS) and the accuracy factor ($A_f$). The ideal values of these performance indices are 0 for RE, 1 for $R^2$, 0 for PBIAS and 1 for $A_f$. The values of these performance indices were computed from the observed and model predicted values of the dependent variable. They were calculated for both the development and validation data sets. The values were calculated using the equations given in Table 2.

Table 2: Numerical indices used to evaluate model performance

<table>
<thead>
<tr>
<th>Performance Indices</th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>RE</td>
<td>$\sum_{i=1}^{n} \frac{</td>
</tr>
<tr>
<td>$R^2$</td>
<td>$\left( \frac{\sum_{i=1}^{n} (O - \bar{O})(P - \bar{P})}{\sqrt{\sum_{i=1}^{n} (O - \bar{O})^2 \sqrt{\sum_{i=1}^{n} (P - \bar{P})^2}}} \right)^2$</td>
</tr>
<tr>
<td>PBIAS</td>
<td>$\frac{\sum_{i=1}^{n} (O - P)}{\sum_{i=1}^{n} O} \times 100$</td>
</tr>
<tr>
<td>$A_f$</td>
<td>$\left( \frac{\sum_{i=1}^{n} \frac{</td>
</tr>
</tbody>
</table>

*O: Observed water demand, P: Model estimated water demand, N: Number of observations.

5. Result and Discussion

The performance indices of the developed multiple linear regression (MLR) and multiple nonlinear regression (MNLR) models for estimating per dwelling monthly water demand for both the model development and validation period are presented in Table 3. As can be seen in Table 3, RE value was found to be lower in MLR model than in MNLR model (i.e. 1.03% and 1.55%) for the model data set. The RE values were 0.46% and 2.49% for the validation data set for the MLR and MNLR model, respectively. The MLR model had an $R^2$ value of 0.70 and 0.88 for the model and the validation data sets, respectively, which were found to be much higher than the $R^2$ values of 0.46 and 0.30 of the MNLR model. In respect to percent bias, the MLR model also outperformed the MNLR model. The PBIAS values for MLR model were found to be 0.65% and 2.07% for the model and
the validation data set, respectively. Similarly, for MNLR model they were 0.44% and -20.79%, respectively. The $A_f$ was found to be 1.07 and 1.04 for MLR model and 1.11 and 1.21 for MNLR model for the model and validation data set, respectively. Based on these $A_f$ values, it has been found that the MLR model performed better than the MNLR model.

Table 3: Results of the performance indices for both the MLR and the MNLR model

<table>
<thead>
<tr>
<th>Performance Indices</th>
<th>MLR</th>
<th>MNLR</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model data set</td>
<td>Validation data set</td>
</tr>
<tr>
<td>RE</td>
<td>1.03</td>
<td>1.55</td>
</tr>
<tr>
<td>$r^2$</td>
<td>0.70</td>
<td>0.46</td>
</tr>
<tr>
<td>PBIAS</td>
<td>0.65</td>
<td>0.44</td>
</tr>
<tr>
<td>$A_f$</td>
<td>1.07</td>
<td>1.11</td>
</tr>
<tr>
<td>RE</td>
<td>0.46</td>
<td>2.49</td>
</tr>
<tr>
<td>$r^2$</td>
<td>0.88</td>
<td>0.30</td>
</tr>
<tr>
<td>PBIAS</td>
<td>2.07</td>
<td>-20.79</td>
</tr>
<tr>
<td>$A_f$</td>
<td>1.04</td>
<td>1.21</td>
</tr>
</tbody>
</table>

Figures 2 and 3 compare the observed monthly water demand for the single dwelling residential sector with the forecasted monthly water demand for the period of July 2009 to September 2011 by MLR and MNLR model, respectively. As can be seen in Figure 2, the MLR model provided the closest estimates to the corresponding observed monthly water demand for the forecast period. On the other hand, MNLR model over estimated the monthly water demand (Figure 3) in comparison to observed water demand during the forecast period. By comparing Figures 2 and 3, it can be said that the MLR models yield significantly better demand predictions.
6. Conclusion

In this study, a multiple linear regression (MLR) and nonlinear regression models (MNLR) were developed for the prediction of monthly water demand for single residential sector in the Blue Mountains Water Supply System, Australia. In the Blue Mountains system, single dwelling residential sector is the highest water consumption sector. Around 75% of total supplied water is used by this sector and the rest is shared between multiple dwelling and commercial sectors. The developed models were validated and tested on monthly data of per dwelling single residential water demand over a period of 12 years. Both the MLR and MNLR were constructed using five independent variables namely, total monthly rainfall, monthly mean maximum temperature, water usage price, water
conservation savings and water restriction savings.

The study shows that the developed MLR model was capable of forecasting monthly water demand with a higher degree of accuracy. On the other hand, performance of the developed MNLR model was relatively poor as compared to MLR model. Moreover, the developed MNLR model was found to have overestimated the monthly water demand by about 20%. However, the suitability of multiple nonlinear regression models need to be investigated further using different combination of random relationships between the dependent and the independent variables in the models to improve its accuracy.

**Acknowledgements:**

Water consumption data were collected from Sydney Water in 4 May 2012. The best available data at the time of study has been used, which may be updated in near future. Daily rainfall and temperature data were collected from Sydney Catchment Authority (SCA). The authors express their sincere thanks to Pei Tillman and Frank Spaninks of SW for their assistance in collating and providing the data. Further, the authors are very grateful to Lucinda Maunsell and Peter Cox of Sydney Water and Mahes Maheswaran of Sydney Catchment Authority for their cooperation and assistance during data collection and analysis.

**References**


Temporal changes in the hydrochemical facies of groundwater quality in two main aquifers in Hanoi, Vietnam

Thuy Thanh Nguyen¹ · Akira Kawamura¹ · Naoko Nakagawa¹ · Hideo Amaguchi¹ · Romeo Gilbuena Jr¹

¹ Tokyo Metropolitan University

Abstract

Groundwater is the major source for drinking and domestic water in Hanoi, Vietnam. A clear understanding of the processes that influence its hydrochemical properties would be of invaluable use in management and protection of this important water resource. In this study, the temporal changes in the hydrochemical facies in the confined and unconfined aquifers in Hanoi were investigated using the water quality data from 10 and 16 sampling wells of Holocene unconfined and Pleistocene confined aquifers, respectively, taken in 1993, 2003 and 2011. The hydrochemical type in each aquifer of each well was determined using the Piper diagram method. Results indicate that the two main aquifers in Hanoi are predominated by the calcium cation and bicarbonate anion types. Results also show that the hydrochemical facies remain mostly unchanged not only in the Pleistocene confined aquifer but also in the Holocene unconfined aquifer, in which, the chemical characteristics of the groundwater in the latter are affected directly by precipitation, infiltration of water through soil, and anthropogenic activities. This implies that the hydrochemical facies is controlled by the materials that are naturally occurring in the aquifers.

1. Introduction

In Hanoi, the capital of Vietnam, nearly the entire population depends on groundwater for daily water consumption because of the uneven distribution and contaminated quality of surface water resources. Recently, the combination of rapid population growth, urbanization and industrialization results in overexploitation of the groundwater resources in the region. The continuous high water demand leads to the unmitigated decline of groundwater levels (Bui et al. 2012) and the deterioration of water quality, as a result of the salinisation and contamination processes (Duong et al. 2003; Montaganero et al. 2007). Sustainable management of groundwater is thus necessary to secure its future availability and ecological value.
Hydrochemical facies, an important diagnostic chemical aspect of groundwater solutions occurring in hydrologic systems, is commonly examined in the assessment of groundwater quality. Hydrochemical facies analysis provides information on the distinct zones of cations and anions along different layers of aquifers (Christopher and Robert 2005). Pollutants, such as heavy metals and organic compounds, generally interact with the ions present in groundwater (William 1997). A clear view of the predominant ions can help understand the origin, interaction and mechanisms of contamination process.

There have been quite a few studies on the groundwater in Hanoi reported in literature. Nguyen and Helm (1996) and Trinh and Fredlund (2000), for example, investigated on land subsidence due to excessive groundwater exploitation. Spatial and temporal analyses of groundwater levels in Hanoi were carried out by Bui et al (2012b). Duong et al. (2003) considered groundwater quality, pollution and monitoring system design. Groundwater arsenic contamination was identified in some parts of Hanoi (Berg et al. 2008). However, there is little available information regarding the groundwater hydrochemical properties in Vietnam, including Hanoi.

Various researchers have carried out extensive hydrochemistry studies for assessing groundwater quality. Marghade et al. (2012) assessed the chemistry of major ions of shallow groundwater to understand the groundwater geochemical evolution and water quality in Nagpur city, central India. Baghvand et al. (2010) studied the groundwater quality of the Kashan Basin, central Iran and characterized the groundwater species by using the Piper diagram. Arumugan and Elangovan (2009) assessed the groundwater quality of the Tirupur region in India for drinking and irrigation purposes by using the Piper diagram and sodium percentage values. However, very few studies have looked at the temporal changes in the hydrochemical properties. In fact, evaluation of temporal changes in hydrochemical facies is a difficult issue because groundwater chemistry data commonly have short record length, limited spatial coverage, and high uncertainty. Investigation of temporal changes in the hydrochemical properties may reflect the groundwater hydrodynamics and circulation, which may help improve the data collection programs for groundwater assessment and enable better use of groundwater supplies.

Through implementing a National Hydrogeological Database Project under the support and nomination of the Ministry of Resources and Environment of Vietnam, we have constructed and maintained a costly groundwater monitoring database to gather all the observed groundwater data. To take advantages of our internally- available data sets, the main objective of this study was to investigate temporal changes in the groundwater hydrochemical properties in Hanoi and to deduce a hydrochemical evaluation of the
aquifer system based on the ionic constituents, water types, and factors controlling groundwater quality. To achieve the expected goals, groundwater quality data of the unconfined and confined aquifers in three years, 1993, 2003 and 2011 during dry and rainy seasons were collected and analyzed. The Piper diagram was used to investigate the hydrochemical facies. Decades of studies have already proven the efficacy and robustness of the Piper diagram method in classifying the ions in the groundwater into various hydrochemical types (Jamshidzahed and Mirbagheri 2011; Joshi and Seth 2011; Arumugan and Elangovan 2009; Tatawat and Chandel 2008; Raji and Alagbe 1997). This study will provide valuable insights in understanding the temporal changes in the groundwater hydrochemical properties in Hanoi, especially under the looming effects of climate change.

Figure 1  Study area and distribution of sampling points
2. Study area

Figure 1 shows the geographical locations of Hanoi and the 10 and 15 sampling wells in HUA and PCA, respectively, used in this study. Hanoi is located at north-eastern Vietnam. It covers a total area of about 3400 km² and has a population of about 7 million (in 2011), which comprises approximately 7.5% of the total population of Vietnam. Hanoi is situated in the tropical monsoonal region with two distinct dry and rainy seasons. The rainy season starts in May and ends in October, while the dry season lasts from November until April. The annual average rainfall is about 1,600 mm, but in 2011, it was measured at 1,795 mm. The annual average humidity is about 80%, and the average temperature is around 24°C. The annual evaporation average is around 900 mm. The river network is quite extensive, with a network density of about 0.7 km/km². More than 100 lakes can be found in Hanoi, with a total surface area of more than 21.8 km². In 2011, the recorded average discharge of the Red River at the Hanoi station, shown by the triangle in Figure 1, was 2182 m³/s during the flood season, and 927 m³/s during the dry season; both are lower than the average discharge in the past (3970 m³/s and 1160 m³/s, respectively). High concentration of suspended solids is always present in the Red River. The lakes, ponds and canals in Hanoi are highly polluted because of untreated domestic and industrial wastewater. Because groundwater is relatively cleaner, and remains generally unaffected by the surface environmental problems, it has become the most trusted water source (Bui et al. 2011).

In terms of regional geology, Hanoi is underlain by the Pleistocene and Holocene sediments, with the latter being partly derived from postglacial marine transgressions and tectonic activity. From our previous studies (Bui et al. 2011, 2012a), HUA consists of silty clay and various sands mixed with gravel. The thickness of this layer varies greatly up to more than 35 m with an average of about 15 m. The transmissivity in HUA is from 20 to 1,788 m²/day. PCA consists of sands mixed with cobbles and pebbles, and is situated lower in the stratigraphic sequence. The thickness of PCA fluctuates over a large range with an average of about 35 m, and gradually increases from north to south. The transmissivity ranges from 700 to 2900 m²/day and indicates a very high potential of groundwater resources. Within the 5 km zone of the Red River, HUA and PCA are mainly recharged by the river. Outside the 5 km zone, PCA is predominantly recharged by the vertical percolation of water coming from HUA through hydrogeological windows (borders between two aquifers where the two aquifers are directly connected without any impermeable layer).
3. Data used

Groundwater samples were collected from the two major aquifers (HUA and PCA) in Hanoi using 10 and 15 observation wells for HUA and PCA, respectively (Figure 1). The samples were collected in February (dry season) and August (rainy season) of three years (1993, 2003 and 2011) and were analyzed according to ISO standard test methods (National technical regulation on underground water quality, 2008) for the following physico-chemical parameters: TDS, pH, major cations (Ca\(^{2+}\), Mg\(^{2+}\), Na\(^{+}\), K\(^{+}\)), major anions (HCO\(_{3}^{-}\), Cl\(^{-}\) and SO\(_{4}\)\(^{2-}\)), NH\(_{4}^{+}\), NO\(_{2}^{-}\), and NO\(_{3}^{-}\). The water analyses were conducted in the laboratories of the Ministry of Natural Resources and Environment. The carbonate ion (CO\(_{3}\)\(^{2-}\)) was calculated from the observed bicarbonate (HCO\(_{3}^{-}\)) and pH data (James 1982). The total hardness (TH) in ppm was calculated from the data of Ca\(^{2+}\) and Mg\(^{2+}\) data (Todd 1980).

4. Results and discussion

The term "hydrochemical facies" is used to describe the occurrence modes of groundwater in an aquifer with respect to chemical composition. To determine the hydrochemical facies of groundwater, the percentages of the equivalents of each physico-chemical parameter are plotted on a Piper diagram. This diagram is then used to identify the dominant cation and anion in each well by using the left and right ternary diagrams, respectively. The left ternary diagram is divided into three cationic classification regions, namely the [Ca\(^{2+}\)], [Mg\(^{2+}\)], and [Na\(^{+}\)] types, whereas the right ternary diagram is divided into three anionic classification regions, namely the [HCO\(_{3}^{-}\)], [Cl\(^{-}\)], and [SO\(_{4}\)\(^{2-}\)] types. Each observation has a dominant cation and anion type. The combination of these predominant ion types is the hydrochemical facies of the aquifer at a specific observation well. After plotting the data, the hydrochemical facies of each well was investigated for temporal changes by comparing the dominant ions.

Figures 2 and 3 show the Piper diagram plot for HUA in dry and rainy season, respectively. The number symbols and their color in this figure correspond to the locations of the observation wells in Figure 1 and the observation year, respectively. As indicated in the left ternary diagram of these figures, the water samples identified as the [Ca\(^{2+}\)], [Na\(^{+}\)], and [Mg\(^{2+}\)] types are 25, 2 and 3 during dry season and 20, 7 and 3 during rainy season, respectively. The right ternary diagram shows 29 out of the 30 water samples to be of the [HCO\(_{3}^{-}\)] type in both seasons. Thus, HUA is mostly of the [Ca\(^{2+}\)-HCO\(_{3}^{-}\)] type (calcium ion-bicarbonate ion type). In general, it is observed from Figs 2 and 3 that the temporal
changes in the hydrochemical facies of the HUA groundwater are not significant except for well H3 and H13. Note that three groundwater samples from well H3 show an obvious difference of water type from other wells, especially anion type. In addition, the temporal changes in the hydrochemical facies are also identified in this well. The water type of groundwater in well H3 in 1993 was $[\text{Ca}^{2+}\cdot\text{SO}_4^{2-}]$, but became $[\text{Ca}^{2+}\cdot\text{HCO}_3^-]$ in 2003 and $[\text{Na}^+\cdot\text{HCO}_3^-]$ in 2011 during both seasons (Figures 2 and 3). With closer inspection of land use, this well is located in an agricultural area of intensive irrigation (Nguyen 2010). Therefore, it is reasonable to infer that agricultural activities cause the groundwater samples of H3 to differ from other wells and change the hydrochemical facies over time.

![Piper diagram for HUA in dry season in 1993, 2003, 2011](image)

**Figure 2**  *Piper diagram for HUA in dry season in 1993, 2003, 2011*
It is also observed that water type of groundwater in well H13 changed from [Na⁺-HCO₃⁻] to [Ca²⁺-HCO₃⁻] in dry season during the period of 1993-2003 (Figure 2) and recently changed from [Na⁺-HCO₃⁻] to [Mg²⁺-HCO₃⁻] in rainy season (Figure 3). These changes may be due to recharge from surface water such as lake, river and rainfall.

The Piper diagrams for PCA were also created to examine the temporal changes in the hydrochemical facies during dry and rainy seasons as shown in Figures 4 and 5, respectively. From the left ternary diagrams, the numbers of the [Ca²⁺], [Na⁺], and [Mg²⁺] types are 27, 15 and 3 during dry season and 29, 14 and 3 during rainy season, respectively. The right ternary diagrams indicate that all water samples during dry season and 44 out of 45 during rainy season are dominated by the [HCO₃⁻] type. Thus, like HUA, the groundwater in PCA is primarily of the [Ca²⁺-HCO₃⁻] type. Figures 4 and 5 indicate that there are no significant temporal changes in the hydrochemical facies for the groundwater samples in PCA.
Figure 4  Piper diagram for PCA in dry season in 1993, 2003, 2011

Figure 5  Piper diagram for PCA in rainy season in 1993, 2003, 2011
To have a better view of the temporal changes, the hydrochemical facies of all observation wells in Figures 2, 3, 4, and 5 are summarized and tabulated as shown in Tables 1 and 2 for HUA and PCA, respectively. As shown in Table 1, the hydrochemical facies of 4 and 6 out of the 10 HUA wells during dry and rainy seasons, respectively, exhibited temporal changes, particularly of the cation type. In rainy season, H2 changed from the [Ca$^{2+}$] to [Na$^+$] type during the period of 2003-2011, while H7 changed from the [Na$^+$] to [Ca$^{2+}$] type during the period of 1993-2003. Water type in the well H8 changed from the [Na$^+$] to [Ca$^{2+}$] type during the period of 1993-2003 and changed again to the [Na$^+$] type in 2011 in rainy season. H12 changed from the [Mg$^{2+}$] to [Ca$^{2+}$] type during the period of 1993-2003 and changed again to the [Mg$^{2+}$] type in 2011 in dry season, whereas in rainy season, it changed from the [Ca$^{2+}$] to [Mg$^{2+}$] type during the period of 1993-2003 and changed again to the [Ca$^{2+}$] type in 2011. H13 and H46 also show the temporal changes in the cation type (e.g. from the [Na$^+$] to [Ca$^{2+}$] or [Mg$^{2+}$] type or from the [Ca$^{2+}$] to [Na$^+$]). Regarding PCA, 8 and 6 out of the 15 observation wells showed temporal changes in the cation type during the dry and rainy seasons, respectively (Table 2). Changes from the [Na$^+$] to [Ca$^{2+}$] were observed in P7, P61 during the period of 1993-2003, P2, P13 and P61 during 2003-2011. Changed from the [Ca$^{2+}$] to [Na$^+$] were observed in P2, P61, P66 and P76 during 1993-2003, in P11 and P13. Change from the [Mg$^{2+}$] to [Ca$^{2+}$] or [Na$^+$] type or from the [Ca$^{2+}$] or [Na$^+$] to [Mg$^{2+}$] type were also observed in P3, P11, P13 and P63. These changes perhaps result from great heterogeneities of groundwater abstraction, recharge from surface water, infiltration of rainfall and characteristic of the aquifers.

Table 1: Water type of groundwater samples in HUA

<table>
<thead>
<tr>
<th>Sampling Well</th>
<th>Dry season</th>
<th>Rainy season</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1</td>
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Table 2: Water type of groundwater samples in PCA

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One interesting finding from Tables 1 and 2 was that there are more HUA groundwater samples showing the temporal changes in the hydrochemical facies during rainy season than during dry season. This may be due to the HUA groundwater affected directly by precipitation, surface water, and anthropogenic activities during rainy season. By contrast, in PCA groundwater samples having the temporal changes during dry season were observed more than during rainy season. This phenomenon could be due to the lag time for rainwater and recharge from surface water to be infiltrated in to the deeper aquifer (PCA).

It is worth to note that in rainy season, 6 out of 25 HUA and PCA samples show the changes in the hydrochemical facies during the period of 1993-2003, whereas 9 out of 25 show the changes during the period of 2003-2011. This is perhaps due to the effect of contemporary anthropogenic activities such as irrigation, industrialization and urbanization on the chemical characteristics of the groundwater.
5. Conclusion

The main objectives of this study are to investigate the temporal changes in hydrochemical facies and to deduce a hydrochemical evaluation of the aquifer system based on the ionic constituents and water type not only in HUA but also in PCA. In this paper, taking advantage of the unique database, hydrochemical parameters from 10 sampling wells for HUA and 15 for PCA in Hanoi acquired during dry and rainy season in 1993, 2003 and 2011 were comprehensively analyzed.

From analysis of the Piper diagrams for HUA and PCA, the following generalizations were obtained as the groundwater properties in Hanoi: the [Ca²⁺] type groundwater is quite abundant in both aquifers; almost all groundwater in the 10 HUA and 15 PCA observation wells is of the [HCO₃⁻] type during the dry and rainy seasons in both aquifers. The results from the Piper diagrams also show temporal changes in hydrochemical facies in 50% of the HUA wells and 46.7% of the PCA wells during both seasons. The change particularly occurs in the cation type (i.e., [Ca²⁺] to [Mg²⁺] or [Na⁺], [Mg²⁺] to[Ca²⁺], [Na⁺] to [Ca²⁺] or [Mg²⁺]), whereas the anion type almost unchanged. It is also observed that there are more groundwater samples showing the changes in the hydrochemical facies during the period of 1993 – 2003 than during the period of 2003 – 2011 in rainy season. This implies that contemporary anthropogenic activities such as irrigation, industrialization and urbanization on the chemical characteristics of the groundwater perhaps affect groundwater chemistry in the study area. The findings of this study provide valuable information regarding the groundwater hydrochemical properties and hydrodynamics in Hanoi, Vietnam.

Acknowledgements

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The Use of Teleconnections for short-term seasonal Climate Prediction in the eastern Seaboard of Thailand

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Abstract
Teleconnections between the oceanic climate states and regional weather variables in the eastern seaboard of Thailand (EST), which has been suffering from water shortage problems in recent years, are assessed by various techniques of stochastic time series analysis. To quantify these far-distance-acting relationships, monthly time series of sea surface temperatures (SST) and various other indices of the Pacific and the Indian oceans as well as temperatures and precipitation in the EST during 1971-2005 are examined using cross-correlation and linear-regression. The results of the statistical analyses show that the El-Niño 1+2 SST of the eastern Pacific Ocean has the strongest influence on the local climate in the study region, with lag-times of 2-4 months. The results of these teleconnective relationships between ocean indices and local climate are then applied for short-term seasonal climate prediction in the EST. To that avail autoregressive models such as ARIMA and ARIMAex (with external regressors) and multiple linear regression (MLR) models between predictors of several GCMs, supplemented by short-term external ocean indices predictors, and observed climate time series (predictands) are set up. Also employed are the common downscaling techniques SDSM and LARS-WG for the selection of the optimal mixed predictor sets of atmospheric variables and ocean indices for short-term seasonal climate forecasting in the study region. The performance of these different models is evaluated for two calibration periods, followed each by a one-year long verification period, using classical error measures (Nash-Sutcliffe and RMSE). The results show that the annual as well as the seasonal forecasting skills of the various GCM-MLR-prediction models can be significantly are improved when the ocean-state indices are used as an additional external predictor-set.

1. Introduction
The Eastern Seaboard industrial zone of Thailand (EST), located in the Chonburi and Rayong provinces in the eastern coastal zone of Thailand (Figure 1), has been promoted by the Thai government to be a major area for industrial development and petrochemical manufacturing since 1984. Because of this industrial campaign to expand the petrochemical industry, water demand in this region has been continuously
increasing over the last two decades. Much of the water used in the EST for serving the industry and irrigation demand as well as the tap-water supply is collected from rainfall falling over the Khlong Yai basin.
The water resources in the EST have increasingly being subjected to stress in recent years, which became particularly imminent during in 2005. Triggered by a long drought, a huge water supply crisis took place in the EST in that year when no rainfall occurred for four months after the beginning of the rainy season which led to the situation that the industrial estates in the area were not able to fully operate. Normally, most of the urban and industrial water used in this coastal region is surface water stored in a large-scale reservoir-network across the main Khlong Yai watershed. Thus the three major reservoirs usually gather water from monsoon storms that blow from the south and provide accumulative 80% of the annual rainfall during the 6 months of the rainy season which normally lasts from May-October. During the dry season (November - April) the winds are blowing from the northern Indo-China land mass and rain drops only a few days in a month. Because of this typical tropical climate system, surface water resources across most of the southeastern Asia-Pacific region and the EST, in particular, rely on the annual occurrence of the monsoon season.

There is now sufficient evidence that the named extreme weather conditions of 2005 occurring in that part of Thailand are not a singularity, but might be another signal of recent ongoing climate change in that country as a whole. In fact, this situation will be accentuated over the whole 21th -century, as indicated by the results of an analysis of downscaled GCM-climate predictions of Bejranonda and Koch [2010] and Bejranonda [2014].

While downscaled GCM (Global Circulation Model) -predictions and their subsequent implications on the hydrology of a region are of interest to understand the impacts of future climate change in the long-run [e.g. Koch, 2008] and are also part of the ongoing study of Bejranonda [2014], the focus of the present paper is on the short-term, seasonal prediction of upcoming meteorological conditions in the EST, for which downscaled predictions from GCM- are known to not bode too well. To that avail various techniques of stochastic time series analysis will be used, namely, ARMA/ARIMA- models which employ the autoregressive nature of monthly meteorological time series. These models will then be improved by incorporating information on teleconnections between oceanic indices and regional weather pattern, as they have been established for Thailand as a whole by Bejranonda and Koch [2010] and as they will be set up for the study region in the present paper. By using these statistical approaches, i.e. autoregressive models and multiple linear regression models describing the teleconnections mentioned a general forecasting tool will be developed for short-term monthly-to-seasonal forecasting of up to one year. Finally the short-term climate prediction power of several recently available GCMs for the region will be investigated again and it will be shown how the former can be improved with the incorporation of oceanic teleconnections.
2. Review of methods and applications of short-term climate prediction

2.1. Teleconnections between oceanic indices and regional weather pattern

Possible connections between oceanic indices and regional weather pattern have been investigated in many regions around the world for some time [e.g. Walker 1924; Pant and Parthasarathy, 1981; Markovic and Koch, 2005]. The inter-connection of one or more of these climate variations over large distances is called a "teleconnection" [Glantz et al., 1991].

The earliest study of a teleconnection is that of Sir Gilbert Walker [Walker, 1924; Walker and Bliss 1932] who examined the correlations between time series of atmospheric pressure, temperatures as well as of rainfall from many parts of the world. Many studies carried out since that time [e.g. Rodó et al., 1997; Kumar, 1999, Kumar et al., 1999; Rajagopalan et al., 2000; Xu et al., 2007; Cai et al., 2011] have shown that much of the observed climate variability in many regions of the world, namely, around the Pacific Ocean and here, in particular, Southeast Asia [e.g. Knutson et al., 2001, Hasegawa and Emori 2005] is influenced by the El Niño Southern Oscillation (ENSO). In particular, Ropelewski and Halpert [1987; 1989], Gershunov and Barnett [1998] and Tsonis [2005] have examined this connection of ENSO with regional climate patterns and found relationships between ENSO signals with rainfall and temperatures, not only for countries around the Pacific, but for the whole earth.

An interesting application of such ocean state - regional weather teleconnections is that they can be used for short-term regional weather prediction, owing to the facts, that (1) the ocean indices are usually well-determined and known and (2) there is some lag-time of the order of some months between them and the regional weather variables of interest [Goddard et al., 2001; Alexander et al, 2002; Nguyen et al., 2007].

For Thailand, Singhrattna et al. [2012] showed that large-scale atmospheric variables such as surface air temperatures and sea level pressures from the GFDL GCM- model relate to the monsoon rainfall in Thailand. However, the general aspects of relationships between ocean indices and the Thai climate has seldom been investigated [Youthao et al., 2008; Singhrattna et al., 2005b; Bejranonda and Koch, 2010]. Likewise, the exact nature of the teleconnections on the nationwide scale in that country still lacks understanding.

2.2. Short-term climate prediction

As there is now some evidence that the seasonal climate in a particular region may be foreseeable, the importance of short-range climate forecasts has been acknowledged
by many researchers [Thompson, 1957; Lorenz 1963; Palmer et al., 1990; Mureau et al., 1993; Palmer and Anderson 1994; Goddard et al. 2001]. As reviewed by Goddard et al. [2001], there exist several approaches of seasonal and inter-annual weather or climate prediction. Whereas the early studies on forecasting seasonal climate focused mainly on the mean temperatures or the total rainfall [Ahago 1992; Briggs and Wilks 1996], the short-term prediction of the monsoon season in South Asia, with its important ramifications on the livelihood in that region, is only later developed [Thapliyal, 1981; Rajeevan et al., 2007; Pattanaik and Kumar, 2010]. Most of the short-term predictions are based on the extrapolation of trends in the observed time series [Dyer and Tyson, 1977; Currie, 1993].

A widely used class of methods for predicting short-time climate variations is so-called statistical forecasting, which derives the future state by extrapolation of the stochastic properties of the previously observed climate time series [Goddard et al., 2001]. Autoregressive (AR) and/or autoregressive/moving average (ARMA) models are particularly well-known members of this class of methods, also called stochastical time series analysis. AR- and/or ARMA methods have been used in climate time series analysis to simulate and forecast the natural variations of stationary processes of precipitation [e.g. Adamowski et al., 1987; El-Fandy et al., 1994; Mentz et al., 2000; Weesakul and Lowanichcha, 2005; Somvanshi et al., 2006; Hurile et al., 2008; Barbulescu and Pelican, 2009; Kim et al., 2011; Sigrist et al., 2011] and temperature [e.g. Gu and Jiang, 2005; Kim et al., 2011; Malvestuto et al., 2011].

In Thailand, Weesakul and Lowanichcha [2005] used ARMA and ARIMA (the integrated version of ARMA, used to make a non-stationary time series stationary by taking appropriate differences) for the forecast of annual rainfall at 21 stations distributed across the entire country, for the purpose of a better yearly agricultural water allocation. Tantanee [2006] also used an AR-model to predict annual rainfall over the northeastern part of Thailand. However, up-to-date, autoregressive models have not yet been applied for seasonal climate prediction in the region. And this is one of the objectives of the present study.

Another technique to perform seasonal forecasting is the use of a (mostly) multiple linear regression model [e.g. Conway et al., 1996; Crane and Hewitson, 1998; Murphy. 1999; Wilby et al., 2002; Goyal and Ojha, 2011] between some predictors and predictands and which has been established from historical records of observed climate variables. This approach to predict the future state of the climate is one of the most common statistical methods [Goddard et al., 2001] and shows good performance among other methods for climate prediction [Wilby and Wigley, 1997]. In the statistical regression approach,
also called SDSM (statistical downscaling method) [e.g. Wilby and Wigley, 1997; Wilby et al., 2002], the distributions of the observed climate variables can be represented by standardized predictors [Karl et al., 1990] and, using the systematic biases in the present-day simulated climate variables [Hay and Clark, 2003; Wood et al., 2004], predictions from GCMs can be used for future climate forecasts [Wilby et al., 2002].

Multiple regression with ocean state variables as predictors has been applied to seasonal climate forecasting by Palmer and Anderson [1994] and Goddard et al. [2001]. In fact, ocean state indices have, in general, extensively been used for seasonal climate forecasting [e.g. Bah, 1987; Uvo et al., 1998; Landman and Mason, 1999], in the Asia Pacific region [Yu et al., 1997; Sahai et al., 2003; Xu et al., 2007], as well as for Thailand [Singhrattna et al., 2005a]. The last authors used a regression method in association with ENSO-predictor variables to predict the summer rainfall and used a "k-nearest-neighbor" model to predict rainfall from atmospheric predictor variables, such as surface air temperature and sea level pressure, that were obtained from the NCEP/NOAA reanalysis grid [Kalney et al., 1996] laid over the region.

In recent decades, the use of simulated atmospheric climate variables from GCMs for predicting seasonal climate has alternatively been studied [Palmer and Anderson, 1994; Kumar and Hoerling, 1995]. Although some of these studies appear to demonstrate that GCM-predicted large-scale atmospheric flow variables are not capable to simulate the local-scale variability in the short-term [Goddard et al., 2001], it has been shown, on the other hand [Krishnamurti et al., 2006; Krishnamurti et al., 2009], that using GCM-output in the statistical models can still somewhat improve the skill of a short-term prediction. Nonetheless, the use of the initial GCM atmospheric predictors alone is usually not sufficient for the prediction of the seasonal variations of climate variables [Branković et al., 1990; Barnett 1995; Branković and Palmer, 1997], but, as will be shown in the present paper, this situation can be improved by appending the GCM-predictors with predictors from ARMA-models and/or teleconnections.

3. Study region and data used

The study region is the Eastern Seaboard of Thailand (EST) which includes Chonburi and Rayong provinces situated in the east of the Gulf of Thailand (see Figure 1). Located in the EST is the Khlong Yai basin which covers an area of about 1,564 km² and contributes water to the Rayong River which flows into the Gulf of Thailand at Rayong City. As mentioned earlier, most of the urban and industrial water used in the region is surface
water stored in a large-scale reservoir-network across the main Khlong Yai watershed, namely in three major reservoirs that collect water during the monsoon rainy season (May-October).

For the objectives of this study, i.e., the short-term and seasonal climate prediction, a manifold of observed local and regional climate data as well as climate prediction data has been collected from various sources. Thus, the historic climate time-series, namely, meteorological data has been compiled by the Thailand Meteorological Department (TMD) and the Thailand Royal Irrigation Department (RID). This data consists of monthly time series of maximum and minimum temperature and rainfall recorded between 1971-2005 at 24 meteorological stations scattered across the EST (Figure 1).

**Figure 2** shows as an example the three time series of the monthly maximum and minimum temperatures as well as of the monthly rainfall at station 48459, which be further discussed in a later section. Suffice to say here, that the annual cycle of these three climate variables is clearly noticeable. From the linear trend lines computed by linear least squares regression one may also recognize a clearly increasing trend for the temperatures and a less-well pronounced decreasing trend for the precipitation during this 35-year time period.

Ocean climate indices that provide information on the ocean’s climate variability [Crosnier et al., 2008] and which will be used for the establishment of teleconnections with the regional climate in the study region (see subsequent section) have been taken from the OOPC (OOPC 2009). This data consists of monthly atmospheric and ocean time series of the sea surface temperature (SST) [Reynolds and Marsico, 1993] and other ocean state indices measure at various locations of the Pacific and Indian ocean during year 1971-2005 (see **Figure 3**).

For the Indian ocean, these are the three monthly SSTs indices: 1) Southeastern Tropical Indian Ocean SST index (SETIO), 2) South Western Indian Ocean SST index (SWIO) and 3) Western Tropical Indian Ocean SST index (WTIO).

The EPO-, WPO-, NOI-, SOI- and PNA-indices are monthly climate variability indices which are based on monthly differences of atmospheric variables measured at different locations over the ocean. The other indices are monthly oceanic variability indices as obtained from sea surface temperatures (SST) and are derived by a linear optimal interpolation of the weekly measured SST [Reynolds and Marsico, 1993] and are also called Reynolds SST.

Simulated climate data, i.e. predictions from GCM's, have been gathered from the Coupled Model

Figure 2 1971-2005 monthly maximum, minimum temperatures and rainfall at station 48459 with linear trend lines.

Figure 3 Locations of ocean state indices in the Pacific and Indian oceans.
Intercomparison Project (CMIP3) [Meehl et al., 2007] which provides multi-model monthly-climate datasets from the World Climate Research Programme (WCRP) [http://www-pcmdi.llnl.gov] with a grid resolution of 2.5° x 2.5°. Some of this data has also been used for the assessment of climate change in the IPCC-AR4 report [Pachauri and Reisinger, 2007]

Based on a screening of the various GCMs output archived in the CMIP3 by the MAGICC/SCENGEN tool [Wigley, 2008], the five models that perform best in predicting temperature and precipitation in the study region have been selected. These are 1) BCM2 [Bjerknes Centre for Climate Research, 2005], 2) ECHAM5 [Max Planck Institute for Meteorology, 2005], 3) ECHO-G [Meteorological Institute of the University of Bonn, 2005], 4) GISS-ER [NASA/Goddard Institute for Space Studies, 2006] and 5) PCM1 [National Center for Atmospheric Research, 2005]. Except for the ECHO-G model, for which also daily output data has been available and used, the output data of all other models is on a monthly scale.

All atmospheric predictors available in these GCMs - which partly differ from GCM to another one - are simulated for the 20th-century reference period 1971-1999 (the 20c3m base-scenario) then for years 2000-2005, using the SRES A2- scenario which turns out to be the best fitting scenario to the recently observed climate in the study area. Finally, a set of 0.5° x 0.5° high-resolution GCMs (Hi-Res GCM) available at the Climatic Research Unit and the Tyndall Centre for Climate Change Research at the University of East Anglia [Harris, 2007] is also bound into the multi-GCMs data set and applied to the study region.

4. Methodology

4.1. Cross-correlation analysis between ocean-state indices and local climate variables

To derive relationships between time-series measured at different geographical locations, also called teleconnections, cross-correlation analysis [Bourkej, 1996] between the various ocean indices series (see Section 2) and the three EST- climate series will be performed. The amount of cross correlation between two time series is defined by the cross correlation coefficient evaluated for different lag-times which, in the present application, can be written as
where $r_{X,S,k}$ is the cross correlation coefficient between a particular ocean state index $S$ and a particular climate time-series $x$ at lag-time $k$ and where $\bar{S}$ and $\bar{x}$ denote the corresponding means. Based on the size and the statistical significance of the $r_{X,S,k}$ computed for different lag-times $k$, which then provide the evidence for teleconnective relationships between correlated ocean state- and climate time series, the corresponding $k$-lagged ocean-state indices will be further used in the subsequent short-term climate predictions.

4.2. Methods for short-term climate prediction

Using the results of the cross-correlation analysis with its information on seasonal teleconnections between the ocean indices and EST local climate pattern, short-term climate prediction models will be developed that employ the - usually known - ocean state indices as predictors. More specifically, several methods will be set up and compared to each other: (1) ARMA/ARIMA models, (2) ARIMAex-models which employ additional external regressors, (3) multiple-linear regression (MLR) models and (4) classical downscaling methods that use climate predictions from the GCM’s, as discussed in the previous section.

4.2.1. ARMA/ARIMA models

ARMA (autoregressive–moving-average) and/or ARIMA (autoregressive integrated moving average) models are used to describe a stochastical univariate time series which appears to be random at first sight, but which possesses, in fact, some kind of autocorrelation- or memory property. ARMA-models were first proposed by Box and Jenkins [1976] and it is for this reason that they are also called Box-Jenkins models.

An ARMA-model is, in fact, a combination of an autoregressive (AR) model with a moving-average (MA) model [Whittle, 1983], whereas an ARIMA model is an "integrated" ARMA model applied to a non-stationary time series that has been made stationary by taking appropriate non-seasonal differences (negative integration) and, in the presence of seasonality, seasonal differences - in the case of which the model is called a SARIMA-model - of the original time series.

The autoregressive model part AR of an ARMA model for the time series $X_t$ can be written as:
\[ X_t = c + \sum_{i=1}^{p} \phi_i X_{t-i} + \epsilon_t \]  

(2)

where \( \phi_1, \ldots, \phi_p \) are the polynomial coefficients of the model, \( c \) is the mean of the process, \( \epsilon_t \) is a white noise error, and \( p \) is the order of the AR-model, i.e. the maximum delay-time over which a series value \( X_t \) at time \( t \) is still dependent on previous values \( X_{t-p} \).

A similar expression can be given for the moving average (MA) part of the ARMA-model

\[ X_t = \mu + \epsilon_t + \sum_{i=1}^{q} \theta_i \epsilon_{t-i} \]  

(3)

where \( \theta_i \) are the coefficients of the random shocks (innovations) \( a_t \) and \( \mu \) is the mean of \( X_t \). Whereas the physical interpretation of the AR-part of an ARMA-model is somewhat intuitive, this is less so for the MA-part. [e.g. Box and Jenkins, 1976].

Combining Equations 2 and 3, the complete ARMA\((p,q)\) - model is obtained:

\[ X_t = c + \epsilon_t + \sum_{i=1}^{p} \phi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \epsilon_{t-i} \]  

(4)

where \( c \) now denotes the mean of the process, and \( p \) and \( q \) are the orders of the AR- and MA-term, respectively. The corresponding ARIMA-model (when the time series is non-stationary) is then a noted as ARIMA\((p,d,q)\) \((P,D,Q)\) model, which can be written in operator form as [Box et al., 2008; Chun et al., 2012]:

\[ \phi_p(B) \Phi_P(B^S)(1-B)^d (1-B^S)^D X_t = \theta_q(B) \Theta_Q(B^S) a_t \]  

(5)

where \( \phi_p(B) \), \( \Phi_P(B) \), \( \theta_q(B) \) and \( \Theta_Q(B) \) are the polynomial functions of the backshift \( B \) or lag operator, \( p, d \) and \( q \) are the order of non-seasonal autoregression, differencing and moving average, respectively and \( P, D \) and \( Q \) are the corresponding seasonal orders (for monthly data, usually, \( D = 12 \)). \( X_t \) is the observed time-series, \( a_t \) is the random error at time \( t \), \( S \) is the length of the season, where usually \( s = 12 \) for time series with an annual cycle.
By dividing Equation 5 by the expression in front of on the right side, the most general seasonal ARIMA model can be written as follows:

\[ P(B)X_t = a_t \]

(6)

where \( P(B) \) is the fractional polynomial with the left side of Equation 5 as nominator and the right side as denominator.

4.2.2. ARIMA models with exogenous predictors (ARIMAex)

The determination of the AR- and MA-coefficients of the classical ARIMA model (Equation 4 or Equation 5) (for details see below) is based only on information inherent in the "stochastic" structure of the time series \( X_t \) itself, which may limit the forecast power of such a model somewhat. However, if there are time-lagged correlations or teleconnections between the various ocean indices on the climate time series in question, the classical ARIMA model can be improved by incorporating the teleconnection indices as "exogenous variables" or "external regressors" into the model [Hyndman and Khandakar, 2008]. Doing so leads to the so-called ARIMAex-model which can be written in the form of a linear regression as:

\[ P(B)X_t = \beta E_t + a_t \]

(7)

where \( E_t \) is the vector of the external regressors which, in the present case consists of the times series of the influential ocean indices, and \( \beta \) is the vector of the regression coefficients, to be determined by classical least-squares.

The set-up and development of the appropriate ARIMA/ARIMAex-model is a non-trivial task and consists basically of four steps [e.g. Box and Jenkings, 1976; Box et al., 2008], namely, (i) model identification; (ii) estimation of the model parameters; (iii) diagnostic checking for the identified model appropriateness and (iv) application of the final model, i.e. validation and/or forecasting.

Step (i) is probably the most difficult one, as it requires essentially the determination of the orders \( p \) and \( q \) of the AR- and MA-process in Equation 4. This is done by visual inspection of the plots of the partial autocorrelation function (PACF) and of the regular autocorrelation function (ACF) (similar to Equation 1), respectively. A more quantitative way to do the optimal selection of \( p \) and \( q \) in a trial ARIMA \( (p,d,q) \) - model is based on the Ljung-Box test (Ljung and Box, 1978) which tests the residuals of the fitted model for remaining autocorrelation. The order \( d \) of the differencing to make the non-stationary
time series stationary is determined by means of the KPSS-test [Kwiatkowski et al., 1992] which tests a time series for stationarity.

Once the structure of the ARIMA model is approximately identified, the corresponding AR- and MA- coefficients $\phi_i$ ($i=1,\ldots,p$) and $\theta_i$ ($i=1,\ldots,q$), respectively, in the polynomial functions are estimated using the maximum likelihood method, a variant of the least-squares method. Practically this amounts to the solution of the so-called Yule-Walker equations. The estimation procedure is repeated several times with various combinations of $p$ and $q$ and applying the Ljung-Box test mentioned.

As the original monthly temperature and precipitation time series analyzed here are non-stationary, and have a $s=12$-month seasonality, they are all differenced non-seasonally at lag $d=1$ month and seasonally at lag $D=12$ months. The appropriateness of this seasonal differencing is also corroborated by application of the seasonal unit root test of Osborn-Chui-Smith-Birchenhall [Osborn, 1988]. The final seasonal ARIMA $(p,d,q)$ $(P,D,Q)_s$ - model is then estimated as described above.

Once the optimal ARIMA- and/or the ARIMAex- model - the latter being estimated by linear regression (Equation 7), after the structure of the underlying ARIMA-model has been determined - has been computed and diagnostically checked (step iii), it can be validated and/or used for short-term forecasting of the time series $X_{t+k}$, $k$ time-steps ahead (step iv), using present values ($k=0$).

The ARIMA-procedures have been programmed in the $R^\circ$ - programming environment [Ripley, 2002], using partly the "forecasting" package (Hyndman and Khandakar, 2008).

4.2.3. Multiple-linear regression (MLR)

In the multiple-linear regression (MLR) model, atmospheric predictors from GCMs and, if desired ocean state indices - are used to forecast monthly climate variables in the EST study region. The MLR model, which is also called a transfer model in the language of statistical downscaling (SDSM) (e.g. Wilby and Wigley, 1997; Wilby et al., 2002), is used here to connect the vector of a climate variable $Y_i$ ($i=1,\ldots,m$) to a predictor matrix $X_{j,i}$ whose columns ($j=1,\ldots,n$) consist of the vectors of the $n$ predictor variables, i.e. GCM- predictors plus ocean state indices. This multiple linear regression model can be written as

$$ Y_i = \beta_1 X_{1,i} + \cdots + \beta_n X_{n,i} + \epsilon $$  \hspace{1cm} (8)
where $\beta_i$ are the unknown regression coefficients and $\epsilon$ is an error term which includes observational and model errors.

The initial selection of the $n$ best GCM-predictors (plus ocean state indices, see below) is based on their cross-correlation ranks with the climate variable (Equation 1). This optimal number $n$ of predictors for use in the regression model (8) is further fine-tuned by the method of stepwise regression [Draper and Smith, 1998], whereby all combinations and subsets of $(1,\ldots,n)$ possible predictors are tested in the model.

For each trial model (8), the residual sum of squares is minimized by linear least squares and the $AIC$ (Akaike's information criterion) [Akaike, 1974] is computed, which is defined by $AIC = 2k - \ln L$, where $L$ is the value of the likelihood-function after minimization, i.e. the sum of the squared residuals of the fit, and $k$ ($k = 1,\ldots,n$) is the number of parameters in the model. Thus $AIC$ essentially penalizes the least-squares fit by the number of parameters in the model.

As mentioned above, to improve the prediction power of the downscaled GCM-model (8), an extension of the classical transfer model is proposed here which consists in enlarging the GCM-predictor matrix $X$ by optimally time-lagged ocean state predictors, namely Nino 1+2 which turns out to be the most influential teleconnector on the local weather in the EST (see next section). To determine the optimal ocean index $x$ and its responding optimal lag-time $\tau_{opt}$ for a particular climate variable $y$, linear regressions of $y$ on various time-lagged ocean indices are performed. The corresponding regression equation is:

$$y = x_{t+\tau} \times \beta_1 + \beta_0 + \epsilon$$

where $x_{t+\tau}$ is the time-lagged (by $\tau$ months) ocean state predictor variable. The regression coefficients $\beta_1$ and $\beta_0$ are found by minimization of the error term $\epsilon$ using again the method of least-squares. The goodness of the regression fit is then measured by the coefficient of determination $R^2$. Equation 9 is solved repeatedly for different lag-times $\tau$ of the observed ocean variable to find the optimal lag-time $\tau_{opt}$ which best predicts the climate variable at a particular station, i.e. has the highest $R^2$.

### 4.2.4. Conventional statistical downscaling

Among the class of "statistical downscaling" techniques, SDSM and LARS-WG are probably the most widely used [Wilby et al., 1998; Hashmi et al., 2011]. The statistical downscaling model (SDSM) (Wilby et al., 1999; Wilby et al., 2002)) is a downscaling tool which is based on a combination of multiple-linear regression (MLR), similar to Equation 9 and
a stochastical weather generator. The MLR is used to set up a linear transfer model between the (coarse-grid) GCM’s predictors and the local-scale weather parameters, whereas the weather generator acts to modify the variance of the downscaled predictors to better represent the variations of the local climate variables. Here the SDSM- method is applied to

LARS-WG is a stochastic weather generator [Racsko et al. 1991, Semenov and Barrow 2002] which is used to simulate temperature and precipitation at a single site under present and future climate conditions whereby in the latter case future predictions from GCMs are used to "delta-correct" the present day stochastic realization of the WG.

By applying these downscaling techniques, the seasonal climate forecasts such as predicting of monsoon rainfall [e.g. Krishnamurti et al., 2002; Kang et al. 2004; Krishnamurti et al., 2006] and monthly climate (e.g. Krishnamurti et al., 2009; Kar et al. 2011) usually occupies downscaling of GCM to perform. Therefore, SDSM and LARS-WG models are experimentally obtained to transfer the information of GCM to small region that are comparatively evaluated in performing short-term climate prediction as an alternative approach besides an ordinary MLR model.

5. Results and discussion

5.1. Establishing teleconnections between ocean states and local climate in the EST

5.1.1. Cross-correlations of ocean state- and climate time series

With its long coastline connected in the eastern and western section to the Gulf of Thailand and the Andaman Sea, respectively, Thailand is directly part of both the Pacific and Indian Ocean (see Figure 1). Because of this peculiar geographic location, Thailand's climate is strongly influenced by the tropical monsoon seasons which, in turn, as discussed in Section 2 [e.g. Singhrrattna et al., 2005a], are highly dependent upon the Pacific- and Indian ocean states (see Figure 3).

To derive possible teleconnections between the various ocean state indices’ series and of the three EST climate series, the time lagged cross correlations (Equation 1) between the two groups have been computed using all combinations of 1971-2005 monthly data from the 13 ocean climate times-series with the 24 precipitation and 4 temperature station time series in the EST study region. For each pair of ocean-state index- climate-
variable time series only negative lags, i.e. lags between 0 to -11 months are considered in Equation 1, in order emphasize the fact that there should be causal effect of the ocean index on the local weather, i.e., a change in the former will have a delayed effect on the latter.

The maximum correlation coefficient in the series of $k = 0,...,-11$ has then been extracted and plotted in the three panels of Figure 4 for each of the three climate variables: maximum, minimum temperature and precipitation and this for all stations and for all 13 ocean indices. One can observe that the average values of the cross-correlation coefficients in the figure are consistently large enough ($r > 0.5$) for the El Niño and EP indices located in the Pacific Ocean, to provide some more evidence of the well-known fact about the strong teleconnections of El-Nino pattern with the local seasonal climate in Southeast Asia [e.g. Ropelewski and Halpert, 1987; 1989; Singhrratna et al., 2005a]]. Interestingly enough, the pattern of wet and dry years following El Nino/La Nina events, which is so typical for the region, manifests itself in the negative sign of $r$ for the correlation of the precipitation with the Nino indices.

Figure 4 does not yet provide information on which lag $k$ results in the largest $r$ for a certain cross-correlation, i.e. information which is needed for potential forecasts of upcoming local weather pattern when knowing the ocean state some months ahead of time. For that purpose the whole cross-correlations for Tmax, Tmin and PCP at climate station 48459 (shown already in Figure 2) with the four El-Niño regional indices Niño1+2, Niño 3, Niño3.4 and Niño 4 are plotted as a function of the lag time (from $k = -11$ to $+11$ months) in Figure 5.

One may notice from the first row of correlations in that figure, i.e. those of the three climate variables with Niño 1+2, that, in general, the optimal lag lies between -5 and -1 months. On the other hand, the climate correlations with the neighborhood ocean indices Niño 3, 3.4 and 4 (see Figure 3 for locations), shown in the same column, result in somewhat smaller optimal lag times which appears to make sense as these Niño regions are located closer to Thailand. Interestingly enough, the absolute values of the cross-correlations coefficients in Figure 5 identify the Niño 1+2 ocean index as the most influential teleconnector on the local weather in the EST. In any case, these consistently negative optimal lags between -1 to -5 months prove the causal effects of these Pacific Ocean state indices on the local weather variables in the EST study region, i.e. evidence for teleconnection between the two has been established.
Figure 4  Maximum cross correlation coefficients for only-negative lags (k = 0 to -11 months) of the climate variables Tmax (a), Tmin (b), (both 4 stations) and PCP (c) (24 stations) with the 13 different ocean indices.

Figure 5  Cross-correlations of the maximum, minimum temperatures and the precipitation at station 48459 with El Niño indices Niño 1+2, 3.4 and 4.
5.1.2. MLR of seasonal climate variables with ocean state predictors

In the next step, the multiple linear regression (MLR)- Equation 9 between observed climate time series and the various time-lagged ocean state predictors is used to quantify the previously detected teleconnections.

Here we only show and discuss the use of the Nino 1+2 ocean index, as the latter turned out to have the strongest time-lagged correlation with the EST-weather variables (see Figure 5). The reader is referred to Bejranonda [2014], for the presentation of the complete analysis.

This regression analysis has been done not only for the whole annual monthly-measured climate series at a station, but also for seasonally split data sets, whereby four seasonal schemes, namely, a no-season (annual), 2-season, 3-season, and a 4-season scheme, whose notations and cyclic divisions are listed in Table 1, are analyzed. The individual regressions are then done with the corresponding seasonal data for four separate lag-times $k = 0,-1,-2,$ and -3 months.

The four panels of Figure 6 show the seasonal regressions between El Niño 1+2 SST and the minimum temperatures for the 4-season scheme (coded as ss4 in Table 1) - which is the most prominent one for describing Thailand's seasonal meteorology (other schemes are analyzed in Bejranonda [2014]) - for these four different monthly lag-times. The goodness of the fits as measured by $R^2$ obtained for each seasonally grouped dataset plus that of using no seasonal separation (annual data), are written in the header of each panel. Also shown are the corresponding regression lines.

<table>
<thead>
<tr>
<th>Scheme</th>
<th>Code</th>
<th>Jan</th>
<th>Feb</th>
<th>Mar</th>
<th>Apr</th>
<th>May</th>
<th>Jun</th>
<th>Jul</th>
<th>Aug</th>
<th>Sep</th>
<th>Oct</th>
<th>Nov</th>
<th>Dec</th>
</tr>
</thead>
<tbody>
<tr>
<td>no variation</td>
<td>ss0</td>
<td>s0</td>
<td>s0</td>
<td>s0</td>
<td>s0</td>
<td>s0</td>
<td>s0</td>
<td>s0</td>
<td>s0</td>
<td>s0</td>
<td>s0</td>
<td>s0</td>
<td>s0</td>
</tr>
<tr>
<td>2 seasons</td>
<td>ss2</td>
<td>s1/2 : dry</td>
<td>s2/2 : wet</td>
<td>s1/2 : dry</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 seasons</td>
<td>ss3</td>
<td>s1/3 : winter</td>
<td>s2/3 : summer</td>
<td>s3/3 : rainy</td>
<td>s1/3 : winter</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4 seasons</td>
<td>ss4</td>
<td>s2/4 : pre monsoon</td>
<td>s3/4 : monsoon1</td>
<td>s4/4 : monsoon2</td>
<td>s1/4 : dry</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 1: The four seasonal schemes of the annual seasonal division of the climate data. Only the 4-season scheme ss4 is analyzed here.

Table 2 summarizes the results of this 4-season scheme ss4, as extracted from Figure 6, again and allows for each of the four seasons the selection of the optimal lag-time as model based on its $R^2$. Thus one may note that the minimum temperature for the dry season (s1) fits best with Nino 1+2 at lag -3 months, while the temperatures for the s3- and s4- (monsoon) seasons are best fitted at lag -2 months, although at a much lower
On the other hand, the regressions for the annual data (no seasonal split) are much better, since for the -3 months lag prediction $R^2=0.54$ is obtained.

The results of this - and those of the other meteorological data [see Bejranonda, 2014] - seasonal analysis will be used later as an add-on in the MLR-climate prediction model to improve the power of the latter.
Table 2: Selection of optimal lag time (bold) for seasonal prediction of Tmin at station 48459 with 1 to 3-months lagged Niño 1+2 data for the 4-season scheme (Figure 6), based on the highest $R^2$ value for the seasonally split data.

<table>
<thead>
<tr>
<th>Season</th>
<th>$R^2$</th>
<th>optimal Lag (months)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lag -1 month</td>
<td>Lag -2 months</td>
</tr>
<tr>
<td>annual (s0) (no season)</td>
<td>0.17</td>
<td>0.43</td>
</tr>
<tr>
<td>dry (s1/4)</td>
<td>0.01</td>
<td>0.02</td>
</tr>
<tr>
<td>pre Monsoon (s2/4)</td>
<td>0.47</td>
<td>0.43</td>
</tr>
<tr>
<td>Monsoon1 (s3/4)</td>
<td>0.13</td>
<td>0.19</td>
</tr>
<tr>
<td>Monsoon2 (s4/4)</td>
<td>0.13</td>
<td>0.13</td>
</tr>
</tbody>
</table>

5.2. Short-term climate prediction in the EST

5.2.1. General approach

With short-term climate prediction in the EST we mean here seasonal forecasting of the monthly maximum and minimum temperature and precipitation of up to 12 months ahead. The validations of these seasonal predictions are separated into two sets, noted in the following as "vrf1" and "vrf2", wherefore "vrf1" is based on a calibration during years 1971-1985 and forecasting (verification or validation) the named climate variables in the following year 1986, and "vrf2" on calibration during years 1971-1999 and subsequent forecasting in year 2000.

The reliability of the prediction models, i.e., its performance is computed by the $RMSE$ (root mean squared error and the Nash–Sutcliffe ($NS$) efficiency coefficient [Nash and Sutcliffe, 1970], for calibration as well as for verification. Values of $NS$ between 0 and 1 are generally viewed as acceptable levels of performance, a $NS$-value of 0 indicates that the model is at least able to predict the mean of the observation, and $NS < 0$ means that the observed mean is even a better predictor than the simulated predictand. Following the classification of Moriasi et al. [2007], the model performance is considered usually unsatisfactory, whenever $NS < 0.5$.

5.2.2. Use of autoregressive techniques AR, ARIMA and ARIMAex

The application of the various autoregressive techniques, i.e., AR-, ARIMA- and ARIMAex-models to the short-term climate prediction at the specific site, station 48459, is investigated in this sub-section. In particular, the ARIMAex-model is compared with the more commonly used ARIMA- and AR- models based on the values of the named two performance measures $RMSE$ and $NS$ for the vrf1- and vrf2- verifications. The results are summarized in Table 3.

From the table one may notice, that, although the predictions of maximum and...
minimum temperatures and precipitation are mostly optimal for the ARIMAex+Hi-Res GCM- combination, second-to-best results are obtained for the ARIMAex+SST- model. For precipitation, the latter model is even better than the former, which shows again the high degree of teleconnections between ocean station indices (Nino 1+2 ocean) and the rainfall pattern in the EST. In all these cases (with one exception) (see Table 3), $NS > 0.5$ are obtained.

Table 3: Average performance (as measured by RMSE and NS) of the various autoregressive models in predicting 12-month monthly temperature and precipitation time-series at station 48459 in vrf1- and vrf2-verification-modes. The best models with the highest NS for Tmax, Tmin, and PCP, respectively, are highlighted in bold italic.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Calibration</td>
<td>Verification</td>
<td>Calibration</td>
</tr>
<tr>
<td></td>
<td>RMSE</td>
<td>NS</td>
<td>RMSE</td>
</tr>
<tr>
<td>Tmax (°C)</td>
<td>AR</td>
<td>0.67</td>
<td>0.61</td>
</tr>
<tr>
<td></td>
<td>ARIMA</td>
<td>0.71</td>
<td>0.51</td>
</tr>
<tr>
<td></td>
<td>ARIMAex+SSTs</td>
<td>0.62</td>
<td>0.80</td>
</tr>
<tr>
<td></td>
<td>ARIMAex+ECHO-G</td>
<td>0.68</td>
<td>0.55</td>
</tr>
<tr>
<td></td>
<td>ARIMAex+HiRes</td>
<td>0.55</td>
<td>0.70</td>
</tr>
<tr>
<td>Tmin (°C)</td>
<td>AR</td>
<td>0.79</td>
<td>0.87</td>
</tr>
<tr>
<td></td>
<td>ARIMA</td>
<td>0.81</td>
<td>0.84</td>
</tr>
<tr>
<td></td>
<td>ARIMAex+SSTs</td>
<td>0.76</td>
<td>0.92</td>
</tr>
<tr>
<td></td>
<td>ARIMAex+ECHO-G</td>
<td>0.78</td>
<td>0.85</td>
</tr>
<tr>
<td></td>
<td>ARIMAex+HiRes</td>
<td>0.54</td>
<td>0.93</td>
</tr>
<tr>
<td>PCP (mm/day)</td>
<td>AR</td>
<td>2.42</td>
<td>0.49</td>
</tr>
<tr>
<td></td>
<td>ARIMA</td>
<td>2.37</td>
<td>0.45</td>
</tr>
<tr>
<td></td>
<td>ARIMAex+SSTs</td>
<td>2.31</td>
<td>0.68</td>
</tr>
<tr>
<td></td>
<td>ARIMAex+ECHO-G</td>
<td>2.32</td>
<td>0.48</td>
</tr>
<tr>
<td></td>
<td>ARIMAex+HiRes</td>
<td>1.93</td>
<td>0.64</td>
</tr>
</tbody>
</table>

In any case, these results demonstrate that the incorporation of teleconnections and/ or downscaled high-resolution GCM- predictors in classical "data-alone"-driven models AR and ARIMA, ie. ARIMAex, can indeed significantly improve the short-term forecasting skills of the former.

The three panels of Figure 7 show the observed and predicted monthly climate time series for the temperatures and precipitation at station 48459 for the time period 1986-1999, using the ARIMAex+SST with different ocean indices (two Niño- and the EPO- SST, as indicated) for the validation case "vrf1" (calibration for years 1971-1985). One may notice that overall a good agreement between predicted and observed values is obtained, although - as is common in ARIMA- forecasting - the peaks, i.e. the extremes of the observed time series are strongly underestimated by the model predictions. However, as will be discussed in the following section there appears to be some outlier behavior for the $T_{max}$-time series for the verification year 2000, when $T_{max}$ drops abruptly over a period of one to two years which, in fact, can also be noticed from the time series plotted in Figure 2.
Figure 7  Predicted and observed monthly a) maximum-, b) minimum temperature and c) rainfall during the time period 1986 to 1999 at station 48459 using the ARIMAex+SST models with different ocean indices (as indicated) under the verification case “vrf1” (calibration for years 1971-1985). The 80%- and 95%- confidence intervals are indicated by the orange- and yellow- colored bands, respectively.
5.2.3. Use of MLR- downscaling

Following the theoretical descriptions in Section 4.2.3, several variants of the multiple-linear regression (MLR)-model, with atmospheric predictors from GCMs and/or ocean-state indices, are used to seasonally forecast the monthly climate variables (temperatures and precipitation) in the EST study region, namely, at climate station 48459 (see Figure 1).

Table 4 summarizes the performance indicators (RMSE and NS) obtained with the three MLR-variants, namely, 1) ocean state indices (SSTs), 2) GCM-atmospheric predictors (GCMs) and 3) combination of GCM-predictors and ocean indices (GCMs+SSTs), for the two verification-schemes vrf1 and vrf2, wherefore in each calibration/verification column the values of the highest NS for Tmax, Tmin and PCP, respectively, are indicated in bold italic.

As indicated by these performance values of Table 4, the short-term prediction power of the MLR-model is significantly improved by adding ocean state indices (SSTs) in a regular GCM predictor-set, as the HiRes+SSTs - and GCMs+HiRes+SSTs-variants have the highest NS-values. One may note, however, that the maximum temperature Tmax time series for year 2000 is poorly predicted in the vrf2 verification-scheme, similar to what has already been found for the AR-group predictions in the previous section. At this stage one can only speculate about the reasons for this strong outlier behavior, although it appears to be somehow related to some anomaly in the observed Tmax-time series during 1999-2001, as once can clearly recognize from Figure 2.

The observed and predicted time series for the maximum, minimum temperatures and precipitation at climate station 48459 (Figure 1) for the time period 1986-1999 (verification case “vrf1”) by using several variants of the MLR-model (see Table 4) are illustrated in the two panels of Figure 8. The corresponding optimal regression predictor equations are exhibited on top of the charts, wherefore for the two temperatures the 3-season-, and for the precipitation the 4-season prediction scheme (see Section 5.1.2) has been used. From the upper panel description one may notice that for the prediction of the maximum temperatures, the HiRes+SSTs - regression model works best, whereas for the prediction of the minimum temperatures the more simple SSTs-MLR-model is the most appropriate one. On the other hand, for the precipitation (Figure 8, bottom panel description), the Hi-Res-GCM-predictor model is optimal.

In any case, in spite of the overall superiority of the coupled GCM+SSTs-MLR-models, these results indicate (see also Table 4), that even the relatively simple SSTs-MLR-model serves well for short-term seasonal climate forecasting in the study-region, particularly, as far as the minimum temperature is concerned. All of this emphasizes again the
important effect of the ocean- teleconnections on the seasonal variability of the local climate in the EST.

Table 4: Performance of the various MLR- model variants for calibration and verification of the monthly temperature and precipitation series for the vrf1- and vrf2- verification-schemes. In each calibration/verification column the values of the highest NS for Tmax, Tmin and PCP, respectively are highlighted in bold italic.

<table>
<thead>
<tr>
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</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Calibration</td>
<td>Verification</td>
</tr>
<tr>
<td></td>
<td></td>
<td>RMSE</td>
<td>NS</td>
</tr>
<tr>
<td>1) SSTs</td>
<td>Tmax (°C)</td>
<td>0.64</td>
<td>0.77</td>
</tr>
<tr>
<td></td>
<td>Tmin (°C)</td>
<td>0.86</td>
<td>0.91</td>
</tr>
<tr>
<td></td>
<td>PCP (mm/day)</td>
<td>2.21</td>
<td>0.79</td>
</tr>
<tr>
<td>2) GCMs</td>
<td>Tmax (°C)</td>
<td>0.81</td>
<td>0.35</td>
</tr>
<tr>
<td></td>
<td>Tmin (°C)</td>
<td>0.91</td>
<td>0.80</td>
</tr>
<tr>
<td></td>
<td>PCP (mm/day)</td>
<td>2.47</td>
<td>0.40</td>
</tr>
<tr>
<td>2) GCMs</td>
<td>Tmax (°C)</td>
<td>0.70</td>
<td>0.52</td>
</tr>
<tr>
<td></td>
<td>Tmin (°C)</td>
<td>0.80</td>
<td>0.84</td>
</tr>
<tr>
<td></td>
<td>PCP (mm/day)</td>
<td>2.06</td>
<td>0.58</td>
</tr>
<tr>
<td>3) SSTs</td>
<td>Tmax (°C)</td>
<td>0.70</td>
<td>0.52</td>
</tr>
<tr>
<td></td>
<td>Tmin (°C)</td>
<td>0.80</td>
<td>0.84</td>
</tr>
<tr>
<td></td>
<td>PCP (mm/day)</td>
<td>2.06</td>
<td>0.58</td>
</tr>
</tbody>
</table>

5.2.4. Model prediction enhancements by the use of teleconnections

In this section the advantage of the incorporation of SSTs in the general GCM-predictor-set is analyzed in more detail. This is done by dividing the predictor datasets into two groups, wherefore the first group includes GCM- predictors alone (no SSTs) and the other one comprises additional ocean state indices (GCMs+SSTs) in the set-up of the MLR- model. The improvement of the predictions when using additionally SSTs in the model is then quantified by the percental reduction of the RMSE of the former relative to the latter.
\[ \text{Tmax (HiRes+SSTs)} \]
\[
\begin{align*}
\text{[season1]} & = 1.1*\text{high_res.tmp} + 0.03*\text{Nino12_lag_1} + 0.04*\text{Nino3_lag_1} + 0.03*\text{soi_lag_2} - 0.3*\text{high_res.vap} + 7.6 \\
\text{[season2]} & = 0.9*\text{high_res.tmp} + 0.1*\text{Nino12_lag_1} + 0.03*\text{high_res.cld} + 8.1 \\
\text{[season3]} & = 0.76*\text{high_res.tmp} + 0.001*\text{high_res.pre} + 0.068*\text{Nino3_lag_1} + 0.029*\text{Nino12_lag_1} - 0.041*\text{high_res.cld} + 12.0
\end{align*}
\]

\[ \text{Tmin (SSTs)} \]
\[
\begin{align*}
\text{[season1]} & = 0.6*\text{Nino12_lag_3} + 1.9*\text{wto_lag_1} - 1.4*\text{Nino3_lag_2} + 1.2*\text{Nino34_lag_1} + 0.1*\text{Nino4_lag_1} + 0.05*\text{soi_lag_2} + 0.3*\text{pna_lag_3} + 0.1*\text{pdo_lag_1} + 0.5*\text{wp_lag_5} + 0.73*\text{noi_lag_2} + 0.3*\text{setio_lag_1} + 9.1 \\
\text{[season2]} & = 0.18*\text{Nino3_lag_1} - 0.65*\text{Nino3_lag_2} + 0.022*\text{Nino4_lag_1} + 0.333*\text{Nino12_lag_3} + 0.077*\text{soi_lag_2} + 0.485*\text{setio_lag_1} + 0.808*\text{wto_lag_1} + 1.77 \\
\text{[season3]} & = 0.182*\text{Nino3_lag_2} + 0.086*\text{Nino12_lag_3} + 0.414*\text{Nino34_lag_1} - 0.159*\text{Nino4_lag_1} + 0.038*\text{wto_lag_1} + 0.49*\text{wto_lag_6} + 0.164*\text{setio_lag_1} + 0.106*\text{wp_lag_5} - 0.041*\text{noi_lag_2} - 0.057*\text{pna_lag_3} - 0.287*\text{pdo_lag_1} + 12.0
\end{align*}
\]

**Figure 8** Observed and predicted (verification case “vrf1”) monthly maximum and minimum temperature (upper panel) and precipitation (lower panel) at climate station 48459 between years 1986 and 1999, using the different MLR-model variants, as indicated by the corresponding regression predictor equations written out on top of the charts. For the two temperatures the 3-season- and for the precipitation the 4-season prediction scheme is used.
The results of this analysis for the two calibration cases *vrf1* and *vrf2* are listed in Table 5 and they show that adding SSTs to the predictor-set improves the prediction skills for all three climate variables, in particular, for the maximum temperature on the seasonal scale. Thus the RMSE-reduction is up to 56% for *Tmax* in the pre-monsoon period. Although the annual temperature prediction in the *vrf2*-scheme is not improved when adding SSTs, the seasonal predictions are still benefiting from doing so. As for the precipitation, the table shows that its prediction error is also reduced on the seasonal scale, though to a lesser degree, when using the GCM+ SSTs - model.

Table 5: Enhancement of seasonal-prediction performances by adding SST-teleconnections into the GCM-MLR-models, as measured by the reduction of the RMSE during the "vrf1"- and "vrf2"-calibration cases.

<table>
<thead>
<tr>
<th>Calibration</th>
<th>Predictand</th>
<th>Annual and seasonal reductions of RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>annual dry pre-monsoon monsoon1 monsoon2</td>
</tr>
<tr>
<td>vrf1 1971-1985</td>
<td>Tmax</td>
<td>13% 3% 54% 18% 35%</td>
</tr>
<tr>
<td></td>
<td>Tmin</td>
<td>3% 2% 4% 17% 0%</td>
</tr>
<tr>
<td></td>
<td>PCP</td>
<td>5% 5% 5% 6% 11%</td>
</tr>
<tr>
<td>vrf2 1971-1999</td>
<td>Tmax</td>
<td>0% 0% 56% 7% 0%</td>
</tr>
<tr>
<td></td>
<td>Tmin</td>
<td>0% 7% 0% 3% 0%</td>
</tr>
<tr>
<td></td>
<td>PCP</td>
<td>0.1% 1% 7% 1% 6%</td>
</tr>
</tbody>
</table>

Finally Figure 9 shows the observed and predicted 1986-1987-monthly precipitation time series using the MLR-model GCM+HiRes+SSTs (with teleconnections) and the same model without SSTs for the "vrf1" scheme. One may notice that for the former MLR-model the fit to the observed time series is slightly better than for the latter, proving again the advantage of using teleconnections in seasonal forecasting.

5.3. Comparison of the various short-term climate prediction methods

In this section all the short-term prediction tools used in this study, i.e., AR, ARIMA, ARIMAex, the various MLR-variants, SDSM and LARS-WG are compared based on their performance - as measured by NS - in the prediction of the three climate variables for the 12 months of year 1986, i.e. the "vrf1"-scheme.

The results of this comparison are shown in Figure 10. Firstly one may notice that the results of conventional downscaling models, i.e., SDSM and LARS-WG, are not acceptable here, as their NS < 0. On the other hand, all the autoregressive techniques (AR, ARIMA and ARIMAex) as well as the group of multiple-linear regression models (MLRs) provide, in general, NS > 0.5, where the particular value depends on the kind of predictors used in the model. Moreover, the MLR-models with multi-domain GCMs and teleconnections have better performances than the autoregressive models for this prediction year 1986,
though the GCM-ensemble predictors have been calibrated over a longer past time period that in some cases extend from 1850 to 1999. Since the forecasting potential of the GCM-predictor will be weaker when the forecasting target time is farther away from this calibration baseline period of the GCM, the incorporation of these short-lag teleconnectors can be helpful for short-term forecasting in the EST for recent or even future times.
6. Conclusions

Our study shows that both the autoregressive techniques, i.e., AR-, ARIMA- and ARIMAex and the GCM- multiple linear-regression- (MLR) models to provide seasonal climate forecasting in the EST study region. Since the various ocean state (SST) indices analyzed show statistically-strong teleconnective relationships with the local climate variables, using these teleconnections in these two sets of prediction tools results in a notable improvement in both the ARIMAex- and the MLR models. Obviously, a constraint of using these ocean teleconnections in such regional climate prediction is the timely delivery of this information. In fact, the optimal lags between the ocean state and the local climate vary between -1 and -5 months, which means that this is also the time limit of how long the forward prediction can perform reliably. Thus, the months-ahead availability of the ocean state indices is the most sensitive point for their use in short-term climate forecasting. As many of these indices are nowadays continuously measured through satellite imagery and/or by telemetric ocean buoys, fixed at irregular locations across the oceans, and are archived online within one or two months [NOAA, 2009], the use of these ocean teleconnectors appears to be feasible in real-time seasonal forecasting in the study region.

The GCM/MLR- predictions, on the other hand, have the advantage of being valid for longer lead-times., however, their forecasting skills depends on their performance in the calibration-baseline period, but they may be the less reliable the farther away the target forecasting period is from this reference period. Therefore, for a meaningful future short-term forecasting, it may be necessary to strike a careful balance between the use of pre-calculated GCM-predictors and/or of more recently updated ocean indices.

Acknowledgments

This research could not have been accomplished without the people who collected and supported the data, namely, employees of the Water Resources System Research Unit at Chulalongkorn University, the Royal Irrigation- and the Thai Meteorological departments. The authors acknowledge also the groups of modelers in PCMDI and WCRP for providing the supporting CMIP3 multi-model dataset and the Tyndall Centre for Climate Change Research for the generation of the high-resolution GCM data.
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Modelling, Methods, Mathematics

Data assimilation in hydraulics, hydrology and water resources
Uncertainty of the hydraulic and transport model based on the tunnel inflow observation

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Abstract

Water inflow data were studied in a 2600 m long compact-granite tunnel of the maximum depth of 150 m located in Bedrichov (the Jizera Mountains, the Czech Republic). The aim of this study was to determine granite massif properties with focus on the inflow data assimilation and the uncertainty analyses (the inflow was measured by two different methods in the collection canal). There are 4 models used in this study. Two numerical models, (1) two-dimensional and (2) three-dimensional one, where inverse calibration of hydraulic conductivity was performed. The concentration of the natural tracers ¹⁸O and ²H from four discharges was used for modeling of transit time using (3) lumped-parameter model. Artificial pulse of concentration in the (4) advection model in the same configuration like the two-dimensional model was used for estimation of transit time. Results of these different models were compared with each other and they are in accordance to values typical for Bohemian massif. Calibration was performed in the UCODE_2005 software. The software FLOWPC was used for modeling of natural tracers. The software Flow123D, developed at our institute, was used for numerical modeling of flow and transport.

1. Introduction

One of the greatest challenges in geoscience in the last decades is to exactly determine underground flow. Even highly sophisticated computation methods focusing on underground flow do not allow exactly to determine and/or to describe underground properties, which change too fast in small area. Therefore uncertainties, negligence and some assumptions have to be considered like representative elementary volume (REV), Darcy law, laminar flow, equivalent continuum etc. [1]. Many of these assumptions produce uncertainties and that is way it is better to define an alternative conceptual model [13] and to assimilate independent data. On the other hand, the natural complexity can be expressed with same in-homogeneities like fractures and or artificially excavated space in a conceptual model. These in-homogeneities (e.g., tunnels), can be a good environment for underground research. It is possible to research a lot of underground rock parameters there and to estimate properties of massif and its local physical behavior.
At present numerical models are often developed to understand conditions of groundwater flow before, during and after the construction of an excavated human-made building [7,10,18,20].

This study is related with a simulation of thermohydromechanochemical (THMC) processes with the aim to do an analysis of deep repositories. Inflow data (used for calibration of two numerical models two-dimensional and three-dimensional ones) were applied for inverse modelling in equivalent conceptual models. The two-dimensional model was considered in each of the five tunnel sections (2DM). The three-dimensional model (3DM) included most important in-homogeneities – fractures or fault zones (further fault zones) [6]. Natural tracers, especially stable isotopes $^{18}$O and $^2$H, were used for transit time modeling in the lumped parameter approach (LPM) and in the two-dimensional advection transport model (ADV). Hydraulic conductivity was derivated from transit time and results were compared with hydraulic models.

This study summarizes the analysis of flow conditions in a vicinity of the tunnel and it is focused on evaluation of uncertainties, which are determined from the hydraulic and the transport models in the granite massif.

![Figure 1](image_url) (a) Three-dimension conceptual model (b) Digital terrain model with the problem domain and the tunnel position (right) [6].

### 2. Observations data

First water flux measurement was performed by means of weirs in shafts of the collection canal in April 2004 and was repeated in September 2004 [2]. According to flux in the collection canal the inflow in the tunnel section was performed. The collection canal was divided by four profiles to five sections marked A to E in chainage 150, 885, 1995 and 2424 m according to its typical flux and rock state and its properties (Figure 1). In this
study, the sections A (0-150 m), D and E (1995 – 2600 m) were marked as shallow sections with the mean depth of A – 20 m, D – 45.3 and E – 35 meters. The other sections C and D (150 – 1995 m) were marked as deep sections with the mean depth of 108.4 and 92.9 m.

Another total flux measurement in collection canal was carried out in February and August 2012 by means of the tracer dilution method in the same sections. The tracer KBr was continually injected into the collection canal and in the five profiles changing water conductivity was measured afterwards. Flux was computed from a mass balance equation [5]. The both methods gave similar flux values in all the intervals.

Further inflow observations were carried out in 14 discharges and other parameters were measured manually or automatically. The samples of stable isotopes $^2$H and $^{18}$O for analysis were sampled monthly from February 2010. Four discharges, marked according to their chainage 76 m, 142 m, 226 m, 125 m, were chosen for modeling. Concentration in precipitation was monthly sampled at Uhliřská a experimental catchment in a distance of 5 km from the tunnel. Both tracers samplings were analyzed by LGR Inc. LWIA2 (Laser water isotope analyzer – 2nd generation) at the Czech Technical University Prague [11].

3. Theory and softwares

3.1. Groundwater flow approach

The groundwater equation in models, which describe single-phase water, is generally governed by the Darcy's law. The combination of discrete fractures and equivalent continuum was considered (= multidimensional concept) [9], [16]. This concept is included in the software Flow123D developed at our institute as an open-source [17]. The advection-dispersion equation was implemented in the transport model. The governing equations of stationary flow was assumed incompressible (porosity $n$ and water density $\rho$ are constant in time $t$) for each dimension $i = 1, 2, 3$ (Equations 1, 2, 3):

$$u_i = -K_i \nabla p_i \quad \text{in} \quad \Omega_i \quad \text{(1)}$$

$$\kappa_i \frac{\partial p_i}{\partial t} - \nabla \cdot u_i = q_i + \sum_{j=1, j \neq i}^3 q_{ji} \quad \text{in} \quad \Omega_i \quad \text{(2)}$$

$$q_y = \sigma_i \left(p_j - p_i \right) \quad j = 1, 2, 3, j \neq i \quad \text{(3)}$$

where $u_i$ is velocity, $K_i$ is tensor of hydraulic conductivity, $p_i$ is pressure head, $\kappa_i$ is storativity (in this case it is null), $q_i$ is flux or Darcy velocity, $q_{ji}$ is flux between the domains, which is
explained in the Equation 3.

### 3.2. Lumped parameter approach

For steady flow through a groundwater system, the output concentration $C(t)$, can be related to the input concentration $C_{in}(t')$ of any tracer by the well-known convolution integral (Equation 4), which is implemented in the software FLOWPC [8]. The lumped-parameter approach is usually limited to one- or two-parameter models. The type of the model and its parameters define the exit-age distribution function (the weighting function) which gives the spectrum of the transit times [8]. The dispersion function was chosen for this study (Equation 5)

$$C(t) = \int_{-\infty}^{0} C_{in}(t')g(t - t')e^{-\lambda(t-t')}dt$$

where $t'$ is time of entry, and $t - t'$ is the transit time. The type of model is defined by the $g(t')$ function:

$$g(t') = \left(\frac{4\prod t^3}{Pc t_i}\right)^{-1/2} e^{-\left[\left(\frac{t-t'}{t_i}\right)^2\frac{Pe}{t}\right]}dt'$$

where $Pc$ is the so-called Peclet number. The reciprocal of $Pc$ is equal to the dispersion parameter, $Pc^{-1} = D/\nu x$, where $D$ is the dispersion coefficient.

### 3.3. Transit time

The lumped parameter approach uses mean transit time (‘transit time’) for modeling of a moving tracer. The artificial pulse in advection model was considered equivalent to the transit time of the lumped parameter approach. The general definition of the transit time is [8]:

$$t_t = \int_{0}^{\infty} tC_i(t)dt / \int_{0}^{\infty} C_i(t)dt$$

where $C_i(t)$ is the tracer concentration observed at the measuring point and the result of an instantaneous injection at the injection point at $t = 0$. 
4. Calibration method

For inverse modeling of the hydraulic conductivity an open-source program the UCODE_2005 [12] was used to minimize the weighted least-squares error. The intention was to minimize the weighted sum of squared deviations between the model output and the measured data [4]:

$$LSE = \sum_{t=1}^{T} \sum_{n=1}^{N} w_{n,t} \left( q_{n,t} - q_{n,t}^{obs} \right)$$

where LSE stands for the least squares error; $q_{n,t}$ and $q_{n,t}^{obs}$ are the simulated values at the location $n$, at period $t$; $N$ is the number of measurements; $T$ is the total number of periods used in the model calibration process; and $w_{n,t}$ are the weights assigned to selected measurements.

In this study, equal weights are assigned to all measurements; hence, $w_{n,t}$ is equal to 1. In this study, observations ($q_{n,t}^{obs}$) are inflow measurements and the concentration of natural tracers and $q_{n,t}$ are their simulated values. Normally, the number of observations is required to be larger than the number of fitted model parameters (an over-determined problem) for a model calibration procedure.

5. Model characteristics

It is necessary to point out, that the groundwater level is near the surface in our research area – and regarding our experience – it can be neglected then. Further the geometry of numerical models was built and discretized in the GMSH software [3]. The vertical fault zones in 3DM geometry was modified manually in GIS.

5.1. Two-dimensional model

The vertical rectangular cross-section made perpendicularly to the tunnel was considered. The model tunnel was assigned for the discretization center and with the diameter of 3.6 m. The size was assumed 500 m × 300 m sufficiently large with respect to the tunnel hydraulic reach. The finest discretization was set on the sites of our interest around the tunnel and near the surface. The model depth of the tunnel was set according the mean depth of tunnel sections respecting the division of flux measurement campaigns. The water flow was driven by the pressure difference between the boundary (hydrostatic on
the surface) and the tunnel (zero/atmospheric pressure) i.e. the linear dependence. It can be calibrated manually in two or three steps.

The impermeable bottom boundary, the zero pressure top boundary (a water table on the surface), and the hydrostatic lateral boundaries were assumed. The five models, each of them with a different tunnel depth, were defined. These models represent an average depth of each tunnel intervals stating the evaluated flux.

5.2. Three-dimensional model
The top surface was determined by the digital terrain model (DTM) of 100 m resolution, which contains main features of the massif working with the coarse mesh avoiding the (useless) fine meshing in the distant part of DTM. The elevation at the tunnel ends was adjusted to avoid penetration of the terrain surface and the tunnel volume. The bottom was flat in the 400 m altitude; with the terrain altitude varying within 550 – 880 m. Two different conductive layers and fault zones were implemented in mesh. The DTM triangulation was deformed or extended to follow exactly the important terrain structure lines: valleys, the dam, and the border (bank) of the reservoir. The whole domain includes – as best as possible – the two watersheds. The model size is about 20 km² and fits the area 5000 × 6000 m (Figure 1 (a,b)).

The definition of the model border assumes simple and realistic values of the boundary conditions the homogeneous Dirichlet condition on the surface and in the tunnel surface, the homogeneous Neumann condition on the vertical sides and at the bottom and the piezometric head defines the dam.

Calibration was performed by the UCODE_2005 in three runs. As there were just three inflow observations considered for the three parameters – $K_{up}$ in the shallow layer, $K_{wp}$ in the deep layer and $K_{faults}$ in the faults zones. The three sections of the tunnel represent those 5, which were adjusted to flux, i.e. the 2 deepest (B+C) and 3 shallowest (A+D+E) had been joined together. The inflow in the deepest sections of the tunnel was assumed to come from half the massif and half the fault zones. There was only one parameter fixed (in each calibration run) – and it varied in the following calibration runs until the LSE was found to be satisfying. The calibration was reached in three runs.

5.3. Lumped parameter approach
We assume that infiltrating water from precipitation goes into discharges in the tunnel. We did observations of precipitation that represented a time series in the length of 82 months that was analyzed for the purposes of our modeling. And about 32 observations
of discharges were done in the tunnel. The dispersion function was considered as the weighting function of the dependency of the infiltration and the discharges. The inverse problem solution was made to estimate the transit time and the dispersion parameter ($P_D$) of the tracer concentration water.

5.4. Advection-transport model
ADV configuration was considered the same for the 2DM and its configuration. The artificial unitary pulse of concentration was infiltrated to estimate the transit time. The dependence of the hydraulic conductivity and the porosity had the linear character. The combination of the porosity and the hydraulic conductivity was computed for the shallow and the deep model configurations. The transit time was determined at the moment, when the highest concentration reached the tunnel. The time was considered the same as the transit time of the lumped parameter models.

6. Results and discussion
We evaluated the hydraulic conductivity by the three and the two-dimensional models. The hydraulic conductivity was within the range from $10^{-8}$ to $10^{-7}$ [m/s] for the shallow sections except the October 2004, when the hydraulic conductivity was close to the deep section $5.1 \times 10^{-9}$ (section D in 2DM) and $2.9 \times 10^{-9}$ (3DM) [m/s]. It was due a lower flux in that campaign. For the deep sections, the hydraulic conductivity was within the range from $6.7 \times 10^{-10}$ to $2.8 \times 10^{-9}$ [m/s] (Tables 1,2). In the two-dimensional model, there was the section D featuring both sections according to the flux regime of the measurement. In the campaign of April 2004 the hydraulic conductivity was close to the deep sections and that in October 2004 was close to the shallow sections (Table 1). In three dimensional model all the differences were included in the deepest section and the hydraulic conductivity was very low $10^{-10}$ [m/s] for April and October 2004 and in February and August 2012 were $1.25 \times 10^{-9}$ [m/s]. Different measurement techniques could be reason for those differences (Table 2).
### Table 1: Hydraulic conductivity of two-dimensional models with variable depth

<table>
<thead>
<tr>
<th>Position [m]</th>
<th>depth [m]</th>
<th>April 2004 K [m/s]</th>
<th>October 2004 K [m/s]</th>
<th>February 2012 K [m/s]</th>
<th>August 2012 K [m/s]</th>
</tr>
</thead>
<tbody>
<tr>
<td>A - 0 – 150</td>
<td>20</td>
<td>$5.58 \times 10^{-7}$</td>
<td>$2.70 \times 10^{-7}$</td>
<td>$2.46 \times 10^{-7}$</td>
<td>$1.73 \times 10^{-7}$</td>
</tr>
<tr>
<td>B - 150 – 885</td>
<td>108.4</td>
<td>$2.84 \times 10^{-9}$</td>
<td>$1.18 \times 10^{-9}$</td>
<td>$1.58 \times 10^{-9}$</td>
<td>$1.18 \times 10^{-9}$</td>
</tr>
<tr>
<td>C - 885 – 1995</td>
<td>92.9</td>
<td>$2.34 \times 10^{-9}$</td>
<td>$1.62 \times 10^{-9}$</td>
<td>$1.62 \times 10^{-9}$</td>
<td>$1.99 \times 10^{-9}$</td>
</tr>
<tr>
<td>D - 1995 – 2424</td>
<td>45.3</td>
<td>$1.44 \times 10^{-8}$</td>
<td>$5.08 \times 10^{-9}$</td>
<td>$5.42 \times 10^{-8}$</td>
<td>$5.34 \times 10^{-8}$</td>
</tr>
<tr>
<td>E - 2424 – 2600</td>
<td>35</td>
<td>$4.15 \times 10^{-7}$</td>
<td>$4.63 \times 10^{-7}$</td>
<td>$3.40 \times 10^{-7}$</td>
<td>$2.74 \times 10^{-7}$</td>
</tr>
</tbody>
</table>

### Table 2: Tunnel division and the mean depth of 3DM with calibrated hydraulic conductivity.

<table>
<thead>
<tr>
<th>Section</th>
<th>Position [m]</th>
<th>April 2004 K [m/s]</th>
<th>October 2004 K [m/s]</th>
<th>February 2012 K [m/s]</th>
<th>August 2012 K [m/s]</th>
</tr>
</thead>
<tbody>
<tr>
<td>shallow</td>
<td>150-885 and 2424-2600</td>
<td>$1.33 \times 10^{-7}$</td>
<td>$2.89 \times 10^{-9}$</td>
<td>$1.14 \times 10^{-8}$</td>
<td>$1.14 \times 10^{-8}$</td>
</tr>
<tr>
<td>deep</td>
<td>885 – 2424</td>
<td>$6.75 \times 10^{-10}$</td>
<td>$3.17 \times 10^{-10}$</td>
<td>$1.25 \times 10^{-9}$</td>
<td>$1.25 \times 10^{-9}$</td>
</tr>
<tr>
<td>faults</td>
<td>4 faults in deep section</td>
<td>$2.43 \times 10^{-7}$</td>
<td>$1.13 \times 10^{-7}$</td>
<td>$8.80 \times 10^{-8}$</td>
<td>$1.82 \times 10^{-7}$</td>
</tr>
</tbody>
</table>

### Table 3: Modeling of transit time and dispersion parameter natural tracer $\delta^{18}$O and $\delta^2$H for five discharges by use software FLOWPC

<table>
<thead>
<tr>
<th>chainage [m]</th>
<th>depth [m]</th>
<th>76</th>
<th>142</th>
<th>226</th>
<th>125</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>18-O</td>
<td>2-H</td>
<td>18-O</td>
<td>2-H</td>
</tr>
<tr>
<td>dispersion parameter</td>
<td></td>
<td>0.39</td>
<td>0.34</td>
<td>0.37</td>
<td>0.33</td>
</tr>
<tr>
<td>transit time [months]</td>
<td></td>
<td>31.6</td>
<td>34.1</td>
<td>36.7</td>
<td>41.1</td>
</tr>
<tr>
<td>LSE</td>
<td></td>
<td>0.68</td>
<td>0.74</td>
<td>0.63</td>
<td>0.71</td>
</tr>
</tbody>
</table>

### Table 4: Modeling of transit time and dispersion parameter natural tracer $\delta^{18}$O and $\delta^2$H for five discharges by use software FLOWPC

<table>
<thead>
<tr>
<th>depth [m]</th>
<th>porosity mobile water</th>
<th>0.05</th>
<th>0.01</th>
<th>-120</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>hydraulic conductivity [m/s]</td>
<td>$10^6$</td>
<td>0.74</td>
<td>0.148</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$10^7$</td>
<td>7.4</td>
<td>1.48</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$10^8$</td>
<td>74</td>
<td>14.8</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$10^9$</td>
<td>740</td>
<td>148</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$10^{10}$</td>
<td>818</td>
<td>81.8</td>
</tr>
</tbody>
</table>
Modeling of the transit time in the lumped parameter models brought results within the range from 31.6 months to 42 months for $^{18}$O and from 34 months to 46.6 months for $^2$H. The dispersion parameter was within the range from 0.25 to 0.43 for $^{18}$O and from 0.32 to 0.46 for $^2$H. The Nash-Sutcliffe coefficient was within the range from 0.62 to 0.68 for $^{18}$O and from 0.67 to 0.74 for $^2$H. The only exception was the discharge at 226 m with the values of 0.05 for $^{18}$O and of 0.28 for $^2$H. Probably due its bigger depth where water can join old water from another aquifer (Table 3).

The advection transport model analyzed the range of the transit time for the porosity of 0.05 and of 0.01 and the hydraulic conductivity within the range from $10^{-6}$ to $10^{-9}$ [m/s] for the discharge at -23 meters under the surface. For the discharge at -120 meters the porosity ranged from 0.01 to 0.001 and the hydraulic conductivity ranged from $10^{-7}$ to $10^{-10}$ [m/s]. The transit time of the lumped parameter was estimated 31.6 months = 2.63 years for $^{18}$O and 34.1 months = 2.84 years for $^2$H for -23 m depth. For that time the hydraulic conductivity reply $10^{-7}$ [m/s] for the porosity varying within the range from 0.05 to 0.01. For the deep discharge at 226 m is approximately $10^{-8}$ [m/s] for the range of porosity varying within the range from 0.01 and 0.001 (Table 4).

The UCODE_2005 software was used for calibration of 3DM and LPM. Only sometimes in the first calibration run on of the calibration parameter had to be set on the starting value because the model badly converged. The model in next calculation runs well converged. The correlations were in all runs less than these critical values and it may be acceptable and rejection of the hypothesis is not necessarily warranted (Figure 2).

The UCODE_2005 calibration of LPM was successful almost in the all calculation. The LSE functions were low. Bad values of LSE were for discharge 226 m. It could be caused by higher mixing of old and young water because of this discharge is deeper than other.
discharges. Method of stable isotopes has not to be good method for this depth. Other analysis of natural tracers could be better for deeper discharges in the tunnel (for example helium-tritium method).

![Calibrated hydraulic conductivity from 2DM for every section and (b) calibrated hydraulic conductivity from 3DM for faults, upper and down layer.](image)

The uncertainty of results it could be caused by the aquifer heterogeneity in the hydraulic conductivity and specific yield. Besides, the structure of the groundwater model, arising from the limitation of measured data in terms of quality and quantity, might be another source to cause this discrepancy. Other uncertainty in boundary conditions or the local distribution of precipitation may also affect the calibration results.

7. Conclusion

Hydraulic conductivity of granite rock in some range likelihood values was calibrated from inflow measurement of the massif in the vicinity of the tunnel. These values due other measurements and calibration with different model and method specification were confirmed.

Real measurements data were used for calibration of hydraulic conductivity manually or by use the UCODE_2005 software, which was successful connected with our developed software FLOW123D for numerical modeling and software FLOWPC used lumped parameter approach.

Firstly calibration of two-dimensional model with some simplification on four inflow measurements campaigns was evaluated in different year seasons. Then calibration of two-dimensional model was confirmed by calibration of three-dimensional model with configuration at equivalent division. Last advection flux was used in two-dimensional model configuration for computing range of pulse time and it was compare with transit
time from lumped parameter model. And results from transport model confirmed results from hydraulic models. This confirmation from different models configurations and calibration on the different tunnel inflow measurements decreased uncertainties.

We demonstrated to determine hydraulic conductivity from different data set and by use two different conceptual models. The range of the varying hydraulic conductivity corresponded with the flux and our assumptions. The results for hydraulic conductivity are from $10^{-8}$ to $10^{-7}$ [m/s] for shallow zone and from $10^{-10}$ to $10^{-9}$ [m/s] for deep zone. Results are in accordance with literature for granite in Bohemian massif [15], [14].

**Acknowledgements**

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Modelling, Methods, Mathematics

Computational methods for optimal management of water resources systems
SWAT – Hydrologic Modeling and Simulation of Inflow to Cascade Reservoirs of the semi-ungaged Omo-Gibe River Basin, Ethiopia

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1 Department of Geohydraulics and Engineering Hydrology, Kassel University

Abstract
Ethiopia has abundant water resources, but they have yet to contribute more than a fraction of their potential to achieving the national economic and social development goals. Because of the uneven distribution of those resources, and the limited financial and technical resources available, Ethiopia has repeatedly suffered from drought and the aridity of much of its lands. Very little has been done to date in harnessing the country’s water resources as engines to propel national economic and social development. Runoff patterns in the Omo Gibe river basin, Ethiopia, have changed over the last twenty years as forests and vegetation have been cleared in this basin through increased human activity. During this time the Omo river itself has been developed hydraulically by the construction of two ungaged cascade reservoirs GIBE I and GIBE II, soon to be augmented by the huge GIBE III dam project, which is presently under construction. While these dams should relieve some of the power shortage problems of the country, concerns still exist that the compensation flow releases from the future GIBE III reservoir may not be enough to sustain a healthy ecological environment in the downstream sections of the Omo river, where many local tribes depend on a regular flow of river water for economic survival.

To get a better grip on the long-term water balance situation in the Omo Gibe River basin, the hydrologic simulation model SWAT is applied to this 79,000km² big watershed. Input in SWAT are climate data recorded at various stations located primarily in the highland of the basin. Output data (calibration targets) of the model are streamflows from several gauging stations, also located mainly in the highland area of the catchment. As much of this recorded data suffered from inaccuracies, inconsistencies and missing gaps, a great deal of effort had to be devoted to generate complete daily time series. To that avail the Statistical Downscaling Model (SDSM) is applied. With the input data filled and cleaned, the 1970-1990 time periods is used for SWAT model calibration, and the 1991-2000 period for validation, whereby the gauged flows in the head- and tail water sub-catchments are the calibration targets. Time series plots, as well as statistical measures, such as the the coefficient of determination ($R^2$) and the Nash-Sutcliffe efficiency (NS) parameter between observed and simulated streamflows are computed on daily and monthly time scales and both of them indicate a good performance of the final calibrated SWAT model.
Using downscaled future climate predictions of the HadCM3 GCM for Ethiopia and the study region in the SWAT model, the future inflow into the three cascade reservoirs has then been simulated up to year 2030. The results indicate that the near-future inflow into these reservoirs is slightly decreasing, a fact which may adversely affect the reservoirs’ targeted management. The next step in this, still ongoing research is the use of the SWAT-calibrated streamflow as inflow into the HEC-ResSim (reservoir) model in order to simulate the optimal operation of the three mentioned cascade reservoirs along the Omo river.

1. Introduction

Ethiopia’s primary water resources management challenges are due the extreme hydrological variability and seasonality and the international nature of its most significant surface water resources. Water is a renewable resource that naturally (without human influence) follows the hydrologic cycle. The hydrologic cycle is a continuous process without a beginning or an end and can be represented as a closed system. For a typical river basin, such as, for example, the Omo-Gibe river basin in southeast Ethiopia which is the focus of the present paper, it is common to cut out a representative control volume out of the hydrological cycle and consider the water balance within this volume while allowing for flow exchange across its boundaries. More specifically, the hydrological system considered in such a basis analysis consists of a set of interconnected components which are the atmospheric water system (i.e., rainfall, evaporation, interception and transpiration), the surface water system (i.e., the overland flow, surface runoff, subsurface, groundwater outflow and runoff to streams) and the subsurface water system (i.e., infiltration, groundwater recharge, subsurface flow and groundwater flow) [e.g. Mays and Tung, 1992].

The water resources of the Omo river basin are generally large and have been utilized over the last decades for hydropower, irrigation, and domestic and commercial purposes. In fact, the upper catchment of the Omo river basin has good potential for the construction of dams for the development of hydropower; whereas the downstream sections are provide water for agricultural irrigation. The outflow of this river serves as the sole input for Lake Turkana, whose waters guarantees the survival of more than 500,000 pastoral tribes around the lake.

To better utilize the water resources of the Omo river basin, the Ethiopian Government has pushed the construction of dams along the river for some time. The latest of
these projects is the Gibe III cascade dam hydropower project which has been under construction since 2006. It is the third in a cascade of hydro projects along the Omo River, and the fourth and fifth dam project, further downstream, (Gibe IV and Gibe V) are being studied at present time [EEPCO, 2006]. On the other hand, there has been criticism voiced in the international media that an Environmental Impact Assessment (EIA) had not been submitted for Gibe III, prior to commencing construction. There has also been criticism about the quality of the EIA studies undertaken for Gibe III, and concerns have been raised that the new dam will have catastrophic downstream effects, which have not been properly considered [ARWG, 2009].

It is obviously impossible to plan the development of the basin without a full knowledge of all its natural resources, of which the water resource is one of the most important. Thus an assessment of these water resources of the Omo Gibe basin, in relation to the existing and potential future demands is an essential base for the development of all sectors in the basin. This requires that all aspects of the water resources of the basin are measured, estimated or simulated using the most appropriate hydrologic models. The outcome of such hydrological simulations can then be used by various water-using sectors to prepare effective and economically viable plans for sustainable future developments.

In this study the SWAT model [e.g. Arnold et al., 1998; Arnold and Fohrer, 2005] has been used for simulating reservoir inflow and watershed runoff, using long-term climatic data, the availability of which is important in this kind of analysis. Since long time river basin has been recognized as the appropriate unit of analysis for water resources management and water resources studies and it has also been named by the United Nations Conference on Environment and Development (UNCED) as the unit of analysis for integrated water resources management [McKinney et al., 1990].

Establishing a relationship among hydrological components is the central focus of hydrological modeling, the latter can be just a simple model of a unit hydrograph but can be, on the other extreme, consist of a rather complex model which solves the fully dynamic flow equations and takes the heterogeneity of a river basin into account. As the computing capabilities are increasing, the use of such, so-called distributed watershed models to simulate a catchment has become standard nowadays. Such models are generally used as a utility in various areas of water resource development, for assessing the available resources, and for studying the impacts of human interference on a basin, for example, in the form of land use change, deforestation and the construction of other hydraulic structures, such as dams and reservoirs [Alamirew et al., 2007].
In contrast to hydrological studies in regions of humid climate, those in semi-arid and arid areas are often hindered by the limited availability of relevant data and information. The main reasons for this are: 1) quite a lot of river basins are un-gauged, 2) the unavailability of high-resolution spatial and temporal data like digital elevation model, soil properties, land use, and climate data of the basin. Moreover, in gauged river basins, finding all the information which is essential for the understanding of the hydrological process, is difficult to collect, not to the least due to the fact that many relevant hydrological parameters are not measured with the necessary spatial and temporal resolution [Beven, 1999]. In such situations, hydrological models provide an alternative approach to understand the basin's hydrology.

There are two basic advantages of using hydrological models, instead of relying only on collected data. Firstly, models can be used to understand the processes that are difficult to measure due to the complexity of their temporal and/or spatial scales. Secondly, a calibrated model can be used to simulate the effects of changes in land cover, water management or climate [Kite and Droogers, 2001].

2. Description of the study area

The Omo-Gibe River basin is almost 79,000 km² in area and is situated in the south-west of Ethiopia, between 4°30’ and 9°30’N and 35° and 38°E with an average altitude of 2800m asl. The Omo Gibe basin is Ethiopian’s second largest river system after that of the Blue Nile, accounting for 14% of Ethiopian’s annual runoff. It flows from the northern highlands through the lowland zone to discharge into Lake Turkana at the Ethiopia/Kenya border in the south (see Figure 1) and is fed along its course by some important tributaries.

The key characteristic of the Omo-Gibe river basin is its complex topography. Thus the basin is divided sharply into highlands in the northern half of the area and lowlands in the southern half. This division is reflected in almost all other aspects of the basin. The northern highlands are deeply dissected with steep slopes and drained by the Gibe and Gojeb systems which merge to form the Omo in a deeply entrenched gorge which slices into the highlands.

During the African pluvial periods, the Omo-Gibe River formed a deep gorge from which it emerges at about latitude 6°30’N at the confluence with the Denchiya River, whence it changes in character as it traverses the flood plain leading Lake Turkana as well defined.
meandering river. The Gibe River is called Omo River in its lower reach, south and south westwards from its confluence with the Gojeb River.

The northern part of the catchment has a number of tributaries emanating from the north-east, of which the largest are the Walga and Wabe rivers. Another two tributaries are the Tunjo and Gilgel Gibe rivers which drain mainly cultivated lands with less permeable soils in the south-west. The Gojeb river is a major right bank tributary to the Omo river, draining the uplands that have been less intensively cultivated than the other parts of the basin. To the south of the Gojeb River are the catchments of the Sherma, Guma and Denchiya rivers, which are tapering streams that join the Omo at the northern end of the flood plain. Except in the driest years, these rivers usually maintain some flow throughout the year. The Sana, Soke, Dame and Zage rivers drain the uplands on the eastern side of the middle and lower Omo-Gibe catchment where the rainfall is relatively high and these rivers are believed to be perennial. Further south, the Meki River, a tapering stream with perennial tributaries drains the highlands along the Omo-Gibe Basin boundary and maintains some flow into the Omo River except the driest years.
3. Materials and methods

3.1. Hydrological watershed modeling

Traditionally, hydrologic models have considered watershed to be homogeneous [Kilgore, 1997]. Weighted averages or mean values are used as inputs to these "lumped" models. The major drawback of lumped models is the incapability to account for spatial variability. As computers had become more powerful and less expensive, many water resources studies have been conducted using distributed parameter models. These models offer the possibility of a significant improvement over lumped models due to the ability to integrate spatial variability of hydrological processes.

Different types of hydrological models have been developed and applied over the past decades. These models have similarities in their attempt to incorporate the heterogeneity of the watershed such as the spatial distribution of various inputs and boundary conditions, such as topography, vegetation, land use, soil characteristics, rainfall and evaporation, and produce spatially detailed outputs such as soil moisture fields, water table positions, groundwater fluxes and surface saturation patterns [Troch et al., 2003]. In those models, spatial variations are approximated by spatial variation of precipitation, catchment parameters and hydrologic responses. Temporal variations of hydrologic responses are modeled by introducing threshold values for different processes to occur or not.

Representation of the catchments by individual sub basins or grids of individual elements are used to integrate the spatial variability of the above mentioned parameters with the model. Subsurface zones or vertical layers of soil for each grid element represent vertical variability. However, these models are yet to become common planning or decision tools. A majority of watershed models simulated watershed responses without or with inadequate consideration of water quality [Arnold, 1998]. On the other hand some authors [Jain et al., 1992, Troch et al., 2003] stated that the substantial data requirement for the available models is one of their biggest shortcomings.

Effective watershed management and ecological restoration require a thorough understanding of hydrologic processes in the watersheds. Spatial and temporal variations in soils, vegetation and land use practices make a hydrologic cycle a complex system, therefore, mathematic models and geospatial analyses tools are needed for studying hydrologic processes and hydrologic responses to land use and climatic changes [Singh and Woolhiser, 2002].
3.2. The hydrological model SWAT

SWAT is a hydrological model that attempts to describe the various physical processes controlling the transformation of precipitation to runoff, namely, evapotranspiration (ET), surface runoff, infiltration, percolation to shallow and deep aquifers, and channel routing [Arnold et al., 1998; Neitsch et al., 2002; Arnold and Fohrer, 2005]. These processes may vary spatially as well as temporarily and are simulated in four subsystems: surface soil, intermediate zone, shallow and deep aquifers, and open channels. Stream flow in a main channel is determined by three sources: surface runoff, lateral flow and base flow from the shallow aquifers.

The model is efficient in computing terms with the ability to perform long simulations. In SWAT, being a so-called distributed hydrological model, the impacts of spatial variations in topography, land use, soil and other watershed characteristics on the hydrology are considered in subdivisions. There are two level-scales of the latter: (1) a basin is divided into a number of sub-basins based upon drainage areas of the tributaries, and (2) each sub-basin is further divided into a number of hydrologic response units (HRUs), defined by sections of similar land cover and/or soil type.

In SWAT, the watershed of interest is divided into sub basins, which are then further subdivided into HRUs that consist of homogeneous land use, management, and soil characteristics. These elements give the model the strength to better represent the properties of land uses and/or soils of each sub-basin that have significant effect on its hydrology. There are two options available to discretize the sub-basin into simulation elements: (1) a single hydrological response unit (HRU) based on dominant land use and soil classes within a sub-basin, or (2) multiple HRUs for each sub-basin considering the percentages of the land use and the soil class within the sub-basin. One may decide whether or not to use multiple hydrologic response units (HRUs) in the modeling application. If multiple HRUs are not employed, the interface will use the dominant land use and soil characteristic for the entire watershed. To model multiple HRUs, one must determine a threshold level which will take account the heterogeneity of the land uses and soil in each sub-basin. Land uses that cover a percentage of the sub-basin area less than the threshold level are eliminated and the area of the land uses is reapportioned so that 100 percent of the land area in the sub-basin is included in the simulation.

The SWAT model streamflow simulations are very sensitive to HRU distribution levels for soil and land use areas [Mamillapalli, 1998]. For this study the default thresholds values were used for controlling the number of hydrologic response units (HRUs) in the watershed. For example, if a 10% soil area is defined in HRU distribution, only soils that
occupy more than 10% of a subwatershed area are considered in HRU distributions. Subsequently, the number of HRUs in the watershed decreases with increasing threshold values.

Full hydrologic balance of each HRU includes accumulation and evaporation of the plants, determination of effective rainfall, water exchange between surface runoff and soil layer, water penetration into deeper layers, evapotranspiration, sub-surface flow and underground flow and water accumulation. Flow generation, sediment yield, and non-point-source loadings from each HRU in a sub watershed are summed, and the resulting loads are routed through channels, ponds, and/or reservoirs to the watershed outlet. The various hydrological processes that move precipitation to streamflow, discussed above, are either described by differential equations governing the hydraulic/hydrological laws within the various compartments of the hydrological cycle or, for sake of simplicity, by semi-empirical algebraic equations with some tunable parameters [Arnold et al., 1998].

No matter what type of problem being studied by SWAT, water balance is the driving force behind everything that happens in the watershed. In order to achieve precise forecast of circulation of the pesticides, sediments or nutrients, hydrologic cycle is simulated by the model which integrates overall water circulation in the catchment area. Hydrologic simulations in the catchment area can be divided into two groups. In the soil phase of the hydrologic cycle the processes on the surface and in the sub-surface soil occur, as well as the circulation of sediments, nutrients and pesticides through the water flows in all sub-catchments. In the second phase, the circulation of water and sediment through the river network up to the exit profile are observed.

The hydrologic component of SWAT partitions precipitation into four control volumes: (1) the surface, (2) the soil profile or root zone, (3) the shallow aquifer, and (4) the deep aquifer. The fundamental hydrology of a watershed in SWAT is based on the following water balance Equation 1.

\[
SW_i = SW_0 + \sum_{i=0}^{t} \left( R_{\text{day}} - Q_{\text{surf}} - E_a - W_{\text{seep}} - Q_{\text{gw}} \right)
\]

where \( SW_i \) is the final soil water content (mm water), \( SW_0 \) is the initial soil water content on day \( i \) (mm water), \( t \) is the time (days), \( R_{\text{day}} \) is the amount of precipitation on day \( i \) (mm water), \( Q_{\text{surf}} \) is the amount of surface runoff on day \( i \) (mm water), \( E_a \) is the amount of evapotranspiration on day \( i \) (mm water), \( W_{\text{seep}} \) is the amount of water entering the vadose
zone from the soil profile on day $i$ (mm water), and $Q_{gw}$ is the amount of return flow on day $i$ (mm water).

The subdivision of the watershed enables the model to reflect differences in evapotranspiration for various crops and soils. Runoff is predicted separately for each HRU and routed to obtain the total runoff for the watershed. This increases accuracy and gives a much better physical description of the water balance [Arnold et al., 1999].

3.3. Preparation of SWAT model input.

Input files needed for daily stream flow computation are the digital elevation model (DEM), land cover, soil layers, and climate data which consists of daily values of precipitation, maximum and minimum air temperature, solar radiation, relative humidity, and wind speed. The climate stations used in the present application are shown in Figure 1. As much of the recorded data at these stations suffers from inaccuracies, inconsistencies and missing gaps, a great deal of effort had to be devoted to generate complete daily time series. To that avail the Statistical Downscaling Model [SDSM] [Wilby and Wigley, 1997; Wilby et al., 2002] has been applied. Details of the various steps involved in the application of this procedure are omitted here and the reader is referred to Seyoum [2014]. As an example, the 1970-2000 original and filled-in daily time series of the precipitation for station Asendabo, which lies approximately in the center of the Gibe III sub-watershed, and of the maximum temperatures at station Hosana, closer to the Gibe III outlet, are shown in the two panels of Figure 2.

The preparation of the map information in the SWAT model is aided by the use of the ArcSWAT modeling surface which, among other things, utilizes the Digital Elevation Model [DEM] to create the stream network, sub basins and helps to delineate the watershed boundary using the elevation or terrain data and also to calculate the sub basin parameters. Land use, and soil maps are reclassified and overlaid to create the Hydrological Response Unit (HRU). The HRU is analyzed for each sub basin based on the threshold value assigned for land use, soil and slope to subdivide the watershed into areas having unique land use and soil combinations that enables the model to reflect differences in evapotranspiration and other hydrologic conditions for different land covers/crops and soils. HRU creation in ArcSWAT requires land use and soil threshold inputs [DiLuzio et al., 2001] in order to define the level of spatial detail to include in the model. These thresholds are applied to each sub-basin and function to control the size and number of HRUs created. For a more detailed description of the ArcSWAT land use and soils threshold application the reader is referred to the ArcSWAT manual. The
The threshold levels set for defining the HRU's depend on the project goal and the amount of detail desired by the modeler. The default SWAT-threshold values for land use, soil and terrain slope, which are 20%, 10% and 10%, respectively, are sufficient for most applications and have also been used here. With this approach, 326 HRUs are obtained for the totality of the Omo river watershed.

Figure 2 1970-2000 original and filled-in daily precipitation for station Asendabo (top) and maximum temperatures at station Hosana (bottom panel)

corresponding maps of the soils and the land use for the Omo river basin are shown in the two panels of Figure 3.
3.4. SWAT model performance and evaluation

3.4.1. Sensitivity Analysis

Sensitivity analysis describes how model output varies when given input variables are varied. It allows, in a particular, identify those model parameters that exert the highest influence on model calibration or on model predictions. The model sensitivity is defined as the ratio of the change in model output to a change in parameter input. Sensitivity analysis and calibration are usually difficult with a large number of parameters. Thus, one important aim of parameter sensitivity analysis is to reduce the number of input parameters, thereby reducing the computation time for the calibration.

As the SWAT model relies on numerous parameters to represent the various hydrological, climatic, soil and plant processes within a watershed the calibration of the model for a specific study area is a challenging task, accentuated by the fact that many of these calibration parameters may be correlated to each other. Therefore many researchers [e.g. Vandenberghe et al., 2002] have proposed that a sensitivity analysis should be performed before model calibration to identify the most sensitive parameters and just use these in the subsequent calibration. For instance, Vandenberghe et al. [2001] presented a calibration approach for ESWAT, a modified version of SWAT, which involves these two steps, i.e. a sensitivity analysis followed by an automatic calibration with those parameters that have been identified as having a significant impact on the model.

Figure 3  Soil- (left panel) and land-use (right panel) maps of the Omo river basin
output. This approach has also been used in the present application of SWAT to the two sub-watersheds of the Omo river basin in order to reduce uncertainty and capture the heterogeneity of the upper highland- and lower low land catchment of the basin and provide parameter estimation guidance for the calibration step.

3.4.2. Calibration, validation and uncertainty analysis

Watershed models like SWAT contain many parameters; these parameters are classified into two groups: physical and process parameters. A physical parameter represents physically measurable properties of the watershed and whereas process parameters represent properties of the watershed which are not directly measurable [Sorooshian and Gupta, 1995]. Hence in order to utilize any predictive watershed model for estimating the effectiveness of future potential management practices, one needs to select values for the model parameters so that the model closely simulates the behavior of the study site. The objective of calibration is the estimation of values for those model parameters, which cannot be assessed directly from field data. As such calibration can be viewed upon as some kind of parameter estimation designed to reduce the uncertainty in the estimates of process parameters, but also of poorly defined physical parameters. According to Refsgaard and Storm [1996], three types of calibration procedures can be differentiated: (1) Trial-and-error, manual parameter adjustment, (2) automatic, numerical parameter optimization by minimization of the misfit objective function or, (3) a combination of the two, whereby manual calibration alone is very tedious, time consuming, and requires some experience of the user. For this reason automated calibration methods are increasingly being used, although Gan [1988] recommended that a combination of the model calibration procedures as the best approach.

The watershed model SWAT provides also the option to perform automatic calibration of its model parameters. The technique implemented in SWAT is based on the Shuffled Complex Evolution algorithm developed at the University of Arizona (SCE-UA). SCE-UA is a global search algorithm that minimizes a single objective function, i.e. the misfit function of the sum of the squared errors between the observed and modeled quantity, for up to 16 model parameters [Duan et al., 1992]. SCE-UA has been generally found to be a robust and efficient and has been applied with success to SWAT for the estimation of hydrologic parameters [Eckhardt and Arnold, 2001], as well as hydrologic and water quality parameters [van Griensven et al., 2002].

For the evaluation of the calibration (and validation) performance of the model two statistical parameters, namely $R^2$ = the squared correlation coefficient between the observed and simulated output, which in SWAT is usually the streamflow, and $NSS$ = the
Nash-Sutcliffe efficiency parameter, are evaluated. Values of $R^2 > 0.6$ and $NS > 0.5$ for
the calibration of the daily and monthly simulated streamflow are usually considered as
adequate for an acceptable calibration [Santhi et al., 2001].

4. SWAT results and discussions

SWAT-modeling of the Omo river watershed is done by dividing the total catchment with
the outlet at the town of Omorate into three sub-watersheds, whereby the upper one
is defined by the outlet gauging station Abelti, the middle one by GIBE III dam gauging
station (see Figure 1) and the lower one by Omorate, where, necessarily, a downstream
sub-catchment encompasses the upper one. Since only stations Abelti and GIBE III are
actually observing streamflow stations, calibration and validation is done only for these
two defining sub-watersheds.

4.1. Modeling of the Abelti sub-watershed

4.1.1. SWAT setup of the sub-watershed

The Abelti sub-watershed, defined by the Abelti outlet station, has an area of 15,495 km²
which makes up 30% of the total watershed delineated at the Omorate outlet point (see
Figure 1).

Climate data used in the SWAT model consists of 1970-2000 daily observations of
precipitation and maximum and minimum temperatures at the various stations within
this sub-watershed (see Figure 1). Monthly time-series of the precipitation and the
maximum temperature, together with the trend lines are shown examplarily for two
stations, which are very representative of the overall climate tendency of most of the
stations in the study region (see Seyoum, 2013, for details), in Figure 4. Thus, one may
notice that during the last 30 years of the 20th century precipitation has been slightly
increasing and maximum temperatures decreasing.

The SWAT-modeled streamflow is calibrated on daily stream flow at the Abelti gaging
station measured over 31 years (1970-2000) by the Ethiopian Ministry of Water and
Energy. Land use was reclassified into 3 broad categories, which are compatible with
the SWAT naming convention. These are AGRC, AGRR and RNGW. AGRC, AGRR and
RNGW cover 43.3%, 6.70% and 50% of the Abelti Watershed respectively. There are 6 soil
categories found inside Abelti Watershed namely, Chromic Luvisols (LVx), Dystric Vertisol
(VRd), Eutric Vertisols (VRe), Humic Alisol (ALu), Humic Nitisols (NTu), and Lithic Vertisol
(LPq) and the soil categories cover 11.35%, 12.99%, 22.28%, 23.29%, 26.65% and 3.43% respectively. The Abelti sub-watershed was delineated into 9 sub-basins which were further divided into 122 HRUs. During delineation process using SWAT, one watershed outlet was manually added at the gauging station of Abelti Village. Simulated flow at the outlet was compared with the observed flow.

4.1.2. Sensitivity analysis

The sensitivity analysis (SA) is performed in order to get a rough idea on the most important input parameters, before adjusting these sensitive parameters during the subsequent calibration process. After the preparation of the data, as discussed earlier, SWAT simulations have been done for the period 1970 to 2000, whereby the simulation period 1970-1972 serves as a "warm-up" for the model and is not considered in the sensitivity- and calibration analyses.

The sensitivity analysis was done in two steps. Initially the sensitivity of 26 SWAT - input parameters was tested by trial and error, and it was found that only about 8 parameters have a significant effect on the stream flow within the Abelti sub-watershed. As this manual SA turned out to be too tedious and not exhaustive enough, the automatic SA implemented in SWAT by means of the SWAT-CUP interface [Abbaspour et al., 2007] was considered in the second round. SWAT-CUP combines essentially the SWAT- forward model with the SUFI-2 parameter estimation procedure [Abbaspour et al., 2004] and delivers the sensitivity coefficients (and also the uncertainty) for each of the calibration parameters during the optimization process. The importance of the relative sensitivity values found in SWAT-CUP is then measured by *t*-statistics and the corresponding *p*-values.

The results of the automatic SA are listed in Table 1 which shows the 17 most sensitive parameters in decreasing order, based on their *p*-values of statistical significance - the smaller its *p*-value, the more significant is the parameter -. A description of these parameters with their effect is provided in the SWAT user manual [Neitsch et al., 2002]. The table indicates that the most sensitive parameters explaining the streamflow at the outlet of Abelti sub-watershed are saturated hydraulic conductivity [SOL_K_sol], surface runoff lag time [SURLAG_bsn], Soil bulk density [SOL_BD], Groundwater "revap" coefficient [GW_REVAP gw] and Groundwater delay [GW_DELAY gw].
### Table 1: Relative sensitivities of the optimized parameters for the Abelti sub-watershed

<table>
<thead>
<tr>
<th>No</th>
<th>Parameter</th>
<th>t-stat¹</th>
<th>p-value²</th>
<th>No</th>
<th>Parameter</th>
<th>t-stat¹</th>
<th>p-value²</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>v_SOL_K(1).sol</td>
<td>6.25</td>
<td>0.00</td>
<td>10</td>
<td>V_ESCO.hru</td>
<td>-0.91</td>
<td>0.37</td>
</tr>
<tr>
<td>2</td>
<td>v_SURLAG.bsn</td>
<td>3.13</td>
<td>0.00</td>
<td>11</td>
<td>V_CH_N2.rte</td>
<td>-0.63</td>
<td>0.54</td>
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<td>3</td>
<td>v_SOL_BD(1).sol</td>
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<td>V_REVAPMN.gw</td>
<td>-0.50</td>
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<tr>
<td>4</td>
<td>v_GW_REVAP.gw</td>
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<td>0.15</td>
<td>13</td>
<td>V_SFTMP.bsn</td>
<td>0.45</td>
<td>0.66</td>
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<tr>
<td>5</td>
<td>v_GW_DELAY.gw</td>
<td>1.34</td>
<td>0.20</td>
<td>14</td>
<td>V_CANMX.hru</td>
<td>0.37</td>
<td>0.72</td>
</tr>
<tr>
<td>6</td>
<td>v_GWQMN.gw</td>
<td>-1.28</td>
<td>0.21</td>
<td>15</td>
<td>V_CN2.mgt</td>
<td>-0.28</td>
<td>0.78</td>
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<td>7</td>
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<td>0.23</td>
<td>16</td>
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<td>0.11</td>
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<td>9</td>
<td>v_ALPHA_BNK.rte</td>
<td>1.16</td>
<td>0.26</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

¹ t-stat provides a measure of the sensitivity. A larger absolute value indicates a sensitive parameter.
² p-value determines the significance of the sensitivity. A value closer to zero denotes more significance.

#### 4.1.3. Flow calibration and validation

**Flow calibration**

After the most sensitive model parameters were identified (Table 1), these were used for the calibration on the SWAT-models, employing a combination of manual and automatic calibration, using SWAT-CUP again. Calibration targets are the daily and monthly streamflow observed at gauge station Abelti between January 1, 1970 and December 31, 1991. The first two years of this 22-year long calibration period served again as "warm-up" to allow for the hydrologic processes to reach initial equilibrium. For each parameter changes were made manually within a default range, recommended by the SWAT-
manual and/or the parameter optimization in SWAT-CUP was used. The performance of the calibration is based on measures of the quadratic deviations of simulated and measured daily and monthly discharge, namely, $R^2$ and the $NS$-efficiency coefficient of the model, but also on a visual comparison of the simulated and measured streamflow. Reiterations of the optimization were taken until satisfactory results were met.

The results of the calibration on measured daily and monthly streamflows are shown in the two panels of Figure 5. The values for the coefficient of determination $R^2$ and for the Nash-Sutcliffe model efficiency ($NS$) parameter for the fit of the daily streamflow are 0.7 and 0.55, respectively, and - is usually the case in SWAT-modeling - slightly better (0.72 and 0.6, respectively) for the monthly streamflows. Also it may be noted that, in spite of an overall good agreement of the observed and the simulated hydrographs, the latter has some problems with the mimicking of the low-flow periods of the streamflow. Further investigations are needed to explain this disagreement.

**Flow validation**

As mentioned earlier, the purpose of model validation is to establish whether the calibrated model has the ability to predict a hydrological response variable (here streamflow) for other (later) time periods or conditions than those which have been used for the calibration of the parameters. In this case, the validation period extends the January 1, 1970 and December 31, 1990 calibration periods by 10 years, i.e. goes from January 1, 1991 to December 31, 2000 period for the validation run. As the two panels of Figure 6 and the corresponding values for $R^2$ and $NS$ indicate, a good - though slightly worse than for the calibration - agreement between daily and monthly observed and simulated flows during this validation period is obtained. From the hydrographs one may notice, in particular, that the validated SWAT model is not able to fully simulate the total range of the Abelti observed streamflow, i.e simulated high flows are too low and low flows are too high. Again, further analyses are needed to unravel this mystery.

### 4.2. Modeling of the Gibe III dam site sub-watershed

**4.2.1. SWAT- setup of the sub-watershed**

The Gibe III sub-watershed, as delineated by the Gibe III outlet streamflow station, has an area of 34159 km², which makes up 48.6% of the total watershed area as delineated by the Omorate outlet. Monthly streamflow data at the Gibe III dam site consists of over 31 years (1970-2000) of data collected by EEPCO. Following Figure 2, land use for this sub-watershed has been reclassified into 4 broad categories, which, following the SWAT naming convention, are AGRC, AGRR, FRSD and RNGW, which are covering 64.68%,
8.23%, 9.31% and 17.79% of the Gibe III sub-watershed, respectively. There are 6 soil categories found inside this sub-watershed, namely, Chromic Luvisols (LVx), Dystric Vertisol (VRd), Eutric Vertisols (VRe), Humic Alisol (ALu), Humic Nitisols (NTu), and Lithic Vertisol (LPq) which make up 11.13%, 13.27%, 13.27%, 18.44%, 30.50% and 13.39% of the area, respectively. The Gibe III sub-watershed has been delineated into 14 sub-basins which have been further divided into 182 HRUs.

4.2.2. Sensitivity Analysis
The sensitivity analysis (SA) of Gibe III dam site has been performed in a similar manner as that of the Abelti sub watershed. After the preparation of the data, as discussed earlier,
SWAT simulations have been done for the period 1970 to 2000, whereby the simulation period 1970-1972 serves as a “warm-up” for the model and is not considered further in the sensitivity- and calibration analyses. The results of the automatic SA are listed in Table 2 and may be compared with those of the SA for the Abelti sub-watershed. The most sensitive parameters explaining the streamflow at the outlet of the Gibe III sub-watershed are the baseflow factor [ALPHA_BNK.rte], the hydraulic conductivity [SOL_K.sol], the threshold depth of water in the shallow aquifer for “revap” to occur [REVAPMN.gw], the average slope of main channel [CH_S2.rte], and the maximum canopy storage [CANMX.hru].
Table 2: Relative sensitivities of the optimized parameters for the Gibe III sub-watershed

<table>
<thead>
<tr>
<th>No</th>
<th>Parameter</th>
<th>t-stat</th>
<th>p-value</th>
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<td>0.36</td>
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</tbody>
</table>

1, 2 see Table 1 for explanations

4.2.3. Flow calibration and validation

Calibration

After the most sensitive model parameters for this sub-watershed have been identified (Table 2), they are used again for in the manual and automatic calibration of the SWAT-models, with the calibration target the monthly streamflow measured at gauge station Gibe III between January 1, 1970 and December 31, 1991. Other details of the calibration procedures are similar to those used earlier for the calibration of the Abelti sub-watershed and the reader is referred to that section.

Calibrated and observed streamflows at Gibe III as well as the values of $R^2$ and $NS$ are shown in the upper panel of Figure 7 and with values of 0.8 and 0.7, respectively, they are thus higher than those obtained for the Abelti sub-watershed. From the hydrographs one may notice, in particular, that the calibrated streamflow is not able to fully reflect the total range of the Gibe III observed streamflow, i.e. simulated high flows are too low and simulated low flows are too high. Again, further analyses are needed to unravel this mystery.

Validation

Hydrographs of the monthly observed and simulated monthly flow at Gibe III for the validation period (January 1, 1991 to December 31, 1999) are plotted in the lower panel of Figure 7. As this plot and the corresponding values for $R^2$ and $NS$ indicate, a good agreement between monthly observed and simulated flows during this validation period is obtained. Although the $R^2$ and $NS$ of this validation are lower than those of the calibration above, the low flows appear to better simulated here, whereas, in contrast, the high flows are more underestimated.
4.3. Simulation of future inflows into the cascade reservoirs in the Omo Gibe river basin

One of the objectives of this study is the simulation of future stream inflow to the cascade reservoirs of Gibe I, Gibe II and Gibe III of the semi ungaged Omo Gibe river basin, for the ultimate purpose of a better water management of these reservoirs. This will be done by the subsequent use of the HEC-ResSim model but which is continuation of this paper [Seyoum, 2014]. As only the Gibe III streamgage has been used so far in the previous section as a defining sub-watershed outlet station, the streamflow at the other two ungaged locations must be simulated in the SWAT-model by setting up "artificial" outlet stations there into the SWAT-GIS map.
In the SWAT watershed delineation process, there are two options for defining initial stream networks and watershed outlets. The first one is using the DEM and the defining streams based on the threshold area which has the later advantage of easy refining the stream network and outlet configuration, and also of adding, deleting and redefine additional sub-basin outlets or draining watershed inlets, depending on the interest of the modeler. The second option which consists in the direct import of pre-defined watershed boundaries and streams is of no benefit here as it disallows the addition of extra additional sub-basin outlets or draining watershed inlets. Therefore the first delineation option has been selected and the additional outlet points at the three cascade reservoirs Gibe I, Gibe II and Gibe III (observing station), and some important outlet/computational points for the latter HEC-ResSim simulations [Seyoum, 2014] have been added in tabular form for defining the corresponding sub-watersheds. Using this procedure 26 sub-basins are defined for the total Omo river basin.

As discussed in Section 3.3, the primary driving parameter for the generation of stream flow in SWAT is the meteorological variable precipitation. As the latter is routed through the catchment towards its outlet, it is affected by various other climate (temperature) and hydrological (topography, soil and landuse) parameters. Thus, in order to make predictions of the future streamflow in the Omo river basin and of the inflows into the three cascade reservoirs, in particular, the expected future changes of these SWAT input parameters must be known. To that avail daily climate predictions of the global climate model (GCM) HadCM3 with the SRES-scenario B2 for Ethiopia and available on a 2.5° latitude x 3.75° longitude grid have been downscaled to the study region using the statistical downscaling model (SDSM) [Wilby and Wigley, 1997; Wilby et al., 2002]. Details of the required steps in this procedure are described in Seyoum [2014] and omitted here. However, to get an impression of the future trends, likewise to Figure 4, the future monthly predictions for the rainfall at station Gibe and of the maximum temperature at station Jima are shown in Figure 8. Thus, one may notice again that the already observed slightly decreasing trend for precipitation and increasing trend for maximum temperatures in the final decades of the last century are well continuing into the near future.

With the input data filled and cleaned, the calibrated and validated SWAT model of Section 4.2 has been used to simulate recent past (2001-2011) and future streamflow (2011-2031) at the three cascade reservoirs. Hence the daily inflows to the Gibe I and Gibe II reservoirs are simulated by using the best calibration parameters of the Abelti sub-watershed (Section 4.1) and those for the Gibe III reservoir with the best calibration parameters of the Gibe III dam site sub-watershed (Section 4.2).
The results of these SWAT simulations for the three reservoirs are shown in the three panels of **Figure 9**. To get a better idea on the medium- and long-term evolution and trends of the streamflow, mean daily inflows for each of three decades of the 30-year long simulation period have been computed and are drawn as horizontal lines in the corresponding time-intervals of the hydrographs.

For the Gibe I reservoir the average daily stream inflow the three consecutive decades 2001-2010, 2011-2020 and 2021-2031 are 68.6, 63.0 and 60.8 m$^3$/s, respectively, for the Gibe II reservoir the corresponding numbers are 74.3, 72 and 68.4 m$^3$/s, and for Gibe III reservoirs they are 521, 552 and 530 m$^3$/s, respectively. These numbers indicate that for Gibe I and Gibe II a slight decrease of inflows for the two future decades is to be expected, whereas for Gibe III a trend is less clear as a large increase of the inflow for the 2011-2020 decade will be followed again by a decrease down to the value close to that one of the past decade. Whether these decreases of the mean stream flow at the three reservoirs will continue also in later decades of the 21st century is currently under investigation by the first author [e.g. Seyoum, 2014]. In any case, they are indicative of climate change in Ethiopia, in general [Cherie, 2013], and in the study area, in particular and reflect the complex interplay of changing precipitation, higher temperatures (which affect evapotranspiration) and - not yet considered in the model - changing land-use. In any case, further investigations on the future integrated water resource management in the Omo river basin are in order.

**Figure 8** 2000-2030 HadCM3-downscaled monthly time series of rainfall for station Gibe and of maximum temperatures of station Jima, together with linear and polynomial trend lines.
5. Summary and conclusions

The hydrologic model SWAT has been applied to the semi-ungaged Omo Gibe river basin for the purpose to estimate the present-day and future inflow to the three cascade reservoirs along the river. To that avail, the total watershed has been delineated upstream of Omorate village and divided into three sub-watersheds, whereby the upper one is...
defined by the outlet gauging station Abelti, the middle one by the GIBE III dam gauging station and the lower one by Omorate. The calibration and validation of the model is done for the time-period 1970-2000, therefore these two tasks are performed piecewise, i.e. firstly, for the upper Abelti sub-watershed, which consists of 7 sub-basins, and then for the middle GIBE III sub-watershed which is divided into 14 sub-basins.

From the sensitivity analysis 17 parameters are found to be important, out of which the 5 most significant ones in decreasing order are for the Abelti sub-watershed the saturated hydraulic conductivity [SOL_K.sol], the surface runoff lag time [SURLAG_bsn], the soil bulk density [SOL_BD], the groundwater "revap" coefficient [GW_REVAP.gw] and the groundwater delay [GW_DELAY.gw] and for the Gibe III sub-watershed the base flow alpha factor for bank storage [ALPHA_BNK.rte], the saturated hydraulic conductivity [SOL_K.sol], the threshold depth of water in the shallow aquifer for "revap" to occur [REVAPMN.gw], the average slope of main channel [CH_S2.rte] and maximum canopy storage [CANMX.hru].

The calibration and validation performance of the SWAT model were measured by the coefficient of determination $R^2$ and the Nash-Sutcliffe model efficiency (NS) parameter of the fit of simulated daily and monthly streamsflows to observed ones. It should be noted, however, that, in spite of an overall good agreement of observed and simulated hydrographs, the validation had some problems with the mimicking of the low-flow periods of the streamflow. Further investigations are needed to explain this disagreement.

Using downscaled future climate predictions of the HadCM3 GCM for Ethiopia and the study region in the SWAT model, the future inflow into the three cascade reservoirs has then been simulated up to year 2030. As the results indicate a slightly decreasing trend of inflow into these reservoirs, a review of the future integrated water resource management of these reservoirs as well as of the overall water resources in the Omo river basin is required. Therefore the next step in this, still ongoing research [Seyoum, 2014], will be the use of the SWAT-calibrated streamflow as inflow into the HEC-ResSim (reservoir) model in order to simulate the optimal operation of the three mentioned cascade reservoirs along the Omo river and, thus, hopefully, to alleviate some of the conflicts of interest between maximum power production and sufficient water availability for the local population in this part of Ethiopia.
Acknowledgments

Thanks are extended to the staff of Ethiopian Ministry of Water and Energy-Hydrology Department and GIS section, Ethiopian Electric Power Cooperation- project managers of Gibe I, Gibe II and Gibe III; and Ethiopian National Metrology Agency -Metrology data section for their assistance in providing the necessary data for the study. The helpful discussions with other PhD candidates of the Engineering Capacity Building program (ECBP), Ethiopian ECBP office coordinators are also appreciated. Finally, the financial support of the DAAD is gratefully acknowledged.

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Assessment of Climate Change Impact on Water Resources in Serbia

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Abstract

This paper presents the main results of application of mathematical model VNC for assessment of the climate change impact on the water resources in Serbia. The theoretical basis for the model VNC will be given in this paper as well as its results applied to two pilot areas – the Nisava and Kolubara river catchments. These catchments represent the southeast and northwest parts of the territory of Serbia. The input parameters are estimates of changes of the basic meteorological functions – precipitation and air temperature in climate changing conditions. In this particular case, the results which are used are obtained from the assessment carried out by the University Center for Climate Changes from Belgrade, under supervision of scientific project "Investigation of Climate Change Effects on Environmental – Following up the Effects, Adaptatio and Mitigation". This paper will be appropriately illustrated by numeric and graphic presentation of results that will show the characteristics and trends of water resources changes which are expected in the pilot areas – the Nisava and Kolubara river catchments in the XXI century.

Keywords

VNC mathematical model; climate changes; river discharge; scenario A1B and A2; precipitation; air temperature; water resources

1. Introduction

Nowadays, there are lots of discussion about climate change and its impact on water resources. At the same time, a large number of global and regional climate and hydrological models had been developed to assess the future state of the basic elements of the hydrologic cycle: temperature, precipitation, evaporation, and water resources, as well as the possible consequences of climate change. There are several global atmospheric-ocean general circulation models used to study the future behaviour of the climate system. The typical resolution of these models ranges from 100 to 200 km, which makes it possible to obtain a satisfactory result of the of climatic conditions simulation on the planet, as well as the increase of observed global temperatures in recent decades
caused by emissions of greenhouse gases (GHG). On the other hand, some climatic characteristics are highly dependent on local physical properties of a region such as complex topography, soil type and vegetation, as well as their distribution, the purpose for which the selected area is used or exploited, interrelation between land and sea. As a consequence we have that the global model results must be treated to one of the integration methods to obtain information in sufficient scale that is smaller than the scale of the global level. One of the methods is the so-called dynamic scaling (dynamical downscaling). This method is used as an introduction of a high-resolution regional climate model (RKM), that global model results use as the lateral boundary conditions, by determining results with a resolution of 10 km in the chosen area.

In order to study possible climate changes in Serbia, the result of integration of a global model SX-G have been down-scaled to the regional level associated with atmospheric-ocean model EBU-POM. Integration SX-G model covering the period 1771-2100 year, with the constant concentration of greenhouse gases in the model in the period 1771-1870, equal to observed values since 1870-2000 and in the period 2000-2100 concentrations varied according to the selected IPCC/STRE scenario. From these integrations three periods of thirty years have been chosen, which are the results of global models downscaling using the regional model, as follows: 1961-1990 as the reference or control period for the current climate and two future time periods: 2001-2030 and 2071-2100. For the period of last 30 years of 21st century A1B was selected as an average, and the A2 scenario as the most extreme with extreme concentrations of greenhouse gases.

For obtaining daily discharge data, a modified model ACR-VNC was used separately. The model is developed at the Jaroslav Cerni Institute for the development of water resource for the assessment of discharges in natural streams, based on known meteorological variables.

This paper presents results of assessing the impact of climate change on water resources in a particular catchment area. The parameters used in the model will be calibrated based on daily data for selected present climate conditions 1961-1990 year as the reference period.
2. Methods

2.1. Theoretical basics of the model VNC

A VNC model implies the linear correlation between standardized variables, the different combinations of cause-effect relationship and considered hydro meteorological time series. In this paper, the dependent variable was from the hydrological profile of gauging station where it is necessary to estimate the impacts of climate change on water regime. For independent variables, known values of time series were taken: discharge on hydrological stations on wider region or different climatic functions, such as precipitation, mean air temperature, humidity, vapour pressure, etc.

The basic of the model is the theory of nonlinear standardized correlation. The model is basically developed for spatial interpolation of hydro meteorological data on sections where there are no data of observation and measurement. However, the model was also adapted for filling and extending the termination of the existing series of meteorological data at measuring stations.

General elements of establishing a dependence correlation in VNC model
Available data: time series $X_j$ observation points in $L$ (or the focus of river basins) in the wider region

$$X_{j1}, X_{j2}, ..., X_{jN} \quad (j = 1, 2, ..., L)$$

2.2. Standardisation of variables

(a) First transformation

Replacement of $N_j$ and time series: $X_{j1}, X_{j2}, ..., X_{jN}$ ($j = 1, 2, ... L$) with its empirical probabilities $P_{j1}, P_{j2}, ..., P_{jN}$ ($j = 1, 2, ... L$), which is defined as:

$$P_j = P_j(X_j) = \frac{m(X_j) - 0.25}{N_j + 0.5} \quad (j = 1, 2, ..., L) \quad (1)$$

where:

$m (X_j)$ - the number of variables $X_j$ in ascending order
$N_j$ total number of $j$- series.
(b) Second transformation

Replacement of the empirical probabilities $p_{ji}$ with their standardized variables $U_{j1}, U_{j2}, ..., U_{jL}, ..., U_{jNj}$ ($j = 1, 2, ..., L$) which are obtained as the inverse functions of normal distribution

$$P_j(X_j) = P_w = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{U_j} e^{-\frac{U_j^2}{2}} dU = \Phi(U_j)$$  \hspace{1cm} (2)

Figure 1  Schematic presentation of variable standardization

2.3. Establishing of dependence

If basic variables are: $X_1, X_2, ..., X_L, X_{L+1} = X_j$, related to each other by monotone correlation, then the correlation between their standardized variables is: $U_1, U_2, ..., U_L, U_{L+1} = U_o$ linear.

In that case dependence can be made:

$$U_o = \alpha_{o1} \cdot U_1(x_1) + \alpha_{o2} \cdot U_2(x_2) + ... + \alpha_{oj} \cdot U_j(x_j) + ... + \alpha_{ol} \cdot U_L(x_L)$$  \hspace{1cm} (3)
where:
\[ \alpha_{oj} = \frac{D_{oo}}{D_{oo}} \]  

(4)

\[ D_{oo} \text{- determinant composed of } r_{jk}. \]

\[ D_{oo} = \begin{vmatrix} 1 & r_{12} & \cdots & r_{1L} \\ r_{21} & 1 & \cdots & r_{2L} \\ \vdots & \vdots & \ddots & \vdots \\ r_{L1} & r_{L2} & \cdots & 1 \end{vmatrix} \]  

(5)

where:
\[ D_{oj} \text{- minor determinate } D_{oo} \text{ which is obtained by replacing the elements of } j \text{- column with coefficients } r_{oj}, r_{o2}, \ldots, r_{oL}. \]

\[ r_{jk} \text{- standardized correlation coefficient} \]

\[ r_{jk} = r_{j,k} = \frac{1}{N_{jk} - 1} \sum_{i=1}^{N_{jk}} U_{ij}U_{ik} \]  

(6)

\[ r_{oj} \text{- standardized correlation coefficient between series } o \text{ and } j. \]

\[ \sigma_{oz}^2(N) = \frac{1}{N - 1} \sum_{i=1}^{N} U_{ij}^2 \geq 1.0 \]  

(7)

Variables are calculated using the formula:

\[ \delta_{oj} = \frac{|r_{oj} \cdot \alpha_{oj}|}{R^2_o} \]  

(8)

\[ R_o \text{- empirical coefficients of multiple correlations} \]

\[ R_o = \sum_{i=1}^{L} |r_{o,i} \cdot \alpha_{o,i}| \]  

(9)
2.4. Application of the VNC model in hydrology

The hydrologic practice the model VNC is used to establish a linear correlation dependence between standardized variables, different combinations of cause-effect relations and considered hydro meteorological time series. Discharge on the hydrologically ungauged profile (spatial interpolation) or on the profile of gauging stations in the case of filling the gaps or extending the observations is usually taken. As independent variables, known time series of discharges at hydrological stations in the wider region and/or different climate features, such as precipitation, mean air temperature, humidity, voltage, vapour pressure, etc., are taken.

In this case one of the non-linear dependence shown below is established:

\[ U(Q_0) = \alpha_{0,1} U(Q_1) + \alpha_{0,2} U(Q_2) + \alpha_{0,3} U(Q_3) + \ldots + \alpha_{0,j} U(Q_j) \]  

\[ U(Q_0) = \alpha_{a,1} U(Q_a) + \alpha_{a,2} U(P) + \alpha_{a,3} U(T) + \alpha_{a,4} U(VL) + \alpha_{a,5} U(NVP) \]  

where:

- \( Q_0 \) - discharge in the zero profile where the series is filled or extended (gauging station with interruption) or spatially interpolated (ungauged hydrological basin),
- \( U(X) \) - standardized variable of random variable \( X \),
- \( Q_j \) - discharge on the \( j \) gauging station,
- \( Q_a \) - discharge at the “analogue” station
- \( P \) - precipitation in the zero-profile basin,
- \( T \) - air temperature in the zero-profile basin,
- \( VL \) - humidity in this basin,
- \( NVP \) - vapour pressure in the zero profile basin.

The basis for calculation of unknown coefficients \( \alpha_{ij} \) is the matrix (5) of simple correlation coefficients of standardized variables, between all combinations of dependent and independent variables \( r_{jk} \) and \( r_{0j} \).

Application of the VNC mathematical model for assessment of river discharge in climate changing conditions on selected pilot catchments in Serbia

At selected pilot areas in Serbia the available data in terms of climate change of the river Nišava and Kolubara catchments were data on daily amounts of precipitation and air temperatures at grid points of the polygon, dimensions 10 km x 10 km, obtained from WP3 users (Climate Change). These data, using techniques presented in other sections,
were reduced to the corresponding average monthly values related to the catchment area to the profile of the considered gauging stations.

For a profile of gauging station all of the available official data were obtained from Republic Hydro-meteorological Service of Serbia on water level and discharge, as well as data on precipitation and mean daily air temperatures at meteorological stations on the particular basin for a multi-year period 1961–1990.

Given the volume and type of available meteorological data in selected pilot area in Serbia, for future assessment of climate impact on water resources (2001-2030 and 2071-2100), the following model structure of VNC was selected, where basic dependence is defined as follows:

\[ U(Q_0) = \alpha_{i1} \cdot U_1(P) + \alpha_{i2} \cdot U_2(T) \]  \hspace{1cm} (12)

where:
- \( Q_0 \) - average daily discharge on the considered gauging station
- \( P \) - daily amount of precipitation in the basin
- \( T \) - daily mean air temperature in the basin.

Therefore, the basic equation for establishing dependence between the mean daily discharges, as dependent variable and daily precipitation sum and mean daily air temperature, as an independent variable, is:

\[ U(q_i^u) = \alpha_{i1} \cdot U_1(p_i) + \alpha_{i2} \cdot U_2(t_i) \]  \hspace{1cm} (13)

where \( i \) is the order number in the corresponding time series.

**Equation 13** is the basic equation of VNC model that was used for simulation of series of mean monthly discharge in the base period, as well as during periods when only independent variable in terms of climate change and the selected climate change scenario are known.

Model parameters and VNC, as well as proper functional dependence of standardized and real values of treated random variables with \( U(Q_0), U_1(P) \) and \( U_2(T) \), were determined using the data from the period 1961-1990 of observation and measurement. Due to relatively low values of correlation coefficients between mean monthly discharge and total monthly precipitation as well as mean monthly discharge and mean monthly
air temperature, an iterative corrective procedure was used for calculating the value of
standardized discharge variable, which ensures obtaining time series of discharge that
have approximately the same statistical parameters like the basic series as it is shown in
Tables 1 and 2 (mean, standard deviation, coefficient of variation and asymmetry, and
maximum and minimum values in the series).

3. Results and discussion

3.1. Results of river discharge assessment in climate change conditions in
selected pilot catchments in Serbia

Using the model parameters in VNC, the control period 1961-1990 and the estimated
value of the sum of a series of monthly rainfall and mean monthly air temperature and
under the conditions of expected climate changes in the selected pilot basin, appropriate
series of monthly mean discharge on the particular profile of gauging stations for the
total period of 1961-1990, was calculated. From these series of calculations for pre-
defined time period 200-2030 and 2071-2100, time series were specially defined.

All obtained results are given in the tabular form as characteristic statistic parameters
of monthly and daily time series: mean, standard deviation, coefficients of variation and
skewness, as well as extremes- maximum and minimum. The results for River Nišava are
given in Tables 1 and 2, and for River Kolubara in Tables 3 and 4.

Mean temperature for the control period is 10.56 °C for the River Nišava catchment, and
12.35 °C for the River Kolubara. The temperature increases in both catchments.
### Table 1: Summary statistics of precipitation (P) and temperature (T) for the River Nišava catchment

<table>
<thead>
<tr>
<th>Type of data</th>
<th>Period</th>
<th>1961-1990 (control)</th>
<th>2001-2030</th>
<th>2071-2100 A1B (scenario)</th>
<th>2071-2100 A2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>P (mm)</td>
<td>T (°C)</td>
<td>P (mm)</td>
<td>T (°C)</td>
<td>P (mm)</td>
</tr>
<tr>
<td>Monthly</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AVER</td>
<td>34.05</td>
<td>10.56</td>
<td>33.89</td>
<td>11.35</td>
<td>29.44</td>
</tr>
<tr>
<td>σ</td>
<td>6.570</td>
<td>0.468</td>
<td>3.178</td>
<td>0.312</td>
<td>4.735</td>
</tr>
<tr>
<td>Cv</td>
<td>0.193</td>
<td>0.044</td>
<td>0.094</td>
<td>0.028</td>
<td>0.161</td>
</tr>
<tr>
<td>Cs</td>
<td>0.422</td>
<td>-1.585</td>
<td>0.813</td>
<td>-0.657</td>
<td>0.214</td>
</tr>
<tr>
<td>MAX</td>
<td>149.09</td>
<td>25.66</td>
<td>120.47</td>
<td>27.61</td>
<td>157.83</td>
</tr>
<tr>
<td>MIN</td>
<td>1.28</td>
<td>-8.38</td>
<td>1.67</td>
<td>-5.65</td>
<td>0.00</td>
</tr>
<tr>
<td>Daily</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MAX</td>
<td>27.53</td>
<td>30.90</td>
<td>45.38</td>
<td>31.05</td>
<td>26.96</td>
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<tr>
<td>MIN</td>
<td>0.00</td>
<td>-18.77</td>
<td>0.00</td>
<td>-12.38</td>
<td>0.00</td>
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</table>

<table>
<thead>
<tr>
<th>Type of data</th>
<th>Period</th>
<th>1961-1990 (control)</th>
<th>2001-2030</th>
<th>2071-2100 A1B (scenario)</th>
<th>2071-2100 A2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Qo (m³/s)</td>
<td>Q (m³/s)</td>
<td>Q (m³/s)</td>
<td>Q (m³/s)</td>
<td>Q (m³/s)</td>
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<tr>
<td>Monthly</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AVER</td>
<td>30.37</td>
<td>28.96</td>
<td>29.14</td>
<td>29.60</td>
<td>29.60</td>
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<tr>
<td>Cv</td>
<td>0.296</td>
<td>0.221</td>
<td>0.228</td>
<td>0.213</td>
<td>0.213</td>
</tr>
<tr>
<td>Cs</td>
<td>1.634</td>
<td>0.051</td>
<td>1.134</td>
<td>0.822</td>
<td>0.822</td>
</tr>
<tr>
<td>MAX</td>
<td>141.46</td>
<td>123.27</td>
<td>126.33</td>
<td>122.84</td>
<td>122.84</td>
</tr>
<tr>
<td>MIN</td>
<td>3.18</td>
<td>5.21</td>
<td>5.90</td>
<td>5.27</td>
<td>5.27</td>
</tr>
<tr>
<td>Daily</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MAX</td>
<td>509</td>
<td>399</td>
<td>339</td>
<td>396</td>
<td>396</td>
</tr>
<tr>
<td>MIN</td>
<td>1.48</td>
<td>2.72</td>
<td>2.72</td>
<td>2.72</td>
<td>2.72</td>
</tr>
</tbody>
</table>

### Table 3: Summary statistics of precipitation (P) and temperature (T) for the River Kolubara catchment

<table>
<thead>
<tr>
<th>Type of data</th>
<th>Period</th>
<th>1961-1990 (control)</th>
<th>2001-2030</th>
<th>2071-2100 A1B (scenario)</th>
<th>2071-2100 A2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>P (mm)</td>
<td>T (°C)</td>
<td>P (mm)</td>
<td>T (°C)</td>
<td>P (mm)</td>
</tr>
<tr>
<td>Monthly</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AVER</td>
<td>42.11</td>
<td>12.35</td>
<td>41.99</td>
<td>13.14</td>
<td>36.70</td>
</tr>
<tr>
<td>σ</td>
<td>6.993</td>
<td>0.475</td>
<td>3.137</td>
<td>0.369</td>
<td>5.795</td>
</tr>
<tr>
<td>Cv</td>
<td>0.166</td>
<td>0.038</td>
<td>0.075</td>
<td>0.028</td>
<td>0.158</td>
</tr>
<tr>
<td>Cs</td>
<td>0.148</td>
<td>-1.487</td>
<td>1.295</td>
<td>-0.176</td>
<td>0.154</td>
</tr>
<tr>
<td>MAX</td>
<td>140.67</td>
<td>27.91</td>
<td>121.83</td>
<td>29.19</td>
<td>154.17</td>
</tr>
<tr>
<td>MIN</td>
<td>1.47</td>
<td>-7.36</td>
<td>0.00</td>
<td>-3.12</td>
<td>0.09</td>
</tr>
<tr>
<td>Daily</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MAX</td>
<td>32.94</td>
<td>33.03</td>
<td>42.55</td>
<td>33.11</td>
<td>35.42</td>
</tr>
<tr>
<td>MIN</td>
<td>0.00</td>
<td>-17.87</td>
<td>0.00</td>
<td>-11.50</td>
<td>0.00</td>
</tr>
</tbody>
</table>
Table 4: Summary statistics of discharge (Q) for the River Kolubara at Hydrological Station Draževac

<table>
<thead>
<tr>
<th>Type of data</th>
<th>Period</th>
<th>1961-1990 (control)</th>
<th>2001-2030</th>
<th>2071-2100 A1B (scenario)</th>
<th>2071-2100 A2 (scenario)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Qo (m³/s)</td>
<td>Q (m³/s)</td>
<td>Q (m³/s)</td>
<td>Q (m³/s)</td>
<td>Q (m³/s)</td>
</tr>
<tr>
<td>Monthly</td>
<td>1.07</td>
<td>1.98</td>
<td>2.24</td>
<td>1.96</td>
<td></td>
</tr>
<tr>
<td>Daily</td>
<td>690</td>
<td>676</td>
<td>690</td>
<td>645</td>
<td></td>
</tr>
</tbody>
</table>

The control and future precipitation for the each scenario were compared (Table 5). By the 2071-2100 period between 10.9% and 13.5% less rainfall is expected under the average and high emission scenarios in the River Nišava catchment. For the River Kolubara average precipitation for the 2071-2100 period was approximately 8.4% and 12.8% less than the control period for the A1B and A2 scenarios respectively. The highest decrease is found for the A1B scenario.

Table 5: Percentage difference between control and scenario precipitation

<table>
<thead>
<tr>
<th>River</th>
<th>2001-2030</th>
<th>2071-2100 A1B</th>
<th>2071-2100 A2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nišava</td>
<td>-0.5</td>
<td>-13.5</td>
<td>-10.9</td>
</tr>
<tr>
<td>Kolubara</td>
<td>-0.3</td>
<td>-12.8</td>
<td>-8.4</td>
</tr>
</tbody>
</table>

The average discharge for each scenario for the future periods compared to the control period are shown in Table 6. The average river discharge is found to be reduced 2.5 and 4.6% between the control and scenario periods for the River Nišava catchment. The largest decreases of 7.4% are found in the River Kolubara catchment for the A1B scenario (2071-2100).

Table 6: Percentage difference between control and scenario river discharge

<table>
<thead>
<tr>
<th>River</th>
<th>2001-2030</th>
<th>2071-2100 A1B</th>
<th>2071-2100 A2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nišava</td>
<td>-4.6</td>
<td>-4.1</td>
<td>-2.5</td>
</tr>
<tr>
<td>Kolubara</td>
<td>-4.7</td>
<td>-7.4</td>
<td>-4.7</td>
</tr>
</tbody>
</table>
Graphical presentation of the results is given in Figures 2 to 5. In this paper we used the 30-year linear trend to check if the mean values are representative for the entire scenario period. The overall trend in the 30-year period is a slight decrease in river discharges in both rivers.

Figure 2  Forecast for mean monthly discharge of the River Nisava catchment for the period 2001-2030. Straight line is the 30 year linear trend showing a slightly decreasing tendency

Figure 3  Forecast for monthly mean discharges in the River Nisava catchment for the period 2071-2100 A1B. Straight line is the 30 year linear trend showing a slightly decreasing tendency
4. Conclusions

It can be concluded that river discharge in Serbian rivers would decrease as a consequence of the warmer climate from a projected future modelled by the ACR-VNC, on the basis of two future time periods 2001-2030 and 2071-2100 for A1B and A2 emission scenarios. Decreases in precipitation between 0.5 and 13.5% are modelled to decrease average
River Nišava discharge 2.5 – 4.6%. For the River Kolubara decreasing in precipitation between 0.3 and 12.8% are modelled to decrease average discharge 4.7 – 7.4%. There are linear trends of slightly decreasing river discharges during the 30-year scenario period.

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References
Mono- and multi-Model statistical Downscaling of GCM- Climate Predictors for the Upper Blue Nile River Basin, Ethiopia

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Abstract
High population increase and poor land- and water-management have led to a decline in recent years of the already low agricultural productivity in the Upper Blue Nile river basin (UBNRB), Ethiopia, where more than 85% of the population depends entirely on rain-fed agriculture. This adverse situation is further exacerbated by imminent climate change in the region as a whole. To analyze the possible impacts of future climate change on, particularly, the water resources in the UBNRB, climate predictions for the basin using downscaled predictor from various GCM’s have been carried out. The two statistical downscaling models used are SDSM and LARS-WG, whereby SDSM is used in a mono-model manner, i.e. employing predictors from only one GCM (ECHAM 5) and LARS-WG is used both in mono-model- (ECHAM 5) and multi-model- (ECHAM5, GFDL21 and CSIRO-MK3) mode. These three models are selected in a pre-screening analysis from about 17 GCMs in the MAGICC/SCENGEN database environment and found to be the most suitable for describing the observed historical (baseline) data (1970-2000 time period) in the UBNRB. The future climate predictors for the GCM’s selected cover the two time periods 2046-2065 (2050s) and 2081-2100 (2090s), respectively, and are available for the two SRES-scenarios A1B and A2.

The future climate predictions for the UBNRB using the SDSM and LARS-WG tools indicate an increase of the seasonal temperatures for both downscaling tools and both SRES scenarios. Thus, for the 2050s time period the seasonal maximum temperatures $T_{\text{max}}$ rise between 0.6°C to 2.7°C and the minimum ones $T_{\text{min}}$ by 2.44°C. Similarly, during the 2090s the seasonal $T_{\text{max}}$ increase by 0.9°C to 4.63°C and $T_{\text{min}}$ by 1°C to 4.5°C, whereby these increases are generally higher for the A2 than for the A1B scenario. For most sub-basins, the predicted changes of $T_{\text{min}}$ are larger than those for $T_{\text{max}}$. Moreover, for both SRES-scenarios and both simulated future time periods, the $T_{\text{max}}$ and $T_{\text{min}}$ for spring and summer seasons are found to be warmer than for autumn and winter. In general, the two LARS-WG downscaling approaches forecast a warmer future climate than SDSM. As for the precipitation, the predictions of the three downscaling methodologies are more variant across the sub-basins and the seasons of the year, however, all of them predict overall decreasing trends for most of the seasons of the year, but the autumn, particularly, for the later 2090s period. The SDSM- predicted negative precipitation changes are generally
higher than those obtained with the two LARS-WG downscaling methods. Surprisingly, the effects of the SRES-scenario used on all climate predictions appear to be only minor. In conclusion, the results indicate that climate change will not spare the UBNRB and significant implications on the water resources in the area are to be anticipated for the near future, the analysis of which is the focus of a concurrent contribution of the authors.

**Keywords:**
Climate change, statistical downscaling, Upper Blue Nile River Basin, UBNRB

### 1. Introduction

The earth’s climate system results from a complex, interaction of atmosphere, land surface, snow and ice, ocean and other bodies of water, and living things [IPCC, 2007; O’Keefe and Kueter, 2004] and it is affected by both its own internal dynamics and external factors. The latter factors describe effects by humans (anthropological) and include burning of fossil fuels and the clearing of forests, both of which lead to changes in the atmospheric composition. According to the IPCC definition and usage, the term ‘climate change’ refers to a change in the state of the climate that can be identified by changes in the mean and/or the variability of its properties that persists for an extended period typically decades or longer [IPCC, 2007].

The very likely cause of the global temperature change in the last 50 years and that to be expected for the near future is believed to be the increased amount of greenhouse gases [Heger et al., 2007], generated mainly in the industrial countries of the world. However, it is the developing countries, like Ethiopia, which suffer the most by climate change, as they do not have the economic resources to cope with and adapt to these changes [IPCC, 2007; NMSA, 2007].

There are many reasons for the high climate-change vulnerability of Ethiopia and the Upper Blue Nile River basin (UBNRB), the study area, in particular, to imminent climate change, such as, the high-climate variability itself, complex topography, poor agricultural practices, poor watershed management, high population pressure, low economic development, low adaptive capacity, inadequate infrastructures and weak institutional (governmental) capacities. Moreover, most of the Ethiopian rural areas, including the highlands of the UBNRB, are prone to high levels of land-degradation, critical soil erosion, deforestation, loss of biodiversity, desertification, recurrent flood as well as water pollution due to poor water use and watershed management policy [Bishaw, 2001].
Because of these factors, water resources, agriculture and human health are among the most vulnerable sectors in the area [Boko et al., 2007; NMSA, 2007].

The goal of the present and the accompanying paper [Koch and Cherie, 2013] is to present some results of a comprehensive study of the authors [e.g. Cherie, 2013] on the expected possible future climate changes and its impacts in the UBNRB, where most the population depends entirely on rain-fed agriculture, whose already low productivity has declined even further in recent years.

Whereas in this paper large-scale future climate predictions of Global Circulation Models (GCM's) for Ethiopia, which are coarsely covering also the UBNRB, will be downscaled by several downscaling methods, in the accompanying paper [Koch and Cherie, 2013] these downscaled basin climate variables will be used further in a hydrological model to simulate their potential impacts on the future hydrology and the water resources in the UBNRB which accounts for about 40% of the total average annual runoff of that country.

2. Study region and previous studies

2.1. The upper Blue Nile river basin
The Blue Nile is originates in the highlands of Ethiopia called Gish-Abbey. The part of the Blue Nile basin which is under Ethiopian territory is named as Upper Blue Nile Basin (UBNRB). The length of the Upper Blue Nile River from the outlet at of Lake Tana to Ethiopian-Sudanese border is about 944.52 km (Figure 1).

The UBNRB basin lies in the western part of Ethiopia, between 7° 45’ and 12° 45’N and 34° 05’ and 39° 45’E. The study area covers 176,652 km², i.e half the size of Germany, and it amounts to 17.7% of Ethiopia’s total land area.

The topography of UBNRB basin is dominated by an altitude ranging from 485 meters to more than 4257 meters. The Blue Nile and its tributaries have a general slope to the northwest; more steep slopes on the east and gentle slopes in the west and northwest are features of the UBNRB. The Blue Nile river in Ethiopia navigates through deep gorges which get shallower at the Ethio-Sudan boarder.
The mean annual areal rainfall over the UBNRB is 1358 mm, ranging between a minimum of 850 mm [Jimma] to a maximum of 1869 mm [Anger and Didessa]), i.e. it is highly variable spatially but also temporarily. Thus, the rainfall shows a decreasing trend as one goes from the southwestern to the eastern parts of the area (see Figure 2).

Most of the precipitation occurs in the wet season, called Kiremt (June through September), but some rain is also falling in the dry season, called Bega (October to January). Similarly, there is a mild season, called Belg (February to May) which also experiences some rain. These small rains originate from the Indian Ocean, and are brought in by southeast winds, while the heavy rains in the wet season are driven by southwest winds from the Atlantic Ocean [BCEOM, 1998].

The mean annual temperature of the area lies in a range of 16.7 °C to 19.6 °C, with an overall mean areal value of 17.8 °C. The maximum temperatures are observed in months of March and April, whereas the lowest temperatures, only by 2.8°C lower than the maximum ones are observed July and August. These temperatures show also less spatial variation across the UBNRB than the precipitation.

2.2. Previous climate studies in the UBNRB

Numerous climate studies in the UBNBR have been conducted over the last two decades [e.g. Conway, 1997; 2000; 2005; Conway and Hulme, 1996; Yates and Strzepek 1998; Kim and Kaluarachchi, 2008; Beyene et al., 2009; Elshamy et al, 2009; Soliman et al.,...
However, the results of these investigations are often divergent and inconsistent. Although a better agreement among authors with regard to the prediction of the future temperature is observed over the UBNRB, conflicting results are often obtained for the GCM-predicted precipitations. Thus, almost all study results indicate a temperature increase from a range of 1.4°C to 2.6 °C depending on the type of GCMs in 2050s [Kim and Kalurachchi, 2009] and 4.7°C (SRES-A2) 3.7°C (SRES-B1) by 2080s [Beyene et al., 2009].

As for the precipitation prediction over the UBNRB, the results of the various authors referenced above are more variant. For example, Conway and Hulme [1996] used 3 GCMs and predicted the change in precipitation ranges from -2 to 7% by the 2025s. Yates and Strzepek [1998] found that for a doubling of the carbon dioxide concentration the annual rainfall by 2060 will range from -9% to 55%. The results of Conway et al. [2000] show no clear evidence, whether precipitation over the UBNRB region increase or decrease for both current and future periods. Later on the same author [Conway, 2005] applied 9 GCMs and obtained changes from -40% to 100% (Dec-Feb), 120% (Jun-Aug) for the 2080s period.

Figure 2  Spatial distribution of 1970-2000 average precipitation in the UBNRB
As climate models have become more sophisticated and more numerous in recent years, so have the outcomes of their applications to the study region. Thus, Beyene et al. [2009] used 11 GCMs and observed data from the CRU and predicted precipitation changes from -16 to 40% for the 2020s (2010-2039) and -24% to 26% for the 2080s (2070-2099). Kim and Kaluarachchi [2009] considered 6 GCMs and observed data from 10 stations. They obtained seasonal precipitation changes for the 2050s, that depend to a large extent on the GCM used, i.e. -32% (CSIRO) and 56% (ECHAM) for the wet season; -55% (CSIRO) and 262% (CCSR) for the Belg (some rain) season; -55% (CSIRO) and 88% (GFDL) for the dry season. Elshamy et al. [2009] considered 17 GCMs and found that the annual precipitation will change between -15% to +14% over the UBNRB, whereby out of the set of GCM’s used, 10 GCMs predict a decrease and 7 GCMs an increase of the precipitation.

The inconsistencies of the results of these studies in predicting future climate change in the UBNRB are due to various reasons:

(i) Number and type of the GCM,
(ii) Number and type of emission scenarios,
(iii) Length of both the predictand- and predictor data sets,
(iv) Period of analysis (time slices),
(v) Type of observed data (gridded or station based).
(vi) Spatial and temporal resolutions of observed and predictor data sets.
(vii) Different downscaling methods for climate- and hydrology predictions.
(viii) Scale of study (ranging from few sub-basins to the whole Nile basin).

So, based on such differences, it is not clear which combination of input give a good insight for the understanding of future plausible climate conditions in the UBNRB. Even, the current hydrological and meteorological parameter values are different in most of the studies mentioned. Most of the previous studies used CRU and other gridded data sets which are constructed based on the interpolation of a few climate stations distributed sparsely across Ethiopia. The accuracy of this data set is not more than 65%, as compared with the station-based data [T. Seyoum, personal communication]. Even in the climate studies that used observed station data, no more than 10 stations were used in most cases. Due to the high spatial variability of the UBNRB, incorporating only a few stations may not be reasonable for such a large area. These data intricacies will be addressed further later in this paper.
3. Methodology

3.1. Some general aspects of GCM’s and downscaling

One approach to investigate the influence of increasing greenhouse gas concentrations in the atmosphere on the future global climate is using Global Circulation Models (GCMs). These models attempt to predict the average synoptic-scale, general-circulation patterns of the atmosphere as well as temperature and precipitation over future decades or centuries [Xu, 1999; O’Keefe and Kueter, 2004]. To date, there is some confidence that GCMs provide plausible quantitative estimation of the major features of climate change, because of the accepted physical principles inherent in these models, and their ability to reproduce present and past observed climate changes [Randall et al., 2007].

However, because of the limited horizontal and vertical resolutions of the present-day GCMs, their outputs can only provide a "broad-brush" view of the climate. Hence GCMs cannot resolve important processes related to sub-grid scale clouds and topographic effects that are of significance in many impact studies. Downscaling is then the methodology to be used to narrow the gap between the coarse-grid GCMs to a fine grid which is suitable to analyze climate-dependent hydrological processes on the small scale [Koch, 2008].

Downscaling methods can be categorized basically in two categories: dynamic and statistical downscaling. Dynamic downscaling involves the nesting of a higher Resolution Regional Climate Model (RCM) into a coarse GCM and executing it over a finite domain, using time-varying atmospheric lateral boundary conditions, derived either from NCEP-reanalysis data [Kalney et al., 1996] or from a global-scale, coarse-resolution GCM [Wilby et al., 2000].

Statistical downscaling methods are, themselves, essentially classified into two major groups, namely, transfer function/weather typing methods and weather generators. The first group involves developing quantitative linear or nonlinear regression relationships between small-scale observed meteorological variables, respective, typical weather pattern (predictands) and large-scale NCEP-reanalysis- or GCM- climate variables (predictors). This class of downscaling approach is implemented in the well-known SDMS-downscaling method [Wilby et al., 2002; Wilby and Dawson, 2004] which has become nowadays probably the most commonly used method, as it has been applied in many regional or local climate change studies [von Storch et al., 1993; Huth, 1999; Goodess et al. 2007; Wilby et al., 2009].
The other class of statistical downscaling methods are the stochastic weather generators, with the LARS-WG as one of most widely known representatives [Semenov and Barrow, 2002; Semenov and Stratonovitch, 2010; Semenov et al., 1998]. Weather generators replicate the statistical attributes of local climate variables (such as the mean and variance), but not the observed sequences of climate time series. Once the statistical properties of a past or present-day reference climate time series have been determined, these parameters can easily be perturbed by GCM-predicted future (“delta”) changes of that climate variable, which then are used further for the generation of future stochastic climate scenarios.

The key strength of all statistical downscaling methods is that they have only low computational demands, which facilitates the generation of large ensembles of climate realizations [Wilby et al., 2000; Hashmi et al., 2009; 2011]. Dynamic downscaling methods, on the other hand, require the numerical solution of the full set of dynamic equations describing flow and transport in the atmosphere/hydrosphere on a fine 3D-grid which hampers their application in routine regional climate studies.

**3.2. MAGICC/SCENGEN - selection of GCMs for downscaling**

Climate modeling is often prone to a variety of uncertainties [Wilby and Harris, 2006; Wilby et al., 2009]. These are mostly due to limitations in the theoretical formulation of a particular climate model, but also due to the type of downscaling techniques used. The IPCC Fourth Report Assessment (AR4) [IPCC, 2007] recommends to use a set of GCMs which have been applied and compared over the years as part of the Coupled Model Inter-comparison Project phase 3 (CMIP3) and these studies show that there are sometimes marked differences between GCM models, especially, with regard to the prediction of precipitation changes [Wilby and Wigley, 2000; Haylock et al., 2006; Hashmi et al., 2009; 2011], and, hence, it may be difficult to draw conclusions from a single GCM model output. The best recommended approach to minimize such uncertainties and to gain more confidence in the projections of climate change, is the inclusion of as many different types of global models, downscaling techniques and emission scenarios as possible [Busuioc et al., 2006; Goodess et al., 2007; Gachon and Dibike, 2007].

One user-friendly, low-cost and flexible tool to explore and to quantify different aspects of uncertainty with regard to future climate changes is the MAGICC/SCENGEN software package [Wigley et al., 2000; Wigley, 2000] and it is employed here to screen the most potential GCMs for the study area. Based on this screening approach (for details see
[Cherie, 2013]), the three GCMs ECHAM5, GFDL2.1 and CSIRO-MK3, are found to be the most suitable for describing the observed historical (baseline) data (1970-2000 time period) in the UBNRB. **Table 1** lists some of the specifications of these three GCM models with their performance characteristics, as measured by the RMSE and the bias, to represent past (1970-2000) rainfall and temperatures over the UBNRB study area.

**Table 1:** Screened GCMs features and their performance to represent past (1970-2000) rainfall and temperatures over the UBNRB study area

<table>
<thead>
<tr>
<th>CMIP3 name</th>
<th>Country</th>
<th>Atmospheric Resolution</th>
<th>Emission Scenarios</th>
<th>RMSE* (mm/day)/ °C</th>
<th>Bias* (mm/day)/ °C</th>
</tr>
</thead>
<tbody>
<tr>
<td>CSIRO-Mk3.0</td>
<td>Australia</td>
<td>1.9 x 1.9</td>
<td>A1B, A2</td>
<td>2.09 /2.41</td>
<td>1.41 / -1.48</td>
</tr>
<tr>
<td>ECHAM5/MPI-OM</td>
<td>Germany</td>
<td>1.9 x 1.9</td>
<td>A1B, A2</td>
<td>1.36 / 1.93</td>
<td>0.49 / 1.15</td>
</tr>
<tr>
<td>GFDL-CM2.1</td>
<td>USA</td>
<td>2.0 x 2.5</td>
<td>A1B, A2</td>
<td>1.43 / 3.19</td>
<td>0.86 / -2.69</td>
</tr>
</tbody>
</table>

* Numbers left and right of the slash denote precipitation and mean temperature, respectively.

**3.3. Preparation and clean-up of observed climate input data**

The observed meteorological data used in this study includes spatially and temporally limited records of rainfall, maximum and minimum temperatures. Although there are many meteorological gauging stations in the study area, most of the gauges have either short record periods, or have plenty of missing and erroneous data. Among the stations in the UBNRB, 53 rainfall- and 33 temperature stations are considered here (see **Figure 1**). The data from these stations are collected by the Ethiopian National Meteorological Service Agency (ENMSA) in the time period 1970-2000. In spite of this 31-years long record length, most of the stations suffer from a variety of errors which include different coordinate units in a gauge, coordinate shifts, typing errors, significant missing records and recording errors. All errors, except those due to missing records, are corrected by a thorough investigation using different sources such as the literature, UBNRB master plans and by referring to the original data.

The complex treatment of missing data, i.e. the filling a record of a particular station in this study area is done, using LARS-WG (Long Ashton Research Station Weather Generator), developed by Semenov et al. [1998]. Hashmi et al. [2011] show the capability of LARS-WG to synthesize and to fill in missing values in daily climate time series (precipitation and temperature).

LARS-WG utilizes semi-empirical distributions (SED), i.e. histograms, to represent series of wet and dry days, daily precipitation, minimum and maximum temperature and solar
radiation. The simulation of precipitation occurrence is modeled as an alternate wet and dry series, whereby a day with a precipitation greater than zero is considered a wet day. The length of each series is chosen randomly from the probability distribution for the wet or dry days for that month.

**Figure 3** Daily mean maximum temperature at station Fitche (top) and mean rainfall at station Dangila (bottom) before and after gap-filling
The time series of daily minimum and maximum temperatures are considered as stochastic processes with daily means and standard deviations conditioned on the wet or dry status of the day and having some persistence that follows the observed autocorrelation. Moreover, maximum and minimum temperatures are assumed to be partly cross-correlated.

The major steps of LARS-WG to fill in missing are: calibration, validation and weather generation. In the calibration, the statistical properties of the observed time series are computed using 'Site Analysis' facilities and the parameters are stored in *.wgx file which later used for weather generation.

The statistical properties of the observed data are then compared with the generated data using the parameter derived 'QTest', to determine how well the model simulates the observed climate data in the validation step. The performance of LARS-WG is tested using the Kolmogorov-Smirnov (KS) test, whereby the cumulative probability distributions of both synthetic and observed data for the lengths of wet and dry series are compared. Moreover, t-tests and F-tests are applied to test for a common mean and standard deviations, respectively, of the simulated and observed weather variable time series.

In the following step the synthetic data is generated using the statistical properties of observed data using 'Generator' facilities. Later, this synthetic data is used to fill the missing records.

The results generally give good agreement between observed and generated weather variables. Sample LARS-WG outputs for Fitche mean maximum temperature and Dangila rainfall before and after gap-filling are shown in Figure 3.

Since the interest of this paper is climate downscaling at the sub-basin level, there is also a need for the computation of areal values of the meteorological variables rainfall and temperature. To this avail, the Thiessen polygon method is most commonly used [Chow et al., 1988]. In this method, the average of any weather variable is the weighted average of all station, i.e.

\[
P_i = \left( \frac{P_{A_1} + P_{A_2} + P_{A_3} + \ldots + P_{A_n}}{A_1 + A_2 + A_3 + \ldots + A_n} \right)
\]  

(1)
where:

\[ P_i \] is the desired average rainfall;

\[ P_1, P_2, P_3, \ldots, P_n \] are the rainfalls at the individual stations, and

\[ A_1, A_2, A_3, \ldots, A_n \] are the areas of the polygons surrounding these stations.

The long-term monthly mean precipitation, maximum and minimum temperature for each sub-basin as obtained by means of a Thiessen polygon analysis is shown in Figure 4.

The annual areal rainfall and temperatures for each sub-basin and the results show that high spatial variation in precipitation variables is observed. Hence, one can see that the spatial sub-basin average of the annual rainfall ranges from a minimum of 850 mm (at Jimma) to a maximum of 1869 mm (at Anger and Didessa) over the UBN-basin, resulting in a mean value of about 1357 mm. Meanwhile, the mean annual areal maximum temperatures is 24.88°C and mean annual minimum temperature is about 10.67°C which gives an overall mean annual temperature value of about 18°C for the basin as a whole. But no spatially significant annual change in both maximum and minimum temperature over the entire basin can be denoted.

3.4. Predictor input data

The three GCMs output data is available on a daily temporal scale and at different spatial resolution and it has been taken from the archives of the World Climate Research Program’s (WCRP’s) CMIP3- multi-model dataset. The data, consisting of classical meteorological variables (maximum and minimum temperatures, precipitation, lengths of dry- and wet spells), as well as numerous atmospheric parameters (see Table 2) covers the historical (reference) time period 1970-2000 and the two future periods 2046-2065 (2050s) and 2081-2100(2090s). From the Special Report on Emission Scenarios (SRES) available in IPCC-AR4 [IPCC, 2007] (A1, A1B and A2), only the extreme A1B- and the, more benevolent, A2- scenario are considered.

Since, depending on the GCM model, the predictor data has different spatial resolutions (see Table 1), transfer of this data is made on a grid with a spatial resolution of 2.5°x2.5°, which is the reference grid size of the NCEP re-analysis data [Kalney et al., 1996], with the latter being used in the later SDSM- calibrations for the observed station data. Figure 5 shows this 2.5°x2.5° NCEP-reanalysis grid overlain over the entire UBNRB with 14 sub-basins and one may notice that the whole basin is covered by only eight grid cells.
Figure 4  Monthly mean observed data in each sub-basins (RF, Tmax and Tmin are represented by a histogram and upper and lower lines, respectively)

Figure 5  NCEP-reanalysis grid overlain on the UBNRB- study area
3.5. Climate modeling /downscaling procedures

3.5.1. Choice of combinations of GCMs and downscaling methods

In this paper downscaling of GCM’s climate change predictions is done using two popular statistical downscaling modeling tools, namely, SDSM [Wilby et al., 2002; Wilby and Dawson, 2004] and, the already discussed, LARS-WG [Semenov and Barrow, 2002]. However, these two downscaling methods will be combined here in different ways with a “parent” GCM. More specifically, whereas SDSM is used in a mono-model manner, i.e. employing predictors from only one GCM (ECHAM 5), LARS-WG is used both in a mono-model manner with one GCM (ECHAM 5) and in multi-model mode, by applying it to the averaged large-scale prediction output of the three GCMs ECHAMS, GFLD21 and CSIRO-MK3. These three combinations of GCMs and downscaling methods are listed in Table 2 and they will all be applied to generate the climate predictors for the UBNRB. It is to be hoped that by using such a multi-facet approach for climate prediction in the study region, uncertainties arising from the GCM as well as from the downscaling method are somewhat minimized.

Table 2: GCM/downscaling combinations used to generate climate predictors for the UBNRB

<table>
<thead>
<tr>
<th>Case</th>
<th>Downscaling tool</th>
<th>GCM</th>
<th>Scenario</th>
<th>Simulation period</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>SDSM</td>
<td>ECHAM5</td>
<td>A1B, A2</td>
<td>1970-2000, 2050s, 2090s</td>
</tr>
<tr>
<td>2</td>
<td>LARS-WG</td>
<td>ECHAM5</td>
<td>A1B, A2</td>
<td>1970-2000, 2050s, 2090s</td>
</tr>
<tr>
<td>3</td>
<td>LARS-WG</td>
<td>Multi-model*</td>
<td>A1B, A2</td>
<td>1970-2000, 2050s, 2090s</td>
</tr>
</tbody>
</table>

* averages of the three GCMs ECHAM5, GFLD21 and CSIRO-MK3

For all three downscaled climate-prediction cases, large-scale prediction output from the associated GCMs for the base (reference) period 1970-2000 (20th -century period) and two future decadal periods 2050s (2046-2065) and 2090s (2081-2100) are used, wherefore for the latter two both the SRES- scenario A1B and A2 are considered separately.

3.5.2. SDSM- preprocessing analysis of predictors for the study region

Climate downscaling using SDSM requires the screening of various potential NCEP-reanalysis- or GCM- predictors, as listed in Table 3, with the help of the screening facility built in the SDSM software and using various off-line screening techniques, such as cross-correlation, partial correlation or step-wise regression methods to select the most influential one [Wilby et al., 2002]. Examples of such correlations between NCEP-predictors and average sub-basin precipitation and maximum temperature are shown in the two panels of Figure 6 for a few UBNRB sub-basins. For further details the reader
is referred to Cherie [2013]. One may notice from the figure that basically the same dominant NCEP- predictor variables of the list in Table 3 are obtained for the different sub-basins, and the former are often correlated with precipitation and temperature in an opposite way which, from a meteorological point of view, appears to make some sense.
<table>
<thead>
<tr>
<th>No</th>
<th>Predictor variable</th>
<th>Designation</th>
<th>No</th>
<th>Predictor variable</th>
<th>Designation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Air pressure at sea level</td>
<td>Mslp</td>
<td>11</td>
<td>Northward wind @850mpa</td>
<td>p8_v</td>
</tr>
<tr>
<td>2</td>
<td>Precipitation flux</td>
<td>Prat</td>
<td>12</td>
<td>Northward wind @500mpa</td>
<td>p5_v</td>
</tr>
<tr>
<td>3</td>
<td>Minimum air temperature</td>
<td>Tmin</td>
<td>13</td>
<td>Meridional surface wind speed</td>
<td>p_v</td>
</tr>
<tr>
<td>4</td>
<td>Maximum air temperature</td>
<td>Tmax</td>
<td>14</td>
<td>Specific humidity @850mpa</td>
<td>s850</td>
</tr>
<tr>
<td>5</td>
<td>Surface air temperature @2m</td>
<td>Temp</td>
<td>15</td>
<td>Specific humidity @500mpa</td>
<td>s500</td>
</tr>
<tr>
<td>6</td>
<td>Air temperature @850mpa</td>
<td>t850</td>
<td>16</td>
<td>Geopotential height @850mpa</td>
<td>p850</td>
</tr>
<tr>
<td>7</td>
<td>Air temperature @500mpa</td>
<td>t500</td>
<td>17</td>
<td>Geopotential height @500mpa</td>
<td>p500</td>
</tr>
<tr>
<td>8</td>
<td>Eastward wind @850mpa</td>
<td>p8_u</td>
<td>18</td>
<td>Relative humidity @500mpa</td>
<td>r500</td>
</tr>
<tr>
<td>9</td>
<td>Eastward wind @500mpa</td>
<td>p5_u</td>
<td>19</td>
<td>Relative humidity @850mpa</td>
<td>r850</td>
</tr>
<tr>
<td>10</td>
<td>Zonal surface wind speed</td>
<td>p_u</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

3.5.3. LARS-WG downscaling

LARS-WG cannot only be used for filling in incomplete data records (see Section 3.3) but also for downscaling of large-scale GCM predictors. As already mentioned, the methodology of LARS-WG downscaling [Semenov and Barrow, 2002] is based on a very different concept than that of SDSM. Historic climate time series at a particular station are generated in LARS-WG by a stochastic procedure, such that the empirical distributional characteristics of the observed time series, are approximately respected, for example, on a monthly scale. This makes LARS-WG particularly adequate for simulating daily data, even if only monthly data is available, which still is the predictor output time-scale of many GCMs. Thus, the weather generator replicates the statistical attributes of a local climate variable (such as the mean and variance), but not the observed sequences of the climate time series. Once the statistical properties of a historical climate time series have been determined, these parameters can easily be perturbed by the GCM-predicted historical (bias) or future "delta"-changes of that climate variable [Semenov et al., 1998] to generate future stochastic climate scenarios. By this approach, at least the distributional properties of the past and future GCM-predictors series are properly represented.

Similar to SDSM, LARS-WG has been used up-to-date in numerous climate-change studies in different regions of the world, with very different climatic conditions (e.g. Bae et al. [2008]; Allen et al. [2010]; Luo et al. [2010]; Rahman et al. [2010]; Abdulharis et al. [2010]; Semenov and Stratonovitch, [2010] and Iizumi et al. [2012]). A comparison of the performances of LARS-WG and SDSM in a precipitation-downscaling application has been made by Hashmi et al. [2011], but they cannot provide a definite conclusion, as to which method works better.
4. Recent and future climate analysis in the UBNRB

4.1. Looking for changes and trends in the 20th-century UBNRB meteorological time series

Prior to any future climate modeling exercises, it is advisable to analyze the past (1970-2000) observed meteorological time series for the UBNRB, in order to see if there are any changes or trends in the former that may hint of some recent systematic climate change in the basin.

The annual observed time series for precipitation and maximum temperature for the various sub-basin of the UBNRB are shown in the two panel groups of Figure 7. At first sight, there appears to be no systematic visible trends in the three series for the UBNRB as a whole, particularly, as far as precipitation is concerned, which has been increasing over time in some sub-basins and decreasing in others. For the maximum and minimum temperatures one may recognize, though, some minor decadal increases from Figure 8, were the annual series have been averaged decadely for the last three decades of the 20th-century.

However, this visual analysis of the annual averaged series may not be sufficiently revealing, as it cannot rule out that there have not been seasonal changes occurring during this past time period. For a better quantitative analysis of possible trends the Mann-Kendall- and the seasonal Mann-Kendall test [Hirsch et al., 1982; Helsel and Hirsch, 2002] have been carried out, which are based on the following test hypothesis (for a detailed description of the method see Cherie [2013]):

- $H_0$: no trend in the series
- $H_1$: trend in the series

Based on the p-value of the test statistics (Kendall’s tau), the null hypothesis $H_0$ is rejected and the alternative hypothesis $H_1$ accepted, whenever $p < \alpha = 0.05$.

The results of the seasonal Mann-Kendall test applied to the monthly measured meteorological time series of the various sub-basins of the UBNRB are shown in Table 4, where the logical for the hypothesis $H_1$ (trend) is listed. From this table one may notice that both maximum and minimum temperatures have indeed increasing trends for a few of the sub-basins, whereas for the precipitation the trends and mixed.
Figure 7  Annual 1970-2000 observed time series for precipitation (top) maximum (middle) and minimum temperature (bottom) for the various sub-basins of the UBRNB
Table 4: Seasonal Mann-Kendall test for a trend (hypothesis $H_1$) in precipitation, maximum and minimum temperature for the various sub-basins of the UBNRB.

<table>
<thead>
<tr>
<th>SN</th>
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<th>Tmin</th>
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<td>No</td>
<td>Sign(+)</td>
</tr>
<tr>
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<td>No</td>
<td>No</td>
</tr>
<tr>
<td>3</td>
<td>Beshilo</td>
<td>No</td>
<td>Sign(+)</td>
<td>No</td>
</tr>
<tr>
<td>4</td>
<td>Dabus</td>
<td>No</td>
<td>No</td>
<td>Sign(-)</td>
</tr>
<tr>
<td>5</td>
<td>Didessa</td>
<td>No</td>
<td>No</td>
<td>Sign(+)</td>
</tr>
<tr>
<td>6</td>
<td>Fincha</td>
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<td>No</td>
<td>No</td>
</tr>
<tr>
<td>7</td>
<td>Guder</td>
<td>Sign(+)</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>8</td>
<td>Jimma</td>
<td>No</td>
<td>No</td>
<td>Sign(+)</td>
</tr>
<tr>
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<td>Muger</td>
<td>Sign(+)</td>
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</tr>
<tr>
<td>10</td>
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<td>No</td>
<td>Sign(+)</td>
<td>Sign(+)</td>
</tr>
<tr>
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</table>

"No" for hypothesis $H_1$ implies that there is no statistically significant trend, "Sign" represents the presence of a significant trend, with (+) and (-) indicated increasing and decreasing trend, respectively.
4.2. Mono-model SDSM- downscaling

4.2.1. 20th - century (reference period) simulations

The calibration of SDSM, using observed station data as predictands and NCEP-reanalysis data as predictors (see Figure 6 and Table 3), has been made on the grid of Figure 5 for the 14 sub-basins of UBNRB. In the SDSM calibration procedure, a conditional approach has been used for the precipitation, since the latter depends indirectly on the probability of a wet-day occurrence, whereas the temperature has been calibrated unconditionally with the various predictors of Table 3. Out of the whole 30 years (1970-2000) base- or control period, 19 years (1970-1988) are used for the calibration of the SDSM- model and the remaining 12 years for its validation.

The results show (see Cherie [2013], for details) that for the precipitation the performance of the SDSM-calibration, as measured in terms of the percentage of explained variance, \( R^2 \), is, with a value of only 10%, rather poor. Better results, with \( R^2 = 54\% \) and \( R^2 = 44\% \), are found for the maximum and minimum temperatures, respectively. This unsatisfactory result for the precipitation may be due to a limited number of daily large-scale predictor variables, as well as due to the complex physio-geographic nature of the UBNRB. On the other hand, it is also well-known in the climate-change community that downscaling of precipitation is problematic [e.g. Hashmi et al., 2009; 2011], which is due to a misunderstanding of the climate's governing fine scale processes but also due to a correct representation of the physics of the precipitation itself in the GCM.

Figure 9 shows the SDSM- 20th - century simulation results for precipitation, maximum and minimum temperatures exemplarily for two UBNRB- sub-basins for which relatively good calibrations results have been obtained. Following the SDSM- methodology, the monthly averaged observed, SDSM- NCEP- reanalysis- and SDSM-ECHAM-5- predictions are illustrated, wherefore the latter are then used in the later future climate predictions as the baseline scenario. From the figure one may note a systematic difference, or so-called bias, between the climate predictors for the two approaches and the observations.

Following the common procedure [e.g. Dibike et al., 2008], the bias has been computed as a relative ratio in percent for the precipitation and as an absolute value for the two temperatures. Results are demonstrated for the same two sub-basins in Figure 10, from which one may notice that the bias of the SDSM- NCEP- reanalysis- downscaling is generally smaller - which is to be expected, given that this data has been generated by ongoing assimilation of observed data into the GCMs used [Kalney et al., 1996] - than that obtained with SDSM-ECHAM-5- downscaling. Either way, this bias must be considered in the subsequent future GCM/downscaling climate predictions when comparing the latter with the present-day observed climate in the region.
4.2.2. 21\textsuperscript{st} - century future climate predictions

Although the performance of the SDSM- mono model downscaling to simulate the past 20\textsuperscript{th} - century climate in the UBNRB appears not to be so good, for a latter comparison with the other downscaling methods, we present a few results of this approach method with regard to the prediction of 21\textsuperscript{st} - century future climate variations in the basin. Figures 11 and 12 shows these future predictions of the monthly averages of the maximum ($T_{\text{max}}$) and minimum ($T_{\text{min}}$) temperatures and the rainfall, respectively, for the sub-basin Tana. More specifically, likewise to all following figures, results for the two future time-slices 2050s and 2090s and the two SRES scenarios A1B and A2 (see Table 2). In addition to the absolute values of the corresponding climate variable, relative changes with respect to the observations of the 20\textsuperscript{th} - century reference period - after additive and multiplicative
"delta"- corrections for the past biases of temperatures and precipitation, respectively, as mentioned earlier, e.g. Cherie [2013] - and the trend-lines over the whole 1970-2000 simulation period (broken-up in three intervals) are shown.

The future SDSM- predicted temperatures, including the changes, shown in Figure 11 for the sub-basin Tana, are pretty much representative for the whole UBNRN, namely, systematic temperatures increases for both $T_{\text{max}}$ and $T_{\text{min}}$, which, depending on the sub-basin and the season, range between 1°C and 4°C. Generally, the increase of $T_{\text{max}}$ is higher for the wet season months (June to August) than for the dry season months (December to February). Also, expectedly, $T_{\text{max}}$ is higher for the 2090- than for the 2050 decade, whereby, particularly, for the 2090 time period, the impact of the (more extreme) SRES-scenario A2 is slightly stronger than that of A1B.

For the minimum temperatures $T_{\text{min}}$ the trends are similar, if not even more consistent across the various sub-basins of the UBNRB. Compared with the 20th –century reference
period, warmer temperatures are observed for the two future time periods considered, whereby, expectedly, those for the 2090-decade are higher than those of the 2050-decade. Moreover, for most sub-basins the warming trend is higher for SRES-scenario A2 than for A1B [Cherie, 2013].
The SDSM- predicted future precipitation (RF) for the various sub-basins of the UBNRB - here only shown for sub-basins Tana and Muger in Figure 12 - are more versatile across the basin and show particularly large seasonal fluctuations, such that, generally, for the wet season (June to September) a decrease, and for the dry months (December to
February) an increase of the precipitation is obtained. However, while a few sub-basins, like Muger show significant increases of the annual precipitation, for most of them, like Tana, the total rainfall will decrease by 30-40% in the future, therefore, similar to the temperatures, these changes are slightly stronger for the SRES A2 than for A1B.

4.3. Mono-model LARS-WG- downscaling

4.3.1. 20th-century (reference period) simulations
The application of the LARS-WG- mono-model downscaling method [Semenov and Barrow, 2002] to the 20th-century observed climate data in the UBNRB, namely, the division into calibration (1970-1988) and validation (1989-2000) period, is identical to the one used previously for SDSM. For the evaluation of the performance of LARS-WG to simulate the observed reference climate variables, various quantitative measures, like the mean error ME, and the root mean squared error RMSE. In addition several statistical tests, namely, the KS- and the t-test, which test the hypothesis:

\[ H_0: \text{simulated and observed time-series have the same distribution (KS-test) and/or mean (t-test), against the alternative hypothesis } H_1: \text{the distributions are different.} \]

Results of these hypotheses tests for the Thiessen-interpolated daily climate time series for each sub-basin of the UBNRB are shown in Table 5. In addition to the three climate variables already discussed, the lengths of the wet- and dry-day periods are also included (see Cherie [2013], for details). Listed in the table are the number of counts that a test has resulted in a p-value < 0.01., which means that the null hypothesis \( H_0 \) has to be rejected in favor of \( H_1 \), i.e. the weather generator's produced data is statistically different from the observed data. This means that a large number of "positive" counts in the table hints of a poor performance of the weather generator for that variable in a particular sub-basin.

Table 5 indicates that LARS-WG performs well for the daily distribution of the minimum temperature \( T_{\text{min}} \) (KS-test), monthly mean minimum temperatures \( T_{\text{min}} \) (t-test), daily distribution of maximum temperature \( T_{\text{max}} \) (KS-test) and monthly mean total precipitation Rain (t-test). On the other hand, positive counts of misses of the null hypothesis \( H_0 \) are obtained for various sub-basins for the seasonal wet-day and dry-day series distributions, and for many sub-basins for the monthly mean total precipitation Rain, as the total numbers of failed tests for these test-groups across all sub-basins amounts to 3.6%, 8.9%, and 11.3%, respectively.
Table 5: LARS-WG statistical performance to simulate the distribution (KS-test) and the mean (t-test) of the various aggregated observed climate variables for each the sub-basin. Numbers indicate how many times the hypothesis \( H_0 \) (simulated and observed variables are the same) has been rejected in favor of the alternative hypothesis \( H_1 \).

<table>
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<th>Rain test</th>
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<th>T_min</th>
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<td>1</td>
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<td>0</td>
<td>0</td>
<td>0</td>
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</tr>
</tbody>
</table>

Average: 0.1, 0.4, 0.0, 1.4, 0.0, 0.0, 0.0, 0.2

Failed tests (%): 3.6, 8.9, 0.0, 11.3, 0.0, 0.0, 0.0, 1.8

Figure 13 shows the LARS-WG- mono-model simulated average monthly climate variables \( T_{\\text{min}}, T_{\\text{max}}, \) and \( Rain \) for the calibration and validation periods for the UBNRB- sub-basins Fincha, Guder and Jimma. Corroborating the statistical results of Table 5 good agreement between Lars-WG- generated and observed monthly data is observed. Wherefore for the daily series, the \( \text{RMSE} \) for the two temperatures range between 1 and 2 °C and that of the precipitation between 2 and 4 mm (see Cherie [2013], for details).

4.3.2 21th - century future climate predictions

By altering the weather generator parameters derived from the observed weather data by the "delta"-change of the GCMs predicted future climate - by making appropriate changes in the scenario file of LARS-WG [Semenov and Barrow, 2002] -, future synthetic climate data at a daily time-scale is generated (which is then used further in the hydrological modeling of the UBNRB which is presented in the accompanying paper [Koch and Cherie, 2013]). Though the future downscaling predictions are on a daily time scale, aggregation on a monthly or even seasonal scale has been done, in order to get a better grasp on the expected climate changes for the entire study area.
Figure 14 shows LARS-WG- mono-model future seasonally averaged predictions - or more specifically changes, relative to the 20th-century reference period - of the maximum and minimum temperatures and the precipitation for the sub-basins South Gojjam and Tana. Results for other sub-basins are presented in Cherie [2013] and are rather similar, particularly as far as temperatures are concerned, whereas seasonal precipitation is somewhat more variable across the various sub-basins.

The most noteworthy feature of the various panels of Figure 14 is the systematic future increase of both the maximum and minimum temperature for all seasons, of up to 4°C for the 2090s decade. This temperature increase is particularly pronounced for $T_{\text{max}}$. 
during the future summer seasons. Moreover, similar to the SDSM-downscaling results of the previous section, the LARS-WG- predicted future warm-up across the UBNRB is also consistently higher for SRES- scenario A2 than for A1B, which should be of no surprise, as the same large-scale GCM (ECHAM5) predictors have been used in the two downscaling methods.

In contrast, the LARS-WG- mono-model future precipitation changes exhibit stronger seasonal variations. As shown in the two corresponding panels of Figure 14 for the two sub-basins - likewise to all other sub-basins - for the 2050s- period the winter precipitation will go up tremendously, but this increase will have tapered down again for the 2090's.
For the future spring and summer seasons the precipitation changes are much smaller and no clear trend is visible for all sub-basin, i.e. the former may be positive for some and negative for others. The influence of the SRES-scenario is such that for most sub-basins the precipitation changes are larger for SRES A1B than for A2. This result is somewhat surprising, as SRES A1B is more benevolent than A2, and requires further explanations.

4.4. Comparison of SDSM- and LARS-WG- mono model downscaling methods
In this section the future seasonal UBNRB- climate predictions of the two mono-models (using the same large-scale GCM, ECHAM5) downscaling methods SDSM and LARS-WG are compared.

The downscaled seasonally averaged maximum temperatures $T_{max}$ shown in Figure 15 (top panel) indicate for both the SDSM- and the LARS-WG- downscaling tool a considerable increase for the two future time-periods, irrespective of the SRES- scenario (A1B, A2) assumed.

However, for both SRES, the LARS-WG- $T_{max}$ -predictions are consistently higher by 1.1-1.5 °C for the 2050s and by 2.4-3°C for the 2090s than the SDSM-ones. At this stage one can only speculate about the reasons for these discrepancies between the two downscaling methods which, as discussed, are using quite different statistical procedures.

The situation is similar for the predicted minimum temperatures $T_{min}$, shown in the middle panel of Figure 15, which increase considerably for all seasons, scenarios and future time periods, particularly, when using LARS-WG downscaling. Thus the latter predicts an increase of $T_{min}$ by 1.1-1.5 °C for the A2_2050- case and of 3.4-4.3 °C for the A1B_2090- case. For both downscaling tools the overall rise of $T_{min}$ is always larger than that of $T_{max}$ and both are higher in the 2090s than in the 2050s which indicates clearly that future climate warming in the UBNRB is an unequivocal fact.

The bottom panel of Figure 15 illustrates the predicted seasonal precipitation. One may notice that for both downscaling approaches and for both future time periods the precipitation for the SRES scenarios A1B and A2 are more or less similar for all, but the winter season. Moreover, SDSM shows a seasonal decrease of the precipitation in the summers and springs of the 2050s, which is accentuated in the 2090s. In contrast, LARS-WG predicts a minor increase of the precipitation for most seasons, but which is especially high for the 2050s winter seasons.
Figure 15  Mono-model- SDMS- and LARS-WG- downscaled average UBNRB future seasonal changes of maximum (top), minimum (middle) temperatures and precipitation (bottom), for the two time-slices 2050s and 2090s and the two SRES-scenarios A1B and A2
4.5. LARS-WG- multi-model downscaling

Since each global climate model (GCM) has its own weakness and strengths in a typical climate analysis, it is to be expected that by using predictors from more than one GCM the prediction bias may be somehow reduced. In the LARS-WG- multi-model downscaling method proposed here as a novel approach, LARS-WG is forced using averages of the corresponding time series’ predictors from the three GCMs GFLD21, SCIRO-MK3 and ECHAM5 (see Table 2). To that avail the LARS-WG- scenario files have been prepared with average of the outputs of these three GCMs. All other procedures are more or less similar to those of the previously used LARS-WG mono-model [e.g. Cherie, 2013].

The results obtained with this methodology reveal unequivocally that for both SRES-scenarios the predicted future maximum and minimum temperatures will increase
consistently across all sub-basins. Thus, the average UBNRB areal $T_{\text{max}}$ will rise by 1.8 °C in the 2050s and by up to 3.2 °C in the 2090s, whereas the corresponding $T_{\text{min}}$ increases are, with 2.0 °C and 3.4 °C, respectively, even higher. For this reason we forgo a sub-basin-wise presentation of the temperature changes, which are more or less similar to those obtained with the LARS-WG- mono-model downscaling method previously, and show in Figure 16 only monthly precipitation predictions for a few sub-basins which, obviously, are much more variant than the temperatures.

Figure 16 illustrates that for most of the sub-basins shown - which holds also for the remaining ones (see Cherie [2013]) - namely, those in the highlands of the UBNRB (Figure 1), precipitation in winter and, to a lesser extent, also in summer is significantly reduced for the 2090s time period, whereas autumn precipitation is going up slightly. When averaging these still for the sub-basins varying precipitation changes over the whole UBNRB, Figure 17 results. This figure shows that for the 2050s time period the UBNRB seasonal precipitation will decline by -2% to -3% in the spring, by -4% to -5% in the summer and by -6% to -7% in the autumn. During the 2090s period, a further decrease is obtained for all, but the autumn season (where an increase of 4% -5% is observed), namely, for winter where a decline by -11% to -15% is predicted.

So far in the paper only the predictions for the three primary meteorological variables maximum, minimum temperatures and precipitation have been discussed. However, the primary GCM's used in the downscaling processes (see Table 2) provide further
climate output, namely, and the lengths of the wet- and dry-spells, already mentioned briefly in Table 5. These two variables provide information on how the day-intervals of precipitation / no precipitation, respectively, are actually distributed over a season or the year, and are thus of particular interest for agriculture, which in fact, is the dominant economic activity in the UBNRB study region.
Figures 18 and 19 show LARS-WG- multi-model future predicted seasonal lengths of the wet-spells and dry-spells, respectively, for various sub-basins. For comparison the 20th century reference predictions are also included in the various panels.

Figure 18 indicates that, for the summer season, in particular, the future predicted wet-spell lengths are in general shorter than the recently observed ones. For the other seasons of the year there are no noticeable differences between future and presence.

For the future dry-spell lengths (Figure 19) the situation is just the opposite, i.e. these will be longer in the future for most sub-basin. This means, obviously, that drought intervals across the UBNRB will be longer by the end of this century.
From the two figures one may also notice that the named changes of both the wet- and the dry-spells do not depend much on the SRES-scenario used.

4.6. Comparison of LARS-WG- mono-model- and multi-model methods
In this section the prediction results of the two LARS-WG downscaling variants, i.e using either mono-model- or multi-model predictor data from the parent GCMs (see Table 2) are compared. The various panels of Figure 20 show the sub-basin-wise predictions of...
maximum-, minimum temperature and precipitation for the two future time periods using the LARS-WG- mono-modal- and the LARS-WG- multi-model downscaling variants.

From the temperature panels of Figure 20 one may notice that with the exception of Belles sub-basin, for all other sub-basins the mono- and multi-model LARS-WG approaches deliver almost the same results for the maximum- and minimum temperature- changes (relative to the 20th - century reference period) in the 2050s future decade. In contrast, considerable differences are obtained for the 2090s, when the multi-model- predicted temperature changes are more than 1°C lower than the ones obtained with the mono-model LARS-WG variant. A more detailed seasonal analysis [Cherie, 2013] shows that these methodology-originating differences are particularly pronounced for the future summer seasons, but are only minor for the other seasons of the year.

The two precipitation panels of Figure 20 indicate clearly that for all sub-basins the annual precipitation changes predicted with the LARS-WG- multi-model approach are also smaller than those of the mono-model variant. However, on the contrary to the temperatures above, these precipitation differences are, surprisingly, more apparent for the 2050s than for the
2090s period for which almost similar results are obtained for most sub-basins. As for the seasonal precipitation predictions [Cherie, 2013] the multi-model approach results in higher changes than the mono-model variant for the winter seasons of the 2050s time slice.

Figure 21 shows in a comparative manner the aggregated UBNRB climate predictions, i.e. $T_{\text{min}}$, $T_{\text{max}}$, and precipitation obtained with the two LARS-WG- downscaling variants. From the figure one may notice that, whereas LARS-WG-mono-model predicts higher future temperature-changes than LARS-WG multi-model, the situation is just the opposite for the 2090s-precipitation, i.e., the latter results in larger decreases than the former.

5. Summary of future climate predictions for the UBNRB

In this section the most salient UBNRB- climate prediction results obtained in the previous sections with the three GCM/downscaling combinations will be summarized again and put in a perspective. As discussed earlier, there are quite a few future seasonal variations across the 14 sub-basins of UBNRB of the three climate variables maximum and minimum temperature and precipitation analyzed, which holds particularly for the latter. For this reason, in order to get a somewhat more reliable idea on the UBNRB basin-wide expected 21st - climate change, these three climate variables have been aggregated across all sub-basins of the UBRNB in the following discussion.

All climate-prediction results obtained with the three downscaling variants SDSM, LARS-WG- mono-model and LARS-WG- multi-model are shown in a comparative manner in Figure 22 and summarized in more detail in Table 6. More specifically, in Figure 22 the predictions of the two SRES-scenarios A2 and A1B which have been found to be more or less similar anyway (see Table 6) have been averaged for illustrative simplification.

Both the table and the figure indicate that all three downscaling/time-period/SRES combinations provide unequivocal evidence that the UBNRB will have an increase of both maximum and minimum temperature in the future, whereby the 2090- decade will be warmer than the 2050-decade. More specifically, the results show that this warming up is generally higher during the spring and summer season than during autumn and winter. With respect to the SRES emission scenarios, there is no noticeable difference between A1B and A2 in 2050s, although, expectedly, during the 2090s, the more extreme SRES A2 predicts a slightly warmer climate than A1B.
Figure 22  Summary of future seasonal UBNRB- predictions of maximum- (top), minimum (middle) temperature- and precipitation (bottom) changes for the three downscaling variants SDSM, LARS-WG- mono-mode (index 1) and LARS-WG- multi-model (index3)
The comparison of the temperature predictions by the three downscaling variants SDSM, LARS-WG- mono-model and LARS-WG- multi-model in Figure 22 shows clearly that both LARS-WG- mono-model and multi-model predict higher temperatures than SDSM, wherefore, in turn, LARS-WG- mono-model- simulated temperatures are higher than the mono-model ones.

Also, for most seasons, the predicted changes of the seasonal minimum temperatures are larger than those for the maximum temperature. Moreover, for both SRES- scenarios the future maximum and minimum temperature increases are larger for spring and summer than for the autumn and winter.

Table 6: Summary of future predicted seasonal climate changes in the UBNRB using the three downscaling/GCM combinations

<table>
<thead>
<tr>
<th>Tool Variable</th>
<th>Scenario</th>
<th>2046-2065 (2050s)</th>
<th>2081-2100 (2090s)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Spring</td>
<td>Summer</td>
</tr>
<tr>
<td>P(%)</td>
<td>A1B</td>
<td>-28</td>
<td>-18</td>
</tr>
<tr>
<td></td>
<td>A2</td>
<td>-27</td>
<td>-17</td>
</tr>
<tr>
<td>Tmax(°C)</td>
<td>A1B</td>
<td>0.68</td>
<td>1.05</td>
</tr>
<tr>
<td></td>
<td>A2</td>
<td>0.58</td>
<td>0.92</td>
</tr>
<tr>
<td>Tmin(°C)</td>
<td>A1B</td>
<td>0.60</td>
<td>0.71</td>
</tr>
<tr>
<td></td>
<td>A2</td>
<td>0.49</td>
<td>0.63</td>
</tr>
<tr>
<td>LARS-WG (mono-model)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P(%)</td>
<td>A1B</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>A2</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Tmax(°C)</td>
<td>A1B</td>
<td>2.21</td>
<td>2.71</td>
</tr>
<tr>
<td></td>
<td>A2</td>
<td>1.73</td>
<td>2.25</td>
</tr>
<tr>
<td>Tmin(°C)</td>
<td>A1B</td>
<td>2.31</td>
<td>2.44</td>
</tr>
<tr>
<td></td>
<td>A2</td>
<td>1.82</td>
<td>2.05</td>
</tr>
<tr>
<td>LARS-WG (multi-model)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P(%)</td>
<td>A1B</td>
<td>-3</td>
<td>-5</td>
</tr>
<tr>
<td></td>
<td>A2</td>
<td>-2</td>
<td>-4</td>
</tr>
<tr>
<td>Tmax(°C)</td>
<td>A1B</td>
<td>1.91</td>
<td>2.00</td>
</tr>
<tr>
<td></td>
<td>A2</td>
<td>1.97</td>
<td>1.98</td>
</tr>
<tr>
<td>Tmin(°C)</td>
<td>A1B</td>
<td>2.03</td>
<td>1.95</td>
</tr>
<tr>
<td></td>
<td>A2</td>
<td>2.10</td>
<td>2.04</td>
</tr>
</tbody>
</table>

In contrast to the temperatures, the precipitation predictions of the three downscaling methodologies are much more variant. This holds particularly for the SDSM method. Because of the already poor calibration performance of this downscaling approach in the 20th - century reference period, its future prediction power turns out also to be limited. Thus, the 21st – century SDSM downscaled precipitation predictions are rather different across the various sub-basins of the UBNRB, showing minor increases in some, but declines in most others. Table 6 and Figure 21 show that overall the SDSM-downscaled future precipitation exhibits a decreasing trend during the spring and summer seasons,
but some increase during autumn and winter, particularly, for the 2090s period.

Compared to SDSM, the two LARS-WG downscaling options predict more congruent precipitation changes across the various sub-basins of the UBNRB. For the basin as a whole a decreasing trend during most of the seasons, - but the winter season of the 2050s using the LARS-WG- mono-model approach - is obtained with the two LARS-WG downscaling methodologies. Thus a better agreement between LARS-WG- mono-model and LARS-WG- multi-model is obtained than both with SDSM.

6. Conclusions

The results and the discussions of the previous sections have shed some more light on the intricacies of the prediction of future climate change in a particular region of the world, like the UBNRB. Thus it is partly understandable, why other previous studies to quantify future climate change in that basin did not come to clear conclusions, since the predictions computed there were using either climate output from a single GCM output or multiple GCM and the use of a single downscaling tool. However, as this study has shown, owing to the fact that each GCM and each downscaling tool has its own strength and weakness, it may not be acceptable to rely alone on the predictors of one GCM in one downscaling tool.

With the present GCM/downscaling methodologies and the results of their climate predictions at hand, the subsequent paper [Koch and Cherie, 2013] will be devoted to analyze the impact of the predicted climate change on the hydrology and water resources in the UBNRB.

References


SWAT-Modeling of the Impact of future Climate Change on the Hydrology and the Water Resources in the Upper Blue Nile River Basin, Ethiopia

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Abstract
The semi-distributed physical based hydrologic model, SWAT (Soil Water Assessment Tool), is used to evaluate the impact of future climate change on the hydrology and water resources of the Upper Blue Nile River Basin (UBNRB). The weather data used as input in SWAT are downscaled predictors from two well-known statistical downscaling models, namely, SDSM and LARS-WG which have been run in both mono- and multi-model manners, i.e. using large-scale output from one or several GCM's. Details of this climate analysis are presented in an accompanying paper. The impacts of both A1B- and A2- SRES scenarios are simulated for two future time periods, 2046-2065 (2050s) and 2081-2100 (2090s) and compared with model results for the 1970-2000 baseline period.

The SWAT-model is calibrated and validated on streamflow observed at the Eldiem gauging station (Ethio-Sudan boarder) during the baseline period. Model performance is evaluated using standard performance parameters, i.e. PBIAS, NS and R2. All these statistical quantities indicate a good adjustment of the modeled to the observed streamflow for both the calibration and validation period.

The results of the future simulations of flow and other hydrological processes in the UBNRB, using SDSM- and LARS-WG downscaled climate predictors in SWAT reveal that, relative to the 20th-century baseline period, the Blue Nile River streamflow declines in both the 2050s and 2090s decade. These reductions range between 10% and 61%, depending on the type of downscaling and of the emission scenarios employed, and are mainly due to higher temperatures and lower precipitation, as predicted by the GCM’s climate models. However, the SWAT-future simulations with the predictors from the LARS-WG mono-model downscaling technique, generally, result in smaller streamflow change for both scenarios and both future periods. In contrast, the SWAT-future simulation using SDSM-predictors leads to the biggest reduction of streamflow, whereas SWAT-results for the water yields obtained, using LARS-WG multi-model predictors, are situated in between the other two downscaling approaches. Other water balance components simulated by the SWAT-model also exhibit some versatile behavior, depending on the downscaling method employed and the SRES assumed. Despite these differences in the
hydrological predictions for the UBNRB, which are mainly due to variations in the GCM / downscaling predictions, a consistent picture for its future climate emerge, namely, warmer temperatures which, in conjunction with a decline in precipitation, will lead to a reduction of future streamflow and water availability in the basin. These adverse climate impacts will require some adaptation measures to be taken.

1. Introduction

Ethiopian highlands generate a discharge of 87% of the total Nile flow at the Aswan dam in Egypt. 60% of this amount is contributed by the Blue Nile and the other 27% of the discharge originates from the Atbara and the Sobat tributaries to the large Nile. The part of the watershed of the Blue Nile River Basin which is under the Ethiopian territory is named the Upper Blue Nile River Basin (UBNRB). The average annual flow of the Blue Nile at the Ethio-Sudan border is 48,660 M (million) m³ which represents more than 40% of Ethiopia's total surface water resources of 122,000 M m³ [World Bank, 2006]. Hence, the UBNRB represents a substantial water resource for Ethiopia and as well for the downstream countries Sudan and Egypt.

ENTRO [2006] estimated the total population of the UBNRB to be at 22.9 million, with the majority (80%) living in the rural areas. More than 85% of the basin population depends entirely on rain-fed agriculture. Owing to increasing intermittent periods of water scarcity, water-use conflicts among different users have become common throughout the region in recent decades. In addition, because of high population pressure, lack of alternative livelihood opportunities and poor land and water management, in general, and, not to the least, due to the impacts of imminent climate change in the UBNRB [e.g. Cherie, 2013; Cherie and Koch, 2013], such problems will most likely be exacerbated in the near future.

In order to reduce or to mitigate such, possibly, adverse effects of the presently already observed, but more so, of the future-expected climate change on the water resources in the UBNRB, a quantitative assessment of the latter in response to the former is needed. This is the subject of the present paper, which is a direct follow-up of the paper of Cherie and Koch [2013], hitherto referred as paper-1. Thus, whereas in paper-1 the results of a comprehensive past and future climate analysis of the UBNRB have been presented, here these climate predictions for the basin will be used as meteorological/climate drivers in the SWAT (Soil and Water Assessment Tool) distributed hydrological watershed model [Arnold et al., 2009] to simulate the 21st – century developments of the upper Blue Nile river streamflow, as well as of other relevant watershed hydrological parameters, and so to get an idea on the future water availability in the UBNRB.
More specifically, in line with the various climate prediction approaches applied in paper-1 [Cherie and Koch, 2013], three different GCM / downscaling combinations will also be used for the driving of the SWAT-simulations. Such a multi-facet approach should, on one hand, provide more confidence in the results obtained, but may, on the other hand, also shed some more light on the general intricacies and uncertainties of climate-change-driven streamflow predictions.

2. Study area

The Blue Nile river is originates in the highlands of Ethiopia, called Gish-Abbay. The upper Blue Nile river basin (UBNRB) encompasses the Ethiopian part of the Blue Nile river basin, in general (Figure 1). The length of the upper Blue Nile river from the outlet at Lake Tana to the Ethio-Sudan border is 944.5 km. The UBNRB study areas is located in the western part of Ethiopia, between 7° 45' and 12° 45'N and 34° 05' and 39° 45'E and covers 176,652 km² - about half of Germany's size - which accounts for 17.7% of Ethiopia's land area.

The altitude of the UBNRB ranges from 485 m to 4257 m. Figure 1 shows that the Blue Nile and its tributaries have a general slope towards the northwest, however the slopes are steeper in the east than in the west and northeast areas of the UBNRB. The Blue Nile river in the Ethiopian territory navigates through deep gorges which get shallower towards the Ethio-Sudan boarder.
The mean annual areal rainfall over the UBNRB is 1358 mm, ranging between a minimum of 850 mm for sub-basin Jimma to a maximum of 1869 mm for sub-basins Anger and Didessa. The rainfall distribution is highly variable both spatially - decreasing from the southwest to the east and northeast - and temporally, i.e. over the yearly seasons (see paper-1, for more details).

Depending on the average altitude of the various sub-basins making up the basin (see paper-1 or later Figure 11, for denominations and locations), the mean annual temperatures in the UBNRB are situated in a range of 16.7 °C to 19.6 °C, with an overall mean of 17.8 °C. The maximum mean temperatures are observed in the months of March and April and the lowest ones (only 2.8°C less than the highest one) in July and August. Obviously, the temperatures of the UBNRB exhibit less spatial variations than the precipitation.

The average Blue Nile streamflow measured at the streamgage station Eldiem, close to the Ethio-Sudan border, over the time period 1970-2000 is 45.345 km³. However, this mean discharge has been varying considerably over time. Thus Conway [2000] reports extreme annual discharge fluctuations that range from 79.1 km³ in 1909 to 20.7 km³ in 1913, whereas Sutcliffe and Parks [1999] indicate mean annual discharges of 50.33, 46.41 and 48.66 km³ for three time periods 1912-1960, 1961-1997 and 1912-1997, respectively.

Moreover, as the rainfall over the UBRNB is highly seasonal, the Blue Nile river also possesses a strongly-varying seasonal flood regime, whereby over 80% of the annual discharge occurs during the four months from July to October. Adding to the problem is the fact that all excess- water is directly drained to the downstream countries, as up-to-date no noteworthy hydraulic infrastructure in the basin exist to store water [Conway, 1997]. This adverse situation may improve in the near future, though, as Ethiopia started a six-year project in 2012 for the construction of a 6,000 megawatt hydroelectric dam on the Blue Nile river.

3. Methodology

3.1. SWAT- model / basic concepts

SWAT (Soil Water Assessment Tool) is a widely-used semi-distributed, physically based and computationally efficient hydrological model which allows the simulation of a number of different physical and hydrological processes occurring across a watershed and, in particular, the streamflow as the ultimate basin characteristic [Neitsch et al.,...
Input to SWAT is geographic information on the basin and its shallow subsurface, like topography, soil and land-use, subsurface parameters and weather data, driving the dynamic hydrological processes. Output of the model is primarily discharge of the major basin stream and/or its tributaries, as well as other water budget components of the basin.

In the SWAT-modeling approach a watershed is divided into a number of sub-basins. Each sub-basin is then further divided into groups of similar soil- and land cover areas which, because they are supposed to give similar hydrological responses, are called HRUs [Arnold and Fohrer, 2005; Neitsch et al., 2005]. The SWAT-hydrological compartments in a watershed consists of a land phase and a water-routing phase. The land phase of the hydrologic cycle controls the amount of water, sediment and pesticide loadings to the main channel in each sub-basin, whereas the routing phase of the hydrologic cycle shows the movement of water, sediment, nutrients, etc., through the channel network of the water of the watershed and then to the outlet [Neitsch et al., 2005].

The land phase of the hydrologic cycle is described by the transient water balance equation applied to water movement through the soil, namely:

$$SW_i = SW_0 + \sum_{j=1}^{i} (R_{d,j} - Q_{surf,j} - E_{a,j} - W_{seep,j} - Q_{gw,j})$$

where:

- $SW_i$, final soil water content after $i$ days (mm water),
- $SW_0$, initial soil water content (mm water),
- $R_{d,i}$, amount of precipitation on day $i$ (mm water),
- $Q_{surf,i}$, amount of surface runoff on day $i$ (mm water),
- $E_{a,i}$, amount of evapotranspiration on day $i$ (mm water),
- $W_{seep,i}$, amount of percolation and bypass flow exiting the soil profile bottom on day $i$ (mm water),
- $Q_{gw,i}$, amount of return flow on day $i$ (mm water),
- $t$, time (days).

Surface runoff occurs, whenever the rate of water application to the ground surface exceeds the rate of infiltration, i.e. it is the excess water that cannot anymore infiltrate into the ground. Because of this process, the correct estimation of the infiltration is crucial for the subsequent evaluation of the surface runoff.
SWAT provides two infiltration methods for estimating the surface runoff volume component from HRUs, namely, the SCS-curve number (CN) method [SCS, 1972] or the Green & Ampt infiltration method [Green and Ampt, 1911]. Whereas the CN-method uses daily rainfall rates, the Green & Ampt technique requires smaller time-steps to properly simulate the infiltration process. This discards the use of the latter method in the present study.

Here the surface runoff is modeled in SWAT using the SCS curve number method, i.e.

\[
Q_{\text{surf}} = \left( \frac{R_{\text{surf}} - I_{a}}{R_{\text{surf}} - I_{a} + S} \right)^{2}
\]

where:

- \(Q_{\text{surf}}\), accumulated runoff or rainfall excess (mm H20),
- \(R_{\text{surf}}\), rainfall depth for the day (mm H20),
- \(I_{a}\), initial abstractions which includes surface storage, interception and infiltration, prior to runoff (mm H20), and which is usually taken as equal equal 0.2S, with
- \(S\), retention parameter (mm H20).

The retention parameter \(S\) is defined by:

\[
S = 25.4 \left[ \frac{1000}{CN} - 10 \right]
\]

where \(CN\) is the SCS-curve number, which ranges from 0 to 100, depending on the soil permeability, land use and the antecedent soil water conditions.

There are numerous other parameters in SWAT which control the various hydrological processes acting across a basin, namely, the transitions and routing of the flow components across the different compartments of the SWAT-simulated section of the hydrological cycle [Neitsch et al., 2005]. Most of these parameters (see Cherie [2013], for further details), though, are empirical and must, therefore, be estimated by trial and error during the calibration of the model. This will be discussed further in Section 4 during the application of the model.

3.2. A review of some SWAT-model applications and intricacies

SWAT is one of the most powerful hydrologic models and it has been applied in different parts of the world, such as: USA, Europe, China, South Asia, Africa and many other parts
of the world [Arnold et al., 2009]. Over the past decade, SWAT has been extended to wider application areas beyond hydrology, such as climate change, sediment and pollutant transport, nutrient loss, pesticides and agricultural management practices, among others [Gassman et al., 2007], and its application in Africa is also shown by Schoul et al. [2006].

SWAT-applications in the Nile basin is also partly addressed by van Griensven et al. [2012]. In this review paper, more than 20 peer reviewed papers have been reported on the application of SWAT to the tropical highlands of the Nile basin countries for a variety of thematic purposes, including climate change impact modeling. More than half of these papers relate to studies in the UBNRB of Ethiopia. The authors present a critical evaluation of model performance, physical representation of model parameters and correctness of the hydrological balances. This SWAT-model evaluation shows that the model results range from satisfactory to very good.

On the other hand, the study of Easton et al. [2010] shows that SWAT-WB (which uses a more physically based soil water balance than is implemented in the classical CN-method, normally used in SWAT) works better in some sub-basins of the UBNRB than SWAT-CN. However, it is also important to consider other factors affecting the mechanism of overland runoff generation, such that vegetation cover, land use, topography and soil types, before any final conclusions with regard to the best approach for the UBNRB basin as a whole can be drawn. These difficulties are accentuated by the fact that the UBNRB has very high spatial variations in almost all of these run-off generating factors.

SWAT has also been applied to some other watersheds of Ethiopia [Alamrew, 2007; Tadele and Foerch, 2007; Zeray et al., 2007; Setegn et al., 2008], whereby the study results provided further evidence of acceptable performances of the SWAT- hydrological model, in general.

3.3. Preparation of SWAT-model input data
SWAT-model input data is usually prepared in an GIS- environment to alleviate the representation of the distributional geographic features of the watershed to be modeled. For this purpose, the ArcSWAT-GIS-software is available, which allows a relatively comfortable incorporation of all relevant hydrological components of the watershed. Among these, the most important ones are the watershed delineation using a digital elevation model (DEM), the soil and land use, the stream network, climate data and, last but not least, streamflow observations, which are the ultimate calibration target.

*Digitized stream network:* The stream network data has been collected in shape file
format from the USGS-EROS GIS stream network database for Africa - available at a 1 km resolution - and from the Hydrology Department of the Ethiopian Ministry of Water Resources (EMoWR). It is used as input for the delineation of the UBNRB stream network during the DEM processing. The threshold value recommended by the SWAT-model manual is used to delineate the watershed at the outlet of Blue Nile River, particularly, at Eldiem stream gauging station which is located near the Ethio-Sudan boarder. After the watershed delineation, 21 sub-basins are produced. These sub-basins are then further subdivided into Hydrologic Response Units (HRU), within which land-use and soil type are homogeneous. It should be noted here that the number of sub-basins delineated here (=21) is higher than those used in the climate analysis of the UBNRB in paper-1 [Cherie and Koch, 2013], which is only 14; a fact which required some grid-interpolation/extrapolation processing to incorporate the climate input drivers into the streamflow model.

**Soil- and land cover data:** The HRUs soil and land-cover data have been collected from the EMoWR where it had been prepared on a 1:250,000 scale during the 1997/98 master plan period [BCEOM, 1998]. But many additional hydrological attributes, such as the saturated hydraulic conductivity, the bulk density, available water capacity, and particle-size distribution, required by SWAT were collected from different sources: WaterBase, National Engineering Handbook [USDA, 1972], International Soil Reference and Information Center (ISRIC) which developed a World Inventory of Soil Emission potential (WISE) and harmonized global soil information [Batije, 2002 and 2008], FAO and the American Soil Survey and Soil Taxonomy.

The soil data has been collected in shape file format from the GIS department of EMoWR and is shown in Figure 2. A more detailed description of these soils is given in Table 1. The soil profile is sub-divided into two soil layers from 0-30 cm and 30-100 cm depth, respectively, that may have different properties with regard to the soil-water processes, including infiltration, evaporation, plant uptake, lateral flow, and percolation to lower layers.

The land use shape file (see Figure 3) has also been collected from EMoWR where it was prepared during the master plan study [BCEOM-1998]. However, as there are some differences between SWAT-land-cover- and BECOM designations, some adjustments of the data prior use in SWAT had to be done.

1. http://eros.usgs.gov/#/Find_Data/Products_and_Data_Available/gtopo30/hydro/africa
The number of HRUs in the watershed is obtained by assigning multiple HRUs for each watershed. This can be done using a number of combinations of land use, soil and slope percentages and by comparing the simulated with the observed flow for each of the combinations based on threshold percentage levels for soil, land use and slope. Though the default threshold settings in SWAT for land cover, soil and terrain slope are 20%, 10% and 20%, respectively, and which are adequate in most applications [Winchell et al., 2007], here these values were set to 10%, 20% and 10%, respectively.

Using this approach, the final number of HRUs obtained for the UBNRB is 221. With this high number, which is similar to the number of HRUs used in the Tana sub-basin SWAT-analysis of Setegn et al. [2008], a good calibration performance of SWAT in the present application is obtained.

Climatic input data: In order to analyze the impacts of future climate change on hydrology and water resources in the UBNRB, observed and downscaled daily areal climate data of precipitation, maximum and minimum temperature obtained from the climate modeling in each sub-basin for both the current (past) and future time periods (see paper-1, [Cherie and Koch, 2013]) are employed as climate forcing input in the SWAT-model. Figure 4
shows the locations of the precipitation and temperature gauges – which are not the actual gauges, since areal values are computed, but the centroids of the 14 sub-basins - and which are used as a gauge locations in the SWAT weather input file, as well as the location of the basin outlet steamflow gaging station Eldiem.

Table 1: Detailed description of the UBNRB soil types

<table>
<thead>
<tr>
<th>Soil Type</th>
<th>BCEOM</th>
<th>SWAT</th>
<th>Coverage (%)</th>
<th>Soil Type</th>
<th>BCEOM</th>
<th>SWAT</th>
<th>Coverage (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Haplic Alisols</td>
<td>V/ShAl</td>
<td>ALh</td>
<td>21.84</td>
<td>Dystric Leptosols</td>
<td>RdLp</td>
<td>LPd</td>
<td>1.37</td>
</tr>
<tr>
<td>Eutric Leptosols</td>
<td>ReLp</td>
<td>LPe</td>
<td>19.53</td>
<td>Calcic Vertisol</td>
<td>VkVr</td>
<td>VRk</td>
<td>1.32</td>
</tr>
<tr>
<td>Haplic Nitosols</td>
<td>RhNt</td>
<td>NTh</td>
<td>9.43</td>
<td>Eutric Regosols</td>
<td>VeRg</td>
<td>RGe</td>
<td>0.8</td>
</tr>
<tr>
<td>Eutric Vertisols</td>
<td>VeVr</td>
<td>VRe</td>
<td>7.68</td>
<td>Vertic Cambisols</td>
<td>RvCm</td>
<td>CMv</td>
<td>0.61</td>
</tr>
<tr>
<td>Eutric Cambisols</td>
<td>ReCm</td>
<td>CMe</td>
<td>7.4</td>
<td>Marsh/Histosol</td>
<td>M</td>
<td>HSF</td>
<td>0.45</td>
</tr>
<tr>
<td>Rhodic Nitosols</td>
<td>V/SrNt</td>
<td>NTr</td>
<td>6.58</td>
<td>Dystic Cambisols</td>
<td>RdCm</td>
<td>CMd</td>
<td>0.43</td>
</tr>
<tr>
<td>Eutric Fluvisols</td>
<td>ReFr</td>
<td>FLe</td>
<td>4.71</td>
<td>Haplic Arenosols</td>
<td>RhAr</td>
<td>ARh</td>
<td>0.41</td>
</tr>
<tr>
<td>Haplic Acrisols</td>
<td>S/RhAc</td>
<td>ACh</td>
<td>4.44</td>
<td>Canbic Arenosol</td>
<td>RbAr</td>
<td>ARb</td>
<td>0.35</td>
</tr>
<tr>
<td>Haplic Luvisols</td>
<td>VhLv</td>
<td>Lvh</td>
<td>4.16</td>
<td>Lithic Leptosols</td>
<td>V/SqLp</td>
<td>Lpq</td>
<td>0.35</td>
</tr>
<tr>
<td>Rendzic Leptosols</td>
<td>RkLp</td>
<td>LPk</td>
<td>3.1</td>
<td>Haplic Chernozem</td>
<td>V/ShNT</td>
<td>CHh</td>
<td>0.21</td>
</tr>
<tr>
<td>Chromic Luvisols</td>
<td>RxLv</td>
<td>LVx</td>
<td>2.88</td>
<td>Haplic Phaeozems</td>
<td>A/RhPl</td>
<td>PHh</td>
<td>0.05</td>
</tr>
<tr>
<td>Water</td>
<td>W</td>
<td>WATR</td>
<td>1.87</td>
<td>Urban</td>
<td>U</td>
<td>URMD</td>
<td>0.03</td>
</tr>
</tbody>
</table>
Table 2: BECOM and SWAT-designations of UBNRB land cover

<table>
<thead>
<tr>
<th>SNo</th>
<th>Land cover</th>
<th>BECOM</th>
<th>Description</th>
<th>Code</th>
<th>Coverage (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Agro-pasture</td>
<td>AP</td>
<td>Dry land, cropland and pasture</td>
<td>CRDY</td>
<td>31.71</td>
</tr>
<tr>
<td>2</td>
<td>Agriculture</td>
<td>A</td>
<td>Agricultural and generic</td>
<td>AGRL</td>
<td>22.73</td>
</tr>
<tr>
<td>3</td>
<td>Traditional</td>
<td>T</td>
<td>Savanna</td>
<td>SAVA</td>
<td>13.59</td>
</tr>
<tr>
<td>4</td>
<td>Sylvo-pasture</td>
<td>SP</td>
<td>Mixed forest</td>
<td>FOMI</td>
<td>9.18</td>
</tr>
<tr>
<td>5</td>
<td>Agro-Sylvoculture</td>
<td>AS</td>
<td>Cropland/woodland mosaic</td>
<td>CRWO</td>
<td>7.86</td>
</tr>
<tr>
<td>6</td>
<td>Pastural</td>
<td>P</td>
<td>Grassland</td>
<td>GRAS</td>
<td>7.59</td>
</tr>
<tr>
<td>7</td>
<td>Sylvoculture</td>
<td>S</td>
<td>Evergreen broadleaf forest</td>
<td>FOEB</td>
<td>3.92</td>
</tr>
<tr>
<td>8</td>
<td>Water</td>
<td>W</td>
<td>Water</td>
<td>WATR</td>
<td>2.02</td>
</tr>
<tr>
<td>9</td>
<td>State farm</td>
<td>SF</td>
<td>Irrigated crop land and pasture</td>
<td>CRIR</td>
<td>0.56</td>
</tr>
<tr>
<td>10</td>
<td>Unused</td>
<td>N</td>
<td>Barren or sparsely vegetated</td>
<td>BSVG</td>
<td>0.41</td>
</tr>
<tr>
<td>11</td>
<td>Marsh</td>
<td>M</td>
<td>Wetlands-mixed</td>
<td>WETL</td>
<td>0.37</td>
</tr>
<tr>
<td>12</td>
<td>Urban</td>
<td>U</td>
<td>Residential-medium density</td>
<td>URMD</td>
<td>0.06</td>
</tr>
</tbody>
</table>

Streamflow data: Monthly streamflow data measured between 1970 and 2000 at the Eldiem gauging station, which is located near the Ethiopia-Sudan boarder at an altitude of 481.2m asl, is used for calibration and validation purposes. As the measured
streamflow time series at this gauging station has some gaps, it has been filled with data at the gauging station Roseires, located 120 km downstream of Eldiem, using a linear regression analysis.

**Figure 5** indicates that this approach is warranted, since the trends and magnitudes of the monthly streamflows at Eldiem and Roseires stations are similar and strongly correlated with a high coefficient of determination \( R^2 = 0.95 \).

### 3.4. SWAT-model performance evaluation

To evaluate the performance of the SWAT-model and to assist with the model calibration, the assessment of the sensitivity of the model to the choice of the numerous SWAT-input parameters, as well as the evaluation of the model uncertainty, a set of tools has been developed by Van Griensven and Srinivasan [2005] and Van Griensven and Meixner [2006] and included into the SWAT2005-ArcSWAT interface.

#### 3.4.1. Sensitivity Analysis

Sensitivity analysis is done to see which input- or calibration parameters have the strongest influence on the model results. Practically this is achieved by perturbing a particular parameter \( x_i \) by a small amount \( \Delta x_i \) and compute the corresponding change \( \Delta y_j \) in the objective function \( y \). Sensitivity \( S \) is then defined as the ratio \( \Delta y_j / \Delta x_i \) [Lenhart et al., 2002].
The sensitivity method used in ArcSWAT2005 is based on Latin Hypercube (LH) and a One-factor-At-a-Time (OAT) sampling [Veith and Ghebremichael, 2009], which means that during the sensitivity analysis, the SWAT-model is run $m*(p+1)$ times, where $m$ is the number of LH loops, and $p$ is the number of hydrological SWAT-parameters being evaluated (=26 in the present application). Hence one LH-loop involves performing $p+1$ model runs to obtain one partial effect for each parameter, i.e. one parameter is varied in each run. The number $m$ determines the number of sub-ranges (loops) in which the total parameter range to be evaluated for sensitivity is divided. For each run a specific objective function $y = O$, as discussed below, is evaluated and percentage differences of the latter, before and after a specific parameter value $x_j$ ($i = 1, \ldots, p$) is changed by a small value $\Delta x_j$, whose size depends on the value $m$ of the sub-ranges considered, are computed. With this procedure the partial parameter sensitivity ($PS$) is then defined as

$$PS_{xy} = \frac{O(x_1, \ldots, x_i + \Delta x_j, \ldots, x_p) - O(x_1, \ldots, x_i, \ldots, x_p)}{\Delta x_j}$$

(4)

where:
- $PS_{xy}$, the relative partial effect of parameter $x_i$ around the LH point $j$,
- $p$, the number of parameters
- $O$, the objective function (model output).

By averaging the partial sensitivities for a particular parameter $i$ over all $m$ LH points the mean sensitivity of that parameter is obtained.

In the present SWAT-2005 program the parameter sensitivity $ParSen$ is computed in a slightly different way [Veith and Ghebremichael, 2009], namely

$$ParSen_i = \frac{50*|Y_i - Y_{i-1}|}{(Y_i + Y_{i-1})}$$

(5)

where:
- $Y_{i-1}$, value of objective function for run $i-1$, before change of a parameter
- $Y_i$, value of objective function for run $i$, after change of a parameter by a certain value, which in the default setting of the program is 5 % of the initial value.

For each parameter, the LH loop, i.e. the objective function (see below), is evaluated $m$ times. From this set, the mean of the function changes, as defined by Equation 5, and
its variance are calculated for each parameter. These means are then ranked in order of decreasing sensitivity, i.e., the parameter with the highest mean ParSen value will have a rank of 1. For further details the reader is referred to Van Griensven and Srinivasan [2005], van Griensven and Meixner [2006] and Veith and Ghebremichael [2009].

SWAT-2005 has two alternatives for choosing the objective function, namely:

a. **Sum of squares of the residuals**, SSQ, defined as

\[
SSQ = \sum_{i=1}^{n} \left( O_i - S_i \right)^2
\]  
(6)

where \( n \) is the number of pairs of measured \( O_i \) and simulated \( S_i \) output variable. SSQ is \( n \) times Mean Square Error (MSE).

b. **Sum of squares of the residuals after ranking**, SSQR.

As discussed by van Griensven and Meixner [2006], the SSQR- method aims at fitting the frequency distributions of the observed and the simulated series, so that in this method the time of occurrence of a given value of the variable is not accounted for [van Griensven and Bauwens, 2001]. After independent ranking of the measured and simulated output variables, new pairs are formed and the SSQR is calculated as

\[
SSQR = \sum_{j=1}^{n} \left( O_j - S_j \right)^2
\]  
(7)

where \( j \) is the rank.

**3.4.2. Model calibration and uncertainty analysis**

The subsequent step after performing the sensitivity analysis, retaining only the parameters in the model which are influential on the model output, is calibration which serves to optimize the unknown model parameters. SWAT allows for manual and automatic calibration [Gupta et al., 1999], whereby it is usually recommended to use a combination of the two, starting with a manual calibration and fine-tune the unknown parameters thereafter by an automatic calibration procedure. The one used in SWAT-2005 is based on the shuffled Complex Evolution Algorithm (SCE-UA) which is a global search algorithm that minimizes a single objective function with up to 16 model parameters [Duan et al., 1992]. It combines the direct search method of the simplex procedure with the concept of a controlled random search, so that a systematic evolution of points in the direction of global improvement is obtained. In SWAT-2005, the automatic calibration is
based on the Parameter Solution (ParaSol) method [Van Griensven and Bauwens, 2003; Van Griensven and Meixner, 2006] that aggregates the objective function defined by SSQ (Equation 6) into a global optimization criterion and then minimizes the former using the SCE-UA.

The search for the optimal calibration parameters during the iterative minimization of the SSQ-objective function in ParaSol can also be used in parallel to delineate uncertainty ranges for the different calibration parameters. This is essentially done by exploring the parameter space for "good" objective functions, and regrouping the corresponding subspace for a particular calibration parameter (see Van Griensven and Meixner [2006], for further details).

3.4.3. Performance measures
To evaluate the predictive capability of the SWAT-model's calibration and validation outputs, various modifications of the sum of squares of the residuals (SSQ) in Equation 6 are used:

(1) **RSR**, which calculates the ratio of the standardized root mean square error to the observed standard deviation, defined as.

$$ RSR = \sqrt{\frac{\sum_{i=1}^{n} (O_i - S_i)^2}{\sum_{i=1}^{n} (O_i - \bar{O})^2}} $$  \hspace{1cm} (8)

(2) **Percent of bias, PBIAS**, defined as

$$ PBIAS(\%) = \frac{\sum_{i=1}^{n} (O_i - S_i) \times 100}{\sum_{i=1}^{n} (O_i)} $$  \hspace{1cm} (9)

(3) **Nash-Sutcliffe model efficiency coefficient, NSE**, defined as

$$ NSE = 1 - \left[ \frac{\sum_{i=1}^{n} (O_i - S_i)^2}{\sum_{i=1}^{n} (O_i - \bar{O})^2} \right] = 1 - (RSR)^2 $$  \hspace{1cm} (10)

(4) **Square of Pearson's correlation coefficient R²** between observed and simulated values, also called the coefficient of determination, defined as
\[
R^2 = \left(\frac{\sum_{i=1}^{n} (O_i - s_i)(s_i - \bar{s})}{\left[\sum_{i=1}^{n} (O_i - \bar{O})^2\right]^{\frac{1}{2}} \left[\sum_{i=1}^{n} (s_i - \bar{s})^2\right]^{\frac{1}{2}}}\right)^2
\]

(11)

One of the limitations of the use of \(R^2\) is that it only evaluates a linear relationship between observed and simulated predictand (streamflow), hence it is insensitive to additives and proportional differences between the model output and observations.

Based on the values of the performance parameters above, the following guideline table for a performance rating of a general watershed simulation model, is set up [Moriasi et al., 2007].

Table 3: Model performance ratings based on the range of values for RSE, NSE and PBIAS for for monthly streamflow

<table>
<thead>
<tr>
<th>Performance rating</th>
<th>RSR</th>
<th>NSE</th>
<th>PBIAS (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very good</td>
<td>0.00 ≤ RSR ≤ 0.50</td>
<td>0.75 &lt; NSE ≤ 1.00</td>
<td>PBIAS ≤ ± 1.00</td>
</tr>
<tr>
<td>Good</td>
<td>0.50 &lt; RSR ≤ 0.60</td>
<td>0.65 &lt; NSE ≤ 0.75</td>
<td>± 10 ≤ PBIAS ≤ ± 15</td>
</tr>
<tr>
<td>Satisfactory</td>
<td>0.60 &lt; RSR ≤ 0.70</td>
<td>0.50 ≤ NSE ≤ 0.65</td>
<td>± 15 ≤ PBIAS ≤ ± 25</td>
</tr>
<tr>
<td>Unsatisfactory</td>
<td>RSR &gt; 0.70</td>
<td>NSE &lt; 0.50</td>
<td>PBIAS ≥ ± 25</td>
</tr>
</tbody>
</table>

4. Results and discussion

4.1. Analysis of trends in the annual streamflow time series

Figure 6 shows the annual streamflow time series for the two gauging stations Eldiem and Roseires were, as discussed earlier, monthly data from the latter has been partly used to fill in gaps for the former (see Figure 5). One may note that the two streamflow series are more or less similar, as the annual average streamflow of the Blue Nile river at Eldiem is 45.35 km\(^3\) and that at Roseires is 49.18 km\(^3\). The trend of the streamflow varies highly over the three decades of the 1970-2000 time period considered. Thus, whereas for the first decade (1970-1979) not much difference from the long-term annual average is observed, this is not the case for the second decade (1980-1989) for which a decrease of 10.9% is obtained. For the final decade (1990-2000) the annual streamflow has increased again by 12.64% over the long-term average.

The trend can also be evaluated on a finer time-scale, using a non-parametric time series regression technique, wherefore the streamflow time series \(Q(t)\) can be decomposed
Figure 6  Annual streamflow at Eldiem and Roseires gauging stations with the averages for the 1970-, 1980-, and 1990- decades indicated by horizontal lines.

Figure 7  Decomposition of streamflow into a trend, annual cycle and random noise.
into three additive parts: (1) a trend $T(t)$, (2) a seasonal, periodic component $S(t)$ and, (3) a residual, random term $e(t)$, where $T(t)$ reflects the long-term change of the mean of the series, $S(t)$ denotes the seasonal variation and $e(t)$ describes the random fluctuation which cannot be accounted for anymore by a deterministic process.

In the \textit{R}-working environment, the decomposition procedure as discussed by Cleveland [1993] is used, whereby firstly the trend, using polynomial regression, is determined, followed by the computation of the seasonal component using locally weighted least squares.

The results of this decomposition of the Eldiem streamflow times series are shown in Figure 7. From this figure one can clearly see the presence of trend. To confirm its significance, the Mann-Kendall- and the seasonal Mann-Kendall test have been carried out, based on the following test hypothesis [Hirsch et al., 1982; Helsel and Hirsch, 2002]:

\[ H_0 : \text{there is no trend in the series} \]
\[ H_1 : \text{there is a trend in the series} \]

For both test procedures $p$-values of $<0.0001$ is found which are less than the significance level $\alpha=0.05$, meaning that one should reject the null hypothesis $H_0$ and accept the alternative hypothesis $H_1$, corroborating the visual impression gained from Figure 7.

It is well understood that the streamflow generated from the UBNRB watershed is highly seasonal and depends, in particular, on the seasonal precipitation. The more detailed analysis of Cherie [2013] shows that the trends in the UBNRB- precipitation (and also temperature) are better captured by the seasonal Mann-Kendall test which, in fact, shows slightly increasing seasonal trends for these two variables over the UBNRB as a whole, although precipitation trends across different sub-basin have sometimes opposite signs over the 1970-2000 period.

\subsection*{4.2. SWAT- sensitivity analysis}

The first step of the UBNRB - SWAT-model analysis consists in the identification of the sensitive SWAT-model parameters, i.e. which have the strongest influence on the model output. To that avail the model has been run using data observed over the entire base period (1970-2000). Following the procedures described in Section 3.4, the identification of the sensitive parameters is made based on monthly aggregated output (streamflow) -
Although the SWAT simulation time steps are daily - using the SSQR-objective Function 7. This analysis can be done, using either only modeled data or both modeled and observed data.

Figure 8 shows the ranking of the sensitivities of the various input parameters, based on the mean of the multiple evaluations of Equation 5 for a particular parameter. One may notice that, with a few exceptions, the rankings are almost similar for the two cases, although the magnitudes of the sensitivity means of the various parameters differ strongly.

Using the sensitivity ranking scheme proposed by Lenhart et al. [2002] (Table 4), the 12 sensitive parameters of Figure 8, with sensitivity indices $I \geq 0.2$ - $I$ corresponds here to the mean value ordinate of the parameter in the figure - are considered for the subsequent calibration and validation of the UNBR-SWAT-model.

These sensitive parameters identified for the UBNRB-SWAT-model are listed together with a short description in Table 4. For a general discussion of these parameters and their specific importance in the present application, the reader is referred to the SWAT-manual [Neitsch et al., 2005] and Cherie [2013], respectively.
Table 4: Sensitivity classes [Lenhart et al., 2002]

<table>
<thead>
<tr>
<th>Class</th>
<th>Index</th>
<th>Sensitivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>0.00 ≤</td>
<td>I</td>
</tr>
<tr>
<td>II</td>
<td>0.05 ≤</td>
<td>I</td>
</tr>
<tr>
<td>III</td>
<td>0.20 ≤</td>
<td>I</td>
</tr>
<tr>
<td>IV</td>
<td></td>
<td>I</td>
</tr>
</tbody>
</table>

Table 5: Description of most sensitive parameters in the SWAT-model for the UBNRB

<table>
<thead>
<tr>
<th>Par*</th>
<th>Parameter</th>
<th>Rank</th>
<th>Description</th>
<th>Unit</th>
<th>File Type</th>
<th>Mean Value</th>
<th>Sensitivity</th>
<th>Process</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Alpha_Bf</td>
<td>1</td>
<td>Baseflow alpha factor</td>
<td>days</td>
<td>.gw</td>
<td>2.87</td>
<td>Very high</td>
<td>GW.</td>
</tr>
<tr>
<td>10</td>
<td>Cn2</td>
<td>2</td>
<td>Initial SCS CN II value</td>
<td>na</td>
<td>.mgt</td>
<td>1.51</td>
<td>Very high</td>
<td>Runoff</td>
</tr>
<tr>
<td>7</td>
<td>Canmx</td>
<td>3</td>
<td>Max. canopy storage</td>
<td>mm</td>
<td>.hru</td>
<td>1.06</td>
<td>Very high</td>
<td>Runoff</td>
</tr>
<tr>
<td>27</td>
<td>Esco</td>
<td>4</td>
<td>Soil evaporation compensation factor</td>
<td>-</td>
<td>.hru</td>
<td>0.748</td>
<td>High</td>
<td>Evaporation</td>
</tr>
<tr>
<td>61</td>
<td>Blai</td>
<td>5</td>
<td>Max. pot. leaf area index</td>
<td>-</td>
<td>Crop.dat</td>
<td>0.658</td>
<td>High</td>
<td>Crop</td>
</tr>
<tr>
<td>54</td>
<td>Ch_K2</td>
<td>6</td>
<td>Channel effective hydraulic conductivity</td>
<td>mm/ hr</td>
<td>.rte</td>
<td>0.379</td>
<td>High</td>
<td>Channel</td>
</tr>
<tr>
<td>17</td>
<td>Sol_Awc</td>
<td>7</td>
<td>Available water capacity</td>
<td>mm/ mm</td>
<td>.sol</td>
<td>0.375</td>
<td>High</td>
<td>Soil</td>
</tr>
<tr>
<td>5</td>
<td>Revapmn</td>
<td>8</td>
<td>Threshold water depth in shallow aquifer for &quot;revap&quot;</td>
<td>Mm</td>
<td>.gw</td>
<td>0.345</td>
<td>High</td>
<td>GW.</td>
</tr>
<tr>
<td>16</td>
<td>Sol_Z</td>
<td>9</td>
<td>Soil depth</td>
<td>mm</td>
<td>.sol</td>
<td>0.336</td>
<td>High</td>
<td>Soil</td>
</tr>
<tr>
<td>6</td>
<td>Gwqmn</td>
<td>10</td>
<td>Threshold depth in shallow aquifer for flow</td>
<td>mm</td>
<td>.gw</td>
<td>0.308</td>
<td>High</td>
<td>GW.</td>
</tr>
<tr>
<td>2</td>
<td>Gw_Delay</td>
<td>11</td>
<td>Groundwater delay</td>
<td>days</td>
<td>.gw</td>
<td>0.291</td>
<td>High</td>
<td>GW.</td>
</tr>
<tr>
<td>3</td>
<td>Gw_Revap</td>
<td>12</td>
<td>Groundwater &quot;revap&quot; coefficient</td>
<td>-</td>
<td>.gw</td>
<td>0.238</td>
<td>High</td>
<td>GW.</td>
</tr>
</tbody>
</table>

*Numbers listed are parameter codes used in SWAT for sensitivity, calibration and uncertainty analysis.

4.3. SWAT-calibration and validation

Using the sensitive SWAT-input parameters of Table 5, the SWAT-model has been calibrated on the observed monthly streamflow at Eldiem gage station. Although the whole observed streamflow data extends over the 1971-2000 time-period, because of many gaps in the data records which, as discussed, have been filled by extrapolation from measured streamflow at gage station Roseires (see Figure 5), the effective calibration period extends only from 1974-1981. The first two years of this period have been used for the "spin-up" or "warm-up" of the simulated hydrological system. Both manual trial-and-error- and automatic calibration, as described earlier, have been used, wherefore for the latter default lower and upper bounds for a particular calibration parameter as well as other optimization specifications are set in the various "Parasol"-files of the SWAT- automatic calibration menu.
The finally calibrated parameter values obtained by this auto-calibration values are listed in the second to last column and the associated parameter uncertainty range in the last column of Table 6.

Table 6: UBNRB–SWAT-optimal calibrated parameter values with uncertainty ranges

<table>
<thead>
<tr>
<th>Parameter name</th>
<th>Lower bound</th>
<th>Upper bound</th>
<th>Imet</th>
<th>HRU</th>
<th>File</th>
<th>Calibrated Value</th>
<th>Uncertainty range (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alpha_Bf</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>7</td>
<td>*.gw</td>
<td>0.219</td>
<td>100</td>
</tr>
<tr>
<td>Blai</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>2001</td>
<td>crop.dat</td>
<td>0.155</td>
<td>61.4</td>
</tr>
<tr>
<td>Canmx</td>
<td>0</td>
<td>10</td>
<td>1</td>
<td>2001</td>
<td>*.hru</td>
<td>9.289</td>
<td>97.3</td>
</tr>
<tr>
<td>Ch_K2</td>
<td>0</td>
<td>150</td>
<td>1</td>
<td>2001</td>
<td>*.rte</td>
<td>5.451</td>
<td>8.49</td>
</tr>
<tr>
<td>Cn2</td>
<td>-25</td>
<td>25</td>
<td>3</td>
<td>2001</td>
<td>*.mgt</td>
<td>10.03</td>
<td>24.6</td>
</tr>
<tr>
<td>Esco</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>2001</td>
<td>*.hru</td>
<td>0.038</td>
<td>30.5</td>
</tr>
<tr>
<td>Gw_Delay</td>
<td>-10</td>
<td>10</td>
<td>2</td>
<td>2001</td>
<td>*.gw</td>
<td>7.414</td>
<td>73.8</td>
</tr>
<tr>
<td>Gw_Revap</td>
<td>-0.036</td>
<td>0.036</td>
<td>2</td>
<td>2001</td>
<td>*.gw</td>
<td>0.035</td>
<td>23.6</td>
</tr>
<tr>
<td>Gwqmn</td>
<td>-1000</td>
<td>1000</td>
<td>2</td>
<td>2001</td>
<td>*.gw</td>
<td>982.7</td>
<td>11.9</td>
</tr>
<tr>
<td>Revapmn</td>
<td>-100</td>
<td>100</td>
<td>2</td>
<td>2001</td>
<td>*.gw</td>
<td>25.18</td>
<td>100</td>
</tr>
<tr>
<td>Sol_Awc</td>
<td>-25</td>
<td>25</td>
<td>3</td>
<td>2001</td>
<td>*.sol</td>
<td>25.00</td>
<td>36.8</td>
</tr>
<tr>
<td>Sol_Z</td>
<td>-25</td>
<td>25</td>
<td>3</td>
<td>2001</td>
<td>*.sol</td>
<td>22.51</td>
<td>44.1</td>
</tr>
</tbody>
</table>

1 Imet = 1: replacement of the initial value of the parameter; Imet = 2: adding a value to initial parameter value; Imet = 3: multiplying initial parameter value by a percentage of its initial value
2 If the number of HRUs >2000, the parameter is changed for all HRUs. For a number < 2000, the parameter is changed for the number of HRUs as indicated.

Using these calibrated parameter values in the SWAT-model, the latter has then been validated on the monthly streamflow observed at Eldiem during 1992-1995.

Figure 9 shows the simulated and observed monthly streamflows for both the calibration- and validation periods. A more quantitative picture of the performance of the calibrated model for the calibration and validation period is gained from the two regression line plots of the simulated versus observed streamflow of Figure 10. For both periods the regression lines have a slope close to 1, indicating a good agreement between the two.

The good performance of the SWAT-model for both the calibration and validation periods is corroborated in a more quantitative way by the values of the statistical parameters RSR (Equation 8), PBIAS (Equation 9), NSE (Equation 10) and $R^2$ (Equation 11), as listed in Table 7.
4.4. SWAT- simulated UBNRB water balance components
The results of the calibration and validation analysis reveal that for the calibration period (1976-1981) the simulated mean monthly streamflow of the upper Blue Nile at Eldiem station is 1438.6 m$^3$/s which, with an UBNRB area of 174962 km$^2$, is equivalent to...
45.80 km³/year. For the validation period (1992-1995), the monthly flow is 1593.9 m³/s, equivalent to 50.3 km³/year.

The various annual SWAT-simulated water balance components for the UBNRB - which are part of the regular output of the model - for the total time period (1971-2000), the calibration- and the validation period are listed in Table 8. Obviously, the differences between the three simulation variants are only minor. More interesting are the numbers, relative to the incoming precipitation, which is the ultimate source of all water in a basin. Thus, one can infer that only 24% of the precipitation in the watershed contributes to the streamflow, whereas 60% of the precipitation is lost by evapotranspiration. Moreover, one can read from the table that 52% of the water yield is generated by the surface runoff, 17% from lateral flow, and about 33% of yield is contributed from base flow. This shows that the contribution of surface runoff to water yield is considerably higher than that of the other water balance components.

Figure 11  Observed precipitation, simulated water yield, PET and ET across the UBNRB.
Table 8: UBNRB simulated annual water balance components for total record time-, calibration- and validation periods

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Precipitation</td>
<td>1358</td>
<td>1338</td>
<td>1348</td>
</tr>
<tr>
<td>Surface runoff</td>
<td>165</td>
<td>143</td>
<td>151</td>
</tr>
<tr>
<td>Lateral flow</td>
<td>55</td>
<td>55</td>
<td>54</td>
</tr>
<tr>
<td>Ground water (base) flow</td>
<td>107</td>
<td>70</td>
<td>38</td>
</tr>
<tr>
<td>Shallow aquifer recharge</td>
<td>63</td>
<td>59</td>
<td>58</td>
</tr>
<tr>
<td>Deep aquifer recharge</td>
<td>10</td>
<td>9</td>
<td>9</td>
</tr>
<tr>
<td>Total aquifer recharge</td>
<td>195</td>
<td>175</td>
<td>171</td>
</tr>
<tr>
<td>Total water yield</td>
<td>320</td>
<td>262</td>
<td>245</td>
</tr>
<tr>
<td>Percolation out of soil</td>
<td>189</td>
<td>168</td>
<td>165</td>
</tr>
<tr>
<td>Evapotranspiration</td>
<td>941</td>
<td>962</td>
<td>960</td>
</tr>
<tr>
<td>Potential evapotranspiration</td>
<td>1603</td>
<td>1586</td>
<td>1617</td>
</tr>
<tr>
<td>Transmission losses</td>
<td>8</td>
<td>6</td>
<td>7</td>
</tr>
</tbody>
</table>

For a better understanding of the hydrology of the UBNRB the water yield, potential evaporation (PET) and actual evapotranspiration have been computed sub-basin wise. The results are shown, together with the observed input precipitation, in the four panels of Figure 11. From this figure one may notice that in those areas of the UBNRB where the precipitation is high, such as in the central and south sub-basins (Didessa and Anger), the potential evaporation (PET) is also high. However, regardless of the prevailing conditions, the water yield in these sub-basins is also bigger than in other sub-basins. On the other hand, the eastern highlands and the parts of the western lowlands have relatively low precipitation, water yield and evapotranspiration.

Though some spatial correlations between the distributions of precipitation, PET and water yield can be observed in most areas of the UBNRB, the correlations between precipitation and water yield appear to be, somewhat expectedly, the strongest. However, as discussed in paper-1 [Cherie and Koch, 2013], confidence in the prediction of the future precipitation in the UBNRB is much lower than that of the future temperatures, which are expected to rise unequivocally, so that the future PET will increase as well. Hence special attention should be given to the future watershed management, as huge water losses due to PET will lead to corresponding decreases of the upper Blue Nile streamflow.
4.5. SWAT-simulations of climate-change impact on UBNRB water resources

4.5.1. Variants of combinations of GCMs and downscaling methods used

The major objective of this study is to quantify the impacts of regional climate change on the water resources in the UBNRB. To that avail, the climate predictors generated by the various downscaling tools in paper-1 [Cherie and Koch, 2013], will be used here as input in the previously calibrated SWAT-hydrological model to simulate the future water budget in the watershed, including the upper Blue Nile streamflow.

Following the methodology presented in paper-1, were the two statistical downscaling methods SDSM [Wilby et al., 2002] and LARS-WG [Semenov and Barrow, 2002] have been used in combination with one or an average of several large-scale GCMs, as indicated in Table 9, to generate the climate predictors for the UBNRB, this multi-facet approach will also be used in the subsequent SWAT-simulations. Doing so, it is to be hoped that uncertainties in the climate-change-driven streamflow predictions arising from the GCM, but also from the downscaling method used, are somewhat minimized.

Table 9: GCM/downscaling combinations used to drive the future SWAT-model predictions

<table>
<thead>
<tr>
<th>Case</th>
<th>Downscaling tool</th>
<th>GCM</th>
<th>Scenario</th>
<th>Simulation period</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>SDSM</td>
<td>ECHAM5</td>
<td>A1B, A2</td>
<td>2050s, 2090s</td>
</tr>
<tr>
<td>2</td>
<td>LARS-WG</td>
<td>ECHAM5</td>
<td>A1B, A2</td>
<td>2050s, 2090s</td>
</tr>
<tr>
<td>3</td>
<td>LARS-WG</td>
<td>Multi-model*</td>
<td>A1B, A2</td>
<td>2050s, 2090s</td>
</tr>
</tbody>
</table>

* averages of the three GCMs ECHAM5, GFDL21 and CSIRO-MK3

4.5.2. Use of SDSM-downscaled climate predictors in the SWAT-model

As indicated in Table 9, this first SWAT- modeling case considers SDSM- downscaled predictors, using ECHAM5-GCM predictions for scenarios A1B and A2 for the two future time periods, the 2050s- and the 2090s decade. The climate predictions obtained for the UBNRB by this GCM/downscaling combination have been discussed in detail in paper-1 [Cherie and Koch, 2013]. Here only the most salient features of the future predictions for mean temperatures and precipitation, as the major input drivers of the SWAT- basin model, are shown in the corresponding two panels of Figure 12.

The SWAT- predictions of the various water balance components are shown in the other panels of Figure 12 for the different months of the two future decades and the two SRES employed. Because the 20th - century reference (base-line) values are also plotted, one can immediately recognize the impacts of future climate change on the future monthly
variation of water yield, PET, ET and surface runoff for the two scenarios and future time periods. The various panels of the figure reveal that, compared with the 20th-century reference period, the future total water yield, which is basically the sum of surface runoff, lateral flow and base flow, decreases in both scenarios. This is mainly due to a future decrease of the precipitation and an increase of the mean temperatures, as predicted by
the GCM/SDSM-downscaling method.

Figure 12 shows that the PET - here computed by the Hargreaves method implemented in SWAT, which considers only maximum and minimum temperatures - for both scenarios and both future periods will be higher than that of the 20th - century reference period. For the actual evapotranspiration (ET), in contrast, the situation is more complicated, as this parameter depends not only on the temperature but also on the availability of soil moisture, actual plant transpiration, canopy interception, etc., i.e. somewhat on the amount of the precipitation itself. Thus, it can be seen from the figure that, relative to the 20th - century reference period, the magnitude of ET is decreasing for most months of the year, but is increasing during the wet season months (June - September).

The average simulated future monthly streamflow is shown in Figure 13. Similarly to the surface runoff shown in the corresponding panel of Figure 12, the streamflow of the upper Blue Nile river at station Eldiem is reduced by 44-45%, with an even higher
percentage of 61% in the 2090s decade for the A1B-SRES scenario. From this figure one may also notice some bias for the average 20th-century SWAT-simulated streamflow which is higher than the observed one. This has to be taken into account when referencing future streamflow changes in the basin.

Figure 14  SWAT-simulated precipitation, water yield, PET and ET, mean temperature and surface runoff water balance components using LARS-WG mono-model predictors.
4.5.3. Use of LARS-WG mono-model downscaled climate predictors in the SWAT-model

Results obtained using LARS-WG/ECHAM5 mono-model (second case of Table 9) downscaled climate predictors in the SWAT-model are illustrated in Figure 14. One may notice from this figure that, despite minor increases of both (GCM-predicted) precipitation and SWAT-simulated surface runoff, the total water yield in the UBNRB is reduced for most months of the years of the two future decades considered. This is due the fact that with higher future temperatures, evapotranspiration will increase substantially. This, in return, will affect the soil moisture content and will lead to a considerable reduction of the percolation out of the soil and, ergo, a reduction of the groundwater/base flow, eventually, paving the way to an overall reduction of the total water yield by 10 to 20%, as compared to the 20th - century base-line period.

Furthermore, in response to the precipitation increase during the future months of December, January, February and August, the water yields during these months will also slightly increase, notwithstanding, the simulated total water yield will still decrease. This
is also reflected in the future simulated streamflow time series, shown in Figure 15, whose two future decadal averages are smaller than that of the 20th-century base-line period.

4.5.4. Use of LARS-WG multi-model downscaled climate predictors in the SWAT-model

As discussed in paper-1 [Cherie and Koch, 2013], the LARS-WG multi-model downscaling option uses an average of large-scale predictors from three GCM (Table 9) and, thus, must be considered as the most reliable approach for providing driving predictors for the SWAT-model.

Results obtained with this downscaling option are shown, similarly to the previous two cases, in Figure 16. One may notice from the figure that, despite the fact that the future precipitation will barely decrease in the UBNRB, unlike than for the SDSM-case 1, there will now be a minor increase of the surface runoff for the 2090s for both SRES-scenarios. However, the total water yield will still be reduced, owing to the fact, that both future precipitation and base flow will diminish. Thus, because of the higher future temperatures, large quantities of water will be lost through evaporation. This will, in return, lead to a considerable reduction of the percolated water which then - as analyzed in more detail by Cherie [2013] - depending slightly on the time period and the SRES scenario, will account for only 7-8% of the precipitation, i.e. a lower base flow contribution of only 11-20% of the total water yield.

5. Summary and conclusions

The most salient results for the SWAT-simulated variables evaporation and water yield, using the precipitation and temperature predictors of the three GCM/downscaling options of Table 9 in the model, are listed in Table 10. As is to be expected the most influential factor on the 20th-century- and future water yields (and streamflow) in the UBNRB is the GCM-downscaled precipitation. Thus, it is of no surprise that the large decrease of the SDSM-downscaled future precipitation, obtained in the downscaling analysis of paper-1 [Cherie and Koch, 2013], in conjunction with the consistently predicted future increase of the temperatures, also results in the highest decrease of water yield and streamflow. On the other hand, as it is well-known that SDSM-downscaling of GCM-precipitations is often prone to errors [e.g. Cherie, 2013] and less reliable than downscaled predictions of future temperatures, the SWAT-modeling results using this option must also be taken with a grain of salt. Thus, the predicted large future precipitation- and ensuing streamflow declines which, depending on the time slice and the SRES-scenario considered, range between -44% (-142mm) and -61% (-194mm), are most
likely an extreme overestimate, not corroborated by the other two downscaling approaches, LARS-WG-mono-model and LARS-WG-multi-model, which both show less severe reductions in precipitation and water yield for the UBNRB.

In summary, Table 10 indicates that the SWAT-modeled water yields using the LARS-WG multi-model predictors will, depending on the future time-slice and the SRES, decrease

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**Figure 16** SWAT-simulated precipitation, water yield, PET and ET, mean temperature and surface runoff water balance components using LARS-WG multi-model predictors.
by -18% (-57mm) to -25% (-80mm), relative to the 20th – century reference period, i.e. by values which lie in between those obtained with the SDSM- (-45% to -61%) and the LARS-WG mono-model (-10% to -20%) options. Also, unlike than for the SDSM- predictors-in-SWAT-case, where a higher streamflow decline is predicted for the 2090s than for the 2050s, for the two LARS-WG/SWAT-combinations, the streamflow differences for these two time slices are only minor.

So, based on the results of the present comprehensive analysis, it can be concluded that the expected climate change in the UBNRB will adversely impact the water resources in the watershed. To minimize or mitigate these impacts, various adaptation methods have been proposed for the study area, in particular, and for the country Ethiopia as a whole by Cherie [2013], which take into account the particular situation of this still developing country with an emphasis on agriculturally based livelihood. These are - independently of whether future climate change will really strike down as predicted - (1) introducing new farming techniques, (2) more efficient land use management, (3) modern livestock production, (4) better surface and ground water resource development at the local level, (5) afforestation and soil conservation programs, (6) electrification of the rural
community, (7) facilitation of the opportunities to participate in other income-generating activities and (8) facilitation of getting financial assistance and loans.

Table 10: Downscaled precipitation, SWAT-modeled actual evaporation and streamflow (in mm) and relative changes (in % relative to the 1971-2000 base-line period) obtained with the three downscaling variants for future time slices 2050 and 2090 under SRES-scenarios A2 and A1B.

<table>
<thead>
<tr>
<th>Modeling Approach</th>
<th>Parameter</th>
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<th>A1B_2050s</th>
<th>A1B_2090s</th>
<th>A2_2050s</th>
<th>A2_2090s</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>mm</td>
<td>mm</td>
<td>%</td>
<td>mm</td>
<td>%</td>
<td>mm</td>
</tr>
<tr>
<td>SDSM (mono-model)</td>
<td>Precipitation</td>
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<td>1151</td>
<td>-15</td>
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<td>-30</td>
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<tr>
<td></td>
<td>Evaporation</td>
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<td>896</td>
<td>-5</td>
<td>782</td>
<td>-17</td>
</tr>
<tr>
<td></td>
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<td>178</td>
<td>-44</td>
<td>126</td>
<td>-61</td>
</tr>
<tr>
<td>LARS-WG (mono-model)</td>
<td>Precipitation</td>
<td>1358</td>
<td>1336</td>
<td>-2</td>
<td>1368</td>
<td>+1</td>
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<tr>
<td></td>
<td>Evaporation</td>
<td>941</td>
<td>1010</td>
<td>+7</td>
<td>1016</td>
<td>+8</td>
</tr>
<tr>
<td></td>
<td>Flow yield</td>
<td>320</td>
<td>256</td>
<td>-20</td>
<td>281</td>
<td>-12</td>
</tr>
<tr>
<td>LARS-WG (multi-model)</td>
<td>Precipitation</td>
<td>1358</td>
<td>1288</td>
<td>-5</td>
<td>1309</td>
<td>-4</td>
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<tr>
<td></td>
<td>Evaporation</td>
<td>941</td>
<td>973</td>
<td>+3</td>
<td>974</td>
<td>+4</td>
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<tr>
<td></td>
<td>Flow yield</td>
<td>320</td>
<td>240</td>
<td>-25</td>
<td>263</td>
<td>-18</td>
</tr>
</tbody>
</table>

References


Modelling, Methods, Mathematics

New tools for improving water use efficiency in irrigation
Evaluation of field and greenhouse experiments with tomatoes using the aquacrop model as a basis for improving water productivity

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¹ Ministry of Agriculture and Fisheries, Sultanate of Oman · ² Dresden University of Technology, Germany

Abstract

Many arid regions are characterized by low rainfall, high temperatures and sandy soils. To improve the situation of irrigated agriculture under these conditions, reliable plant growth models can be efficiently used via optimizing both irrigation control and scheduling. For setting up such models, we conducted field and greenhouse experiments with tomatoes in Oman. The experiments consisted of three irrigation treatments covering 40%, 70% and 100% of the reference evapotranspiration (ET₀) and three replicates in a randomized complete block design. The treatment were simulated using the Aquacrop model (FAO, 2009a) Different plant parameters such as plant yield, water use efficiency, and LAI, were measured throughout one growing season. Four meteorological stations were implemented at the entrance, the middle, and the end of the greenhouse and one on the open field. The reference evapotranspiration was calculated using the ET₀CALC software (FAO, 2009b) and the soil hydraulic parameters were obtained from multistep outflow experiments. TDR probes and pF-meters provided soil moisture status and soil water potential during the experiment.

The 40% ET₀ treatment provided the highest water use efficiencies for both the greenhouse and field treatments as compared to 70 and 100% ET₀. While the yield from both the 40% ET₀ and the 100% ET₀ treatments were similar in open field as well as in the greenhouse, the water productivity obviously differed significantly.

Keywords

AquaCrop model, deficit irrigation, tomato, soil water content, soil water productivity

1. Introduction

Climate of arid and semiarid regions for example Oman is characterized with little rainfall, high temperatures and the dominant soils are sandy. Farmers usually asking about information related to irrigation scheduling to a certain crops. Tomato is the second most valuable vegetable crop next to potato (FAO, 2011). Current world production of
This crop is gaining its importance both in developing and developed countries. Greenhouse technology is a breakthrough in the agricultural production technology that integrates market driven quality parameters with the production system profits (Aldrich and Bartok, 1989). Greenhouse is the best alternative for quality and quantity production of tomato because in addition to higher yield; the production is also free from dust, insect, disease and pest. Moreover, due to favorable environment the size of the fruit remains uniform.

Processing tomato consumes 400-800 mm of water from emergence/transplanting to harvest, depending on climate, plant type, soil, irrigation and crop management. Over the peak growing period, maximum water use averages 4-7 mm/day in a sub humid climate, but can reach 8-9 mm/day in more arid areas. Tomato water productivity for biomass (WPB/ET) ranges from 1.3 to 3.5 kg/m² being considered as common for favorable conditions and practices (Battilani, 2006). High water status stimulates vegetative growth and commonly leads to the dropping of flowers and newly set fruit early in the season. On the other hand, mild to moderate water stress early in the season, if lasting for many days, can result in a markedly smaller canopy, and hence, less biomass production resulting from reduced radiation capture. Photosynthesis per unit leaf area is moderately resistant to water stress. Thus, the crop is fairly resistant to moderate drought once good canopy cover is achieved. Over irrigation causes excessive leaf growth and plants high in vegetative vigor tend to produce low quality fruit because of reduced content of soluble solids. Moreover, excess water near harvest can cause nitrate accumulation in the fruit. For some cultivars, wide fluctuations in soil moisture levels during fruit maturation can cause fruit cracking, blotchy ripening, blossom-end rot and varied size and shape. A good commercial fresh fruit yield ranges from 60 to 120 ton/ha for processing tomatoes and up to more than 150 ton/ha for fresh market cultivars. Yield can be much higher in greenhouse production for fresh markets. Dry matter content of fresh fruit ranges from 4.0 to 7.0 percent (Leoni, 2002). Harvest Index (HI, the ratio of yield measured as dry matter to total above ground biomass) normally ranges from 0.5 to 0.65. HI decreases when plants are over watered or receive excessive nitrogen fertilization because of
excessive vegetative growth, but yield may not be affected or even slightly increased, as long as the increased biomass production compensates for the lower HI.

Postel (2000) mentioned that a growing scarcity of water relative to human demand occurs in many parts of the world, but appropriate water management practices can help ensure the survival and sustainability of agricultural and economic activities related to water. Water deficits and insufficient water are the main limiting factors affecting worldwide crop production. Deficit irrigation (DI) can reduce production costs, conserve water and minimize leaching of nutrients and pesticides into ground water. However, before DI can be adopted as a management tool, its effect on fruit yield and quality should be examined (Kirda, 2002). Measurements of pan evaporation, soil moisture content, or simulations of the soil water balance (Hoffman et al., 1990) have been used to estimate irrigation requirements both in terms of timing and quantity (Heermann et al., 1990). However, not all stages of development are equally sensitive to soil moisture deficits; for example, the flowering and fruit setting stages of tomato have long been known to be the most sensitive to water deficits in terms of yield (Salter, 1954). Lower or deficitary irrigation rates generally decrease yield and fruit size (Giardini et al., 1988), therefore, if deficit irrigation is applied for fresh market greenhouse production to limit costs and potential pollution, one is faced with the prospect of also reducing yield. Consequently, a judicious application of irrigation water is necessary.

Molla et. al. (2003) studied the effects of water stress at different growth stages on greenhouse tomato yield and quality. Two available soil water (ASW) deficit thresholds, 65% and 80%, at which plants were irrigated to field capacity were factorially combined with five irrigation timing patterns: 1) no water stress; 2) stress throughout the entire growing season; 3) stress during first cluster flowering and fruit set; 4) stress during first cluster fruit growth; and 5) stress during first cluster fruit ripening. They found that water stress throughout the growing season significantly reduced yield and fruit size, but plants stressed only during flowering showed fewer but bigger fruit than completely non-stressed plants. Consequently, on a weight basis the stressed at flowering and non-stressed plants had similar yields. Non-stressed and lowering-stressed fruit showed lower soluble solids and a lighter color of red ripe fruit than the other stress treatments. No significant differences in yield or quality were found between the two stress levels (65% vs. 80% ASW depletion before irrigation). Water stress only during flowering resulted in better yields and quality than stress at other specific developmental stages or at all times, but equal or poorer yields and water use efficiency than non-stressed plants.
In India, Gulshan et al. (2006) studied the response of greenhouse tomato to irrigation and fertigation in a two year study. They found that Drip irrigation at 0.5×Epan along with fertigation of 100% recommended nitrogen resulted an increase in fruit yield by 59.5% over control (recommended practices) inside the greenhouse and by 116.2% over control (recommended practices) outside the greenhouse, respectively. The drip irrigation at 0.5×Epan irrespective of fertigation treatments giving a saving of 48.1% of irrigation water and resulted in 51.7% higher fruit yield as compared to recommended practices inside the greenhouse. Total root length was more in drip irrigated crop as compared to surface irrigated crop. Greenhouse tomato fruits founded superior than fruits of open field crop in view of fruit size, TSS content, ascorbic acid content and pH. Further, drip irrigation in greenhouse crop caused significantly improvement in all the quality characteristics.

The objectives of this experiment was to investigate the ability of Aquacrop model to simulate field and greenhouse experiments, to investigate optimal irrigation scheduling for improving water productivity of deficit and full irrigated tomato in greenhouse and field using (GET-OPTIS) framework. Also, to end up with an irrigation scheduling model that is applicable in most of the farmers fields, and to inference the relationships between the plant growth, soil moisture and tension and weather factors.

2. Materials and Methods

2.1. Site description

This study was carried out both in the field as well as in the greenhouse in which the experimental units were the same for both locations. The greenhouse was covered with an ultra violet stabilized low-density polyethylene film having 200µm thickness. A semicircular shaped greenhouse, with a side wall ventilation, covering a floor area of 9m×30m (270m²). The orientation of the greenhouse was set in a way that the long axis was placed in the north-south direction, in the agricultural research center, at Alrumais region, Muscat, Oman during 2011-2012. The study area was between 23° 41′ N latitude, 58° 00′ E longitude and 13m altitude. This region is located on the south of Batinah coastal plain. Its climate is hot and humid in summer, and temperate and cool in winter.

2.2. Land preparation

The tomato cultivar Jinan, widely grown by the farmers in the field was used in the field and in the greenhouse to compare the same variety inside the greenhouse as well. Tomato seeds were planted in October 10th, 2011 in the Jiffy-7. Seedlings of tomato
were transplanted at 0.5×1.5 m spacing on December 10th, 2011. The plots consisted of 18 plants in 13.5m² (the planting density was 1.333 plant.m⁻²). Organic matter were implemented before transplanting, and 19.6 kg.ha⁻¹ mono ammonium phosphate, 14 kg.ha⁻¹ phosphoric acid and ammonium nitrate were applied with irrigation water by drip system after transplanting, and also agricultural pest control were done during the growing period (from starting of the experiment in December till the end of the experiment in April). Fertilizer was applied according to the recommendations of the agricultural research center for the tomato crop. Weeds and diseases were controlled using recommended post emergence herbicides and fungicides if required.

2.3. Soil characteristics

The soil hydraulic parameters were obtained from multistep outflow experiments. The field soil was sandy-loam, and the dry soil bulk density was 1.37 g cm⁻³ throughout the 0.9m deep profile. The total available soil water content within top 0.9m of soil profile was 240 mm and no water problem was found. The Greenhouse soil was sandy-loam, and the dry soil bulk density was 1.37 g cm⁻³ throughout the 0.9m deep profile. The total available soil water content within top 0.9m of soil profile was 240 mm and no water problem was found. Some soil characteristics related to irrigation are presented in Table 1.

Table 1: Some physical characteristics of the soil.

<table>
<thead>
<tr>
<th>Depth (cm)</th>
<th>Sand (%)</th>
<th>Silt (%)</th>
<th>Clay (%)</th>
<th>θs</th>
<th>θr</th>
<th>α [cm⁻¹]</th>
<th>n</th>
<th>Ks (cm.h⁻¹)</th>
<th>l</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-15</td>
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<td>7</td>
<td>7</td>
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<td>0.036</td>
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<td>7</td>
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<td>12</td>
<td>10</td>
<td>0.28</td>
<td>0.100</td>
<td>0.036</td>
<td>1.3</td>
<td>5.4</td>
<td>0.5</td>
</tr>
<tr>
<td>75-200</td>
<td>85</td>
<td>7</td>
<td>7</td>
<td>0.32</td>
<td>0.058</td>
<td>0.036</td>
<td>1.2</td>
<td>5.4</td>
<td>0.5</td>
</tr>
</tbody>
</table>

2.4. Irrigation system

Irrigation water is pumped from the main tank that having a capacity of 5000 Jallon into the main line of 2" in diameter which direct the water into the sub-main line of 1" in diameter and the valves and water meter of 1" in diameter and eventually to the treatments of 13mm in diameter pipes. The laterals length for each replicate was 9 meter. The discharge rate of the irrigation water in the laterals was 5.1 Lh⁻¹ on the average. Drip Irrigation system consisted of polyethylene laterals of 13mm in diameter inline type drippers working under a pressure of 1 bar. One lateral was placed in each plant row. The irrigation water salinity was in between 0.5 and 1.2 dS.m⁻¹ and the pH was around 6 and 8.
2.5. Experiment design and treatments

The experiments consisted of three irrigation treatments covering 40%, 70% and 100% of the reference evapotranspiration (ET\textsubscript{o}) and three replicates arranged in a randomized complete block design. Plots were irrigated up to field capacity at the beginning of the irrigated growth period. Irrigation water was applied through drip irrigation method 2-3 times a week during the growing period. Irrigation was initiated based on the average monthly values of ET\textsubscript{o} for six years and used in the calculation of the amount of water to be applied for 40% and 100% of ET\textsubscript{o}. Different plant parameters such as plant yield, water use efficiency, and LAI, were measured throughout one growing season.

2.6. Soil water measurements

TDR probes and pH-meters provided soil moisture status and soil water potential during the experiment. Soil water content was measured using the a Campbell Scientific's Time Domain Reflectometry (TDR) system which is comprised of the TDR100 Time Domain Reflectometer, a Campbell Scientific CR800, SDMX50 coaxial multiplexers, TDR probes and PCTDR software, in which the probes were buried into the soil at 10, 25 and 50 cm depths. Those probes were connected to the TDR100 by cables to measure the moisture content and then connected to the CR800 Series logger to store the data in order to be collected any time they are required by connecting the laptop computer to that CR800 Series logger via RS232 port. The TDR100 measures the soil moisture content on volume basis (\(\theta_v\)) and the bulk salinity every 15 minutes. Moisture content (\(\theta_v\)) was determined for all the depths. Total soil water content for the entire 50 cm depth was calculated as a sum of the three depth increment measurements within each treatment.

Soil water tension was also measured using the pH-meter which measures to a range of about pH 0 to 7, (USM-H probes, Campbell Scientific, USA). Also, the probes were buried into the soil at 10, 25 and 50 cm depths. Those probes were connected to the data taker (DT80) logger, which is a tool to measure and record a wide variety of quantities and values in the real world. The Channel Expansion Module (CEM20) is mounted on the DT80 logger. The CEM20 is a 20-channel analog multiplexer which can be used to expand the number of analog input channels on a DT80. The soil moisture tension data were collected from the DT80 logger by the laptop computer when they are connected via NIC or USB wire. The DT80 measures the soil moisture tension every 15 minutes. Both TDR100 sensors and DT80 probes are placed horizontally to the specified depths opposite to each other, in which the dripper is located in between of the two sensors.
2.7. Meteorological Data
Four meteorological stations (WatchDog) were implemented at the entrance, the middle, and the end of the greenhouse and one at the open field to monitor the air temperature, wind speed, relative humidity, solar radiation and rainfall throughout the growing season. The meteorological station logger was taking the data and stores them every fifteen minutes. Those data were used later in Matlab software to plot them. The weather station data were analyzed later on to calculate the reference evapotranspiration using the ET\texttextt{c}_CALC software (FAO, 2009b).

2.8. AquaCrop
AquaCrop is a crop water productivity simulation model developed by the Food and Agriculture Organization (FAO) of the United Nations (FAO, 2009; Hsiao et al., 2009; Steduto et al., 2009). It simulates crop yield response to water, and is particularly suited to address conditions where water is a key limiting factor in crop production. The model evolved from the concepts of crop yield response to water developed by Doorenbos and Kassam (1979). AquaCrop attempts to balance accuracy, simplicity, and robustness. It uses a relatively small number of explicit and mostly intuitive parameters and input variables requiring simple methods for their derivation (FAO, 2009; Steduto et al., 2009). Simulations of crop growth and development are executed with daily time steps, using either thermal time, i.e., growing degree days (GDDs) or calendar days. The ability of AquaCrop to simulate yields for different crops has been extensively tested by several researchers around the globe in diverse environments and all have reported positive results. However, the model has not been tested in Oman, particularly in the coastal plains, where the most agricultural activities occur, and where crop yields are often limited by moisture deficit. Besides simulating crop yield, AquaCrop also simulates soil water content using basic soil and weather data. Aquacrop performs a water balance that includes evaporation, transpiration, runoff, infiltration, internal drainage, deep percolation and uptake (FAO, 2009; Raes et al., 2009; Steduto et al., 2009). Aquacrop has also been used to derive and or optimize deficit irrigation schedules (Geerts et al., 2010; Garcia-Villa and Fereres, 2012).

3. Results

3.1. Soil water content modeling
Figure 1 shows the soil moisture content on volume basis, the soil moisture tension and the soil bulk salinity for the different depths. In the field after running the simulation, the average of observed soil water content was 91.1mm and the average of simulated
soil water content was 91.1mm. The Willmott's index of agreement was 0.90 as shown in Figure 2. Whereas, in the greenhouse after running the simulation, the average of observed soil water content was 98.9mm and the average of simulated soil water content was 100.0mm. The Willmott's index of agreement was 0.93 as shown in Figure 3.

Figure 1  Soil moisture, soil tension and bulk salinity.

Figure 2  Average observed and simulated soil water content for the field.

Figure 3  Average observed and simulated soil water content for the greenhouse.
3.2. Evaluation of simulation results

Evaluation of model performance is important to provide a quantitative estimate of the ability of the model to reproduce an observed variable, to evaluate the impact of calibrating model parameters and compare model results with previous reports (Krause et al., 2005). Several statistical indicators are available to evaluate the performance of a model (Loague and Green, 1991). Comparisons of soil water content were made between the observed and simulated values of corresponding treatments. The goodness of fit of these comparisons was evaluated graphically and statistically. The performance of the model was evaluated by several statistical indicators, the coefficient of determination ($r^2$), root mean square error (RMSE), Normalized Root Mean Square Error (NRMSE), Nash-Sutcliffe model efficiency coefficient (EF) and the Willmott index of agreement ($d$) were used as the error statistics to evaluate both the calibration and validation results of the model and the $r^2$ and EF were also used to access the predictive power of the model.

The coefficient of determination ($R^2$) for the field and greenhouse for the treatment T1, which have the highest yield and water use efficiency, were 0.69 and 0.83, respectively. Their values are higher than 0.5 which is acceptable for the watershed simulations. The root mean square error (RMSE) for the field and Greenhouse were 4.0 and 2.6 for the field and greenhouse, respectively. They are close to 0 which is good since the range is from 0 to infinity. The normalized root mean square error (NRMSE) was 4.4 and 2.6% for the field and greenhouse, respectively. Since they are less than 10%, they are considered as excellent. The Nash-Sutcliffe model efficiency coefficient (EF) was 0.58 and 0.77 for the field and greenhouse, respectively. They are very close to 1 and 0 as compared to the minus infinity. So, there are a perfect match between model and observation. The Willmott’s index of agreement ($d$) range is from 0 to 1, in which 0 indicates no agreement between observed and predicted values and 1 indicates a perfect agreement. The treatment values were 0.90 and 0.93 for the field and greenhouse, respectively. Therefore, their values indicate a good agreement. Since the entire five statistic parameters are positive this indicates that AquaCrop model can be used for simulating soil water content. From the results we can see that the model provides good simulations of field and greenhouse experiments.
Table 2: Model comparison statistics between observed and predicted values for the greenhouse and field.

<table>
<thead>
<tr>
<th>Statistic parameter</th>
<th>Field T1</th>
<th>Greenhouse T1</th>
<th>Range</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>R2</td>
<td>0.69</td>
<td>0.83</td>
<td>0 to 1</td>
<td>&gt; 0.5: acceptable for watershed simulations.</td>
</tr>
<tr>
<td>RMSE</td>
<td>4.0</td>
<td>2.6</td>
<td>0 to ∞</td>
<td>Closer to 0 is good.</td>
</tr>
</tbody>
</table>
| NRMSE               | 4.4      | 2.6           | %     | < 10: excellent  
|                     |          |               |       | 10-20: good  
|                     |          |               |       | 20-30: fair  
|                     |          |               |       | >30: poor |
| EF                  | 0.58     | 0.77          | -∞ to 1| ≈1: perfect match between model and observation. model predictions are as accurate as the average data. observations means are better prediction than model. |
| d                   | 0.90     | 0.93          | 0 to 1| 1: perfect agreement. |
|                     |          |               |       | 0: no agreement. |
| Average of observed SWC | 91.1     | 98.9          |       |                |
| Average of simulated SWC | 91.1     | 100.0         |       |                |

The actual biomass produced in the field was 6.189 ton.ha⁻¹ and the estimated by the Aquacrop simulation was 7.465 ton.ha⁻¹, the potential biomass was 7.513 ton.ha⁻¹. The dry tomato yield produced in the field was 4.535 ton.ha⁻¹ and the estimated by the aquacrop simulation was 4.255 ton.ha⁻¹. The water productivity was estimated by the Aquacrop simulation to be 2.47 kg (yield)/m³ water evapotranspired. In the greenhouse the actual biomass produced was 8.035 ton.ha⁻¹ and the estimated by the aquacrop simulation was 8.747 ton.ha⁻¹, the potential biomass was 8.883 ton.ha⁻¹. The dry tomato yield produced in the greenhouse was 5.207 ton.ha⁻¹ and the estimated by the aquacrop simulation was 3.936 ton.ha⁻¹. The water productivity was estimated by the Aquacrop simulation to be 2.64 kg(yield)/m³ water evapotranspired as shown in Table 3.
Table 3: Yield, biomass and water productivity comparison of the field and greenhouse treatment of the observed and simulated values.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Field-T1</th>
<th>Greenhouse-T1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fresh weight (ton/ha)</td>
<td>67.8</td>
<td>65.3</td>
</tr>
<tr>
<td>Dry weight (ton/ha)</td>
<td>4.535</td>
<td>5.207</td>
</tr>
<tr>
<td>Dry weight using Aquacrop simulation (ton/ha)</td>
<td>4.255</td>
<td>3.936</td>
</tr>
<tr>
<td>Actual Biomass (ton/ha)</td>
<td>6.189</td>
<td>8.035</td>
</tr>
<tr>
<td>Biomass using Aquacrop simulation (ton/ha)</td>
<td>7.465</td>
<td>8.747</td>
</tr>
<tr>
<td>Potential biomass (ton/ha)</td>
<td>7.513</td>
<td>8.883</td>
</tr>
<tr>
<td>Water productivity (kg/m³ water evapotranspired)</td>
<td>2.47</td>
<td>2.64</td>
</tr>
</tbody>
</table>

3.3. Irrigation water applied

At the end of the growing season the amounts of irrigation water consumed for cooling the greenhouse was measured to be 859mm from date of sawing to the last harvest. While it was 696mm from transplanting to the last harvest. In the open field the total amount of irrigation water applied for the treatments were 273, 574 and 689mm for T1, T2 and T3, respectively. Whereas in the greenhouse the total amount of irrigation water applied for the treatments were 274, 573 and 682mm for T1, T2 and T3, respectively. This indicates that the amount of irrigation water used for cooling the greenhouse is 3.1, 1.48 and 1.24 times the amount used for T1, T2 and T3 in the greenhouse, respectively.

Figure 4 shows the total irrigation water applied for the different treatments.
3.4. Fresh fruits weight

The tomato plant is very versatile and the crop can be divided into two categories; fresh market tomatoes, which we are concerned with and processing tomatoes, which are grown only outdoors for the canning industry and mechanically harvested. In both cases, world production and consumption has grown quite rapidly over the past 25 years. Fresh fruits weight were also weighted and calculated to the end of the growing season and analyzed statistically for treatments variability. In the open field the analysis of variance showed that there is no significant difference between T1: 67.8ton.ha\(^{-1}\) and T3: 71.3ton.ha\(^{-1}\), but there are significant differences between T2: 60.8ton.ha\(^{-1}\) as compared to T1 and T3. In the greenhouse the analysis of variance showed that there is no significant difference between T1: 65.3ton.ha\(^{-1}\) and T3: 66.5ton.ha\(^{-1}\), but there are significant differences between T2: 54.9ton.ha\(^{-1}\) as compared to T1 and T3 as shown in figure (5). As a result, in the open field each plant produces 5.1, 4.6 and 5.4kg.plant\(^{-1}\) for T1, T2 and T3, respectively. While in the greenhouse each plant produces 4.9, 4.1 and 5.0 kg.plant\(^{-1}\) for T1, T2 and T3, respectively.

![Figure 5](image.png)

**Figure 5**  *Field and Greenhouse fresh fruits weight.*

Part of the tomato fruits from each treatment were taken to the laboratory and put in an oven. Fresh and dry weight were taken and analyzed statistically. The results showed that in the open field there were no significant differences between treatment means. Whereas, in the greenhouse T2 differed significantly from T1 and T3, but T1 and T3 did not differs significantly. **Figure 3** shows the greenhouse and field dry fruits weight.
3.5. Water use efficiency:

Water use efficiency is a quantitative measurement of how much biomass or yield is produced over a growing season, normalized with the amount of water used up in the process. The statistical analysis for the water use efficiency of the greenhouse showed that there is no significant difference between T2: 9.6 and T3: 9.7 kg.m\(^{-3}\). But there is a significant difference between T1: 23.8 kg.m\(^{-3}\) as compared to T2: 9.6 kg.m\(^{-3}\) and T3: 9.7 kg.m\(^{-3}\). The same thing is applicable for the field where there is no significant difference between T2: 10.6 and T3: 10.3 kg.m\(^{-3}\). But there is a significant difference between T1: 24.8 kg.m\(^{-3}\) as compared to T2: 10.6 kg.m\(^{-3}\) and T3: 10.3 kg.m\(^{-3}\) as shown in Figure 7.
4. Conclusion

Aquacrop is simple, robust and powerful tool for simulating soil water balance, biomass, crop development. Aquacrop model reproduces the real system very well showing high correlation with the measured data, i.e. moisture and yield. Therefore, it can be used to simulate field and greenhouse irrigation systems. Therefore, more measured variables can be assimilated in future experiments. Deficit irrigation has a great potential in future, it is planned to optimize deficit irrigation and to improve the water productivity works. The first treatment (40% ET$_o$) both inside and outside of the greenhouse was the best; because it produced a high yield with minimum application of irrigation water.

References


Optimal irrigation scheduling for fodder crops under multiple resource constraints in an arid zone environment

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1 Ministry of Agriculture and Fisheries, Sultanate of Oman · 2 Dresden University of Technology, Germany · 3 United Arab Emirates University, Al Ain UAE

Abstract
The potential water productivity (WP) (kg/m³) of irrigation schemes in arid regions is generally rather low. Therefore we investigate the potential of optimal irrigation control and scheduling for improving water use efficiency (WUE) on the basis of open field experiments with Maize (Zea Mays) (maize sow cultivar = pioneer_3527) under micro irrigation. The trials were conducted in three replicates and a randomized complete block design at the Agricultural Research Station, Oman. We used three irrigation rates 100%, 125% of potential crop evapotranspiration (Etc, FAO) and a controlled deficit irrigation schedule (CDIS) which was based on references local soil and weather conditions and a simulation based optimization employing the APSIM-SWIM model (Keating et al. 2003) within the new evolutionary algorithm for optimal irrigation scheduling of deficit irrigation systems GET-OPTIS (Schütze et al. 2010). The results of the experiments revealed that increasing amounts of irrigation water from 100% to 125% Etc increased productivity of fresh biomass yield by 14% (from 19 to 22 ton/ha). However, the CDIS yielded superior water productivity (WP) of 5.5 kg m⁻³ of fresh biomass yield compared to 4.8 kg m⁻³ for the treatment using 125% Etc.

The results of CDIS experiment were subsequently compared to the outcome of the modeling approach. Both results agreed very well and recommend the new approach as promising tool for improving irrigation efficiency. In the next steps of this investigation we will include different irrigation water qualities (EC 1, 3 & 6 dS/m).

1. Introduction and Literature Review

Water is the limiting constraint for almost 600 million hectares of potentially suitable arable land around the globe (http://www.fao.org). The fresh water resources available for agriculture are declining quantitatively and qualitatively. E.g. for the Gulf countries it has been estimated that to the year 2030 the water requirements will increase about two times in Bahrain, Oman and Qatar and three times in Kuwait, Saudi Arabia, UAE and Yemen (Adel El-Beltagy. 2004). At the same time unsustainable practices in irrigation
will lead to increased salinization of soil, nutrient depletion and erosion. Globally, some 20% of irrigated land (450,000 km²) is salt-affected, with 2,500–5,000 tons km⁻² of lost production every year as a result of salinity (UNEP, 2008).

To face water scarcity problems which increasingly affect the development of the arid and semiarid countries, innovative solutions for water saving irrigation techniques are needed which allow for high water use efficiencies (WUE) or water productivities (WP) like e.g. deficit irrigation strategies.

The improvement of WP requires the characterization of the relationship between irrigation practice and grain yield by e.g. crop-water production functions (CWPF) (Schütze et al. 2011a). Efforts to investigate WP are numerous and can be divided into two main groups; (a) field experiments which relate crop growth and water stress by experimental evaluation and (b) simulation-based studies, based on calibrated and validated crop growth models which are used to calculate the impacts of water stress for a range of environmental boundary conditions.

Due to the manifold of possible water stress situations and their specific impact on crop yield mere field testing of all possible combinations is difficult, complex, expensive and time-consuming (Prathapar et al. 1999). The scope of simulation-based studies ranges from field level investigations to water resources management on catchment scale using stochastic planning tools. Using the 1D mechanistic crop growth model APSIM (Keating et al. 2003) Kloss et al. (2012) investigated the performance of APSIM within the frame of a stochastic simulation-based approach on field level. They found that, based on a sound calibration, the simulations with APSIM yielded realistic results for intensely monitored field experiments.

![Figure 1](image-url)  
**Figure 1** Framework for generating crop water production functions (Schütze and Schmitz 2010).
In this study we evaluated the performance of different irrigation experiments with respect to their WP. The experiments were conducted on a research farm in Al-Batinah region Oman with the irrigation treatments of 100%, 125% ETc and a controlled deficit irrigation schedule (CDIS) which was based on a simulation based optimization approach employing the APSIM-SWIM model (Keating et al. 2003) together with a new evolutionary algorithm for optimal irrigation scheduling of deficit irrigation systems GET-OPTIS (Schütze et al. 2010, Schütze et al. 2011b). Figure 1 shows the framework that we used to generate the crop water production functions (CWPF) for the local soil and climatic conditions.

2. Experimental Setup, Data and Methods

2.1. Study site description
The experiment was conducted in the Directorate General of Agricultural and Livestock Research in Rumais, Sultanate of Oman (latitude 23.6° N, longitude 58.0° E at 24 m above MSL). The experimental site is located in semiarid climate with a mean annual precipitation of 100 mm. The soil properties for the experimental site are presented in Table 1.

Table 1: The experimental site's soil properties at Rumais, Sultanate of Oman with van Genuchten/Mualem parameters. $\theta_s$ and $\theta_r$ (cm$^3$ cm$^{-3}$) are saturated and residual water content, $\alpha$ (cm$^{-1}$) and $n$ are empirical parameters determining the shape of the retention curve, $K_s$ (cm h$^{-1}$) is saturated conductivity, and $I$ is a pore connection parameter.

<table>
<thead>
<tr>
<th>Soil layer (cm)</th>
<th>Clay (%)</th>
<th>Silt (%)</th>
<th>Sand (%)</th>
<th>$\theta_s$</th>
<th>$\theta_r$</th>
<th>$\alpha$ (cm$^{-1}$)</th>
<th>n</th>
<th>$K_s$ (cm h$^{-1}$)</th>
<th>I</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-15</td>
<td>7</td>
<td>7</td>
<td>85</td>
<td>0.32</td>
<td>0.058</td>
<td>0.036</td>
<td>1.2</td>
<td>5.4</td>
<td>0.5</td>
</tr>
<tr>
<td>15-35</td>
<td>7</td>
<td>9</td>
<td>84</td>
<td>0.32</td>
<td>0.058</td>
<td>0.036</td>
<td>1.2</td>
<td>4.8</td>
<td>0.5</td>
</tr>
<tr>
<td>35-75</td>
<td>10</td>
<td>12</td>
<td>77</td>
<td>0.28</td>
<td>0.1</td>
<td>0.036</td>
<td>1.3</td>
<td>5.4</td>
<td>0.5</td>
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<tr>
<td>75-200</td>
<td>7</td>
<td>7</td>
<td>85</td>
<td>0.32</td>
<td>0.058</td>
<td>0.036</td>
<td>1.2</td>
<td>5.4</td>
<td>0.5</td>
</tr>
</tbody>
</table>

2.2. Experimental treatments and design
The experiment consisted of two main investigation factors; irrigation water quality (electrical conductivity of 1, 3 & 6 dS/m) and three irrigation rates 100% [W2], 125% [W3] of ETc and a controlled deficit irrigation schedule (CDIS) [W1] which was based on references local soil and weather conditions and a simulation based optimization employing the APSIM-SWIM model within the new evolutionary algorithm for optimal irrigation scheduling of deficit irrigation systems (GET-OPTIS framework). The two factors were replicated 3 times in a split block design as shown in Figure 2. Total numbers of
plots were 27 (3 x 3 x 3 = 27). Area of each plot area was 14 m² (3.5 x 4 m). The plots were 0.5 meters apart from each other and 1 m was kept between the replicate.

**Experimental design**

![Experimental design diagram]

Figure 2  The experimental design. (Red boxes indicate the plot with TDR and pF meter sensors).

### 2.3. Seeding, fertilizing and the irrigation system

Maize (Pioneer_3527) was planted for grain on 29 November 2011 and harvested on 24 March 2012. It was sown with a row spacing of 0.5 m and the seeds were planted 25 cm apart along eight rows. The planting density was 9.7 plants m⁻². The surface drip irrigation system (DI) with an emitter spacing of 50 cm was installed with two drip tubes for one plant row resulting in an emitter spacing of 0.25 m. The emitter flow rate was 4.2 L h⁻¹ at a pressure of 1 bar with dripper uniformity of 92%. Plants that were irrigated based on Class-A Pan evaporation measurements (W2) and (W3), were irrigated every two days. Water meters were used to measure the applied amount of irrigation.

The soil surface was leveled and chemical fertilizer was applied before sowing with 100 kg ha⁻¹ P₂O₅ (200 kg/ha triple super phosphate) and 50 kg ha⁻¹ K₂O (100 kg ha⁻¹ potassium sulphate) for grain. The plants were fertilized by 150 kg/ha nitrogen (326 kg ha⁻¹ Urea) in three split doses as follows: ¼ before sowing, ½ one month after germination and ¼ at flag leaf stage. The fertilizers were applied manually at 8-10 cm distance from
the plants. Necessary preventive measures were taken to protect plants from pests, diseases and birds during the growth period. The plants were kept under an agril cover for the first two weeks.

2.4. Data collection during the experiment
Meteorological data were obtained from a meteorological station on the site. Hourly data were obtained for maximum and minimum temperature, radiation, wind speed and relative humidity. Soil samples were obtained before planting (pre trial) and at the harvesting day (post trial). These soil samples were analyzed for 1:5 ECE. Time domain reflectometry (TDR) probe (used to measure soil water content, Campbell Scientific, USA) and a pF-Meter (measurement range of about pF 0 to 7) next to each other as one sensor pair were installed at four different soil depths (10, 20, 50 and 100 cm) in 6 plots at the second replication (Figure 2). Soil tensions and soil water contents were observed by TDR probes and pF-Meters every 15 minutes as shown in Figure 3.

![Figure 3](TDR probes and pF-Meters data for W1 treatment for different depths.)

At each development stage three plants at each plot were randomly selected and recorded for plant height, number of leaves, leaf length and leaf width. Furthermore, a height classification work with dripper discharge test and soil samples was conducted due to the observation of the present of variation in the plant height within the replicates, treatments and within each plot, the entire field plants were classified according to their height on 23 January 2012 (for 3672 plants). In addition, the LAI data were collected on 18 January and 12 March 2012.

At the harvesting day, the green forage yield and plant parameters were recorded for each plot separately. In addition, at each plots in that day five plants were randomly selected and recorded for plant height, number of leaves, leaf length and leaf width.
Furthermore, wet and dry matter weight for leaves, stem, cob and seeds were recorded for each selected plant in each plot.

2.5. Model based optimal scheduling of the deficit irrigation treatment

The SVAT crop model APSIM (the Agricultural Production System Simulator) (Keating et al. 2003) was set up for maize (which was sown at a crop density of 9.7 (plants/m²) and row spacing of 0.5 m). Simulation was set to start 7 days prior to crop sowing in order to allow the model to properly simulate a bare soil water balance.

For the soil water balance, APSIM-SWIM is designed to run within APSIM and calculate all flows of water and nutrients through and out of soil for a given simulation. It is used based on a numerical solution of the Richards’ equation combined with the convection-dispersion equation to model solute movement. These flows include infiltration, runoff, plant uptakes, movement through soil, etc and related nutrient flows. The SWIMv2 that was used is a one-dimensional model and does not consider lateral flow or horizontal heterogeneity.

The optimization technique GET-OPTIS was applied with the calibrated APSIM-SWIM model, to determine the optimal irrigation scheduling and control. The optimization run was set to start one month after the sowing day. The optimization results were used to calculate the potential yield and WP.
3. Results

3.1. Harvested yield measurements

![Graph showing yield measurements for different treatments and salinities.]

Figure 4  Fig 4: The average of plant total height (cm), fresh weight biomass (g) and dry weight biomass (g) from five plants randomly selected at each plot out of three replications for W1, W2 and W3 treatments with S1 water salinity.

3.2. Crop yields and water productivity

The results of the experiments revealed that increasing the amounts of irrigation water from 100% [W2] to 125% Etc [W3] increased productivity of fresh biomass yield by 14% (from 19 to 22 ton ha⁻¹). Meanwhile, the CDIS [W1] increased productivity of fresh biomass yield by 4% in comparison to 100% Etc respectively (Figures 4 and 5). However, the CDIS proved superior with (WP) of 5.5 kg m⁻³ of compare to 5.2 and 4.8 kg m⁻³ for the treatment of 100% and to 125% ETc respectively as shown in Figure 5.

![Graph showing yield and water productivity for different treatments.]

Figure 5  Fresh biomass yield (ton ha⁻¹) on the left and water productivity (kg m⁻³) on the right, out from three replications for W1, W2 and W3.
3.3. Simulation runs for calibration soil water contents

The simulated soil water contents showed mostly a fit agreement with the observed data for treatment W1 as shown for the different depths in Figure 6:

![Graphs showing simulated vs observed soil water contents](image)

Figure 6 The simulated soil water contents Vs the observed for W1 at different soil depths.

The reason for the low fit at the beginning of the simulation is probably due to cover management that is used to protect the seed from birds for the first 12 days after the seeding, which could affect the soil evapotranspiration. The reason for the low fit at the end of the simulation is due to a leaching event at the end of the experiment, which was not included as a simulation input.

Meanwhile, the simulation run showed a good fit for the plant data compared to the observed experiment data as shown in the Table 2.
Table 2: The simulation run plant data output vs. the observed experimental data.

<table>
<thead>
<tr>
<th></th>
<th>Yield (grain yield dry weight) (kg ha(^{-1}))</th>
<th>Biomass (total above-ground biomass) (kg ha(^{-1}))</th>
<th>Height (mm)</th>
<th>LAI (m(^{2}) m(^{-2}))</th>
<th>Root Depth (mm)</th>
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<td>17858.8</td>
<td>2057.247</td>
<td>2.824</td>
<td>844.554</td>
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</table>

3.4. Optimized irrigation scheduling and control

The optimization technique GET-OPTIS was applied with the calibrated APSIM-SWIM model, to determine the optimal irrigation scheduling. The optimization run was set to start one month after the sowing day. The optimization results were used to calculate the potential yield and WP. The maximum water productivity (high productive + deficit irrigation systems) was achieved at about 400 mm water application as shown in Figure 7.

![Figure 7](image)

*Figure 7* The calculated potential yield (grain dry yield weight in kg ha\(^{-1}\)) vs. potential water productivity (kg m\(^{-3}\)) from the irrigation scheduling and control optimization run according to water application depths from 200 mm to 500 mm with an increment of 20 mm.

4. Summary and Conclusion

In this study, an open field experiment was conducted with maize under a micro irrigation system using different treatments for water quantity and quality. The impact on crop yield was calculated by the new evolutionary algorithm GET-OPTIS for optimal irrigation scheduling of deficit irrigation systems together with the SVAT-model APSIM.
The simulated results match very well with the observations and the results with the new optimization strategy showed a high potential to increase irrigation efficiency. Optimal irrigation schedules were determined and considerable irrigation water savings were feasible, the optimized irrigation schedule would highly increase WP compared to the current practice. The model output for the optimal irrigation schedule (380 mm for the present study case) is similar to the applied controlled deficit irrigation schedule (CDIS) treatment which was based on references local soil and weather conditions and APSIM-SWIM model within the evolutionary algorithm GET-OPTIS framework, it also agree with those appearing in the literature, evidencing the robustness of this methodology for simulating the behavior of maize crops under such arid zone climatic condition.

The study showed to what extent modeling efforts can contribute to the permanent reduction of irrigation water use. The new evolutionary algorithm GET-OPTIS for optimal irrigation scheduling of deficit irrigation systems together with the SVAT-model APSIM, that was calibrated by field experiment where observed weather and soil input data were used, showed plausible results for potential yields and a high potential increase in the irrigation efficiency. Within this study, APSIM confirms to be a promising model within the OCCASION optimization framework. Nevertheless, further investigations are still necessary to validate and generalize the results.

In the next steps of this investigation, we will include different irrigation water qualities (EC 1, 3 & 6 dS/m), bearing in mind that APSIM is 1 dimensional model and the side salt accumulation is not considered within its application. Furthermore, this study could also be used for further investigation of the impact of climate change on potential yield using the OCCASION optimization framework.
References


Sediment

Addressing the catchment sediment management challenge
Polychlorinated biphenyls contamination in pond sediment of central India

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1Pt. Ravishankar Shukla University · 2Institute of Marine Environmental Chemistry and Ecology

Abstract
The polychlorinated biphenyls (PCBs) are persistent organic pollutant, exhibiting a wide range of hazardous effects to living organisms, including mutagenicity and carcinogenicity. Ponds are often very rich in habitats, particularly important for aquatic invertebrates, wetland plants and amphibians. In the present study, the distribution and sources of PCBs in the pond sediments of three industrialized cities: Bhilai, Raipur and Korba (21° 13′ 12″ N, 82° 40′ 48″ E) of central India is described. The sum of total concentration of PCBs in 22 sediments was ranged from 201 – 773 μg/kg with mean value of 433±67 μg/kg. The highest concentration of the ΣPCBs was found in the Korba city, may be due to huge coal burning. The total congeners observed in the sediments (n = 22) were ranged from 45 – 88 with mean value of 63±5 out of 209. Generally, higher concentration of congeners i.e. 1, 3, 8+5, 17, 56+60, 85, 138+158, 185 and 194 was observed in all pond sediments. Among them, the highest concentration congener 3 was observed. The spatial variations, sources and toxicities of the PCBs are discussed.

Keywords
Polychlorinated biphenyls, pond, sediment, India

1. Introduction
The ponds are defined as man-made or natural bodies of freshwater which hold water for all or part of the year [1]. They are often very rich habitats, particularly important for aquatic invertebrates, wetland plants and amphibians. They are also used by a variety of mammals, birds, duck and fish, especially where ponds form part of a mosaic of wetland habitats. Their structure and sediments may contain important historical information relevant to the history of the water body, its surroundings and the wider environment (pollen record, historical artifacts, etc.). In some cases, particularly in more remote areas, these sediment records may span thousands of years [2].

Pollution and mismanagement are also important problems facing by ponds. Recent evidence from a range of pond surveys suggested that, in the modern landscape,
pollution now has an even more pervasive and damaging influence on ponds than pond loss [3]. Ponds are particularly vulnerable to pollution because of their small size and the small volumes of water available to dilute pollutants. Ponds which are connected to streams and ditches are at particular risk since, in many areas; these water sources carry significant pollutant loads. The main sources of pond sediments are suspended soil particles that enter via the water supply or originate from erosion of the wet sides of pond embankments [4]. Suspended soil particles settle and accumulate in deeper areas of aquaculture ponds. Pond sediment is rather fluid in comparison to the original pond bottom soil beneath it.

The sediments are polluted with black carbon (BC), heavy metals, organic pollutants, etc. due to large anthropogenic activities [6 – 10]. The BC can reduce bioavailability of contaminants such as PAHs, PCBs, dioxins and PDBEs, etc. through strong sorption which can fundamentally control uptake and the effective toxicity of these chemicals in aquatic systems [11-12].

The PCBs are persistent in the environment, resistant to any degradation processes, and bio-accumulative through the food chain, with several of them exhibiting a wide range of hazardous effects to living organisms, including mutagenicity and carcinogenicity [13]. The aquatic sediment contaminations caused by PCBs have received great attention worldwide [14–26].

In the present study, the distribution and sources of 88 out of 209 PCBs in the 22 pond sediments, Chhattisgarh state, India is described. Their variations, sources, correlation and toxicities are discussed.

2. Experimental

2.1. Study area

Three most industrial cities of Chhattisgarh state, India: Raipur (21° 23’ N, 81° 63’ E), Bhilai (21° 18’ N, 81° 28’ E) and Korba (22° 21’ N, 82° 40’ E) lie above > 250 m from the sea level were selected for the proposed investigation, Figs. 1-3. Raipur is the capital city of the Chhattisgarh state with population of ≈ 2.5 million. The Raipur city and its neighborhood are now becoming an important regional commercial and industrial destination for the coal, power, steel and aluminum industries. Raipur is India’s biggest iron market as several steel rolling mills, sponge iron plants, steel plants, agro–industries and ferro–alloy plants are running in and around the city.
Bhilai is the second-largest city in Chhattisgarh with population of \( \approx 1.0 \) million and is located in the west of Raipur \( \approx 22 \) km away. The town is famous for the operation of one of the largest steel plant in the World (capacity: 3.153 MT/Yr).

Korba is another city in Chhattisgarh with \( \approx 0.5 \) million population, famous for power supply and aluminum plant. In these cities, a huge amount of coal is burnt to produce metals, cements and electricity.

2.2. Collection of sediment

The sediment samples were collected using a stainless-steel scoop in the summer, 2008 [27]. Total 22 samples were collected from cities: Bhilai, Raipur and Korba. They were kept in glass bottle (250-ml) and dried at 30°C in an oven for overnight. The samples were crushed into fine particles by mortar and sieved out the particles of mesh size < 0.1 mm. The samples were stored in aluminum foil.
2.3. Analysis of pH
The sediment (5.0 g) was extracted with 25–ml distilled water for 12 hr. The extract was decanted out for the pH value measurement. The HANNA pH-meter type-HI 8424 was used for measurement of pH value.

2.4. Analysis of carbons
Three types of carbons: black carbon (BC), organic carbon (OC) and carbonate carbon (CC) were analyzed in the dusts. The CHNSO–IRMS analyzer by SV instruments analytical Pvt. Ltd. was used for analysis of the total carbon (TC). The dust samples were oxidized with O$_2$ at 1020°C with constant helium flow. The combustion gas mixture was driven through an oxidation catalyst (WO$_3$) zone, then through a subsequent copper zone which reduced nitrogen oxides and sulfuric anhydride (SO$_3$) eventually formed during combustion on catalyst reduction to elemental nitrogen and sulfurous anhydride (SO$_2$) and retains the oxygen excess. The resulting four components of the combustion mixture were detected by a thermal conductivity detector in the sequence of N$_2$, CO$_2$, H$_2$O and SO$_2$.

The CC content was analyzed by treating the sample with HCl acid in the CO$_2$ free atmosphere. The resulting CO$_2$ was measured by colorimetric titration method. The OC was analyzed by titration method using K$_2$Cr$_2$O$_7$ as oxidant, and the excess of K$_2$Cr$_2$O$_7$ was determined by titrating with the FeSO$_4$$\cdot$7H$_2$O solution. The BC content in the dust was evaluated by subtracting the CC and OC contents from the TC.

\[ BC = TC - (CC + OC) \]

2.5. Analysis of PCBs
The quantitative analyses were performed by HP 5890–GC (gas chromatography) and HP 5970–MS (mass spectrometer) in the SIM mode for PCBs using method described by Sericano et al. [28]. The sediment samples were dried with sodium sulfate and extracted using a Dionex accelerated solvent extraction (ASE) system. The surrogate standards were added and the samples were extracted with solvent, methylene chloride. The extract was treated with copper to remove sulphur and was purified by silica/alumina column chromatography to isolate the PCB fractions [29]. The quantification of the PCBs was based on the primary ion and two additional masses for each analyte to identify the peaks.
3. Results and discussion

3.1. Physicochemical characteristics

The color and pH of the sediments are presented in Table 1. The pH value \( (n = 22) \) was ranged from 7.15 – 8.21 with mean value of 7.78±0.11. All sediment extracts were found to be slightly alkaline. The highest pH value of the sediment extract of Raipur city was observed. The pH value of the extract was increased with the increasing depth profile from 0 to 30 cm (slope = 0.18, intercept = 7.48).

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<th>OC, %</th>
<th>CC, %</th>
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</table>

Br = Brownish, LG = Light Green, B = Brown, DB = Dark Brown, Rd = Reddish, LB = Light Brown, BI = Blackish, R = Red

3.2. Concentration of carbons

The carbon contents of the sediments are presented in Table 1. The concentration of BC, OC and CC \( (n = 22) \) was ranged from 4.87 – 10.31, 0.07 – 0.21 and 0.05 – 0.16% with mean value of 8.33±0.56, 0.14±0.01 and 0.10±0.01%, respectively. The BC had fair correlation
with the OC and CC content ($r = 0.81 – 0.84$), indicating their origin from the same sources.

The BC, OC and CC concentration in the sediments of Raipur city ($n = 10$) was ranged from 7.54 – 9.43, 0.1 – 0.18 and 0.06 – 0.15% with mean value of 8.74±0.38, 0.15±0.02 and 0.12±0.01%, respectively. The BC concentration in Bhilai ($n = 6$) and Korba ($n = 6$) was ranged from 4.87 – 10.31 and 6.89 – 8.76 % with mean value of 7.87±1.90 and 8.08±0.55%. The highest value of BC, OC and CC was observed in Raipur city, may be due to higher fuel (i.e. coal, biomass, gasoline, diesel, etc.) combustion. No significant spatial variation in the BC concentration in the pond sediment of Raipur city was observed. However, a large spatial variation in the OC and CC concentration was observed.

The BC, OC and CC concentration was found to decrease with increasing depth profile from 0 to 30 cm (slope = -1.00, -0.04 and -0.05), respectively. The BC content in the pond sediments of the Raipur area was found to be higher than other region of the World, probably due to higher fuel burning [5-6, 9].

### 3.3. Concentration of PCBs

The concentration of PCBs in the sediments is summarized in Tables 2-4. The sum of total concentration of PCBs in 22 sediments was ranged from 201 – 773 μg/kg with mean value of 433±67 μg/kg. The concentration of ΣPCBs in Bhilai ($n = 6$), Raipur ($n = 10$) and Korba ($n = 6$) city sediments was ranged from 201 – 648, 241 – 538 and 404 – 773 μg/kg with mean value of 480±120, 328±61 and 561±124 μg/kg, respectively. The highest concentration of the ΣPCBs was found in the Korba city, may be due to higher coal burning. Generally, much higher concentration of congeners i.e. 1, 3, 8+5, 17, 56+60, 85, 138+158, 185 and 194 of MCBs, DCBs, TCBs, TeCBs, PeCBs, HCBs, HeCBs and OCBs was observed in all pond sediments. Among them, the congener 3 showed the highest concentration, may be due to chlorination of the biphenyls during the burning processes.

<table>
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<th>$S_3$</th>
<th>$S_4$</th>
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<tr>
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<tr>
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<td>HCBs</td>
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<td>135+144</td>
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<td>2.0</td>
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<tr>
<td>49</td>
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<td>137+130+176</td>
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<td>4.4</td>
<td>11.7</td>
<td>6.2</td>
<td>3.4</td>
<td>10.5</td>
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<td>0.5</td>
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<tr>
<td>52</td>
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<td>153</td>
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<td>0.0</td>
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<tr>
<td>53</td>
<td></td>
<td>163</td>
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<td>0.0</td>
<td>4.7</td>
<td>0.0</td>
</tr>
<tr>
<td>54</td>
<td></td>
<td>HeCBs</td>
<td>177</td>
<td>0.0</td>
<td>0.9</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
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<td>55</td>
<td></td>
<td>183</td>
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<td>0.0</td>
<td>0.0</td>
<td>2.2</td>
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<tr>
<td>56</td>
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<td>185</td>
<td>0.0</td>
<td>1.2</td>
<td>0.0</td>
<td>0.3</td>
<td>0.4</td>
<td>0.0</td>
</tr>
<tr>
<td>57</td>
<td></td>
<td>OCBs</td>
<td>194</td>
<td>0.0</td>
<td>3.8</td>
<td>2.9</td>
<td>1.6</td>
<td>0.0</td>
</tr>
<tr>
<td>58</td>
<td></td>
<td>196+203</td>
<td>0.0</td>
<td>4.9</td>
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<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>59</td>
<td></td>
<td>208+195</td>
<td>0.0</td>
<td>6.6</td>
<td>6.1</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
</tbody>
</table>
The total congener numbers in the sediments of all cities \((n = 22)\) were ranged from 45 – 88 with mean value of 63±5. The congener numbers in Bhilai, Raipur and Korba city sediments were ranged from 60 – 88, 45 – 76 and 47 – 63 with mean value of 76±8, 60±6 and 55±5, respectively. The highest congener frequency was observed in the Bhilai sediments, may be due to running of the Asia biggest steel plant, Fig. 4.

![Figure 4](image1)

**Figure 4**  
Spatial variation of congener numbers

Generally, the \(\Sigma PCBs\) concentration was found to be increased with increasing depth profile from 0 to 30 cm with slope and intercept of 144 and 111, Fig. 5. However, following three different scenarios for the PCBs depth profile was observed.

![Figure 5](image2)

**Figure 5**  
\(\Sigma PCBs\) depth profile concentration variation in the Siltara pond
(A) The concentration of large number of congeners (i.e. 1, 3, 6, 8+5, 17, 18, 19, 41+64+71, 77+110, 85, 97 and 185) was increased as the depth profile was increased, may be due to less adsorption by the sediment particles.

(B) The concentration of congeners (i.e. 105, 118, 123+149, 132, 134, 137+130+176 and 153) was decreased as the depth profile was increased, may be due to their retention by the sediment particles.

(C) Few congeners (i.e. 4+10 and 24) were present only in the deep sediment, may be due to their relatively higher solubility.

3.4. Toxicities
The coplanar PCBs, known as non ortho PCBs, (i.e. 77, 126, 169, etc.) having dioxin–like properties were reported to be the most toxic congeners [23-24]. Among them, the congener 77 was found to exist in all sediments, and its concentration was increased sharply with respect to the depth profile from 0 to 30 cm. The tolerance limit of the PCBs recommended in the soil is 60 µg/kg [19, 25]. The concentration of ΣPCBs in the 22 pond sediments was ranged from 201 – 773 µg/kg with mean value of 433±67 µg/kg. In the present study, the mean ΣPCBs concentration was found at least 7–folds higher than the recommended limits.

3.5. Correlation and sources
The highest PCBs concentration was observed in pond sediment of Korba city. Therefore, they were selected for the correlation studies, Tables 5. The ΣMCBs content had fair correlation (r = 0.61 – 0.70) with the carbon contents, indicating origin from the coal burning processes. In addition, the ΣMCBs content was found to be well correlated (r = 0.87) with the ΣPCBs, indicating their formation by further chlorination. The content of tri, tetra, penta, hexa, hepta and octachlorobiphenyls was well correlated to each other. It means they could be expected to be generated by the chlorination of the lower derivatives.
Table 5: Correlation (r) matrix of the PCBs in sediment

<table>
<thead>
<tr>
<th></th>
<th>MCBs</th>
<th>DCBs</th>
<th>TCBs</th>
<th>TeCBs</th>
<th>PeCBs</th>
<th>HCBs</th>
<th>HeCBs</th>
<th>OCBs</th>
</tr>
</thead>
<tbody>
<tr>
<td>MCBs</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DCBs</td>
<td>0.16</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TCBs</td>
<td>-0.11</td>
<td>0.48</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TeCBs</td>
<td>-0.16</td>
<td>0.49</td>
<td>0.78</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PeCBs</td>
<td>-0.35</td>
<td>0.33</td>
<td>0.57</td>
<td>0.79</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HCBs</td>
<td>0.12</td>
<td>0.62</td>
<td>0.10</td>
<td>0.26</td>
<td>0.25</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>HeCBs</td>
<td>-0.17</td>
<td>0.59</td>
<td>0.42</td>
<td>0.65</td>
<td>0.61</td>
<td>0.62</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>OCBs</td>
<td>-0.14</td>
<td>0.26</td>
<td>0.32</td>
<td>0.35</td>
<td>0.07</td>
<td>-0.14</td>
<td>0.14</td>
<td>1.00</td>
</tr>
</tbody>
</table>

\[2\text{C}_{12}\text{H}_{7}\text{Cl}_3 + 2\text{Cl}_2 \rightarrow 2\text{C}_{12}\text{H}_6\text{Cl}_4 + 2\text{HCl}\]

\[2\text{C}_{12}\text{H}_6\text{Cl}_4 + 2\text{Cl}_2 \rightarrow 2\text{C}_{12}\text{H}_5\text{Cl}_5 + 2\text{HCl}\]

\[2\text{C}_{12}\text{H}_5\text{Cl}_5 + 2\text{Cl}_2 \rightarrow 2\text{C}_{12}\text{H}_4\text{Cl}_6 + 2\text{HCl}\]

The highest concentration of the MCBs is observed in the Korba city, may be due to a huge burning, Fig. 6. Whereas, the highest concentration of higher chlorobiphenyals (i.e. TeCBs to OCBs) was seen in the Raipur city, may be due to their industrial applications, Fig. 6. The chlorination of the biphenyl is expected to be main sources of the MCBs (i.e. congener 1 and 3). The PCBs are released in the environments by processes i.e. emissions, chlorination, applications, etc, and reached in the ponds by atmospheric depositions and diffused sources i.e. runoff water, sludge, sewages, etc.

Table 6: Comparison of concentration of $\Sigma$PCBs in various sites of the World, $\mu$g/kg

<table>
<thead>
<tr>
<th>Location</th>
<th>Sampling year</th>
<th>Sample number</th>
<th>Concentration</th>
<th>Ref.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Taiwan</td>
<td>2001 &amp; 2005</td>
<td>25</td>
<td>0 – 83.9</td>
<td>12</td>
</tr>
<tr>
<td>Moldova</td>
<td>2001</td>
<td>3</td>
<td>68 – 763</td>
<td>19</td>
</tr>
<tr>
<td>Sunderban wetland, India</td>
<td>2006</td>
<td>42</td>
<td>0.47 – 26.84</td>
<td>20</td>
</tr>
<tr>
<td>Singapore</td>
<td>2003</td>
<td>13</td>
<td>1.4 – 329.6</td>
<td>21</td>
</tr>
<tr>
<td>Belgium</td>
<td>2000</td>
<td>18</td>
<td>105 – 400</td>
<td>22</td>
</tr>
<tr>
<td>West Bengal</td>
<td>2003</td>
<td>10</td>
<td>0.18 – 2.33</td>
<td>23</td>
</tr>
<tr>
<td>Suzhou Creek, China</td>
<td>–</td>
<td>6</td>
<td>1.08 – 7.82</td>
<td>24</td>
</tr>
<tr>
<td>Central India</td>
<td>2008</td>
<td>22</td>
<td>201 – 772</td>
<td>PW</td>
</tr>
</tbody>
</table>

PW = Present work
3.6. Comparison

The comparative statement for the PCBs concentration in the sediments is summarized in Table 6. The higher PCBs congeners are widely used as lubricating oils in high thermal instruments. They are distributed in the ecosystem either by leakage or/and evaporation. However, the lower PCBs (i.e. congener 1 and 3) are supposed to be formed by the atmospheric reaction (i.e. chlorination of biphenyls). The concentration of the higher PCBs congeners was found to be comparable to the sediments of other regions. The concentration of the lower PCBs is seemed to be several folds higher than sediment of other regions. Overall, the highest PCBs concentration was marked in the sediments of central India may be due to huge coal burning in this region.

4. Conclusion

Significantly higher concentrations of BC and PCBs in the pond sediments of central India were observed. The concentration of PCBs was increased with respect to depth profile of the sediment unlikely to BC. In the case of PCBs, the major fraction was contributed by monochlorobiphenyls (i.e. 1 and 3 congeners). The monochlorobiphenyls content had good correlation with the BC, indicating origin from the burning processes. The multiple sources (i.e. atmospheric depositions, runoff water, sewages, etc.) are postulated for the origins of carbons and PCBs in the pond sediments of this region.
Acknowledgement
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References


Sediment

Modern hydraulics structures for better hydrodynamics and hydromorphology of streams and rivers
Hydrodynamics and hydromorphology of river structures constructed by natural materials

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¹ Department of Civil Eng., Kobe University, Japan · ² Akashi National College of Technology, Japan · ³ Former Graduate Students, Kobe University, Japan

Abstract

The ecological quality of many channelized rivers has degraded in the past few decades. The paradigm has shifted in the direction of near-nature river work. Natural materials such as sand, stones, boulders, logs, woods and vegetation are widely used for construction of river structures. However, discussion has been made only qualitatively or empirically on their performance in controlling hydraulic and fluvial processes. In this study, attention is paid on hydrodynamics and hydromorphology, especially of weir, groyne and riparian constructed by rubbles, natural stones and vegetation, and their characteristics are quantitatively evaluated by using an experimental and a numerical model. Common hydrodynamic features found in this type of structures are permeability, solid-liquid phase flows, mass-momentum exchange within and outside of the structure, etc., which are taken into account in the numerical model. This study will discuss how the model would be applied as an engineering tool for planning and designing sustainable and nature-friendly river structures.

1. Introduction

In order to re-create a sustainable river environment, the paradigm has shifted in the direction of near-nature river work. Flood control structures such as groynes, spurs, riparian works, etc., tend to be constructed by natural permeable materials such as stones, boulders, logs, vegetation, etc. Some of them have derived from traditional technologies developed before the modern ages but they are rather state-of-the-art hydraulic structures from the viewpoint of this new paradigm in river restoration. In most cases, however, hydraulic, morphological and ecological performances of the structures have been evaluated only qualitatively or rather empirically. They should be evaluated as quantitatively as possible based on modern hydraulics for creation of a proper structural design. With increasing severe flood disasters and degrading of natural environment with global warming, it is an urgent task to establish an engineering design tool for these types of structures to meet the demands in both flood control and nature conservation.
In this study, attention is paid on hydrodynamics and hydromorphology, especially of weir, groyne and riparian constructed by rubbles, natural stones and vegetation. In the old days, they were widely used as construction materials for protecting embankment, shoreline and river channel. They have some common hydraulic features as follows:

- The structure has a permeable body and the flow consists of multi-phases of liquid and solid.
- Velocity and turbulence intensity are extremely different between the inside and outside of the structure.
- A significant shear stress is generated around the structure’s boundary.
- Mass and momentum are exchanged between the structure and the ambient water.

The authors developed a two-dimensional two-layer (2D2L) model to describe the flow dynamics mentioned above (Michioku et al., 2005b). In the model, the computational domain was divided into a liquid-phase flow outside of the structure and a liquid-solid-phase flow inside of the structure. Momentum and mass exchange between the two domains were taken into account by using the concept of entrainment velocity. Flow resistance formulae proposed in the previous studies were applied in modeling hydrodynamics in the rubble mound body (for example, Arbhabhirama and Dinoy, 1973, Hansen, Garga and Townsend, 1994, Mustafa and Rafindadi, 1989, Ward, 1964).

In the present study, the model was applied to three types of rubble mound structures; (a) weir, (b) groyne and (c) riparian. In the analysis of rubble mound weir, a stage-discharge rating curve, backwater profiles and drag force on the rubble element were successfully estimated on a wide range of hydraulic conditions. Hydrodynamics and hydromorphology in and around the rubble mound (groyne) were also numerically and experimentally investigated in a model and through prototype channels. A flow field along a rubble mound riparian was also discussed. Moreover, the model was applied to describe hydrodynamics in a vegetated channel, where a small modification to the model was added in the drag force modeling.

2. Modeling of rubble mound structures

2.1. Outline

In the first step of study, the authors (Michioku et al., 2004, Michioku et al., 2005a) experimentally and theoretically investigated hydrodynamics of a rubble-mound weir. As shown in Figure 1, the system is one-dimensional in the stream-wise direction. The
study is classified into two cases; (1) emerged weir and (2) submerged weir. The former is a flow running through the weir in a low water level condition. The weir's performance as a water use facility was discussed focusing on water storage capacity and through-flow discharge. A solution for the stage-discharge rating curve was obtained and verified by a laboratory experiment. On the other hand, the submerged weir generates a flow consisting of a free surface flow over the weir and a turbulent seepage flow in the weir, which occurs in a high water level condition. In this case, weir's performance as a flood control facility was investigated, such as structure's stability against flow force, influence of structure's dimension on flow fields, local scouring, etc.

Figure 1  System diagram of rubble mound structures.

Furthermore, the rubble mound weir analysis was extended to a horizontally two-dimensional flow system denoted as (3) in Figure 1 (Michioku et al., 2005b). Hydrodynamics was investigated for an open channel flow with (4) an emerged, and (5) a submerged rubble mound groyne, where each corresponds to a low and high water level condition, respectively.

Additional discussions were noted in respect to a riparian constructed with rubbles, where a laboratory experiment and a one-dimensional uniform flow analysis were carried out to obtain a solution of velocity profile both in and out of the riparian.
2.2. Rubble mound weir

Depending on water surface level and weir height, three different flow systems appear as shown in Figure 2.

Performing a one-dimensional analysis on a steady non-uniform flow around the rubble mound for the emerged weir, strict theoretical solutions were obtained in respect to water surface profile and discharge. In order to obtain the solution of discharge, a critical flow principle was applied to the control section appearing at the downstream corner of the weir. The governing parameters were water depths at the upstream and downstream sides of the weir, length and porosity of the weir, average diameter of the rubble mound, and bed slope. An example of the theoretical stage-discharge rating curve is shown in Figure 3, which is consistent with the laboratory data.
Figure 5 A functional dependency of discharge $Q$ on water depth in the weir $h_0$, rubble's diameter $d_w$, weir's height $W$ and weir's length $L$ are plotted in dimensionless forms. Symbols are the laboratory data and lines are the solutions from the one-dimensional two-layer (1D2L) model (Michioku et al., 2004).

Hydrodynamics on a submerged weir in Figure 2(a) was examined by using a one-dimensional flow model, as well. Assuming a two-layer flow structure consisting of a free surface flow over the weir and a confined seepage flow in the weir, a non-uniform flow was analyzed to obtain solutions not only for longitudinal flow development but also for discharge. In determining discharge, the critical flow principle was employed again as in the case of the emerged weir.

Figure 4 shows a solution example for water surface profile $h(x)$ compared with the experimental data, where the coordinates are normalized in term of the water depth $h_0$. The analysis provides a solution for discharge $Q$ as a function of height and length of the weir, ($W$, $L$), the rubble’s mean diameter $d_w$, porosity $n$ and so on. Figure 5 shows a functional dependency of dimensionless discharge defined as $F = U / \sqrt{gh} = Q / B \sqrt{gh}$ on grain diameter $d_w / h_0$, weir length $L / h_0$ and weir height $W / h_0$. All the solutions are well correlated with the experimental data.

2.3. Extension of the one dimensional analysis to a horizontally two-dimensional system; development of two-dimensional two-layer model, "2D2L model"

Consider an open channel system with a permeable rubble mound structure as shown in Figure 6. The domain consists of two areas: "Domain A", or the outer region of the structure, and "Domain B", to which the rubble mound belongs. The heights of the water surface and the rubble mound are defined as $h$ and $h_g$, respectively. The flow in the whole domain is considered to be two-layered with a thickness of $h_1 = h_g$ in the lower layer and $h_2 = h - h_g$ in the upper layer. Flow in Domain A is in a liquid phase both in the upper and lower layers. On the other hand, in Domain B, the upper layer is a free surface flow over the permeable rubble mound’s surface, and the lower layer is a confined seepage flow in a solid-liquid-phase that consists of pore water and rubble. Mass and momentum
are exchanged between the upper and lower layers both in Domains A and B, a key point which is taken into consideration in the model.

Figure 6  Two-dimensional analytical domain with submerged rubble mound structures.

Figure 7  Discharge in a dimensionless form $F_Q$ versus normalized water depth $h_0/L$ for various rubble diameter $d_r$, weir height $W$ and water head difference between the up- and downstream sides of the weir $\Delta h$. The rubble mound weir was emerged. A numerical solution from the 2D2L model, a strict theoretical solution from the one dimensional analysis and the laboratory data are compared together.

2.4. Application of the 2D2L model to the rubble mound weir

Before applying the 2D2L model to a two-dimensional flow system, the model was verified by comparing with the laboratory data from a one-dimensional flow system discussed above.

For the case of emerged rubble mound weir in Figure 2(c), the non-dimensional discharge $F_Q = Q / B \sqrt{gh_r}$ is plotted against dimensionless water depth $h_0/L$ in Figure 7. The
numerical solutions from the 2D2L model and the laboratory data are shown in black and open symbols, respectively, and the curves denotes the strict solutions from the one-dimensional analysis mentioned above. Results from the three different approaches are well correlated with each other.

Regarding the submerged rubble mound weir in Figure 2(a), solutions of longitudinal water surface profiles from the 2D2L and 1D2L models are compared with the laboratory data in Figure 8. In most of the sections, the water surface profile is in satisfactory agreement between the analyses and the experiment. However, estimation error from the 2D2L model appears around the downstream corner of the weir, since flow is rapidly varied there and hydrostatic assumption is no longer valid. A non-hydrostatic three dimensional analysis would be needed, if details of flow structure play an important role in controlling discharge. Actually, a three dimensional model is not always necessary from a viewpoint of engineering practice. In the one dimensional model, a rapidly varied flow analysis was performed around the downstream corner of the weir in order to determine discharge by using a critical flow principle. The discharge analysis was quite successful as already discussed in Figure 5, although the solution of water surface profile was absent there.
In Figure 9, a stream-wise development of discharge per unit-width in the upper and lower layers (\(M^2, M_1\)) are respectively shown, where solutions from the 2D2L and 1D2L models and the laboratory data are compared. (\(M^2, M_1\)) are normalized in terms of total discharge \(M=M_2+M_1\). The 1D2L model can describe non-uniform flow structure in most of the middle section of gradually varied flow, while no solution is provided around upstream and downstream corners of the weir. The 2D2L model gives a satisfactory accuracy in reproducing flow development not only over the weir but also through the weir.

Table 1: Hydraulic conditions in laboratory and numerical models.

(a) Emerged weir

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<th>Type</th>
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<th>Case A-3</th>
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(b) Submerged weir

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</tbody>
</table>

Figure 10: A groyne installed perpendicularly to the side wall.
2.5. Application of the 2D2L model to two dimensional flow systems; rubble mound groyne and riparian

First, the 2D2L model is applied to a two dimensional flow system with a rubble mound groyne installed perpendicularly to the side wall. As shown in Figure 10, the emerged and submerged groynes are investigated. Variables and a coordinate system are defined in Figure 11. Hydraulic conditions in physical and numerical models are listed in Table 1.

![Figure 11: Definition of variables in a flow system with a rubble mound groyne.](image)

![Figure 12: Water depth profiles in x-direction (emerged groyne).](image)
2.6. Emerged groyne

Computed results from the 2D2L model are exemplified for the emerged groyne in Figures 12, 13 and 14, where stream- and span-wise profiles of water depth and velocity are compared with the experimental data. The figures indicate that dependency of hydraulic characteristics on governing parameters is well reproduced by the 2D2L model with satisfactory agreement.

2.7. Submerged groyne

When the groyne is submerged under water, the flow is vertically separated to two layers consisting of a fast flow over and a slow flow through the rubble mound. In Figure 15, longitudinal profiles of water depth is plotted for the two longitudinal cross sections passing through middle of the groyne ($y/h_0=1.3$) and center of the main channel ($y/h_0=4.0$). Agreement between the experiment and analysis is satisfactory for different grain diameters and groyne porosities.
Velocity fields were successfully reproduced by the model in the case of submerged groyne, as well. Figure 16 is an example of velocity vector solution compared with experimental data, where velocity is the one that is depth-averaged. More detailed description of flow structures is shown in velocity profiles in x- and y- cross sections in Figures 17 and 18.

![Figure 15](image1.png)

**Figure 15** Water depth profiles in x-direction (submerged groyne).

![Figure 16](image2.png)

**Figure 16** Velocity vectors in Case B-2 ($d_m=3.5\text{cm}$, $n=0.373$, submerged groyne).

A special and original function of the 2D2L model is to provide a velocity solution not only in the water but also in the rubble mound. Figure 19 shows a closed-up flow structure over and inside of the rubble mound groyne, while the corresponding experimental data is absent. By using the model, drag force acting on rubble is additionally evaluated and stability of the rubble mound structure against flow force can be discussed.
Figure 17  Velocity profiles in x-direction (submerged groyne).

Figure 18  Span-wise velocity profiles in a cross sections at up- and downstream sides of the groyne, $x/h_0=0.6$ and $2.5$, respectively, (submerged groyne).
Figure 19  Longitudinal development of velocities over and through the groyne along a stream-wise cross section that passes through the groyne edge, $y/h_0=2.5$. $(u_1, v_1)$ and $(u_2, v_2)$ are velocity components in the lower and upper layers, respectively, (submerged groyne).

Photo 1  A group of rubble mound groyne in Akashi River.

Figure 20  Experimental setup of a group of rubble mound groyne (Li et al 2007).
3. Application to other rubble mound structures

The model concept mentioned above can be applied to other types of facilities constructed with rubbles or boulders. In this paper, hydrodynamics is discussed for three examples of rubble mound structures.

3.1. A group of rubble mound groyne

In practice, a set of groynes is popularly used in river restoration as shown in Photo 1. Field and laboratory experiments were carried out to investigate hydrodynamics and failure mechanism of a group of rubble mound groynes. A laboratory experiment was conducted by using a physical model shown in Figure 20. Eight sets of rubble mound groyne were installed at the left bank of a straight flume in 20m long, 0.9m wide and 0.5m high. The length, width and height of the groyne model were 0.45m, 0.2m and 0.1m, respectively. Each groyne was arranged with inclined angles of $\theta=70^\circ$, $90^\circ$ and $110^\circ$ to the left bank. The interval between every two groynes was 0.8m, and the rubble's diameter was 0.02m, respectively.

The 2D2L model was applied in analyzing flow structure around the group of groynes. In Figure 21, the numerical solutions and the laboratory data of velocity vectors are compared for the case of submerged groynes installed with an inclined angle of $\theta=70^\circ$.

The span-wise profile of the velocity is shown in Figure 22, where $x=-0.20, 2.80, 3.80$ and $6.80$m correspond approximately to the cross sections a little upstream side of the groynes No.1, 4, 5 and 8, respectively. The numerical analysis is consistent with the experiment.

Moreover, the 2D2L model was also applied to the prototype in Akashi River in Photo 1 (Michioku, Li and Kanda, 2008). Some of the groynes were partially damaged during a flood in 2004. Flow drag force on each groyne estimated by the model was well correlated with the damaged level of groynes. The model is found to be capable of estimating damage potential of rubble mound structures.
Figure 21 Velocity vectors around submerged groynes for a case of $\theta=70^\circ$ (Li et al. 2007).

Figure 22 Span-wise velocity profile. The hydraulic conditions are the same as Figure 21.

Figure 23 An experimental model for rubble mound riparian.
3.2. Rubbles riparian

In recent river restorations, riparian constructed by natural stones or porous materials are popularly used. An open channel flow with rubble mound riparian was examined in an experimental model as shown in Figure 23. The channel had a dimension of 20m in long, 0.9m in width and 0.45m in depth. The experiment was conducted in a uniform flow condition and the 2D2L model was modified into a one-dimensional version. The riparian model had a dimension of $l_g=3.0m$ in length, $b_g=0.3m$ in width and $h_g=0.15m$ in height. Mean grain diameter and porosity of the riparian were $d_m=2.0cm$ and $n=0.35$, respectively.

![Figure 24](image1.png)  
**Figure 24** A velocity profile in an open channel flow with a rubble mound riparian.

![Figure 25](image2.png)  
**Figure 25** Effect of grain diameter and porosity on velocity profile.

Figure 24 shows an example of horizontal velocity profile, where the solid line is an analytical solution and the plotted symbols are the laboratory data. The velocity was measured at two cross sections in order to confirm the flow to be longitudinally uniform. They are denoted as "Exp.A" and "Exp.B". No measurement was made inside of the riparian. Figure 25 indicates how the velocity profile is influenced by grain diameter and porosity. It is confirmed that flow in the riparian is accelerated with increasing porosity of the riparian.

![Figure 26](image3.png)  
**Figure 26** Local scouring around the rubble mound groyne (experiment).
3.3. Local scour around rubble mound groyne

Since the rubble mound groyne is permeable and fragile compared to conventional solid structures, it is expected to have a function to regulate flow with minimum local scouring. In order to investigate sedimentation characteristics around the rubble mound groyne, a laboratory experiment was carried out in an open channel with movable bed. Integrating a fluvial process model developed by Shimizu (2001) to the 2D2L model, local scouring around the rubble mound groyne was analyzed. In the fluvial model, transport rates of bed and suspended loads are described by formulae proposed by Ashida and Michiue (1972) and Itakura and Kishi (1980), respectively.

An experimental result of time-dependent river bed profile is shown in Figures 26, which is compared with the numerical result obtained from the fluvial version of 2D2L model in Figure 27. Although the model qualitatively reproduces time dependent behaviors of channel morphology, the model slightly overestimates scour. In this sense, fluvial process modeling in the 2D2L model is still challenging and needs to be improved further by collecting additional information from laboratory experiments and field measurements. The key point in local scour modeling is to take three dimensionality of flow structure into consideration.
A laboratory experiment on an impermeable solid groyne with the same dimension was additionally carried out as a reference case to examine effect of groyne’s permeability on local scouring behaviors. Figure 28 shows time-development of the maximum scour depth in which the results are compared with the rubble mound groyne. It is recognized that local scouring is reduced in the case of rubble mound groyne. The analytical results shown in solid lines have the same tendency but it tends to overestimate the scour depth as discussed before.

4. Application of the 2D2L model to vegetated channel hydraulics

Growing tree vegetation or forestation in river channels is a world-wide issue in many restored river channels, which decreases flow conveyance capacity and eventually increases the risk potential for flood disasters. The 2D2L model is available also in the vegetated river channels, where the vegetation is treated to be a permeable porous body like a rubble mound. The vegetation is emerged or submerged depending on the relative height of vegetation canopy to the water level. As shown in Figure 29 the whole system can be vertically divided into two layers by an interface that encompasses the vegetation canopy. A fundamental hydrodynamics is exactly the same as the open channel flow with rubble mound structures. Exception is in modeling of the drag force caused by trees that should be modified so as to be suitable for vegetation hydrodynamics (Nepf, 1999,
Passche and Rouve, 1985). The model was successfully applied in describing flood flows in a vegetated channel not only in a laboratory model but also in prototype. Damaged areas of the vegetation were well identified by the model, as well. Details should be referred to the authors' published papers (Michioku et al., 2011, 2012).

Figure 29  Configuration of 2D2L flow model in a vegetated river (Michioku et al., 2011).

5. Concluding remarks

Hydrodynamics was investigated on open channels with weir, groyne, riparian constructed by natural construction materials and vegetation. Laboratory experiments, field measurements and numerical analysis were carried out. A two-dimensional two-layer (2D2L) model was developed to describe flow fields and drag force acting on the structures. The computational domain was divided into a liquid-phase flow outside of the structure and a liquid-solid-phase flow inside of the structure. Momentum and mass exchange between the two domains were taken into account by using the concept of entrainment velocity. The model was applied to various types of rubble mound structure. By integrating a fluvial process model to the 2D2L model, the effect of the structure's properties on river morphology was discussed in the case of rubble mound groyne. Moreover, the model was successfully applied to a vegetated open channel flow by giving a minor modification in a drag force term. The present study could provide a hydraulic design tool for river restoration works through the use of natural construction materials.
Acknowledgments

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References


Hydrological Extremes

Extreme precipitation: how to use past measurements and climate projections for urban hydrologic design?

(Addendum, see page 43)
Regional depth-duration-frequency curves for Mumbai City

Sherly M A¹ · S. Karmakar² · T. Chan³ · C. Rau⁴

¹ IITB-Monash Research Academy · ² Indian Institute of Technology Bombay · ³ Monash University · ⁴ Shantou University

Abstract

Regional design rainfall is a prerequisite for any flood modeling studies. The bivariate rainfall frequency analysis, that captures the association between rainfall depth and duration, has proved to yield better results than univariate analysis of rainfall depth. The peak-over-threshold method of selecting the rainfall events of various durations above a specified threshold may be used, when the record length is too short to be represented by the annual maxima values. The joint return period of rainfall depth and duration can be determined using copulas, which has the advantage of deriving joint probability from two different marginal distributions. Here a novel approach of combining General Pareto Distribution and a nonparametric kernel function to obtain the depth-duration-frequency curves has been performed for severely flood prone Mumbai city in India. An optimization technique has been applied to derive the regionalized depth-duration-frequency curves from two raingauges at Colaba and Santacruz in Mumbai (installed by India Meteorological Department). The data conditioning has been done to ensure consistency and continuity of the rainfall timeseries. Well established goodness of fit tests including Root Mean Square Error, Akaike Information Criterion and Bayesian Information Criterion support the accuracy of the results with the empirical probability values. It has been estimated that the rainfall of 944 mm occurred in 24 hours which caused the catastrophic flood event in Mumbai on 26 July 2005, had a return period of more than 200 years, which is consistent with the results of OECD (2010).

1. Introduction

Mumbai city in India is severely flood-prone and flood disasters occur almost annually. The most devastating urban flood in India occurred on 26 July, 2005 in Mumbai with the historic highest rainfall of 944 mm in 24 hours. The highest rainfall intensity (120 mm/h) was observed in 4 hours between 1430:1830 IST (9 GMT to 13 GMT). In the twelve hour period between 8 AM and 8 PM, the India Meteorological Department (IMD) recorded 644 mm of rainfall at Santa Cruz (see location map in Figure 1) and hourly rainfall exceeded 190mm/h during 1430 to 1530 IST (GoM, 2005). This was much higher than the previously recorded highest rainfall in a 24 hour period in Mumbai, 575 mm in 1974. The average annual rainfall of the city is around 2400 mm (IWRS, 2005; Gupta, 2006; OECD, 2010).
The design rainfall is one of the critical inputs for urban flood modelling studies, which depicts the spatio-temporal characteristics of rainfall across a region. The depth-duration-frequency (DDF) curves form a major component of design rainfall that shows the rainfall depth-duration relationship corresponding to various return periods. DDF curves plot rainfall depth versus duration for a given return period. The DDF curves have been widely applied to rainfall data (Baghirathan and Shaw, 1978; Buishand, 1991; Burlando and Rosso, 1996; Overeem et al., 2008). For a reliable flood prediction modelling, accurate DDF estimates are important. There are univariate analyses performed on Mumbai daily rainfall for assessing the spatio-temporal pattern of rainfall (Srinivasan and Nair, 2005; Gupta and Lokanadham, 2008; Kumar et al., 2008; Lokanadham et al., 2009; Zope et al., 2012). The construction of regional equations can condense the information from available records in an efficient and reusable manner, allowing extrapolation and prediction of longer return period events (Alila, 2000). This can be done in two ways: one method is spatial interpolation from a network of raingauges to estimate the rainfall at a specific ungauged location (Brath et al., 2003; Durrans and Kirby, 2004; Xu et al., 2011) and the other is the estimation of a single design curve for a climatologically similar region within a network of raingauges. The statistical methods of regional estimation of the second type are the station-year method (Buishand, 1991), regional averaging of at-site statistics of the data (Buishand, 1991; Overeem et al., 2009) and maximization of a joint likelihood function (Buishand, 1991; Overeem et al., 2009; Yang et al., 2010).

There have been many attempts at the univariate and multivariate frequency analysis of rainfall. Univariate analysis is easy to implement, however it does not capture the association among the variables like rainfall depth, duration and intensity. A more comprehensive and realistic analysis can be brought in through bivariate analysis of either intensity and duration or depth and duration. However, to simplify the analysis, often the assumption is made that the marginals of the bivariate distribution are identical (Bacchi et al., 1994) which may not always be true. A bivariate copula can be used to overcome this simplistic assumption by modeling the dependence structure between two random variables. Copulas have become popular in bivariate analysis because of the flexibility that the marginal distributions need not be from the same parent distribution (Genest and MacKay, 1986; Joe, 1997; Frees and Valdez, 1998; Grimaldi and Serinaldi, 2006; Bardossy and Pegram, 2009; Vandenberghhe et al., 2010; Fontanazza et al., 2011). In the analysis of extremes in rainfall studies, the two most popular models are Generalized Extreme Value Distributions or GEV, also known as the block maxima (Jenkinson, 1955; Buishand, 1991; Durrans and Brown, 2001; Overeem et al., 2009; Buishand and Hanel, 2010; Fontanazza et al., 2011) and the Generalized Pareto Distribution or GPD (Montfort
and Witter, 1986; Norlida et al., 2011). Both methods have been widely used in the depth-frequency analysis of daily or hourly rainfall data. Coles (2001) states that GEV may exhibit good fit for the upper quartile of a rainfall frequency distribution; however it overlooks many significant values inside block maxima which are lower than the highest single value. In case of rainfall depth, values during a drought year may also be considered for extreme values of upper quartile. The GPD has been found to be better in terms of capturing all potential extreme events that are chosen by applying a threshold value.

The objectives of this study are to perform a bivariate frequency analysis to obtain the DDF curves from two marginal distributions of depth-frequency and duration-frequency distributions and, to develop regionalized DDF curves by combining the at-site statistics of individual DDF curves of two raingauge stations. Here the copula method has been applied to obtain the DDF curves as the marginal distributions are from two different families of distributions. Also, the regionalization has been implemented through an optimization approach, as one of the two marginals is nonparametric due to which none of the commonly used regionalization methods is feasible.

2. Site Description and Methodology

The city of Mumbai (Greater Mumbai) consists of two administrative districts: the Island City District and the Suburban District. It extends between 18° and 19.20° N and between 72° and 73° E, and has an area of 472.25 square kilometres (GoM, 2005). In this study, regional DDF curves have been derived for Mumbai city using rainfall data from two long record raingauge stations operated by IMD, Colaba and Santacruz as shown in Figure 1.

2.1. Selection of rainfall events

The individual rainfall events are segregated based on the criterion of minimum threshold intensity to ensure sufficient dry periods between two consecutive rainfall events, which serve to ensure that these events are approximately independent. In the present study, the missing data in the time series have been filled using 75th percentile imputation from time-of-day historical records. The flood event of 2005 has not been included in the analysis, so as not to bias the results. OECD (2010) investigated that including such an outlier in an analysis based on short record size had the potential to skew the findings of the study. Here an optimum threshold of rainfall depth for peak-over-threshold (POT) analysis is chosen based on the selection criteria of thresholds in GPD (Brabson and Palutikof, 2000). In this method, scale and shape parameters of GPD are plotted against varying thresholds. An optimal threshold is chosen at which the parameters remain
reasonably stable. To ensure that the storm events are from a stationary series, Ljung-Box Q-test (Ljung and Box, 1978) for residual autocorrelation is performed. The goodness of fit to GPD model has been checked using Kolmogorov-Smirnov (K-S) test (Stephens, 1979).

Here, DDF curves may be derived for each point rainfall data. So, two curves may be obtained each for Santacruz and Colaba raingauge sites. The joint return period (recurrence interval) of a rainfall event of depth ‘x’ and duration ‘d’ is,

\[ T = \frac{m}{N(1 - F)} \]  

where \( m \) is the total length of the precipitation time series (years); \( N \) is the total number of sampled extremes used for calibration of the distribution; \( F \) is the joint cumulative probability of \((x, d)\) for a given return period \( T \) (Williems, 2000).

### 2.2. Selection of marginal distributions

As already mentioned, GPD has been fitted suitably for the POT delineated depth series after checking for its stationarity, which is a well accepted method (Brabson and Palutikof, 2000; Coles, 2001; Rootzen and Tajvidi, 2006). To obtain the best model for marginal duration-frequency distribution, a set of parametric (Beta, Binomial, Negative Binomial, and Poisson) and nonparametric density functions (Normal, Epanechnikov, Boxcar and Triangle) were analysed. Of the parametric methods examined, we found only the negative
binomial fit satisfactorily. However, all non-parametric methods yielded highly accurate results out of which Gaussian kernel showed the highest accuracy in terms of RMSE (Root Mean Square Error), AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion). Non-parametric methods have advantages including fewer assumptions or restrictions on the data generating process, and can provide a consistent estimator for the unknown function, whether linear or nonlinear (Lall, 1995). This method can be applied to marginal duration-frequency curve. Thus, nonparametric methods can reduce potential systematic biases unlike parametric models. However, there exists a danger of over-fitting (Tschernig and Yang, 2000). Here it is obvious that when rainfall depth and duration follow different family of distributions, copula can show better results for bivariate distribution (Nelson, 2006).

2.3. Generation of bivariate distribution

Copulas have been widely used in bivariate analysis due to their flexibility in deriving joint probability from two different marginal distributions. A bivariate copula \( C \) models the dependence structure between two random variables \( X \) and \( D \), which can in the present context be thought of as the total rainfall depth \( x \) and duration \( d \). It is a function that couples the marginal cumulative distribution functions (CDF) \( F_x(x) \) and \( F_D(d) \) in order to construct the bivariate CDF \( F_{X,D}(x,d) \), as expressed by the theorem of Sklar (1959):

\[
P(X < x, D < d) = F_{X,D}(x,d) = C(F_x(x), F_D(d)) = C_{u_1, u_2}(u_1, u_2) \tag{2}
\]

where \( u_1 = F_x(x) \), and \( u_2 = F_D(d) \) respectively.

In bivariate frequency analysis using copulas, tail dependence refers to the amount of dependence in the upper-right quadrant tail or lower-left quadrant tail (Sibuya, 1960; Joe, 1997; Poulin et al., 2007). The upper tail dependence coefficient is given by:

\[
\lambda_U = \lim_{t \rightarrow -\infty} P\{F_X(X) > t \mid F_D(D) > t\} \tag{3}
\]

Similarly, the lower tail dependence coefficient is given by:

\[
\lambda_L = \lim_{t \rightarrow +\infty} P\{F_X(X) < t \mid F_D(D) < t\} \tag{4}
\]

In design rainfall analysis, upper tail dependence is important due to the extreme values of upper side. The value of \( \lambda_U \) should be > 0 for an upper tail dependence and the upper tails are independent if \( \lambda_U = 0 \). There are different families of copulas namely, Gaussian, Archimedean, Empirical, Extreme Value type and so on. However, taking into consideration of upper tail dependence, for this study, we have chosen two types of extreme value type copulas, Gumbel-Hougaard and Mixed type for which \( \lambda_U > 0 \) (as shown in Table 1).
Table 1: List of copulas used in this study

<table>
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<th>Copulas</th>
<th>Generating function [ϕ(t)]</th>
<th>(τ = 1 + 4\int_0^t \frac{ϕ(t)}{ϕ'(t)} dt)</th>
<th>(θ_{\text{Colaba}})</th>
<th>(θ_{\text{Santacruz}})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gumbel-Hougaard / Logistic Extreme Value (G-H)</td>
<td>(\exp\left{-\left[(\ln u_1)^{\theta} + \frac{1}{\theta}\right]\right}) (θ \in [1, \infty))</td>
<td>((1 - θ^\theta))</td>
<td>1.705</td>
<td>1.650</td>
</tr>
<tr>
<td>Mixed Extreme Value (MEV)</td>
<td>(\theta, t^\theta - \theta, t + 1) (\frac{8\pi\arctan\left(\frac{θ}{4-θ}\right)}{\sqrt{θ(4-θ)}})</td>
<td>0.991</td>
<td>0.953</td>
<td></td>
</tr>
</tbody>
</table>

At-site DDF curves have been generated for the two stations considering the conditional probability of bivariate copulas for various pairs of return period and duration values. The conditional probability values have been used in estimating the cumulative rainfall depth probability value, the inverse of which yields the design rainfall depth corresponding to a given return period and duration. The conditional probability is given by:

\[
C[u_1 | u_2] = \frac{(N* T_d(\bar{x}, d) - m)}{(N* T_d(\bar{x}, d))}
\]

or

\[
\frac{∂C[u_1,u_2]}{∂u_2}
\]

\[
C[u_1 | u_2]_{G-H} = u_2^{-1} * \left(\frac{1}{\theta}(-\ln u_1)^{\theta} * \left\{(-\ln u_1)^{\theta} + (-\ln u_2)^{\theta}\right\}\right)^{1/\theta}
\]

\[
C[u_1 | u_2]_{MEV} = \left\{u_1 * \exp\left[-\left(\frac{-\ln u_1}{\ln(u_1u_2)}\right)\right]\right\} * \left\{1 + \frac{\theta * (-\ln u_1)* \left[\ln(u_1u_2) - \ln u_2\right]}{(\ln(u_1u_2))^2}\right\}
\]

The goodness of fit of a model may be checked using RMSE, AIC and BIC. Here, marginal depth-frequency curves can be obtained through the cumulative probability distribution for a GPD given by:

\[
F(x) = 1 - \left(1 + \frac{k(x - μ)}{α}\right)^{-1/k}
\]

where, \(μ\): location parameter; \(α\): scale parameter; \(k\): shape parameter, and \(μ, α > 0\) and \(-1/2 < k < 1/2\).
2.4. Regional design rainfall

For a climatologically homogeneous region, each parameter of at-site DDF curves may be averaged to obtain a single set of regionalized curves (Buishand, 1991; Overeem et al., 2008, 2009). However, this approach would be infeasible if either or both of the marginal distributions is follow a nonparametric model as obtained in this study. Hence, an optimization framework has been proposed through two different approaches. In the first approach of Combined Averaging-Optimization or CAO (referred as Case I), the three GPD parameters of marginal depth-frequency curve namely, shape parameter \(k\), location parameter \(\mu\) and scale parameter \(\alpha\) are averaged, while a nonlinear optimization approach is used to obtain the regional bandwidth \(h\) for the kernel density function of marginal depth-frequency. In the second approach of Complete Optimization or CO (referred as Case II), optimization is performed considering the three GPD parameters and kernel bandwidth, thus obtaining four optimal values as outputs. Here the objective function is to minimize root mean square error (RMSE) at the individual stations, resulting from the regional model. The regionalized copula parameter \(\theta\) can be obtained by proportional weighting as per record length from each station. Mathematically, the optimization formulation may be expressed as:

Minimize \(F(x) = (\text{RMSE})_C + (\text{RMSE})_S\)

subjected to:

\[x_i > 0, \ i=1 \quad \text{(CAO or Case I)}\] (10)
\[i=1, 2, 3, 4 \quad \text{(CO or Case II)}\] (11)

where \((\text{RMSE})_C\) and \((\text{RMSE})_S\) are root mean square error values at individual raingauge stations of Colaba and Santacruz respectively, calculated as the difference between empirical bivariate probability and copula-based bivariate probability. Here \(x\) is an array consisting of one kernel bandwidth \((i = 1)\) and three GPD parameters \((i = 2, 3, 4)\).

Here, a design storm time series for a region can be derived by combining the rainfall depth \((X_{\text{Region}})_{T^*,d^*}\), and storm temporal pattern \((TP)_{d^*}\) corresponding to a given design return period \(T^*\) and duration \(d^*\). The design temporal pattern may be chosen from a set of observed patterns or any synthetically derived pattern may be used.

3. Results and Discussion

The hourly rainfall data during 1969-2012 has been collected from India Meteorological Department (IMD) at Pune and Regional Meteorological Centre at Andheri, Mumbai. The individual rainfall events were delineated based on the criteria of minimum hourly value as 0.1mm which is the least depth of rainfall measured at the stations (providing an average of 6h dry period between consecutive rainfall events). As per MCGM, the design
capacity of the drainage system in Mumbai is 25mm/h with 50% runoff; however the actual capacity is much lower as the system is more than 100 years old with almost 100% runoff. Hence, the least value of hourly rainfall will agree upon the concept of independence of rainfall events for flood modelling studies and this will also ensure sufficient dry periods between consecutive rainfall events.

![Figure 2](image_url)

**Figure 2**  Delineated rainfall events for (a) Colaba and (b) Santacruz (from peak-over-threshold analysis)

DDF curves have been obtained individually for the raingauge stations using bivariate copula method, where GPD has been used to derive the marginal depth-frequency curve while a kernel function has been used to obtain the marginal duration-frequency curve. The POT analysis has been performed on the rainfall event series. The optimal thresholds for Colaba and Santacruz were found to be 44mm and 28.4mm respectively, based on the method proposed by Brabson and Palutikof (2000). The autocorrelation was checked up to 10 lags and has been found to be within 95 percentile confidence limits both for Colaba and Santacruz to verify stationarity and suitability for fitting GPD. **Figure 2** shows the generated rainfall event series for Colaba and Santacruz. The parameters have been estimated using maximum likelihood estimate (MLE). The results of GPD fit for Colaba and Santacruz stations are shown in **Table 2**. It was found that RMSE value was lower for MLE compared to LM which was consistent with earlier work (Koutsoyiannis, 2004; Kharin and Zwiers, 2005).
Table 2: **GPD parameter estimates using MLE**

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Colaba</th>
<th>Santacruz</th>
</tr>
</thead>
<tbody>
<tr>
<td>$k$</td>
<td>0.2897</td>
<td>0.2329</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>37.33</td>
<td>34.6</td>
</tr>
<tr>
<td>$m$</td>
<td>44</td>
<td>28.4</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.0066</td>
<td>0.0073</td>
</tr>
</tbody>
</table>

To derive the marginal duration-frequency curve, different parametric and nonparametric frequency distributions were tested to obtain the marginal duration-frequency relationship (See Table 3 and Figure 3). Most of the parametric methods failed to give a reasonable fit except for negative binomial distribution. The commonly used nonparametric kernel distributions like Gaussian, Epanechnikov, Boxcar and Triangular kernels were tested for the best fit kernel and compared with negative binomial distribution. The comparison with empirical density showed Gaussian kernel had the best fit.

Table 3: **Kernel selection for marginal duration-frequency curve for Colaba and Santacruz**

<table>
<thead>
<tr>
<th>Sl.No.</th>
<th>Representative distributions</th>
<th>RMSE</th>
<th>Colaba</th>
<th>Santacruz</th>
<th>AIC</th>
<th>BIC</th>
<th>AIC</th>
<th>BIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Gaussian</td>
<td>0.0097</td>
<td>-275.8</td>
<td>-274.4</td>
<td>-275.8</td>
<td>-274.4</td>
<td>-258.3</td>
<td>-257.1</td>
</tr>
<tr>
<td>2</td>
<td>Epanechnikov</td>
<td>0.0099</td>
<td>-274.9</td>
<td>-273.4</td>
<td>-274.9</td>
<td>-273.4</td>
<td>-256.7</td>
<td>-255.5</td>
</tr>
<tr>
<td>3</td>
<td>Boxcar</td>
<td>0.0098</td>
<td>-275.3</td>
<td>-273.9</td>
<td>-275.3</td>
<td>-273.9</td>
<td>-255.9</td>
<td>-254.7</td>
</tr>
<tr>
<td>4</td>
<td>Triangle</td>
<td>0.0098</td>
<td>-275.4</td>
<td>-274.0</td>
<td>-275.4</td>
<td>-274.0</td>
<td>-257.8</td>
<td>-256.6</td>
</tr>
<tr>
<td>5</td>
<td>Negative Binomial</td>
<td>0.0164</td>
<td>-244.8</td>
<td>-243.4</td>
<td>-244.8</td>
<td>-243.4</td>
<td>-194.3</td>
<td>-193.1</td>
</tr>
</tbody>
</table>
3.1. At-site DDF

The results based on AIC, BIC and RMSE are shown in Table 4. Here, bivariate frequency was derived using GPD and Gaussian kernel. In bivariate frequency analysis of design rainfall estimation, joint return periods of various combinations of rainfall depth and duration are obtained. Figure 4 shows the bivariate distributions for the two stations using the two copulas. Here the value of $C[u_1|u_2]$ calculated from Equation 5 can be substituted in Equation 6 to obtain the value for $u_1$, the inverse of which will give the design rainfall depth ($x$). The conditional probability for the two copulas is given in Equations 7 and 8. Figure 5 shows the DDF curves for Colaba and Santacruz stations respectively, generated using Gumbel-Hougaard copula and mixed copula for the joint return periods of 5, 10, 50, 100, 200 and 300 years. Mixed copula estimates higher rainfall depth for lower tail (shown between 100-400mm/h), than Gumbel-Hougaard (100-300mm/h). However, both the copulas exhibit similar trend towards upper tail of the curve as these two are extreme value copulas.
Table 4: Goodness of fit of bivariate copula for Colaba and Santacruz

<table>
<thead>
<tr>
<th>Station</th>
<th>Copula</th>
<th>RMSE</th>
<th>AIC</th>
<th>BIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Colaba</td>
<td>*G-H</td>
<td>0.0123</td>
<td>-261.9</td>
<td>-260.5</td>
</tr>
<tr>
<td></td>
<td>#MEV</td>
<td>0.0123</td>
<td>-261.7</td>
<td>-260.3</td>
</tr>
<tr>
<td>Santacruz</td>
<td>*G-H</td>
<td>0.0093</td>
<td>-231.9</td>
<td>-230.7</td>
</tr>
<tr>
<td></td>
<td>#MEV</td>
<td>0.0093</td>
<td>-231.9</td>
<td>-230.6</td>
</tr>
</tbody>
</table>

* Gumbel-Hougaard  # Mixed Extreme Value

Figure 4  Bivariate distribution of Gumbel-Hougaard and Mixed extreme value copulas for Colaba (a and b) and Santacruz (c and d)

Figure 5  DDF curves of Gumbel-Hougaard and Mixed extreme value copulas for Colaba (a and b) and Santacruz (c and d)
3.2. Regionalization method

The regionalization approach is very common in design rainfall analysis. In this study, the two raingauge stations Colaba and Santacruz stations fall under homogeneous monsoon region due to its geographical proximity, climate, altitude etc. (as per monsoon region division published by Indian Institute of Tropical Meteorology, 2005). A regional DDF relationship may be established either in deterministic or in stochastic fashion. Here a stochastic approach is applied through two different approaches, CAO (referred as Case I) and CO (referred as Case II), thus obtaining four output values through the optimization (Cases I and II are tabulated in Table 5). Here the objective function is to minimize RMSE at the individual stations. The regionalized copula parameter has been obtained by the proportional weighting as per record length from each station. Table 5 shows the goodness of fit for the two copulas using the two methods. The results clearly indicate that Case II involving simultaneous optimization of all three parameters of GPD and kernel bandwidth is more accurate with lower error values. Figure 6 shows the bivariate distributions for the two stations using the two copulas. Figure 7 shows that mixed copula estimates higher rainfall depth for lower tail (shown between 100-400mm/h), than Gumbel-Hougaard (100-300mm/h). However, both copulas have similar trend towards upper tail of the curve as these two are extreme value copulas.

![Figure 6](image)

**Figure 6** Regional bivariate distribution of Gumbel-Hougaard and Mixed extreme value copulas for Case-I (a and b) and Case-II (c and d)
Figure 7  Regional DDF curves of Gumbel-Hougaard and Mixed extreme value copulas for Case-I (a and b) and Case-II (c and d)

Table 5:  Goodness of fit of regional distribution considering individual stations of Colaba and Santacruz

<table>
<thead>
<tr>
<th>Approach</th>
<th>Copula</th>
<th>Colaba</th>
<th>Santacruz</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RMSE</td>
<td>AIC</td>
<td>BIC</td>
</tr>
<tr>
<td>Case I</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>G-H</td>
<td>0.0432</td>
<td>-217.9</td>
</tr>
<tr>
<td></td>
<td>MEV</td>
<td>0.0432</td>
<td>-217.9</td>
</tr>
<tr>
<td>Case II</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>G-H</td>
<td>0.0568</td>
<td>-227.4</td>
</tr>
<tr>
<td></td>
<td>MEV</td>
<td>0.0568</td>
<td>-227.4</td>
</tr>
</tbody>
</table>

* Gumbel-Hougaard  * Mixed Extreme Value

4. Summary and Conclusions

In urban flood modelling studies, regional design rainfall estimation forms an integral component. The bivariate frequency analysis of rainfall, considering the association between rainfall depth and duration, depicts the inherent structure of rainfall patterns. Here, a novel approach has been brought forth by combining GPD with nonparametric method. GPD has been used to derive the marginal rainfall depth-frequency curve as it can capture all flood causing rainfall events above a threshold. A nonparametric Gaussian kernel has been applied for duration-frequency curve as none of the parametric methods could give a better fit than the former. A set of goodness of fit tests (RMSE, AIC and BIC) have been performed. Here a non-linear optimization approach was used to derive the regional bandwidth for the kernel function which is the first attempt in design
rainfall analysis. The current study may be extended to include temporal patterns which are critical in determining flood severity corresponding to a particular rainfall depth. Moreover, to address the spatial variability, additional raingauge records are necessary.

Acknowledgements
This study was supported by Tata Consultancy Services (TCS). We acknowledge the supply of hourly rainfall data from India Meteorological Department (IMD) Pune and Regional Meteorological Centre, Mumbai. We also thank IITB-Monash Research Academy for their administrative support.

References
Durrans SR, Kirby JT (2004) Regionalization of extreme precipitation estimates for the


Hydrological Extremes

Technological and social adaptation to extreme water hazards

(Addendum, see page 53)
Assessment of Flood Hazards and Vulnerability in Cambodian Floodplain

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Abstract
Lower Mekong Basin (LMB) is frequently affected by floods, particularly, within the low-lying floodplains of Cambodia. Populations living in the Mekong River floodplain of Cambodia are vulnerable to flood disasters. It is thus necessary to identify flood vulnerability in flood-prone areas of the LMB to support decisions for flood management. This study identified flood hazard areas and flood vulnerability in LMB of Cambodian floodplain and developed Flood Vulnerability Indices (FVI). The flood vulnerability was defined in terms of amount of potential damages. The agricultural and house damages were considered to identify flood vulnerability indices, because both are major income and stocks in the area. The agricultural damage was defined as the function of flood water depth during the cultivation period and its duration. The maximum daily water depth and their duration for each grid were calculated and agricultural damages at each grid were calculated according to damage curves. The house damage was defined as the function of maximum flood water depth by relating with average year flood level. The calculated house damages were compared with the statistical data of house damages. The FVI were developed for agricultural, houses and total damages by normalizing the calculated values of damages. The flood vulnerability indices spatial distribution of risk area in average flood and flood vulnerability indices of gap rate between an extreme flood and average flood were developed.

Keywords
Cambodian Floodplain, Flood Hazards, Flood Vulnerability, Agricultural Damages, House Damages

1. Introduction
In recent years the risk of flood disasters has been increasing by climate change, urbanization and development activities constituting an increasing threat to economies, population and sustainable development. It is a matter of serious concern that many countries face catastrophic flood disasters, while having few resources to cope with
them (Hoff et al., 2003). The low-lying floodplains of the Lower Mekong Basin (LMB) in Cambodia are frequently affected by floods (Dutta et al., 2007). Populations living in LMB area of the Cambodian floodplain are vulnerable to flood disasters. The flooding process is part of regular life in the LMB and it provides irrigation for crops, water for the fisheries and navigation purpose (Bonn et al., 2005). However, exceptional floods seem to occur more frequently in recent years, which cause damage to agricultural and houses in the area (Bonn et al., 2005). It is thus necessary to identify flood hazards and vulnerability in flood-prone area of LMB to support decisions for flood management.

The floods are serious problems in LMB area even it provides some benefits in the areas. Every year floods severely damaged agricultural, house and infrastructures. Many people also affected from the floods in the areas. Figure 1 shows the LMB in Cambodian floodplain and major river system in the region. Figure 2 shows the trend of economic losses and affected people due to flooding in Cambodia from 1991 to 2011. In terms of economic loss, 2011 flood is biggest flood in the period. However, in terms of affected people, 2000 flood is the biggest flood in the areas. The 2000 floods resulted in damage to 37,000 hectares of rice fields, destruction of 6,081 houses, loss of 2,444 livestock, and affected 3.44 million people in 132 districts (MWRM and CNMC, 2003). In recent flood of 2011, about 423,449 hectares of rice fields have been affected with 265,804 hectares reported as damaged and 1.64 million people has been affected (UN Cambodia, 2011). The fatalities and injuries during the floods in 2011 are about 247 and 23, respectively.
(UN Cambodia, 2011). The total estimated damages by the year 2000 and 2011 floods are 164 million US$ and 521 million US$ respectively.

The flood vulnerability in LMB is still poorly identified, although FMMP (2010a, 2010b) provided valuable information on floods in LMB and some socio-economic damages. However, these information are only limited to few districts level. Furthermore, some investigation in LMB area can be found only on flood inundation and hydrological analysis (Kite, 2001; Fujii et al., 2003; Morishita et al., 2004; Dutta et al., 2007; Tarekegn and Sayama, 2013) and satellite based flood inundation (Begkhuntod, 2007).

This study identified flood hazards and vulnerability in LMB of Cambodian floodplain and developed Flood Vulnerability Indices (FVI). The flood vulnerability was defined as the amount of potential damages, considering damage to agricultural production and houses. Flood damages depend on flood water depth and vulnerability of each area and the development of relationship between flood water depth and flood damage is very important to assess the flood damages. The agricultural damage was defined as the function of maximum flood water depth during the cultivation period and its duration. The house damage was defined as the function of maximum flood water depth by relating with average year flood level. The household survey data for 2006 flood from Flood Management and Mitigation Programme (FMMP) of Mekong River Commission Secretariat (MRCS) was used to determine damage ratio curve and probability distribution of house value. The calculated house damages in 2006 flood were compared with districts statistical data based on household survey of FMMP (2010b). The FVI were developed for agricultural, houses and total damages by normalizing the calculated values of

![Figure 2](image.png)
damages. The FVI were developed by normalizing the calculated damage values. The flood vulnerability indices of gap rate between an extreme flood and average flood were also analysed.

2. Methodology for identification of flood hazards and vulnerability

The grid-based distributed ICHARM's Hydro-Geo Method (IHGM) has been developed to identify the flood hazards and vulnerability in Cambodian floodplain. The flood vulnerability was defined as the amount of potential damages (Jones and Boer, 2003). The agricultural and house damages were considered to identify flood vulnerability. Agriculture damages here refer to damage to wet-season rice crops, which is a major source of rice production in Cambodia. House damages account for damages occurring to household residential assets and were calculated based on household survey data for 2006 flood from FMMP, MRCS. Figure 3 shows the methodology of flood vulnerability assessment. Through IHGM, integrating hydro-meteorological analysis and Digital Elevation Model (DEM) of HydroSHEDS which obtained from Shuttle Radar Topography Mission (SRTM) data (Farr et al., 2007), flood water depth was calculated as difference between flood water level and ground level at 3 arc-second cell (approximately 91.8m×91.8m cell size). In HydroSHEDS data, the corrections were made in original SRTM elevation data where necessary for accuracy assessment. As DEM data is available at 3 arc-second resolution, flood water level is calculated at 3 arc-second cell. Then, by
integrating damage curves for both crops and houses, amounts of both agricultural and house damages were calculated at each grid cell.

2.1. Flood water depth calculation

Based on study of FMMP component-5, the inundation water level in Cambodian floodplain has approached river water level during past floods; indeed, when floods are large enough, flood level and river water level coincide (Plinston, 2007). This characteristic was then extrapolated to the entire zone considered. Based on this concept, water depth in floodplain was calculated as difference between flood water level and elevation at grid level. The long term 1991 to 2007 years water level and rainfall data of all the stations in Cambodia were collected and were analyzed to calculate water level. Water level in the floodplain or flood level is approached as the river water level at the closest gaging station or by interpolation between two consecutive gaging stations. The flood water depth was calculated for each 3 arc-second (91.8m) cell for the whole Cambodian floodplain. The detail explanation of water depth calculation can be found in Shrestha et al. (2013) and Okazumi et al. (2013).

2.2. Agricultural damages calculation

Rice crops are the major agricultural production in Cambodia. About 80% rice in Cambodia produces from wet-season rice (Hortle et al., 2004) and these crops are damaged during flood. Thus, wet-season rice crops damages were considered as agricultural damage. Usually farmers in Cambodia start cultivation of wet-season rice when land becomes soft enough to be cultivated which corresponds to the time that accumulated rainfall reaches approximately 500 mm (Taniguchi et al., 2009). It takes 90 days for rice growth (Figure 4). During that period of 90 days, damages occur if flood water depth reaches over 0.5m as it is minimum damageable depth of water (FMMP, 2010b). The transplanting date of young rice crops and growing period were determined by using Thiessen Polygon of rainfall and cumulative rainfall of that area. An agricultural damage was defined as function of flood water depth and its duration (Shrestha et al., 2013). From IHGM, the maximum daily water depth and their duration for each grid were calculated. Agricultural damages in each grid were calculated according to damage curves as shown in Figure 5 developed by FMMP (2010b). Then amount of agricultural damage for each grid was calculated by multiplying damage ratio with average yield (average yield 392 US$/ha, based on data of Ministry of Planning, Cambodia, 2009). The cultivation area of wet-season rice was considered based on agricultural land use data made in 2003 by Ministry of Public Works and Transport, Cambodia. The agricultural damages were calculated for each 3 arc-second cell (91.8m cell).
Figure 4  Schematic of agricultural cultivation and damage with water level hydrograph.

Figure 5  Damage curves for wet-season rice according to flood water depth and flood duration (FMMP, 2010b).
2.3. House damages calculation

People living in Cambodian floodplain often face floods. So they construct elevated house using stilts to avoid the residential damages due to flooding. House damages are the damages encountered at household level and defined as the function of water depth. The household survey data for 2006 flood of FMMP project, MRCS, Cambodia, was used to calculate house value distribution and house damage curve (Sugiura et al., 2013; Shrestha et al., 2013). **Figure 6** shows the house value distribution curve and **Figure 7** shows the house damage curve (ratio of house damage to house value) (Sugiura et al., 2013; Shrestha et al., 2013). Then by integrating multiplication of house value distribution curve and damage ratio curve, the house damages can be obtained as follows.

\[
HD_k = N_k \times HV \int_{h_{k-1}}^{h_k} (g(h, \alpha, \beta) \times DR(h)) \times dh
\]

where, \(HD_k\) and \(N_k\) are the house damage and total number of people respectively in cell \(k\), \(HV\) is the average house value per people, \(h\) is the water depth at yard, \(g(h,\alpha,\beta)\) is the gamma distribution function of the house value, \(\alpha\) and \(\beta\) are the parameters of gamma distribution function and \(DR(h)\) is the unit damage at \(h\). The house value 245 US$ per person was used, which was determined based on household survey for 2006 flood from FMMP project (FMMP, 2010b). Population data derived from the LandScan 2009 global population at 30 arc-seconds (918m cell) was used to consider household distribution in the each cell (Bhaduri et al, 2007). As LandScan population data is available at 30 arc-seconds grid size, the house damages were calculated for each 30 arc-second cell (918m cell). In Cambodian floodplain, people usually construct elevated houses by using stilts to avoid flood damages. So, if we use relative water depth from average peak flood level of each location, we can deal with them using house value distribution obtained from household survey data in other area.
Figure 7  Damage ratio curve of house value.

Table 1:  Average income and expenditure per capita in Cambodia based on years 2009-2011 data (Data source: National Institute of Statistics, Cambodia).

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Phnom Penh</td>
<td>1248</td>
<td>876</td>
<td>1211</td>
<td>924</td>
<td>1386</td>
<td>948</td>
</tr>
<tr>
<td>Other urban area</td>
<td>708</td>
<td>642</td>
<td>984</td>
<td>636</td>
<td>1272</td>
<td>612</td>
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<tr>
<td>Rural area</td>
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<td>432</td>
<td>456</td>
<td>428</td>
<td>492</td>
<td>451</td>
</tr>
</tbody>
</table>

Table 2: Minimum required consumption for flood affected people and amount of consumption per capita per month in case of rural area based on data of National Institute of Statistics, Cambodia.

<table>
<thead>
<tr>
<th>Description of consumption</th>
<th>2009 Rural area US$</th>
<th>2010 Rural area US$</th>
<th>2011 Rural area US$</th>
<th>Average value Rural area US$</th>
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<tbody>
<tr>
<td>Food and non-alcoholic beverages</td>
<td>27</td>
<td>26</td>
<td>28</td>
<td>27</td>
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<tr>
<td>Clothing and footwear</td>
<td>1</td>
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<td>1</td>
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<td>Health</td>
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<td>5</td>
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<td>5</td>
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<td>Transportation</td>
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</tr>
<tr>
<td>Education</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Average values of consumption per capita per month (US$) =</td>
<td>36</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
2.4. Total damages calculation

As flood vulnerability is defined as amount of potential damages, total flood vulnerability is a combination of agricultural damages and house damages. In this study, additive combination of agricultural and house damages was used to calculate flood vulnerability for total damages. However, agricultural and house damages do not have same impact on a household. The values of agricultural damages and income are in per year. However, the values of house damages are for several years, which can be determined by recovery years required for house damages. To calculate total flood vulnerability, it is necessary to calculate values of house damages into per year values. Then, Total Damages (TD) can be calculated as follows.

\[
TD = AD + \frac{1}{RY} HD
\]  

in which, \( AD \) is the agricultural damages, \( HD \) is the house damages and \( RY \) is the recovery year required for house damages. The recovery year required for house damages depends on amount of house damages, income and saving amount of the household in the areas. If house and assets of a household damage, the same amount of house damage or greater than amount of house damage is necessary for rehabilitation of house and assets damages. The average annual per capita income and expenditure in Phnom Penh, other urban area and rural area are shown in Table 1. As our target area is flood prone rural area, income and expenditure of flood prone rural area was considered to determine recovery year of house damage. The affected people have to save their income for recovery cost of house damages by reducing their expenses. In Table 1, the annual expenditure per capita was calculated based on the minimum required consumptions for flood affected people. For example, Table 2 lists the minimum required consumptions and amount of expenditure per capita per month in case of rural areas of Cambodia. Only minimum required consumptions were considered as their expenditures to allocate recovery cost of house damages. The income and expenditure of rural area listed in Table 1 are the average of flooded and non-flooded areas. However, income and expenditure in flooded and flood prone are relatively lower than income and expenditure of rural area listed in Table 1. The population density in flooded area and flood-prone area are also lower than non-flooded area. To calculate income and expenditure in flooded area, relationships between income and expenditure with population density were analyzed by using population data, per capita income and per capita consumption of Phnom Penh, other urban area and rural area as shown in Figure 8.
Figure 8  Relationships between income and expenditure with population density (expenditures shown in the figure were estimated by considering only data of minimum required consumption).

Table 3:  Average house damages per household in three surveyed districts and calculation of recovery year for house damages.

<table>
<thead>
<tr>
<th>Relative water depth with average year water level (m)</th>
<th>House Damages in US$ per household</th>
<th>Calculated Recovery Year = Damage / Recovery cost per year</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>129.34</td>
<td>0.7</td>
<td>Actual damages in 2006</td>
</tr>
<tr>
<td>0.5</td>
<td>162.307</td>
<td>0.9</td>
<td>Potential damages</td>
</tr>
<tr>
<td>1</td>
<td>193.20</td>
<td>1.0</td>
<td>Potential damages</td>
</tr>
<tr>
<td>1.5</td>
<td>327.23</td>
<td>1.8</td>
<td>Potential damages</td>
</tr>
<tr>
<td>2</td>
<td>468.73</td>
<td>2.5</td>
<td>Potential damages</td>
</tr>
</tbody>
</table>

Figure 9  Recovery year for house damages in Cambodian floodplain.
To calculate the recovery years for house damage, the household survey data of FMMP project in three districts Koh Andet in Takeo province, Koh Thom in Kandal province and Kampong Trabek in Prey Veng province were used. Based on the LandScan population data, the average value of population density in these three districts is about 56 populations per km². By using relationships of income and expenditure with population density shown in Figure 8, the average annual household income and expenditure respectively are about 2,078 and 1,892 US$. The saving amount of household as recovery cost is about 186 US$ per year (income minus expenditure). This saving amount can be used as recovery cost. Then, the years require for recovery can be calculated by using amount of house damages and recovery cost per year. The data of actual damages of 2006 flood and potential damages that would have occurred if 2006 water depth had been 0.5m, 1.0m, 1.5m and 2.0m higher, were used as house damages. Table 3 shows the average house damages per household and calculation of recovery year. The recovery year was calculated by dividing house damage with recovery cost. Figure 9 shows the recovery year of house damages with relative water depth from average year water level (2006 flood level) for Cambodian floodplain. The calculated recovery year of house damages in 2006 flood is less than a year.

3. Assessment of flood vulnerability indices

In this study, flood vulnerability indices were developed for LMB areas in Cambodian floodplain. The average flood water depth recorded during the 2006 flood is similar to the average flood water depth between 1991 and 2007 and the average water depth of the 2000 flood is higher than any other flood recorded during this period. Thus, the 2006 flood and 2000 flood were considered as approximation of average flood and extreme flood, respectively. The flood vulnerability indices ($FVI$) were calculated by using damages in average and the gap rate between average flood and extreme flood were also analysed. The flood vulnerability indices-spatial distribution of risk area ($FVISD$) were identified by normalizing calculated value of damages in each grid by using damages in average flood case (2006 flood). $FVISD$ shows the high to low flood risk areas. To normalize the value, the calculated value in each grid was divided by maximum value of calculated damages in the areas and $FVISD$ for agricultural damages ($AD$) or house damages ($HD$) or total damages ($TD$) were defined as follows.

$$FVISD = \frac{\text{Value of damage in a grid}}{\text{Maximum value of damage in all grids}}$$ (3)
Flood vulnerability indices-gap rate ($FVI_g$) was defined to identify damages gap area between average floods and extreme floods. The average flood brings some damages but extreme flood brings big damages. It means serious preparedness for extreme flood is needed in such area. The variations of gap area of flood vulnerability were identified by calculating ratio between damages in 2000 flood and damages in 2006 flood. The $FVI_g$ was calculated in each grid by using the damages values of 2006 flood and 2000 flood of the same grid as follows.

$$FVI_g = \frac{\text{Value of damage in a grid (2000 Flood)}}{\text{Value of damage in a grid (2006 Flood)}}$$  \hspace{1cm} (4)

4. Results and discussions

As house damage calculation is in 30 second cell (918m), calculated water depth and agricultural damages data from 3 second (91.8m) (100 cells) are up-scaled to 30 second cell (918m). Figure 10 shows the maximum flood inundation depth in average flood (2006 flood) and in extreme flood (2000 flood) and compares calculated inundation area with actual inundation area based on RADARSAT SCANSAR images. The calculated flood extents are consistent with the actual flood extent areas. The flood inundation depth is higher in downstream reach of Cambodian floodplain.

Figure 11 shows distribution of agricultural damages in cases of 2006 flood and 2000 flood. The total estimated amount of agricultural damages in Cambodian floodplain are found to be 123,374,768 US$ and 155,085,380 US$ respectively in 2006 flood and 2000 flood cases. In average flood case (2006 flood) also, the Cambodian floodplain experiences agricultural damages in the areas. The agricultural damages in middle and downstream area of floodplain are higher compared to upstream area.
Figure 10  Flood inundation depth (a) 2006 flood, (b) 2000 flood.

Figure 11  Distribution of agricultural damages in Cambodian floodplain (a) 2006 flood and (b) 2000 flood.

Figure 12(a) shows flood vulnerability indices—spatial distribution of flood risk areas of potential agricultural damages in average floods. The $FVI_{SD}$ is defined from low to very high flood risk areas of damages based on normalization value ranges from 0 to 1. The normalized value ranges 0 to 0.25, 0.25 to 0.5, 0.5 to 0.75 and 0.75 to 1 respectively defined as low, medium, high and very high risk areas of damages. In average flood also, people living in the area often faced agricultural damages. Based on the $FVI_{SD}$ map they can identify which area is highly risk to flood and which area is low risk to flood.
Figure 12: (a) Flood vulnerability indices-spatial distribution of risk area, $FVI_{sd}$, and (b) Flood vulnerability indices of gap area between extreme flood and average flood, $FVI_{gb}$, in case of agricultural damages.

Figure 13: Exposed population per km$^2$ in (a) 2006 flooding area and (b) 2000 flooding area.

Figure 14: Distribution of house damages in Cambodian floodplain (a) 2006 flood and (b) 2000 flood.

Figure 12(b) shows flood vulnerability indices of gap rate of agricultural damages. This figure shows identification of gap areas in agricultural damages between an extreme flood (2000 flood) and average flood (2006 flood). In red colored areas of figure, agricultural damages are very higher in extreme flood than average flood. In other colored areas, agricultural damages in average flood are equal to or higher than extreme flood case.
During the growing period, flood water depth in some area is higher in average flood than extreme flood case. In average year also agricultural damages can be higher than extreme flood case because the agricultural damage is caused by significant inundation during growing period which is determined with accumulated rainfall of that area. By using this figure, gap rate of agricultural damages between extreme flood and average flood can be identified.

Figure 15 (a) Flood vulnerability indices-spatial distribution of risk area, $FVI_{SD}$, and (b) Flood vulnerability indices of gap area between extreme flood and average flood, $FVI_G$, in case of house damages.

Figure 13 shows the exposed population distribution in 2006 and 2000 flooding areas based on 2009 LandScan population data. Figure 14 shows the distribution of calculated house damages in Cambodian floodplain. The total estimated amount of house damages in Cambodian floodplain are found to be 30,081,274 US$ and 60,073,462 US$ respectively in 2006 flood and 2000 flood cases. The calculated house damages in 2006 floods in Koh Andet and Koh Thom districts are found to be 826,585 US$ and 1,404,623 US$, respectively. The statistical data of house damages based on FMMP survey for 2006 flood are about 508,000 US$ and 1,817,632 US$ in Koh Andet district of Takeo province and Koh Thom district of Kandal province, respectively. The calculated house damages are reasonable with statistical data. Figure 15 shows (a) $FVI_{SD}$ of flood risk areas of house damages in average floods, and (b) $FVI_G$ of house damages. During average flood, they experienced some house damages. However, in extreme flood, they experienced big house damages in the area. The map of house damages gap area between average flood and extreme flood is very useful to identify the area where big house damages occur during extreme flood. By using $FVI_{SD}$ maps, highly vulnerable risk areas of house damages can be identified for preparedness.
The total damages were calculated for 2000 and 2006 floods using Equation 2 by considering additive combination of agricultural damages and house damages. Figure 16 shows (a) $FVI_{SD}$ of risk areas of total damages in average floods, and (b) $FVI_{G}$ of total damages. By utilizing $FVI_{SD}$, we can easily obtain information of risk areas in average floods and we can easily identify where preparedness is needed. In average floods also, the Cambodian floodplain experiences agricultural and house damages. But when extreme flood occurs, extensive damage occurs in these areas. This indicates that serious preparations for extreme flooding are necessary in these areas. By utilizing $FVI_{G}$ to identify gap areas between extreme floods and average floods, we can identify areas where preparedness for extreme floods is needed. The high to low vulnerable areas of damages in risk areas can be identified by using FVI maps and this information is useful for preparedness, decision making, prioritization of the project and project implementation.

5. Conclusions

The flood vulnerability was defined as amount of potential damages. The agricultural damages and house damages were considered to develop FVI. The agricultural damages depend on flood water depth and its duration as well as accumulated rainfall in the area. It was also found that in some area agricultural damages can be also higher in average flood with compared to extreme flood case. The house damages depend on maximum flood water depth and house value distribution and it was defined by relating flood water depth with average flood level of each area. For the validation of house damage calculation, the estimated results of Koh Andet district in Takeo province and Koh Thom district in Kandal province were checked with statistical data of house damages. The FVI were developed for agricultural, houses and total damages in LMB of Cambodian
floodplain by normalizing the calculated values of damages.

The FVI identify area which easy to be affected by flood. The results of FVI guide well preparedness for flood in agricultural as well as house and assets. The FVI can be used by local community people, community leaders, decision makers, developers and policy makers. It is useful to identify and develop preparedness plans to deal with floods and flooding. It will help to improve local decision-making processes by selecting preventive measures to reduce vulnerability at local and commune levels. The use of flood vulnerability indices can produce helpful understanding into vulnerability and capacities for using it in planning and implementing projects. Also the FVI make it possible for decision makers, developers and policy makers to identify the priority area for implementation of disaster related projects.

The $FVI_{SU}$ of risk areas can be used to identify high to low risk areas and the information of vulnerable area can be easily identified to make preparedness in the vulnerable areas. In average flood also, Cambodian floodplain experiences some damages of agricultural and houses. But when extreme flood occurs, the big damages occur in the area. It means serious preparedness for extreme flood is needed in such areas. By using $FVI_{G}$, the damages gap areas between extreme flood and average flood can be identified and it can be recognized the area where serious preparedness for extreme flood is needed.

The proposed methodology of flood vulnerability assessment can be applied in other river basins. In this study, flood vulnerability of agriculture and houses was considered to develop FVI. However, vulnerability of other socio-economic factors is also necessary to consider in future study.

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