A Hydro-Climatic Analysis with Policy Implications for the Logone catchment, Lake Chad Basin.

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The candidate confirms that the work submitted is his own, except where work which has formed part of jointly authored publications has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

Chapter 2

NKIAKA, E. and J. C. LOVETT. Using Q methodology to explore climate change discourse in Cameroun: Progress, challenges and strategies for improving adaptation action. Under review with Regional Environmental Change

Given the difficulty of using scientific evidence to support decision making, the aim of this chapter was to reveal the different discourses surrounding climate change in Cameroun with particular attention to the relationship between science and policy and how it can be applied in hydro – climatic research. After a review of the different methods available for discourse analysis in social sciences, Q methodology was adopted in this study because it had both qualitative and quantitative research techniques which fit well with the candidate's background. The candidate conducted a stakeholder analysis to identify the different participants, carried out the interviews using Q methodology, analysed the data, interpreted the results and wrote the paper. J.C. Lovett gave critical feedback on a draft manuscript.

Chapter 3

NKIAKA, E., N. R. NAWAZ and J. C. LOVETT. 2016. Using self-organizing maps to infill missing data in hydro-meteorological time series from the Logone catchment, Lake Chad basin. Environmental Monitoring and Assessment, 188(7): 1-12.

Quality control of hydro-meteorological data is a pre-requisite in any hydro-climatological studies. Scrutiny of the available data revealed that the datasets were fraught with gaps. To render the datasets useful, the gaps had to be infilled which led to the development of this chapter. The candidate performed the simulations, interpreted the results and wrote the paper. All co-authors commented on a draft manuscript.

Chapter 4

NKIAKA, E., N. R. NAWAZ and J. C. LOVETT. 2017. Analysis of rainfall variability in the Logone catchment, Lake Chad basin. International Journal of Climatology. 37(9): 3553-3564.

The motivation to carry out trend analysis of past rainfall in the catchment was discussed and agreed upon by both the candidate and his supervisors. This was motivated by the fact that, such scientific analyses that place past seasonal and multi-annual precipitation trends in a historical context are necessary for setting up plans for future water resources management. The candidate performed all statistical analyses, interpreted the results and wrote the paper. All co-authors commented on a draft manuscript.

Chapter 5

NKIAKA, E., N. R. NAWAZ and J. C. LOVETT (Accepted). Assessing the reliability and uncertainties of projected changes in precipitation and temperature in CMIP5 models over the Lake Chad basin. International Journal of Climatology.

Given the contrasting results obtained from previous climate models validation studies in the region in general and the absence of such studies in the LCB in particular; the candidate judged it scientifically inappropriate to directly use output from climate models with such contrasting results to project future streamflow in the LCB. The candidate performed all statistical analyses, interpreted the results and wrote the paper.

Chapter 6

NKIAKA, E., N. R. NAWAZ and J. C. LOVETT. 2017. Effect of single and multi-site calibration techniques on hydrological model performance, parameter estimation and predictive uncertainty: A case study in the Logone catchment, Lake Chad basin. Stochastic Environmental Research and Risk Assessment. 32 (6): 1665-1682. DOI:10.1007/s00477-017-1466-0.

In order to understand the hydrological behaviour of the Logone catchment which is an essential step for setting up catchment management plans and simulating the impacts of climate change streamflow, WFDEI was used to drive the SWAT model for an in-depth hydrological study of the Logone catchment. The candidate built, calibrated and validated the model, interpreted the results and wrote the paper. All co-authors commented on a draft manuscript.

Chapter 7

NKIAKA, E., N. R. NAWAZ and J. C. LOVETT. (Accepted). Using standardized indicators to analyse dry/wet conditions and their application for monitoring drought/floods: A study in the Logone catchment, Lake Chad basin, Hydrological Sciences Journal. 62(16): 2720-2736. DOI: 10.1080/02626667.2017.1409427

Given that the inhabitants of the Logone catchment are frequently affected by both drought and flood events, the candidate decided to use standardized indicators of long term rainfall and streamflow data to identify localities prone to droughts/floods. The candidate performed all statistical analyses, interpreted the results and wrote the paper. All co-authors commented on a draft manuscript.

Rationale for Thesis by Alternative format

The decision to present a thesis by publication was taken based on the fact that the candidate intends to continue his career in the academia or related field. Secondly, given the acute shortage of relevant research output from the Central Africa region; it was thought that undertaking a thesis by publication will be the fastest means to disseminate the findings from this work to a wider audience. Four of the six chapters that form the main chapters of the thesis have either been published or accepted for publication in peer review journals while the other two are under review. The aims and objectives of the thesis, research context, rationale for the investigation, strategy employed in the research and its novelty and contribution are presented in chapter one. The main conclusions, policy implications, challenges faced and future research direction are presented in chapter eight.

The direction and vision presented in this thesis was developed by the candidate. All data compilation, analysis, model development and simulations, interpretation of results and writing of manuscripts was carried out by the candidate. The candidate put in considerable amount of time working independently on this thesis and believes that his contribution is extensive enough to meet the criteria for the award of a doctorate degree whilst not underestimating the input from his supervisors.

Acknowledgements

I would like to express my profound gratitude to the Commonwealth Scholarship Commission in the UK for the award of a PhD scholarship to undertake this research at the University of Leeds, and for generously funding my fieldwork to Yaoundé – Cameroun.

The candidate would also like to acknowledge the support and guidance provided by his supervisors throughout the course of this project; Professor Jon Lovett and Dr. Rizwan Nawaz. Valuable contributions from members of the Research Support Group (RSG); Dr. Alan Granger and Dr. Mark Smith are also gratefully acknowledged.

The candidate equally wish to acknowledge the contribution of the School of Geography IT support team led by Qamir Zia and David Appleyard for helping to install all the software used during the thesis.

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I have had the opportunity to work alongside many people during the course of this project especially other PhD students including: Samuel, Arizka, Pip, Usman, Alice, Tariq, Tayo, Eusebio, Marta, Asa, Hifza and Magaly. Their advice, moral support and enthusiasm have been very valuable throughout the past three years.

I will also like to thank my parents Philip and Elizabeth and my siblings Douglas, Dian, Solette and Clovis for their love, unconditional support and fervent prayers throughout these years.

Finally, I wish to dedicate this PhD thesis to Delphine (my wife) and Dellia, Bryant and Blessing (my children).

To God be all the Glory.

Abstract

As a response to the generally perceived divide between the scientists and policy makers in decision making, this thesis seeks to bridge the gap between science and policy by framing the research questions based on the views expressed by policy makers. The thesis attempts to develop an approach for linking biophysical and social sciences research to support the use of scientific knowledge in decision making within the policy arena. Q methodology was used to derive discourses obtained from interviews with a range of stakeholders in government, non-governmental organizations, civil society, and academia in Cameroun. The aim was to reveal the different discourses in climate change in general and on the relationship between science and policy and how it can be applied in hydro – climatic research. Three different discourses emerged from the study. These highlighted concerns that water resources in the Sudano-Sahel zone of the country were vulnerable to climate change owing to past climate variability which could lead to food insecurity in Cameroun. The policy makers expressed the need for the scientists to conduct climate change impact studies on water resources in the region, stating that results from such studies could be useful for developing climate change adaptation policies.

Results from the different homogeneity tests indicated that rainfall was homogenous across the Logone catchment during the period under study (1951 – 2000). A yearly trend analysis revealed the presence of statistically significant negative trends in annual rainfall time series at all stations across the catchment; while trend analysis using a monthly time-step revealed the presence of statistically insignificant positive trends at 32% of rain gauge stations. CMIP5 model validation against historical observations (1980 – 2005) indicated that the models were able to simulate the annual precipitation cycle in the LCB although some models overestimated precipitation during the dry season and underestimated during the rainy season. Furthermore, analysis revealed that by the middle of the century (2050 – 2075), future annual precipitation is projected to increase in the LCB by 2.5% and 5% while monsoon precipitation will decrease by 11.60% and 5.30% respectively under RCP4.5 and RCP8.5 scenarios relative to the historical period. The uncertainty range for annual precipitation is about 12% and 17% for annual and monsoon precipitation respectively under RCP4.5 and RCP8.5 scenarios. Although the uncertainty range for future precipitation projections for most models and the reliability ensemble average (REA) mean lie within the range of natural climate variability, additional analysis are needed for results to be useful for any future planning to enhance water resources management in the study area.

Hydrological modelling in the Logone catchment using the SWAT model indicated that by using different calibration techniques, it is possible to reveal differences in the hydrological behavior in the different parts of the catchment using different parameter values. Results of SPI and SSI analysis showed that both the Sudano and Sahelian zones of the catchment are equally prone to droughts and floods. However, the Sudano zone is more sensitive to drier conditions while the Sahelian zone is sensitive to wetter conditions.

In this thesis, meeting the needs of the policy makers could not be achieved without gaining an understanding of the hydrological behaviour of the study area which is a pre-requisite for any such studies that involves the simulation of climate change impacts on water resources. Therefore, the hydrological modelling exercise and the different statistical analysis carried out in the context of this thesis were all aimed at developing a rich portfolio of peer reviewed information database which the policy makers will find useful to develop relevant climate change adaptation policies and also enhance the management of water resources in the region.

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List of Abbreviations

AI	Artificial Intelligence
ALMIP	AMMA Land surface Model Intercomparison Project
AMMA	African Monsoon Multidisciplinary Analysis
ANN	Artificial Neural Networks
BMU	Best Matching Unit
BR	Buishand Range
CFSR	Climate Forecasting System Reanalysis
CHMs	Catchment Hydrological Models
CIFOR	Centre for International Forestry Research
CMIP5	Climate Model Intercomparison Project phase 5
COMIFAC	“Commission des Forêts d’Afrique Centrale”
CRU	Climate Research Unit
CSO	Civil Society Organization
CV	Coefficient of Variation
DEM	Digital Elevation Model
GCM	Global Circulation Model
GHGs	Green House Gases
GIZ	German Technical Cooperation
ITCZ	Intertropical Convergence Zone
IUCN	International Union for Conservation of Nature
JJAS	June July August September
LCB	Lake Chad Basin
LCBC	Lake Chad Basin Commission
MCS	Mesoscale Convective System
MINADER	Ministry of Agriculture and Rural Development
MINEE	Ministry of Energy and Water Resources
MINEPDED	Ministry of Environment, Sustainable Development and Protection of Nature
MINFOF	Ministry of Forestry and Wildlife
MINRESI	Ministry of Scientific Research and Innovation
MK	Mann-Kendall
MLP	Multilayer Perceptron
NSE	Nash Sutcliff Efficiency
OCHA	United Nations Office for Coordination of Humanitarian Assistance
PCA	Principal Component Analysis
PET	Potential Evapotranspiration
SIEREM	“Système d'Informations Environnementales sur les Ressources en Eau et leur Modélisation”
RCM	Regional Climate Model
RCP	Representative Concentration Pathway
REA	Reliability Ensemble Averaging
SC	Sequential Calibration
SMSC	Simultaneous Multisite Calibration
SMA	Simple Model Averaging
SSC	Single Site Calibration
SNHT	Standard Normal Homogeneity Test
SOMs	Self-Organizing Maps
SPI	Science Policy Interface
SPI	Standardized Precipitation Index
SSI	Standardized Streamflow Index
SST	Sea Surface Temperatures
SWAT	Soil and Water Assessment Tool
TFPW	Trend-Free Pre-Whitening
WFDEI	Watch Forcing Data methodology applied to ERA Interim

Chapter 1: Introduction

1.1 Background

Climate change is expected to cause major alterations to the global hydrological cycle, with substantial socio-economic impacts including increased frequency of extreme events and could exacerbate regional and global water scarcity (Arnell 2004; Coumou and Rahmstorf 2012; Schewe et al. 2014). Although it is a global issue, its impacts will mostly be noticeable at regional and local scale where the majority of the population depend on climate-sensitive sectors like agriculture and water resources for their livelihood (Xu et al. 2012). In cities with poor urban planning, an increase in the frequency of storm events could reduce flood return periods thereby increasing the level of poverty due to repeated shocks from frequent flood events. Such recurrent events could also increase the risk of waterborne disease outbreaks as a result of poor sanitation in some of these areas. Regions at risk are mostly those with high climate variability where it is difficult to distinguish between natural climate dynamism and human induced climate change thereby, making adaptation in those areas to appear very complex due to high uncertainty.

Even so, adapting to a complex issue such as climate change is a multidimensional and dynamic process that requires informed decisions based on the potential impacts of climate change, public perceptions, knowledge and experience (Iyalomhe *et al.* 2013). In turn the science needed to support adaptation policies must understand the link between biophysical and social processes of change in a way that supports the appropriate societal response to change (Weaver *et al.* 2014). Although higher level policy has emphasized the importance of adaptation (Conway 2011), lack of progress in delivering adaptation action may result from the failure to connect climate change science to societal needs (Moss *et al.* 2013).

Therefore, an appropriate "science-policy interface" (SPI) approach is required to translate climate change scenarios into adaptation policies. However, due to the uncertainty, complexity, diverse values and the involvement of many sectors in climate modelling and linking the models to different policies with multiple objectives, it is difficult to communicate modelling results to non-specialists (Young *et al.* 2013; Lovett 2015). Thus, there is "need to understand and analyse all of the interacting drivers and stressors, and identify policies and practices that can simultaneously address more than one issue at a time p 473" (Watson 2005). The aim of SPI is to bridge the gap between the scientific community and policy makers in order to enhance the use of scientific knowledge in decision making (Sarkki *et al.* 2014). The SPI framework does not occur in a vacuum, institutions and their configurations play key roles in contributing towards its implementation (Koetz *et al.* 2012), and different actors express a range of discourses around the complexity of climate change. In fact, the importance of coupling climate impact research information with policy to enhance adaptation especially in Africa has been highlighted (Conway 2011; Jones *et al.* 2015) but climate dynamics in the region are complex.

This is especially the case in the Sudano-Sahel region where the climate is very dynamic and this dynamism has sometimes caused serious alterations to the hydrological cycle resulting in devastating drought or flood events in some years. The most conspicuous example was the widespread Sahelian drought observed in the region from the 1970s to the late 1980s. Such events generally have serious socio-economic impacts on the local population through the loss of livelihoods, given that most of the population depend on rain-fed agriculture and lack adaptive capacity to cope with disasters of such magnitudes. In fact, climate change and other biophysical stressors like land use change already limit freshwater availability and crop yields in many areas of the Sudano-Sahel (Mertz *et al.* 2012; Yengoh 2012). The situation is expected to be exacerbated by additional stressors e.g. poor economic growth and increasing social problems, spread of diseases and a general decay of ecosystems (Bele *et al.* 2011).

One of the most remarkable environmental consequences of the Sahelian droughts was the significant shrinkage in size of Lake Chad which lost over 80% of its surface area reducing from 25,000 km^2 to 1,350 km^2 (Figure 1.1). Despite this remarkable shrinkage in lake size, the Lake Chad Basin (LCB) remains one of the most poorly studied basins in Africa in terms of understanding the hydro-climatic dynamics in the basin and how it will be affected by future climate change. This issue is further exacerbated by acute hydro-meteorological data scarcity in the region as observed by e.g. (Conway *et al.* 2009; Haensler *et al.* 2013; Nkiaka *et al.* 2017a).

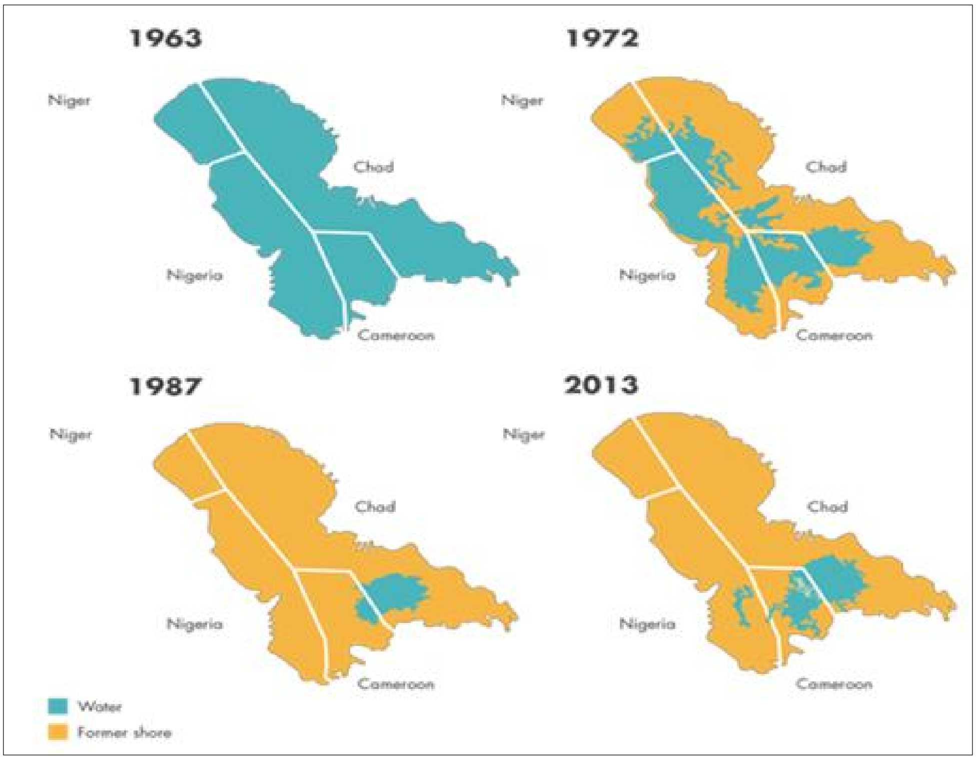

Figure 1.1 Desiccation of Lake Chad 1963 – 2013. Source: UNEP DIVA-GIS

With the progressive recovery of rainfall in the region, widespread floods with considerable socio-economic consequences have been reported recently e.g. the 2012 Sahel floods (Boyd *et al.* 2013). Despite this recovery in rainfall in the LCB; water availability for agriculture, pastoral activities, ecosystem sustainability and contribution as inflow into the lake is still under threat due to the erratic nature of rainfall. In addition, water resources in the LCB are becoming increasingly vulnerable due to rising population resulting in tension amongst water users (Ngatcha 2009). There are also concerns of generalized insecurity in the LCB as the terrorist group "boku haram" continue to wage internal conflict among the member states of the LCB causing internal displacement of people. A study by King and Burnell (2017) has shown that, water stress in some regions especially in the Middle East and Africa, could provide an opportunity for terrorist organizations waging internal conflict to use water as a weapon to drive conflicts that transcend national boundaries. Okpara *et al.* (2015) have reported that, climate-induced water scarcity in the LCB could combine with other human factors such as rising population, poverty and political instability to create the necessary conditions for armed conflict due to water scarcity. Such conflicts resulting from the scarcity of natural capital such as water resources caused by environmental change, internal conflicts and socio-economic challenges could result in mass migration resulting to threats to global security.

The UN Office for the Coordination of Humanitarian Assistance (OCHA) estimate the cost of humanitarian assistance in the LCB to amount to about US$ 1.5 billion in 2017. With these myriad of challenges, there is need for research that can enhance our understanding of the past hydro-climatic dynamics in LCB and how it will be affected by future climate and environmental change.

1.2 Aims and objectives of the thesis

The research lacuna this thesis seek to fill was to bridge the gap between science and policy by framing the research questions based on the views expressed by policy makers in order to link biophysical and social sciences in a way that enhances the use of scientific knowledge (evidence) to support decision making within the policy arena with specific application in hydro-climatic research. Following the supervisor's advice, a research framework matrix was developed in which the research objectives, methods to be used to achieve each objective, data requirements and skills needed to accomplish each of the objectives were elaborated (Appendix C).

The research matrix was formulated on the basis of an overarching, generic, research question (how to bridge the gap between science and policy) that was broken down into a series of sub-questions grouped under the three different themes, each of which formed the basis for a scientific paper. The thesis objectives were framed based on theoretical underpinnings, the challenges of conducting relevant research in the area, and also to cover many areas that the policy makers may find useful for enhancing water resources management and formulating climate change adaptation policies for the region. Based on this research matrix, the following objectives were identified:

1) ***Science-Policy-Interface***

a) The objective was to select the most appropriate scientific method to be used to reveal different discourses in climate change in general and the relationship between science and policy and how it can be applied in hydro – climatic research. The other objectives of the thesis were framed as a direct response to the views expressed by the policy makers in Cameroun under this objective with the hope that, the results obtained from this thesis will contribute to policy development to enhance water resources management in a changing climate in the LCB.

2) Climatology

a) Review the different methods available for infilling missing observations in time series, and select the most effective and less onerous technique for performing this task using hydro-meteorological time series from the study area;

b) Carry out homogeneity tests of available rain gauge data and spatio-temporal analysis of rainfall trends in the catchment over a 50-year period (1951 – 2000);

c) Evaluate the performance of CMIP5 models in simulating historical climate in the LCB (1980-2005) and assess the future projections by mid of the present century (2050 – 2075) using two Representative Concentration Pathways (RCPs 4.5 and 8.5).

3) Hydrology

a) Compile datasets, develop, calibrate and validate a hydrological model of the Logone catchment using the SWAT model with the aim of understanding the hydrological behaviour of the catchment;

b) Analyze the frequency of occurrence and the spatial distribution of droughts and floods prone localities in the catchment using the Standardized Precipitation Index (SPI) and use the SPI and Standardized Streamflow Index (SSI) to assess the relationship between rainfall and streamflow in the Logone catchment.

1.3 Thesis strategy, research context, novelty and contribution

Given the perceived dichotomy between researchers and policy makers in translating scientific research results into policies that can solve societal problems, the strategy adopted in this thesis was to connect biophysical and social science research using the science – policy interface approach. The over-arching goal was for the policy makers to orientate the research direction adopted in this thesis so as to understand their perspective on how they expect climate research to be conducted in a way that the research results can be used for policy development to enhance adaptation. To reduce researcher-bias, Q-methodology was used to interview a range of stakeholders in government, non-governmental organizations, civil society and academia working in the area of climate change in Cameroun.

Based on the results of the Q methodology, the following statements were selected from a list of 36 statements from policy makers obtain by Q methodology. These statements were used to guide the physical sciences that is reported in this thesis.

- All ecological zones in Cameroun are vulnerable to climate change although the Sudano-Sahel and coastal zones remain the most vulnerable.
- Water resources are vulnerable to climate change so have to be managed in a more sustainable and efficient way.
- Climate change adaptation will be enhanced if scientists can translate the uncertainty inherent in climate models output into risk relevant for planning and decision making.
- Climate change impact studies do not offer any opportunities for local adaptation.
- Policy experts find it convenient to work with results from ensemble models because they give a more comprehensive assessment of risk than individual climate models.
- Sufficient technological skills and infrastructure, and consistent observational records, needed for impact studies to enhance policy development are available to climate scientists in Cameroun.
- To enhance decision making, climate and weather forecast information should answer practical questions such as changes to the onset of the rainy season, frequency and duration of dry spells early in the growing season, water availability for irrigation, intensity of extreme weather events etc.

Firstly, the study region and research topic were chosen based on the following statements from policy makers "*all ecological zones in Cameroun are vulnerable to climate change although the Sudano-Sahel and coastal zones remain the most vulnerable*" and "*water resources are vulnerable to climate change so have to be managed in a more sustainable and efficient way*". Based on these two statements, the candidate decided to assess water resources variability in the Sudano-Sahel region with particular attention to the LCB.

However, in most hydro-climatic research studies, quality control of the existing data to be used for water resources assessment has to be carried out to ensure that gaps in data can be accounted for. This is because, the presence of gaps in a hydro-meteorological time series can hinder the calculation of important statistical parameters as data patterns maybe hidden. This can compromise their use for water resources planning as it increases the level of uncertainty in the datasets (Ng *et al.* 2009; Campozano *et al.* 2015). Quality control of existing data revealed that the available time series were fraught with gaps thus raising issues of uncertainty. The policy makers pointed out that "*climate change adaptation will be enhanced if scientists can translate the uncertainty inherent in climate models output into risk relevant for planning and decision making*".

To reduce the uncertainty in the datasets used in the different scientific analyses carried out this thesis, the gaps in the datasets had to be infilled.

After a review of the existing methods available for infilling missing observations in hydro-meteorological time series, an artificial intelligence technique was selected owing to its ability to model complex non-linear systems without prior knowledge of the system (Mwale *et al.* 2012). Within the artificial intelligence family, previous studies showed that Self-Organizing Maps (SOMs) outperformed other commonly used artificial intelligence techniques such as Multilayer Perceptron (MLP) based on its robustness, easy implementation and its extensive application for infilling missing observations in hydrology (Adeloye *et al.* 2012; Mwale *et al.* 2014; Kim *et al.* 2015). From the multiple advantages presented by SOMs, the method was adopted to infill gaps in hydro-meteorological time series in this thesis which is the first application of the method in the region.

Meanwhile, the sustainable management of water resources within a given hydrographic unit requires a thorough understanding of the past climate variability occurring locally or regionally. Although the reality of managing water resources under climate change may require water managers to go beyond traditional methods based on using historical rainfall and streamflow data (Borgomeo *et al.* 2015), the increasing scientific and humanitarian need to place past seasonal and multi-annual precipitation trends in a historical context have been recognized (Funk *et al.* 2015). Contrary to the following statement that "c*limate change impact studies do not offer any opportunities for local adaptation*", the policy makers agreed that "c*limate change impact studies can offer opportunities for local adaptation*". In fact, the importance of impact studies to enhance adaptation is evidence by the increasing number of studies assessing past climate variability and its impact on water resources availability, biodiversity and agricultural production (Conway *et al.* 2009; Nilsson *et al.* 2016; Xu *et al.* 2017). For example, the study of Conway *et al.* (2009) revealed that rainfall was highly variable across Africa both in space and time and this spatio-temporal variability has severe implications for the management of water resources in the continent.

Since the Sahelian droughts of 1970s and 1980s, the region has received much attention from the scientific community and many international coordinated research activities such as African Monsoon Multidisciplinary Analysis (AMMA) and AMMA Land surface Model Intercomparison Project (ALMIP) have been conducted in the region. Through such coordinated research initiatives, the rainfall regimes of most basins in West Africa and the Horn of Africa have been studied (Lebel and Ali 2009; Jury 2010; Williams *et al.* 2012; Panthou *et al.* 2014). However the LCB remains largely under-represented in such collaborative research efforts albeit the studies of (Niel *et al.* 2005; Okonkwo *et al.* 2013). To narrow this research gap in the region, the strategy adopted in this thesis was to carry out trend analysis of historical rainfall from rain gauge stations in the basin using different statistical techniques. Analysis were limited only to the Logone catchment due to the scarcity of rain gauge data over the entire LCB. Assessing rainfall variability will give an indication of the impacts climate variability in the catchment and the opportunity to design local adaptation strategies as requested by the policy makers.

Given the increasing awareness of climate change impacts on water resources, many studies are now using output from global climate models (GCMs) and regional climate models (RCMs) to drive hydrological models in order to project the impacts of climate change on water resources at different spatial scales ranging from catchment to global (Schewe *et al.* 2014; Thompson *et al.* 2016; Shrestha *et al.* 2017). The level of uncertainty in the hydrological model outputs from such studies may then be converted to risk that can be used for adaptation planning. Based on this increasing awareness on the use of ensemble GCMs and the importance of uncertainty assessment, the policy makers expressed the following statements "*climate change adaptation will be enhanced if scientists can translate the uncertainty inherent in climate models output into risk relevant for planning and decision making*" and "*policy experts find it convenient to work with results from ensemble models because they give a more comprehensive assessment of risk than individual climate models*". However, to be able to use outputs from GCMs or RCMs for future streamflow projections, their ability to simulate the present-day and future climate has to be assessed against observed climate data to be able to judge individual or ensemble model performance.

Furthermore, results from many GCMs and RCMs used to project future precipitation over the Central African region have shown contradictory results with some models projecting an increase in future precipitation while others project a decrease. Haensler *et al.* (2013) evaluated an ensemble of climate models intercomparison project (CMIP3/5) and RCMs in Central Africa and concluded that no significant changes in precipitation may be observed in the region by the end of the present century under two representative concentration pathways (RCPs) RCPs 4.5 and 8.5. In a separate study, Aloysius *et al.* (2016), reported that CMIP5 models were projecting an increase in future precipitation by the end of the present century in the area of their study domain covering the LCB under RCPs 4.5 and 8.5. Meanwhile, in a different study using the regional climate model REMO forced by two GCMs (Europe wide Consortium Earth System Model (EC-Earth) and Max-Planck Institute Earth System (MPI-ESM)), Fotso-Nguemo *et al.* (2017), reported that future precipitation over the area of their study domain covering the LCB will decrease by the end of the present century under RCPs 4.5 and 8.5. Results from those studies are quite contrasting and cannot be directly used for any impact studies in the region, hence the necessity to assess the performance of CMIP5 models in simulating historical climate in the LCB.

To achieve this, the approach adopted in this thesis was first to validate the CMIP5 models against present-day climate over the hydrologically active basin area of LCB. The models were then used to project future precipitation and average surface temperature in the basin with relative to the historical period. Unlike statistical analysis of historical rainfall in the previous section, the present analyses were carried out for the active LCB and at the level of each ecological zone (sudano, semi-arid and arid) that make-up the active basin area. Thus evaluating the climate models using an ensemble approach and assessing the level of uncertainty in the models output using the reliability ensemble averaging (REA) technique directly addresses the issues of uncertainty and increased confidence using ensemble models as highlighted by the policy makers.

Chapter six and seven were developed based on the following statement from policy makers "*water resources are vulnerable to climate change so have to be managed in a more sustainable and efficient way* and *to enhance decision making, climate and weather forecast information should answer practical questions such as changes to the onset of the rainy season, frequency and duration of dry spells early in the growing season, water availability for irrigation, intensity of extreme weather events etc*". To address these issues hydrological models have been recognized as important tools for water resources management under different land use management and climate change scenarios (Mango *et al.* 2011; Aich *et al.* 2015; Akpoti *et al.* 2016). Considering also that streamflow represents the integral response of a system/catchment to climate forcing; it is often used by researchers to assess the impacts of climate change on water resources (Nawaz *et al.* 2010; Xu *et al.* 2012; Shrestha *et al.* 2017). Despite the significant changes observed in the hydrological dynamics of the LCB over the past decades, literature on hydrological modelling in this basin and its sub-basins is scarce. Due to this scarcity, the hydrological behaviour of the LCB and its sub-basins is poorly understood among the scientific community which is a hindrance to efficient water resources management in the study area. The active LCB has an estimated surface area of 1.1x10^6 km^2 (approximately the size of UK, Germany and Spain combined together) and covers different ecological zones with a high spatio-temporal variability in rainfall as observed in the Logone catchment (Nkiaka *et al.* 2017b). Therefore, conducting basin-wide hydrological research and generalizing results from such studies as representative of the whole active basin may not be useful for effective planning of water resources especially in the event of prevailing extreme hydro-meteorological conditions such as droughts and floods at sub-basin level.

Therefore, the strategy adopted in this thesis was to reduce the spatial scale of the hydrological modelling investigation to sub-basin scale. Considering the numerous sub-basins that make up the active LCB, the Logone was selected as the study catchment in this thesis. This was motivated by the fact that: (i) the catchment covers two different ecological zones (sudano and semi-arid); (ii) it contributes significant volume of inflows into Lake Chad; (iii) it is a transboundary catchment shared by three riparian countries (Cameroun, Chad and the Central Africa Republic); and (iv) it has very rich extensive wetlands which contribute significantly to the livelihood of the local population.

For hydrological analysis, the Soil and Water Assessment Tool (SWAT) was used in this thesis. The model was selected because it is a versatile tool capable of simulating hydrological processes, land use changes, water use management, water quality and quantity assessments, climate change impact assessment at catchment scale and has extensively been used in Africa (Gassman *et al.* 2007; Mango *et al.* 2011; Faramarzi *et al.* 2013; Chaibou Begou *et al.* 2016). Secondly, it is an open source software that can easily be coupled with other open source GIS interfaces e.g. MapWindow (MW) and Quantum GIS (QGIS). Therefore, the hydrological modelling technique used in this thesis can easily be repeated by researchers from the region who do not have access to licensed GIS packages such as ArcGIS used to couple SWAT in this study.

The consequences of climate change on future water resources availability in a given region or catchment, can also be evaluated by assessing the relationship between climate variability and water resources taken into account different hydrological systems such as streamflow (Lorenzo-Lacruz *et al.* 2010; López-Moreno *et al.* 2013). Typically this can be done by using multiple standardized indicators such as the standardized precipitation index (SPI) and standardized streamflow index (SSI) (Lorenzo-Lacruz *et al.* 2010; López-Moreno *et al.* 2013). Such studies can give an indication of how meteorological droughts (characterized by the absence of rainfall) are propagated to hydrological droughts (characterized by a decrease in streamflow) (Lorenzo-Lacruz *et al.* 2010; López-Moreno *et al.* 2013; Barker 2016). While SPI analysis could be used to identify flood and drought prone areas in the catchment; the relationship between SPI and SSI can be used to enhance the understanding of the hydrological behaviour of a catchments which is important for developing water management policies. This relationship could also be used to understand catchment response time which is equally important for preparing disaster relief operations.

Furthermore, the characteristics of dryness and wetness conditions using multiple standardized indicators such as SPI and SSI obtained from long term data may be invaluable for establishing an effective and comprehensive drought/flood monitoring system. Although the number of rain gauge stations may be limited for a comprehensive assessment of vulnerable zones; rain gauges are mostly located in habitable areas to facilitate the collection of readings. Therefore, even with a limited number of rain gauges, it may still be possible to identify droughts/floods prone areas using rain gauge data. Such studies have been carried out in many river basins in the Sudano-Sahel region (Roudier and Mahe 2010; Traore and Owiyo 2013; Louvet *et al.* 2016) but the LCB remains largely understudied except the few studies conducted by (Okonkwo *et al.* 2013; Ndehedehe *et al.* 2016). To reduce this research gap, standardized indicators of rainfall and streamflow from different stations across the Logone catchment were used in this thesis to study the spatial distribution of localities that are prone to floods/droughts in the Logone catchment.

Therefore, hydrological modelling and hydrological analysis using different standardized indicators can help policy makers to efficiently manage water, identify droughts and floods prone zones and monitor drought events in the study area.

Another important statement raised by the policy makers was the absence of "*sufficient technological skills and infrastructure, and consistent observational records, needed for impact studies*". To overcome the challenge of meteorological data scarcity, this thesis proposes the use of reanalysis datasets as input for hydrological modelling in the region. Reanalysis datasets have been used to drive hydrological models in other data-scarce locations (Dile and Srinivasan 2014; Krogh *et al.* 2015; Monteiro *et al.* 2015). In fact, reanalysis products offer a unique opportunity to enhance our understanding of the hydrological functioning of catchments in data-scarce regions and for conducting climate change impact studies and developing adaptation strategies in such areas (Hartmann and Buchanan 2014; Fernandez *et al.* 2015; Aich *et al.* 2016).

Given that the performance of reanalysis datasets in hydrological modelling is mostly determined by the quality of the precipitation estimates, the correlation between rain gauge data and estimates from reanalysis has to be assessed before the latter can be used as input for hydrological modelling (Krogh *et al.* 2015; Monteiro *et al.* 2015; Essou *et al.* 2016). This requirement was fulfilled in this thesis by validating monthly precipitation estimates from two reanalysis datasets; Climate Forecasting System Reanalysis (CFSR) and ERA-Interim with rainfall data from 25 rain gauge stations unevenly distributed across the Logone catchment. The results of the study are presented in Appendix A of this thesis. Furthermore, since there are many reanalysis datasets that can be used for hydrological modelling; in this thesis two reanalysis datasets (CFSR and ERA-Interim) and a bias corrected reanalysis dataset (WFDEI) were used to drive the SWAT model. The aim was to compare which of the datasets could adequately simulate streamflow in the Logone River. The results of the study are also presented in Appendix B of this thesis. The dataset with the best streamflow simulation results was subsequently used for detailed hydrological modelling to understand the hydrological behaviour of the Logone catchment. By using reanalysis datasets for hydrological modelling, this thesis directly addresses the issue of consistent observational datasets needed for impact studies as highlighted by policy makers.

1.4 Target audience for the research

Generally the Central Africa region is faced with many challenges in the water and climate science sectors which may constraint the region's ability to cope with emerging challenges posed by climate change. The most remarkable include:

- There are very few trained scientists in the water and climate science sector;
- Generalized absence of electronic science infrastructure in most universities and only few research institutions that can conduct relevant research exist in the region;
- Lack of meteorological data; at required time and spatial scale needed for conducting impact research and the available data is not digitized;
- The region has the lowest number of published research articles in climate change, land use change, agriculture and water resources research compared to West, East and Southern Africa (Haensler *et al.* 2013).

This research seeks to fill this knowledge gap in the region in general and the LCB in particular by providing robust and reliable scientific information on hydro-climatic variability in the basin. This PhD research is setting the foundation in hydro-climatic research in the region with the hope that future research on the hydrological modelling to enhance the impacts of climate change on water resources in the region in general and the LCB in particular will build from the results presented in this thesis. Therefore, the target audience for this research include:

i. The staff of the Lake Chad basin commission (LCBC) which is the statutory body mandated by member states of the commission to conduct relevant research in the basin;
ii. Another important target group is the scientific community (universities and research institutions) both within and outside the Central Africa region;
iii. The research presented in this thesis is also targeted to reach policy makers in the different member states of the LCBC.
iv. Another group of target users include International Development Agencies e.g. the Department for International Development (DFID) through the Future Climate for Africa (FCFA), Science for Humanitarian Emergencies and Resilience (SHEAR) research programme, the German Technical Cooperation etc.
v. Other potential users are international humanitarian relief agencies such as the United Nations Office for the Coordination of Humanitarian Assistance (OCHA) and Aid Agencies working in the sudano-sahel the region.

1.5 Thesis outline

Chapter one of this thesis presents the global context of the research, the rationale of the investigation, the thesis objectives, its novelty, contribution and the strategy employed in the development of the various chapters.

Chapter two focuses on the science-policy interface whereby Q-methodology was used to elucidate stakeholder perspectives on climate change discourse in Cameroun and to orientate the objectives of the thesis so that they align with the views and aspirations of the stakeholders.

In chapter three, a brief review of the various methods used for infilling missing data in hydro-meteorological time series was conducted with particular focus on artificial intelligence (AI) techniques. Among the AI techniques, SOMs was selected owing to its multiple advantages.

Chapter four presents the results of trend analysis of past rainfall time series from the study area.

Chapter five presents the results of the validation of CMIP5 models for precipitation and average surface temperature for the LCB using the reliability ensemble averaging (REA) technique. The models were then used to project future precipitation and average surface temperature in the LCB with special attention given to the quantification of uncertainties in the future projections.

Following from the results presented in Appendix B, WFDEI was used as the main dataset to conduct a detailed hydrological analysis of the Logone catchment and the results are presented in the chapter six.

In chapter seven, standardized indicators were used to identify drought/flood prone areas in the catchment using past records of rainfall and streamflow and also to establish the relationship between rainfall and streamflow.

The main conclusions of the thesis are elaborated in chapter eight.

Appendix A presents the results of validating precipitation estimates from global reanalysis datasets with rainfall measurements in the study area and finally in Appendix B, reports on the use of different reanalysis dataset to simulate streamflow in the Logone catchment and also the impact of reanalysis spatial resolution on streamflow simulation.

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Chapter 2 Science – Policy Interface

This chapter is based on the manuscript:

NKIAKA, E. and J. C. LOVETT. Using Q methodology to explore climate change discourse in Cameroun: Progress, challenges and strategies for improving adaptation action. Under review with Regional Environmental Change

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Abstract

Research conducted in developing countries often does not contribute to policy development that can solve societal problems as the research does not provide the information needed by policy makers. In this study, Q methodology was used to explore climate change discourses among policy makers in Cameroun. The views expressed by policy makers resolved into three discourses. The first discourse focused on vulnerability and the impact of climate change. Policy makers considered that water resources and agriculture were particularly vulnerable to climate change and this could lead to food insecurity in the country. They also identified the Sudano-Sahel and the coastal regions as the most vulnerable to climate change. The second discourse focused on adaptation planning and identified political leadership as crucially important for driving the adaptation action. The third discourse centred on policy incentives and identified key areas where new policies and institutions need to be put in place to enable the country cope with emergent challenges pose by climate change. Overall the policy makers were of the opinion that, despite uncertainties in climate models, this should not obstruct the use of these models to conduct relevant impact research especially in the area of water resources and agriculture. However, they cautioned that for the results to be useful, scientists need to translate the uncertainties in climate models output into risk and provide options relevant for planning and decision making.

2.1 Introduction

Adapting to a complex issue such as climate change is a multidimensional and dynamic process that requires informed decisions based on the potential impacts of climate change, public perceptions, knowledge and experience (Iyalomhe *et al.* 2013) to understand the link between biophysical and social processes of change in a way that supports societal response to change (Weaver *et al.* 2014). Although higher level policy has emphasized the importance of adaptation (Conway 2011), lack of progress in delivering adaptation action may result from failure to connect climate change science to societal needs (Moss *et al.* 2013).

An appropriate "science-policy interface" (SPI) approach is required to translate climate change scenarios into adaptation policies. However, uncertainty, complexity, diverse values and the involvement of many sectors in climate modelling and linking the models to different policies with multiple objectives makes it difficult to communicate modelling results to non-specialists (Young *et al.* 2013; Lovett 2015). Therefore, there is "need to understand and analyse all of the interacting drivers and stressors, and identify policies and practices that can simultaneously address more than one issue at a time p 473" (Watson 2005). The aim of SPI is to bridge the gap between the scientific community and policy makers in order to enhance the use of scientific knowledge in decision making (Sarkki *et al.* 2014). The SPI framework does not occur in a vacuum, institutions and their configurations play key roles in contributing towards its implementation (Koetz *et al.* 2012), and different actors express a range of discourses around the complexity of climate change, particularly in area with high climate variability.

The importance of coupling climate impact research information with policy to enhance adaptation in Africa has been highlighted (Conway 2011; Jones *et al.* 2015) but climate dynamics are complex. For example the Sudano-Sahel zone of Cameroun has witnessed high climate variability over the past several decades (Nkiaka *et al.* 2017), making it difficult to distinguish between natural dynamism and human induced climate change. Climate change and other stressors already limit freshwater availability and crop yields in many areas of Cameroun, especially in the Sudano-Sahel (Molua 2007; Yengoh 2012). The situation is expected to be exacerbated by additional stressors such as rapid land degradation, high population growth rate, poor economic growth and increasing social problems, spread of diseases and a general decay of ecosystems (Bele *et al.* 2011). Terrorist activities in the Lake Chad basin are also resulting in the internal displacement of people; and influx of refugees from neighbouring countries into the region may further strain the socio-ecological system.

Climate change affects many different economic and policy sectors, so a wide range of institutions are involved in adaptation decisions. In designing scientific research of relevance to adaptation, a first step is to explore what policy makers think and which kind of scientific information they consider to be a priority for policy development. This is especially so given the rapid rate at which new and detailed scientific information on climate change is being produced. The way stakeholders understand issues related to climate change and assimilate information will shape and determine their actions towards designing and implementing policies that can enhance adaptation, and at the same time fit with the sustainable development goals (SDGs) of the United Nations (UN 2015). The nature of this understanding is a key knowledge gap in Central Africa in general and Cameroun in particular.

The main objective of this study was to use Q methodology to explore the climate change discourses among policy makers in Cameroun in order to guide research directions to focus on what is relevant for them. This is also important for development partners because it will help them to know which sectors the policy makers consider to be important so that relevant funds can be channelled to enhance adaptation in those sectors.

2.2 Methodology

2.2.1 Study area

The Republic of Cameroun (Figure 2.1) is a bilingual (English and French) and democratic country in Central Africa situated in the Gulf of Guinea between West and Central Africa. It is bounded on the West by Nigeria, on the North East by Chad, on the East by Central Africa Republic and by Gabon, Equatorial Guinea, and Republic of Congo in the South. The country has about 420km coastline stretching from the South West to the south region passing through the Littoral; also bordered by Lake Chad in the Extreme North and is part of the Congo basin which is the second largest rain forest in the world (Bele *et al.* 2011; Tiani *et al.* 2015). The country is also part of the Niger and Lake Chad basins and has total surface area of about 475,650 km^2 (Alemagi 2011).

The country’s proximity to the sea and topography gives it a varied climate with wide differences in rainfall and vegetation. Monsoon circulation is the main source of rainfall in Cameroun with the coastal areas receiving the highest amount of rainfall where sometimes annual totals reach 3850mm. Meanwhile, in the northern Sudano-Sudano part of the country, rainfall varies between 600 – 1500 mm (Nkiaka *et al.* 2017). The country has a population of about 20 million people and is classified as a low middle income country (Water 2009). There are four main agro-ecological zones in Cameroun (Sudano-Sahel, Savanna, Coastal and Maritime, and Forest) (Molua and Lambi 2006). Agriculture is the backbone of country's economy, accounting for about 41% of Gross Domestic Product (GDP) and employing more than 55% of the workforce (WRI 2007).

Figure 2.1 Map of Africa showing the location of Cameroun

2.2.2 Identification of participants/stakeholders

The method of stakeholder identification proposed by Ballejos and Montagna (2008) was adopted in this study. It offers a systematic approach for identifying participants using different dimensions and criteria, as well as stakeholder roles, interests and influence and has been used to identify stakeholder participation in climate change related studies (André *et al.* 2012). The method uses a five-step procedure which includes: (1) specify stakeholder types, (2) specify stakeholder roles, (3) select stakeholders, (4) associate stakeholders with roles and (5) analyse influence and interest.

In the first step, a broad inventory of potential stakeholders was carried out using four criteria (a) function, (b) geographical location, (c) knowledge and abilities, and (d) hierarchical level. The function criterion refers to stakeholders that are formally responsible for climate change issues in Cameroun. These include government officials who prepare and implement, policy, legal and regulatory decisions in the area of environment and climate change. The institutions where these officials work include the Ministry of Environment, Sustainable Development and Protection of Nature (MINEPDED), Ministry of Energy and Water Resources (MINEE), Ministry of Agriculture and Rural Development (MINADER), the Ministry of Forestry and Wildlife (MINFOF), and Ministry of Scientific Research and Innovation (MINRESI).

Table 2.1 Classification of stakeholders according role and criteria

Stakeholder role	Stakeholder/ Organisation	Definition	Criteria
Supporters	IUCN	Stakeholders who prepare and support adaptation through advice and guidance and evaluation of adaptation	Functional
Providers	Universities, Ministry of Scientific Research and Innovation, Consultants	Stakeholders who provide research, knowledge and information on climate change causes, impacts, vulnerabilities and adaptation	Knowledge
Disseminators	NGOs, Media	Those who disseminate climate knowledge and information	Knowledge
Funders/Sponsors	CSC, JICA, EU, (Not included in the study)	Funders of adaptation measures and climate related research	Functional
Experts	Ministry of Environment, Sustainable Development and Protection of Nature	Local experts on climate systems, and impacts of climate change and technical adaptation solutions	Functional/Knowledge/Hierarchical
Implementers	Ministry of Energy and Water Resources, Ministry of Agriculture and Rural Development, and the Ministry of Forestry and Wildlife. NGOs	Stakeholders responsible for implementing adaptation measures	Functional/Geographical
Coordinators	Administrators, Mayors (Not included in the study)	Stakeholders that coordinate other actors, research or adaptation strategies in general	Functional
Responsible and/or decision-makers	Ministry of Environment, Sustainable Development and Protection of Nature	Stakeholders that have an explicit responsibility for climate policies, climate adaptation or activities that are affected by climate change	Functional/Hierarchical
Regulators	Ministry of Environment, Sustainable Development and Protection of Nature and National Assembly (Not included in the study)	Initiators of new legislation, as well as changes in norms and standards	Functional/Hierarchical
Affected	Local communities (Not included in the study)	Stakeholders exposed and/or vulnerable to climate impacts or the responses	Geographical/ Knowledge

Table adapted from (André *et al.*, 2012)

The geographical location criterion complements the function criterion as it is made up of decentralized services responsible for implementing decisions at local level. This criterion was not used in this study because the study was conducted at the national level. The knowledge and abilities criterion refers to stakeholders who have relevant knowledge and skills related to climate change. They include technical ministries, universities, research institutions, consultants, NGOs and international organizations. The hierarchical criterion consists of influential stakeholders who can indirectly facilitate communication between government and the local communities. They include parliamentarians and influential politicians (not included in this study). Table 2.1 gives a classification of stakeholders according roles and criteria outlined above. From the table it can be observed that some stakeholders have multiple roles and the same roles are represented by many stakeholders.

Apart from the method described above, snowball sampling technique was also used to identify other stakeholders who were interviewed during the fieldwork. Contacts were established between the researcher and permanent secretaries in the earmarked ministries/institutions. The permanent secretaries then established the link between the researcher and the different directors and staffs in the ministries/institutions responsible for the different policy aspects of climate change such as impacts, mitigation and adaptation.

Table 2.2 Distribution grid for Q-sort

Most disagree				**Neutral**				**Most agree**
-4	**-3**	**-2**	**-1**	**0**	**+1**	**+2**	**+3**	**+4**

2.2.3 Implementation of Q – Methodology

Developed by Stephenson (1953), Q methodology is one of the most widely used methods of discourse analysis in social science research in general and environmental studies in particular.

It has been applied to scrutinize a wide range of environmental issues; e.g. Howard *et al.* (2016) used the method to explore the plural notions of fairness in Fairtrade Carbon Projects, Lansing (2013) applied the method to analyse stakeholder perspectives in land use change in Costa Rica, Albizua and Zografos (2014) applied Q methodology to elucidate on a values-based approach to vulnerability and adaptation to climate change, Frantzi *et al.* (2009) applied the method to explore discourses on international environmental regime effectiveness.

The popularity of Q methodology is due to the fact it offers the users both qualitative and quantitative research techniques. Quantitatively, it explores the "discourse" of participants concerning a particular theme under study through data collection and analysis using statistical and mathematical techniques; while qualitatively, it extracts qualitative, subjective data (information) from the participants about their views (Frantzi *et al.* 2009). In contrast to standard survey methods, the objective of Q methodology is not to establish patterns across individual characteristics such as age, gender and class but instead to look at patterns within and across individuals by focusing on their discursive understanding of a particular issue. One of the main advantages of this method is that the statements used in the Q-sort are generated by the participants at an earlier stage of the research and it allows these various statements to be manipulated through ranking by the respondents so that the researcher has limited influence on the outcome of the results (Cuppen *et al.* 2010). Furthermore, it does not require a large population sample to produce statistically valid results (Frantzi *et al.* 2009). The implementation of the method requires five distinct stages after identification of the theme to be investigated.

After identifying the participants, the next step was to generate the concourse (set of statements) broadly representative of opinions surrounding a particular issue. This was achieved through semi-structured interviews open ended interviews. This first phase of the fieldwork was carried out in Yaoundé-Cameroun from November 2nd to December 31st 2015. During this phase, an initial set of 165 statements was generated from 20 face to face interviews, complemented by information from relevant policy documents. The participants interviewed were stakeholders actively involved in climate change issues at different capacities and most of them were from government ministries.

The interview questions were framed to cover a wide range of issues relevant for understanding the climate change discourse in Cameroun. The main sectors included agriculture and food security, water resources, energy, forestry, institutional and political economy, climate services, education and training and infrastructural development. The interviews were conducted in both English and French depending on the preferred language of the interviewee. The interviews generally lasted for more than one hour and all interviewees were asked the same questions which were audio recorded and later transcribed. It was observed that there were some slight variations in the responses of the interviewees depending on the sector of activity that of each stakeholder was involved with. Stakeholders in the agriculture sector were more confident responding to questions in that sector likewise those in the forestry, water resources and energy. Officials in the Ministry of Environment were able to articulate their responses with more confidence irrespective of the sector. The main obstacle faced was false appointments especially from senior government officials who could keep the candidate waiting for several hours only to cancel the interview for that day and reschedule it for another day.

In the second step of Q methodology implementation, the statements were then reduced by filtering, while still conserving the diversity of viewpoints, claims and ideas of the stakeholders who generated the statements (Cuppen *et al.* 2010). Using our theoretical underpinnings, the statements were filtered to represent four sensitive sectors that are vital to the country's economy and the socio-economic wellbeing of the population (agriculture, water resources, energy and forestry) grouped under the themes vulnerability, impact, mitigation and adaptation and institutional structures. Conway and Mustelin (2014) have stressed the role of institutions in the design, implementation and coordination of multilevel and multisector activities to enhance climate change adaptation. Using this approach, the statements were reduced to 36 to create the Q-sort or (Q sample). According to Van Exel and De Graaf (2005) the sample normally should be between 40 and 60 statements, however, Barry and Proops (1999) argue that a Q-sort of 36 statements is more easily manageable for both researchers and respondents.

The second phase of the fieldwork was carried out from October 24th to December 23rd 2016. The Q-sort was given purposively to the participants (stakeholders) who were interviewed during the first phase of the fieldwork. In situations where the expert interviewed during the first phase was not available, the person was replaced by a colleague working in the same service at equivalent capacity. During the second phase of the fieldwork, the number of participants increased because some participants who declined to be interviewed during the first phase in some government ministries were encouraged to take part by officials from other ministries taking part in the study. This was possible due to the network established by the researcher. The number of participants also increased in the MINEPDED and NGOs because some key participants who were away during the first phase had returned.

The statements were prepared as a pack of cards and presented to participants in both English and French depending on his/her language preference and participants were asked to read all the statements in the first instance, followed by separating the statements into two packs "agree" and "disagree". They were then asked to rank the statements according to individual perceived importance of each on a Likert scale from strongest agreement to strongest disagreement on a 9-column forced normal distribution grid (Table 2.2). Participants were asked to rank the statements based on their personal viewpoints on the basis that they deal with issues related to climate change. In total 27 participants took part in this exercise.

The Q set was analysed using the PQMethod software, version (2.35). A 27 x 27 correlation matrix was produced from the Q-sort and subjected to factor analysis using Principal Component Analysis (PCA). The results of the PCA are a number of factors with each representing a group of respondents who share similar viewpoints in relation to the statements used in the study. The PCA analysis identified eight groups or discourses which were then rotated using the Varimax method to extract fewer but more meaningful discourses.

2.3 Results and Discussion

Three discourses were extracted following rotation using the Varimax method. Different criteria were used to determine the number of factors that comprise the (discourses): (i) the Kaiser-Guttman criterion which states that a factor should have an eigen value (EV) >1; (ii) select only factors that have two or more sorts loading significantly on that factor alone (Watts and Stenner 2012). The significance is calculated using the expression $2.58(1/\sqrt{N})$, where N is the number of statements in the Q-sort; (iii) the third criterion is the Humphrey's rule which states that a "factor is significant if the cross-product of its two highest loadings (ignoring the sign) exceeds twice the standard error" (Brown 1980). The standard error is calculated as $(1/\sqrt{N})$, where N is the number of statements. A number of different outputs were compared before selecting the three-factor solution which explained 59% of the study variance. Study variance above 35% is ordinarily considered to be a sound solution in factor analysis according to Kline (2014). The study variance obtained in this study is higher compared to previous studies (Frantzi *et al.* 2009; Davies *et al.* 2016; Howard *et al.* 2016). This high variance can be attributed to the fact that, most of the participants were able to identify positively with viewpoints expressed in each of the discourses. The statement score for each discourse are presented in Table 2.3.

Table 2.3 Statement score for each discourse (factor array)

Statements	**No**	**Discourse**		
		A	**B**	**C**
Climate change adaptation must take into account the complexity of societal processes and actors.	1	2	4	1
One impediment to policy development is that the results of climate change impact studies are not communicated to decision makers.	2	1	0	-1
Solving immediate development challenges is more important than climate change which is an issue for future generations.	3	-2	-3	-2
Climate change adaptation will be enhanced if scientists can translate the uncertainty inherent in climate models output into risk relevant for planning and decision making.	4	0	3	-1
Climate change impact studies do not offer any opportunities for local adaptation.	5	-1	-2	-3
Water resources are vulnerable to climate change so have to be managed in a more sustainable and efficient way.	6	4	1	4
Some REDD projects at local level fail not because the local communities are left out during project inception and execution but due to lack of transparency in project management.	7	0	2	1
Modern farming techniques like dissolving fertilizer in water to reduce wastage and improved crop variety may increase the adaptive capacity of farmers.	8	0	-1	0
Mainstreaming climate change adaptation into existing policies is better than developing standalone policies.	9	1	2	0
The tree planting policy under implementation to mitigate the consequences of climate change should be abandoned because it offers no immediate benefits to the local population.	10	-3	-3	-3
Developing hydroelectric dams across the country will significantly reduce the Cameroun's carbon footprint.	11	-1	2	-1
It is urgent for government to implement policies that reduce energy wastage in public buildings and encourage waste recycling.	12	2	0	3
Food security in Cameroun will not be threatened by climate change.	13	-2	-4	-4
Government should invest in public transportation systems in urban areas and setup an agency to monitor carbon use efficiency of imported cars.	14	-1	1	0
Forest conservation and management represent an effective way to mitigate climate change and reduce the vulnerability of water resources.	15	4	1	2
Most adaptation projects at local level fail because the beneficiary population is not consulted prior to project conception and execution.	16	0	0	3
Even if women had access to land for agriculture, this may not increase their adaptive capacity because they lack basic farm inputs (e.g fertilizers).	17	0	-1	1
Policy makers and the climate science community need to engage in a more interactive dialogue so that both producers and users of scientific information can clearly state their needs.	18	0	2	2
Mainstreaming climate change adaptation into national development planning will receive additional impetus if it is backed by a strong political leadership (Head of State) together with key government ministries responsible for finance and development planning.	19	0	3	-1
Policy experts find it convenient to work with results from ensemble models because they give a more comprehensive assessment of risk than individual climate models.	20	-2	-1	0
Uncertainty about risks and impacts of climate change should be an excuse for inaction by the government.	21	-4	-2	-3

The upgrading of drainage infrastructure to reduce flooding is just solving an existing problem and not a climate change adaptation strategy.	22	0	0	0
Individual households can also adapt to climate change through efficient energy and water use at homes.	23	1	1	1
Lack of basic infrastructure in rural areas (e.g. pipe borne water, farm-to-market roads, hospitals etc.) increase the vulnerability of the rural population to climate change.	25	1	0	2
Diversification of livelihood activities will not enhance the adaptive capacities of the local population.	26	-3	-2	-1
The government should put in place an insurance scheme to compensate victims of climate induced disasters	27	3	-1	0
There is no need to include climate change education in academic programs because the media will educate everybody.	28	-1	-1	-4
Land grabbing from local communities by multi-national companies increase their vulnerability to climate change and compromise the opportunities offered by carbon credits from forest conservation.	29	2	0	0
Developing water harvesting and storage infrastructure will enhance the adaptive capacity of the local population in drought prone areas.	30	3	0	3
Developing climate change adaptation policies using the multi-sectoral approach present better options for adaptation than sectoral approaches.	31	2	4	0
All ecological zones in Cameroun are vulnerable to climate change although the Sudano-Sahel and coastal zones remain the most vulnerable.	32	3	1	2
Government should provide incentives for renewable energy use across the country e.g. by reducing custom duties on the importation of installation equipment.	33	1	0	4
Sufficient technological skills and infrastructure, and consistent observational records, needed for impact studies to enhance policy development are available to climate scientists in Cameroun.	34	-4	-4	-2
To enhance decision making, climate and weather forecast information should answer practical questions such as changes to the onset of the rainy season, frequency and duration of dry spells early in the growing season, water availability for irrigation, intensity of extreme weather events etc.	35	-1	3	1
The government is making significant investments in climate science and climate change research and training.	36	-3	-3	-2

Using this approach, factor 1 (Discourse A), had 6 significant loaders, factor 2 (Discourse B) had 7 significant loaders and factor 3 (Discourse C) had 6 significant loaders. Six confounders were identified and two non-significant loaders. Confounders are Q-sorts that loaded significantly on more than one factor while non-significant loaders are Q-sorts that did not load significantly on any factor (Table 2.4).

Table 2.4 Participant loading for each discourse

Participant	Structure	Discourse		
		A	**B**	**C**
P1	Academia*	*0.5014*	0.1933	*0.5677*
P2	Academia*	-0.0694	*0.6011*	*0.6389*
P3	Academia*	*0.5527*	*0.5302*	0.1700
P4	COMIFAC**	0.3673	0.4053	0.2148
P5	COMIFAC	**0.7788X**	0.1791	0.2383
P6	CSO	0.3874	0.1012	**0.7055X**
P7	CSO	**0.5541X**	0.2906	0.3948
P8	CSO	0.3893	**0.5622X**	0.2406
P9	CIFOR	0.4285	**0.6206X**	0.173
P10	CIFOR	**0.6617X**	0.0553	0.1609
P11	GIZ	0.3201	0.413	**0.5626X**
P12	GIZ*	*0.499*	*0.6334*	0.173
P13	IUCN*	*0.5005*	*0.6525*	0.1122
P14	MINADER	**0.7383X**	0.2323	0.3391
P15	MINADER	0.1704	0.2936	**0.7055X**
P16	MINADER	0.3896	0.3788	**0.4309X**
P17	MINEE	0.1304	0.0749	**0.6256X**
P18	MINEE	0.3528	0.2042	**0.7442X**
P19	MINFOF	**0.6209X**	0.351	0.1573
P20	MINFOF**	0.3129	0.1808	0.3524
P21	MINEPDED	**0.6978X**	0.1961	0.4204
P22	MINEPDED	0.0721	**0.6787X**	0.057
P23	MINEPDED	0.1053	**0.7930X**	0.1579
P24	MINEPDED*	*0.5366*	0.203	*0.6454*
P25	MINEPDED	0.3516	**0.5016X**	0.3254
P26	MINEPDED	0.3375	**0.5550X**	0.3506
P27	MINRESI	0.042	**0.6745X**	0.4177
	Eigen values	5.67	5.40	4.86
	% study variance	21	20	18
	% cumulative variance	59		

* Confounder, ** non-significant sorts. Bold text with X indicates that the participant significantly loaded on this factor (P<0.01)

Significant loading sorts

Discourse A: (6) 5,7,10,14,19,21

Discourse B: (7) 8, 9, 22, 23, 25, 26, 27

Discourse C: (6) 6, 11, 15, 16, 17, 18

Confounders: (6) 1, 2, 3, 12, 13, 24

Non-significant sorts: (2) 4, 20

2.3.1 *Discourse A. Vulnerability and Impacts*

Discourse A explained 21% of the study variance and focused mainly on vulnerability and impacts of climate change to the society and had significant loaders from across various institutions representing different interest groups. The discourse strongly agrees with the following statements: Water resources are vulnerable to climate change so have to be managed in a more sustainable and efficient way (No 6, +4). All ecological zones in Cameroun are vulnerable to climate change, although the Sudano-Sahel and coastal zones remain the most vulnerable (No 32, +3). The government should put in place an insurance scheme to compensate victims of climate induced disasters (No 27, +3). Land grabbing from local communities by multi-national companies increase their vulnerability to climate change and compromise the opportunities offered by carbon credits from forest conservation (No 29, +2). Lack of basic infrastructure in rural areas (e.g. pipe borne water, farm-to-market roads, hospitals etc.) increase the vulnerability of the rural population to climate change (No 25, +1).

However, this discourse disagrees with the following statements: Sufficient technological skills, infrastructure, and consistent observational records, needed for impact studies to enhance policy development are available to climate scientists in Cameroun (No 34, -4). Uncertainty about risks and the impacts of climate change should be an excuse for inaction by the government (No 21, -4). Discourse A also disagrees with the statement that food security in Cameroun will not be threatened by climate change (No, 13, -2) and that impact studies do not offer any opportunities for local adaptation (No 5, -1).

The vulnerability and impacts of climate change across different sectors of the economy and socio-economic wellbeing of the population is emphasized by the respondents. Many respondents from different institutions identified water resources to be particularly vulnerable to climate change as this is perceived to pose a major threat to food security across the country. Many respondents under this discourse also agree with the concept of an insurance scheme that could be put in place by government to compensate victims of climate induced catastrophes. Climate change has been identified as a major cause of disasters in Cameroun with major socio-economic consequences, especially for rural communities (Gaston *et al.* 2012; Ndille and Belle 2014).

Under this discourse the lack of basic infrastructure was identified as a factor that increases vulnerability in rural areas. During discussion after the Q-sort, many respondents, especially in the government ministries, were of the opinion that lack of financial investments for infrastructure and technological development were major impediments to climate change adaptation in the country. In addition, respondents considered that uncertainty about risks and impacts of climate change should not be a reason for the government not to take any action towards reducing the risk pose by climate change.

Generally, the role of scientific research in enhancing adaptation to climate change through impact studies was well recognized. However, if sufficient technological skills and climate related observational datasets are not available to the scientific community, this group of stakeholders will not be able to carry out the impact studies needed and so compromise the possibility of reducing uncertainty about risks and impacts of climate change.

Some respondents in different institutions working in the REDD+ sector remarked after the Q-sorts ranking that land grabbing was a serious issue in Cameroun that increased vulnerability and could cause future social unrest amongst forest dependent communities. In the words of one of the respondents, "Local community leaders are invited by foreign investors sometimes in the absence of government representatives for consultation only when all the contractual agreements have been signed between them and the government at the national level. This often leaves the community leaders frustrated, as they do not know how to inform the population they lead that the forest that they all depend on for their livelihood has been sold to foreign investors".

2.3.2 Discourse B. Adaptation planning

This discourse explained 20% of the study variance and was concerned with climate change adaptation planning. The discourse strongly agrees with the following statements: Climate change adaptation must take into account the complexity of societal processes and actors (No 1, +4). Therefore, developing adaptation policies using the multi-sectoral approach and mainstreaming adaptation into existing policies present better options for adaptation than sectoral approaches (No 31, +4; No 9, +2). Climate change adaptation planning will receive additional impetus if it is backed by a strong political leadership together with key government ministries responsible for finance and development planning (No 19, +3). Furthermore, climate change adaptation will be enhanced if scientists can translate the uncertainty inherent in climate models output into risk relevant for planning and decision making (No 4, +3). To enhance decision making, climate and weather forecast information should answer practical questions such as changes to the onset of the rainy season, frequency and duration of dry spells early in the growing season, water availability for irrigation, intensity of extreme weather events etc. (No 35, +3). Some REDD+ projects at local level fail not because the local communities are left out during project inception and execution but due to lack of transparency in project management (No 7, +2). In the area of energy, developing hydroelectric dams across the country will significantly reduce Cameroun's carbon footprint (No 11, +2). Government should invest in public transportation systems in urban areas and setup an agency to monitor carbon use efficiency of imported cars (No 14, +1) to further reduce the country's carbon footprint,

Disagreement statements included: Solving immediate development challenges is more important than climate change which is an issue for future generations (No 3, -3) and diversification of livelihood activities will not enhance the adaptive capacities of the local population (No 26, -2).

During discussions after the Q-sort, respondents emphasized the importance of political leadership in driving the adaptation agenda forward and such leadership has been demonstrated in other countries in Africa e.g. Rwanda (Byamukama *et al.* 2011). The respondents also said that the people who need adaptation information most are farmers living in rural areas, so climate information has to give them practical information, for example onset of the rainy season and duration of dry spells in the rainy season. The responsibility lies with the government to make this information available to farmers given that direct access to such information is complex and expensive and most farmers cannot afford to pay. This can be done by joining existing networks that provide regional climate information in Africa such as the Famine Early Warning System (FEW). The weather information could then be sent to the farmers through short telephone messages (SMS) or broadcasted through Community Radios.

The failure of some REDD+ projects as a result of the lack of transparency in project management reinforces the importance of governance and accountability. Most adaptation finance to developing countries is channeled as development aid, which limits the control of the target countries over these funds (Scoville-Simonds 2016). Governance, management and accountability over these funds remains an important issue that has to be tackled to ensure that the funds are used for the purpose for which it was intended.

2.3.3 Discourse C. Policy incentives

Discourse C explained 18% of the study variance and focuses mostly on policy incentives that need to be put in place by the government to enhance adaptation. Discourse C strongly agrees with the statement that government should provide incentives for renewable energy use across the country. For example by reducing custom duties on the importation of renewable energy installation equipment, by implementing policies that reduce energy wastage in public buildings and encourage waste recycling (No 33, +4; No 12, +3). This discourse is also in favour of managing water resources in a more sustainable and efficient way (No 6, +4) as they are vulnerable to climate change. In addition, developing water harvesting and storage infrastructure will enhance adaptive capacity of the local population in drought prone areas (No 30, +3). This discourse also supports the statement that most adaptation projects at local level fail because the beneficiary population is not consulted prior to project conception and execution (No 16, +3). Policy makers and the climate science community need to engage in a more interactive dialogue so that both producers and users of scientific information can clearly state their needs (No 18, +2). Forest conservation and management represent an effective way to mitigate climate change and reduce the vulnerability of water resources (No 15, +2).

However, Discourse C disagrees with the statements that an impediment to policy development is the non-communication of impact studies results to decision makers and that the latter do not offer any opportunities for local adaptation (No 2, -1; No 5, -3). Other statements that this discourse does not agree with are: even if women have access to land for agriculture this may not increase their adaptive capacity because they lack basic farm inputs (No 17, -1); and that there is no need to include climate change education in academic programs because the media will educate everybody (No 28, -4).

In discussion after the Q-sort the respondents agreed that if government reduces custom duties on the importation of renewable energy equipment, prices will drop in the local market and this will encourage individuals and private companies to purchase and install them. Reduction of the dependence of industries and households on energy supplied from the national grid could boost industrial production, especially during the dry season. During the dry season in Cameroun there is now often a drop in water levels in the reservoirs used for hydro-power generation, resulting in frequent power cuts. Significant economic losses are incurred by industries as a result of power cuts or load shedding (Diboma and Tatietse 2013). However, the implementation of this policy remains solely a government responsibility because reducing custom duties on renewable energy installation equipment may result in a reduction of state revenue generated from custom duty.

Due to the vulnerability of water resources to climate change, integrated water resources management (IWRM) has been adopted in Cameroun as a starting point for developing policies that can enhance sustainable water resources management and guarantee water security (Ako *et al.* 2010). Development of water harvesting and storage infrastructure especially in the drought-prone Sudano-Sahel zone, is recognized as a means to improve adaptive capacity of rural population and increase agricultural production (Cheo *et al.* 2014). This needs to be integrated into government policies on climate change adaptation and a financial allocation set aside for that.

The respondents said that most adaptation projects at local level fail due to lack of consultation prior to project conception and execution. More meaningful consultations with the local communities are needed to assess if infrastructure investment envisaged in any locality will significantly improve livelihoods and reduce vulnerability to climate change.

During post Q-sort interviews, all the stakeholders in the academic sector expressed frustration about the lack of funding and basic infrastructure needed to conduct relevant research. This implies that the government should put emphasis on financing climate change studies in national universities instead of allocating such projects to foreign consultancy firms at high costs. Development partners could also channel climate finance to in-country research based institutions. This will have a long term positive impact of capacity building through younger researchers and enhancing research facilities in universities and research institutions thereby reducing the country's dependence on foreign experts.

This discourse also disagrees with the statement that the media will educate the population on issues related to climate change, instead the subject should be included in academic programs such as the school curriculum. The lack of information available to the general public on issues related to climate change and the environment can be attributed to the absence of a government policy to disseminate relevant information to the general public. Furthermore, the lack of logistical support, insufficient information and training among journalists; and the high cost of accessing information on the internet discourage private media from reporting relevant issues (Tiani *et al.* 2015). The respondents said that government has to focus on developing a policy to enhance dissemination of relevant information to the general public through public and private media organs.

Discourse C disagrees with the statement that if women had access to land, this will not increase their adaptive capacity because they lack basic farm inputs. The respondents said that the legal framework in Cameroun gives equal land-rights and access to natural resources to both men and women, but the customary tenure system inhibits women from owning land even though they are the main food producers (Nvenakeng 2016). In a previous study Yengoh *et al.* (2011) reported that reduced agricultural production in Cameroun could be attributed to the scarcity of land among women although free distribution of farm inputs could also boost production. Nevertheless, respondents expressed the hope that the new land policy under preparation will take into consideration the possibility for women to own land which could have a positive feedback effect on food security in the country given their contribution in food production in the country.

2.3.4 Consensus statements

The PQMethod software also produced a list of consensus statements that did not distinguish between any of the factors and are thus non-significant at $P < 0.01$ and $P < 0.05$. Of particular interest were statements No 3, 10, 23, and 24.

The tree planting policy under implementation to mitigate the consequences of climate change should be abandoned because it offers no immediate benefits to the local population (No 10, -3). The government is making significant investments in climate science and climate change research and training (No 36, -3). All the participants were of the opinion that the current investment portfolio of government in climate change adaptation was quite small. As explained in Discourse A, the lack of investment increases vulnerability and is a major impediment to climate change adaptation. Solving immediate development challenges is more important than climate change which is an issue for future generations (No 3, -2). During post Q-sort interviews, most of the participants were of the opinion that, although the government investment portfolio was low, the government consider the issue of climate change adaptation to be very important in her development agenda.

There is sufficient collaboration between the different stakeholders in the area of climate research in Cameroun (No 24, -2). Most stakeholders working in government ministries expressed frustration that there was little collaboration among them on issues related to climate change although this was not the case among stakeholders working in international and civil society organizations.

Given the uncertainties, complexities and high stakes involve in climate change adaptation, different arguments have been raised in favour of a participatory approach in the production of knowledge and decision making on issues related to climate change adaptation. André *et al.* (2012) and Wilsdon and Willis (2004) argue that, knowledge co-produced through deliberative dialogue with different stakeholders e.g. researchers, policy-makers, local communities may be used to provide new perspectives and contextualize findings. Few *et al.* (2007) argue that stakeholder dialogue could contribute to more effective adaptation to climate impacts by increasing the robustness of research results as well as the legitimacy of policies and measures. Meanwhile, Reed (2008) see stakeholder participation in environmental decision making as a democratic right.

From these different perspectives, the importance of reinforced collaboration between different institutional stakeholders in the area of climate change adaptation planning was emphasized by the respondents. In fact, Bhave *et al.* (2013) argues that from their experience of understanding the local biophysical and socio-economic systems, stakeholders are valuable knowledge bearers of potential adaptation options and their preferences can play a significant role in adaptation planning and implementation. This points to the fact that there is need for increased collaboration between stakeholders dealing with issues related to climate change in Cameroun especially given the uncertainties and stakes related to adaptation decision making.

2.4 Conclusion

The shared patterns among different participants/stakeholders involve in policy development and implementation in the climate change adaptation sector in Cameroun was revealed using Q-methodology.

The different discourses demonstrated that there are still many issues that need attention by the government and development partners. These challenges range from technological and infrastructural development, governance and accountability, reinforced stakeholders collaboration and development of new policies, creation of new institutions to deal with new and emergent challenges posed by climate change. Land grabbing from forest dependent communities is an important issue as it could lead to future social unrest, and could also compromise the opportunity to benefit from new forest conservation policies such as carbon credits.

To be able to meet these challenges, the government needs to increase its financial investment in the area of climate change adaptation. However, for this to be successful, a strong political leadership and the personal commitment of influential ministries responsible for budget planning and execution is required. Furthermore, a new disaster management institution need to be created and given financial autonomy and decentralized services to replace the existing department of civil protection. Policy makers were of the opinion that creating such a structure with decentralized services and financial autonomy will make this institution proactive and able to intervene in case of disaster be it climate related or not.

From the views expressed by policy makers, it is evident that despite the uncertainties inherent in climate models, the scientific community is still encouraged to conduct research on the impacts of climate change. However, they expressed the opinion that the scientific community has to work to translate the uncertainty inherent in climate models output into risk relevant for planning and decision making. The policy makers stressed the need for scientific research to focus on the impacts of climate change on water resources and agriculture given the vulnerability of water resources and the risk of food insecurity with particular attention given to the Sudano-Sahel region. This is an important outcome of the study given that most often researchers conduct studies that lack a clear pathway to policy uptake because it does not address issues that are relevant to policy development. In a previous study, Nkiaka (under review), reported that most climate change research in Cameroun was conducted in foreign universities and may not contribute to policy development in the country because it may fail to address the priority areas pertinent to policy makers.

Cameroun has experienced social unrest in past as a result of food insecurity such as the 2008 hunger strike and currently there is a violent conflict unfolding in the Lake Chad basin as result of terrorist activities by “boku haram” (OCHA 2017). This situation coupled with challenges pose by climate change and variability, population increase and mounting tension due to water scarcity makes the country and the region particularly vulnerable to weather vagaries which could lead to mass migration, posing a threat to global security. Therefore, the results of scientific research on the impacts of climate change on water resources and agriculture in the Sudano-Sahel zone are particularly needed to develop policy that can enhance water resources management and increase agricultural output.

Meanwhile, from the views expressed by stakeholders, part of the climate change fund may have to be channeled to upgrade research facilities in universities and train new scientists to take up the challenge of scientific research. In our opinion, this is an important area that needs particular attention from the international community because it will reduce the dependence of the country on foreign experts as expressed by the respondents. On the other hand, we think that part of the Official Development Assistance (ODA) funds could be used to upgrade or develop pipe borne water and health facilities in the most vulnerable areas to reduce the vulnerability of the population to the risk pose by climate change.

To conclude, results from this study suggest that it is very important for climate scientists to engage with policy makers to know the key knowledge gap areas and the kind of scientific information needed for policy development. This is particularly important because it will help to generate knowledge that is relevant to both the scientific community and the society as a whole.

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Chapter 3 Infilling missing observations in time series

This Chapter is based on the paper:
NKIAKA, E., N. R. NAWAZ and J. C. LOVETT. 2016. Using self-organizing maps to infill missing data in hydro-meteorological time series from the Logone catchment, Lake Chad basin. Environmental Monitoring and Assessment, 188(7), pp.1-12.

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Abstract
Hydro-meteorological data is an important asset that can enhance the management of water resources. But existing data often contains gaps, leading to uncertainties and so compromising their use. Although many methods exist for infilling data gaps in hydro-meteorological time series, many of these methods require inputs from neighbouring stations, which are often not available, while other methods are computationally demanding. Computing techniques such as Artificial Intelligence can be used to address this challenge. Self-Organizing Maps (SOMs), which are a type of Artificial Neural Network, was used for infilling gaps in hydro-meteorological time series in a Sudano-Sahel catchment. The coefficients of determination obtained were all above 0.75 and 0.65 while the average topographic error was 0.008 and 0.02 for rainfall and river discharge time series respectively. These results indicate that SOMs are a robust and efficient method for infilling missing gaps in hydro-meteorological time series.

3.1 Introduction

Economic progress, rising standard of living, growing populations and expansion of commercial agriculture in developing countries is putting increasing pressure on fresh water resources (Connor 2015). At the same time climate extremes such as droughts and floods are becoming more frequent (Coumou and Rahmstorf 2012). Better informed water resource management is needed to respond to demand and climate variability. A major requirement for planning is the availability of good quality and long term hydro-meteorological data. This data provides indicators of past hydro-climatic behaviour of a region/catchment and is fundamental to the development of models for prediction of system behaviour (Harvey *et al.* 2012).

Existing hydro-meteorological time series used for planning and management decisions often contains missing observations, particularly in developing countries. The gaps are caused by many reasons, including equipment failure, destruction of equipment by natural catastrophes such as floods, war and civil unrest, mishandling of observed records by personnel or loss of files containing the data in a computer system (Elshorbagy *et al.* 2000). The presence of gaps, even if there are very short, in a hydro-meteorological time series can hinder the calculation of important statistical parameters as data patterns maybe hidden. This can compromise their use for water resources planning as it increases the level of uncertainty in the datasets (Ng *et al.* 2009; Campozano *et al.* 2015). This problem is particularly acute in the Sudano-Sahel region where rainfall is highly variable in both space and time, meteorological and flow gauging stations are scarce and the available datasets are riddled with gaps.

Several methods exist for infilling gaps in hydro-meteorological time series. However, the application of each method depends on a range of factors including the information available for that station; additional datasets from neighbouring stations; the percentage of gaps present within the time series to be infilled; the season within which the gaps are present; the length of the existing data series; and the type of application that the infilled series will be used for (Mwale *et al.* 2012). These infilling methods range from simple techniques such as linear interpolation, Inverse Distance Weighting (IDW) and Thiessen polygons; to more complicated advanced techniques such as time series models, Markov models, Global Imputation, Multiple Regression models, Artificial Intelligence (Kalteh and Berndtsson 2007; Lo Presti *et al.* 2010; Kalteh *et al.* 2008; Ismail *et al.* 2012; Mwale *et al.* 2012; Campozano *et al.* 2015).

Most of the methods, require additional input data from neighbouring stations in order to produce reliable results and these additional inputs are often not available. Furthermore, some of the methods are time consuming and demand substantial computer power for simulation because of the complicated algorithms involved (Lo Presti *et al.* 2010). Some methods also require that the time series be split into different seasons to obtain reliable results. Although these challenges could be overcome by using numerical models (e.g. hydrological models); models also demand high data inputs and cannot be applied to many stations at the same time due to parameter calibration requirements which are site specific and consequently results cannot be transferred to other stations even within the same catchment (Harvey *et al.* 2012).

Some of these challenges can be overcome by using computing techniques such as Artificial Intelligence (AI) (Daniel *et al.* 2011). In this class of technique, the most promising approaches include Artificial Neural Networks (ANN), Fuzzy Logic (FL) and Genetic Algorithms (GA). The application of Artificial Intelligence in hydrology and water resources management is well established (Govindaraju 2000; Kingston *et al.* 2008a; Kingston *et al.* 2008b; Daniel *et al.* 2011). Among the AI class of models, ANNs are probably the most popular as these use available data to learn about the behaviour of a time series. In addition, they possess capabilities for modelling complex nonlinear systems; do not require prior knowledge of the system process(s) under study and are robust even in the presence of missing observations in the time series (Mwale *et al.* 2012). The main advantage of ANNs over conventional methods is their ability to model physical processes without the need for detailed information of the system (Daniel *et al.* 2011); and they have often been used for infilling gaps in hydro-meteorological time series (Kalteh and Hjorth 2009; Dastorani *et al.* 2010; Adeloye *et al.* 2012; Ismail *et al.* 2012; Mwale *et al.* 2012; Mwale *et al.* 2014; Kim *et al.* 2015).

Within the ANN family, the Multilayer Perceptron (MLP) is one of the most widely used for infilling gaps in hydro-meteorological time series (Kalteh and Hjorth 2009; Dastorani *et al.* 2010; Adeloye *et al.* 2012; Ismail *et al.* 2012; Mwale *et al.* 2012; Mwale *et al.* 2014; Kim *et al.* 2015). Although MLP is robust for performing this task, it usually demands a long time series for training; and if part of the data to be used for training is missing, additional pre-processing of the time series will have to be carried out to provide estimates in the input space before the training can begin (Rustum and Adeloye 2007; Mwale *et al.* 2012). This therefore limits its application in situations where significant portions of the time series to be used for training have incomplete data; or for short time series as the data may not be sufficient for training. It is also computationally intensive and needs additional storage memory (Kalteh *et al.* 2008).

Another member of the class of ANNs known as Self-Organizing Maps (SOMs), which is a competitive and unsupervised ANN, is becoming popular for infilling gaps in hydro-meteorological times series and has been shown to outperform ANNs-MLP. Many studies have successfully applied SOMs for infilling gaps in hydro-meteorological time series with satisfactory results (Kalteh and Hjorth 2009; Adeloye *et al.* 2012; Mwale *et al.* 2012; Mwale *et al.* 2014; Kim *et al.* 2015).

Self-Organizing Maps (SOMs) were first introduced by Kohonen, (Kohonen 1995). The success of their application in other research disciplines led to their wide application in water resources processes and systems research especially for data mining, infilling of missing data, estimation and flow forecasting, clustering etc. (Kalteh *et al.* 2008). This is due to their ability to convert nonlinear statistical relationships between high dimensional data onto a low dimensional display (Ismail *et al.* 2012). Data points that show similar characteristics are placed closed to each other or clustered together in the output space. This mapping approach does a quasi-preservation of the most important topological and metric relationship of the original data (Rustum and Adeloye 2007). Adeloye *et al.* (2012) asserted that, the ability of SOMs to cluster data together makes them robust for data mining and infilling datasets with gaps and outliers as the gaps/outliers are replaced by their features in the map. The SOMs algorithm generally executes assigned tasks using an unsupervised and competitive learning approach to discover patterns in the data (Kalteh and Berndtsson 2007) thus, the whole process in entirely data driven. A SOM is made up of two layers: a multi-dimensional input layer and an output layer. Both layers are fully connected by adjustable weights and the output layer is made up of neurons arranged in a two dimensional grid of nodes (Figure 3.1). Each neuron in the output layer of the SOM contains exactly the same set of variables contained in the input vectors. Despite its wide application for infilling missing data in many studies around the world, it has rarely been used Africa in general and the Sudano-Sahel region in particular.

A Self-Organizing Maps approach was applied to infill missing data in monthly rainfall and daily river discharge time series from January 1950 to December 2007 in the Logone river catchment covering Cameroun, the Central Africa Republic and Chad. Infilling of missing gaps in hydro-meteorological time series usually precedes most hydro-climatic studies (Kashani and Dinpashoh 2012), and this work is part of an on-going research project to assess the vulnerability of this catchment to drought and flood events under anticipated increased climate variability. The paper is structured as follows: Section 2 describes the data and methodology used in the study. In Section 3 the results obtained are presented and discussed. Section 4 gives a general summary and conclusion of the study.

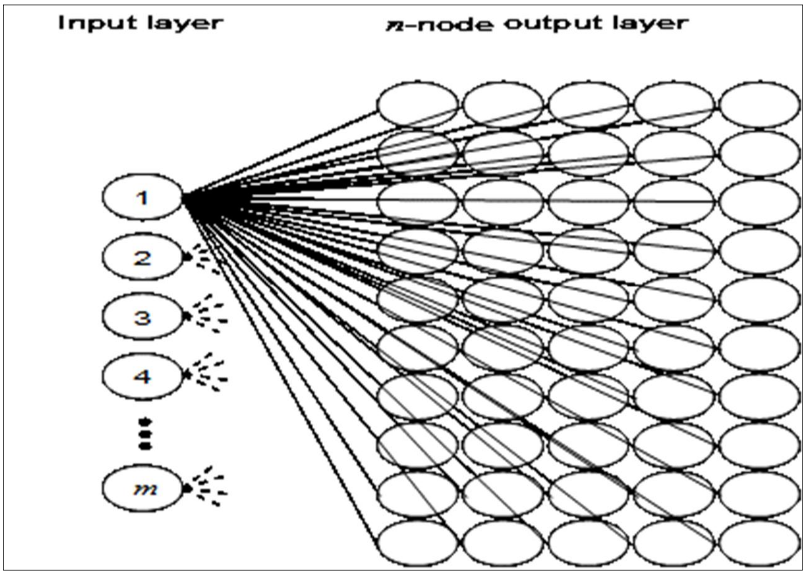

Figure 3.1 Architecture of a SOM (Adapted from Kagoda et al., 2010)

3.2 Methodology

3.2.1 Study area

The Logone catchment is part of the greater Lake Chad basin. It lies between latitude 6˚-12˚N and longitude 13˚-16˚E and is a transboundary catchment in the Sudano-Sahel transitional zone in Central Africa with an estimated catchment area of 86,500 km^2 (Figure 3.2). The Logone River has its source in Cameroun through the Mbere and Vina Rivers, which flow from the north eastern slopes of the Adamawa Plateau. It is joined in Lai by the Pende River from the Central Africa Republic and flows from south to north to join the Chari River in Ndjamena (Chad) and continue flowing in a northward direction before finally emptying into Lake Chad. The climate in the catchment is characterized by high spatial variability and is dominated by seasonal changes in the tropical continental air mass (the Harmattan) and the marine equatorial air mass (monsoon) (Candela *et al.* 2014).

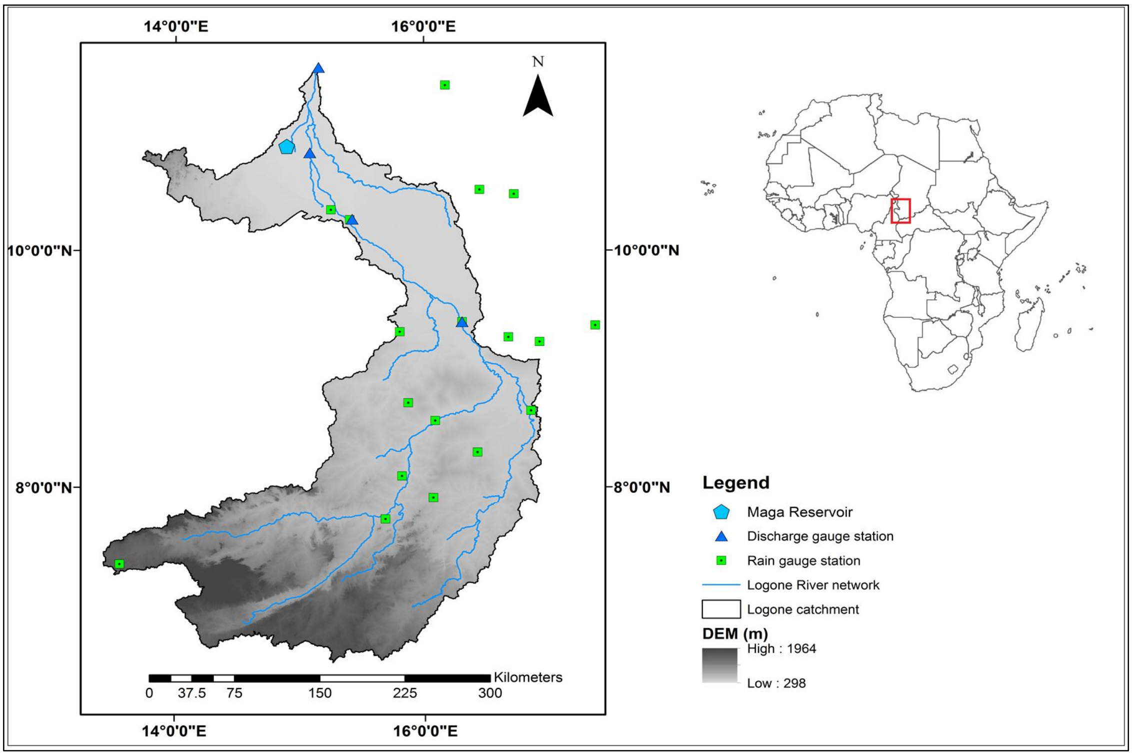

Figure 3.2 Map of the study area showing rain and flow gauging stations

3.2.2 Data Sources

Monthly gauge rainfall was obtained from SIEREM (Boyer *et al*. 2006) available for 18 stations covering the period 1950-2000 while daily river discharge data was obtained from the Lake Chad Basin Commission (LCBC). Discharge time series are available for the stations of Lai, Bongor, Katoa and Logone Gana covering the period 1973-1998 for Lai and 1983-2007 for the rest of the stations (Table 3.1).

3.2.3 Implementation of the SOM Algorithm

A SOM algorithm is implemented in a series of steps.

The multi-dimensional input data is first standardized to make sure that very high or low value variables do not dominate the map. Since SOMs use Euclidian metrics to measure distances between vectors, standardization gives equal weight to all the input variables (Vesanto *et al*. 2000). In this analysis, data was not standardized because rainfall and river discharge time series were trained separately.

The input vector is then chosen at random and presented to each of the individual neurons for comparison with their weight vectors in order to identify the weight vector most similar to the presented input vector. The identification uses the Euclidian distance defined as:

$$D_i = \sqrt{\sum_{j=1}^{n} m_j (x_j - w_{ij})^2} ; \quad i = 1, 2, 3 \dots . \ M \tag{3.1}$$

Where:

D_i = Euclidian distance between the input vector and the weight vector i; x_j = j element of the current vector; w_{ij} = j element of the weight vector I; n = the dimension of the input vector; m_j = "mask".

When the input vector contains missing elements, the mask is set to zero for such elements and because of this, the SOM algorithm can conveniently handle missing elements in the input vector. The neuron whose vector closely matches the input vector (i.e. with D_i minimum) is chosen as the winning node or best matching unit (BMU).

After finding the BMU, the weight vector of the winner neuron is adjusted so that the BMU and its adjacent neurons move closer to the input vectors in the input space, thereby increasing the agreement between the input vector and the weight vector. This adjustment is carried out using the following equation:

$$w_t(t + 1) = w_t(t) + \alpha(t) h_{ci}[x(t) - w_t(t)] \tag{3.2}$$

Where: w_t = element of the weight vector; t = time; $\alpha(t)$ = learning rate at time t; $h_{ci}(t)$ = neighbourhood function centred in the winner unit c at time t.

From here, each node in the map develops the ability to recognize input vectors that are similar to itself. This ability is referred to as self-organizing as no external information is added for this process to take place. The learning procedure continues until the SOM algorithm converges. Generally, the learning rate decreases monotonically as the number of iterations increase as shown by the following equation:

$$\alpha(t) = \alpha_0 \left(\frac{0.005}{\alpha_0}\right)^{\frac{t}{T}} \tag{3.3}$$

Where: $\alpha(t)$= learning rate; α_0 = initial learning rate; T = training length

The neighbourhood function used in this analysis is Gaussian centred in the winner unit c, calculated as:

$$h_{ci}(t) = \exp\left\{-\frac{||r_c - r_i||^2}{[2\sigma^2(t)]}\right\} \tag{3.4}$$

Where:

$h_{ci}(t)$ = neighbourhood function centred in the winner unit c at time t; r_c and r_i = positions of nodes c and i on the SOM grid; $\sigma(t)$ = neighbourhood radius which also decreases monotonically as the number of iterations increases.

The quality of the trained SOM is measured by the total average quantization error and total topographic error. The average quantization error is a measure of how good the map fits the input data (it measures the average distance between each data vector and its Best Matching Unit (BMU)). The smaller the quantization error, the smaller the average of the distance from the vector data to the prototypes, meaning that the data vectors are closer to its prototypes; it is a positive real number with a value close to zero indicating a good fit between the input and the map. The quantization error is calculated as:

$$q_e = \frac{1}{N}\sum_{i=1}^{N} ||X_i - W_{ic}|| \tag{3.5}$$

Where: q_e = quantization error; N = number of input vectors used to train the map; X_i = ith data sample or vector; W_c =prototype vector of the best matching unit for X; ||.|| = denotes the Euclidian distance.

Topographic error measures how well the topology of the data is preserved by the map by considering the map structure. The lower the topographic error, the better the SOM preserves the topology of the data. It is a positive real number between 0 and 1 with a value close to 0 indicating good quality. It is calculated as:

$$t_e = \frac{1}{N}\sum_{i=1}^{N} u(X_i) \tag{3.6}$$

Where: te = topographic error; N = number of input vectors used to train the map;

ui = binary integer such that it is equal to 1 if the first and second BMU for Xi are not adjacent units; otherwise it is zero.

Since there is always a trade-off between which of the two can be minimized at the expense of the other, in this study, effort was focused on reducing the topographic error to ensure that the infilled values reflect the seasonal trend of the different time series. The coefficient of determination (R^2) was used to check the quality of the newly generated time series. R^2 gives the proportion of the variance of one variable that is predictable from the other variable and varies between 0 and 1. R^2 is calculated as:

$$R^2 = \frac{\sum_{i=1}^{n}[(x_i - \bar{x})(y_i - \bar{y})]}{\sum_{i=1}^{n}\ [(x_i - \bar{x})^2]\sum_{i=1}^{n}[(y_i - \bar{x})^2]} \tag{3.7}$$

Where: x_i = the *i*th observed value; y_i = the ith trained value; $\bar{x}$= the mean of observed value; $\bar{y}$ = the mean of the trained value; n = the number of observations.

3.2.3.1 Setting of SOM algorithm parameters

According to Gabrielsson and Gabrielsson (2006), the radius of the SOM should be chosen wide enough at the beginning of the learning process so that the map can be ordered globally as the radius decreases monotonically with time. To determine the optimum number of neurons, if M is the total number of input elements, García and González (2004), propose that the number of neurons in the output can be calculated as:

$$N = 5\sqrt{M} \tag{3.8}$$

Where: M = total number of samples and N = the number of neurons.

Once N is known, García and González (2004) further propose that the number of rows and columns of N can be calculated by:

$$\frac{l_1}{l_2} = \sqrt{\frac{e1}{e2}} \tag{3.9}$$

Where l_1 and l_2 are the number of rows and columns respectively, $e1$ is the biggest eigenvalue of the training data set and $e2$ is the second biggest eigenvalue.

In the initialization phase of the algorithm, since the learning process involve in the computation of a feature map is a stochastic process, according to Gabrielsson and Gabrielsson (2006) the accuracy of the map depends on the number of iterations executed by the SOM algorithm. These authors recommend that for good statistical accuracy, the number of iterations should be at least 500 times the number of network nodes. In this study, the random initialization option was used as it is recommended for hydrological applications e.g. (Kalteh *et al.* 2008), while the default parameters set by the SOM software for map size and lattice (rows and columns) were adopted that were exactly the same as using equations (3.8) and (3.9).

The basic steps required to complete the infilling process consists of the following:

1) *Data gathering and normalization*: The data to be infilled (e.g. rainfall and discharge time series) is assembled together and standardized; these are the depleted input vectors;
2) *Training*: The depleted input vector (data matrix) is introduced to the iterative training procedure to form the SOM. At the beginning of the training, weight vectors must be initialized by using either a random or a linear initialization method. The process of comparison and adjustment continues until the optimal number of iteration is reached or the specified error criteria are attained.
3) *Extracting information from the trained SOM:* Check all the minimum Euclidian distances and isolate the SOM's BMU for the depleted input vector (i.e. with missing values). The BMU identified in this step is a node of trained SOM and thus has the full complement of the missing values;
4) *Replacement of missing values*: Replace the missing values of the input depleted vector by their corresponding values in BMU identified in step 3 above.

3.2.3.2 Application of SOM

For the application of the SOM algorithm for infilling of missing data in this analysis, a SOM toolbox developed at Helsinki University of Technology Finland (www.cis.hut.fi/projects/somtoolbox/) was used in the Matlab® 2014b environment and a batch training algorithm was adopted. Due to the fact both datasets (rainfall and river discharge) had different time-steps, each of the datasets were trained separately. The data was presented in columns with each column representing measurements from each station. The entries without data were recorded as NaN (Not a Number) to meet Matlab® data entry requirements. To train all the data together in a single simulation, the data entries should overlap such that there is no single day/month for all the stations with no data entry.

Given that previous studies have demonstrated that the performance of SOMs is affected by the homogeneity/correlation in the input vector (Kalteh and Berndtsson 2007; Mwale *et al.*

2012), in this study, the input vector was ordered in such a way as to take into account this homogeneity in the stations as shown in Table 3.1. It can be observed in Table 3.1 that stations were ordered according to their spatial location to take into account the homogeneity/correlation that exist between stations located within the same spatial zones.

Note that in SOM terminology, “the input vector” is a single dataset comprising data from different station locations to be infilled. For example, in this study, two different input vectors were used with one comprising streamflow data from four flow gauging stations and the other comprising rainfall data from 18 rain gauge stations.

Table 3.1 Station location, percentage of missing data, results of statistical evaluation and average topographic error

Flow gauging	**Latitude**	**Longitude**	**Time interval**	**Proportion of missing data (%)**	**R^2**	**Average topographic error**
Lai	11.55	15.15	1973-1997	17.5	0.85	0.02
Bongor	10.83	15.08	1983-2007	19.2	0.80	
Katoa	10.27	15.42	1983-2007	26.8	0.65	
Logone Gana	9.40	16.30	1983-2007	6.45	0.91	
Rain gauge stations						
Ngaoundere	7.35	13.56	1950-2000	7.52	0.86	0.008
Baibokoum	7.73	15.68	1950-2000	8.82	0.88	
Bekao	7.92	16.07	1950-2000	5.88	0.90	
Pandzangue	8.10	15.82	1950-2000	14.2	0.81	
Donia	8.30	16.42	1950-2000	12.9	0.84	
Moundou	8.57	16.08	1950-2000	5.39	0.94	
Doba	8.65	16.85	1950-2000	4.08	0.94	
Delli	8.72	15.87	1950-2000	5.88	0.91	
Donomanga	9.23	16.92	1950-2000	16.2	0.76	
Guidari CF	9.27	16.67	1950-2000	12.3	0.85	
Goundi	9.37	17.37	1950-2000	6.05	0.91	
Kello	9.32	15.80	1950-2000	8.99	0.88	
Lai	9.40	16.30	1950-2000	5.23	0.92	
Bongor	10.27	15.40	1950-2000	10.8	0.80	
Yagoua	10.35	15.25	1950-2000	8.17	0.92	
Bousso	10.48	16.72	1950-2000	6.37	0.93	
Bailli	10.52	16.44	1950-2000	5.23	0.95	
Massenya	11.40	16.17	1950-2000	5.72	0.95	

Latitude and Longitude in degrees

The stations with the longest period of continuous missing observation were Katoa with 1418 consecutive days (01/04/1997-18/025/2001) approximately 4 years and Lai with 1200 consecutive days (31/01/1979-15/05/1982), approximately 3 years. Donomanga had the longest period of missing monthly rainfall observations.

3.3 Results and Discussion

Initial simulation results using discharge time series produced an average topographic error of 0.04 and a visual inspection of the time series was carried out to check the seasonal trends. Sporadic cases of numerical instability were noticed especially in portions of the time series with extensive gaps where infilling was done. In some cases, high flow values were observed in the dry season and low flow values observed in the rainy season. This was not logical as periods of high flows could not be followed by a single day of abrupt low flow and vice versa. These values were manually deleted for all the stations and a second simulation was performed using the same initial parameters. After this second simulation, these abnormalities disappeared and the average topographic error reduced to 0.02. Results of the overall performance of the model are shown in Table 3.1.

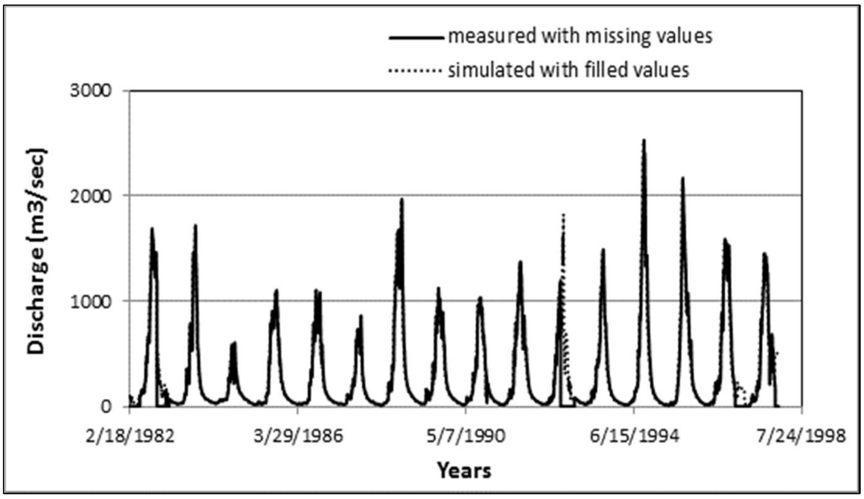

Figure 3.3 Observed and Simulated discharge for Lai (1973 – 1997)

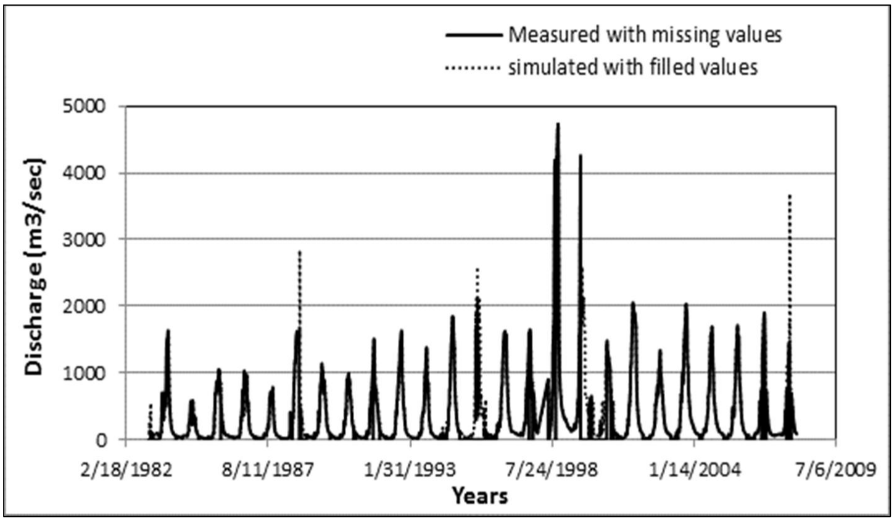

Figure 3.4 Observed and simulated discharge for Bongor (1983 – 2007)

The results indicate that after the second simulation, the model was able to replicate with high accuracy the trends and flow magnitudes (high and low) in the respective seasons as shown in Figures 3.3 to 3.6. This justifies the low value of average topographic error 0.02 and the high values of R^2. From these results, the newly trained time series were used to infill missing gaps in the different time series in the Logone catchment. The preservation of topology, especially for discharge time series is important because seasonal variation causes high and low flows. The results obtained indicate that this seasonal variation was well preserved across all the gauging stations during the infilling process. In this research more emphasis was put on reducing the topographic error to ensure that the infilled values reflect the seasonal variation of the time series. However, a visual observation of flow hydrographs (Figures 3.3 to 3.6) indicate that, the possibility of errors in the original river discharge time series may not be discounted especially for the Bongor station, and this may have had a negative impact on the overall performance of the SOM algorithm in this study.

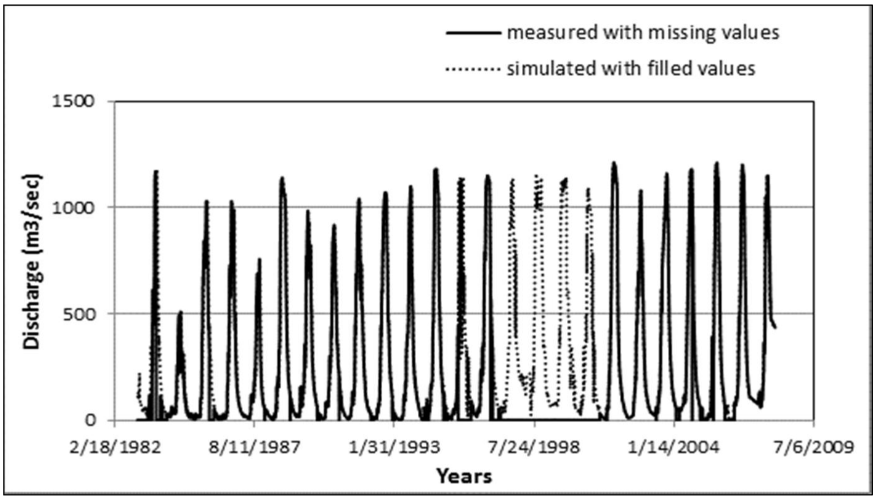

Figure 3.5 Observed and simulated discharge for Katoa (1983 – 2007)

The results obtained for rainfall observations were similar to those obtained for discharge with the lowest R^2 value of 0.76 and average topographic error of 0.008. Of the 18 rainfall stations, 10 had R^2 values of 0.90 and above while 7 stations had R^2 values of 0.80 and above with only one station (Donomanga) which had the highest percentage of missing observations producing an R^2 value of 0.76. As proposed by (Kalteh and Berndtsson 2007; Mwale *et al.* 2012) it can be observed in Table 3.1 that there was some clustering in the results of the infilled data according to spatial location of the stations. Stations like Yagoua, Bousso and Baili located close to each other all produced R^2 values above 0.92, likewise stations like Moundou, Doba and Delli. These results also demonstrate infilling missing gaps in SOMs according to the stations homogeneity can significantly improve the results as suggested by other researchers (Kalteh and Berndtsson 2007; Mwale *et al.* 2012). Since the graphs of the all the 18 rain gauge stations cannot be shown, (Figures 3.7 & 3.8) are used for illustration. Furthermore, it was observed that the SOM algorithm was able to preserve seasonal variation when infilling missing data in rainfall time series just as it did for discharge.

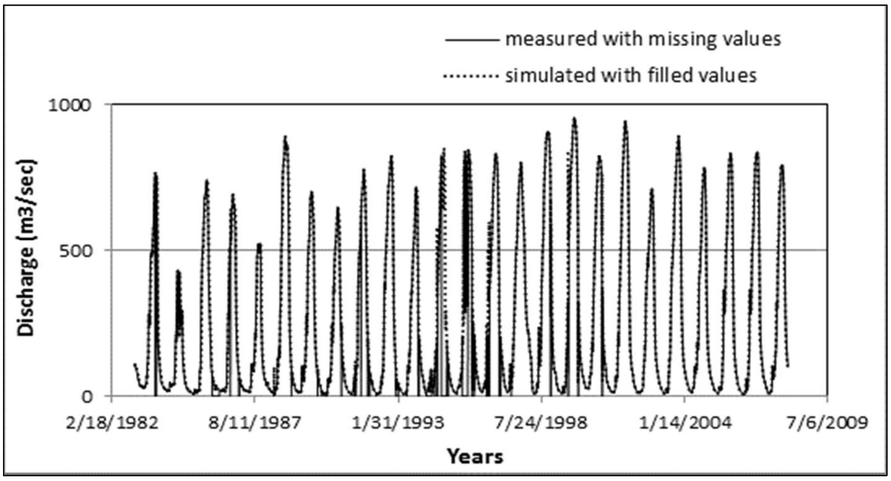

Figure 3.6 Observed and simulated discharge for Logone Gana (1983 – 2007)

The results also indicate that, although this method is quite robust for infilling gaps in hydro-meteorological time series, it cannot be used for infilling gaps in time series with extended periods of missing observations as model performance starts diminishing. This is logical as in such situations the model does not have sufficient data to learn from, thus cannot correctly replicate the pattern in the data. For example time series of measured discharge at Katoa had 1200 consecutive days of missing observations, which represent 13% of the total data entries, produced an R^2 of 0.65 compared to Logone Gana with 97 consecutive days of missing observations with an R^2 of 0.91. This implies that time series with extended periods of missing observations should not be used as the model may infill the missing observations but still fail to replicate the pattern in the data. Although, as shown by Kalteh *et al.* (2008) and Mwale *et al.* (2012) this issue can be resolved for rainfall time series by training such time series with data from the same spatial zone.

For example, using monthly precipitation data obtained from stations in Iran, Kalteh and Berndtsson (2007) trained some station data together by repeatedly eliminating 1-, 2-, 5- and, 10-year precipitation data from each of the stations used for simulation. All data used for training was also used for validating in a jack-knife procedure and the results were validated using the correlation coefficient (r) and the root mean square error (RMSE) between observed and simulated monthly precipitation. It was shown that using homogeneous station data obtained from the same spatial zone or region to train the SOMs greatly improved the validation results. A similar procedure was applied in the Shire river basin in Malawi by Mwale et al. (2012) and it was also shown that the predictive capacity of SOM in infilling missing observations was dependent on the correlation between the stations. Such performance was attributed to the ability of the SOM to capture efficiently the pattern in the datasets from the same region making the algorithm robust to interpolate missing data with high accuracy (Kalteh and Berndtsson, 2007).

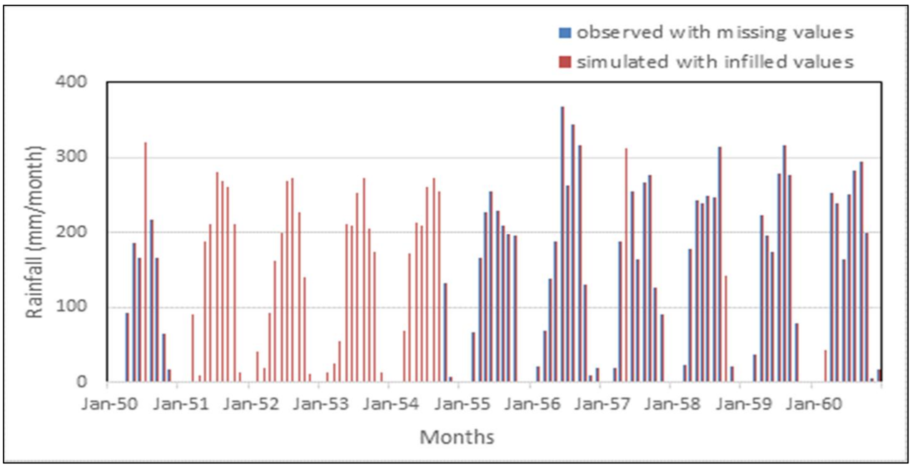

Figure 3.7 Observed and simulated rainfall for Ngaoundere (1950 2007)

Nevertheless results obtained suggest that SOMs are suitable for infilling gaps in hydro-meteorological time series in Sudano-Sahel catchments. Results obtained from this study are comparable to those obtained by (Mwale *et al.* 2012; Mwale *et al.* 2014) in the Lower Shire Floodplain in Malawi, (Kang and Yusof 2012) in the Kelantan and Damansara river basins in Malaysia and (Kim *et al.* 2015) in the Taehwa watershed in Korea.

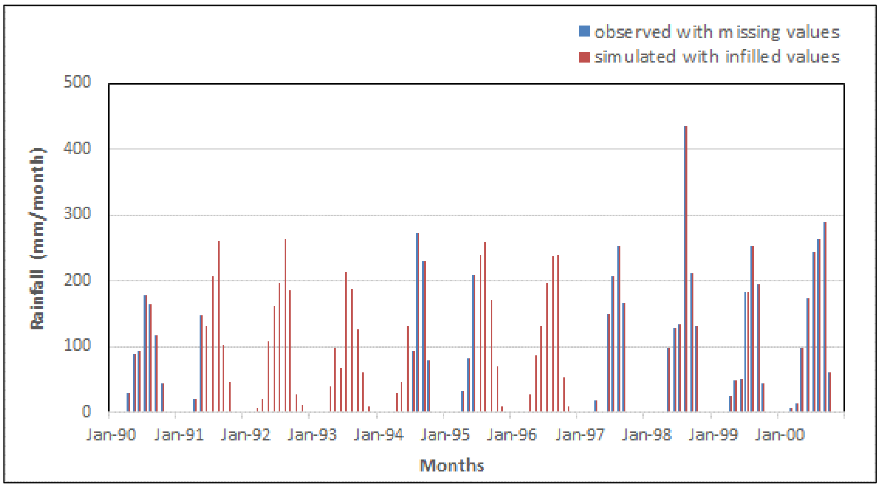

Figure 3.8 Observed and simulated rainfall for Kello (1990 - 2000)

To illustrate that there is no relationship between the discharge time series, Figure 3.10 shows that the discharges measured at Katoa and Logone Gana gauging stations, which are located downstream of Bongor, are paradoxically lower than discharge measured at Bongor station upstream. This can partly be explained by the fact that during the rainy season when the river overflows its banks, immediately after Bongor station, part of the flow is diverted to fill the Maga dam and part is lost to the floodplains. During the dry season, water is withdrawn from the river without control for various purposes by the inhabitants thus reducing the quantity that eventually reaches Logone Gana station located downstream. This can also be attributed to transmission losses as a result of infiltration to the aquifer through channel bed. Seeber (2013) observed that the discharge recorded at Ndjamena flow gauging station located downstream was lower than that recorded upstream at the Logone Gana station. Candela *et al.* (2014) reported that a significant proportion of groundwater in the Lake Chad aquifer system was from the Logone River through river and aquifer interactions.

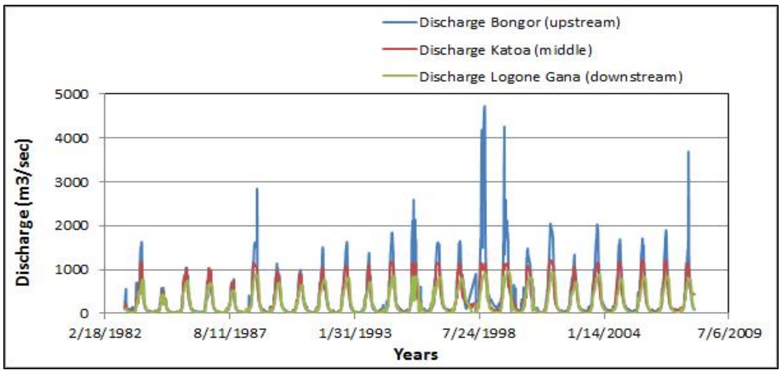

Figure 3.9 Discharge at Bongor, Katao and Logone Gana (1983 - 2007)

Figure 3.10 shows a scatter plot of the proportion of missing data plotted against R^2 after infilling the missing values for rainfall across the Logone catchment. It can be observed that as the proportion of missing data increases, the value of R^2 reduces indicating that as the proportion of missing data increases, the ability of the SOMs algorithm to perform the task of infilling reduces as mentioned earlier. Although it was not the main reason applied in this study, we observed that the performance of stations from the same spatial zone in the study area was similar. For example stations like Yagoua, Bousso, Bailli and Massenya located in the same spatial zone were clustered together. However, in this study the reason for R^2 values clustering together is attributed to the proportion of missing values because the performance of one of the stations with high proportion of missing values is below that of the others. Nevertheless, Kalteh *et al.* (2008) and Mwale *et al.*

(2012) have previously suggested that rain gauge stations from the same spatial zone can be trained together to increase the performance of the SOMs algorithm for infilling missing observations.

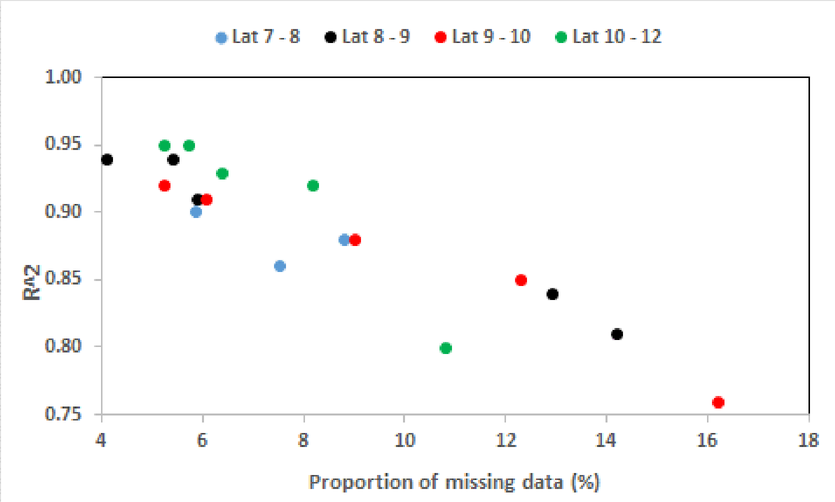

Figure 3.10 Scatter plot showing proportion of missing data against R2 for rainfall

3.4 Conclusion

The main objective of this study was to use Self-Organizing Maps (SOMs) to infill missing gaps in hydro-meteorological time series in the Logone catchment using data from four river discharge and 18 rain gauge stations riddled with gaps

The combination of artificial intelligence and human intelligence (to be able to distinguish the seasonal discharge trends, patterns and magnitudes) greatly improved the overall performance of the SOM algorithm in handling missing data. Other advantages of SOMs include: (i) it does not require input data from neighbouring stations; (ii) unlike other ANN methodologies it does not require extra datasets to train the time series; (iii) it is not computationally intensive; and (iv) it does not require extra storage capacity.

Results obtained from this study indicate that, the SOMs algorithm is quite robust for infilling gaps in hydro-meteorological time series, though it is not suitable for infilling gaps in time series with extended periods of missing observations as model performance starts diminishing. This methodology can be used by practitioners to enhance the planning and management of water resources in areas where available records are infested with missing observations. Preservation of topology through a good replication of trends and discharge magnitudes in the time series obtained in this study will reduce the data input uncertainty in our future modelling studies in the catchment.

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Chapter 4 Variability in seasonal and annual rainfall

This chapter is based on the paper:

NKIAKA, E., N. R. NAWAZ and J. C. LOVETT. 2017. Analysis of rainfall variability in the Logone catchment, Lake Chad basin. International Journal of Climatology. ***37****(9), pp.3553-3564.*

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Abstract

The socio-economic consequences posed by climate change in Africa are giving increasing emphasis to the need for trend analysis and detection of changes in hydro-climatic variables in data deficient areas. This study analyses rainfall data from seventeen rain gauges unevenly distributed across the Logone catchment in the Lake Chad basin (LCB) over a fifty-year period (1951-2000). After quality control of the rainfall data using homogeneity tests, non-parametric MannKendall (MK) and Spearman rho tests were applied to detect the presence of trends. Trend magnitude was calculated using Sen's Slope Estimator. Results of the homogeneity test showed that rainfall was homogeneous across the catchment. Trend analysis revealed the presence of negative trends for annual rainfall at all the stations. Results of long term trend analysis at monthly time scale revealed the presence of statistically insignificant positive trends at 32% of the stations. Spatially, the analysis showed a clear distinction in rainfall magnitude between the semi-arid and Sudano zones. The slope of the trend lines for annual rainfall averaged over the respective zones was higher in the semi-arid zone (-4.37) compared to the Sudano zone (-4.02). However, the station with the greatest reduction in annual rainfall (-8.06 mm) was located in the Sudano zone.

4.1 Introduction

Precipitation in the African Sudano-Sahel is highly variable both spatially and temporally, and experiences periods of prolonged drought such as that which affected the region in the 70s and 80s (Boyd *et al.* 2013; Nicholson 2013). According to Nicholson (2013), rainfall in the Sudano-

Sahel region is controlled by mesoscale convective systems (MCS). Its variability can be attributed to several factors. Firstly, as over the rest of Africa, annual rainfall variability can be attributed to global sea surface temperature (SST) anomalies (Giannini *et al.* 2008). Secondly, for the Sudano-Sahel, fluctuations in high altitude jet streams circulation are responsible for the spatio-temporal variability of rainfall in the region. This includes the African Easterly Jet (AEJ), the Tropical Easterly Jet (TEJ), the African Westerly Jet (AWJ), Low Level Jets, the West African Westerly Jet (WAWJ), the Nocturnal Low Level Jets (NLLJ), the Saharan Heat Low (SHL), and the Saharan Air Layer (SAL) (Nicholson 2013).

Rainfall variability in the region is also strongly influenced by seasonal regime changes. The oceanic regime (monsoon), characterized by the progressive increase of moist air flow from the Atlantic Ocean into the continent up to about 11°N in May, is associated with seasonal migration of the Intertropical Convergence Zone (ITCZ) from its southern position in the boreal winter to its northern position in the boreal summer (Lebel *et al.* 2003). The continental regime is characterized by large convective systems during July to September embedded in the easterly circulation (Lebel *et al.* 2003), and also plays a key role in rainfall variability.

Decadal rainfall variability in the region has been associated with several possible causes. Jury (2010) attributed it to the interaction of Hadley Walker cells over Africa at decadal frequency through anomalous north-south displacement of the near-equatorial trough; Caminade and Terray (2010) linked it to atmospheric variability; Paeth and Hense (2004) attribute it to global warming while (Zeng *et al.* 1999) attribute it to vegetation feedback processes.

Despite the significant shrinkage in the size of Lake Chad in recent decades, research on rainfall variability over the Lake Chad basin (LCB) has received relatively little attention compared to other basins in the region (Ndehedehe *et al.* 2016; Karlson and Ostwald 2016). Nevertheless, (Okonkwo *et al.* 2014) used gridded gauge monthly time series (1970-2010) to show an increasing trend in annual rainfall over the LCB, while Niel *et al.* (2005) analyzed rainfall data from rain gauges covering the period 1950-2002 and reported a significant drop in annual rainfall in the central part of the basin (11° - 13°N). Armitage *et al.* (2015) also used paleo-climate records from the LCB to support the fact that the African monsoon responds to insolation forcing in a nonlinear manner and that Lake Mega-Chad exerted strong control on global biogeochemical cycles.

Given the numerous sub catchments that make up the LCB, the Logone catchment was selected for this analysis. This was motivated by the fact that: (i) the catchment covers two different ecological zones (Sudano and semi-arid); (ii) it contributes significantly to inflows into Lake Chad due to relatively high rainfall received in the Sudano zone; (iii) it is a transboundary catchment shared by three countries (Cameroun, Chad and Central Africa Republic); and (iv) it has extensive floodplains with great wildlife diversity and socio-economic value.

Floods have become frequent in recent years in the Logone catchment causing widespread socio-economic damage. Despite the floods, water availability for agriculture, pastoral activities, ecosystem sustainability and contribution as inflow into the lake, is still under threat due to the erratic rainfall. Yet, there is limited hydro-climatological documentation about the catchment and future rainfall projections in the region based on recent climate models show considerable spread (Aloysius *et al.* 2016; Haensler *et al.* 2013). Analysis of historical rainfall could therefore be a valuable source of information to gain insight into the sensitivity of the catchment to natural and human induced climate perturbations. This is important for informing water management and adaptation policies under climate change conditions.

The objective of this study was to: (i) check the spatial and temporal homogeneity of rainfall data in the Logone catchment; and (ii) analyse rainfall trends data in different space and time scales. Similar analysis at sub catchment scale have been conducted across many large basins in Africa, for example in the Bani, Kariba and Upper Blue Nile catchments, located in the Niger, Zambezi and Nile basins (Louvet *et al.* 2016; Muchuru *et al.* 2016; Tabari *et al.* 2015). A study limitation is the absence of gauge rainfall data after the year 2000, so the trends in recent rainfall variability after this period could not be explored. However, recent trends in rainfall within the LCB have been analysed using gridded gauge data (Okonkwo *et al.* 2014). Another limitation of this study is the use of rain gauge data, which are point measurements, to evaluate rainfall that is highly variable both in time and space. To be able to capture this variability a dense network of rain gauges equally distributed spatially across the catchment is needed, and this remains a major challenge in most hydro-climatic studies. Although this issue may be resolved by using satellite or reanalysis datasets, these too also need to be validated against in-situ rain gauge measurements e.g. (Nkiaka *et al.* 2016a). Accuracy, of satellite and reanalysis rainfall forecast models thus depends on the quality of gauge data used for calibration and are inevitably affected by the sparsity of gauge data or temporally incomplete gauge time series in the region under investigation.

This study is part of an on-going project aimed at understanding hydro-climatic variability in the Logone catchment that assesses vulnerability of the catchment to global climate change and the type of policy measures which can be put in place to improve water resources management and adaptation to climate change.

4.2 Study area and data

4.2.1 Study area

The Logone catchment covers an area of about 86,240 km^2 at the Logone Gana hydrometric station and lies between latitude 6˚ - 12˚ N and longitude 13˚ - 16˚ E in the south western part of Lake Chad basin (Figure 4.1). It is a major tributary of the Chari River and the two rivers jointly contribute about 95% of the inflow into Lake Chad. It has its source in Cameroun from the Mbere and Vina Rivers in the Adamawa Plateau. In Lai, it is joined by the Pende River from the Central Africa Republic and flows in a south-north direction. Elevation ranges from about 1200 masl on the Adamawa Plateau in the south to 300 masl in Ndjamena in the north. The basin topography is relatively flat with an average slope of less than 1.3%. It flows through three different countries, Cameroun, Central Africa Republic and Chad. The catchment is located in a Sudano-Sahelian climatic regime under the tropical continental regime air mass (the Harmattan) and the oceanic regime equatorial air mass (monsoon). It has a strong north-south rainfall gradient with a single rainy season between April and October. Average annual rainfall varies between 600 mm/year in the north to about 1500 mm/year in the south. Landuse in the catchment is dominated by forest (53%) and agriculture (34%).

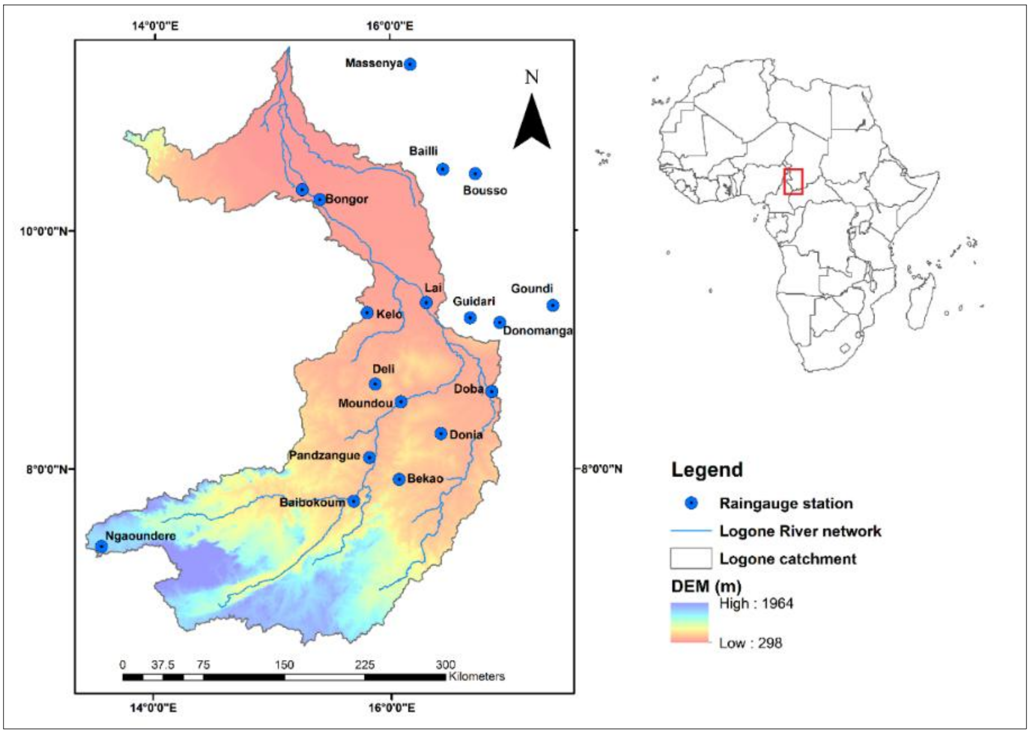


Figure 4.1 Map of study area. DEM: (Digital Elevation model at mean sea level)

4.2.2 Data sources

Monthly rainfall data was obtained from "Système d'Informations Environnementales sur les Ressources en Eau et leur Modélisation" (SIEREM) (Boyer *et al.* 2006). To improve reliability of analysis, only stations that had monthly data covering the period 1950-2000 with missing data points of not more than 10% were selected. Using these criteria, only 11 rain gauge stations located inside the catchment were acceptable, so six rain gauge stations located outside the catchment with the same climatic conditions were included in order to increase the data available.

Gaps in the data were infilled using Artificial Neural Network (ANN) Self-Organizing Map (SOM) technique (Nkiaka *et al.* 2016b). The time series were further screened and comparisons between stations made using statistical metrics including coefficient of variation (C_v), skewness (C_s) and actual excess kurtosis (K_u).

The monthly time series were aggregated to annual and seasonal time series for each station. The rainy season in the catchment generally lasts from April to October, aggregation was done for the months of April, May and June (AMJ) to correspond with the pre-monsoon season; then July, August and September (JAS) for the monsoon season. Table 4.1 shows the station name, coordinates, long term mean, maximum, minimum, C_v, C_s, and K_u of the annual rainfall time series for each station. The C_v of annual rainfall varies between 0.10 - 0.24; rainfall is slightly positively skewed (C_s=0.36) and leptokurtic (K_u=0.34) (higher and sharper central peak with longer and flatter tails) compared to a normal distribution where C_s=0 and K_u=0. Long term mean annual rainfall varies between 642 mm/year (Massenya) in the semi-arid zone to 1514 mm/year (Ngaoundere) in the Sudano zone.

4.3 Methodology

The catchment was divided into two parts. The northern part was termed "semi-arid" for stations located between latitude 10° -12° N and the southern part termed "sudano" for stations located between latitude 6° - 10° N. Stations 1-13 lie in the sudano zone and 14-17 are located in the semi-arid area (Table 4.1). Annual rainfall from stations located in each of the zones was averaged and plotted as shown in Figure 4.2. Different statistical tests were used for homogeneity and trend testing (Sonali and Kumar, 2013).

4.3.1 Homogeneity test

The importance of the homogeneity test is to ensure that the data is not affected by non-climatic factors such as station location, station environment, observation practices and instruments. According to Yozgatligil and Yazici (2016) homogeneity testing is a critical quality control method in hydro-climatological studies and underpins the reliability of any inferences drawn from the data. For homogeneity testing, the standard normal homogeneity test (SNHT), Buishand Range (BR), Pettitt and Von Neumann ratio tests were applied (Yozgatligil and Yazici 2016; Buishand *et al.* 2013; Wijngaard *et al.* 2003). Under the null hypothesis, all four tests assume that the annual values of the variable under investigation are independent and identically distributed while under the alternative hypothesis, SNHT, BR and Pettit tests assume there is a break or step-wise shift in the mean of the variable. The first three tests can locate the year in which the break occurred. SNHT is useful for detecting inhomogeneity at the beginning or end of the time series while BR and Pettitt tests are useful for detecting inhomogeneity at the middle of the time series. While the SNHT and BR tests assume that the variable is normally distributed, the Pettitt test does not use this assumption because it is a non-parametric test based on the ranks of the observations in the series rather than on the values themselves. Finally, under the alternative hypothesis, the Von Neumann ratio test assumes that the series is not randomly distributed.

Generally, a combination of different statistical methods is recommended to be most effective to track down inhomogeneities in hydro-climatic time series (Wijngaard *et al.* 2003). Critical values for all these tests are available in Wijngaard *et al.* (2003).

4.3.2 Trend test

After testing and ascertaining the homogeneity of the data, the time series was deseasonalized using the Seasonal Trend Decomposition procedure based on Loess (STL) (Cleveland *et al.* 1990). This technique was used to decompose the time series into three components: trend, seasonal, and the remainder component. STL is widely used for deseasonalizing hydro-climatic data (Buma *et al.* 2016; Aguilera *et al.* 2015).

Trend tests were used to detect if the trend component of the deseasonalized rainfall time series monotonically increased or decreased with time. The non-parametric tests used for trend testing included MannKendall (MK) and Spearman rho tests while Sen's Slope estimator was used to calculate the magnitude of the trend (Onyutha *et al.* 2015; Sonali and Kumar 2013; Kumar *et al.* 2010). Only the trend component was used for analysis to avoid distortion due to seasonality or irregularity in the data. The deseasonalized monthly rainfall time series were further aggregated into annual and seasonal time scales to check for potential changes that could have occurred at these time scales. Note that for analysis at monthly time scale, the rainfall data was not deseasonalized.

Because the ability to detect trends in a time series using the MK test can be influenced by the presence of autocorrelation, Yue *et al.* (2002) proposed the use of trend-free pre-whitening (TFPW) to remove autocorrelation. However, many authors have criticized the use of TFPW for this purpose (Sonali and Kumar 2013; Kumar *et al.* 2010; Bayazit and Önöz 2007). These authors argue that, when the sample size is large ($n \geq 50$) and the slope of the trend is high (≥ 0.01), pre-whitening is not needed because there will be negligible effect of serial correlation especially for a type-I error, and could also result in significant power loss of the test. Given that the sample size of data used in this study is large ($n \geq 50$) and the MK test was not the only test used for trend testing, TFPW was not applied.

Although most trend analysis consider only long term time series, short significant events may also exist within data series that do not have any significant influence on the overall long term time series, but could have profound impact on livelihoods, ecosystems and infrastructure. For this reason, trend analysis was also conducted at monthly and seasonal time scales.

Table 4.1 Overview of meteorological stations and annual rainfall properties

Station No	Rain gauge station		Location		Elevation (m)	Annual rainfall (mm/yr)					
	Station ID	Name of locality	Lat	Long		Max	Min	Mean	C_v	C_s	K_u
1	1050042800	Ngaoundere	7.35	13.56	1113	1864	1152	1514.32	0.10	-0.16	-0.06
2	1460009500	Baibokoum	7.73	15.68	1323	1672	881	1277.36	0.15	-0.14	-0.69
3	1460017500	Bekao	7.92	16.07	528	1630	853	1180.98	0.17	0.32	-0.62
4	1460072500	Pandzangue	8.10	15.82	345	1892	919	1242.44	0.18	1.00	0.67
5	1460034500	Donia	8.30	16.42	414	1782	796	1085.42	0.19	0.83	1.13
6	1460066000	Moundou	8.57	16.08	410	1843	783	1102.72	0.17	1.26	4.22
7	1460033000	Doba	8.65	16.85	387	1475	680	1057.18	0.18	0.44	-0.21
8	1050630400	Deli	8.72	15.87	427	1539	705	1064.04	0.17	0.56	0.11
9	1460035000	Donomanga	9.23	16.92	370	1519	681	981.60	0.17	0.50	0.81
10	1460044500	Guidari	9.27	16.67	369	1562	629	1005.16	0.20	0.57	0.36
11	1460041500	Kélo	9.32	15.80	378	1413	503	979.68	0.18	-0.28	0.23
12	1460049000	Goundi	9.37	17.37	368	1519	681	981.60	0.17	0.50	0.81
13	1460053000	Lai	9.40	16.30	358	1491	669	1021.92	0.16	0.25	0.29
14	1460025500	Bongor	10.27	15.40	328	1070	400	789.86	0.18	-0.32	0.37
15	1460027000	Bousso	10.48	16.72	336	1365	423	844.24	0.24	0.19	-0.39
16	1460010000	Bailli	10.52	16.44	330	1146	463	797.32	0.19	0.3	-0.07
17	1460060500	Massenya	11.40	16.17	328	977	410	641.48	0.21	0.34	-0.2

4.4 Results

4.4.1 Homogeneity analysis

Results obtained using the different homogeneity tests were not in total agreement with each other. While SNHT and BR tests produced similar results, Pettitt test produced different results and the changes observed did not occur in the same year. However, according to Wijngaard *et al.* (2003), the different tests could have different sensitivities to changes in rainfall series explaining the differences in results.

In this study, a time series was considered homogenous if the critical values of SNHT, Pettitt test and Von Neumann ratio test statistics were less than 11.38, 293 and 1.36 respectively. Since SNHT and BR tests produced identical results, only the results of SNHT are shown in Table 4.2. These results were further grouped into classes A, B and C using the criteria proposed by Wijngaard *et al.* (2003) at the 1% significance level. The results are grouped into: class A (useful) zero or one rejection; class B (doubtful) two rejections; and class C (suspect) three or more rejections. From Table 4.2, 47% of the stations fall under class A classified as homogeneous; 29% of the stations fall under class B meaning that these time series are doubtful, thus results of trend analyses should be regarded critically due to the possible existence of inhomogeneities; and 24% of the stations were grouped under class C suggesting that the results of the trend analysis should be rejected due to the existence of inhomogeneities.

However, the dates of the breaks observed in classes B and C fall mostly within the period of droughts or its onset in the region, so we considered that these breaks were as a result of natural climate variability. None of the time series exhibited significant break points at the 99% confidence interval, so we assumed that the data were free from any artefacts that could cause artificial trends in the rainfall time series, and that these time series could be regarded as homogeneous and thus qualify for trend analysis.

Furthermore, despite the smoothing effect caused by averaging over large areas, the trend in annual rainfall still shows a general downturn in rainfall beginning around the mid-1960s for all stations as shown in Figure 4.2. Figures 4.3a&b also confirm the homogeneity in the time series as the mean monthly range is the same for stations located in each of the zones with no outlier detected.

Table 4.2 Results of homogeneity tests for annual rainfall (1951 - 2000)

Station name	SNHT		Pettitt		Von Neumann	Test Class
	Statistics	Break	Statistics	Break	Statistics	
Ngaoundere	11.04	1966	340		1.44	B
Baibokoum	5.42		240		2.10	A
Bekao	6.42		239		2.00	A
Pandzangue	3.51		192		1.45	A
Donia	9.05		331	1982	1.66	B
Moundou	9.13		254		2.03	A
Doba	11.89	1970	317		1.43	C
Deli	3.95		205		2.26	A
Donomanga	16.25	1955	350		1.51	C
Guidari	12.55	1964	310		1.74	C
Kélo	4.86		205		1.97	A
Goundi	18.31	1962	453	1976	0.97	B
Lai	4.43		234		1.86	A
Bongor	12.24	1969	367	1969	1.30	B
Bousso	14.77	1961	394	1971	1.38	C
Bailli	9.5	1962	342		1.87	B
Massenya	7.98		290		1.41	A

4.4.2 Trend analysis

The results obtained using the various statistical trend tests are elaborated in the following sub sections divided into annual, seasonal and monthly rainfall trend analysis.

4.4.2.1 Annual rainfall

Figure 4.2 shows the trend component of the annual rainfall time series averaged over the semi-arid and sudano areas of the catchment. From the figure it can be observed that there was a general decline in annual rainfall over the two ecological zones. Although the trend remained negative during the period under study, the figure shows a general recovery in rainfall beginning from mid-1980 but has not yet reached the level observed before the droughts. The figure also shows that although the trend was generally negative, annual rainfall was very variable in both parts of the catchment during the period under study. Table 4.3 shows the results of MK, Spearman Rho and Sen's Slope tests at 5% significance level. Results from both tests indicate the presence of negative trends for annual time series, therefore the null hypothesis was rejected for all stations. The magnitude of Sen's Slope further indicated that annual rainfall reduced by 1-9 mm/year across stations with a maximum drop observed at Goundi (-8.06 mm/year), while the minimum was observed at Pandzangue (-1.48 mm/year). Apart from Bousso which is located in the semi-arid area, the decrease in annual rainfall was more severe for stations located in the Sudano area of the catchment.

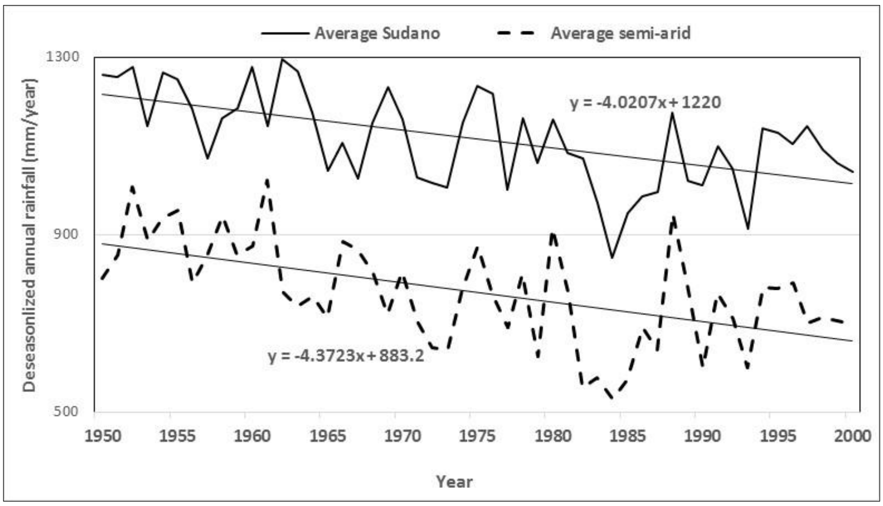
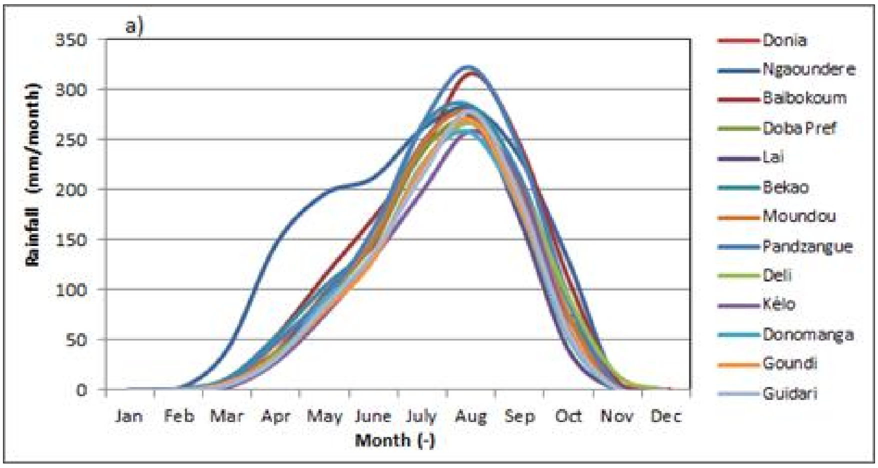


Figure 4.2 Annual rainfall trend in the Logone catchment

4.4.2.2 Seasonal rainfall

Analysis of seasonal rainfall using both tests revealed negative trends during the pre-monsoon and monsoon seasons with almost equal severity in both zones as the drop varied from -0.27 to 2.25 mm/season. The magnitude of the Sen's Slope showed that Goundi station witnessed the most dramatic drop in both the pre-monsoon and monsoon rainfall (-2.25 mm/season). Stations with statistically significant negative trends were recorded only in the Sudano area during the pre-monsoon and monsoon seasons even at annual time scale.

The negative trends in annual and seasonal rainfall observed in the Logone catchment correspond to the onset of the Sahelian drought that lasted from the mid-1960s-1980s and was associated with a significant drop in rainfall throughout the region. Similar trends in annual rainfall in the LCB were reported by Niel *et al.* (2005) and elsewhere in the region by Ifabiyi and Ojoye (2013), and Conway *et al.* (2009). Meanwhile for seasonal rainfall, Sarr (2012) reported a general decline in seasonal July, August and September (monsoon) rainfall throughout the 1961–1990 period in the Sudano-Sahel zone of Nigeria.



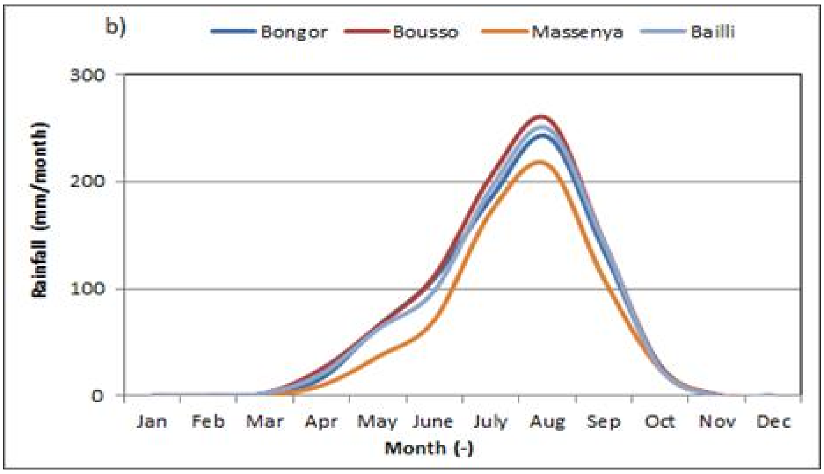


Figure 4.3 Long term mean monthly rainfall for (a) Sudano zone, (b) semi-arid zone

4.4.2.3 Monthly rainfall

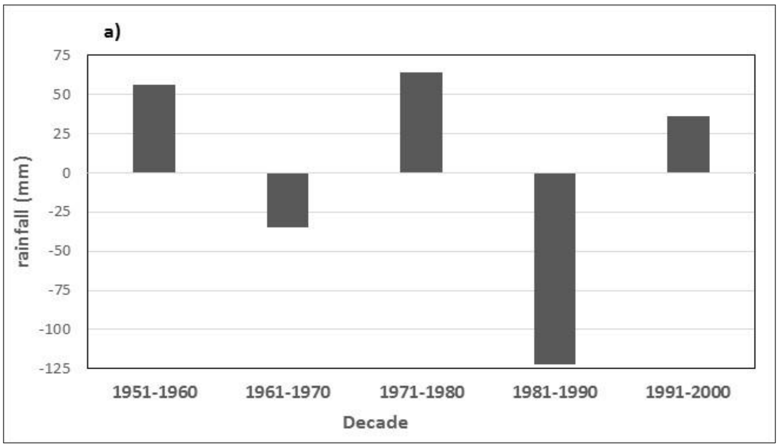
Results of long term trend analysis at a monthly time scale shown in Table 4.4 revealed that, apart from negative trends, statistically insignificant positive trends were also observed at some stations. Positive trends were observed in July at 35% of the stations while April, May and June recorded positive trends at 29% of the stations. The increase in monthly rainfall was random with no station observing a systematic increase during all the months. Furthermore, positive trends were observed across the catchment in August at only two stations (Pandzangue and Kello) and a statistically significant positive trend was observed at one station (Deli) in September. This finding is important as hitherto the highest rainfall was recorded in the catchment during August and September (Loth and Acreman 2004).

Table 4.3 Results of annual and seasonal rainfall analysis using MannKendall's Tau (Z_{MK}), Spearman's Rho (*SR*) and Sen Slope (*SE*)

Station	Annual rainfall			Pre-monsoon			Monsoon		
	Z_{MK}	SR	SE	Z_{MK}	SR	SE	Z_{MK}	SR	SE
Ngaoundere	-0.32	-0.47	-4.00	-0.26	-0.39	-1.15	-0.28	-4.30	-1.16
Baibokoum	**-0.24**	**-0.35**	-4.11	**-0.24**	**-0.34**	-1.15	**-0.20**	**-0.30**	-0.98
Bekao	-0.16	-0.26	-3.00	-0.13	-0.21	-0.70	-0.15	-0.24	-0.95
Pandzangue	-0.10	-0.16	-1.48	-0.07	-0.12	-0.27	-0.07	-0.12	-0.37
Donia	-0.30	-0.43	-5.31	-0.29	-0.43	-1.44	-0.28	-0.40	-1.37
Moundou	**-0.23**	**-0.33**	-3.12	**-0.20**	**-0.30**	-0.78	-0.18	-0.24	-0.72
Doba	-0.25	-0.36	-4.31	**-0.23**	**-0.33**	-1.03	**-0.24**	**-0.34**	-1.12
Deli	-0.12	-0.15	-1.87	-0.13	-0.17	-0.59	-0.10	-0.14	-0.33
Donomanga	-0.37	-0.49	-6.02	-0.36	-0.44	-1.45	-0.33	-0.44	-1.57
Guidari	**-0.25**	-0.37	-5.04	**-0.25**	**-0.34**	-1.39	-0.18	-0.25	-1.59
Kello	-0.16	-0.23	-2.84	-0.13	-0.18	-0.54	-0.12	-0.18	-0.51
Goundi	-0.40	-0.59	-8.06	-0.40	-0.58	-2.07	-0.39	-0.57	-2.25
Lai	-0.13	-0.19	-1.96	-0.08	-0.13	-0.37	-0.10	-0.16	-0.52
Bongor	-0.31	-0.47	-3.34	-0.27	-0.41	-0.87	-0.28	-0.43	-0.95
Bousso	-0.40	-0.56	-7.55	-0.38	-0.52	-0.87	-0.37	-0.52	-1.94
Bailli	-0.40	-0.58	-4.66	-0.35	-0.52	-1.18	-0.35	-0.51	-1.40
Massenya	-0.15	-0.21	-2.11	-0.16	-0.21	-0.55	-0.14	-0.19	-0.57

*Bold values indicate that the trend is statistical significant at 5% level as per the 2 tail test (+ for increasing and - for decreasing) pre-monsoon season (April, May and June) while monsoon season (July, August and September)

The increase in rainfall in the months of April, May, June and July with little or no increase in August and September suggest that there might have been a backward shift in the occurrence of rainfall in the catchment. However, further analysis is needed using daily rainfall data extending into the recent decade to confirm this. Lebel and Ali (2009) also reported the disappearance of peak rainfall previously observed in August in the Central Sahel region, and Sarr (2012) asserted that there was a general decline in July, August and September rainfall throughout the 1961–1990 period in the region. The backward shift in rainfall could increase crop production in the catchment as it coincides with the planting season.



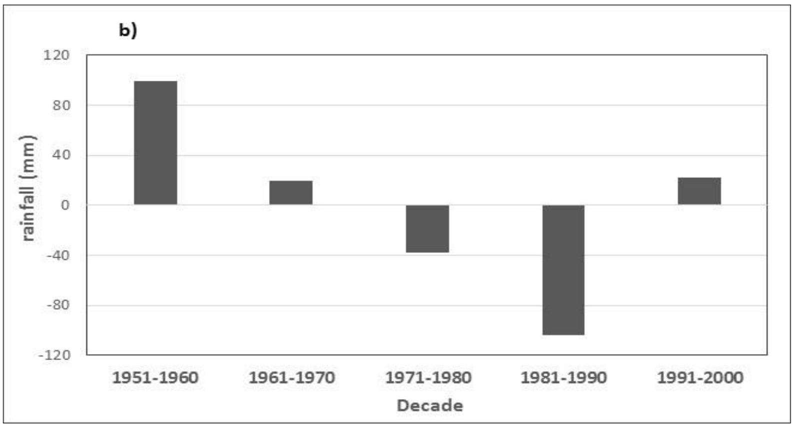


Figure 4.4 Difference between decadal and long term mean (1951 - 2000) for annual rainfall in a) Sudano area at Pandzangue and b) semi-arid area at Massenya

Following Ma *et al.* (2013), Table 4.5 summarises the differences between annual, seasonal and monthly decadal mean rainfall data in the catchment from their long-term means. In this table, the values represent the decadal means minus the long-term mean 1951-2000. From the table it can be observed that higher than normal rainfall was recorded across the catchment during the 1950 and 1960 decades. This was followed by a general drop during the 1970 and 1980 decades which correspond to the period of drought in the region. Although decadal rainfall in 1990 was still generally low compared to 1950 and 1960 decades in most stations, positive values were observed at 24% of the stations (Lai, Pandzangue, Deli and Massenya).

Analysis further revealed that, between 1980 and 1990 decades, pre-monsoon (April, May and June) rainfall increased in 65% of the stations. Three stations (Baibokoum, Pandzangue and Massenya) recorded a decadal increase of more than 120 mm/decade during the monsoon season in the 1990 decade. Generally, decadal rainfall was very variable across the catchment because the difference between the long term and decadal means oscillated between high and low values from decade to decade (Figures 4.4a&b and 4.5a&b). Furthermore, the difference between mean decadal rainfall for 1990 and 1980 showed that decadal rainfall increased by an average of 15 mm across the catchment during the 1990 decade compared to the previous decade.

The increase in decadal rainfall during 1990 decade suggest that the catchment may be recovering from drought, as is the case in other Sudano-Sahel catchments. Increasing rainfall trends in the region have been widely reported. Maidment *et al.* (2015) in their analysis observed a positive trend in rainfall in the LCB covering the semi-arid zone of the Logone catchment while Okonkwo *et al.* (2014) also reported a similar trend in the southern part of LCB covering the Sudano zone of the catchment. In a recent study, Ndehedehe *et al.* (2016) also reported an increasing trend in rainfall over the LCB since 1990. In addition, the positive trends in rainfall observed in the catchment are reported to be a global trend (Westra *et al.* 2013).

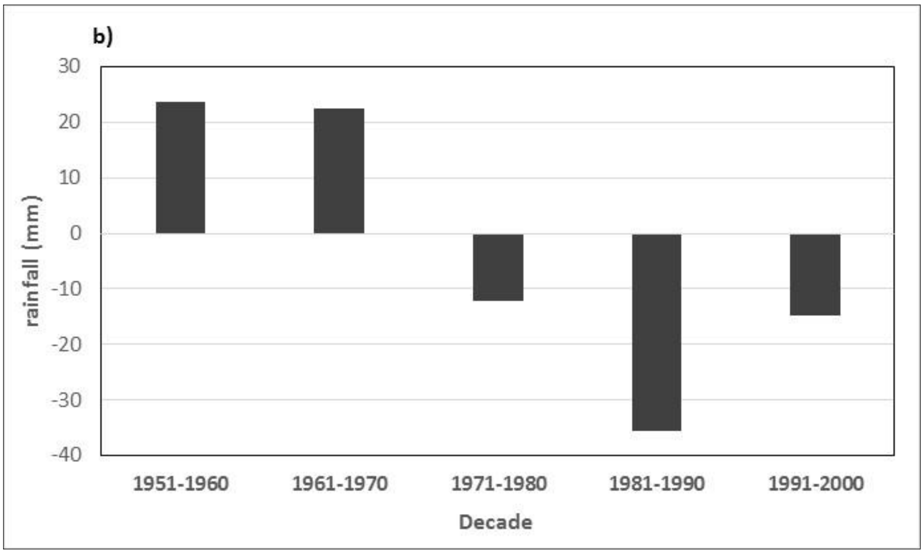


Figure 4.5 Difference between decadal mean and long term mean (1951 - 2000) for seasonal rainfall in Lai a) pre-monsoon and b) monsoon

4.5 Spatial variability in rainfall

The first evidence of spatial rainfall variability in the catchment is in the difference in annual and monthly means between stations located in the semi-arid and sudano zones. As shown in Table 4.2, mean annual rainfall varies between 600 – 900 mm/year for stations located in the semi-arid zone and 900 – 1500 mm/year for station in the sudano zone. It can also be observed from Figures 4.3a&b that monthly rainfall varies between 200-300 mm/month in the semi-arid and 250-350 mm/month in the sudano zones. Additional proof of spatial variability of rainfall in the catchment is evident in the strong north-south gradient in rainfall over the catchment with rainfall increasing in a southward direction as shown in Table 4.1.

The coefficient of variation (C_v), which measures dispersion around the mean, was also calculated to analyze the spatial variability of annual precipitation for each station. As shown in Table 4.1, this coefficient varied from 10% in Ngaoundere to 24% in Bousso. Average annual variability was 18%, 17% and 21% for the whole catchment, the sudano, and the semi-arid zones respectively. This indicates that stations located in the semi-arid zone displayed a higher degree of rainfall variability compared to stations located in the sudano zone.

Furthermore, the slope of the trend lines for annual rainfall averaged over the respective zones is steeper for the semi-arid zone (-4.37) compared to the sudano zone (-4.02) (Figure 4.2). This implies that the semi-arid zone witnessed a more severe drop in rainfall compared to the

Sudano zone during the period under study. At the level of individual stations, results in Table 4.3 show that the most significant drop in rainfall was registered in Goundi (-8.06 mm/year) located in the Sudano zone compared to Bousso (-7.55 mm) in the semi-arid zone. These results are similar to those obtained in other catchments in the region (Mertz *et al.* 2012; Conway *et al.* 2009; Mahé and Paturel 2009). As shown in Figure 4.3b and Table 4.1, Massenya, the most northerly station, recorded the lowest long term mean annual and monthly rainfall; while Ngaoundere which is the most southerly station recorded the highest of both. Results of trend analysis further indicated that, although negative trends were recorded across all the stations in the catchment, statistically significant negative trends were observed only in the Sudano zone.

Although there are significant differences in total rainfall over the zones, there are common characteristics among them, including a single rainy season and a high variability in rainfall across individual stations from year to year. All stations show a severe drop in rainfall around 1984 and a general recovery observed after 1985 (Figure 4. 2).

Table 4.4 Results of monthly rainfall analysis using MannKedall's Tau (Z_{MK}), Spearman's Rho (SR) and Sens Slope (SE)

Station	March			April			May			June		
		SR	SE	ZMK	SR	SE	ZMK	SR	SE	ZMK	SR	SE
Ngaoundere		-0.14	-0.34	0.07	0.15	0.48	-0.13	-0.21	-0.70	-0.19	**-0.28**	-1.19
Baibokoum		-0.20	0.00	**-0.20**	-0.28	-0.74	-0.09	-0.14	-0.45	-0.13	-0.19	-0.79
Bekao		**0.15**	0.00	-0.04	-0.07	-0.18	-0.01	-0.02	-0.05	0.03	0.06	0.14
Pandzangue		-0.25	0.00	-0.15	-0.24	-0.47	0.00	-0.02	0.00	-0.09	-0.13	-0.38
Donia		**-0.38**	0.00	-0.25	-0.37	-0.67	0.09	-0.12	-0.30	-0.18	-0.26	-0.82
Moundou		-0.37	0.00	**-0.20**	-0.30	-0.68	-0.13	-0.20	-0.43	-0.06	-0.08	-0.27
Doba		**-0.10**	0.00	**-0.22**	-0.29	-0.53	0.00	-0.02	0.00	-0.11	-0.15	-0.56
Delli		-0.35	0.00	**-0.22**	-0.35	-0.50	-0.26	**-0.36**	-1.22	-0.05	**-0.07**	-0.21
Donomanga		0.03	0.00	0.00	0.00	0.00	-0.01	-0.03	-0.04	0.04	0.05	0.24
Guidari		-0.26	0.00	-0.04	-0.08	-0.08	-0.05	-0.06	-0.24	-0.03	-0.03	-0.23
Kello		**-0.12**	0.00	-0.16	-0.25	-0.37	0.03	0.04	0.13	0.07	0.11	0.29
Goundi		**-0.28**	0.00	-0.08	-0.13	-0.20	-0.15	-0.22	-0.78	0.01	0.01	0.03
Lai		-0.23	0.00	0.04	0.02	0.09	-0.01	0.03	0.00	0.02	0.02	0.08
Bongor		-0.30	0.00	-0.14	-0.18	-0.18	-0.08	-0.12	-0.30	**-0.22**	-0.31	-1.04
Bousso		-0.15	0.00	-0.17	-0.24	-0.25	0.03	0.04	0.10	-0.18	-0.23	-0.86
Bailli		-0.19	0.00	0.02	0.02	0.00	0.00	0.00	0.00	-0.14	-0.22	-0.64
Massenya		-0.16	0.00	0.09	0.14	0.03	**-0.22**	**-0.32**	-0.43	-0.11	-0.16	-0.36

Station name	July			August			September			October		
	ZMK	SR	SE	ZMK	SR	SE	ZMK	SR	SE	ZMK	SR	SE
Ngaoundere	0.01	0.01	-0.11	-0.09	-0.13	-0.50	-0.06	-0.10	-0.43	-0.10	-0.13	-0.71
Baibokoum	-0.12	-0.15	-0.86	-0.02	0.02	-0.19	-0.06	-0.09	-0.57	-0.16	-0.21	-1.02
Bekao	-0.08	-0.13	-0.58	-0.17	-0.24	-1.43	-0.19	-0.30	-1.41	-0.08	-0.10	-0.43
Pandzangue	0.08	0.12	0.57	0.11	0.18	1.08	-0.11	-0.18	-1.12	-0.01	0.00	0.00
Donia	-0.11	-0.14	-0.89	-0.22	-0.33	-1.29	-0.14	-0.21	-1.03	-0.10	-0.15	-0.38
Moundou	-0.02	-0.05	-0.14	-0.16	-0.24	-1.00	-0.09	-0.12	-0.62	0.02	0.02	0.13
Doba	0.02	0.03	0.17	-0.22	-0.32	-1.59	-0.29	-0.40	-1.61	-0.06	-0.08	-0.21
Delli	-0.09	-0.13	-0.68	-0.30	-0.43	-2.08	0.07	0.13	0.56	0.09	0.13	0.61
Donomanga	-0.17	-0.23	-1.31	-0.21	-0.32	-1.32	-0.23	-0.34	-1.50	-0.25	-0.37	-0.92
Guidari	-0.13	-0.20	-1.00	-0.21	-0.29	-1.84	-0.18	-0.26	-1.71	-0.20	-0.28	-0.85
Kello	-0.15	-0.21	-1.12	0.09	0.14	0.66	-0.15	-0.23	-1.11	-0.16	-0.21	-0.58
Goundi	-0.22	-0.31	-1.79	-0.17	-0.26	-1.82	-0.29	-0.43	-2.06	-0.17	-0.24	-0.83
Lai	0.19	0.28	1.78	-0.11	-0.18	-0.85	-0.29	-0.41	-2.45	-0.23	-0.30	-0.69
Bongor	0.08	0.11	0.49	-0.10	-0.15	-1.07	-0.19	-0.27	-1.20	-0.04	-0.06	-0.03
Bousso	-0.20	-0.31	-1.43	-0.22	-0.34	-2.00	-0.19	-0.25	-1.71	-0.10	-0.16	-0.24
Bailli	-0.15	-0.23	-0.89	-0.12	-0.18	-1.27	-0.21	-0.31	-1.63	-0.11	0.12	-0.20
Massenya	0.00	0.02	0.00	-0.04	-0.06	-0.31	-0.15	-0.20	-0.57	0.05	0.05	0.10

*Bold values indicate that the trend is statistical significant at 5% level as per the 2 tail test (+ for increasing and - for decreasing). January, February, November and December are excluded from the table.

Table 4.5 The difference between mean decadal rainfall and the long-term mean (1951 - 2000). Differences represent the decadal mean minus the long term mean (mm)

	Decade	Ngaoundere	Baibokoum	Bekao	Pandzangue	Donia	Moundou	Doba	Deli	Donomanga	Guidari	Kélo	Goundi	Lai	Bongor	Bousso	Bailli	Massenya
Annual rainfall	1951-1960	128.68	100.24	105.22	56.46	95.28	71.98	96.02	49.36	135.6	130.54	65.02	197.32	31.28	108.24	192.66	102.58	99.32
	1961-1970	19.08	28.64	46.12	-34.74	86.88	78.18	142.52	38.86	38	81.64	31.72	29.52	70.98	54.64	59.46	36.58	20.02
	1971-1980	25.88	5.54	-78.78	64.36	14.48	2.28	-53.28	-49.84	-46.5	-20.06	1.32	24.82	-20.12	-32.66	-24.14	3.78	-37.48
	1981-1990	-86.22	-102.86	-71.18	-122.44	-115.12	-120.12	-98.78	-47.24	-90.8	-144.6	-89.48	-180.08	-98.92	-120	-138.34	-53.22	-103.98
	1991-2000	-87.42	-31.56	-1.38	36.36	-81.52	-32.32	-86.48	8.86	-36.3	-47.56	-8.58	-71.58	16.78	-10.26	-89.64	-89.72	22.12
Monthly	1951-1960	10.75	8.36	8.78	4.71	7.99	6	8.05	4.11	11.31	10.89	5.47	16.44	2.65	9.02	16.06	8.55	8.28
	1961-1970	1.48	2.35	3.78	-2.9	7.05	6.52	11.66	3.24	3.12	6.75	2.44	2.46	5.74	4.55	4.96	3.05	1.67
	1971-1980	2.18	0.47	-6.55	5.36	1.26	0.19	-4.39	-4.15	-3.86	-1.66	0.16	2.07	-1.63	-2.72	-2.01	0.32	-3.12
	1981-1990	-7.16	-8.56	-5.92	-10.2	-9.55	-10.01	-8.18	-3.94	-7.55	-12.03	-7.41	-15.01	-8.2	-10	-11.53	-4.44	-8.67
	1991-2000	-7.26	-2.62	-0.1	3.03	-6.75	-2.69	-7.15	0.74	-3.01	-3.95	-0.66	-5.97	1.44	-0.86	-7.47	-7.48	1.84
pre-monsoon	1951-1960	42.90	25.43	-6.41	-15.86	-0.49	27.63	5.29	37.57	43.73	-22.49	9.72	46.25	29.03	-5.18	30.05	-5.20	22.05
	1961-1970	55.90	21.83	35.19	33.94	24.01	14.03	3.69	48.27	9.33	37.21	45.22	34.05	28.83	24.02	18.05	50.30	2.75
	1971-1980	-15.30	-4.17	7.39	0.84	-37.19	4.53	19.19	-16.13	34.23	-2.89	10.42	-26.85	4.83	-23.08	-8.25	-20.20	23.85
	1981-1990	-59.00	18.43	-29.81	-51.86	-2.09	-46.07	5.59	-48.53	17.13	-36.69	-42.88	-17.85	-22.67	-35.88	-63.35	-47.80	-14.95
	1991-2000	-13.30	-68.97	-3.11	37.74	8.61	-7.97	-43.31	-24.73	-98.67	15.81	-12.28	-24.45	-44.57	38.22	24.55	20.80	-30.05
Monsoon	1951-1960	40.1	32.85	41.95	85.13	23.63	86.78	6.85	24.18	55.95	31.48	53.17	163.85	40.48	33.99	108.43	120.67	94.27
	1961-1970	13.2	-22.55	3.55	0.23	22.43	24.78	80.85	-44.72	7.45	75.18	3.17	2.55	109.98	70.29	7.73	22.17	26.97
	1971-1980	88.7	68.35	-10.75	0.83	-12.17	-59.32	17.05	43.18	-20.15	-47.32	7.37	-28.25	-12.92	18.39	-25.27	23.47	-5.63
	1981-1990	-41.4	-17.65	-93.75	-14.17	-35.67	-50.22	-55.45	-92.52	-60.65	-24.22	-54.73	-85.05	-48.82	-66.21	-48.87	-94.23	-78.43
	1991-2000	-100.6	-53.95	38.25	-94.07	-14.87	-26.12	-44.25	52.58	12.25	-31.72	-12.43	-78.65	-79.82	-72.31	-74.57	-99.73	-70.43

Figures in bold represent increases

4.6 Discussion

The significant negative trends in annual and seasonal rainfall recorded across the catchment suggest that there has been a significant change in the processes that influence rainfall. This indicates that the catchment is sensitive to natural climate perturbations and could thus be vulnerable to anthropogenic climate change.

Generally, rainfall variability in the Logone catchment can be attributed to the seasonal north-south movement of the intertropical convergence zone (ITCZ) as its strength and position strongly influence the processes that generate rainfall over the region (Nicholson 2013). Furthermore, given the location of the catchment (6˚-12˚N), the spatiotemporal variability in rainfall can also partly be attributed to the AWJ and WAWJ. These jet streams develop around this latitudinal zone from May to September coinciding with the period of peak rainfall in the catchment (Nicholson 2013). The Northern African Easterly Jet (AEJ-N) and Southern African Easterly Jet (AEJ-S), which blow over the Logone catchment in August, also play a major role in influencing rainfall variability in the catchment (Farnsworth *et al.* 2011).

Factors such as topography also influence the spatial variability of rainfall in the Logone catchment. For example the southern flank of the Adamawa Plateau in Cameroun acts like a shield that prevents the progress of the oceanic regime (monsoon winds) towards the north around the month of March when the southern part of Cameroun is experiencing rain. This causes the displacement of the ITCZ towards the Western Highlands of Cameroun, so the continental regime (harmattan) with its dryness continues to prevail in the catchment (Molua and Lambi 2006). During the month of May, the wetter oceanic regime pushes the continental regime northwards and displaces the ITCZ towards the north into the Logone catchment. Rainfall amounts recorded in the catchment during this period are indicative of the strength of the monsoon and position of ITCZ (Molua and Lambi 2006).

The differences in rainfall between the semi-arid and Sudano zones can also be attributed to the kind of regime (oceanic or continental) that prevail in each of the zones at a given period of the year. In the Sudano zone the oceanic regime from the Atlantic Ocean dominates, causing high annual rainfall, while in the semi-arid area the continental regime from the Sahara Desert dominates resulting in low annual rainfall. High rainfall in the Sudano zone can also be attributed to orographic effects due to the high altitude of Adamawa Plateau in Cameroun and the Karre Mountains in the Central Africa Republic.

At the decadal time scale, Okonkwo *et al.* (2014) reported that El Niño Southern Oscillation (ENSO) events occurring around the months of July, August and September usually lead to a decrease in rainfall over the LCB so the absence of positive trends in rainfall during August and September across the catchment could be attributed to ENSO events. In addition, (Okonkwo *et al.* 2015) reported that the warm phase of Atlantic Multi Decadal Oscillation (AMO) could play a major role by influencing the increasing trends in decadal precipitation in the region as observed in this study.

The increase in monthly rainfall during the 1990 decade could be attributed to an increase in the intensity of localised rainfall as observed by Panthou *et al.* (2014) and Giannini *et al.* (2013) in other areas across the region. For example, after analysing rainfall trends in the Sudano-Sahel zones of Nigeria, (Ifabiyi and Ojoye 2013) concluded that increasing rainfall trend was responsible for the frequent floods observed in the area recently. Furthermore, Okonkwo *et al.* (2015) have reported that there is a slow recovery in Lake Chad level as a response to recent increases in rainfall in the basin.

Giannini *et al.* (2003) attribute increasing rainfall trends in the region to a rise in SST of the Northern Atlantic Ocean. Meanwhile, Dong and Sutton (2015) have attributed this increase to the rising levels of greenhouse gases (GHGs) in the atmosphere and the consequent increase in atmospheric temperature. In a separate study, Evan *et al.* (2015) partly attribute this rainfall recovery in the region to an upward trend in the Saharan heat low (SHL) temperature resulting from atmospheric greenhouse warming by water vapour.

Temporal changes observed in rainfall patterns, with increasing trend in pre-monsoon rain earlier, could increase crop production in the catchment as it coincides with the planting season. However, more advanced forecasting techniques are needed so that information on the early onset of rainfall can be communicated to farmers in real time and with certainty. In general, the observed increase in rainfall could be beneficial to biodiversity, agriculture and pastoral activities, but floods also have negative socio-economic consequences such as destruction of property and crops. Flooding could also increase the risk of water related diseases such as malaria, diarrhoea, cholera and typhoid fever. Spatial rainfall analysis is important because it enables local authorities to know where to focus attention for developing water conservation measures and develop infrastructure to prevent damage due to floods.

4.7 Conclusion

Rainfall time series in the Logone catchment were analysed at monthly, seasonal, annual and decadal time scales with the aim of finding trends and variability using data from 17 rain gauge stations unevenly distributed across the catchment and beyond. Based on available data, the following conclusions can be drawn:

- Annual rainfall was homogeneous but very variable from year to year across the catchment.
- While negative trends were observed for annual rainfall in all the stations, statistically insignificant positive trends were obtained in all but one station at a monthly time step for some months.
- The negative trends in precipitation observed in the catchment correspond to the onset of the Sahelian drought in the mid-1960s to the 1980s that led to a significant drop in rainfall across the region.
- Although the statistically insignificant monthly positive trends in rainfall did not have any influence on the long term trend, it highlighted the importance of conducting trend analysis at shorter time scale.
- Increase in catchment rainfall observed during the 1990 decade indicate that the Logone catchment could be recovering from drought similar to catchments across the region.
- Analysis at monthly time scales revealed a backward shift in rainfall during the 1990 decade as more rainfall was observed during the pre-monsoon season, while the monsoon season witnessed a significant drop.
- These results indicate that the Logone catchment is sensitive to natural climate perturbations and could thus be vulnerable to anthropogenic climate change.

Results from this study may be useful to water managers and farmers for planning monthly and seasonal management of water resources, and to policy makers for informing adaptation policies under anticipated climate change given the highly sensitive nature of the catchment to climate perturbations. Nevertheless, due to natural climate variability in the region, it is difficult to predict if observed positive trends in rainfall will continue in the future. We acknowledge that the results of trend analysis obtained in this study might yield different results if gauge data beyond the year 2000 were available because this would have added another 1.5 decades to the length of the available gauge records.

Future research in the catchment will seek to analyse dry/wet conditions in the catchment using the standardized precipitation index and other relevant drought analysis indices and their application for monitoring droughts/floods.

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Chapter 5 Future climate projections from CMIP5 models

This chapter is based on the manuscript:

NKIAKA, E., N. R. NAWAZ and J. C. LOVETT (Accepted). Assessing the reliability and uncertainties of projected changes in precipitation and temperature in CMIP5 models over the Lake Chad basin. International Journal of Climatology

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Abstract

Lake Chad lost more than 80% of its surface area over the past decades as a result of environmental change and climate variability. It is not yet known how climate change will affect water resources availability in the basin over the coming decades. In this study, the Reliability Ensemble Average (REA) technique was applied to evaluate the ability of CMIP5 models to simulate present-day precipitation and temperature (1980 – 2005) and to quantify the uncertainties in future projections (2050 – 2075) relative to the historical period using two Representative Concentration Pathways (RCPs) in the Lake Chad basin (LCB). Analyses were carried out at both annual and seasonal time-scales. Overall, the CMIP5 models simulated precipitation better than temperature in the study area. Although the models were able to simulate the annual precipitation cycle in the basin, most models overestimated precipitation during dry season and underestimated it during the monsoon season. Future annual basin precipitation is projected to increase by 2.5% and 5% respectively under RCP4.5 and RCP8.5 scenario by the middle of the century by most of the models and majority of the models projections lie within the REA uncertainty limits. The uncertainty limits obtained especially for precipitation were mostly within the bounds of natural rainfall variability across the LCB. All the models also project a decrease in monsoon precipitation under both RCPs despite the increase in projected annual rainfall.

5.1 Introduction

Climate change is expected to cause major disruptions to the global hydrological cycle as a result of changes in precipitation patterns with the impacts expected to be exacerbated by rising global population (Arnell 2004; Trenberth 2011; Gosling and Arnell 2016). For example in some tropical regions like the Sahel, the frequency of storm events has increased by three folds over the past three decades as a result of global warming (Taylor et al. 2017). Therefore, developing future water resources management and planning strategies under anticipated climate change requires the estimation of current and future precipitation magnitude and variability (Wehner 2013). This can be achieved through the application of Global Circulation Models (GCMs) which are used to predict climate change associated with future scenarios of greenhouse gas concentrations (Siam *et al.* 2013).

For these climate models to be used for impact studies, they need to be evaluated against observed data to assess how they are able to simulate the present-day climate. Even so, it has been reported that GCM skill in simulating the present-day climate relates very weakly to its ability to simulate projected climate (Knutti *et al.* 2010).

Notwithstanding, different techniques have been applied to evaluate the performance of GCMs in simulating present and future precipitation and temperature changes. These methods range from simple statistical techniques e.g. mean errors, correlations, root-mean-square errors (Akurut *et al.* 2014) to more advanced statistical techniques e.g. volumetric hit index (VHI) (Mehran *et al.* 2014). Such methods are used to compare model output with observations. The second widely used evaluation method is the diagnostics approach that provide information on the sources of model errors and how to identify processes connected with these errors e.g., analysis of energy and water cycles, and analysis of atmospheric and land processes (Siam *et al.* 2013). Another approach is the evaluation of GCMs based on their ability to simulate specific atmospheric processes such as the monsoon precipitation in the tropics, ENSO events and other atmospheric processes that influence the climate of a region (Rowell 2013).

Despite the various evaluation techniques available, a fundamental problem associated with the application of GCMs is how well they can simulate climate at the regional scale. While GCMs projections may be consistent in terms of global mean changes, they generally disagree on the magnitude, and in many cases the sign, of change at a regional scale, especially precipitation patterns (Meehl *et al.* 2007). This raises the issue of uncertainty associated with the use of GCMs.

Many methods used in evaluating GCMs do not consider the issue of uncertainty inherent in climate models. In fact, there are many sources of uncertainties associated with the use of GCMs including: natural climate variability, variability between and within models and uncertainty caused by the future emissions of greenhouse gases (GHGs). How this uncertainty can be quantified to enhance decision making remains a challenge. It has been recognized that, uncertainty quantification is a critical component in the description and attribution of climate change (Katz *et al.* 2013). The most popular method used to deal with uncertainties in GCMs projections is the application of large independent multi model ensembles (MMEs) from different modelling groups under different scenarios to determine future climate projections (Tebaldi and Knutti 2007; Knutti *et al.* 2010). For example, using an ensemble of different GCMs and global hydrological models (GHMs), Schewe *et al.* (2014) showed that climate change is likely going to significantly exacerbate regional and global water scarcity.

Generally, the approaches available for uncertainty estimation in GCMs are limited in the literature. Despite this limitation, Koutsoyiannis *et al.* (2007) used a combination of analytical and Monte Carlo methods to determine the uncertainty limits for temperature, precipitation and runoff projections from GCMs for a catchment in Greece. Woldemeskel *et al.* (2012) developed and tested the square root of error variance (SREV) method for quantifying uncertainty in future precipitation and temperature projections from GCMs at global scale. Min and Hense (2006) applied the Bayesian model averaging (BMA) technique for uncertainty assessment in global mean surface temperature from an ensemble of GCMs projection. Giorgi and Mearns (2002) developed and tested the Reliability Ensemble Averaging (REA) technique for uncertainty estimation in GCMs at regional scale.

Many models participating in the fifth phase of the Coupled Model Intercomparison Project (CMIP5) (Taylor *et al.* 2012) have been evaluated across different regions in Africa. E.g. Akurut *et al.* (2014) evaluated precipitation estimates from CMIP5 models over the Lake Victoria, Siam *et al.* (2013) evaluated the performance of CMIP5 models in the Congo and Upper Blue Nile river basins, Biasutti (2013) tested the performance of CMIP5 models on the prediction of Sahel rainfall. Despite these numerous studies in Africa, none of them considered the quantification of GCM uncertainty. Meanwhile, the Lake Chad basin (LCB) remains poorly represented in these studies despite the significant changes that have been observed in the hydrological dynamics of the basin in the past several decades.

From 1960 to 2000, Lake Chad, an endorheic lake located in Central Africa experienced one of the most significant and sustained reduction in rainfall recorded anywhere in the world causing the lake area to shrink by more than 80% (Odada *et al.* 2009) (Figure 5.1). Despite this remarkable shrinkage in lake size, the LCB remains one of the most under-studied basins in Africa in terms of understanding the climate dynamics in the basin and how it will be affected by future climate change. This issue is further exacerbated by inadequate observational records in the region as observed by (Nkiaka *et al.* 2017a). Despite the scarcity in research output, Armitage *et al.* (2015) used paleo-climate records from the LCB to show that Lake Mega-Chad exerts a strong control on global biogeochemical cycles. Nkiaka *et al.* (2017b) analyzed past annual and seasonal rainfall in the southern part of the LCB and reported of a general decline in monsoon precipitation over the period 1951 – 2000. However, no study has focused specifically on future rainfall and temperature projections in the LCB using the recent or previous generations of climate models.

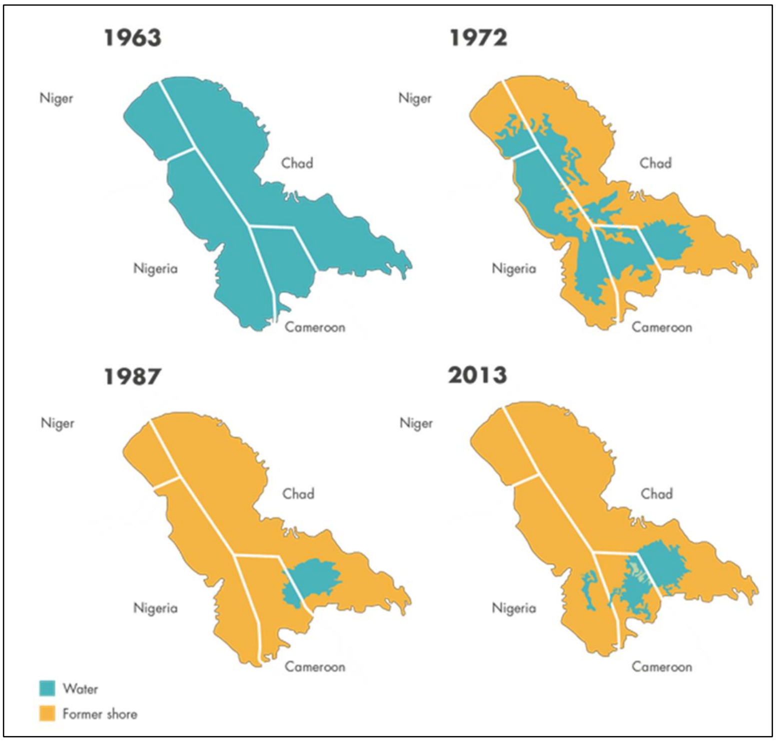


Figure 5.1 Desiccation of Lake Chad 1963 - 2013. Source: UNEP DIVA-GIS

Even so, results from previous studies using climate models to project future precipitation in Central Africa have produced contrasting results in the region. Haensler *et al.* (2013) evaluated an ensemble of CMIP3/5 and RCMs in the Central Africa region and concluded that no significant changes in precipitation may be observed in the region by the end of the present century under two representative concentration pathways (RCPs) RCPs 4.5 and 8.5. In a separate study; Aloysius *et al.* (2016), reported that CMIP5 models were projecting an increase in future precipitation by the end of the present century in the area of their study domain covering the LCB under RCPs 4.5 and 8.5. Meanwhile, using the regional climate model REMO forced by two GCMs (Europe wide Consortium Earth System Model (EC-Earth) and Max-Planck Institute Earth System (MPI-ESM)), Fotso-Nguemo *et al.* (2017), reported that future precipitation over the area of their study domain covering the LCB will decrease by the end of the present century under RCPs 4.5 and 8.5. Results from those studies are quite contrasting and cannot be used for any impact studies to enhance adaptation planning in the region, hence the necessity to carry out the present study in the LCB.

Although floods have become recurrent in recent years across the LCB causing widespread socio-economic damages, water availability for agriculture, pastoral activities, ecosystem sustainability and contribution as inflow into Lake Chad, is still under threat due to the erratic nature of rainfall. In addition, water resources in the LCB are becoming increasingly vulnerable due to rising population causing tension among water users (Ngatcha 2009). A study by Okpara *et al.* (2015) has shown that climate-induced water scarcity in the LCB could combine with other human factors such as population increase, poverty and political instability to create the necessary conditions for armed conflict due to water scarcity. Given the increasing number of refugees in the LCB as a result of “boku haram” terrorist activities in the region (OCHA 2017), climate change could aggravate the current situation resulting in mass migration with multiple negative facets including threat to global security.

With these myriad of challenges, there is need for research that can enhance our understanding on how precipitation and temperature which determine the availability of water resources will be affected by future climate change in the LCB. This is a crucial knowledge gap in the LCB that this research seeks to fill. This information will be relevant for conducting impact studies which are needed to inform adaptation strategies.

The objectives of this study were to: (i) evaluate the ability of CMIP5 models to reproduce the present-day climate conditions in the LCB (1980 – 2005); (ii) assess the future climate projections for the basin by the middle of century (2050 – 2075) relative to the historical period, and quantify the uncertainties associated with these projections using two representative concentration pathways (RCP4.5 and 8.5); and (iii) evaluate the performance of each ensemble member. This was achieved using the Reliability Ensemble Averaging (REA) technique. The method has been widely applied in different studies to established uncertainty limits in GCMs projections e.g. (Giorgi and Mearns 2002; Rawlins *et al.* 2012; Miao *et al.* 2014) but its application in Africa has not been reported. The advantages of the REA technique compared to other methods include the fact that the uncertainty range around the simulated changes can be reduced by minimizing the influence of ‘‘outlier’’ or poorly performing models and it also offers the possibility to calculate the uncertainty range around the REA average.

5.2 Study area

The Lake Chad basin (LCB) is situated in Central Africa, lying between 5° - 24°N and 7° - 24°E (Figure 5.2). The entire basin covers an estimated area of 2 434 000 km^2 shared by Algeria, Cameroun, Central Africa Republic, Chad, Libya, Niger, Nigeria and Sudan. This study focuses only on the active drainage basin which covers an area of about 1 053 455 km^2 (Adenle 2001) and lies between 5° - 16°N and 7° - 24°E (Cameroun, Central Africa Republic, Chad, Niger, Nigeria and Sudan). The reason for chosen only the active basin area is because, only this area contributes inflows into the lake while the rest of the northern portion is covered by desert. Apart from some local mountains and plateaus located in northern and southern parts of the basin, the central part of the basin is very flat with an average slope of <1.3%. Some of the most extensive and ecologically rich wetlands in the Sahel region are located in the LCB.

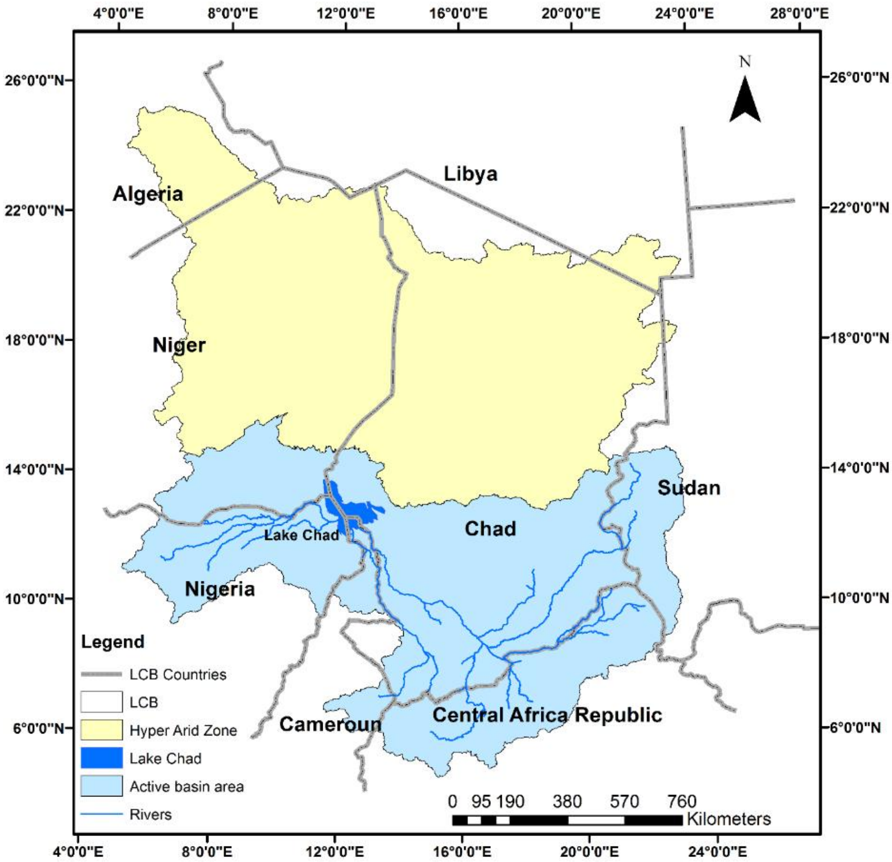


Figure 5.2 Lake Chad basin: 5 - 10N (sudano), 10 - 12N (semi-arid) and 12 - 16N (arid)

Using data from Climate Research Unit (CRU) covering the period 1901 – 2000, average rainfall over the basin was estimated to measure about 900 mm/year, varying between 1400 mm/year in the south to 370 mm/year in the north while average temperature was estimated at 26.5°C. Figure 5.3 shows the contour plots of annual precipitation and average surface temperature for the active basin area averaged over the period 1980 – 2005. The raining season in the basin usually lasts from May to October with the highest rains recorded in August. The climate in the basin is mostly hot and dry and rainfall is controlled by the north-south seasonal migration of the intertropical convergence zone (ITCZ) as observed in the Logone catchment (Nkiaka *et al.* 2017b). 95% of inflows into the lake is contributed by the Logone and Chari rivers which originate from the south (Odada *et al.* 2009).

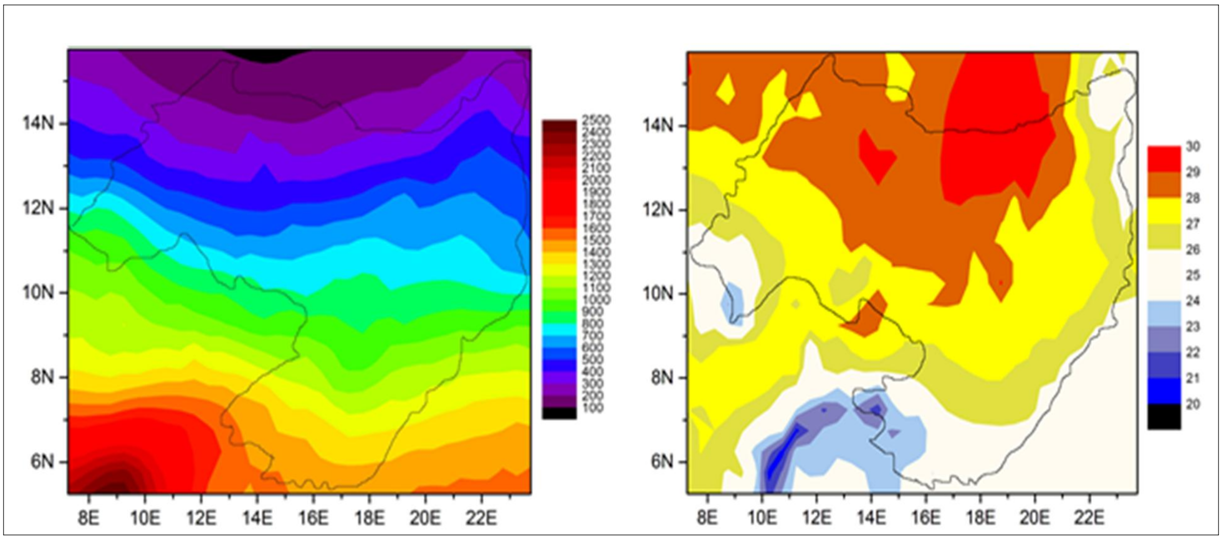


Figure 5.3 Contour plots for annual precipitation (left panel) and average surface temperature (right panel) in the active basin area (1980 - 2005) calculated from CRU

Due to the high spatial variability in precipitation across the LCB, for the purpose of this study, the active drainage basin was divided into three different ecological zones: 5° - 10°N "Sudano", 10° - 12°N "semi-arid" and 12° - 16°N "Arid". These ecological zones represent some simplified climatic zones based on Köeppen Geiger's climate classification for Africa (Peel *et al.* 2007). Rainfall across all the ecological zones is unimodal with the peak occurring in August. The highest rainfall is recorded in the Sudano zone while the lowest occurs in the arid zone. The CMIP5 models were assessed at the basin level and for each ecological zone. The advantage of this approach is that in regions with high spatial variability and strong rainfall gradients such as the LCB, model output averaged over the whole basin may lead to loss of signal such that the true expected change could be larger than what is suggested by the model average (Knutti *et al.* 2010).

5.3 Data

5.3.1 Observed Data

Due to the scarcity of observational data in the LCB, the observed rainfall and temperature data used in this study was derived from climate research unit (CRU) Time Series 3.20 (TS3.2) dataset described by Harris *et al.* (2014) and made available free of charge by the British Atmospheric Data Centre. This provides monthly-mean precipitation totals and average surface temperature on a resolution of (0.5x0.5 degree) grids for the period 1901–2011. This dataset has been used as the reference to evaluate CMIP5 models in previous studies e.g. (Rowell 2013; Miao *et al.* 2014;

Pattnayak *et al.* 2017). An additional precipitation dataset Watch Forcing Data methodology applied to ERA-Interim (WFDEI) (Weedon *et al.* 2014) was used to complement the CRU dataset. WFDEI has been applied for hydrological modelling studies in the region (Nkiaka *et al.* 2017a).

Table 5.1 List of climate models used in the study

Model No	Model Name	Institute/Country	Spatial Resolution Latitude X Longitude
M1	ACCESS1.0	Commonwealth Scientific Industrial and Research Organization, Bureau of Meteorology Australia	1.25 × 1.875
M2	BCC-CSM1.1-m	Beijing Climate Center, China	2.8 × 2.8
M3	CMCC-CMS	Centro Euro-Mediterraneo sui Cambiamenti Climatici Climate Model, Italy	2 x 2
M4	CNRM-CM5*	Centre National de Recherches Météorologiques, France	1.4 × 1.4
M5	GFDL-CM3	Geophysical Fluid Dynamics Laboratory, USA	
M6	HadGEM2-ES	Hadley Centre for Climate Prediction and Research, UK	1.875 × 1.25
M7	MPI-ESM-LR	Max Planck Institute for Meteorology, Germany	1.80 1.80

5.3.2 Climate model data

Climate model data used in this study was sourced from the 5th phase of the Coupled Model InterComparison Project (CMIP5) (Taylor *et al.* 2012). The focus in this study is primarily on the evaluation of the performance of these models in simulating the present-day (1980 – 2005) and future climate projection by mid of the century (2050 – 2075) under two RCPs (RCP4.5 and RCP8.5). The RCP4.5 is a stabilization scenario, in which the total radiative forcing is stabilized before the end of the present century by the application of a range of technological innovations and policies to reduce greenhouse gas (GHG) and aerosol emissions. On the other hand, the RCP8.5 scenario is considered a business as usual scenario characterized by increasing GHGs and aerosol emissions leading to high concentrations beyond 2100. The labels for the RCPs provide a rough estimate of the radiative forcing reaching the earth by the year 2100 (relative to preindustrial conditions).

Although there are many models available from CMIP5 that can be used for impact studies, not all models maybe able to simulate key climate processes across all regions of the globe. In this study therefore, the CMIP5 models were selected based on the fact that they have been reported in previous studies by Rowell (2013) and McSweeney *et al.* (2015) to “realistically” simulate some key climate processes across Africa. These processes include: (i) annual cycles of precipitation and temperature (ii) the West African monsoons and (iii) a minimum of 20 teleconnections in Africa. Given that uncertainty assessment is an important component of this study, by eliminating some models because of their inability to simulate key processes relevant for climate dynamics in the region, it is thought that the uncertainty range in the climate projections maybe reduced thereby making the results of our study more robust.

Many other studies have used a similar approach by focusing only on 5 – 7 models (Brands *et al*. 2013; Schewe *et al*. 2014; Pattnayak *et al*. 2017; Quesada *et al*. 2017). The models used in this study together with their spatial resolution and country of origin are shown in Table 5.1. Monthly precipitation and average surface temperature from each of the climate models and observed datasets was averaged over the whole basin and for each ecological zone (Sudano, semi-arid and Arid). Analysis were conducted at annual time scale for average surface temperature and annual and seasonal time scales for precipitation. The seasonal precipitation was averaged for the months of June, July, August and September (monsoon season). The reason for choosing this period was to evaluate the ability of the GCMs models to track the north – south seasonal migration of the intertropical convergence zone (ITCZ) responsible for maximum rainfall in the region.

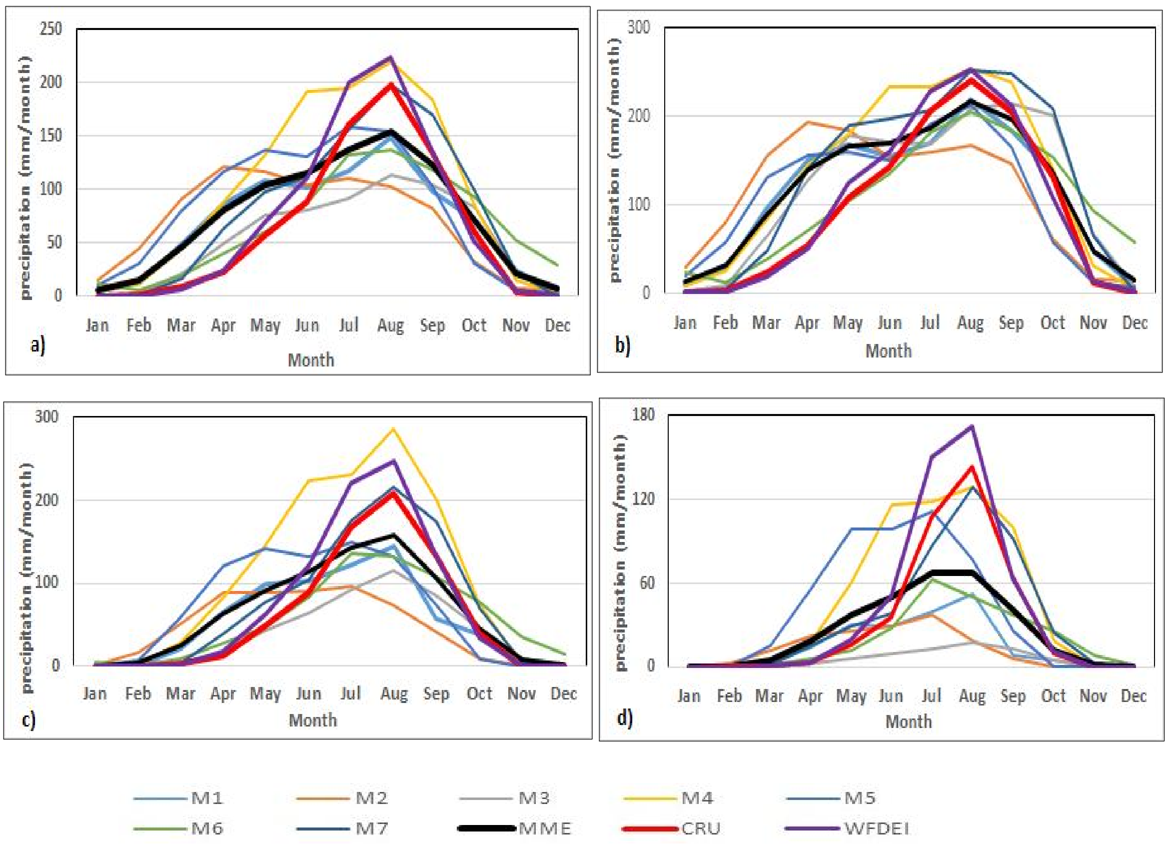


Figure 5.4 Annual precipitation cycle over a) Lake Chad basin, b) sudano zone, c) semi-arid zone and d) arid zone

5.4 Methodology

The Reliability Ensemble Averaging (REA) technique (Giorgi and Mearns 2002) is based on the assignment of weights to GCMs based on model evaluation. These weights are assigned on the basis of model performance and model convergence. Details of the method are elaborated in the following steps:

***Step1*:** The simple model average method (SMA) whereby the estimated average change in precipitation for all the models is calculated as:

$$\overline{\Delta P} = \frac{1}{N}\sum_{i=1,N} \Delta P_i, \tag{5.1}$$

where N is the total number of models and the overbar indicates the ensemble averaging and ΔP indicates the model-simulated change in precipitation. In the SMA method, all models are given equal weight (One man, One-vote).

Step 2: The model reliability factor is calculated whereby, the average change, $\widetilde{\Delta P}$, is given by a weighted average of the ensemble members.

$$\widetilde{\Delta P} = \tilde{A}\,(\Delta P) = \frac{\sum_i^N R_i \Delta P_i}{\sum_i^N R_i}, \tag{5.2}$$

where the operator $\tilde{A}$ denotes the REA averaging and R_i is the model reliability factor defined as

$$R_i = \left[\left(R_{B,i}\right)^m X \left(R_{D,i}\right)^n\right]^{[1/(mxn)]} = \left\{\left[\frac{\epsilon_P}{abs\left(B_{P,i}\right)}\right]^m \left[\frac{\epsilon_P}{abs\left(D_{P,i}\right)}\right]^n\right\}^{[1/(mxn)]} \tag{5.3}$$

In Eq (5.3), R_i is the reliability factor, $\in$ is the natural variability (as described in step 5 below). $R_{B,i}$ is a factor that measures the model reliability as a function of the model bias $(B_{P,i})$ in simulating the present-day precipitation. It is defined as the difference between the model simulated estimate and observed and the higher the bias, the lower the model reliability. $R_{D,i}$ is a factor that measures the model reliability in terms of the distance $(D_{P,i})$ of the change calculated by a given model from the REA average change, the higher the distance, the lower the model reliability. Therefore, the distance is a measure of the degree of the model convergence of a given model with other ensemble members. In other words, $R_{B,i}$ is a measure of the model performance criterion while $R_{D,i}$ is a measure of the model convergence criterion.

Step 3: An iterative procedure is used to calculate the distance parameter $D_{P,i}$ starting with an initial guess value as the distance of each ΔP from the ensemble average change $\overline{\Delta P}$, as shown in Eq. (1), i.e. $[D_{P,i}]_1 = [\Delta P_i - \overline{\Delta P}]$. The first guess values are then substituted in Eq. (5.3) to obtain a first-order REA average change $[\widetilde{\Delta P}]_1$, which is then used to recalculate the distance of each individual model as $[D_{P,i}]_2 = [\Delta P_i - \widetilde{\Delta P}]_1$ and the iteration is repeated until the values converge. According to Giorgi and Mearns (2002), the distance from REA average is only an estimated measure of the model convergence criterion given that the future real conditions are not known.

Step 4: The parameter *m* and *n* in Eq. (5.3) can be used to weigh each criterion. In this study *m* and *n* are assumed to be 1, giving equal weight to both criteria. $R_{B,i}$ and $D_{P,i}$ are set to 1 when *B* and *D* are smaller than $\in_P$, respectively. Thus Eq. (5.3) states that the model projection is considered "reliable" when both its bias and distance from the ensemble average are within the natural variability $\in$, so that R_B=$D_{P,}$ = 1. As the bias and/or distance grow, the reliability of a given model simulation decreases.

Step 5: The parameter $\in_P$ in Eq. (5.3) is a measure of natural variability in the 30-year average annual or seasonal precipitation and temperature. To calculate $\in$ in this study, the time series of observed monthly precipitation and average temperature covering the period 1901 – 2005 obtained from CRU were employed. Then, 30-year moving averages of the series are calculated after linearly detrending the data (to remove century-scale trends), and $\in$ estimated as the difference between the maximum and minimum values of these 30-year moving averages. Natural variability in rainfall and average surface temperature was calculated for the whole basin and for each ecological zone (Sudano, semi-arid and Arid).

Step 6: In order to calculate the uncertainty range around the REA average change, the REA root mean square difference (RMSD) of the changes $\tilde{\delta}_{\Delta P}$, has to be obtained and is defined by

$$\tilde{\delta}_{\Delta P} = \left[\tilde{A}\left(\Delta P_i - \widetilde{\Delta P}\right)^2\right]^{1/2} = \left[\frac{\sum_i R_i\left(\Delta P_i - \widetilde{\Delta P}\right)^2}{\sum_i R_i}\right]^{1/2} \quad (5.4)$$

The upper and lower uncertainty limits are defined as

$$\Delta P_+ = \widetilde{\Delta P} + \tilde{\delta}_{\Delta P} \quad (5.5a)$$

$$\Delta P_- = \widetilde{\Delta P} - \tilde{\delta}_{\Delta P} \quad (5.5b)$$

The total uncertainty range is then given by $\Delta P_+ - \Delta P_- = 2\tilde{\delta}_{\Delta P}$. According to the REA method, when the changes are distributed following a Gaussian PDF, the rmsd is equivalent to the standard deviation so that the $\mp\delta$ range would imply a 68.3% confidence interval. For a uniform PDF, that is, one in which each change has the same probability of occurrence, the $\mp\delta$ range implies a confidence interval of about 58%. Moreover, in the REA method, the normalized reliability factors of Eq. (5.3) are interpreted as the likelihood of a GCM outcome, meaning that; the greater the factor, the greater the likelihood associated with the model simulation. In this study the analysis was carried out for the whole basin and for each of the ecological regions.

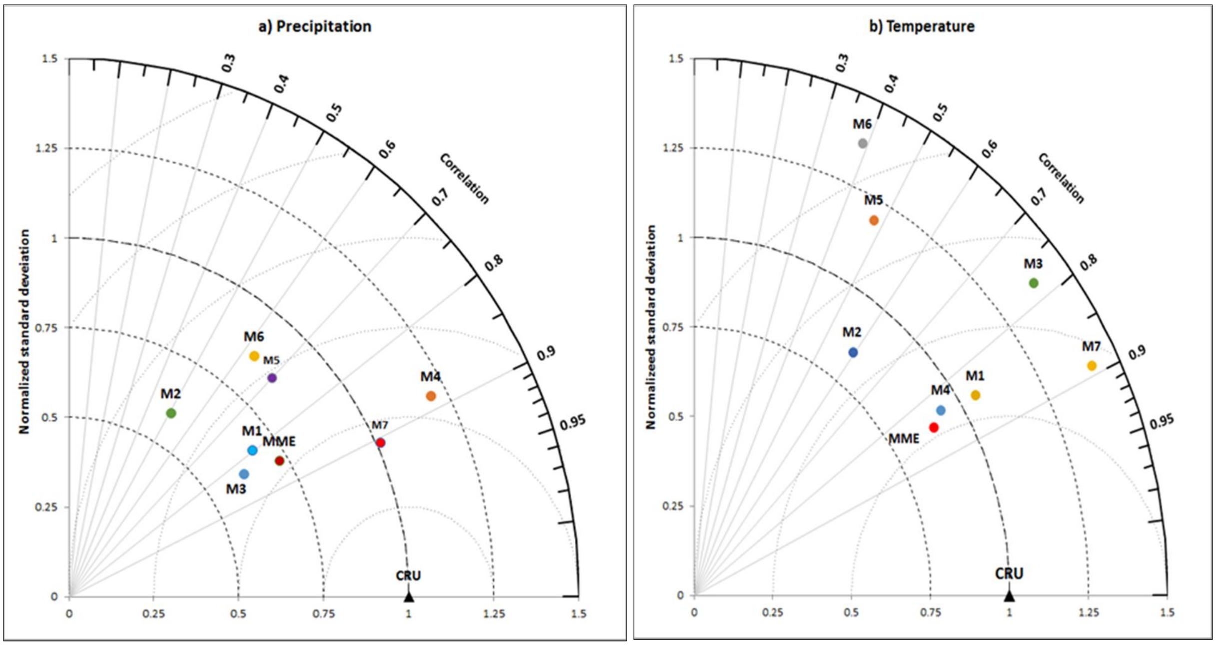


Figure 5.5 Taylor diagram showing comparison of monthly a) precipitation and b) average surface temperature simulated over the LCB with observations from CRU for period 1980 - 2005

5.5 Results

5.5.1 Precipitation

5.5.1.1 Historical precipitation

Evaluation of historical precipitation over the LCB indicate that all CMIP5 models used in this study were able to replicate the annual precipitation cycle over the basin and at the level of different ecological zones (Figure 5.4). A strong feature of rainfall over the LCB is its unimodal cycle which follows the north – south seasonal migration of ITCZ. Most models were able to capture this feature satisfactorily at basin scale. Despite this, some models appear to be bimodal or have very broad peak (e.g. M2 has a peak of 6 months) as opposed to 3 months in observations. Furthermore, across the basin, most models overestimate dry season rainfall and all but two underestimate wet season rainfall (Figure 5.4a).

It was also observed across the basin that, there was a large spread among models in monthly precipitation estimates during the dry season (January – May) compared to other months (Figure 5.4). Overall seasonal precipitation was more variable in the semi-arid zone (75 – 235 mm) compared to the Sudano zone (160 – 240 mm). Furthermore, the multi model ensemble (MME) monthly mean precipitation estimates were consistently lower than estimates from CRU and WFDEI across the basin and at the level of the ecological zones (Figure 5.4).

Agreement in observed and simulated monthly precipitation was also evaluated using Taylor diagram (Figure 5.5a). In the polar plot, the reference or observed data are plotted on the x-axis (abscissa), and the model-simulated values are expected to lie in the first quadrant if the correlation coefficient is positive. The radial dimension indicate the normalized standard deviation (calculated as the ratio of standard deviation of simulated over standard deviation of observed, ratios >1 indicate that the simulated values are more variable than observed), and the angular dimension shows the correlations. These statistics were computed using the 1980 – 2005 monthly precipitation. The similarity between model-simulated and observed precipitation is quantified in terms of their correlation and the amplitude of the variability. The correlation coefficients between each model and the monthly observations from CRU are in the range 0.50 – 0.95 and between the MME and observation is 0.85. This indicates that there are strong correlations between the estimates from the models and CRU. The strong correlation value between MME and CRU indicate that the MME performs slightly better than some individual GCM models (M1, M2, M3, M5, and M6). Models M4 and M7 show large variability compared to other models with normalized standard deviation >1 although both models have high correlation coefficients >0.85.

As a first step to quantify uncertainty using the REA method, the model performance criteria based on its ability to simulate the present-day climate was assessed using the bias factor. At the annual time-scale the GCMs produced mostly positive biases in the range 7 – 60% of the observed precipitation and only M3 produced a negative bias (-11%) (Table 5.2) indicating that, most of the models have a wet bias. At the level of ecological zones, all the models overestimated annual precipitation in the Sudano zone in the range 10 – 40% of observed (wet bias). The results are mixed in the other ecological zones ranging between -30 – 80% in the semi-arid and -80 – 50% in the arid zone (Table 5.2). At the seasonal time-scale, the GCMs mostly underestimated monsoon precipitation (JJAS) over the whole basin and the level of the ecological zones except M4 and M7 (Table 5.2) indicating a dry bias in the monsoon season.

Table 5.2 Model simulated biases of present-day precipitation (%) and average surface temperature (°C)

Time scale	Ecological Zone	GCM							
		M1	M2	M3	M4	M5	M6	M7	MME
Annual precipitation	LCB	12.11	13.39	-11.71	59.16	30.20	7.08	27.28	19.65
	Sudano	21.81	20.21	25.78	39.73	17.15	11.89	38.36	24.99
	Semi-arid	-6.07	-20.86	-33.70	82.14	17.31	-3.61	22.78	8.28
	Arid	-51.86	-59.17	-82.19	48.37	27.35	-38.63	2.80	-21.90
Monsoon (JJAS) precipitation	LCB	-26.08	-41.14	-32.77	35.51	-12.65	-22.88	9.24	-12.97
	Sudano	-8.16	-20.93	-3.93	20.55	-9.30	-11.10	13.61	-2.75
	Semi-arid	-28.31	-48.72	-40.38	57.59	-18.31	-23.04	12.41	-12.68
	Arid	-62.74	-73.90	-84.99	31.77	-10.58	-49.22	-6.02	-36.52
Annual average temperature	LCB	-2.98	-2.31	-2.96	-6.03	-4.37	-4.69	-3.85	-3.88
	Sudano	-2.30	-2.17	-3.27	-4.99	-4.68	-3.75	-4.22	-3.62
	Semi-arid	-2.80	-2.33	-2.35	-6.79	-4.28	-4.80	-4.25	-3.94
	Arid	-3.83	-2.42	-3.25	-6.33	-4.16	-5.52	-3.09	-4.09

5.5.1.2 Future precipitation projections in the LCB (2050 – 2075)

Analysis using the REA technique indicate that, future annual precipitation in the LCB is projected to increase by about 2.5% across the basin under the RCP4.5 scenario relative to the historical period (1980 – 2005). At the level of the different ecological zones, future precipitation is projected to increase by about 22% in the Sudano zone, 4% in the semi-arid and a decline of about -12% in the arid zone relative to the historical period. Under the same scenario monsoon precipitation is projected to decrease across the basin by -11% and at the level of different ecological zones with the arid zone experiencing a significant decline of about -23% relative to the historical period (Table 5.3).

Table 5.3 Natural variability, projected precipitation changes and uncertainty range

Time scale	Ecological zone	Natural variability (εP) (mm)	RCP4.5		RCP8.5	
			ΔP (%)	Uncertainty (±δΔP)	ΔP (%)	Uncertainty (±δΔP)
Annual precipitation	LCB	84.40 (11.43)	2.54	11.37	5.26	12.13
	Sudano	81.81 (7.24)	22.61	8.29	30.56	8.97
	Semi-arid	95.23 (11.89)	4.15	15.69	9.72	16.92
	Arid	88.33 (23.15)	-12.32	34.77	-4.77	36.34
Monsoon precipitation	LCB	16.45 (11.32)	-11.61	16.52	-5.29	17.11
	Sudano	12.68 (6.38)	-0.72	12.55	3.14	12.39
	Semi-arid	21.59 (14.44)	-16.63	18.39	-9.28	18.58
	Arid	20.75 (23.59)	-23.11	25.49	-13.79	28.35

Under the RCP8.5 scenario, future annual precipitation is projected to increase by about 5% across the LCB which is double the RCP4.5 scenario. For the ecological zones, projections for the Sudano zone show an increase of about 30% relative to the historical period, 8% higher than the projection from RCP4.5 scenario. Precipitation is also projected to increase by 9% in the semi-arid zone while the arid zone may experience a drop of about of about -5% relative to the historical period. Compared to the RCP4.5 scenario, this represents an increase of more than 100% and 200% respectively for the semi-arid and arid zones respectively (Table 5.3). Under the same scenario, monsoon precipitation across the LCB is projected to drop by about -5% relative to the historical period representing an increase of more than 100% compared to the RCP4.5 scenario. At the level of ecological zones, monsoon precipitation is projected to increase in the Sudano zone by about 3% relative to the historical period. Meanwhile, in the semi-arid and arid zones, monsoon precipitation is projected to drop by -9% and -13% respectively relative to the historical period representing an increase of 7% and 10% respectively for semi-arid and arid zones compared to the RCP4.5 scenario. At the annual time-scale, these results corroborate the findings of Aloysius *et al.* (2016) in the Central Africa region covering the LCB whereby, the authors also projected an increase in precipitation in the region from an ensemble of CMIP5 models by the end of the present century.

Regarding the uncertainties in future precipitation projections, the REA average changes are all within the bounds of natural variability $\in_P$ across the LCB under the two concentration pathways RCP4.5 and RCP8.5 (Table 5.3). Although this does not discount the fact that the changes in future precipitation are not statistically significant. At the level of the different ecological zones, the uncertainty limits are also in the same order of magnitude with the natural variability although there is an increase of more than 10% in the arid zone. Comparing the three different ecological zones together, uncertainty is lower in the Sudano zone while the arid zone displays the highest level of uncertainty which follows the same trend that was observed for natural variability (Table 5.3). This indicates that precipitation is more variable in the arid zone compared to the other ecological zones in the LCB.

Considering projections from individual CMIP5 models, under the RCP4.5 scenario, M1, M4, M5, M6, and M7 project an increase in future annual precipitation while M2 and M3 project a decrease at the basin scale. M1 M2, M3 and M6 lie within the uncertainty limits but only M1 and M6 project an increase while M2 and M3 project a decrease (Figure 5.7a, left panel). The results are varied for the different ecological zones. In the Sudano zone, all models project an increase in future annual precipitation with M1, M2, M5, and M6 lying within the uncertainty limits (Figure 5.7b, left panel). Within the semi-arid zone, all models project an increase in future precipitation except M2 and M3, although only projections from M1, M6 and M7 fall within the uncertainty limits (Figure 5.7c, left panel). In the arid zone only M4 and M5 project an increase in future precipitation although their results are outside the uncertainty limits while the rest project a decrease. (Figure 5.7d, left panel).

Under the RCP4.5 scenario, M4 and M7 project an increase in future monsoon precipitation while the other models project a decrease at basin scale with results lying outside the uncertainty limits (Figure 5.8a, left panel). In the Sudano zone, M3, M4 and M7 project an increase in future monsoon precipitation while the other models project a decrease although only projections from M3 lie within the uncertainty bounds (Figure 5.8b, left panel). Results in the semi-arid zone are similar to those obtained in the Sudano zone (Figure 5.8c, left panel). In the arid zone, only M4 project an increase in future monsoon precipitation while the rest of models project a decrease however and results do not lie within the uncertainty limits (Figure 5.8d, left panel).

Under the RCP8.5 scenario, future annual precipitation is projected to increase across the LCB by all models except M2 and M3 with projections from M1 and M6 lying within the uncertainty limits (Figure 5.7a, right panel). In the Sudano zone, all models project an increase in future annual precipitation with projections from M1, M2, M5 and M6 lying within the uncertainty limits (Figure 5.7b, right panel). In the semi-arid zone, all models except M2 and M3 project an increase with projections from M1 and M6 lying within the uncertainty limits (Figure 5.7c, right panel). Models that project an increase in the arid zone include M4, M5 and M7 while the other models project a decrease with projections from M7 lying within the uncertainty limits (Figure 5.7d, right panel). Individual model projections for monsoon precipitation under this scenario are similar to what was obtained under the RCP4.5 scenario although with different magnitudes (Figure 5.8a-d right panel).

5.5.2 Temperature

5.5.2.1 Historical temperature

The results of historical annual average surface temperature cycle over the LCB were quite varied among the CMIP5 models with only M1, M4 and M7 accurately reproducing the temperature cycle with maximum average temperature observed in April and minimum in August. Most of the models underestimate average surface temperature in April and systematically overestimated it in August with the exception of M4 and M5. This is consistent with too much rainfall in April (causing a cooling) and too little rainfall in August causing an increase in temperature (Figure 5.6).

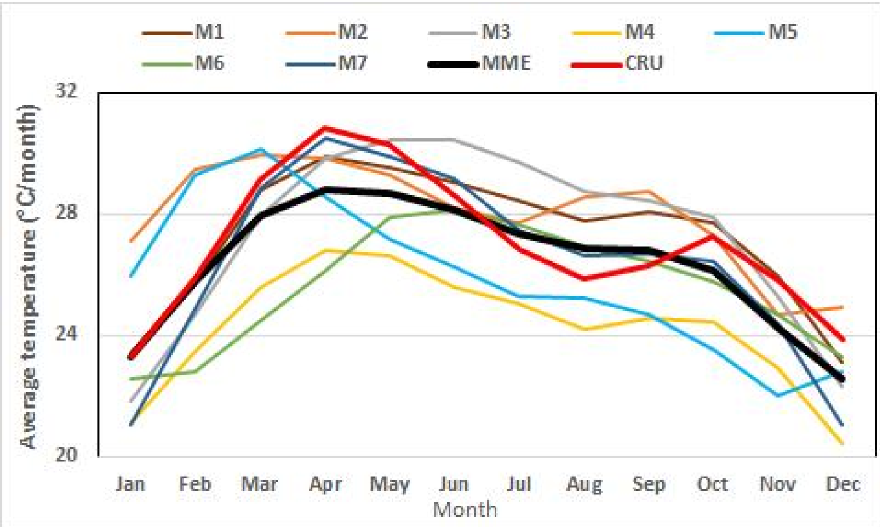
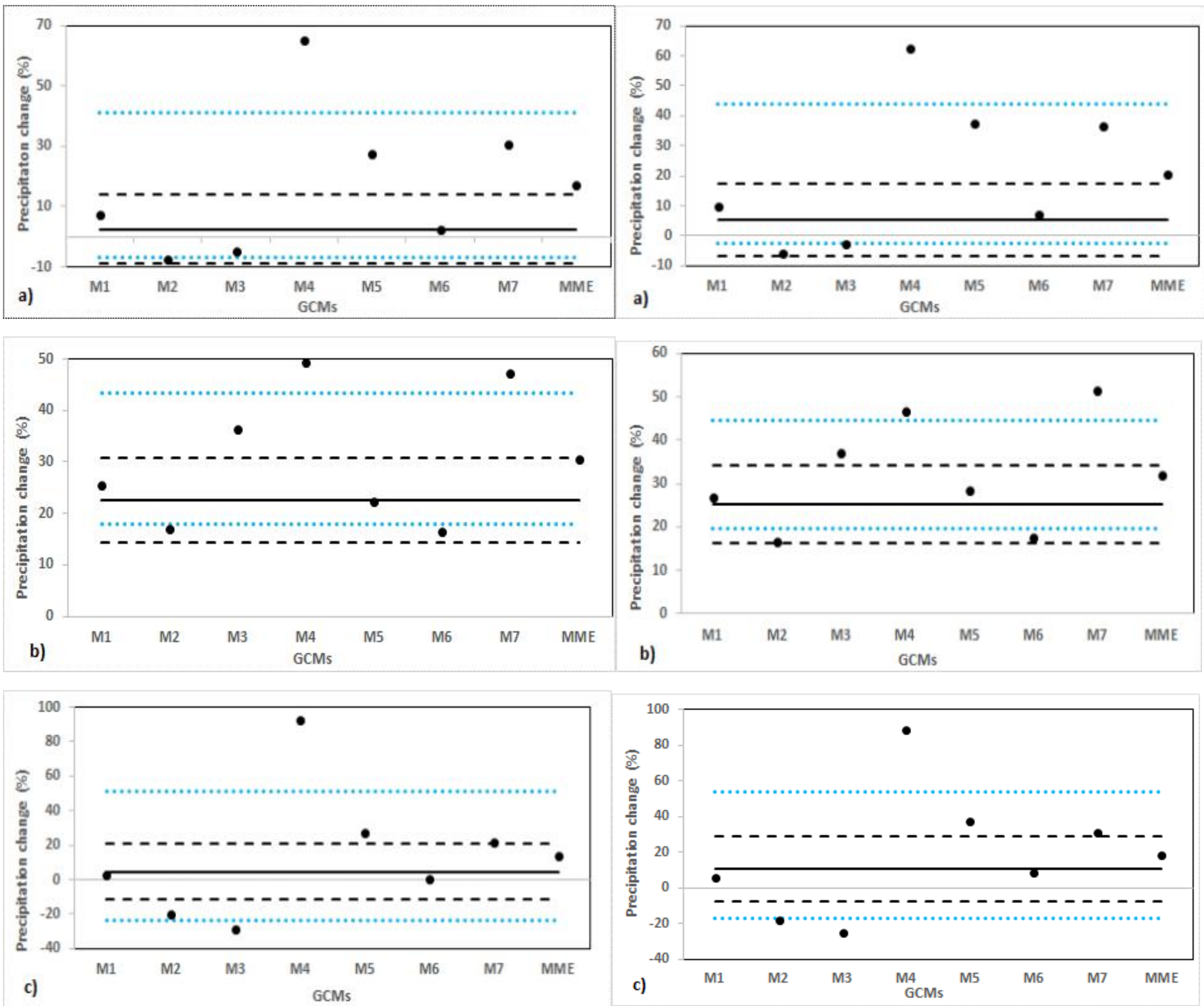


Figure 5.6 Annual average surface temperature over the LCB

The simulation of historical average surface temperature over the basin was further evaluated using the Taylor diagram (Figure 5.5b). The correlations between the observed and simulated monthly temperature was in the range 0.40 – 0.90. However, most GCMs show large variability with normalized standard deviations >1 (M1, M3, M5, M6, M7). Four models produced correlation coefficients >0.75 which could be considered as strong. Meanwhile, the MME produced a correlation coefficient of 0.86 stronger than what was obtained for some individual models (M2, M5, and M6).

The model performance criteria based on its ability to simulate the historical climate was also assessed using the bias factor. At the annual time-scale all the GCMs produced negative biases, underestimating historical average surface temperature throughout the LCB and at the level of the different ecological zones indicating a generalized cold bias. Annual average surface temperature was underestimated in the range of -2°C to -6°C (Table 5.4). These results are contrasting with those of precipitation whereby results showed both positive and negative biases were obtained.



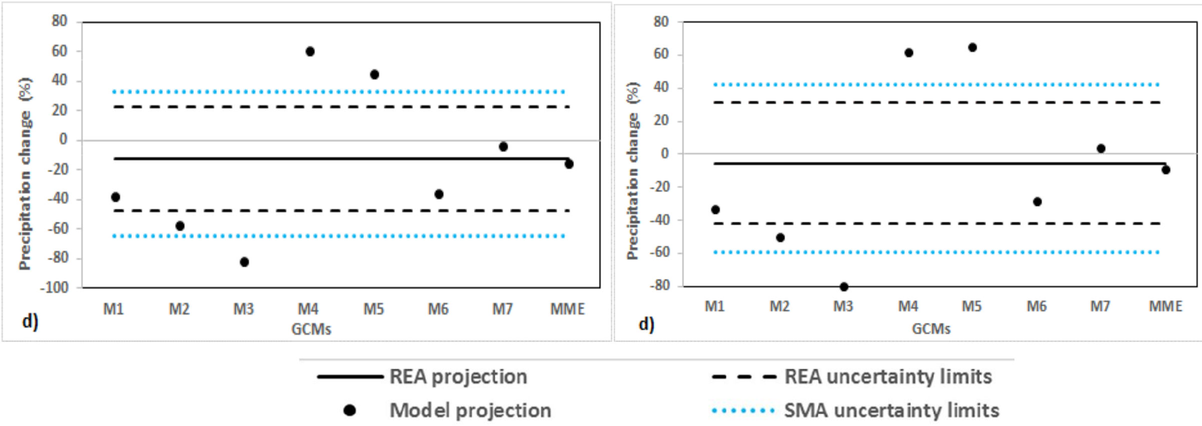


Figure 5.7 Annual precipitation projection RCP4.5 (left panel) and RCP8.5 right panel. a - d represent the LCB, sudano, semi-arid and arid zones respectively

5.5.2.2 Future average surface temperature projections in the LCB (2050 – 2075)

Analysis using the REA technique showed that future annual average surface temperature across the LCB under the RCP4.5 and RCP8.5 scenarios is projected to decrease by about 1°C relative to the historical period (1980 – 2005) and by almost the same amount across the different ecological zones (Table 5.6). These results are quite contrasting with what has been observed globally from CMIP5 models which generally project an increase in future global average surface temperature (Knutti and Sedláček, 2013) and in the African continent (Dike *et al.* 2015).

Regarding uncertainty in the future annual average temperature projections, the REA average changes are well beyond the bounds of natural variability $\in_T$ across the LCB and at the level of the different ecological zones under both RCPs (Table 5.6). Like precipitation, natural variability in annual average surface temperature is highest in the arid zone and lowest in the Sudano zone. However, uncertainty in model projections of annual average surface temperature is highest in the semi-arid zone and lowest in the arid zone (Figure 5.9).

Considering future projections from individual CMIP5 models, under the RCP4.5 scenario, only M1 consistently projects an increase in future annual surface average temperature over the LCB and at the level of different ecological zones while all the other models project a decrease (Figure 5.9, left panel). Under the RCP8.5 scenario, M1 and M3 consistently project an increase in projected future annual temperature over the basin and at the level of the Sudano and semi-arid zones while only M3 project an increase in the arid zone. The projections from models showing an increase in future average temperature all lie outside the uncertainty limits while the results are mixed for those projecting a decrease (Figure 5.9 right panel).

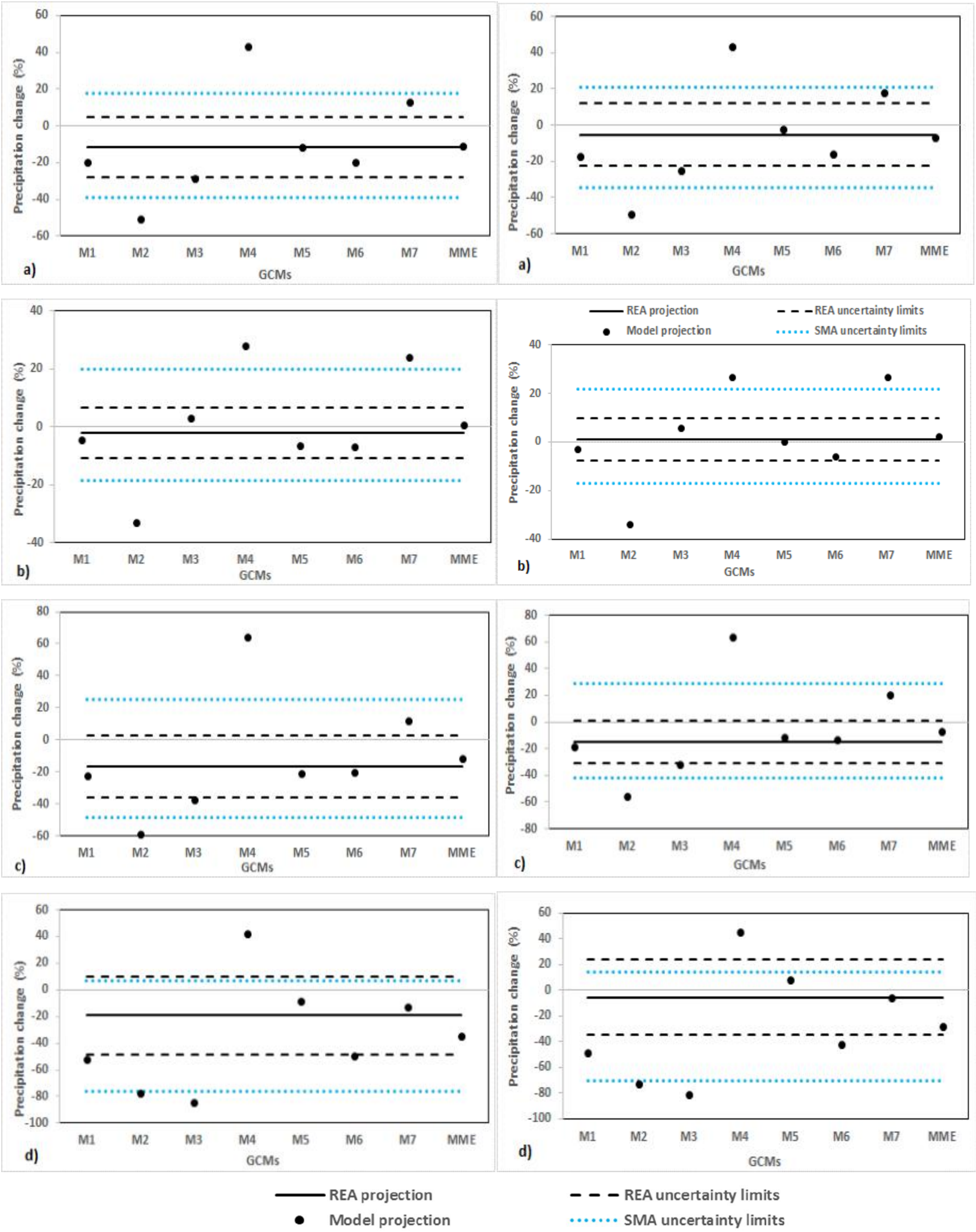


Figure 5.8 Seasonal precipitation projection RCP4.5 left panel and RCP8.5 right panel, a - d represents the LCB, sudano, semi-arid and arid zones respectively

5.5.3 Reliability analysis of CMIP5 models for precipitation and temperature projections

Under RCP4.5 and RCP8.5 scenarios; M1, M2, M3 and M6 produced model reliability factors ≥0.85 for future annual precipitation projection in the LCB and all projections from these models lie within the REA uncertainty limits (Figure 5.7a). This performance can be attributed to the fact that (i) the bias factor (difference between the model simulated estimate and observed), and under both RCPs, (ii) the convergence factor (distance between the model projection and REA average) for each of the models are within the bounds of natural variability $\in_P$. Models with low reliability factors equally produced low bias and convergence factors (Table 5.5). In addition, projections from these models all lie outside the bounds of REA uncertainty limits (Figure 5.7a).

At the seasonal scale only M5 produced a reliability factor >0.80 and the projection from this model is very close to the REA average (Table 5.5). The low performance of the CMIP5 models for monsoon projection can be attributed to the fact that apart from M5 and M7, most of the models produced very low bias factors mostly below 0.5 as a result of their consistent underestimation of monsoon precipitation relative to the historical period. It can also be observed that even though M1, M5, and M6 produced high convergence factors for projected monsoon precipitation, these models were penalized because of their low bias factors. On the other hand, M7 which produced a high bias factor for monsoon precipitation was penalized because of its low convergence factor (Table 5.5). By given equal weights to criteria *m* and *n* in Eq. (5.3) any model which performs well in one criteria and does not equally perform well in the other is penalized.

Table 5.4 Natural variability, projected temperature change and uncertainty range

Time scale	Ecological zone	Natural variability (εT) (°C)	RCP4.5		RCP8.5	
			ΔT (°C)	Uncertainty (±δΔT)	ΔT (°C)	Uncertainty (±δΔT)
Annual average temperature	LCB	0.50	-1.02	0.89	-0.99	0.98
	Sudano	0.28	-0.84	0.78	-0.55	0.90
	Semi-arid	0.48	-0.70	1.04	-0.70	1.19
	Arid	0.68	-0.85	0.72	-0.72	0.79

The reliability factors of the various models for annual average surface temperature projection in the LCB under RCP4.5 and RCP8.5 scenarios are generally very low with some values <0.10 (Table 5.6). This low performance can be attributed to the inability of the models to simulate historical annual average temperature resulting in a generalized low bias factors among the CMIP5 models. Even though all models except M1 and M4 under the RCP4.5 scenario and

M2, M5, M6 and M7 under the RCP8.5 scenario produced high convergence factors, these models were penalized because of their low ability to simulate historical average temperature.

Comparing the results from REA average and simple model average (SMA) for annual precipitation and average temperature projections, it was observed that, under the two RCPs, estimates from SMA do not deviate very much from the REA average and in most cases lie within the REA uncertainty limits (Figures 5.7 and 5.9). This shows that both methods produce ensemble averages that are similar in magnitude. This is an interesting finding given that each model received a different weight through the application of either techniques. In the SMA technique, each model received the same weight while with REA technique the weight attached to each model was based on its reliability factor which was determined by both the bias and convergence factors. Previous studies have also shown that both methods produced similar results e.g. (Miao *et al.* 2014; Mani and Tsai 2016). However, it can also be observed from the figures that the uncertainty bound calculated using the SMA is larger than that calculated using the REA technique.

Table 5.5 Model performance for historical and future projections for precipitation

Model	Annual precipitation					Monsoon precipitation				
	Bias factor	RCP 45		RCP 85		Bias factor	RCP 45		RCP 85	
		Convergence factor	Reliability factor	Convergence factor	Reliability factor		Convergence factor	Reliability factor	Convergence factor	Reliability factor
M1-ACCESS1.0	0.94	1.00	0.94	1.00	0.94	0.43	1.00	0.43	0.96	0.42
M2-bcc_ESM1-1-M	0.85	1.00	0.85	1.00	0.85	0.28	0.29	0.08	0.26	0.07
M3-CMCC_CMS	0.98	1.00	0.98	1.00	0.98	0.35	0.66	0.23	0.59	0.20
M4-CNRM-CM5	0.19	0.18	0.04	0.20	0.04	0.32	0.21	0.07	0.23	0.07
M5-GFDL-CM	0.38	0.46	0.17	0.36	0.13	0.89	1.00	0.89	1.00	0.89
M6-HadGEM-ES	1.00	1.00	1.00	1.00	1.00	0.49	1.00	0.49	1.00	0.49
M7-MPI-ESM-LR	0.42	0.41	0.17	0.36	0.15	1.00	0.47	0.47	0.48	0.48

Table 5.6 Model performance for historical and future projection average surface temperature

Model	Annual temperature				
	Bias facto r	RCP 45		RCP 85	
		Convergence factor	Reliability factor	Convergence factor	Reliability factor
M1-ACCESS1.0	0.17	0.30	0.05	0.35	0.06
M2-bcc_ESM1-1-M	0.21	0.92	0.20	1.07	0.23
M3-CMCC_CMS	0.17	0.86	0.14	0.31	0.05
M4-CNRM-CM5	0.08	0.15	0.01	0.15	0.01
M5-GFDL-CM	0.11	0.67	0.08	0.61	0.07
M6-HadGEM-ES	0.11	0.64	0.07	0.58	0.06
M7-MPI-ESM-LR	0.13	0.78	0.10	1.00	0.13

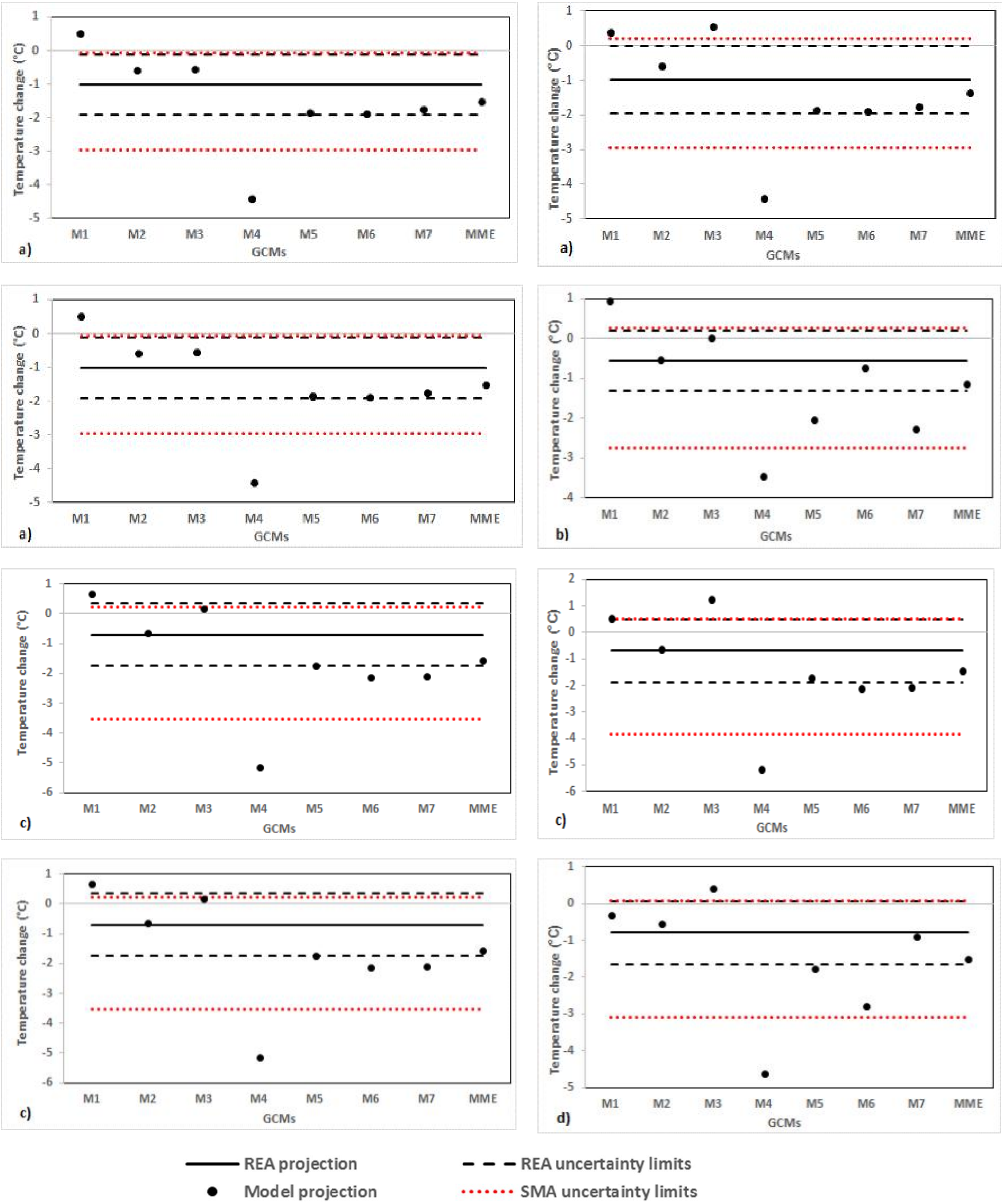


Figure 5.9 Annual average surface temperature projection RCP4.5 (left panel) and RCP8.5 (right panel). a - d represents the LCB, sudano, semi-arid and arid zones respectively

5.6 Discussion

Given the fact that some models showed systematic biases in the seasonal rainfall estimates indicate that they were not able to tract the north-south displacement of the ITCZ as they are consistently too wet in the dry season, and too dry in the wet season.

The fact that MME (SMA) produced stronger correlations compared to some individual models in the Taylor diagram for both precipitation and average temperature can be attributed to the fact that, by averaging all the models together, the individual model biases cancel out thus resulting to an ensemble that outperforms some of the individual CMIP5 models.

Even though the CMIP5 models used in this study were reported to simulate some key climate processes in the region based on the findings of Rowell (2013) and McSweeney *et al.* (2015), results from our study show that, there was still a large spread in the model output which can be attributed to individual model physics. Despite this spread, most of the models were able to replicate the historical annual rainfall cycle across the basin and at the level of the different ecological zones indicating some level of objectivity in the selection process. Furthermore, the ensemble projections from the MME (SMA) average were mostly within the bounds of uncertainty limits across the basin and at the level of the ecological zone which can also be attributed to the model selection process.

Apart from biases associated with model physics, biases in the model simulations could also be attributed to the inability of the individual CMIP5 model to simulate other local scale atmospheric processes and mesoscale convective systems (MCSs) and non-climatic effects like orography that also influence climate in the region. This is largely due to their coarse spatial resolutions. In fact, MCSs are difficult to be modelled because these events organize dynamically on spatial scales that cannot be resolved by the current generation of GCMs (Taylor *et al.* 2017). Other mechanisms that influence regional climate in LCB include the low level Bodele Jets (Washington *et al.* 2006), the high level Tropical Easterly Jets (TEJ) and the West African Westerly Jets (WAWJ) which are stronger in the eastern Sahel where the LCB is located (Nicholson 2013) and the high level African Easterly Jet (AEJ) which influence precipitation over the Central African region (Farnsworth *et al.* 2011). It is not known how these jet streams are simulated in the CMIP5 models although their influence on regional rainfall is very considerable.

Despite the poor performance of the GCMs to continuously underestimate historical monsoon precipitation in this study, previous studies also reported the decline in monsoon precipitation in the region (Polson *et al.* 2014; Nkiaka *et al.* 2017b) albeit causes of this decline are not yet well understood. Nevertheless, Devaraju *et al.* (2015) attributed it to large scale deforestation in the northern middle and high latitudes which force the ITCZ to shift southwards resulting in a significant decrease in monsoon precipitation. Quesada *et al.* (2017) also attributed the decline in monsoon precipitation to biophysical effects of large scale land use/cover changes. Despite this, recent studies by Taylor *et al.* (2017) have shown that, extreme precipitation events from MCSs during the monsoon season has increased in the region. Nonetheless the study by Taylor *et al.* (2017) did not mention the contribution of MCSs extreme precipitation events to the total monsoon precipitation although their contribution to total annual precipitation in that study was estimated to be < 25%.

By applying the REA technique, the level of uncertainty especially for annual rainfall projection under both RCPs was significantly reduced. This is because most of the model projections lie within the uncertainty limits except M4. Therefore, by selecting climate models based on their ability to simulate key atmospheric processes that control climate in the region and applying the REA technique which gives higher weight to models that perform well and lower weight to poorly performing models, the uncertainty in climate model projections can be considerably reduced.

Generally, results from this study show an increase in projected annual precipitation by mid of the century with five models projecting this increase under both RCPs. These results are also supported by the MME (SMA) average whereby equal weights are attached to each model and REA average whereby weights are attached to a model based on the model reliability factor. In each case, future annual precipitation is projected to increase in the LCB. At the level of the different ecological zones, all models project an increase in future precipitation in the Sudano, five models project an increase in the semi-arid and three models project an increase in the arid zone under both RCPs. This indicate that by using a reduced number of models based on their ability to simulate key processes responsible for climate dynamics in the region, the results may be more robust. This may be preferable to studies that use a larger number of CMIP5 models for future climate projections but which produce divergent results at the end of the analysis. Nevertheless, this explanation is not aimed at discrediting the results from such studies because the models with opposing results could each be giving a plausible response of future climate projection depending on the level of GHGs concentration in the atmosphere.

Another significant finding from this study is the fact that, although CMIP5 models project a decrease in future monsoon precipitation which is known to contribute to most of the rainfall in the region, overall, annual precipitation is still projected to increase by the middle of the century under both RCPs. This implies that in future, the seasonal north – south migration of the ITCZ which brings monsoon precipitation into the region may no longer be the dominant mechanism responsible for rainfall in the region. This is in agreement with other studies in the region that have reported of a dryer onset of the monsoon season and an intensification of the late rainy season (Biasutti 2013). Another study by Monerie *et al.* (2016) has also reported of an increase in late rainy season (September and October) rainfall and a delay in the retreat of the monsoon. Results from the above studies including the present study therefore indicate that, more rainfall may be recorded outside the core monsoon season. This can partly explain why even though the CMIP5 models are projecting a decrease in monsoon precipitation, annual precipitation is still projected to increase across the LCB.

The increase in projected annual precipitation in the region under climate change have been attributed to many reasons e.g. Dong and Sutton (2015) attribute it to the rising levels of GHGs in the atmosphere, Evan *et al.* (2015) attribute it to an upward trend in the Sahara heat low (SHL) temperature resulting from atmospheric greenhouse warming by water vapor. In separate studies, Biasutti (2013) and Park *et al.* (2015) attributed the increase in future precipitation in the region as projected by CMIP5 models to increased moisture convergence in the region under climate change. Despite the good performance in predicting historical and future precipitation changes, the models were generally biased in simulating historical and future projected average temperature in the LCB.

5.7 Conclusion

The objectives of this study were to evaluate the ability of CMIP5 models to reproduce the present-day climate conditions in the LCB (1980-2005), assess the future climate projections for the basin by the middle of century (2050 – 2075) relative to the historical period and quantify the uncertainties associated with these projections using two Representative Concentration Pathways (RCP4.5 and 8.5). This is the first study that uses climate models to assess future precipitation and average temperature projections in the LCB. Results indicate an increase in precipitation across the study domain under RCP4.5 and RCP8.5 by mid of the century, with the Sudano zone expected to experience the highest amount of future annual precipitation.

Results further indicate that, the CMIP5 models simulated precipitation better than temperature as a result of a cold bias observed in the simulation of annual average temperature by the models. Although results from the study vary from one model to another, overall M4 performed poorly as it consistently overestimated future projected precipitation and underestimated annual average temperature across the basin and at the level of the different ecological zones under both RCPs. In addition, no projections from this model lie within the uncertainty limits suggesting that, M4 is an outlier within the ensemble used in this study and may not be recommended for future impact studies in the LCB. For impact studies in the LCB using CMIP5 models, M1 and M6 with future precipitation projections that consistently lie within the REA uncertainty limits under both RCPs may be recommended. Meanwhile M1 which projected increasing temperature trends in agreement with global and continental trends may be recommended for impact studies in the basin. Overall M1 will be suitable for hydrological modelling studies in the LCB.

Results from this study also show that the REA technique which uses a reliability factor whereby weights are attached to a model based on its ability to simulate both the historical climate through the bias factor and future climate through the convergence factor is a robust method that can used for uncertainty quantification in climate models compared to the Simple model averaging (SMA) technique. The weights attached to each model are calculated based on past natural climate variability observed in the area. Using this approach, uncertainty limits obtained in this study especially for precipitation were mostly within the bounds of natural rainfall variability across the LCB.

Nevertheless, it is thought that biases observed in the models could be reduced and results obtained in this study refined by using regional climate models. Results could also be fine – tuned in future as high resolution GCMs become available.

5.8 Policy implication

Our results show that, projected future annual precipitation will increase in the basin despite the drop in projected future monsoon precipitation. This implies that most of the rainfall may be recorded outside the monsoon season. Nevertheless, considering the large uncertainty range in the REA mean results obtained from the climate projections, the results obtained in this study may not have any policy implication for the LCB. Furthermore, given the vagaries of weather in the region and the uncertainty associated with future climate projections, governments in the LCB will need to adopt high resolution weather forecasting measures to supply farmers with information relating to the onset of the rainy season, duration of dry spells at the onset of the rainy season and the probable length of the rainy season. Despite the challenges inherent in seasonal weather prediction, it will greatly enhance the adaptive capacities of farmers and could significantly improve crop yield and reduce seed wastage.

For results obtained in this study to have any meaningful policy implication, additional analysis are needed using regional climate models to confirm the same results obtained from GCMs projections. However, for this to be successful, detailed hydrological modelling studies are needed to assess how other biophysical factors such as land use/cover changes and human factors such as water abstraction and population increase will interact with climate change to affect the volume of discharge channeled into the lake. Furthermore, given that majority of the population also depend on resources from the wetlands, this will give an indication on how the wetlands will also be affected by climate change and other biophysical and human factors.

Results from such impact studies in the LCB are needed to inform policy in the event of sudden environmental shock such as droughts in order to take appropriate policy decisions to prevent the kind of humanitarian catastrophe observed in the region in the past.

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Chapter 6 Hydrological modelling

This chapter is based on the paper:

NKIAKA, E., N. R. NAWAZ and J. C. LOVETT. 2017. Effect of single and multi-site calibration techniques on hydrological model performance, parameter estimation and predictive uncertainty: A case study in the Logone catchment, Lake Chad basin. Stochastic Environmental Research and Risk Assessment. 32(6): 1665-1682. DOI:10.1007/s00477-017-1466-0.

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Abstract

Understanding hydrological processes at catchment scale through the use of hydrological model parameters is essential for enhancing water resource management. Given the difficulty of using lump parameters to calibrate distributed catchment hydrological models (CHMs) in spatially heterogeneous catchments, a multiple calibration technique was adopted to enhance model calibration in this study. Different calibration techniques were used to calibrate the Soil and Water Assessment Tool (SWAT) model at different locations along the Logone river channel. These were: single-site calibration (SSC); sequential calibration (SC); and simultaneous multi-site calibration (SMSC). Results indicate that it is possible to reveal differences in hydrological behavior between the upstream and downstream parts of the catchment using different parameter values. Using all calibration techniques, model performance indicators were mostly above the minimum threshold of 0.60 and 0.65 for Nash Sutcliff Efficiency (*NSE*) and Coefficient of Determination (R^2) respectively, at both daily and monthly time-steps. Model uncertainty analysis showed that more than 60% of observed streamflow values were bracketed within the 95% prediction uncertainty (95PPU) band after calibration and validation. Furthermore, results indicated that the SC technique out-performed the other two methods (SSC and SMSC). It was also observed that although the SMSC technique uses streamflow data from all gauging stations during calibration and validation, thereby taking into account the catchment spatial variability, the choice of each calibration method

will depend on the application and spatial scale of implementation of the modelling results in the catchment.

6.1 Introduction

The rate of hydrological change in the Lake Chad Basin (LCB) has increased in recent decades. Lake Chad is an endorheic lake located in the Sudano-Sahel transition zone of the Central Africa region. Between 1960 and 2000 the lake experienced one of the most significant and sustained reductions in rainfall recorded anywhere in the world, which caused the lake area to shrink by more than 80% (Odada *et al.* 2009). However, the shrinkage in lake size cannot be attributed wholly to a reduction in rainfall. Construction of numerous dams on the Feeder Rivers of the lake for irrigation projects have reduced inflows into the lake by about 50% (Odada *et al.* 2009).

More recently, drought has given way to floods due a recovery in rainfall (Nkiaka *et al.* 2016a). However, water availability for agriculture, pastoral activities, wetland ecology and contribution as inflow into the lake continues to be variable due to the erratic nature of this rainfall. Under future projected climate change Sahelian semi-arid ecosystems such as the LCB are expected to witness increased frequency of droughts and floods (Yang *et al.* 2016). This will lead to social and economic problems as the rising population in the LCB is leading to tension among water users (Ngatcha 2009). A study by Okpara *et al.* (2015) reported that climate-induced water scarcity and droughts in the LCB could combine with factors such as population increase, poverty and political instability to create the necessary conditions for armed conflict. An improved understanding of the main hydrological processes and feedback mechanisms in the LCB will contribute to guiding future water management policy.

The LCB is a very heterogeneous basin with spatially variable land use, soil classes, topography and a wide range of rainfall. To fully understand the hydrological characteristics of the basin, this spatial variability needs to be included in the modelling process. This can be achieved by using distributed catchment hydrological models (CHMs), which require careful calibration and validation. This process is a pre-requisite for model application because it reduces model uncertainty and increases user confidence in the model predictive capabilities.

Spatially distributed CHMs can be used for modelling different catchment processes, including evapotranspiration, surface runoff, interception, infiltration, percolation and groundwater flow. They can also be used to investigate the impacts of land use change, climate change and agricultural activities at a catchment scale (Wu and Chen 2013; Athira and Sudheer 2015; Zhou *et* *al.* 2015; Shi *et al.* 2016), making them a useful tool to help decision makers better understand environmental problems and design appropriate mitigation. Given the current technological advancement in the acquisition and storage of hydro-meteorological data, the use of spatially distributed, physically based CHMs to enhance management decisions at basin scale is receiving increasing attention from the scientific community (Golmohammadi *et al.* 2014; Leta *et al.* 2017). The high degree of spatial variability in catchment characteristics requires careful calibration of the model so as to obtain consistent results among all the gauging stations within the catchment. However, calibration of CHMs to determine a suitable set of parameter values that can describe the hydrology of the catchment is not always an easy task (Zhang *et al.* 2016). Studies have shown that the parameter set used to calibrate CHMs against flow measured only at the catchment outlet (single-site calibration (SSC) may not produce similar results at other internal hydrometric stations within the catchment (Wang *et al.* 2012; Wi *et al.* 2015; Leta *et al.* 2017). Furthermore, several researchers have demonstrated the effectiveness of calibrating CHMs with data from different parts of the catchment using simultaneous multi-site calibration (SMSC) over SSC (Wang *et al.* 2012; Wi *et al.* 2015; Chaibou Begou *et al.* 2016).

SMSC techniques that use data from different sites within the catchment to constrain the model are expected to produce better results because spatial variability in the catchment is represented through different parameter values. Nevertheless, some researchers e.g. (Shrestha *et al.* 2016) have reported that no significant improvements were observed by applying the SMSC compared to SSC especially for flow simulation. Despite this, the application of SMSC and SSC techniques in hydrological modelling is well established, and many studies have demonstrated the superiority of the former technique to the latter (Wang *et al.* 2012; Chaibou Begou *et al.* 2016; Shrestha *et al.* 2016).

While hydrological modelling has been conducted across most major African basins (Cohen Liechti *et al.* 2014; Ollivier *et al.* 2014; Aich *et al.* 2015; Chaibou Begou *et al.* 2016), there are few studies on hydrological modelling in the LCB and its associated sub-basins. Li *et al.* (2005) investigated hydrological variability in the LCB using the land surface model Integrated Biosphere Simulator (IBIS), and the Hydrological Routing Algorithm (HYDRA). They concluded that the hydrology of the LCB was very variable in space and time. Candela *et al.* (2014) also carried out a groundwater modelling study in the LCB using MODFLOW and concluded that groundwater plays a non-negligible role in the hydrology of the basin.

Results from the studies by Li *et al.* (2005) and Candela *et al.* (2014) are highly generalized for the LCB and could be misinterpreted at sub-basin scale given the size of the LCB (approximate area 2.5×10^6 km^2) and the fact it covers a range of ecological zones (hyper arid, arid, semi-arid and Sudano). Such generalizations may not be useful for effective and robust planning and management of water resources. Thus, it is necessary to reduce the spatial scale of similar studies in the basin to gain an insight into the dominant hydrological processes at sub-basin scale. Of the numerous sub-basins that make up the LCB, the Logone catchment was selected for this analysis. The reasons for selecting the Logone catchment include: (i) it covers two ecological zones (Sudano and semi-arid), (ii) it contributes significantly to Lake Chad inflows, (iii) it is a transboundary catchment shared by three countries (Cameroun, Chad and Central Africa Republic).

The aim of this study was to develop a hydrological model of the Logone catchment using the Soil and Water Assessment Tool (SWAT) model. This was achieved through the following specific objectives: (i) to compile datasets to implement the SWAT model on the Logone catchment; (ii) to calibrate and validate the model at daily and monthly time-steps at three gauging stations including the outlet of the catchment; (iii) examine the benefits of multiple calibration techniques (SSC, SMSC and sequential calibration (SC)) for hydrological analysis; and (iv) select from the different calibration techniques the model that best describes the hydrological processes of catchment and use that model to attempt a description of the catchment hydrology.

6.2 Materials and Methods

6.2.1 Model description

The SWAT model is a semi-distributed, continuous time-step simulation model that can run at a daily, monthly or yearly time-steps (Gassman *et al.* 2007; Arnold *et al.* 2012). It is capable of simulating hydrological processes, impacts of climate and land use changes, water use management, water quality and quantity assessments (Gassman *et al.* 2007; Wu and Chen 2013; Athira and Sudheer 2015). The model was used in this study because it has been successfully applied in other catchments in Africa e.g. (Cohen Liechti *et al.* 2014; Akpoti *et al.* 2016; Chaibou Begou *et al.* 2016). However, previous application of SWAT in the LCB has not been reported in the literature.

In this study, we focus only on water quantity simulation accomplished through two steps: (i) the land phase of the hydrological cycle, which controls the amount of water transferred to the main channel from each sub-catchment, and (ii) the routing phase, which involves the movement of water through the channel network to the outlet. The hydrologic cycle in the land phase of the model is simulated using the water balance equation as:

$$SW_t = SW_0 + \sum_{i=1}^{n}(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}) \qquad (6.1)$$

SW_t is the final soil water content (mm), SW_0 is the initial water content (mm), R_{day} is the amount of precipitation on day i (mm) Q_{surf} is the amount of surface water runoff on day i (mm), E_a is the amount of actual transpiration on day i (mm), W_{seep} is the amount of water entering the vadose zone from the soil profile on day i (mm) and Q_{gw} is the amount of return flow on day i (mm). Details of equations and methods used to estimate various hydrological components can be found in Neitsch *et al.* (2011).

During model development, SWAT divides a catchment into sub catchments using digital elevation model data. The spatial distribution of hydrological processes over each sub-catchment is represented through hydrologic response units (HRUs), which are used to further divide the sub-catchments into smaller units based on a homogeneous combination of land use class, soil type, slope class and management within each sub-catchment.

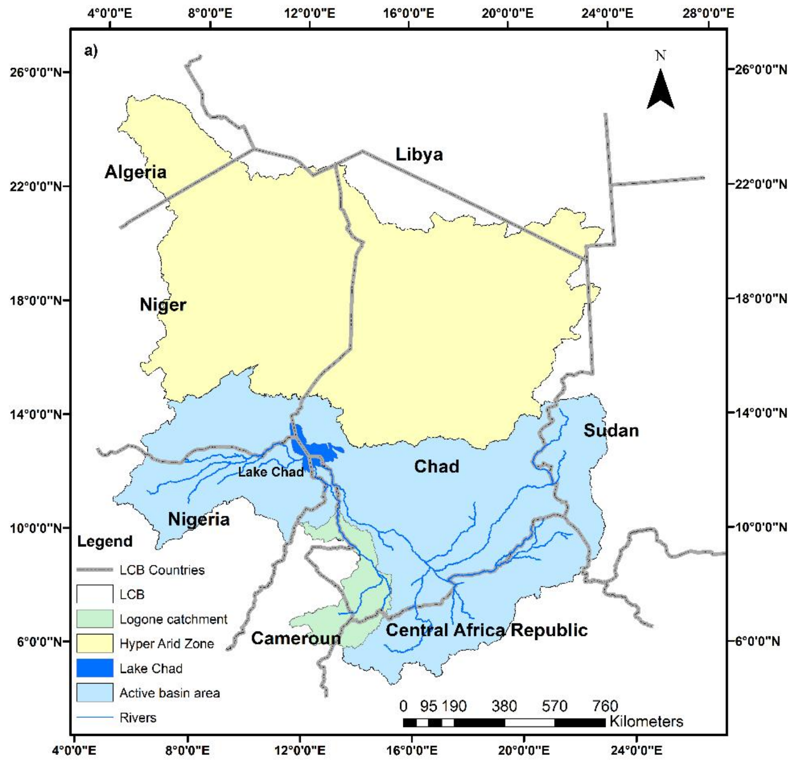
Three options are available for estimating potential evapotranspiration (PET) in the SWAT model: Hargreaves, Priestley–Taylor and Penman–Monteith. The Hargreaves method was applied owing to the less onerous data demands (minimum and maximum temperature). This method has been used in other modelling studies in the region using SWAT model with reasonable results obtained (Chaibou Begou *et al.* 2016). Furthermore, Droogers and Allen (2002) compared Penman–Monteith and Hargreaves reference evaporation estimates on a global scale and found reasonable agreement between the two methods (R^2 = 0.895, RMSD = 0.81). These authors suggested that, the Hargreaves method could be used in regions where reliable weather data was not available. Surface runoff was calculated using the Soil Conservation Service's curve number (CN2) method while flow routing was accomplished through the variable storage method (Neitsch *et al.* 2011). Model parameters that affect streamflow generation and propagation were summarized in Table 1. The equations used for modelling wetlands are also available in relevant SWAT documentation (Neitsch *et al.* 2011).

6.2.2 Study area

The Logone catchment lies between latitude 6˚-12˚ N and longitude 13˚-17˚ E. This is about 8% of the active basin area that covers about more than a million square kilometres (Adenle 2001)

(Figure 6.1a). It is a transboundary catchment located in the Sudano-Sahel transitional zone within the Lake Chad basin with an estimated catchment area of 86,240 km^2 at the Logone Gana outlet (Figure 6.1b). The catchment area is shared by Cameroun, Chad and Central Africa Republic. The Logone River has its source in Cameroun through the Mbere and Vina rivers, which flow from the north-eastern slopes of the Adamawa Plateau in Cameroun. It is joined in Lai by the Pende River from the Central Africa Republic and flows from south to north to join the Chari River in Ndjamena (Chad) after, which it continues flowing in a northward direction and finally empties into Lake Chad. The river has an estimated length of 1000 km.

The climate in the catchment is characterized by high spatial variability and is dominated by seasonal changes in the tropical continental air mass (the Harmattan) and the marine equatorial air mass (monsoon) (Candela *et al.* 2014). There is a strong north-south rainfall gradient with a single rainy season occurring between April-October. Estimated average rainfall varies between 900 mm/year in the north to 1400 mm/year in the south Nkiaka *et al.* (2016a) while mean annual temperature is 28°C. Apart from some local mountains in the south and north-west, the catchment is very flat with an average slope of less than 1.3% in a south– north gradient.



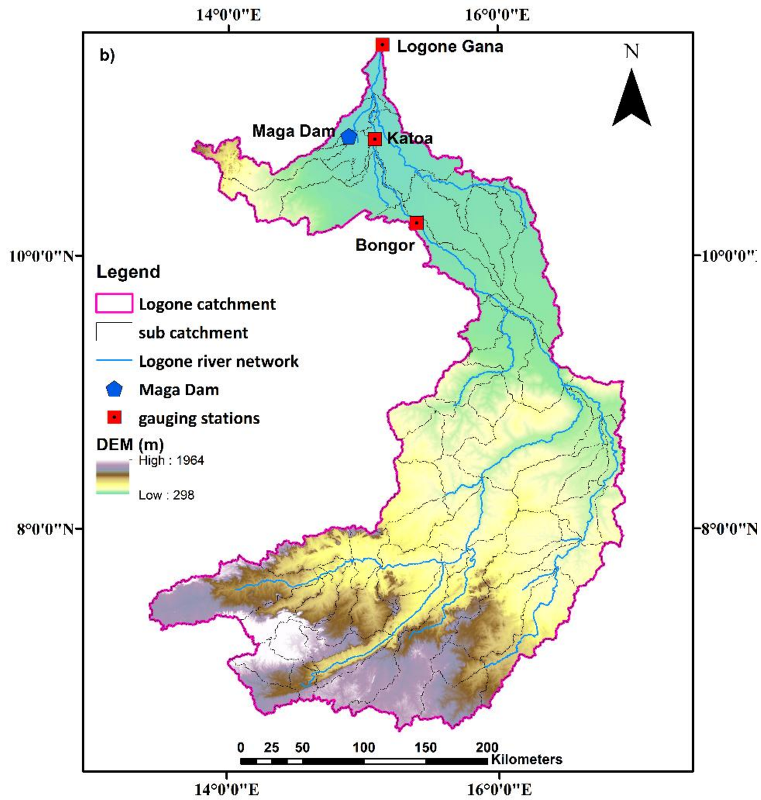


Figure 6.1 Map of study area: a) LCB showing the Logone catchment; b) detailed map of the catchment

Table 6.1 **Description of model parameters, results of sensitivity analysis, parameters ranges used for calibration and optimized values**

Parameter	Description	Model process	Unit	Global Sensitivity		Parameter range used	SSC	SC-Katoa	SC-Bongor	SMSC
				t-sat	***p-value***		Best parameter value	Best parameter value	Best parameter value	Best parameter value
CN2[a]	Curve number for moisture condition II	Surface runoff generation. High values lead to high surface flow	%	-30.24	0.00	-0.5 – 0.2	-0.31	-0.40	0.05	-0.35
GW_Delay	Groundwater delay	Groundwater (affects groundwater movement). It is the lag between the time water exits the soil profile and enters the shallow aquifer	days	9.73	0.00	0 – 140	137.690	99.000	66.220	125.800
GW_REVAP	Groundwater “revap” coefficient	Affects the movement of water from the shallow aquifer to the unsaturated soil layers. Low values lead to high baseflow	-	9.59	0.00	0.10 – 0.20	0.177	0.199	0.157	0.182
GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur	Groundwater (when reduced streamflow increases)	mm	6.05	0.00	0 – 100	44.809	11.700	20.750	5.900
Revapmn	Threshold depth of water for "revap to occur"	Groundwater (when increased, base flow will increase)	mm	-2.49	0.01	0 – 100	18.805	8.420	12.139	0.260
Rchrg_DP	Deep aquifer percolation	Groundwater (the fraction of percolation from the root zone which recharges the deep aquifer. Higher values lead to high percolation).	-	2.19	0.02	0.05 – 0.50	0.195	0.116	0.178	0.151

ESCO	Soil evaporation compensation factor	Controls the soil evaporative demand from different soil depth. High values lead to low evapotranspiration	-	-1.89	0.03	0.25 – 0.95	0.751	0.366	0.597	0.476
SOL-AWC[a]	Available Water Capacity or available is calculated as the difference between field capacity the wilting point	Groundwater, evaporation. When increased less water is sent to the reach as more water is retained in the soil thus increasing evapotranspiration	%	0.93	0.35	-20 – 20	0.06	1.9	-0.03	-0.04
SLSUBBSN[a]	Slope sub-basin	Suface runoff	%	0.797	0.42	-0.01 – 0.10	0.057	0.041	0.071	0.033
ALPHA_BF	Base flow alpha factor	Shows the direct index of groundwater flow response to changes in recharge	day	0.63	0.53	0.03 – 0.90	0.391	0.475	0.605	0.395
Ov_N	Manning's N	Overland flow	-	0.49	0.62	0.01 - 0.30	0.015	0.031	0.012	0.065
Surlag	Surface runoff lag coefficient	Surface runoff	day	0.32	0.75	0.5 - 12	4.395	-	-	3.620

[a] Parameter value is multiplied by (1 + a given value). For example if CN2 = 85 then the calibrated CN2 value will be (1 +(-0.5)) * 85 = 0.5* 85 = 42.5

6.3 Data sources

6.3.1 Meteorological data

Due to data scarcity in the LCB, global meteorological forcing data WATCH Forcing Data methodology applied to ERA Interim (WFDEI) (Weedon *et al.* 2014) was used to drive the model. WFDEI is a bias corrected dataset produced from Watch Forcing Data and ERA-Interim reanalysis via sequential interpolation to a 0.5° resolution, elevation correction and monthly-scale adjustments based on CRU TS3.1/TS3.21 and GPCCv5/v6 monthly precipitation observations for 1979–2012 (Weedon *et al.* 2014). These are combined with new corrections for varying atmospheric aerosol-loadings and separate precipitation gauge corrections for rainfall and snowfall under the Water and Global Change (WATCH) programme. Only daily precipitation, minimum and maximum temperature values were used in this study.

The use of WFDEI for hydrological modelling is widely reported. For example Monteiro *et al.* (2015) used WFDEI and Climate Forecasting System Reanalysis (CFSR) as input to drive the SWAT model in the Tocantins catchment in Brazil and reported that WFDEI outperformed CFSR in simulating streamflow. Andersson *et al.* (2015) used WFDEI as input to drive Hydrological Prediction of the Environment (HYPE) across different basins in Europe and Africa and concluded that, this dataset improved streamflow simulation compared to Watch Forcing Data (WFD) based on ERA-40. In a previous study Nkiaka *et al.* (2017), compared the performance of CFSR, ERA-Interim and WFDEI for hydrological modelling in the Logone catchment and concluded that, WFDEI outperformed the other two datasets in simulating streamflow.

For the Logone catchment, the data was obtained for an area bounded by latitude 6°-12° N and longitude 13°-17.25°E from https://dataguru.lu.se/ at a spatial resolution of 0.5°. 96 grid points were selected within this rectangular area. Elevation data for WFDEI was obtained from the International Institute of Applied System Analysis (IIASA) available at ftp://ftp.iiasa.ac.at/WFD-land-long-lat-z.dat.

6.3.2 River discharge data

River discharge data was obtained from the Lake Chad Basin Commission (LCBC) at both daily and monthly time-steps covering the period 1997 - 2010. Gaps in the discharge data were infilled using Artificial Neural Networks Self-Organizing Maps (ANN-SOM) (Nkiaka *et al.* 2016b).

6.3.3 Spatial data

Digital Elevation Model (DEM) data used to delineate the catchment was obtained from the Shuttle Radar Topographic Mission (SRTM) at a spatial resolution of 90 m downloaded from http://www.cgiar-csi.org/. The quality of DEMs have been shown to vary from one source to another, which could have an impact on model parameters thereby compromising the quality of model results (Wu *et al.* 2008; Lin *et al.* 2013). However, Lin *et al.* (2013) investigated the impact of DEM spatial resolution on SWAT model results and reported that, the latter had a significant impact on water quality and sediment load simulation but simulated streamflow was not sensitive to DEM spatial resolution. Given that the purpose of this study was streamflow simulation, a DEM with spatial resolution of 90 m was used. Land cover/use maps were obtained from Climate Change Initiative Land Cover (CCI-LC) at a spatial resolution of 300 m, obtained from https://www.esa-landcover-cci.org/. Soil data was obtained from the Food and Agricultural Organisation (FAO), Harmonize World Soil Database (HWSD) at a spatial resolution of 1km. The land use and soil maps of the study area is shown in Figure 6.2. Soils are grouped according textural classes.

Table 6.2 Land use/cover distribution in the Logone catchment

Land use/cover class	**Area (km^2)**	**Area (%)**
Agriculture	28,311.71	32.83
Range	10,288	11.93
Wetland	1,800.63	2.09
Forest	45,356	52.59
Urban	96.95	0.11
Barren land	1.98	0.00
Water	387.34	0.45
Total	86,242	100

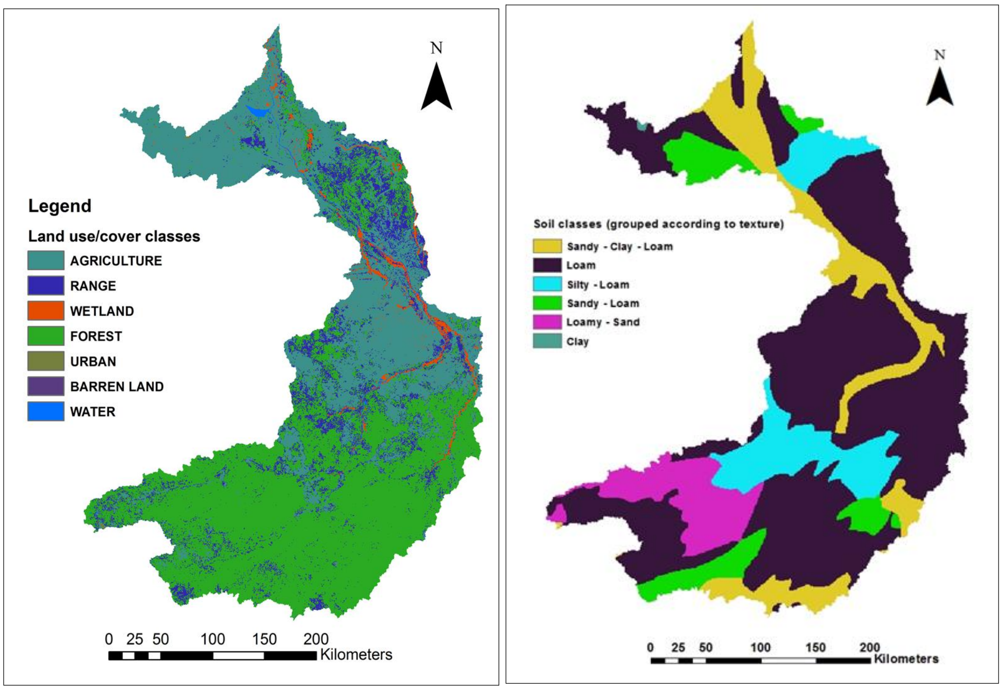


Figure 6.2 Land use/cover (a) and soil classes (b) in the Logone catchment

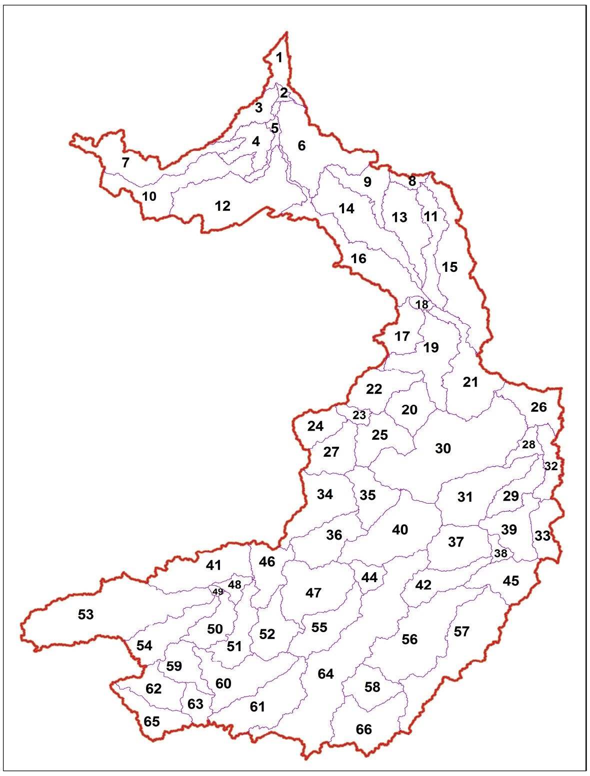


Figure 6.3 Logone sub-basin numbers

6.3.4 Model setup

To maximize the number of meteorological grid points used for simulating the model, a minimum drainage area of 750 km^2 was used to delineate the catchment into 66 sub-basins (Figure 6.3) and 34 meteorological grid points were selected. The land cover was reclassified in ArcSWAT according to model input requirements with forest and agriculture dominating the land cover (Figure 6.2 and Table 6.2). The land use map indicated 59 wetland areas in the catchment spread over 59 sub-basins occupying a total surface area of 1800 km^2, making up about 2% of the study area. ArcGIS tools were used to create an artificial reservoir (the Maga dam) draining two rivers (Mayo Tsanaga and Mayo Boulo) and an outlet downstream of the reservoir. Multiple HRUs and area criteria were used for HRUs creation to take into account all land use classes especially wetlands. Threshold values for HRUs creation were fixed at 5 ha for land use given that the smallest wetland occupied an area of 5 ha while 2500 ha was used for slope and soil classes thereby, creating 406 HRUs.

Minimum and maximum water levels in the wetlands were assumed to vary within the range 0.50 - 1.0 m (Jung *et al.* 2011). This information was used to calculate the storage capacity of each wetland. The normal storage volume of the wetland was calculated as the product of the wetland area by minimum water level ($V_{min} = 0.5*SA$) while the maximum storage was taken as the product of wetland area by maximum water level ($V_{max} = 1.0*SA$). The fraction of each sub-basin draining into the wetland fr_{imp} was estimated as the ratio of the wetland area to the area of the corresponding sub-basin. As suggested by Wang *et al.* (2010), three wetland parameters (fr_{imp}, V_{max} and V_{min}) were calibrated. According to Wang *et al.* (2010), when fr_{imp} takes a lower limit or is very small, the wetland may not receive any inflow from the remaining portion of the sub-basin. On the other hand, when fr_{imp} takes the upper limit, the wetland is considered to intercept all runoff generated in the sub-basin.

6.4 Model sensitivity analysis, calibration, validation and uncertainty analysis

Sensitivity analysis, calibration, validation and uncertainty analysis were implemented by the automated SWAT Calibration and Uncertainty Program software (SWAT-CUP) using the commonly applied Sequential Uncertainty Fitting algorithm (SUFI-2) (Abbaspour 2008). A global sensitivity analysis approach was used whereby all parameters are allowed to change at the same time. Sensitivity analysis was carried out for all the 26 flow related parameters using their ranges defined in relevant SWAT documents although only the most sensitive are reported in (Table 6.1). In Table 6.1, the larger the *t*-stat value in absolute terms, the more sensitive is the parameter. On the other hand, the *p*-values are used to determine the significance of the sensitivity results with values closer to zero considered to be more statistically significant.

In this study, the following calibration techniques were applied: single-site calibration (SSC), sequential calibration (SC) and simultaneous multi-site calibration (SMSC). The SSC consist of changing and optimizing model parameters using flow data measured at the catchment outlet only. The SC technique is an approach whereby, the model is calibrated using flow data from different parts of the catchment beginning with the most upstream station and subsequently moving to downstream stations. Given that sub-catchments that contribute to flow may have different characteristics (soils, land use, topography), in the SC technique, only the parameters of the sub-basins located upstream of that hydrometric station are calibrated. Since all the hydrometric stations in the studied catchment are hydrologically connected, the model was first calibrated for the most upstream station Bongor (sub-basins 16-66) and subsequently Katao (sub-basins 5&12 and 16-66) (Figure 6.3). SC was not carried out at Logone Gana because this station had already been calibrated using the SSC technique. Migliaccio and Chaubey (2007) recommend the use of SC technique for calibrating nested sub-basins with hydrologic connections.

Contrary to the SC technique used by Wi *et al.* (2015), Shrestha *et al.* (2016) and Leta *et al.* (2017), whereby the calibrated and optimized parameter set obtained in the upstream gauge is fixed while calibrating the downstream counterpart, that approach was not adopted in this study because of the hydrological connection between upstream and downstream hydrometric stations. Note that the same number of parameters and their ranges were used to initiate each calibration. During SC, the parameter "Surlag" was not calibrated at Bongor and Katoa stations because it is a basin-scale parameter.

In contrast to SC and SSC techniques, the SMSC consisted of using flow data from all the hydrometric stations to calibrate the model by changing and optimizing parameters of all the sub basins at the same time. The aim of this approach is to look for suitable parameter values capable of producing satisfactory model results at all gauging stations at the same time. The advantage of this technique is a considerable reduction in computational time compared to the SC technique because all the gauging stations are calibrated at the same time. The SMSC technique has been applied by many researchers e.g. (Wi *et al.* 2015; Leta *et al.* 2017).

The model was simulated from 1997-2010 of which 1997-1999 was used as the warm-up period, 2000-2007 served as the calibration period for daily and monthly time-steps while 2008-2010 served as validation period for monthly time-step only. Due to the lack of sufficient daily observed streamflow data, the model was validated only at monthly time-step. In the calibration process, parameters such as soil water holding capacity (SWC) and surface runoff curve number at soil moisture condition II (CN2) that are spatially variable were adjusted using global multipliers or relative change to their original values. This approach is used to preserve the natural variability and heterogeneity of the catchment. The calibration process consisted of running 500 simulations in each iteration with the parameter set shown in Table 6.1. The ranges of the best parameter set obtained in the previous iteration was substituted and used in the next iteration until the results were judged to be acceptable.

Model validation consisted of running 500 iterations using the best parameter set obtained from the last calibration. The results of the SSC were also validated at upstream gauging stations (Katoa and Bongor) at daily and monthly time-steps by running the model during the same time period used for SSC with the behavioral parameter set obtained at the outlet. A similar approach has been used for validating the SSC technique by several researchers e.g. (Wang *et al.* 2012; Wi *et al.* 2015; Chaibou Begou *et al.* 2016). While SC results were validated at Bongor using independent monthly flow and rainfall data from 2008-2010, SMSC was validated at Logone Gana and Bongor using data from the same time period. Finally, the SMSC simulation number that produced the best output was used to calculate the water balance for the whole catchment during the calibration and validation periods.

Recently, Onyutha (2016) stated that the choice of a particular statistical “goodness-of-fit” measure greatly influences the judgement of the model performance. To eliminate subjectivity in assessment of the model performance, the well-known Nash Sutcliffe Efficiency (*NSE*) was complemented by two other metrics (i) coefficient of determination (R^2), and (ii) Percent Bias (*PBIAS*). The *NSE* is used to assess the predictive capacity of the model and measures how well the observed and simulated flows match. The R^2 measures how well the observed data is correlated to the simulated data and varies from 0 – 1. *PBIAS* indicates the average tendency of the simulated flows to be over/underestimated compared to observed flows. Although Moriasi *et al.* (2007) stated that *NSE*>0.50, R^2>0.60 and *PBIAS* ±25% for calibrated models results at monthly time-step may be considered to be satisfactory, in this study, the threshold was set at *NSE*>0.60, R^2>0.65. The model evaluation metrics are calculated as:

$$NSE = 1 - \left[\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(x_i - \overline{x})^2}\right] \tag{6.2}$$

$$R^2 = \frac{\sum_{i=1}^{n}[(x_i - \bar{x})(y_i - \bar{y})]}{\sum_{i=1}^{n}\ [(x_i - \bar{x})^2]\sum_{i=1}^{n}[(y_i - \bar{x})^2]} \tag{6.3}$$

$$PBIAS = \left[\frac{\sum_{i=1}^{n}(X_i - Y_i)}{\sum_{i=1}^{n} X_i}\right] X100 \tag{6.4}$$

Where: x_i = observed discharge; y_i = simulated discharge; $\bar{x}$= mean of observed discharge; n = number of observations.

The degree of uncertainty in the calibrated/validated model was quantified using the *p-factor* and *r-factor*. The *p-factor* represents the percentage of observations bracketed by the 95% prediction uncertainty (95PPU) while the *r -factor* is the average width of the 95PPU band. The 95PPU is calculated at the 2.5% and 97.5% confidence interval of observed streamflow obtained through Latin hypercube sampling. In SUFI-2, the goal is to minimize the width of the uncertainty band and enclose as many observations as possible (Abbaspour 2008). The *p-factor* can vary between 0 – 1 with 1 representing the most preferred value which means, all the observations are captured by prediction uncertainty, while the desirable value for *r -factor* is <1.5. Therefore, a compromise has to be made between reducing *r –factor* closer to <1.5 and *p-factor* >0.70 (Abbaspour 2008).

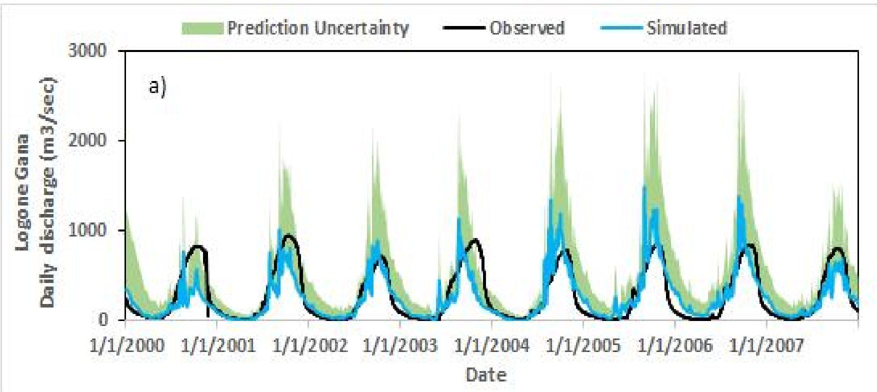
6.5 Results and Discussion

Sensitivity analysis was carried out using the SMSC technique because this approach uses streamflow data from all the hydrometric stations in the catchment. Results obtained indicated that, soil moisture condition curve number (CN2), which controls surface water runoff is the most sensitive parameter (Table 6.1). This was followed by parameters that control groundwater storage and flow. GW_revap, which controls the movement of water from the shallow aquifer to the unsaturated soil layers was also ranked among the most sensitive. The sensitivity analysis results suggest that soil water plays an important role in the catchment hydrology.

6.5.1 Model performance

6.5.1.1 Model performance for Single site calibration

The SSC technique was used to calibrate the model at the outlet (Logone Gana) and to validate it at Katao and Bongor located upstream. The model was also validated using independent data at monthly time-steps at the outlet. The *NSE* and R^2 values obtained during calibration and validation lie in the range $0.64 \leq NSE \leq 0.78$ and $0.65 \leq R^2 \leq 0.88$, respectively. These results are above the threshold defined in this study (Table 6.3). Results for model calibration and validation at monthly time-steps using independent data are mixed with cases of peak flow over/underestimation observed in some years (Figure 6.4a & 6.7a). It was also observed during SSC validation at upstream stations that the model overestimated peak flows in most years at Katoa and slightly underestimated it in some years at Bongor (Figure 6.4b & c). The same results were obtained at monthly time-steps (Figure 6.7b & c). Notwithstanding, results obtained at the outlet of the catchment are comparable to those obtained at the outlets of other Sudano-Sahel catchments e.g. by Chaibou Begou *et al.* (2016) at the outlet of Bani catchment using SWAT and by Aich *et al.* (2015) at the outlet of Niger basin using SWIM model.



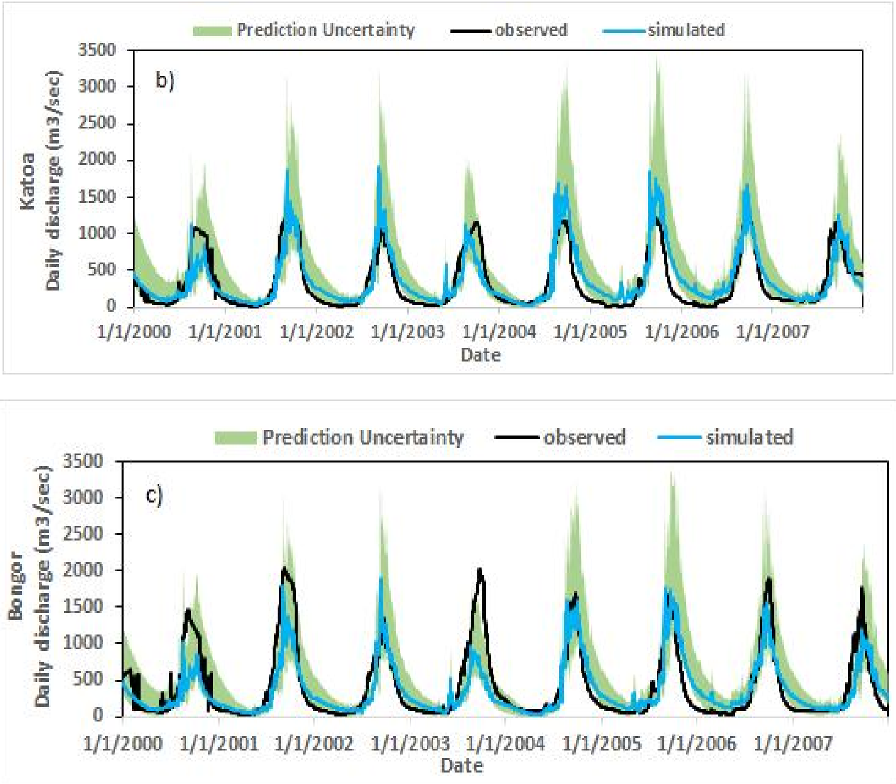


Figure 6.4 Comparison of daily observed and simulated hydrographs for SSC (a) and validation at upstream gauging stations (b & c)

From streamflow hydrographs, it can be observed that although the model had difficulties in simulating peak flows at some stations, low flows were adequately simulated at both time-steps (Figures 6.4a-c & 6.7a-c). It can also be observed from those hydrographs that despite the over/underestimation of peak flows, the timing of peak flows was well reproduced at both time-steps with only a few cases of lag observed in some years especially at the outlet (Figure 6.4a). Model prediction of water balance using the SSC technique at both time-steps can be considered to be satisfactory during calibration at the outlet and validation at the upstream stations given that PBIAS values obtained all lie within the limits defined in this study (Table 6.3).

Results obtained from the SSC technique indicate that the model performed better during validation at upstream gauging stations compared to calibration at the outlet during the same period. These results indicate that the parameters used to constrain the model at the outlet may not be representative of the whole catchment. The underperformance could be attributed to hydraulic modifications that exit downstream before the gauging station at Logne Gana as explained in below. This could also suggest that by using SSC technique it may not possible to adequately represent all the hydrological processes taking place in the catchment. Therefore, the optimized model parameters may not be considered to be representative of the catchment and justifies the need for different calibration techniques.

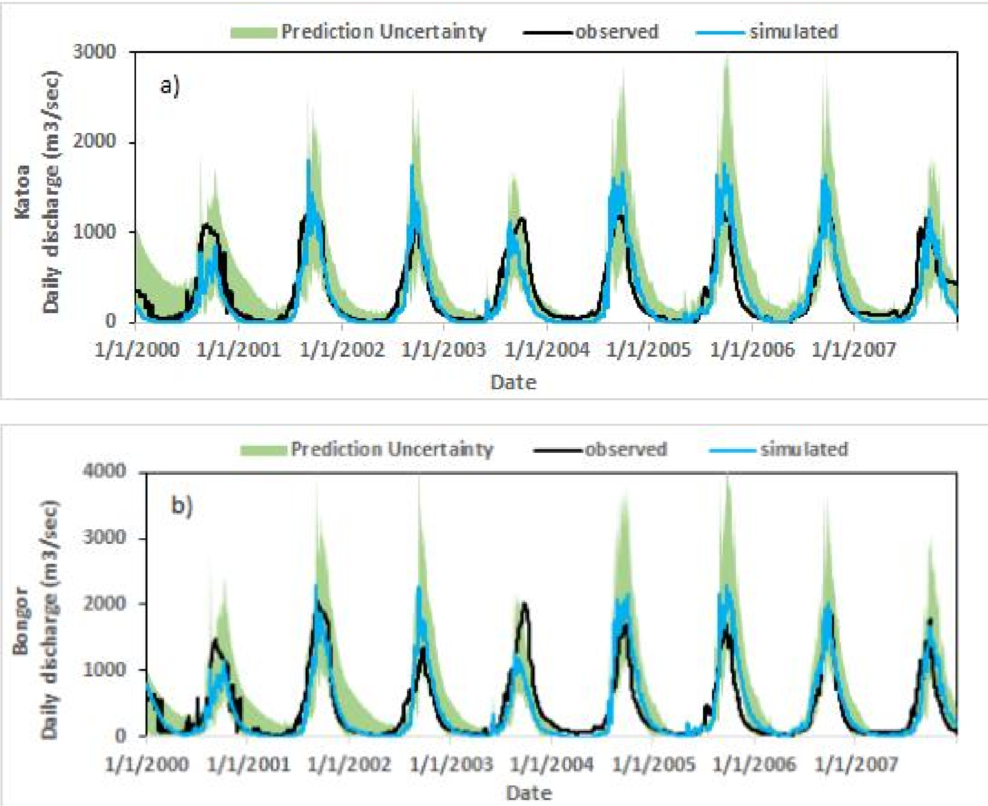


Figure 6.5 Comparison of daily observed and simulated hydrographs for SC (a & b)

6.5.1.2 Model performance for sequential calibration

This technique was used to calibrate the model at two internal stations located upstream of the catchment outlet so as to take into account the variability in the spatial characteristics of the sub-basins that contribute to streamflow. Model evaluation statistics at both time-steps show that the *NSE* and R^2 values obtained lie in the range $0.71 \leq NSE \leq 0.81$ and $0.74 \leq R^2 \leq 0.86$, which are all above the threshold defined in this study (Table 6.3). Results for peak flow simulation using SC at Katoa and Bongor are mixed with cases of flow overestimation/underestimation in some years while baseflow is adequately simulated (Figure 6.5a & b). The results for peak flow simulation at monthly time-step are comparable to what was obtained at daily time-step but baseflow is slightly overestimated in some years during validation at Bongor station (Figures 6.6b & c). Using this technique, the water balance predicted by the model at both time-steps during calibration and validation all lie within the threshold defined by in this study (Table 6.3).

From *NSE* and R^2 values obtained, it can be observed that this technique out-performed the SSC (Table 6.3). For example, by changing the calibration technique from SSC to SC, the *NSE* value for Bongor increased from 0.66 to 0.71 while *PBIAS* at the same station dropped from 11.60% to 3.50% at the daily time-step. This shows a significant improvement in the model performance. This suggest that by using the SC technique, the model parameter values representing the spatial variability and processes taken place at sub-basins located upstream of the calibrated gauging station are adequately represented.

6.5.1.3 Simultaneous multi-site calibration

In the SMSC approach, all the gauging stations were calibrated at the same time. Results obtained show that, at both time-steps, *NSE* and R^2 values lie in the range $0.44 \leq NSE \leq 0.80$ and $0.57 \leq R^2 \leq 0.81$ (Table 6.3). It can be observed that by using this technique, the model performed better during calibration at monthly time-step at all the gauging stations compared to the daily time-step (Figures 6.6a-c and 6.7a-c). At the monthly time-step the model performance slightly improved during validation at Bongor whereas it deteriorated at Logone Gana (Table 6.3). At the outlet, the model systematically overestimated peak flows during calibration at both time-steps and during validation at monthly time-step with the exception of 2009 during the validation period when the model underestimated peak flows (Figure 6.5a and 6.6a). On the other hand, the model underestimated peak flows at Katao in some years during calibration at both time-steps (Figure 6.6b and 6.7b). Meanwhile at Bongor, the model systematically underestimated peak flow in all the years at the daily and monthly time-steps (Figure 6.6.6c & 6.7c).

The *PBIAS* values obtained during calibration lie within the threshold defined in this study except for Logone Gana during validation at monthly time-step and Bongor during calibration at both time-steps.

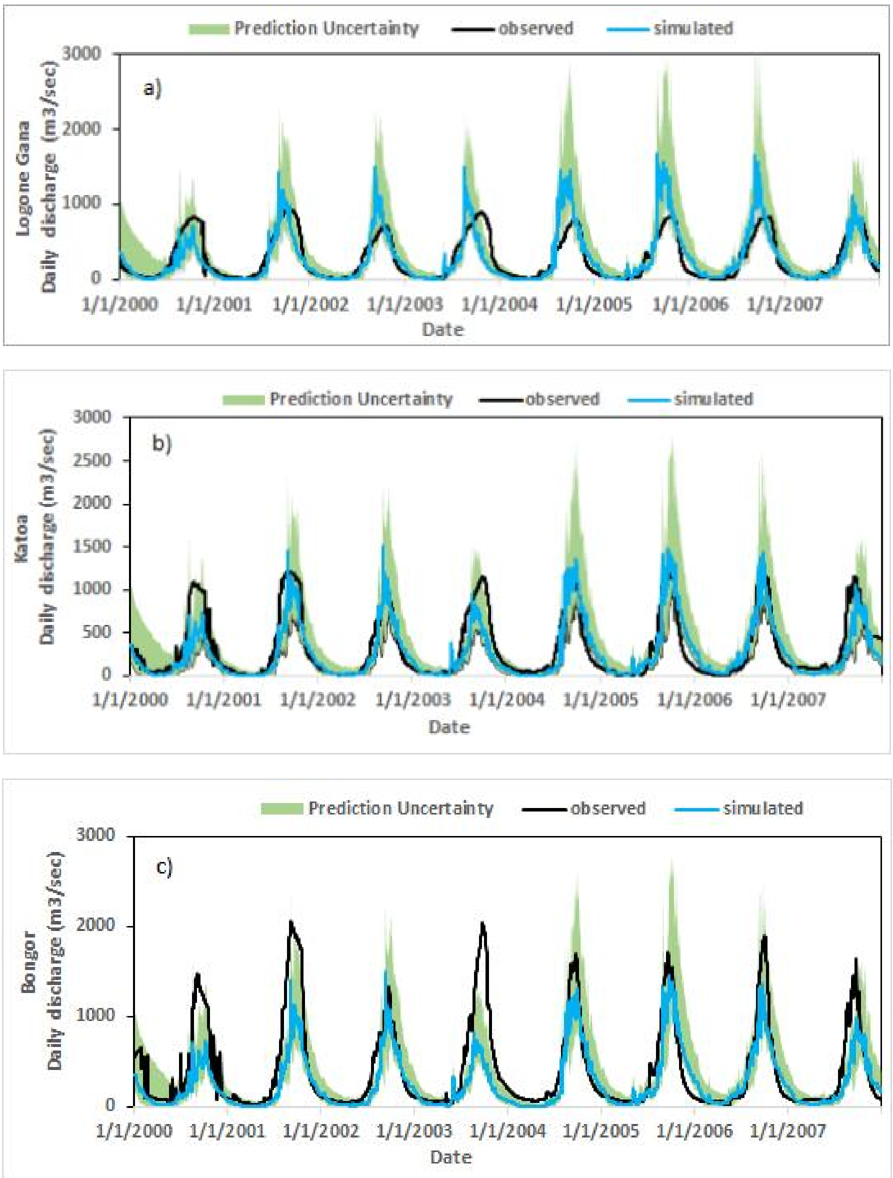


Figure 6.6 Comparison of daily observed and simulated hydrographs for SMSC (a - c)

6.5.2 Comparison of different calibration methods

Comparing the results obtained using the three calibration techniques, SC produced the best performance considering all the three model performance metrics, followed by SSC while SMSC produced average performance although still above the minimum criteria defined in this study (Table 6.3). These results follow the findings of Leta *et al.* (2017) who observed that SC out-performed the SSC technique in their study. Comparing the streamflow hydrographs obtained using the three techniques, it can be observed that; (i) with the SSC technique peak flows were overestimated at the outlet and at Katoa during validation upstream (Figures 6.4a & b and 6.7a & b). Validating this technique using data from Bongor further upstream led to the underestimation of peak flows in most years (Figures 6.4c and 6.7c). (ii) SC technique lead to the overestimation of peak flows in some years at Bongor during the calibration and validation periods (Figure 6.7c). (iii) SMSC technique led to the overestimation of peak flows at the outlet and underestimation of peak flows at the upstream stations (Figure 6.7a-c). However, using this technique, baseflow was systematically overestimated during validation at Logone Gana and Bongor during validation at monthly time-step (Figure 6.7a & c). Model under-performance during the validation period can be attributed to the fact that there was no warm-up period during validation so the model could not acclimatize. Generally, using all the techniques, baseflow was well simulated across all stations except at Logone Gana and Bongor using the SSC and SMSC techniques during the validation period (2008 – 2010).

Applying all the three calibration techniques, it was observed that the model performance increased from upstream (Bongor) to downstream (Katoa). However, moving further downstream at the outlet, there was a drop in model performance. This drop can be explained by the fact that between Katoa and Logone Gana (outlet), there is a dam on the left bank of the Logone River. There are also discharge elements (weirs, spillway) located on the left bank of the river downstream of Katoa, which provide a hydraulic connection between the river and the dam. These structures can send water either way depending on the water level in the river channel and the dam and contribute to modifying the hydraulic/hydrologic behavior of the river/catchment. The approach adopted in this study was for the dam to release water whenever its storage capacity was exceeded. Thus the drop in model performance at the outlet can be attributed to this complexity, which was not implemented in the model.

Despite the marginal performance of SMSC at some stations compared to SC, this technique may be preferable to SC because it can represent the spatial variability in the catchment using lump parameters and all gauging stations are calibrated at the same time. Therefore, for basin wide application of model results, it may be preferable to use the SMSC technique. More so, because of the hydrologic connectivity between the gauging stations so there is information exchange between the stations during calibration. In addition, using the SMSC technique it is possible to calibrate the model at all spatial levels (basin, sub-basin and HRU). Despite these advantages offered by SMSC, the use of each calibration technique should be guided by the type of management decision and the spatial scale of implementation in the catchment.

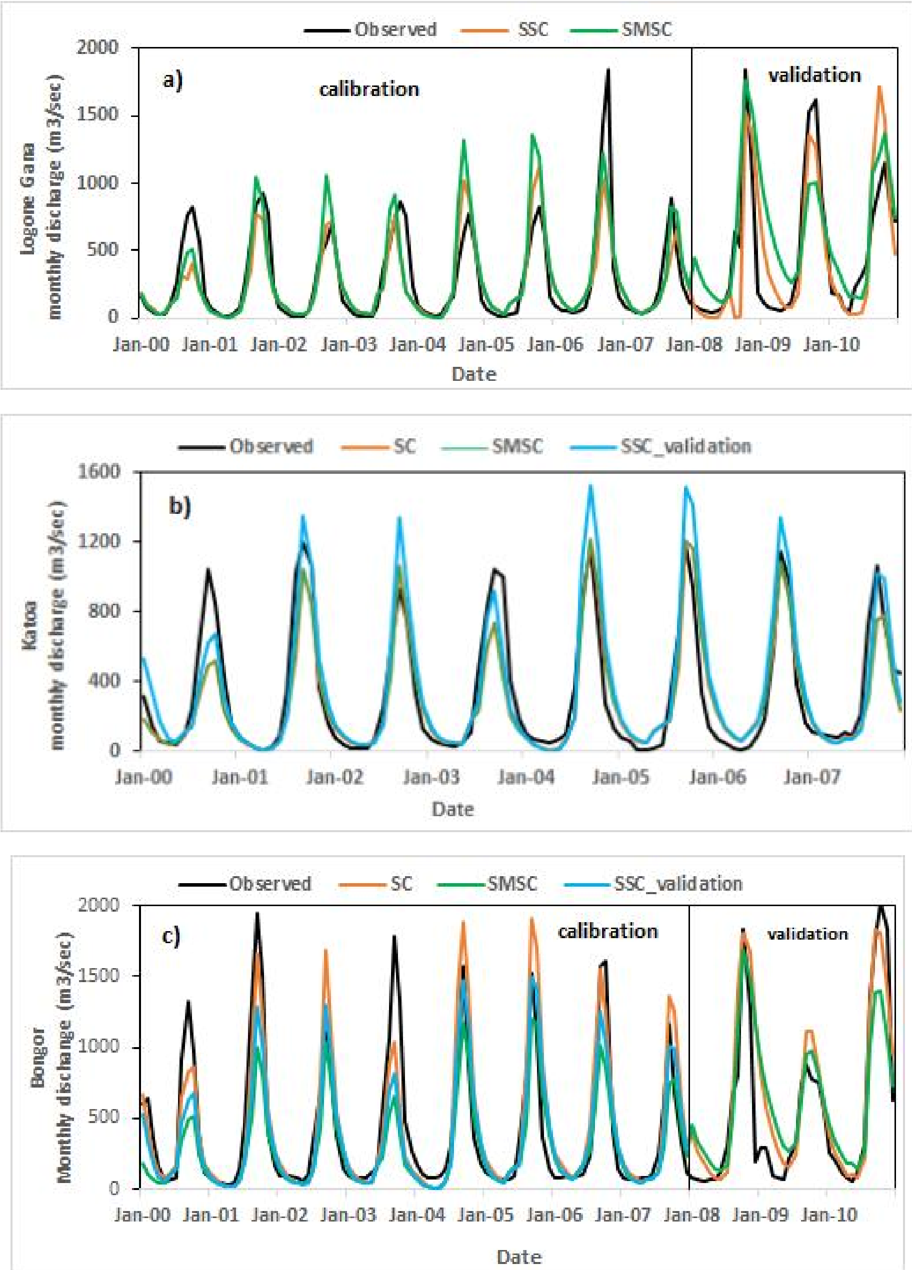


Figure 6.7 Comparison of monthly observed and simulated hydrographs using the different calibration techniques. The uncertainty band is not shown because the hydrographs have been obtained using different calibration techniques. Notice that at Katoa, SC and SMSC produced almost identical hydrographs

Table 6.3 Results of model calibration, validation and uncertainty analysis

Time step	Calibration method	Gauge location	Calibration/Validation Period	Performance Index			Uncertainty analysis	
				NSE	R^2	PBIAS (%)	p-factor	r-factor
Daily	SSC	Logone Gana (outlet)	2000-2007	0.64	0.65	6.10	0.42	0.50
		Katoa (middle ridge)	2000-2007	0.72	0.75	-15.12	0.65	0.92
		Bongor (upstream)	2000-2007	0.66	0.68	11.60	0.64	0.65
	SC	Bongor (upstream)	2000-2007	0.71	0.74	3.50	0.76	0.89
		Katoa (middle ridge)	2000-2007	0.75	0.79	13.70	0.84	1.01
	SMSC	Logone Gana (outlet)	2000-2007	0.53	0.66	-3.10	0.79	0.90
		Katoa (middle ridge)	2000-2007	0.75	0.77	16.10	0.71	0.69
		Bongor (upstream)	2000-2007	0.56	0.69	35.10	0.61	0.49
Monthly	SSC	Logone Gana (outlet)	2000-2007	0.68	0.88	10.30	0.85	0.88
			2008-2010	0.66	0.72	5.20	0.50	0.56
		Katoa (middle ridge)	2000-2007	0.78	0.83	-12.40	0.88	1.12
		Bongor (upstream)	2000-2010	0.72	0.76	21.00	0.75	0.74
	SC	Bongor (upstream)	2000-2007	0.76	0.79	-5.12	0.85	0.93
			2008-2010	0.76	0.86	-22.90	0.81	0.91
		Katoa (middle ridge)	2000-2007	0.81	0.81	9.80	0.85	1.05
	SMSC	Logone Gana (outlet)	2000-2007	0.64	0.68	-4.70	0.82	1.06
			2008-2010	0.44	0.57	-33.20	0.47	0.67
		Katoa (middle ridge)	2000-2007	0.80	0.81	10.00	0.84	0.94
		Bongor (upstream)	2000-2007	0.61	0.73	31.10	0.71	0.69
			2008-2010	0.69	0.72	-16.10	0.61	0.52

Calibration period (2000 – 2007) while the validation period (2008 – 2010). Note that for single site calibration, the model was also validated using data from upstream gauging stations (Kato and Lai)

6.5.3 Model prediction uncertainty

The model predictive uncertainty was evaluated using the *p-factor* and *r-factor* with the objective to minimize the width of the uncertainty band and enclose as many observations as possible. Results of SSC model predictive uncertainty indicated that low *r-factor* values (<1.50) and high *p-factor* values (>0.70) were obtained during model calibration at the monthly time-step compared to daily time-step (Table 6.3). However, this was not the case during model validation at the monthly time-step because only 50% of observed flows were bracketed within the 95PPU band. This under-performance during validation can be attributed to the short period used for validation so there was no warm-up period. It was also observed that more than 60% of observed daily streamflow was bracketed within 95PPU during validation and the *r-factor* values obtained at the two sites used for validation were <1.50 (Figure 6.3a-c). Uncertainty analysis using the SC technique showed that more than 75% of observed streamflow was bracketed within the 95PPU band with very low *r-factor* values <1.50 recorded at both time-steps but the model performed better at monthly time-step compared to daily (Table 6.3). Using the SMSC technique, uncertainty analysis results indicated that across all the stations, >60% of daily observed streamflow was bracketed within the 95PPU with *r-factor* values obtained generally <1.50. Apart from model validation at Logone Gana, similar model prediction uncertainty values were recorded at a monthly time-step (Table 6.3).

Generally, it was observed that the SC technique out-performed the other two methods (SSC and SMSC) in terms of model prediction uncertainty. Meanwhile, Katoa station registered the best performance at both daily and monthly time-steps. This is because the percentage of observed flow bracketed within the 95PPU band was generally above 65% irrespective of the technique used. The improved performance of the model predictive uncertainty and other evaluation indices at monthly time-step compared to daily can be attributed to the fact that, monthly rainfall is a cumulative measurement in which, all the daily variability within the month is summed thus reducing the variability and uncertainty in the data. This reduced variability consequently led to an improvement in the model performance.

Despite the positive results obtained, model bias (uncertainty band) was slightly wider at some stations (Figures 6.4 – 6.6). This could be attributed to the uncertainty inherent in the rainfall estimates (WFDEI) used in driving the model and reinforces the importance of using accurate rainfall estimates in hydrological modelling. In fact, Weiland *et al.* (2015) have shown that the uncertainty in rainfall estimates used in driving a hydrological model is propagated through the model to the streamflow estimates. This bias could also be linked to the uncertainty in the observed streamflow data used to calibrate the model. The uncertainty in streamflow could arise from the inability to accurately measure high flows at the river gauging stations or from rating equations when converting gauge heights of high flows to discharge (Juston *et al.* 2014). What could not be ruled out here was the possibility of observations errors in discharge resulting from poor or irregular maintenance of the gauge stations and/or the measurement equipment. Other sources of uncertainty e.g. model structural uncertainty and parameter uncertainty were not deemed out of scope of this study and therefore are not discussed herein.

Table 6.4 Results of simulated average water components (mm)

Hydrologic water components	**Model with SWAT**	
	Calibration (2000-2007)	Validation (2008-2010)
Precipitation	1229.20	1163.80
Surface runoff	8.87	6.09
Lateral flow	14.61	15.26
Shallow groundwater flow	157.65	152.36
Groundwater re-evaporation	94.49	84.31
Total water yield	210.47	308.02
Percolation out of the soil	307.27	296.88
Evapotranspiration	900.10	844.00
Potential Evapotranspiration*	1958.60	1966.20

* Potential Evapotranspiration is not part of the water balance

6.5.4 Parameter estimation

Given that we had no prior knowledge of the dominant hydrological processes that take place in the catchment, in this study feasible ranges of the calibrated parameters obtained from the literature were used (as is often the case in most automatic hydrologic model calibration).

Comparing the values of the optimized parameters using the different techniques, it was observed that there were significant differences in the parameter values obtained using each of the techniques. Using the SSC and SMSC techniques indicated that streamflow was consistently high therefore, CN2 was reduced by factor of -0.35 across the catchment. However, it can be observed from the flow hydrographs that reducing CN2 led to the underestimation of peak flow at Bongor (Figures 6.4c, 6.6c & 6.7c). On the contrary, by applying the SC technique at Bongor, CN2 increased by 0.05 and peak flows were instead slightly overestimated in some years at this station

(Figures 6.5b and 6.7c). This suggest that, the response of the upstream and downstream parts of the catchment to streamflow are different.

In fact, 65% of the total catchment area upstream of Bongor station is located in the Sudano zone which is mostly covered by forest and receives the highest amount of rainfall. While the remaining part of the catchment from Bongor to Logone Gana is located in the semi-arid zone with low rainfall and very flat topography with numerous wetlands (Figure 6.1b). Thus the differences in response to streamflow in the two parts of the catchment could be partly attributed to their physical characteristics. This suggest that CN2 values could be slightly higher in the upstream part (Sudano zone) of the catchment compared to downstream (semi-arid zone).

During the calibration process, SMSC uses streamflow data from different parts of the catchment. In this study, streamflow data from two stations located in the semi-arid part of the catchment (Katoa and Logone Gana) was used for calibration while data from only one station in the Sudano area was used. Therefore, the calibration process may have been dominated by semi-arid characteristics while the characteristics of the Sudano area that had data from only one gauging station were obscured. This could partly explain why by applying the SMSC technique, streamflow was systematically underestimated at Bongor due to a reduction in CN2 across the catchment. By using the SC technique, it is possible to unmask the differences in catchment characteristics that may not be revealed by SSC and SMSC. This is because these techniques use lump parameter values which may not represent the physical characteristics of the catchment.

The average values of GW_delay and Alpha_BF obtained using the SC at Bongor indicate that the Sudano area of the catchment has moderate response to groundwater recharge (Table 6.1). This follows the findings of Candela et al. (2014) who reported that in the southern part of the LCB covering the Logone catchment, high rainfall, the gentle topography and the kinds of soils found there favour aquifer recharge through rainfall infiltration. In contrast, the high GW_delay and low Alpha_BF values obtained by applying the SSC and SMSC techniques at the outlet and the SC technique at Katoa indicate that infiltration and groundwater recharge are low in this part of the catchment. These results are in agreement with the findings of Westra and De Wulf (2009) who attributed flooding in Logone wetlands to high soil water content during rainy season as a result of low infiltration capacity of the soils.

6.5.5 Evaluation of water balance

Given the ability of the SMSC technique to take into account the spatial variability in catchment processes, the water balance in the catchment was evaluated using output derived by this technique. Results of average annual water balance components during calibration indicate that, 73% of total precipitation in the catchment was lost through evapotranspiration, 7.68% contributed to re-evaporation, 12.83% contributed to groundwater (shallow and deep groundwater flow) while <8% contributed to lateral flow and surface runoff (Table 6.4). Similar evapotranspiration and groundwater flow estimates were obtained in the Ouemé river basin using SWAT e.g. (Ollivier *et al.* 2014). The surface runoff values produced by SWAT in this study are comparable to those obtained by Li *et al.* (2005) at Ndjamena gauging station located downstream of Logone Gana. Analysis further showed that, more than 50% of the total catchment water yield was contributed by groundwater flow. Water yield is comprised of surface water (Surf Q), lateral flow (Lat Q) and base flow contribution to discharge (GW Q) minus transmission losses through the channel bed, which contribute to groundwater recharge.

6.5.6 Impact of wetlands flow regime

Our analysis showed that within the study domain, the model was not sensitive to the impacts of wetlands on flow hydrographs using the different wetland modelling options available in SWAT (Neitsch *et al.* 2011). When this was observed, the normal storage volume was changed to maximum storage as suggested by Wang *et al.* (2010) by increasing the value of fr_{imp} from 0.50 to 1.0 the hydrograph did not change after simulation. The water level in the wetland was changed from 0.50 to 1.0 and multiplied by wetland area (*SA*) yet no change was observed. The maximum storage volume was multiplied by 2 as suggested by Almendinger *et al.* (2014) and there was no change in the hydrographs after simulation. All changes to implement the wetland options were effectuated in project database before running the model to see the changes. Note that it was not possible to model the impact of wetlands at individual sub-basin level because this required discharge data the outlet of each sub-basin, which practically is not possible.

We therefore, attribute this minimal change in flow hydrographs to the relatively small surface area occupied by wetlands (2%) compared to the total surface area of the study domain (86,240 km^2). In previous studies, Cohen Liechti *et al.* (2014) and Feng *et al.* (2013) questioned the capability of SWAT model to simulate water fluxes from wetlands. In another study using SWAT, Martinez-Martinez *et al.* (2014) reported that wetland restoration did not have any significant impact on peak flows. The minimal impact of wetlands on the flow regime of the Logone as observed in this study may also be attributed to the location of the wetlands with respect to the main river channel (most wetlands are located on tributary channels) and also because many of the wetlands especially in the upstream part of the catchment had surface areas <50 ha. This follows the findings of Martinez-Martinez *et al.* (2014) who asserted that wetlands with surface area measuring <50 ha or those located on tributary channels had negligible impact on streamflow hydrograph(s) of the main channel.

6.6 Conclusion

The objectives of this study were to develop, calibrate, and validate a hydrological model of the Logone catchment using the SWAT model, test the benefits of the different calibration techniques (Single-Site Calibration, Sequential Calibration and Simultaneous Multi-site Calibration) and attempt a description of the catchment hydrology.

By using the different calibration techniques, it was possible to show using different parameter values, the differences in hydrological behavior between the upstream and downstream parts of the catchment, which was not possible using only one calibration technique. This demonstrates that by using different calibration techniques, it is possible to unmask the differences in catchment characteristics that cannot be revealed by one technique especially in heterogeneous catchments.

Results also showed that using many streamflow gauges from only one spatial zone within the catchment at the expense of the other zone(s) during the SMSC may lead to parameter values from the zone with many gauges dominating the parameter space. This may obscure the spatial variability, which is the most important catchment attribute that this technique is supposed to reveal. This reinforces the importance of installing many hydrometric stations along the river network.

Results from this study showed that the SC technique out-performed the other two methods (SSC and SMSC). Although the SMSC takes into account the spatial variability in the catchment, information exchange between the stations during calibration, and reduced simulation time, it may be preferable to the other methods albeit marginal performance. However, the choice of each calibration method will depend on the scale of application of the modelling results.

Evaluation of catchment water balance using SMSC indicated that evapotranspiration was the dominant hydrological process through which about 73% of total precipitation received in the catchment is lost. Furthermore, more than 50% of the total water yield is contributed by groundwater flow suggesting that, groundwater plays a significant role in the catchment hydrology. Results also indicated that within the catchment domain studied wetlands did not play a significant role in the hydrological regime of the Logone River.

Given the complexity of the study area and the fact that this is the first large-scale hydrological modelling attempt in the catchment, the results obtained in this study can be considered to be satisfactory given that more than 60% of daily observed streamflow values were captured within the 95PPU band. Analysis of the catchment hydrology carried out in the present study may be invaluable to enhance water resources management to increase agricultural production, investigate the impact of land use change, simulate rainfall-runoff prediction and conduct climate change impact assessment. It is hoped that future modelling studies in the catchment will build from results obtained in the present study. Results from this study also show that WFDEI could be used for hydrological modelling in data-scarce regions like the Sudano-Sahel.

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Chapter 7 Spatio – temporal analysis of droughts and floods

This chapter is based on the paper:

NKIAKA, E., N. R. NAWAZ and J. C. LOVETT. (2017). Using standardized indicators to analyse dry/wet conditions and their application for monitoring drought/floods: A study in the Logone catchment, Lake Chad basin, Hydrological Sciences Journal. 62:16, 2720-2736. DOI: 10.1080/02626667.2017.1409427

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Abstract

The Standardized Precipitation Index (SPI) and Standardized Streamflow Index (SSI) were used in this study to analyse dry/wet conditions in the Logone catchment over a 50-year period (1951-2000). SPI analysis at different timescales showed several meteorological drought events ranging from moderate to extreme. SSI analysis showed that wetter conditions prevailed in the catchment from 1950-1970 interspersed with few hydrological drought events. Overall, results indicated that both the Sudano and Sahelian zones are equally prone to droughts and floods. However, the Sudano zone is more sensitive to drier conditions, while the Sahelian zone is sensitive to wetter conditions. Correlation analysis between SPI and SSI at multiple timescales revealed that the catchment has a low response to rainfall at short timescales, though this progressively changed as the timescale increased with strong correlations (≥0.70) observed after 12 months. Analysis using individual monthly series showed that the response time reduced to 3 months in October.

7.1 Introduction

Large scale droughts are complex environmental phenomena with significant effects on agriculture, society and ecosystems. Generally, drought can be defined as a period of deficient rainfall over a long period of time and can be grouped into four main categories (meteorological, agricultural, hydrological and socioeconomic) (Wilhite and Glantz 1985). In semi-arid areas in developing countries, such as the Sudano-Sahel region of Africa, rainfall plays a crucial role in the socio-economic wellbeing of the population because they depend on it for livelihood activities especially agriculture which is mostly rain-fed. However, in recent decades, food security in the region has been threatened following drought and rainfall variability (Gautam 2006; Traore and Owiyo 2013). In this region, drought can result in the loss of assets in the form of crops, livestock, and other productive capital as a result of low rainfall (meteorological droughts) which after extended periods can result in water shortages (hydrological droughts).

Despite a history of droughts, recent studies have, indicated a gradual increase in rainfall in the region (Odekunle *et al.* 2008; Nkiaka *et al.* 2017a) but less attention has been given to extreme rainfall events compared to droughts probably because little information exists about floods and other damaging rainfall events in the Sudano-Sahel (Tschakert *et al.* 2010). The socio-economic impact of weather extremes, and predictions that extremes will become more frequent (Field *et al.* 2014), requires a change in paradigm so that equal attention is given to both droughts and floods in this region.

The Standardized Precipitation Index (SPI) (McKee *et al.* 1993) is a probability based indicator that indicates the degree to which accumulative precipitation for a specific period departs from the average state. This index is generally used to detect, monitor and assess dry and wet conditions and identify their variability at different spatial and temporal scales. Compared to other methods for calculating drought conditions e.g. the Palmer Drought Severity Index (PDSI), Standardized Precipitation Evapotranspiration Index (SPEI), the Surface Water Supply Index (SWSI), and the Standardized Anomaly Index (SAI), the SPI offers many advantages: (i) only a single input variable (precipitation) is necessary, (ii) provides a means of analyzing both wet and dry periods, (iii) it can be calculated for different time scales, (iv) it can allow the user to classify droughts into different categories, and (v) it is probability based and hence can be used in risk management and decision analysis. Due to its robustness and convenience, the SPI has been widely used to study droughts around the world (Roudier and Mahe 2010; Du *et al.* 2013; Barker 2016). It has also been used extensively to monitor wetness conditions (Seiler *et al.* 2002; Guerreiro *et al.* 2008), and to analyse both dryness and wetness conditions (Machado *et al.* 2011; Du *et al.* 2013; Ionita *et al.* 2015). Furthermore, the World Meteorological Organisation (WMO 2012) recommends the use of the SPI to assess and monitor drought conditions and identify wet periods.

Despite its wide application, the SPI has been subjected to criticism by several authors e.g. (Lloyd-Hughes and Saunders 2002). They argue that the use of the SPI for short time scale analysis (1, 2, 3-month) within regions characterized by low seasonal precipitation may result in over-estimation or under-estimation of the positive or negative SPI values. Golian *et al.* (2015) argue that using only a single index to monitor droughts may be misleading due to the complex nature of drought phenomena in both their causation and impact. As a result of these criticisms, the multivariate standardized drought index (MSDI) (Hao and AghaKouchak 2013) was developed. Despite these advances, application of the SPI remains popular even though it requires a minimum of 30 years of monthly rainfall data which may limit its application in data-scarce regions and has been applied in many studies across the world (Seiler *et al.* 2002; Guerreiro *et al.* 2008; Roudier and Mahe 2010; Machado *et al.* 2011; Cheo *et al.* 2013; Louvet *et al.* 2016).

Despite wide application of the SPI, the lack of understanding on how meteorological droughts are propagated to hydrological droughts is still a major obstacle to the development of a drought-focused monitoring and early warning system (Barker 2016). However, Vicente-Serrano *et al.* (2011) developed and tested the standardized streamflow index (SSI), which can be used to obtain a hydrological drought index that is useful for making spatial and temporal comparisons over a wide variety of river regimes and flow characteristics. Many studies for gaining insight on how meteorological droughts are propagated to hydrological droughts using SPI and SSI have been published (Du *et al.* 2013; López-Moreno *et al.* 2013; Zhang *et al.* 2015; Barker 2016). In Africa, although there are drought studies utilizing the SPI (Roudier and Mahe 2010; Cheo *et al.* 2013; Louvet *et al.* 2016), the use of both SPI and SSI techniques for monitoring dryness and wetness conditions in the continent has not been reported.

Unlike the rest of the Sudano-Sahel region, studies on dryness and wetness conditions in the Lake Chad basin (LCB) are relatively few and largely undocumented. Insufficient research output from the basin may be attributed to limited rain gauge stations in Central Africa and the steady decline in the number of existing hydro-meteorological facilities in the region (Washington *et al.* 2006; Nkiaka *et al.* 2017c). Despite this decline, a number of studies analysing dryness and wetness conditions in the LCB have been carried out. Okonkwo *et al.* (2013) used the SPI to analyse monthly gridded rainfall and different satellite precipitation datasets for the period 2002-2011 and demonstrated that extreme wetness conditions prevailed in the basin in the year 2010; and Ndehedehe *et al.* (2016) applied independent component analysis (ICA) to reveal the prevalence of wetness conditions in the LCB during the period 2012 – 2014 by analysing different satellite precipitation datasets.

However, previous studies are generalized for the whole LCB, cover a short time horizon and may be misconstrued as insignificant in a particular location (i.e. at local or sub-catchment scale). The LCB covers an estimated area of 2.5×10^6 km^2 and a population of about 30 million and contains a range of ecological zones (hyper arid, arid, semi-arid and Sudano) with a high spatiotemporal variability in rainfall. Therefore, generalizing results from such studies as representative of smaller basins may not be useful for effective and robust planning of water resources management and development of adaptation strategies in the event of droughts and floods.

Reducing the spatial scale of such analysis enables to gain an insight into the likelihood of occurrence of extreme dryness and wetness conditions at sub-basin level and station locations. The Logone catchment was selected for this analysis for the following reasons: (i) the catchment covers two ecological zones (Sudano and semi-arid); (ii) it contributes a significant amount of inflow into Lake Chad; (iii) it is a transboundary catchment shared by three countries (Cameroun, Chad and Central Africa Republic); and (iv) it has extensive floodplains that contribute significantly to the livelihood of the local population.

The Logone catchment has experienced a series of floods in recent years with widespread socio-economic effects. However, even with the prevailing wetter climate, erratic rainfall means that water availability for agriculture, pastoral activities, ecosystem sustainability and inflow into Lake Chad is unpredictable. Yet there is limited detailed hydro-climatological documentation that can be used to enhance water resources management in the catchment. Analysing the characteristics of dryness and wetness conditions using long term data is an important step for establishing an effective and comprehensive monitoring and early warning system in the catchment. Understanding the context-specific nature of the likelihood of dryness/wetness conditions will facilitate the identification of policy interventions to enhance adaptation even in the context of climate change.

The main objectives of this study were to use the Standardized Precipitation Index (SPI) to: (i) calculate the frequency of occurrence and spatial distribution of dryness and wetness conditions, (ii) analyze their spatio-temporal characteristics, (iii) analyze the SPI and SSI trends in the catchment using the Mann-Kendall test, and (iv) use the two indicators to assess the relationship between rainfall and streamflow. This study is part of an on-going project aimed at understanding hydro-climatic variability in the Logone catchment that assesses vulnerability of the catchment to global climate change and the type of policy measures which can be put in place to improve water resources management and adaptation to climate change.

7.2 Study area and data

The Logone catchment is located in the south western part of the LCB. It covers an estimated area of 86,240 km^2 at the Logone Gana hydrometric station and lies between latitude 6˚ - 12˚ N and longitude 13˚ - 17˚ E (Figure 7.1). This is about 8% of the conventional LCB area of 1,053,455 km^2 (Adenle 2001). The Logone is a major tributary of the Chari River, and the two rivers jointly contribute about 95% of inflow into Lake Chad (Loth and Acreman 2004). The Logone has its source in Cameroun from the Mbere and Vina Rivers originating from the Adamawa Plateau. In Lai, it is joined by the Pende River from Central Africa Republic and flows in a south-north direction. The altitude ranges from about 1200 masl around the Adamawa Plateau in the south to 300 masl in Ndjamena in the north. It flows through three countries, Cameroun, Central Africa and Chad with a flat topography with average slope of less than 1.3%. The catchment is located in a Sudano-Sahelian climatic regime controlled by the tropical continental regime air mass (the Harmattan) and the oceanic regime equatorial air mass (monsoon) (Nkiaka *et al.* 2017a). It has a strong north-south rainfall gradient with a single rainy season between May and October and an average annual rainfall varying between 500 mm/year in the north to about 1400 mm/year in the south. There is a strong spatio-temporal variability in rainfall (Nkiaka *et al.* 2017a) and mean temperature in the catchment is 28° (Loth and Acreman 2004).

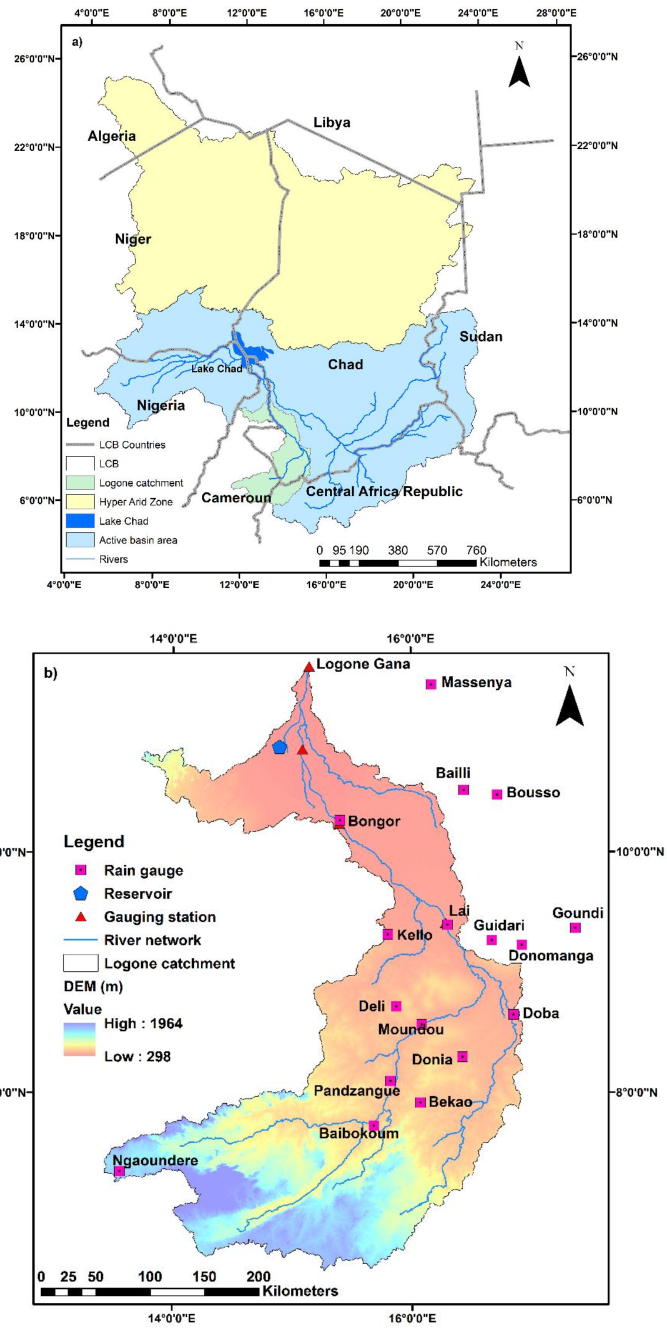


Figure 7.1 LCB showing the Logone catchment (a) and the Logone basin showing the location of rain gauges (b)

7.2.1 Data sources

Monthly rainfall and streamflow data were obtained from "Système d'Informations Environnementales sur les Ressources en Eau et leur Modélisation" (SIEREM) (Boyer *et al.* 2006). According to Boyer *et al.* (2006), the SIEREM data was obtained using the POLLEN method adapted from the Object Modelling Technique. To increase robustness of our results, only stations that had monthly data covering the period 1951-2000 were selected; with missing data points of not more than 10%. Given that only 11 rain gauge stations located inside the catchment could fulfil these criteria, six additional rain gauge stations located outside the catchment, but within its immediate surroundings, were selected to increase the number of rain gauges. In Table 7.1, stations 1-13 lie in the Sudano ecological zone (5° - 10°N) and stations 14-17 are located in the Sahelian ecological zone (10° - 12°N). These ecological zones represent simplified climatic zones based on the Köeppen Geiger climate classification for Africa (Peel *et al.* 2007). Streamflow time series were available for the period 1955-2000. The data was quality controlled using different homogeneity tests and all the time series were found to be homogeneous (Nkiaka *et al.* 2017a). Gaps in the time series were infilled using Artificial Neural Network (ANN), Self-Organizing Maps (SOMs) techniques (Nkiaka *et al.* 2016).

A limitation of the study is the absence of rainfall data after the year 2000 so the influence of recent rainfall measurements on SPI values could not be evaluated. However for an insight into the recent characteristics of drought indices in the area covering the period 2002-2014, the reader can refer to Okonkwo *et al.* (2013) and Ndehedehe *et al.* (2016). A limitation of those studies is that only 10 years of satellite precipitation data was used in the SPI analysis. According to McKee *et al.* (1993), the application of the SPI for drought monitoring requires a minimum of 30 years data. Another limitation of those studies is that satellite precipitation analysis depends on the quality of gauge data used for satellite calibration, and are thus inevitably affected by the sparsity of gauge data or temporally incomplete gauge time series in the region under investigation.

Table 7.1 Overview of rain gauge stations and annual rainfall characteristics

Station No	**Location**	**Geographic coordinates**		**Elevation (m)**	**Annual rainfall (mm/year)**			**Catchment zone**
	Station name	**Lat**	**Long**		**Max**	**Min**	**Mean**	
1	Ngaoundere	7.35	13.56	1113	1864	1152	1514	Sudano
2	Baibokoum	7.73	15.68	1323	1672	881	1277	
3	Bekao	7.92	16.07	528	1630	853	1181	
4	Pandzangue	8.1	15.82	345	1892	919	1242	
5	Donia	8.3	16.42	414	1782	796	1085	
6	Moundou	8.57	16.08	410	1843	783	1103	
7	Doba	8.65	16.85	387	1475	680	1057	
8	Delli	8.72	15.87	427	1539	705	1064	

9	Donomanga	9.23	16.92	370	1519	681	982	
10	Guidari	9.27	16.67	369	1562	629	1005	
11	Kello	9.32	15.8	378	1413	503	980	
12	Goundi	9.37	17.37	368	1519	681	982	
13	Lai	9.4	16.3	358	1491	669	1022	
14	Bongor	10.27	15.4	328	1070	400	790	semi-arid
15	Bousso	10.48	16.72	336	1365	423	844	
16	Bailli	10.52	16.44	330	1146	463	797	
17	Massenya	11.4	16.17	328	977	410	641	

7.3 Methodology

7.3.1 The Standardized Precipitation Index (SPI)

The methodology adopted in this study involves application of the SPI software (McKee *et al.* 1993) and fitting a gamma probability density function to a given frequency distribution of monthly precipitation totals for each station. Generally, the gamma distribution has been found to fit precipitation data quite well. The probability density function is calculated as:

$$G(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)}\int_0^c x^{\alpha-1}\, e^{\frac{-x}{\beta}} dx \qquad (7.1)$$

where, β is the scale parameter, α is the shape parameter, x is the monthly rainfall data, and $\Gamma(\alpha)$ is the gamma distribution function. The parameters of the gamma distribution function are estimated for each station for the chosen time scale (1, 3, 12-month, etc.). The gamma distribution parameters α and β are estimated using the maximum likelihood method. The gamma distribution is undefined for $x = 0$, but the precipitation may have zero value, so the cumulative probability distribution given a zero value is derived as follows:

$$H(x) = q + (1 - q)G(x) \qquad (7.2)$$

where q is the probability of the zero precipitation value. The cumulative probability distribution is then transformed into the standard normal distribution to calculate SPI. A full description of the methodology on the calculation of SPI is available in Lloyd-Hughes and Saunders (2002).

According to McKee *et al.* (1993), the index has a normal distribution, so it can be used to estimate both dry and wet periods. A wet period according to the SPI value may be defined, for a time scale *i*, as the period during which the SPI is continuously positive and reaches a value of +1 or higher and a drought period begins when the SPI value is continuously negative and reaches a value of -1.0 or lower. SPI at different time scales, e.g. 3-month SPI of a particular month represents the deviation in precipitation totals for the same month and current plus previous two months, respectively. It indicates how the precipitation for a specific period compares with the complete record at a given station. In this study, analysis were conducted for multiple time-scales ranging from 1 to 24 months.

When interpreting SPI, one should bear in mind that dryness and wetness are relative to the historical average rather than the total of precipitation of a particular location. For example a given magnitude of precipitation at a dry station may produce a negative SPI value, while at a different extremely dry location within the same catchment the same precipitation magnitude may give a positive SPI value. Table 7.2 shows the classification scheme of SPI values according to WMO standards (WMO 2012). SPI analysis were carried out for timescales of 1 to 24 months successively.

Table 7.2 SPI values

SPI value	Category
≥ 2.00	Extremely wet
1.5 to 1.99	Very wet
1.00 to 1.49	Moderately wet
-0.99 to 0.99	Near normal
-1.0 to -1.49	Moderately dry
-1.5 to -1.99	Severely dry
≤ -2.0	Extremely dry

Table adapted from (WMO, 2012)

7.3.2 Standardized Streamflow Index (SSI)

Streamflow is an important variable used for monitoring both droughts and floods. To assess the best SPI timescale for explaining the temporal variability in the streamflow time series, a Pearson correlation analysis was performed between the monthly SSI and SPI series at timescales of 1 to 24 months. Given that streamflow is the integrated response of the catchment to rainfall from different parts of the catchment, SPI values used in the analysis were obtained by calculating the arithmetic average of SPI values from rain gauge stations located upstream of each gauging station. The arithmetic average was used on the basis that, once the rainfall data from the various stations have been converted to SPI values, the influence of “areal average rainfall” does not longer apply. This is because the transformation of SPI to the standard normal distribution with a mean of zero and a standard deviation of one makes the SPI comparable over time and space (Barker 2016).

The comparison between SSI and SPI provides an indication of the time taken for precipitation deficits to propagate through the hydrological cycle to streamflow deficits. This technique has been applied by several researchers for meteorological and hydrological drought analysis (López-Moreno *et al.* 2013; Barker 2016). Note that rainfall data from 6 rain gauge stations located outside the catchment domain were not used because they do not contribute to streamflow measured inside the catchment. Table 2 is also valid for the classification of SSI.

Generally, the calculation of the SSI is mathematically similar to the SPI calculation shown in the preceding section and uses the same principle as the SPI, by aggregating streamflow data over selected accumulation periods. Given the heterogeneity in river and catchment characteristics (Vicente-Serrano *et al.* 2011), the most suitable probability distribution that can be used to fit individual streamflow series measured along the river may vary. Due to this variation, different probability distributions (lognormal, Pearson Type III, gamma distribution, Weibul, Generalized Pareto, General Extreme Value) have been applied to fit streamflow data for SSI calculation (Vicente-Serrano *et al.* 2011). In this study the gamma distribution was used to fit streamflow. This distribution has extensively been used to fit global streamflow datasets in previous studies (Vogel and Wilson 1996; McMahon *et al.* 2007; Du *et al.* 2013; Zhang *et al.* 2015).

SSI was calculated at two gauging stations along the Logone River; upstream at Bongor with an estimated drainage area of 73,000 km^2 and downstream at Logone Gana (outlet) with an estimated drainage area of 86,240 km^2. These stations were selected based on available river discharge records and also because Bongor is the only reliable station located downstream of the Sudano zone of the catchment while Logone Gana is located at the outlet in the semi-arid zone.

Table 7.3 Frequency of drought and flood events in the Logone catchment

Frequency of occurrence of droughts and floods (%)									
Station	Extreme wet	Very wet	Moderately wet	Near normal	Moderate drought	Severe drought	Extreme drought	Total Flood episodes	Total Drought episodes
Ngaoundere	1.53	3.06	11.04	69.95	6.79	3.9	3.74	15.62	14.43
Baibokoum	0.51	5.09	10.02	66.89	10.02	3.74	3.74	15.62	17.49
Bekao	1.7	5.1	9.69	63.78	13.78	4.93	1.02	16.5	19.73
Pandzangue	3.9	3.4	11.54	65.7	12.05	3.4	0	18.85	15.45
Donia	2.04	2.72	10.02	68.76	12.56	2.89	1.02	14.77	16.47
Moundou	2.55	3.4	6.96	71.99	7.3	6.11	1.7	12.9	15.11
Doba	3.72	5.49	9.2	70.27	6.73	2.3	2.3	18.41	11.33
Delli	3.74	4.75	4.92	75.72	6.45	2.04	2.38	13.41	10.87
Donomanga	3.57	11.04	16.47	68.93	0	0	0	31.07	0

Guidari	4.24	2.72	7.81	70.63	7.64	4.24	2.72	14.77	14.6
Kello	2.21	1.36	9.68	72.67	4.92	6.28	2.89	13.24	14.09
Goundi	2.72	7.64	6.96	65.03	11.04	4.58	2.04	17.32	17.66
Lai	2.04	4.41	9.68	67.74	8.32	4.24	3.57	16.13	16.13
Bongor	0.68	4.41	8.32	70.29	8.15	3.9	3.9	13.41	15.96
Bousso	1.87	1.7	14.77	66.38	7.64	4.75	2.89	18.34	15.28
Bailli	1.53	7.3	5.94	69.61	8.49	3.57	3.57	14.77	15.62
Massenya	3.39	13.39	18.31	64.92	0	0	0	35.08	0

7.3.3 The Mann-Kendall trend test

The nonparametric Mann–Kendall test was applied to the SPI time series to examine the presence of trends. This test is widely used to detect trends in hydrology and climatology because it is robust against non-normal distributions and is insensitive to missing values. The null hypothesis H(0) states that there is no significant trend in the examined time series. The hypothesis is rejected if the p value of the test is less than the significance level (e.g. 0.05 indicating a 95% confidence level). The Mann–Kendall test has been used in several drought studies (Du *et al.* 2013; Golian *et al.* 2015; He and Gautam 2016). Detailed information on the application of this test is widely available in the literature. In this study the results were calculated for the 95% confidence interval.

The catchment was divided into two parts; the northern part termed the Sahelian zone for stations located between latitudes 10°-12° N and the southern part termed the Sudano zone for stations located between latitudes 6°-10° N. The main difference between the two zones is an increase in annual rainfall total from stations located in the north to those in the south (Nkiaka *et al.* 2017a). Table 1 gives the station name, coordinates, long term mean, maximum and minimum of the annual rainfall time series for each station.

7.4 Results

7.4.1 Frequency of dry/wet years

A 12-month SPI analysis was used for the 17 stations in order to show the prevalence and spatial distribution of dryness and wetness conditions across the catchment. Using the threshold values in Table 7.2, a particular year was considered dry if the SPI ≤ -1.0 and wet year if the SPI ≥ 1.0. Figure 7.2 shows the spatial distribution and frequency of occurrence of dry and wet years respectively. For example stations belonging to group 0.16 – 0.20 in Figure 7.2(a) experienced dry episodes in 16-20% of all the years used in the study, while stations belonging to group 0.18-0.20 Figure 7.2(b) experienced wet conditions in 18-20% of all years used (1951-2000). The analysis also showed that the frequency of occurrence of drought conditions was high for stations located in the Sudano zone of the catchment. For example stations like Ngaoundere, Baibokoum, Bongor and Bekao with high annual rainfall instead experienced the highest frequency of occurrence of severe dryness conditions. Meanwhile, no drought conditions were observed in Massenya, the most northerly station located in the Sahelian zone of the catchment. This station instead witnessed the highest frequency of wetness conditions (35.0%) which is surprising. These results are consistent with the findings of Roudier and Mahe (2010) who observed in the Bani basin, located in the same latitudinal zone with the Logone catchment that the semi-arid northern part of the basin was less prone to droughts compared to the southern part.

Overall the results indicated that both the Sudano and Sahelian zones of the catchment are prone to both droughts and floods as shown in Figure 2, although the average frequency of occurrence of floods is slightly higher (17.60%) compared to droughts (13.50%). Table 3 gives a detailed analysis of the results.

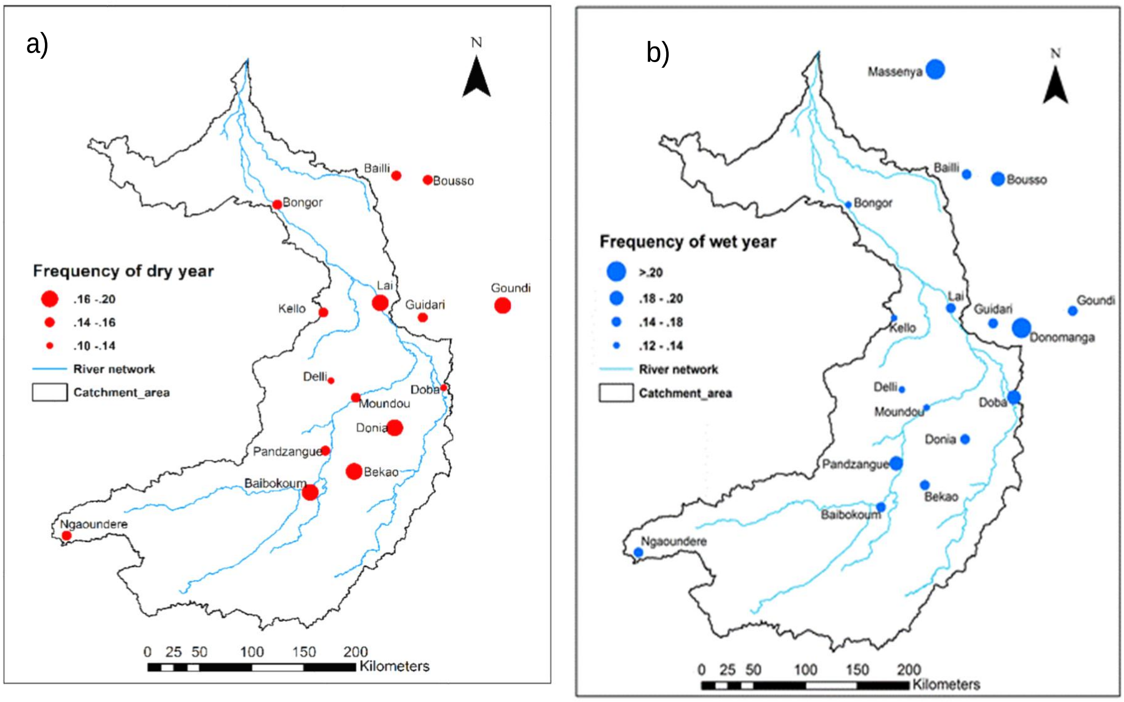
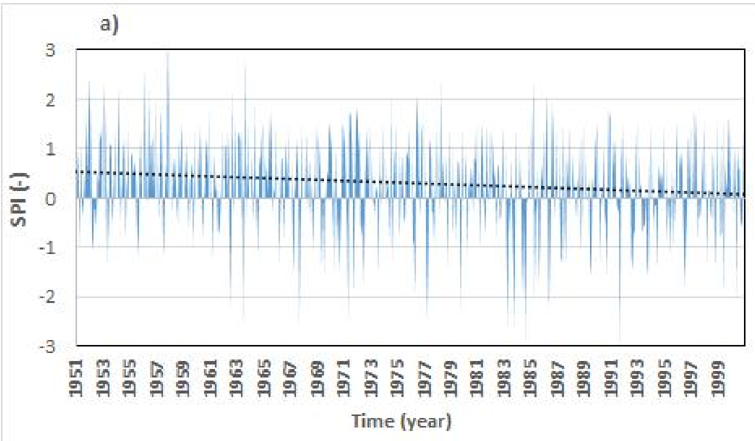


Figure 7.2 Frequency of occurence and spatial distribution of dry and wet years in the Logone catchment for the period 1951 – 2000. The frequency was calculated as percentage according to the 12-month SPI for each year; a dry year a) was defined when SPI ≤-1.0 and b) wet year when SPI ≥ 1.0

7.4.2 *Analysis of dryness/wetness conditions at multiple time scales*

Analysis of SPI at 1- and 3-month time-steps showed that SPI values frequently fluctuated above and below zero with no extended periods of dryness or wetness but short episodes of dry and wet conditions (Figure 7.3a&b). The results are consistent with the findings of Ndehedehe *et al.* (2016) in the southern part of the LCB covering the Logone catchment. Using the Effective Drought Index (EDI), Roudier and Mahe (2010) also reported that, droughts were more frequent but of shorter duration in the southern area of the Bani basin. SPI analysis at shorter time scale are mostly useful for monitoring past dryness and wetness conditions. This may be useful in reconstructing the flood history of a catchment.

SPI analysis at a 12-month time-step demonstrated a strong variation in annual rainfall fluctuating between wet and dry years (Figure 7.3c). Generally, results showed that drought events were frequent at shorter time-scales but lasted for shorter durations while at longer timescales, droughts were less frequent but persisted for longer periods (Figure 7.3a, b & c). Furthermore, the period of occurrence and duration of dry and wet years vary from one station to another. These results are consistent with the findings of Cheo *et al.* (2013). Cheo *et al.* (2013) using SPI analysis at a 12-month time-step reported that, there was a significant spatial variability in drought occurrence and intensity across the northern regions of Cameroun located adjacent to the Logone catchment.



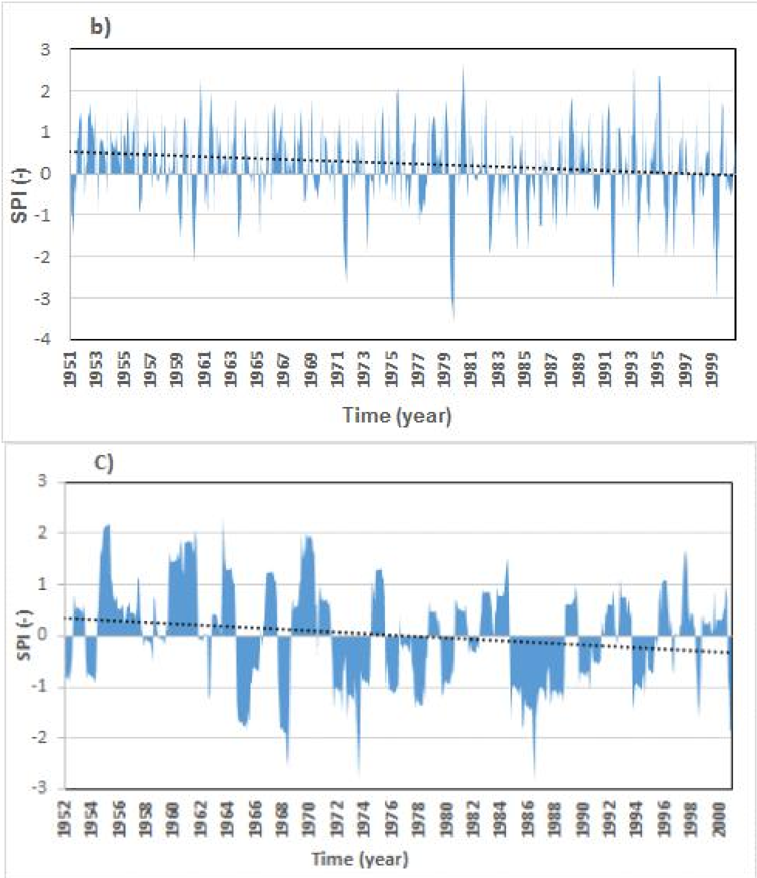


Figure 7.3 SPI time series for selected accumulated periods at different rain gauge stations. a) Ngaoundere, b) Bailli and c) Bekao corresponding to 1, 3, and 12 months respectively

7.4.3 Spatio-temporal variation of dryness conditions

Analysis of 12-month SPI across all the stations showed that all but one station in the catchment experienced a minimum of three periods of drought. These droughts could be categorised as ranging from moderate to extreme with different durations beginning as early as the mid-1960s at some stations before becoming very noticeable at most station locations after 1970. Drought episodes with extended durations occurred around (1971-1973), (1981-1984) and (1991-1993). Nevertheless, the total duration, severity and period of occurrence of the drought episodes varied from one station location to another.

Based on Table 7.2 and using 12-month SPI to analyze drought categories showed that, the Sahelian zone experienced extreme droughts of averagely longer duration (20 months) compared to 14 months in the Sudano zone. Meanwhile, severe droughts lasted for almost the same duration (24 months) in both parts of the catchment. Moderate droughts persisted longer in the Sudano zone with an average duration of 52 months compared to 47 months in the Sahelian zone. The results follow the findings of Ndehedehe *et al.* (2016) who reported that the Sudano zone of the LCB was more vulnerable to drought conditions compared to the Sahelian zone. Roudier and Mahe (2010) also reported that the duration of droughts was slightly longer in the southern zone of the Bani basin compared to the extreme north part.

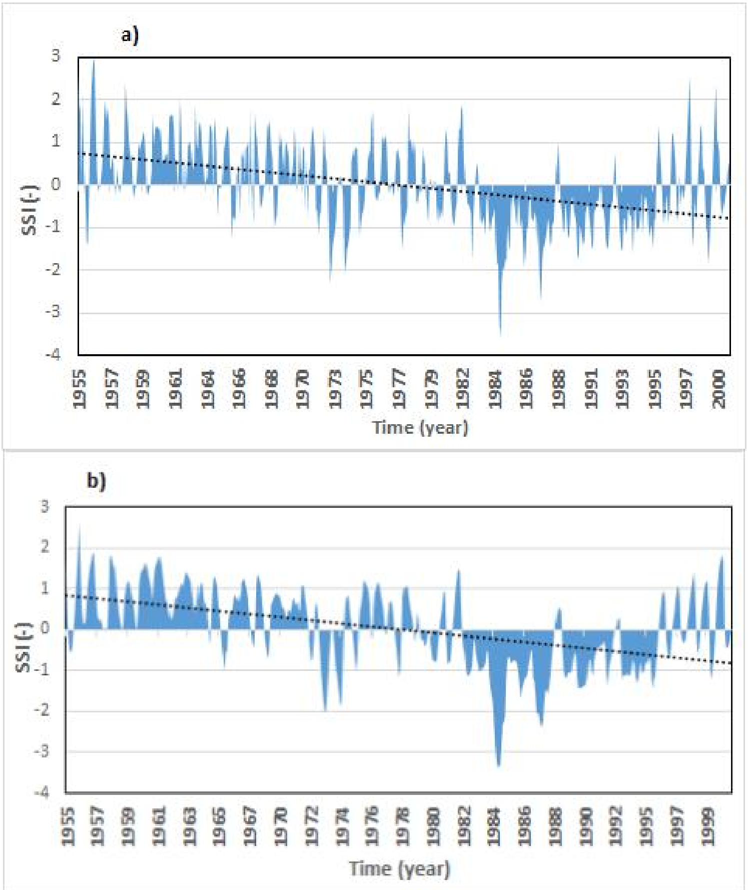
Further scrutiny of 12-month SPI time series revealed that, apart from 1980 decade when most severe to extreme droughts seemed to concentrate in the middle of the decade, severe and extreme drought conditions appear to be mostly concentrated around the beginning or end of a decade interspersed with moderate drought conditions. Results also show that moderate/severe droughts were mostly intra-annual and lasted for shorter time-scales while extreme droughts were inter-annual and persisted for longer periods (e.g. September 1971-April 1972, October 1983- May 1985, September 1999-July 2000) for Baibokoum, Ngaoundere and Bousso stations respectively.

The temporal and spatial evolution of drought variability using a 12-month SPI further indicated that, the driest months in the catchment were recorded in the 1980 and 1990 decades with varying degrees of severity. In the Sahelian zone the driest months were recorded in Bailli (SPI = -2.78) in April 1980 and Bongor (SPI= -3.30) in May 1985. Meanwhile, in the Sudano zone the driest months were observed in Deli (SPI= -4.38) in August 1992, Kello (SPI= -3.85) in May 1985, Baibokoum (SPI= -3.77) in June 1984 and Ngaoundere (SPI= -3.22) in August 1984. These values further indicate that droughts were more severe in the Sudano zone where the lowest SPI value was observed (-4.38) compared to (-3.30) in the Sahelian zone. Analysis also showed that extreme droughts prevailed during the period of rainy season especially around the months of July, August and September, and were generally preceded by periods of moderate to severe drought conditions. The prevalence of extreme droughts conditions in the catchment during these months is consistent with the findings of Nkiaka *et al.* (2017a) who reported that there was a general decline in July, August and September rainfall in catchment during the period 1951–2000.

7.4.4 Spatio-temporal variation of wetness conditions

Analysis of 12-month SPI also revealed that, all stations witnessed periods of wetness conditions with different durations which can be classified as ranging from moderate to extreme (Table 7.2). The average duration of extreme wetness conditions was slightly longer (16 months) for the Sudano zone compared to the Sahelian zone (11 months). Severe and moderate wetness conditions persisted longer (39 and 70 months) in the Sahelian zone compared to (27 and 56 months) in the Sudano zone respectively. Although the whole catchment experienced many periods of wetness with varying durations across individual station locations, wetter conditions prevailed longer in the Sahelian zone (120 months) compared to the Sudano zone (96 months). Surprisingly, Massenya station located in the Sahelian zone continuously experienced repeated periods of wetness ranging from moderate to extremely wet conditions stretching into the year 2000. This suggest that the Sahelian zone may be more prone to floods than the Sudano zone.

Temporal analysis using 12-month SPI values showed that the wettest period in the catchment was recorded during the 1950 decade with the highest SPI value observed in Moundou (3.58). A close examination of Figures 3-5 revealed that, wetness conditions prevailed in most stations during the 1990 decade ranging from moderate to extreme wetness with different durations across individual station locations. These results are consistent with those of other studies that reported on the prevalence of extensive floods in the region during this period (Odekunle *et al.* 2008; Tschakert *et al.* 2010; Okonkwo *et al.* 2014; Louvet *et al.* 2016).



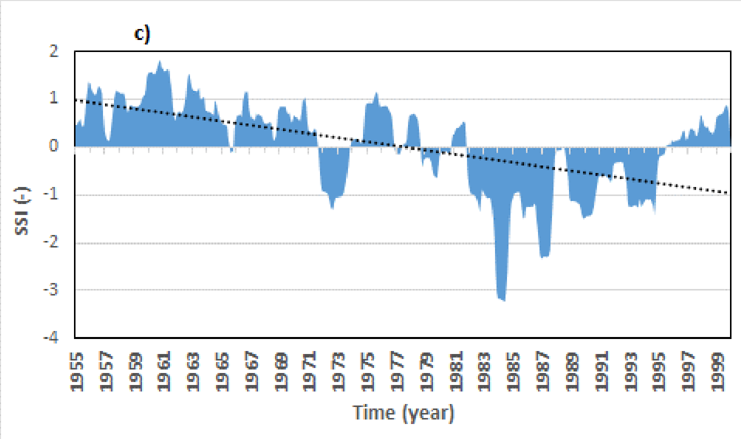


Figure 7.4 SSI time series for selected accumulated periods at the Logone Gana gauging station. a, b, and c correspond to 1,6 and 12 months respectively.

7.4.5 Evaluation of hydrological droughts

Results of SSI at different timescales are generally similar to those of SPI at equivalent timescales (Figure 7.4). Unsurprisingly, more hydrological drought events were observed at shorter timescales but as the timescales increased, the number of drought events reduced but the duration increased. The results indicated that wetness conditions prevailed in the catchment from 1950-1970 decades even though interspersed with few episodes of hydrological droughts during the 1970 decade. Prolonged hydrological droughts prevailed in the catchment from 1980 to mid-1990 with the drought categories ranging from mild to severe (Figure 7.4). Meanwhile, from mid-1990 stretching into the year 2000, humid conditions dominated in the catchment. Similar observations were made using the SPI at different station locations across the catchment which correspond to previous studies in the region as mentioned in the preceding section.

7.4.6 Results of trend analysis

The results of Mann-Kendall trend test indicated that across the catchment and at all time scales considered, negative trends in SPI were obtained with different significant levels indicating that the null hypothesis of no trend was rejected (Table 7.4). It can be observed that 7, 14 and 17 stations showed statistically significant negative trends at the 5% significant level for 1-month, 3-month and 12-month time scales respectively (Table 7.4). These negative trends in SPI values follow the general decline in rainfall over the catchment and are consistent with reported trends in the region (Odekunle *et al.* 2008; Nkiaka *et al.* 2017a). Although no drought conditions were observed at Massenya station, it is worth noting that there was a significant negative trend in rainfall at this station during the period under study.

Results of Mann-Kendall trend analysis also show the presence of statistically significant negative trends for all SSI time series (Table 7.4). Our results are consistent with findings in region whereby a deficit in rainfall led to a corresponding drop in streamflow in most rivers across the Sudano-Sahel region (Paturel *et al.* 2003).

Table 7.4 Results of MannKendall trend test for different SPI and SSI aggregation periods

Rainfall Station	**1-month**		**3-month**		**12-month**	
	Z_{MK}	*p*-value	Z_{MK}	*p*-value	Z_{MK}	*p*-value
Ngaoundere	-0.08	**7.00E-03**	-0.16	**1.05E-08**	-0.99	**2.22E-16**
Baibokoum	-0.05	9.40E-02	-0.12	**1.86E-05**	-0.99	**2.22E-16**
Bekao	-0.03	3.49E-01	-0.04	1.04E-01	-0.99	**2.22E-16**
Pandzangue	-0.02	4.70E-01	-0.04	1.70E-01	-0.99	**2.22E-16**
Donia	-0.09	**2.00E-03**	-0.15	**1.07E-07**	-0.99	**2.22E-16**
Moundou	-0.07	**1.30E-02**	-0.12	**1.67E-05**	-0.99	**2.22E-16**
Doba	-0.86	**2.00E-03**	-0.16	**5.38E-08**	-0.99	**2.22E-16**
Deli	-0.03	2.46E-01	-0.07	**8.00E-03**	-0.99	**2.22E-16**
Donomanga	-0.06	4.50E-02	-0.12	**4.10E-05**	-0.99	**2.22E-16**
Guidari	-0.07	**1.20E-02**	-0.12	**1.65E-05**	-0.99	**2.22E-16**
Kello	-0.03	2.36E-01	-0.05	1.06E-01	-0.99	**2.22E-16**
Goundi	-0.09	**2.00E-03**	-0.19	**1.58E-11**	-0.99	**2.22E-16**
Lai	-0.02	3.80E-01	-0.05	8.15E-02	-0.99	**2.22E-16**
Bongor	-0.07	**8.00E-03**	-0.11	**8.52E-11**	-0.99	**2.22E-16**
Bousso	-0.09	**2.00E-03**	-0.17	**2.89E-09**	-0.99	**2.22E-16**
Bailli	-0.05	9.90E-02	-0.11	**1.43E-04**	-0.99	**2.22E-16**
Massenya	-0.07	1.18E-02	-0.05	6.30E-01	-0.99	**2.22E-16**
Gauging station						
Bongor	-0.33	**2.22E-16**	-0.36	**2.22E-16**	-0.46	**2.22E-16**
Logone Gana	-0.31	**2.22E-16**	-0.33	**2.22E-16**	-0.43	**2.22E-16**

*Bold values indicate that the trend is statistical significant at 5% level as per the 2 tail test for SPI and 1% for SSI

7.4.7 Relationship between SPI and SSI

Results of Pearson correlation analysis between monthly SSI and SPI at different timescales (1–24 months) showed that all correlations were positive although strong correlations were observed only at longer timescales (Figure 7.5). The correlations showed that the Logone River has a low response to rainfall at short timescales from weak correlations obtained. However, this progressively changed as the timescale increased with strong correlations (≥0.70) observed after 12 and 15 months at Bongor and Logone Gana gauging stations respectively. López-Moreno *et al.*

(2013) observed similar strong correlations between SSI and SPI at longer timescales across catchments in southern Spain where catchments had permeable limestone headwaters. Barker (2016) also reported similar findings across several catchments underlain by major aquifers in England.

Figure 7.6a&b show the result of monthly lagged correlations between SSI and SPI for selected months. It can be observed from the figure that the correlations changed seasonally according to SPI timescale but generally became very strong (≥0.70) after 12 months. During the month of March, the correlation values dropped to minimum after 4 and 5 months at Bongor and Logone Gana respectively before rising steadily to become very strong (≥0.70) after eight months. The same phenomenon was observed during the month of July where the correlation values decreased to 0.20 after 9 months before increasing rapidly (≥0.70) within 3 months. The lagged correlations for each month were summarized using contour plots for the two gauging stations (Figure 7.7a&b). From the figure, it can be observed that the response time of the catchment is 5-6 months at the beginning of the rainy season (June/July). Meanwhile, towards the end of the rainy season (September/October) the response time reduces to 3 months as indicated by very strong correlation values (≥0.70).

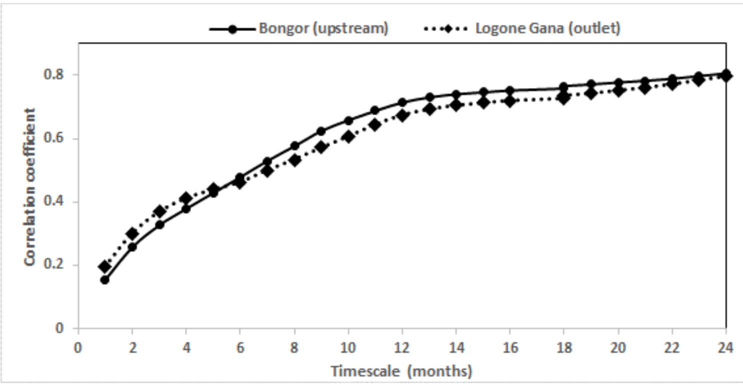


Figure 7.5 Correlation coefficients between monthly SSI and the 1- to 24-month SPI

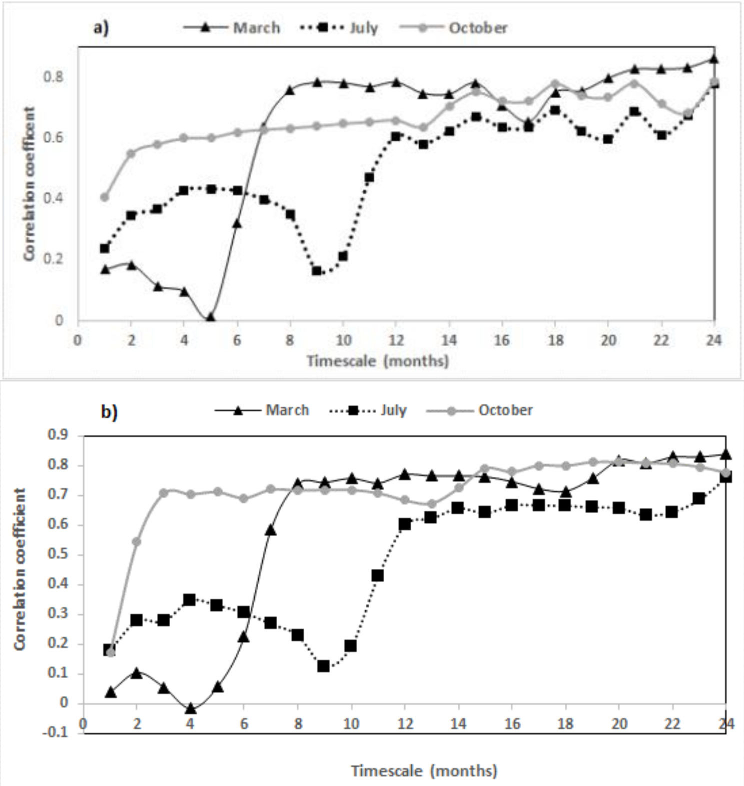


Figure 7.6 Lagged correlation coefficients between monthly SSI and SPI for different individual months: a) Logone Gana and b) Bongor. The X-axis indicates the timescale of SPI.

7.5 Discussion

Results from this study show that stations located in both parts of the catchment (Sudano and Sahelian) are prone to droughts of all categories that could last for different durations. However, stations located in the Sudano zone are more likely to experience extreme droughts of shorter duration, while those in the Sahelian zone experience droughts of slightly lesser intensity but longer durations. Furthermore, the Sahelian zone of the catchment may be more prone to floods than the Sudano. The significant negative trends in SPI and SSI values suggest that there has been a significant change in the processes that influence rainfall and streamflow in the catchment. This indicates that the catchment is sensitive to natural climate perturbations and could thus be vulnerable to anthropogenic climate change.

Reasons why the Sudano zone may be more sensitive to extreme droughts compared to the Sahelian zone are not clear. Generally, the position and strength of ITCZ strongly influences the processes that generate rainfall over the region (Nicholson 2013).

Causes of droughts have mostly been attributed to changes in global Sea Surface Temperatures (SST) in particular the warming of the Pacific and the Indian Oceans, which led to changes in atmospheric circulation over the region (Giannini *et al.* 2008). In addition, droughts over the Sudano-Sahel have also been attributed to the occurrence of El Niño Modoki and canonical El Niño events which are known to cause below average rainfall over the northern latitudes, especially over this region (Preethi *et al.* 2015). Furthermore, in the LCB, (Okonkwo *et al.* 2014) asserts that, during the period under study, El Niño Southern Oscillation (ENSO) events may have contributed to a decrease in rainfall over the Southern portion of the LCB where the Logone catchment is located.

Rainfall recovery in the region have been attributed to several factors: Giannini *et al.* (2013) associates it with warming of the Northern Atlantic Ocean and asserts that, if this warming continues to exceed that of the global tropics, rainfall will intensify in the region. Dong and Sutton (2015) attributed it to rising levels of greenhouse gases (GHGs) in the atmosphere, while Evan *et al.* (2015) linked it to an upward trend in the Saharan heat low (SHL) temperature resulting from atmospheric greenhouse warming by water vapour.

The slow response of streamflow to rainfall in the Logone River could partly be attributed to the physical characteristics of the catchment given the low surface gradient (≤1.3%) and the length of the river, which is almost 1000 km from the upper parts of catchment to the outlet at Logone Gana. The influence of topography and catchment size on the response times of river catchments have been reported in several studies (López-Moreno *et al.* 2013; Soulsby *et al.* 2006). Soulsby *et al.* (2006) reported that small and mountainous catchments have short and steep flow paths, which are generally associated with a fast hydrological response to rainfall events. The Logone catchment is an extensive medium-size lowland catchment; its size and gradient may significantly contribute to increase the response time from different parts of catchment after rainfall. The slow response could also be attributed to extensive wetlands in the catchment so runoff is generated only after all depressions in the wetlands area filled.

The reasons why strong correlations occur at the outlet of the catchment (Logone Gana) after 15 months compared to 12 months upstream can be attributed to the fact that; after the Bongor gauging station, the wetland area increases significantly compared to the upstream area thereby increasing the volume of water stored in the wetlands. Furthermore there is a dam that captures and store water from the Logone during peak flow periods, further delaying the propagation of floodwater downstream. The influence of dams in delaying the response time of river catchments have also been reported in other studies (López-Moreno *et al.* 2013).

Given that the highest rainfall in the catchment is recorded in the Sudano zone located upstream, the slow response of the catchment to rainfall also suggest that most of the rainfall received upstream infiltrates into the groundwater aquifer as observed by (Nkiaka *et al.* 2017b) Indeed, Candela *et al.* (2014) reported that the kinds of soils found in the southern portion of the LCB covering the Sudano zone of the Logone catchment where rainfall is high favour aquifer recharge through rainfall infiltration and that groundwater contribution to total streamflow in the Logone River was significant. Nkiaka *et al.* (2017b) also observed that groundwater contribution to streamflow was significant in the catchment. Given that these previous studies indicate a major role played by groundwater in the hydrology of the catchment; the delay in the response time of the catchment may also be attributed to groundwater storage from rainfall infiltration. Indeed, previous studies have identified groundwater storage as a major reason for delays in the response times of catchments (López-Moreno *et al.* 2013; Barker 2016).

The decrease in correlation values between SSI and SPI during the dry season may be attributed to the depletion of the water table due to high evapotranspiration rates in the catchment during this period. This suggest that as the water table drops, the contribution of groundwater to streamflow reduces. This can explain why the response time of the catchment increases to 5-6 months. At the onset of the rainy season, the water table starts to rise due to increased infiltration from rainfall. Towards the end of the rainy season, the water table becomes saturated and groundwater contribution to streamflow becomes significant thus reducing the catchment response time to about three months. The reduced response time towards the end of the rainy season could also be attributed to high runoff coefficient resulting from wet antecedent soil moisture conditions as the soil moisture threshold becomes exceeded which reduces the infiltration capacity of the soil (Penna *et al.* 2011). Therefore, as the water table becomes saturated and soil moisture threshold is exceeded, any rainfall received in the catchment during this period directly contributes to runoff generation thus, reducing the catchment response time.

Although flood events typically occur in time steps of hours to days, positive SPI values at longer timescale may not necessarily translate to flood(s) but may give information on the antecedent moisture conditions of the soil. Furthermore, positive SPI in the Logone catchment in particular will not translate directly to flood events in the river given the considerable lag between rainfall and streamflow as observed in this study. Apart from that, SPI peaks at longer time scale(s) are not suitable for detecting flood peaks because the averaging effect of long-term accumulated precipitation may obscure the signal of extreme precipitation events over a short period (Du *et al*. 2013). On the other hand, SPI at longer timescales like 12-month are suitable for representing droughts because these event usually take a longer time to manifest as SPI responds more slowly to short-term precipitation variation.

The aim of spatiotemporal assessment of dryness/wetness conditions and their duration was to provide a weighted assessment for each zone and individual station location. From the drought severity ranking, it is possible for policy makers to focus attention to localities that are very prone to droughts by creating coping strategies such as developing irrigation and water storage infrastructure, improving soil water conservation techniques and diverting water to ensure environmental flows for wetlands ecosystem sustainability.

Although the whole catchment experienced many periods of wetness conditions with varying severity and duration across individual station locations, wetter conditions prevailed longer in in the Sahelian zone. This implies that this part of the catchment may be more prone to extreme wetness and hence floods especially because of the low surface gradient. Policy orientation here may seek to reduce flooding risk through effective implementation of building regulations to prevent people from constructing houses on flood prone zones and develop/improve flood control infrastructure. Government through decentralized structures could also seek to provide weather forecasting information to the local population through community radios or SMSs given that many such radio stations exist in the area, and mobile telephone network coverage is high. Meanwhile, understanding the response time of a catchment can enhance disaster preparation.

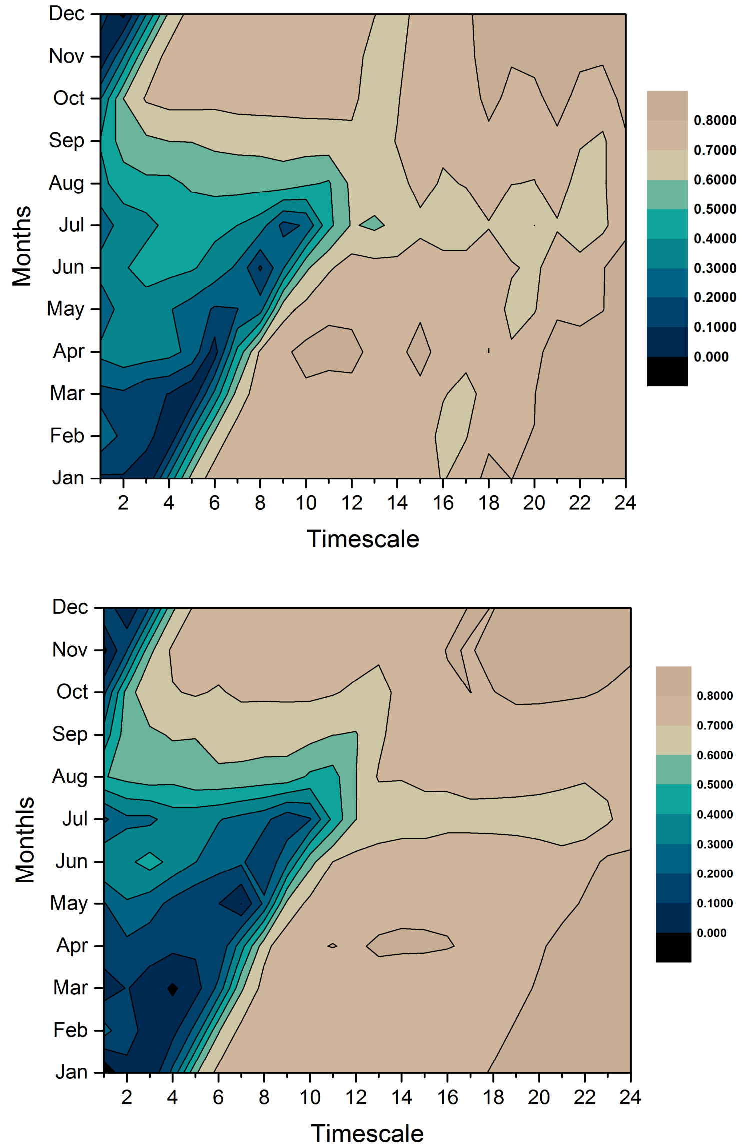


Figure 7.7 Contour plots summarizing monthly lagged correlation coefficients for Bongor (top) Logone Gana (bottom). The X-axis indicates the timescale of SPI.

7.6 Conclusion

The aim of this study was to use the standardized indicators to calculate the frequency of occurrence of drought/flood events and the spatial distribution of dryness and wetness conditions; analyze their spatio-temporal characteristics and trends and use the standardized precipitation index and standardized streamflow index to assess the relationship between rainfall and streamflow.

Analysis using 12-month SPI values showed that annual rainfall was very variable in the catchment as there was a strong variation between SPI values from year to year. However, rainfall in the catchment during the period under study could be described as near stable given that near normal (-0.99 to 0.99) conditions dominated in most the rain gauge stations with an average frequency of occurrence above 65%.

Analysis of SPI at different timescales showed several periods of meteorological droughts ranging from moderate to extreme. SSI analysis also showed that while wetter conditions prevailed in the catchment from the 50s to 70s decades interspersed with episodes of hydrologic droughts in the 1970s; hydrological droughts persisted in the catchment from 1980 to mid-1990. Our findings also indicate that, both the Sudano and Sahelian zones are equally prone to drought and flood conditions although the Sudano zone is more sensitive to drier conditions while the Sahelian zone is sensitive to wetter conditions. Rainfall and streamflow analysis show that the catchment response very slowly to rainfall at short timescales but the situation changes at longer timescales.

This study has permitted us to identify localities within the catchment that are prone to dryness/wetness conditions using available rainfall data. Results obtained can help farmers to decide which crops to cultivate in which part of the catchment e.g. drought resistant crops in areas prone to droughts. Furthermore, the identification of the drought/flood-prone areas can enhance management planning to improve the socioeconomic conditions of the population living in these localities e.g. through the protection of assets of small-scale farmers and herders.

However, given the considerable small number of rain gauge stations used for analysis compared to the catchment size, these results should be regarded with caution as they may not represent the actual situation in the catchment especially in the semi-arid zone where only four rain gauges were used. Furthermore, given that rainfall data was not available from the year 2000 onwards, the results presented in this study may no longer represent the recent situation prevailing in the catchment given that the time lapse is >16 years.

SPI and SSI analysis at longer time scale can give an idea on the duration of either the wet or dry periods in the catchment given that SPI responds more slowly as the time scale increases so the cycles of positive or negative SPI values become more visible. This can give an indication of the abundance of water resources over a given time period or shortage of water which is usually manifested by the occurrence of droughts.

Using this study, it was possible to show that in catchments with physical, climatic and hydrological regimes that vary, the SPI and SSI can be effectively used to analyse droughts and floods conditions. By using both indicators, it is possible to show how physical catchment characteristics e.g. surface gradient, wetlands and man-made structures (e.g. dams) and soil types that influence surface and groundwater movement can significantly affect the catchment response time.

Application of SPI and SSI can be used to enhance the understanding of the hydrological behaviour of catchments, which is indispensable for developing water management policies for adaptation in the context of climate change. This can be used for disaster preparation in remote areas where modern facilities for disaster risk preparation are often absent, thereby allowing preventative measures to be implemented, and so reducing vulnerability of the local population to climate related disasters.

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Chapter 8 Conclusions

The main objective of this thesis was to frame the research questions based on the views expressed by the policy makers as a means to link biophysical and social sciences research in order to reinforce the use of scientific knowledge to support decision making that can enhance societal response to environmental change. The over-arching generic research question the thesis seek to answer was how to bridge the gap between science and policy with specific application to hydro – climatic research. This was achieved through the use of the science – policy interface approach and Q-methodology was used to interview a range of stakeholders in government, non-governmental organizations, civil society and academia working in the area of climate change in Cameroun. However, initial questions used for the interviews were framed based on theoretical underpinnings, the challenge of conducting relevant research in the region and to also cover many areas relevant for enhancing water resources management and formulating climate change adaptation policies in the country.

Three different discourses emerged from the study; Firstly, policy makers acknowledged the vulnerability of water resources to climate change which could lead to food insecurity in the country. The same discourse revealed that the Sudano-Sahel zone covering the northern regions and located within the Lake Chad basin was the most vulnerable zone to climate change in Cameroun owing to the past climate variability observed in the region. Furthermore, the policy makers expressed the need for scientific research to focus on conducting climate change impact studies on water resources in the Sudano-Sahel zone. The second discourse highlighted the important role of political leadership in driving climate change adaption action. Here the policy makers were of the opinion that influential ministries responsible for budget planning and execution need to be involved in all discussions and negotiations around climate change in order to realize the necessity to include climate change into budget allocation and execution. The third discourse focused on policy incentives and recommended the putting in place of new policies and institutions to cope with new and emerging challenges posed by environmental change.

The general conclusions drawn from the Q methodology were based on a set of 36 statements generated from policy makers and which were subsequently used for the Q sort. Based on the candidate's theoretical underpinnings in hydrology, the following statements used in the Q sort were selected and used to guide the physical sciences that has been reported in physical science chapters of this thesis:

- All ecological zones in Cameroun are vulnerable to climate change although the Sudano-Sahel and coastal zones remain the most vulnerable.
- Water resources are vulnerable to climate change so have to be managed in a more sustainable and efficient way.
- Climate change adaptation will be enhanced if scientists can translate the uncertainty inherent in climate models output into risk relevant for planning and decision making.
- Climate change impact studies do not offer any opportunities for local adaptation.
- Policy experts find it convenient to work with results from ensemble models because they give a more comprehensive assessment of risk than individual climate models.
- Sufficient technological skills and infrastructure, and consistent observational records, needed for impact studies to enhance policy development are available to climate scientists in Cameroun.
- To enhance decision making, climate and weather forecast information should answer practical questions such as changes to the onset of the rainy season, frequency and duration of dry spells early in the growing season, water availability for irrigation, intensity of extreme weather events etc.

8.1 Contribution of physical science chapters to the main thesis and summary of findings

The following statements were made by policy makers "*all ecological zones in Cameroun are vulnerable to climate change although the Sudano-Sahel and coastal zones remain the most vulnerable*" and "*water resources are vulnerable to climate change so have to be managed in a more sustainable and efficient way*". Considering these two statements, the study area was selected to cover the Sudano-Sahel zone of Cameroun with particular focus to the Lake Chad basin owing to past climate variability in the region. In the post Q sort interviews, it was revealed that results from such studies could be useful for enhancing water resources management and developing climate change adaptation policies in the study area.

In chapter three, a scrutiny of the available rainfall and river discharge data needed for different statistical analysis and for the calibration and validation of hydrological models, it was observed that the data was fraught with gaps which could increase the level of uncertainty in results.

In one of the statements the policy makers stated that "*climate change adaptation will be enhanced if scientists can translate the* ***uncertainty*** *inherent in models output into risk relevant for planning and decision making*". To deal with the issue of gaps in the data which is an important aspect that need to be addressed in any hydro-climatic research to reduce the level of **uncertainty** in the data, Self-Organizing Maps (SOMs) was used to infill missing observations in the time series used for different analysis in this thesis. Due to the easy implementation of the algorithm and because the method does not require data from neighbouring stations and extra data for training; this thesis conclude that the application of SOMs can be used for infilling missing observations in hydro-meteorological time series. Results from this study showed that a combination of artificial intelligence and human intelligence (to be able to distinguish the seasonal discharge trends, patterns and magnitudes) greatly improved the overall performance of the SOM algorithm in handling missing data. Infilling the missing observations in the time series can significantly reduce the level of uncertainty in the data thereby making the results obtained from subsequently analysis using that data useful for planning and decision making.

The increasing scientific and humanitarian need to place past seasonal and multi-annual precipitation trends in a historical context have been recognized as important for enhancing adaptation at local scale. This can explain why the policy makers agreed that "*climate change impact studies offer opportunities for local adaptation*". To address this concern, in chapter four different homogeneity tests were used for quality control of meteorological data and results showed that the annual rainfall time series from the study area covering the period 1951 – 2000 was homogeneous but temporally and spatially variable. Furthermore, the results of the different trend analysis revealed the presence of statistically significant negative trends in annual rainfall time series for all the stations and statistically insignificant positive trends in monthly time series for 32% of the stations across the catchment. The negative trends correspond to the onset of the Sahelian drought from the mid-1960s to the late 1980s. The difference between long term mean and decadal means across the stations showed an increase in decadal rainfall during the 1990 decade.

The results from the different statistical analysis showed that the Logone catchment is sensitive to natural climate perturbations and could be vulnerable to anthropogenic climate change. This is in agreement with the statement made by the policy makers that the "*Sudano-Sahel is one of the most vulnerable zones to climate change in Cameroun*". Due to the sensitivity of the catchment to natural climate perturbations, it is therefore very important to conduct impact studies in the catchment as requested by the policy makers given that results from such studies will offer *opportunities for local adaptation*. However, due to the challenges pose by climate change and the climate variability in the region, further analysis may be needed before the results obtained in this thesis are useful for policy development.

Chapter five was developed as a response to the following statements by policy makers "*climate change adaptation will be enhanced if scientists can translate the uncertainty inherent in climate models output into risk relevant for planning and decision making*" and "*policy experts find it convenient to work with results from ensemble models because they give a more comprehensive assessment of risk than individual climate models*". The following factors were also taking into consideration: (i) the significant shrinkage in the size of Lake Chad over the past decades which has partly been attributed to climate change and variability, (ii) the contradictory results obtained from previous climate model validation studies in the Central Africa region and, (iii) the absence of such studies dedicated to the Lake Chad basin in particular. Therefore, in this thesis an ensemble of CMIP5 models was validated exclusively for the LCB. This analysis was conducted in order to have a general appraisal of the performance of these models in the basin especially how they are able to simulate historical and project future climate in the basin and assess the level of uncertainty in the model output to ascertain if the results can be relevant for policy development.

The results from the thesis showed that overall, the CMIP5 models simulated precipitation better than average surface temperature in the LCB. Most of the models were able to simulate the annual precipitation cycle in the LCB although precipitation was overestimated during the dry season and underestimated during the rainy season. Future annual precipitation in the LCB is projected to increase by 2.5% and 5% respectively under two representative concentration pathways (RCPs) RCP4.5 and RCP8.5 respectively by the middle of the century (2050 – 2075) in most of the models. Furthermore, analysis revealed that by the middle of the century (2050 – 2075), future annual precipitation is projected to increase in the LCB by 2.5% and 5% while monsoon precipitation will decrease by 11.60% and 5.30% respectively under RCP4.5 and RCP8.5 scenarios relative to the historical period. The uncertainty range for annual precipitation is about 12% and 17% for annual and monsoon precipitation respectively under RCP4.5 and RCP8.5 scenarios. The uncertainty range obtained especially for precipitation were mostly within the bounds of natural rainfall variability across the LCB. All the models also project a decrease in monsoon precipitation under both RCPs despite the increase in projected annual rainfall.

Although the uncertainty range for future precipitation projections for most models lie within the range of natural climate variability, additional analysis may also be needed using regional climate models for results to have any meaningful policy implication that can enhance water resources management in the study area. Such analysis could include bias correction using other global datasets to reduce uncertainty and driving hydrological models using the multi model ensemble to investigate how streamflow will change under different representative concentration pathways (RCPs). This technique was advocated by policy makers because it gives a more comprehensive assessment of risk than individual climate models. Considering that the CMIP5 models performed very poorly in the simulation of historical annual rainfall in the basin by overestimating precipitation during the dry season and underestimating during the rainy season which is not logical; this implies that the models have a wet bias during the dry season and a dry bias during the rainy season. Furthermore, the models also fail to simulate historical annual surface temperature. **Therefore, the results obtained from CMIP5 models projections in this thesis are not useful for any long-term policy development in the area as requested by policy makers**. Despite this, the overall aim of evaluating CMIP5 models in this thesis was to have a general appraisal of the model performance in the Lake Chad basin given that such studies dedicated to the basin are lacking. Notwithstanding, these results can give model developers an idea of the performance of CMIP5 models in an understudied region such as the Lake Chad basin which unfortunately is one of the regions in the world worse affected by climate change.

To enhance decision making, climate and weather forecast information should answer practical questions such as changes to the onset of the rainy season, frequency and duration of dry spells early in the growing season, water availability for irrigation, intensity of extreme weather events etc" and *water resources are vulnerable to climate change so have to be managed in a more sustainable and efficient way*. To response to these concerns cannot be possible without understanding the hydrological behavior of the catchment which is necessary for planning water allocation and management. This was achieved in this thesis using two methods; hydrological modelling whereby the model was calibrated and validated using different techniques in order to gain an understanding of hydrological behaviour of the catchment which is necessary to enhance water management. Furthermore, hydrological model development, calibration and validation is a pre-requisite for any such study that uses output from climate models.

Hydrological modelling results reported in this thesis showed that by using different calibration techniques it is possible to reveal differences in hydrological behavior in the different parts of the catchment using different parameter values. Using the different calibration techniques, model performance indicators were mostly above the minimum threshold of 0.60 and 0.65 for Nash Sutcliff Efficiency (*NSE*) and Coefficient of Determination (R^2) respectively. Model uncertainty analysis showed that more than 60% of observed streamflow values were bracketed within the 95% prediction uncertainty (95PPU) band after calibration and validation.

The good hydrological model performance obtained in this thesis indicate that the model can used to enhance water management in the Logone catchment by facilitating the allocation of water resources to various sectors (agriculture, urban water supply and hydropower production). Apart from helping the policy makers to manage water in a sustainable way, the hydrological model may be used for flow forecasting to determine river discharges which is necessary to determine the flooding extent in the event of prevailing hydrological conditions. Such results may be useful in flood preparation planning, weekly, monthly and seasonal planning for water resources allocation using forecasts information so that alternative measures are put in place to manage surplus or shortage in supply in different sectors such irrigation, urban water supply, environmental flows and hydropower management.

To be able to identify droughts and flood prone zones in the study area, the standardize precipitation index and standardize streamflow index were employed in *Chapter seven*. Results showed that both the Sudano and Sahelian zones of the catchment are equally prone to droughts and floods conditions. However, the Sudano zone is more sensitive to drier conditions while the Sahelian zone is sensitive to wetter conditions. The lagged correlation analysis between standardized precipitation index (SPI) and standardized streamflow index (SSI) at multiple timescales revealed that the catchment has a low response to rainfall at short timescales although, this progressively changed as the timescale increased with strong correlations ($\geq$0.70) observed after 12 months.

The identification of droughts and floods prone areas can help decision makers to know the different policy interventions that can be applied in each of the localities to reduce the vulnerability of the population to such climate related events. Furthermore, SPI technique could be used to analyse seasonal rainfall forecasts to determine zones that may be affected by future droughts in the catchment so that farmers are informed about the potential zones that may not be suitable for agriculture before the onset of the farming season. In addition, the technique was also used to determine the characteristics of such events and also to calculate the response time of the catchment. It is also hoped that such analysis may be used for preparing disaster relief operations such as floods.

The policy makers also raised the issue of the absence of "*sufficient technological skills and infrastructure, and consistent observational records, needed for impact studies*". In this thesis, precipitation estimates from different reanalysis datasets were first validated against rain gauge data from the catchment in order to evaluate how these datasets are able to replicate the annual and decadal precipitation cycle and variability in the catchment. This is an important step when using reanalysis dataset(s) for hydrological studies especially given that precipitation is an important variable for driving these models. After this step, the different reanalysis datasets were then used to drive a hydrological model in order to select which of them could be used for detailed hydrological modelling in the catchment. The results from those separate studies are reported in Annex A and B of this thesis.

The results showed that reanalysis datasets can be used for hydrological modelling in data scarce regions which is a very important finding given that acute data scarcity in most developing countries and as highlighted by policy makers. This is a very significant finding from this research which is very useful to other hydrologists in developing countries in general and Africa in particular given the acute shortage of relevant data. It is also worth noting that validating reanalysis datasets in remote locations like the Lake Chad basin may help the developers to appreciate the quality of model performance in regions where only few observation stations used to constraint the reanalysis model parameters exists.

8.2 Policy implication of the research

Given that the main aim of this thesis was to bridge the gap between science and policy through the use of scientific knowledge to support decision making especially within the area of hydro-climatology, the results obtained from this work have important policy implications for the Lake Chad basin in general and the Logone catchment in particular.

Although the primary aim of using Q methodology was not to test the knowledge of stakeholders on issues relating to climate change, the results indicate that the stakeholders are sufficiently knowledgeable in this field as evident from the results obtained. This is a significant step towards attaining the adaptation agenda given that knowledge of the subject may play a key role especially as new knowledge and information relating to climate change is evolving at a fast rate.

The results from this thesis have confirmed the claim of the policy makers given the significant negative trends observed in annual and seasonal rainfall recorded across the Logone catchment during the period under study. Analysis of seasonal rainfall show that the temporal changes in rainfall patterns with increasing trend in pre-monsoon rainfall could increase crop production in the area given that it coincides with the beginning of the planting season. However, analysis of recent daily rainfall trends in the region are needed to confirm these results given the limited number of stations from which the present analysis were conducted. Notwithstanding, results obtained from this thesis can also be used in other areas such as regional climate outlook initiatives such as “Rainwatch” which uses past climate observations from rain gauge stations to make short and medium range forecasts within the West Africa.

Our results of future precipitation projection in the Lake Chad basin using a sub-set of CMIP5 models also indicate that projected annual precipitation will increase in the basin despite a drop in projected monsoon precipitation. Considering the poor performance of the CMIP5 models in the basin, additional analysis using regional climate models are needed for results to have any meaningful policy implication. However, given the vagaries of weather and climate variability in the region and the uncertainties associated with future climate projections; the use of advance forecasting techniques especially for short-term weather information may become unavoidable in the region to help farmers to cope with this weather vagaries and climate uncertainty. Using such techniques, information on the onset of rainfall, duration of dry spells during the onset and the number of rainfall days in the rainy season maybe communicated to the farmers before planting season begins so that they plan for any eventualities ahead of time. Nevertheless, this remains a policy decision which needs to be taken at the level of each country given that the cost of acquiring forecasted information is quite high and most farmers in the region cannot afford to pay for such services.

Using the drought severity ranking obtained in this thesis, policy orientation in the catchment may focus on localities that are prone to droughts by providing farmers with adaptation strategies such as developing irrigation and water storage infrastructure, improving soil water conservation techniques through the introduction of agroforestry, afforestation of bare lands and tree planting in urban areas and village squares. Meanwhile water storage infrastructures may also need to be developed to help farmers store water for agriculture during the rainy season. In other zones of the catchment prone to flood conditions, policy intervention could include the effective implementation of building regulations to prevent people from constructing houses in flood prone zones and develop/improve flood control infrastructure.

8.3 Study limitations and recommendations

The main limitation to this thesis is the fact that it was impossible to collect any data related to vulnerability from the study area due to armed conflict as a result of "boku haram" terrorist activities in the Lake Chad basin. The intervention of the UN Security Council may be needed to help member states of the LCBC to deal with this terrorist group especially as the conflict has already led to the internal displacement of millions of people in the region. The continuous displacement of the population may result to the over exploitation of water resources which its scarcity is already causing tension among users. This could lead to mass migration of people from the region as a result of limited water resources which could spark a massive refugee crisis.

Another significant limitation of this study was the lack of sufficient hydro-meteorological data from the study area at required spatial and temporal scale to calibrate and validate model results. Although this gap was filled by using reanalysis datasets, it is still important for member states of the LCBC to collect this data at country level and forward it to the LCBC so that the data can be centralized and digitized to facilitate future relevant studies in the basin. This will go a long way to reinforce the collaboration between member states and the commission and improve future modelling studies in the basin.

Due to financial and time constraints, the objectives of the thesis were framed based only on the views expressed by policy makers in Cameroun. The input from policy makers from other member states of the Lake Chad basin and staff of the commission were not taken into account.

8.4 Future research

Despite the considerable volume of information generated from this thesis, there is still much research work to be conducted in the LCB. Firstly, given the changes observed in rainfall patterns during the period under study, an analysis of recent daily rainfall trends in the region is needed to confirm the results obtained in this study. Considering the scarcity of rain gauge data from the region, this could be accomplished by using rainfall data obtained using remote sensing techniques.

Secondly, considering that the hydrological modelling study in the Logone catchment revealed that groundwater plays an important role in the hydrology of the catchment; it will be important to scale-up the present study to cover the whole active LCB to fully understand the groundwater – surface water interactions in the basin given that such studies are still lacking the basin.

Thirdly, it will also be important to investigate the impact of land use/cover change on the hydrology of the basin over the past decades and how this has influenced inflows into Lake Chad given such studies are yet to conducted in the LCB despite significant shrinkage of the lake. Furthermore, it will also be valuable to simulate the impacts of climate change on the lake inflows using output from CMIP5 models validated in this thesis and converting the uncertainty from the future projected streamflow from that study into risk which can be used for decision making. This will serve as a direct response to one of the views expressed by the policy makers.

Hydrological modelling studies in the Logone catchment carried out in this thesis showed that the SWAT model was not sensitive to the impacts of wetlands on the catchment hydrology. Therefore, future research in the LCB should seek to study the impact of wetlands on the basin hydrology using a wetland model. In addition to investigate how environmental change will affect environmental flows which are needed to sustain the abundant biodiversity in the Chari-Logone-Waza wetlands and National Parks. Such studies have the potential to provide policy makers with information that can be used to plan for conservation efforts in the LCB.

Meanwhile, adaptation research should seek to work with different stakeholders from member states of the LCBC, hydro-climatologists and biologists to engage in a collaborative modelling exercise to develop a Decision Support System (DSS) for the basin. Such a system will be used to analyse different management and climate change adaptation options for basin under different RCPs. This will ensure the sustainable use of water resources under a changing climate and maintain the ecological integrity of the wetlands and National Parks while ensuring that the required volume of inflow is channeled into Lake Chad to prevent the lake from disappearing as a result of environmental change.

Appendix A: Validating reanalysis precipitation estimates

Appendix A is based on:

NKIAKA, E., N. R. NAWAZ and J. C. LOVETT. 2017. Evaluating global reanalysis precipitation datasets with rain gauge measurements in the Sudano-Sahel region: case study of the Logone catchment, Lake Chad Basin. Meteorological Applications, 24(1), pp.9-18.

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Abstract

Africa has a paucity of long-term reliable meteorological ground station data and reanalysis products are used to provide the climate estimations that are important for climate change projections. This paper uses monthly observed precipitation records in the Logone catchment of the Lake Chad Basin (LCB) to evaluate the performance of two global reanalysis products: the Climate Forecasting System Reanalysis (CFSR) and ERA Interim datasets.

The two reanalysis products reproduced the monthly, annual and decadal cycle of precipitation and variability relatively accurately albeit with some discrepancies. The catchment rainfall gradient was also well captured by the two products. There are good correlations between the reanalysis and rain gauge datasets though significant deviations exist, especially for CFSR. Both reanalysis products overestimated rainfall in 68% of the rain gauge stations. ERA Interim produced the lowest bias and mean absolute error (MAE) with average values of 2% and 6.5mm/month respectively compared to 15% and 34mm/month for the CFSR. Although it has a coarser spatial resolution, the ERA Interim outperformed the CFSR in this study. This research demonstrates that evaluating reanalysis products in remote areas like the Logone catchment enables users to identify artefacts inherent in reanalysis datasets. This will facilitate improvements in certain aspects of the reanalysis forecast model physics and parametrisation to improve reanalysis dataset quality. The study concludes that the application of each reanalysis product in the catchment will depend on the purpose for which it is to be used and the spatial scale required.

A.1 Introduction

Scarcity of meteorological data is a major bottleneck that retards advancement of knowledge on water management and climate change in many parts of the world, especially in developing regions (Buytaert *et al.* 2012). Reliable, long-term, and well distributed climate information is essential to informing policies that aim to address the consequences of climate variability and change (Baisch 2009; van de Giesen *et al.* 2014) and enhance water resource management.

In Sub Sahara Africa there is uneven distribution of hydro-meteorological stations and many of these are in decline, with the result that most areas of Africa, particularly those in Central Africa, are unmonitored (Washington *et al.* 2006). Another challenge in these regions is that, even when data is collected and archived, accessing it requires much effort and money as the data are not digitised or readily available (Fuka *et al.* 2013). Data scarcity in Central Africa in particular has been identified by many researchers as a constraint to modelling and validation e.g. (Haensler *et al.* 2013; Candela *et al.* 2014; Maidment *et al.* 2015).

To overcome this challenge, multiyear global gridded representation of weather known as reanalysis datasets are now available. The large number of variables makes reanalyses datasets ideal for investigating climate variability and to enhance management of water resources. Examples of reanalysis datasets currently in use include: National Centers for Environmental Prediction (NCEP)/National Center for Atmospheric Research (NCAR) Climate Forecasting System Reanalysis (CFSR) (Saha *et al.* 2014); European Center for Medium-Range Weather Forecasts (ECMWF) ERA-Interim (Dee *et al.* 2011); and Modern-Era Retrospective Analysis for Research and Applications (MERRA) (Rienecker *et al.* 2011). These reanalysis datasets have spatial resolutions of 0.3125° (~38km), 0.703° (~82km) and 0.50° (~50km) for CFSR, ERA Interim and MERRA respectively.

The reanalysis products have been used for many different applications around the world (Fuka *et al.* 2013; Blacutt *et al.* 2015; Krogh *et al.* 2015; Sharifi *et al.* 2016). Many studies have also been carried out in Africa to evaluate the accuracy of precipitation estimates from reanalysis datasets at monthly time scale or more e.g. (Maidment *et al.* 2013; Zhang *et al.* 2013; Worqlul *et al.* 2014; Koutsouris *et al.* 2015). However, in the course of modelling climate change impacts on the Logone catchment of the Lake Chad Basin (LCB), no evaluation studies were found for Central Africa. Before reanalysis datasets are used in this region, their accuracy needs to be tested against in situ measurements.

The main objectives of this study are to: (i) evaluate the accuracy of precipitation estimates from two reanalysis datasets, CFSR and ERA Interim against rain gauge data in the Logone catchment of the LCB, and (ii) evaluate how data from these reanalysis datasets are able to reproduce the monthly, annual and decadal rainfall cycle. The results will identify which of the reanalyses products better reproduces precipitation and variability estimates for the catchment and so validate their use in hydrological and climate models in this data scarce region.

The paper is structured as follows: Section 2 describes the data and methodology used in the study; Section 3 presents the results obtained; Section 4 provides a general discussion on the results and Section 5 gives a general summary and conclusion.

A.2 Methodology

A.2.1 Study area

The Logone catchment is a transboundary catchment shared by Cameroun, Chad and the Central Africa Republic with an estimated catchment area of 86500km^2 at Logone Gana discharge station (Figure A-1). It lies between latitude 6˚ - 12˚ N and longitude 13˚ - 16˚ E. The Logone River forms part of the international boundary between Cameroun and Chad. The Logone floodplains are the most extensive and among the richest ecological wetlands in the African Sahel covering an estimated area of 6000 km^2 (Loth and Acreman 2004). There is a high concentration of wildlife, which is protected in two National parks (Waza and Kalamaloue). The Waza National Park is a Ramsar site and a Biosphere Reserve of international importance. Many migratory birds make use of the seasonally abundant food resources (Loth and Acreman 2004).

The Logone has its source in Cameroun through the Mbere and Vina Rivers which flow from the north eastern slopes of the Adamawa plateau (Molua and Lambi 2006). In Lai, the Logone is joined by the Pende River from the Central Africa Republic and flows from south to north. In this region elevation ranges from 300 masl around Kousseri to about 1200 masl in the Adamawa plateau. Apart from some local mountains in the south the basin topography is quite flat with an average slope of about 1.3% in a south to north gradient (Le Coz *et al.* 2009).

The catchment has both a Sudano climate in the south and semi-arid climate in the north. Estimated average annual rainfall varies between 600 mm/year in the north to about 1200 mm/year in the south (Molua and Lambi 2006). The climate in the region is characterized by high spatial variability and is dominated by the tropical continental air mass (the Harmattan) and the marine equatorial air mass (monsoon) (Candela *et al.* 2014). Almost all rain falls during the rainy season from April/May/ to September/October and mean annual temperature is 28°C.

A.2.2 Data Sources

A.2.2.1 Rain gauge data

Monthly gauge rainfall was obtained from "Système d'Informations Environnementales sur les Ressources en Eau et leur Modélisation" (SIEREM) available online at www.hydrosciences.fr/sierem for the period 1979-2002 (Boyer *et al.* 2006). Quality control of the gauge data was done in three steps: (i) selecting only stations that had monthly data dating back to 1979 to match the period of the reanalysis data; (ii) selecting stations that had data for a minimum of 15 years and (iii) eliminating stations that had extended gaps of more than six months in each year. Gaps in the monthly rainfall time series were filled using the Artificial Neural Network (ANN) Self-Organizing Map (SOM) technique (Nkiaka *et al.* 2016). Using these criteria, out of 55 rain gauge stations located inside the catchment, only 19 stations had consistent data spanning the period 1979 - 2002. To increase the number of rain gauges, six additional stations located outside the catchment but with the same climate conditions were selected.

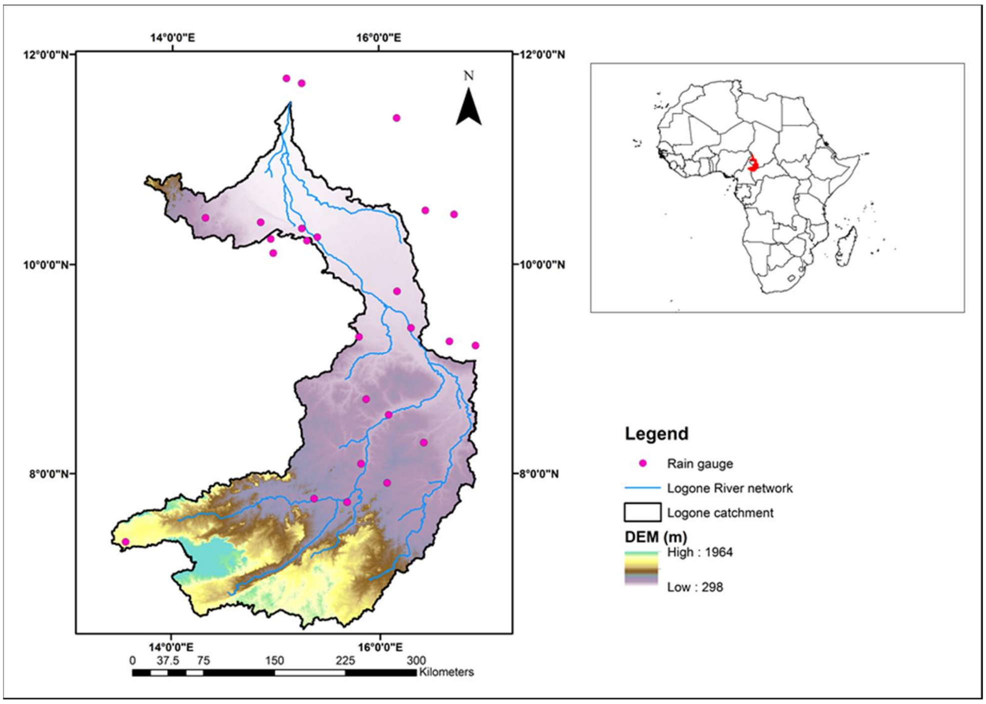


Figure A-1 Map of the study area

A.2.2.2 Reanalysis datasets

A reanalysis project involves the reprocessing of observational data spanning an extended historical period: “It makes use of a consistent modern analysis system, to produce a dataset that to a certain extend can be regarded as a "proxy" for observation with the advantage of providing coverage and time resolution often unobtainable with normal observational network” (Morse *et al.* 2013). It is generated by a data assimilation system combining observations with a numerical weather prediction model. For the entire reanalysis period, the model physics remain unchanged in the forecast model for consistency of the output data. The reanalysis consequently provides a picture of the global climate over a period during which observational data are available. Reanalysis data can provide a multivariate, spatially complete, and coherent record of the global atmospheric circulation (Dee et al., 2011).

The Climate Forecast System, NCEP version 2 (CFSv2; http://cfs.ncep.noaa.gov) is an upgraded version of CFS version 1 (CFSv1). It is a reanalysis product first developed as part of the Climate Forecast System by NCEP in 2004 with quasi-global coverage and is a fully coupled atmosphere-ocean-land model used by NCEP for seasonal prediction (Saha *et al.* 2014). CFSR has a 3D-variational analysis scheme of the upper-air atmospheric state with 64 vertical levels and a horizontal resolution of 38km spanning the period 1st January 1979 to present day (Saha *et al.* 2014).

ERA-Interim is the latest global atmospheric reanalysis produced by ECMWF and covers the period from 1st January 1979 to present day (Dee *et al.* 2011). The core component of the ERA-Interim data assimilation system is the 12-h 4D-variational analysis scheme of the upper-air atmospheric state, which is on a spectral grid with triangular truncation of 255 waves (corresponding to approximately 80 km) and a hybrid vertical coordinate system with 60 vertical levels. Details concerning the two reanalysis products can be found in Dee *et al.* (2011) and Saha *et al.* (2014) for ERA Interim and CFSR respectively.

Reanalysis data for the study area was obtained for an area bounded by latitude 6°N-12.0°N and longitude 13°E-17.25°E from the Texas A&M University website (globalweather.tamu.edu) and ECMWF website for ERA Interim (http://apps.ecmwf.int/datasets/). What is not known is whether data from the stations used for validating the reanalysis datasets in this study were used for assimilation purposes, as rainfall data in reanalysis products is constrained from surface observations to initialize the forecast model.

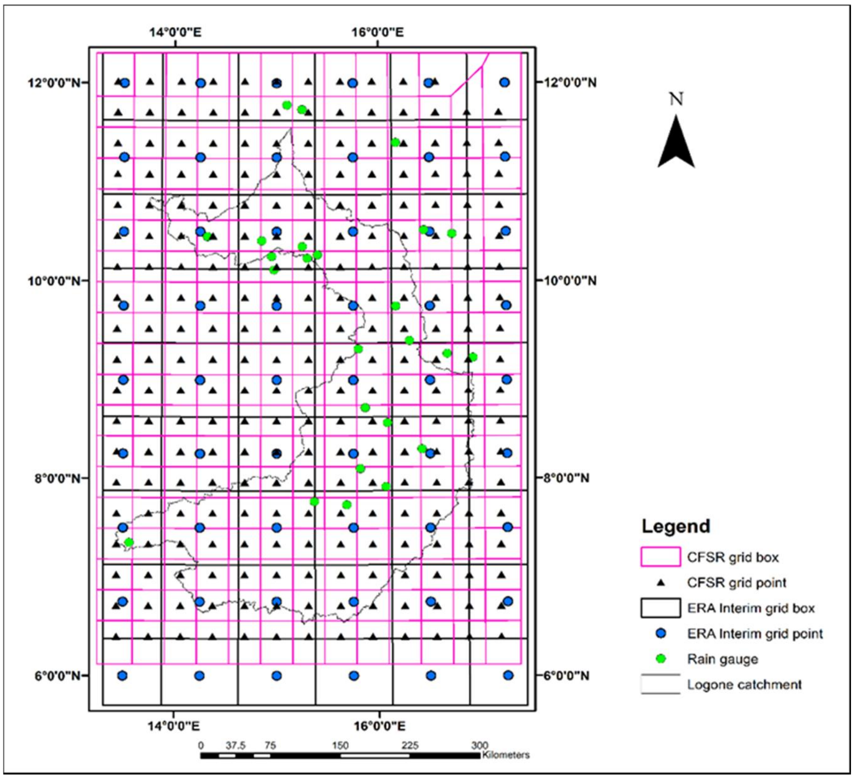


Figure A-2 Illustration of grid boxes used in the assignment of a reanalysis rain gauge station(s) Climate Forecasting System Reanalysis (CFSR) and ERA Interim grid points are represented by triangular and circular points regularly spaced while rain gauge stations are also represented by circular points irregularly spaced located inside either of the grid boxes.

A.3 Methods for comparison

To identify which reanalysis grid point to compare with which rain gauge station(s), grid boxes were created with the same native resolution for all reanalysis grid points (Figure A-2). Where two or more rain gauges were located inside the same grid box, their precipitation estimates were compared with the precipitation estimate of that grid box. This method has been used to evaluate reanalysis datasets with in situ measurements by Diro *et al.* (2009); Worqlul *et al.* (2014) and (Hu *et al.* 2014). Pairwise statistical analyses were carried out between reanalysis grid point precipitation estimates and rain gauge data located within the grid box. This was done assuming that the reanalysis grid point precipitation estimate within each grid is the average for the whole of that grid box.

Five different statistical measures were used to evaluate the results: correlation coefficient (R), coefficient of determination (R^2), mean absolute error (MAE), Bias and the Nash Sutcliff

Efficiency (*NSE*) (Maidment *et al.* 2013; Worqlul *et al.* 2014; Koutsouris *et al.* 2015; Sharifi *et al.* 2016).

Graphical plots were used to compare monthly, annual and decadal rainfall located inside the grid box with the rainfall estimate of that grid box. Reanalysis precipitation estimates were aggregated to monthly and annual totals to match the available rain gauge data. Mean annual rainfall of the reanalysis products and gauge data were also calculated for each station with their respective error bars. In addition, a graphical plot of mean annual rainfall was made to show variation of rainfall with latitude.

Annual and monthly rainfall data for each station was averaged over two different climatic zones in the catchment: Sudano and semi-arid. The distinction between the climatic zones was based on rainfall gradients in the catchment. Stations located between latitude 6°-10°N were grouped together in the Sudano area while stations located above latitude 10°N were grouped together as the semi-arid area. Following these criteria, 12 stations were located in the semi-arid area and 13 were located in the Sudano area. Diro *et al.* (2009) and Maidment *et al.* (2013) also used this approach to evaluate reanalysis products in Ethiopia and Uganda respectively.

Table A.1 Overview of rain gauge stations and corresponding grid points with their annual rainfall totals

Rain gauge station	Latitude	Longitude	Elevation (m)	Period of rainfall record	Mean annual rainfall rain gauge	Mean annual rainfall CFSR	Mean annual rainfall ERA Interim
Longone Birni	11.78	15.10	300	1979-1996	517.06	672.96	536.61
Mandalia	11.73	15.25	300	1979-1996	529.76	686.78	536.61
Massenya	11.40	16.17	328	1979-2001	607.45	711.59	659.59
Bailli	10.52	16.44	330	1979-2003	726.25	891.74	750.06
Bousso	10.48	16.72	336	1979-2001	743.59	845.07	789.36
Maroua	10.45	14.32	384	1979-2003	811.46	688.86	632.23
Mouvouday	10.41	14.85	336	1979-1994	657.93	759.99	721.68
Yagoua	10.35	15.25	325	1979-1997	747.78	897.69	742.78
Bongor	10.27	15.40	328	1979-1999	707.94	914.67	810.27
Kalfou	10.25	14.95	340	1979-1996	692.06	919.83	732.59
Dana	10.23	15.30	310	1979-1995	680.00	914.67	724.18
Doukoula	10.12	14.98	340	1979-1996	789.18	919.83	909.75
Deressia	9.75	16.17	344	1979-1998	757.84	891.77	943.26
Lai	9.40	16.30	358	1979-2002	980.13	890.98	873.26
Kello	9.32	15.80	378	1979-2003	909.00	945.64	971.14
Guidari CF	9.27	16.67	369	1979-2001	929.18	927.79	1007.78
Donomanga	9.23	16.92	370	1979-2001	925.45	916.96	1035.84
Delli	8.72	15.87	427	1979-2002	1027.21	1015.72	971.14
Moundou	8.57	16.08	410	1979-2003	1043.57	1015.72	1033.11
Donia	8.30	16.42	414	1979-2001	1000.18	1149.91	1125.16
Pandzangue	8.10	15.82	345	1979-1999	1154.65	1150.89	1111.67
Bekao	7.92	16.07	528	1979-2002	1150.40	1150.89	1052.18
Touboro	7.77	15.37	1430	1979-1995	1206.59	1102.62	1256.88
Baibokoum	7.73	15.68	1323	1979-1999	1090.50	1489.02	1163.57
Ngaoundere	7.35	13.56	1113	1979-2003	1420.61	2584.17	1246.67

A.4 Results

A.4.1 Monthly rainfall variation

Results shown in Figures A-3a&b reveal that, despite the smoothing effect over large areas, rainfall estimates from the two reanalysis datasets follow the same monthly cycle shown by gauged rainfall in the two spatial zones. The general pattern is that rainfall in the area begins in April/May and lasts until September/October (Loth and Acreman 2004; Molua and Lambi 2006). CFSR overestimated monthly rainfall in most stations while ERA-Interim underestimated in some stations and over-estimated in others. The ability of CFSR and ERA Interim to efficiently capture monthly precipitation cycles has been reported from Ethiopia, Australia, Tanzania and South America (Worqlul *et al.* 2014; Fu *et al.* 2015; Koutsouris *et al.* 2015; Krogh *et al.* 2015). Blacutt *et al.* (2015)

reported that; CFSR consistently overestimated precipitation estimates in three basins in South America (La Plata, Altiplano and Amazon) while Koutsouris *et al.* (2015). (2015) reported that CFSR underestimated seasonal precipitation in the Kilombero Valley in Tanzania. Maidment *et al.* (2013) also reported that ERA Interim overestimated seasonal precipitation in Uganda.

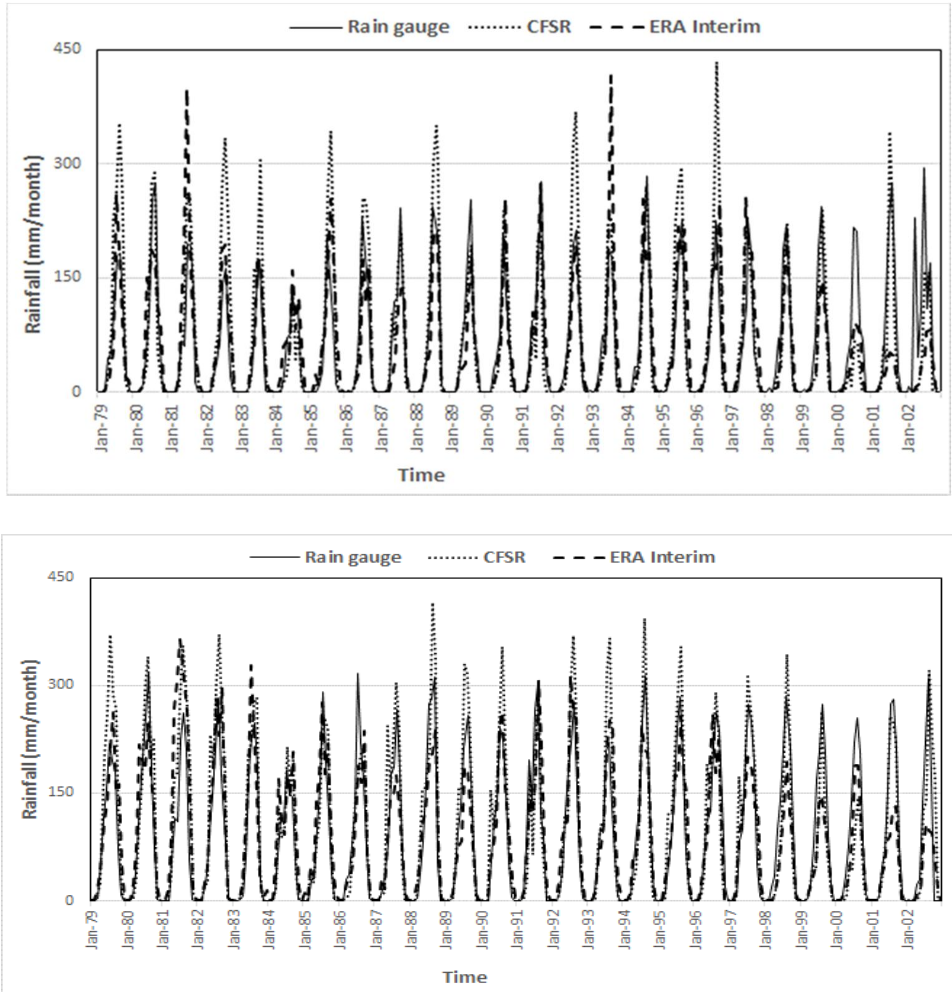


Figure A-3 Average monthly time series for (a) semi-arid and (b) sudano areas
The time series are obtained by averaging monthly rainfall for all stations located in the semi-arid and sudano areas respectively for a & b.

Annual gauge rainfall varies between 500-1500mm/year, ERA Interim varies between 500 – 1300mm/year while CFSR rainfall varies between 600 – 2600mm/year and consequently has the highest spread among the three datasets (Figure A-4a and Table A.1). Koutsouris *et al.* (2015) observed a similar spread in CFSR precipitation estimates in the Kilombero Valley in Tanzania.

Both reanalysis products overestimate annual rainfall in 68% of the stations in the catchment but overestimation is greater for CFSR (27%) compared to 8% for ERA Interim.

Figures A-4b&c show the average annual rainfall from stations located in the semi-arid (latitude 10° - 12°) and Sudano (latitude 6° -10°) areas respectively. The figures show that both reanalysis products were able to capture inter-annual rainfall variability in the catchment, though with some differences. Figures A-4b&c show that the reanalyses products were able to capture the droughts that affected the region especially in 1984 which is reported as the driest year in the region during the period under study (Molua and Lambi 2006). However, for this extreme drought year (1984) CFSR slightly under estimated rainfall in the semi-arid area and over-estimated rainfall in the Sudano area, while ERA Interim overestimated in both.

CFSR generally overestimated annual rainfall in the catchment with overestimation slightly higher with average of 19% in the semi-arid area compared to 11% in the Sudano area. ERA Interim demonstrated almost perfect performance in the semi-arid area and overestimated by 3% in the Sudano area. Dile and Srinivasan (2014) and Worqlul *et al.* (2014) reported that CFSR over/underestimates rainfall in some stations within the same catchment in their respective studies, de De Leeuw *et al.* (2015) and Sharifi *et al.* (2016) reported that ERA Interim generally underestimated rainfall in their respective study areas. Fu *et al.* (2015) also reported that ERA Interim underestimated mean annual rainfall in Australia while CFSR overestimated it in some regions and underestimated in others.

The analysis also shows that both products captured the spatial distribution of rainfall in the Sudano and semi-arid areas of catchment fairly well. Annual rainfall generally ranges between 600-900mm/year and 900-1400mm/year in the semi-arid and Sudano areas respectively (Loth and Acreman 2004); see Figures 4b&c. Fu *et al.* (2015) reported that CFSR and ERA Interim were able to reproduce the observed spatial patterns of annual rainfall in Australia. Results also show that annual CFSR rainfall estimates for the grid box (grid point) located in Ngaoundere is significantly higher than gauge data by more than 1000mm/year while ERA Interim underestimated rainfall in that station by more than 150mm/year. Haensler *et al.* (2013), reported that data from the National Climatic Data Center (now National Centers for Environmental Information) strongly overestimated precipitation in this station. Furthermore, CFSR systematically underestimated annual rainfall during the period 1998 – 2000 across most stations in the catchment. A similar artefact was identified in the CFSR dataset by Monteiro *et al.* (2015) while modelling the Tocantins catchment in Brazil.

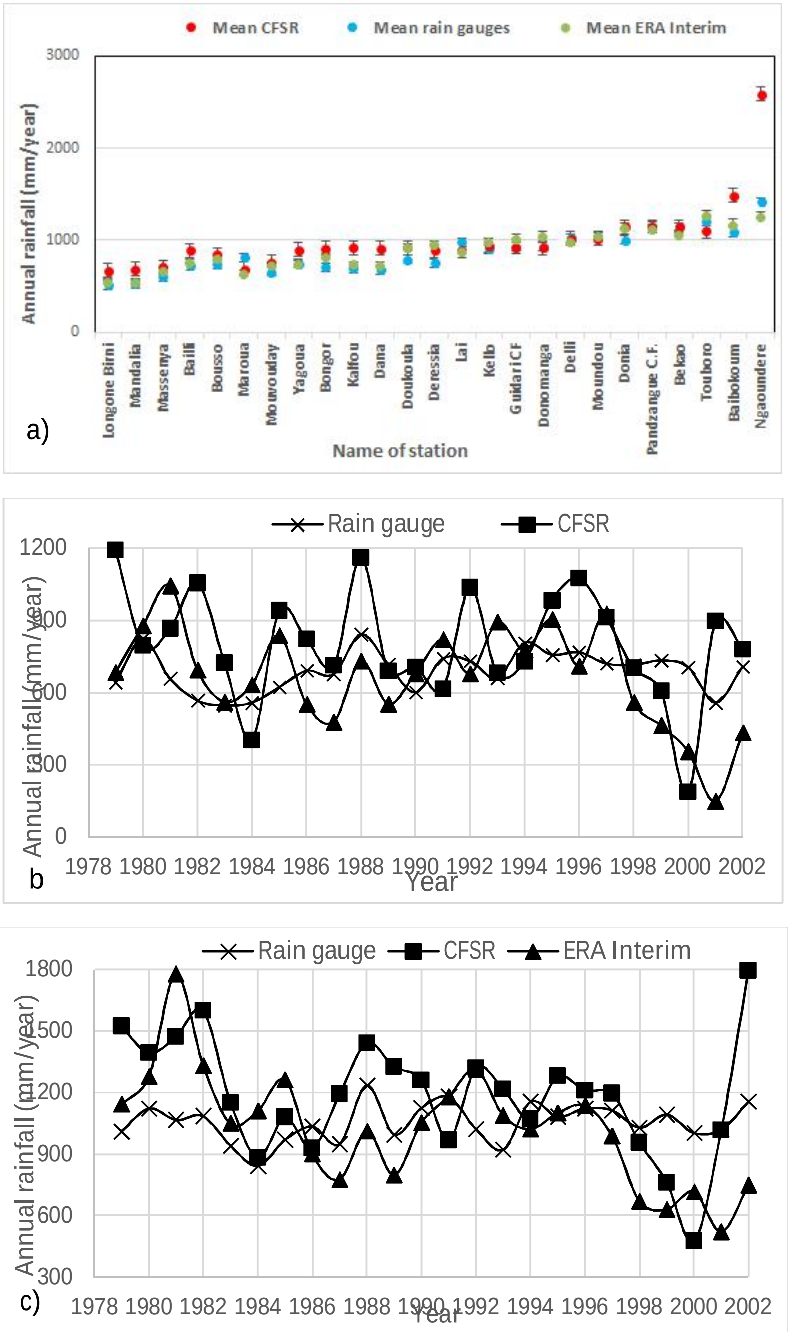
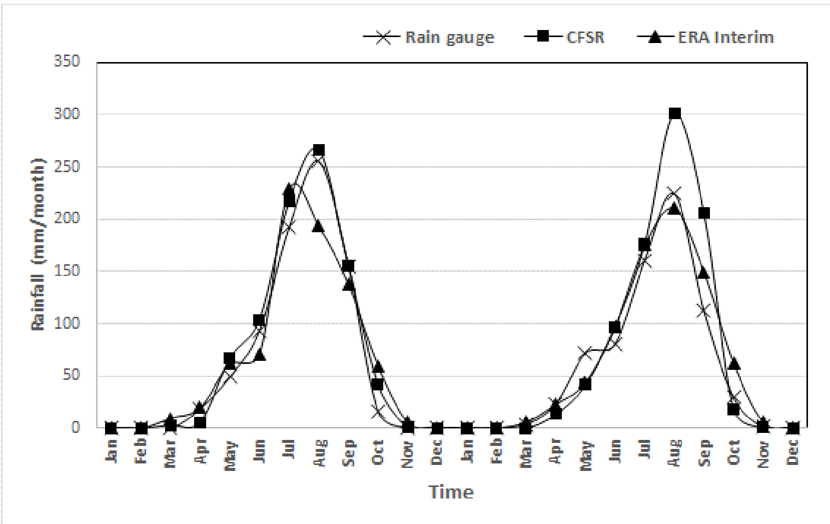


Figure A-4 Mean annual rainfall with error bars for all stations (1979 - 2002), (b) mean annual rainfall for semi-arid zone and (c) sudano zone

A.4.2 Decadal monthly rainfall variability

To compare the monthly rainfall cycle between gauge and reanalysis grid points a 10-year mean was calculated for each month starting from the first year of the data period in each decade i.e. for the 1980 decade (1981-1990) and for the 1990 decade (1991-2000). Figure 6a&b show that at a decadal time scale both reanalysis datasets follow the same monthly cycle as the gauge data for stations located in the semi-arid (Bailli) and Sudano (Bekao).

Monthly precipitation estimates from the CFSR are similar to measured data with the peak occurring in the month of August in the 1980 decade in Bailli while peak rainfall during the same period in the ERA Interim occurred in July. For Bekao station, peak rainfall in the ERA Interim coincides with measured data and occurred in July while CFSR peak rainfall occurred in August during the 1980 decade. During the 1990 decade, peak rainfall in CFSR and ERA Interim occurred during the same month but ERA interim underestimated peak decadal monthly rainfall in both stations. Similar results on decadal monthly rainfall by both reanalysis products were reported by Zhang *et al.* (2013) in the Southern African region.



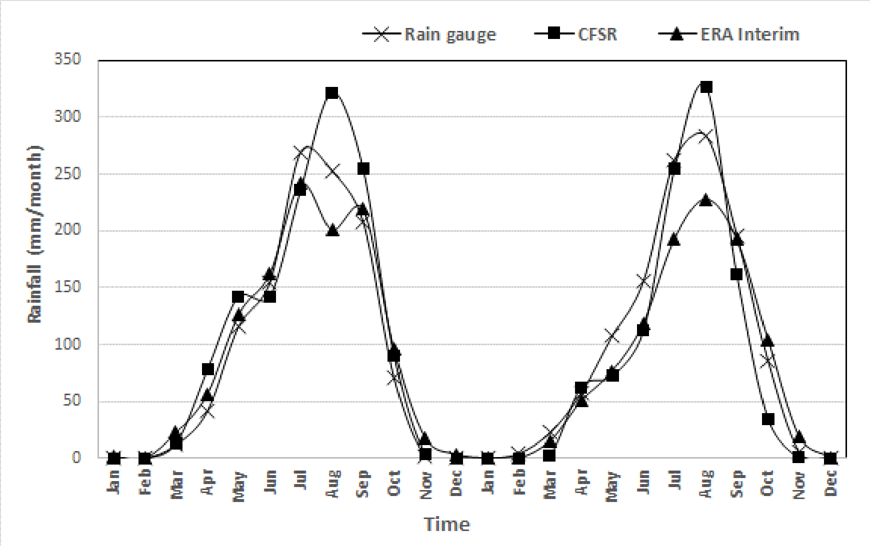


Figure A-5 Monthly decadal rainfall variation 1980 - 1999 (a) Bailli (semi-arid zone) and (b) Bekao (sudano zone)

A.4.3 Variation of rainfall with latitude

Figure A-5 shows the variation of mean annual rainfall with latitude in the study area. In general rainfall isohyets in the Lake Chad basin form parallel east to west lines. Both reanalysis datasets are able to reproduce the rainfall gradient in the catchment with rainfall increasing as latitude decreases southwards. Annual rainfall is the highest in the south of the Logone catchment at the source of the Logone River in Cameroun on the Adamawa Plateau (Loth and Acreman 2004). Rainfall is lower in the north because of the Saharan anticyclone and dry continental trade winds that blow as far south as 5° N (Molua and Lambi 2006). The Adamawa plateau acts like a shield preventing progress of the Atlantic air masses northwards and forcing the Intertropical Convergence Zone (ITCZ) towards the western part of Cameroun. (Ardoin-Bardin 2004; Molua and Lambi 2006). During the rainy season, the monsoon winds blow from the south and push the continental trade winds northwards. Higher rainfall during this period is indicative of the strength of the monsoon winds (Molua and Lambi 2006). Both reanalysis products could accurately capture the rainfall gradient in the catchment.

A.4.4 Statistical Analysis of monthly variation in rainfall

Although both reanalysis products generally show good correlation with monthly rain gauge data ($0.70 \leq R \leq 0.85$ and $0.60 \leq R^2 \leq 0.78$; Table A.2), some large deviations exist between the reanalysis datasets and rain gauge data. Similar values were obtained by Worqlul *et al.* (2014) in the Lake Tana Basin in Ethiopia. There are also variations in gauge rainfall measurements within the same grid box (Table A.2). For example: Mouvouday, Kalfou, Yagoua and Dana; Bailli and Bousso; Pandzangue, Bekao and Moundou located inside the same ERA Interim grid boxes respectively all produced different values after statistical correlation with rainfall from the same grid points. A similar situation was observed for Moundou and Delli; Dana and Bongor; Doukoula and Kalfou; Bekao and Pandzangue located inside the same CFSR grid boxes respectively.

The monthly bias values shown in Table A.2 indicate that, both reanalysis products generally overestimated rainfall in 68% of the stations with highest overestimation recorded in Ngaoundere for CFSR. Analysis also showed that ERA Interim had the lowest bias and MAE with average values of 2% and 6.5mm/month respectively compared to 15% and 34mm/month for CFSR.

Results of NSE as shown in Table 2 are in the range ($-1.15 \leq NSE \leq 0.56$) and ($0.11 \leq NSE \leq 0.63$) for CFSR and ERA Interim respectively indicating that both forecasting models produced modest results even though ERA Interim outperformed CFSR.

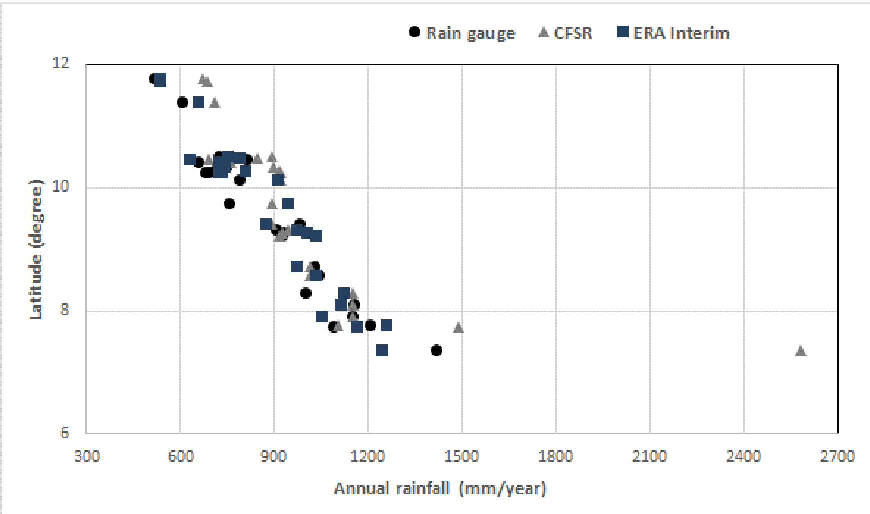


Figure A-6 Variation of rainfall with latitude in the Logone catchment

A.5 Discussion

Rainfall over/under estimation by both reanalysis products over the Logone catchment as observed in this study may be attributed to the fact that reanalysis forecast models rely upon both surface observations and satellite measurements. Rainfall in the region is highly variable and there are only few surface observation stations in Central Africa, leading to uncertainty in forecast model input. In a study of observed and simulated precipitation changes over Africa using different datasets, Maidment *et al.* (2013) attributed the large discrepancies in results observed over Central Africa to low rain gauge station density. Dee *et al.* (2011) reported that the large differences observed in precipitation estimates from ERA Interim over Central Africa were due to uncertainties as a result of sparse radiosonde coverage. The authors also attributed it to the possible presence of a substantial warm bias in the model associated with underestimated aerosol optical depth. Wang *et al.* (2016) also reported on the paucity of radiosonde observations for different reanalysis products over Central Africa.

A variable such as precipitation is not directly measured but constrained by observations used to initialize the forecast model, so the accuracy of model-generated estimates depends on the quality of the model physics as well as that of the analysis. In addition, according to Zhang *et al.* (2013), the quality of precipitation estimates from reanalysis products also depends on sea surface temperature boundary conditions, other assimilated observations and on the physical parameterization of the model.

The large discrepancy between CFSR and rain gauge data in Ngaoundere could be attributed to the complex topography in this region, as suggested by Zhang *et al.* (2013) in southern Africa. The Intertropical Convergence Zone (ITCZ) creates a complex and unpredictable movement of air masses in the Sudano-Sahelian region making it difficult for the CFSR forecast model to produce accurate precipitation estimates. Furthermore, given that rainfall estimates from the two reanalysis products for the station are opposite, with CFSR producing high and ERA Interim producing low estimates, the ITCZ could be located in different positions in the two forecast models.

There are also potential errors due to the comparison being made between the rain gauge point measurement and grid point, which is the average of a grid box measuring 38km x 38km and 80km x 80km for CFSR and ERA Interim respectively. For example, grid boxes with two or more rain gauges can have significant differences in gauge measurements that can be attributed to the generally high spatio-temporal precipitation variability in the region. It could also be due to elevation differences between reanalysis grid average and the individual rain gauge station site(s). Furthermore, rain gauge measurements could also be subject to under catch, measurement errors or may not register rain showers less than 1mm; while reanalysis forecast models can produce rainfall estimates which are less than 1mm and these estimates when accumulated over a longer time scale could have a significant influence on reanalysis estimates compared to gauge data.

Wang *et al.* (2011) attributed the artefact identified in CFSR precipitation estimates during the period 1998-2000 as observed in this study to be related to possible changes in the assimilation of solar radiation and surface wind data by CFSR. It could also be due to changes in instrument(s) used for obtaining the data, faulty instrument(s), and/or recalibration of the data acquisition instrument after replacement of defective part(s).

Table A.2 Statistical performance of reanalysis datasets

Rain gauge station	CFSR					ERA Interim				
	R	R^2	Bias	MAE	NSE	R	R^2	Bias	MAE	NSE
Longone Birni	0.76	0.57	1.30	12.99	0.18	0.80	0.64	1.04	1.63	0.60
Mandalia	0.72	0.52	1.26	11.58	-0.15	0.80	0.64	0.95	2.46	0.60
Massenya	0.75	0.57	1.14	7.36	0.11	0.78	0.62	1.04	1.92	0.56
Bailli	0.81	0.65	1.20	12.12	0.45	0.70	0.49	1.04	2.31	0.41
Bousso	0.82	0.67	1.14	8.46	0.51	0.78	0.61	1.06	3.81	0.55
Maroua	0.70	0.49	0.85	10.22	0.35	0.64	0.41	0.71	19.35	0.36
Mouvouday	0.85	0.72	1.13	7.84	0.58	0.78	0.60	1.03	1.98	0.58
Yagoua	0.81	0.66	1.20	12.49	0.35	0.79	0.62	0.99	0.42	0.60
Bongor	0.81	0.66	1.26	15.60	0.38	0.79	0.63	1.12	7.48	0.56
Kalfou	0.78	0.61	1.35	20.04	0.17	0.77	0.59	1.00	0.19	0.52
Dana	0.63	0.40	1.33	18.83	-0.20	0.55	0.30	1.07	3.82	0.11
Doukoula	0.83	0.69	1.17	10.89	0.48	0.77	0.59	0.99	10.05	0.51
Deressia	0.72	0.52	1.12	7.84	0.22	0.65	0.42	1.21	13.59	0.16
Lai	0.76	0.58	0.91	7.43	0.52	0.74	0.55	0.89	8.91	0.53
Kello	0.82	0.68	1.02	1.19	0.61	0.72	0.51	1.07	5.09	0.47
Guidari CF	0.81	0.65	1.00	0.12	0.56	0.81	0.66	1.08	6.55	0.63
Donomanga	0.79	0.63	0.99	0.71	0.52	0.82	0.67	1.12	9.20	0.61
Delli	0.68	0.46	0.97	2.28	0.29	0.71	0.50	0.93	6.04	0.48
Moundou	0.81	0.66	0.99	0.96	0.57	0.75	0.57	1.01	0.49	0.54
Donia	0.80	0.64	1.24	18.70	0.34	0.78	0.62	1.22	16.64	0.50
Pandzangue	0.81	0.66	1.07	6.69	0.59	0.79	0.62	0.97	3.34	0.62
Bekao	0.81	0.65	1.00	0.21	0.55	0.78	0.60	0.91	8.44	0.59
Touboro	0.78	0.61	1.37	33.21	0.20	0.73	0.53	1.15	13.86	0.47
Baibokoum	0.75	0.56	0.91	8.69	0.52	0.72	0.52	0.95	5.03	0.51
Ngaoundere	0.81	0.66	1.82	96.96	-1.15	0.76	0.58	0.89	13.24	0.52

A.6 Conclusions

The main objectives of this study were to evaluate the accuracy of precipitation estimates from two reanalysis datasets; Climate Forecasting System Reanalysis and ERA Interim with field station rain gauge measurements, and compare how these products reproduce the monthly, annual and decadal rainfall cycle in the Logone catchment. Results obtained show that;

- Both reanalyses products could reproduce the precipitation cycle in the catchment at monthly, annual and decadal time scale and the inter-annual variability is well captured.
- Both products were also able to reproduce the rainfall gradient in the catchment, although they overestimated rainfall in 68% of the stations across the catchment.
- At the monthly time scale both reanalysis products show good correlation with rain gauge data although differences still exist between the reanalyses datasets and rain gauge data especially for CFSR.

Results from in this study are comparable to those obtained from Africa by other researchers (Maidment *et al.* 2013; Zhang *et al.* 2013; Dile and Srinivasan 2014; Worqlul *et al.* 2014; Koutsouris *et al.* 2015) and globally (Blacutt *et al.* 2015; Fu *et al.* 2015; Krogh *et al.* 2015; De Leeuw *et al.* 2015; Sharifi *et al.* 2016) Albeit at a coarser spatial resolution, ERA Interim outperformed CFSR in this study. From these results, the application of each reanalysis product in the catchment will depend on the purpose for which it is to be used and on the spatial scale required, given that both products have the same temporal resolution.The research also shows that evaluating reanalysis products in remote locations like the Logone catchment may enable users to identify artefacts inherent in reanalysis datasets and so may enable the model developers to improve on certain aspects of the model physics and parametrisation scheme to improve the reanalysis datasets quality.

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Appendix B: Streamflow simulation using reanalysis datasets

Appendix B is based on the paper:

NKIAKA, E., N. R. NAWAZ and J. C. LOVETT. 2017. Evaluating global reanalysis datasets as input for hydrological modelling in the Sudano Sahel region. Hydrology, **4**(1), p13.

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Abstract

This paper investigates the potential of using global reanalysis datasets as input for hydrological modelling in the data-scarce Sudano-Sahel region. To achieve this, two global atmospheric reanalyses (Climate Forecasting System Reanalysis and ERA-Interim) datasets and one global meteorological forcing dataset WATCH Forcing Data methodology applied to ERA-Interim, (WFDEI). These datasets were used to drive the Soil and Water Assessment Tool (SWAT) in the Logone catchment, Lake Chad basin. Model performance indicators after calibration showed that at daily and monthly time steps, only WFDEI produced Nash Sutcliff Efficiency (*NSE*) and Coefficient of Determination (R^2) values above 0.50. Albeit a general underperformance compared to WFDEI; CFSR performed better than ERA-Interim. Model uncertainty analysis after calibration showed that more than 60% of all daily and monthly observed streamflow values at all hydrometric stations were bracketed within the 95 percent prediction uncertainty (95PPU) range for all datasets. Results from this study also show significant differences in simulated actual evapotranspiration estimates from the datasets. Overall results showed that biased corrected WFDEI outperformed the two reanalysis datasets; meanwhile CFSR performed better than ERA-Interim. We conclude that in the absence of gauged hydro-meteorological data, WFDEI and CFSR could be used for hydrological modelling in data-scarce areas such as the Sudano-Sahel region.

B.1 Introduction

Long-term and well distributed climate information is essential to enhance water resources management and to guide policies aimed addressing the consequences of climate variability and change from local to global scale (van de Giesen *et al.* 2014). This data is needed because the quantitative estimation of water balance components is important to understand the variations taking place at catchment/global level (Buma *et al.* 2016). However, in many developing and arid regions of the world the assessment and management of water resources is still a major challenge due to data scarcity (Buytaert *et al.* 2012). According to Gorgoglione *et al.* (2016), the difficulty in collecting data in semi-arid and other remote areas can be attributed to several reasons: (i) lack of reliable equipment, (ii) absence of good archiving system and software to store and process the data, and absence of funds to organize data collection campaigns. Another challenge in these regions is that even when data is collected and archived, the effort and money required to access them can be quite substantial (Liu *et al.* 2008). Hydrological models are designed to fill some of these gaps, and their application to enhance water resources management is widely acknowledged (Worqlul *et al.* 2014).

Rainfall is one of the most important inputs used to drive hydrological models; hence it is important to obtain rainfall data of sufficient temporal and spatial resolution. Nevertheless, due to the high spatiotemporal variability of rainfall, it can only be accurately captured by a dense network of rain gauge stations (Fuka *et al.* 2013). However, most often, rain gauges may be located outside the area of interest or could exhibit significant gaps in spatial coverage especially in remote and ungauged areas (Liu *et al.* 2008).

Current advances in remote sensing offer many advantages, as satellites observing the Earth have generated potentially useful data that can be used to improve water resources management. Even so, satellite data is usually developed for application in large areas e.g. at continental or global scale. Therefore, its application at catchment scale for hydrological modelling requires further downscaling, transformation or interpolation which may increase uncertainties in the data (Skinner *et al.* 2015).

To overcome this challenge, multiyear global gridded representations of weather known as reanalysis datasets are now available. Examples of widely used reanalysis datasets include: National Centers for Environmental Prediction (NCEP)/National Center for Atmospheric Research (NCAR), Climate Forecasting System Reanalysis (CFSR) (Saha *et al.* 2014), European Center for Medium-Range Weather Forecasts (ECMWF) ERA-Interim (Dee *et al.* 2011) and Modern-Era Retrospective Analysis for Research and Applications (MERRA) (Rienecker *et al.* 2011). However, it has been shown that significant differences exist in precipitation estimates from these products

(Lorenz and Kunstmann 2012). Lorenz and Kunstmann (2012) asserts that, the quality of precipitation estimates from reanalyses datasets depends on the geographic location, especially in tropical regions. Furthermore, a recent study Essou *et al.* (2016) demonstrated that the performance of reanalysis datasets may vary from one climatic zone to another.

To address the issue of bias inherent in reanalysis products; global forcing datasets have been developed using post processing techniques (e.g., bias correction) based on observations (Weedon *et al.* 2014). An example of such bias corrected dataset is the WATCH Forcing Data methodology applied to ERA Interim (WFDEI) (Weedon *et al.* 2014).

Another issue often overlooked in most studies evaluating the performance of reanalysis datasets in hydrological modelling is the impact of spatial resolution of each dataset on the quality of the simulated streamflow. In fact, the effect of rainfall spatial variability on streamflow and water balance components have been shown to be significant in catchments with high spatial variability (Zhao *et al.* 2013). Lobligeois *et al.* (2014) in their study demonstrated the importance of spatial representation in areas subjected to high spatial variability in rainfall. Given that the distance between reanalysis grid points is quasi uniform, these datasets could be used to investigate the impact of rainfall spatial variability on hydrological processes such as streamflow and evapotranspiration in large catchments.

Recently, reanalysis datasets have been used as input for hydrological modelling in many studies with different degrees of successes recorded. For example, Essou *et al.* (2016) used CFSR, ERA-Interim, MERRA and WFDEI as input for streamflow simulation using a conceptual model in several watersheds in the US and concluded that these datasets had good potential to be used for hydrological modelling. Monteiro *et al.* (2015) used CFSR and WFDEI to drive the Soil and Water Assessment Tool (SWAT) for hydrological modelling in the Tocantins catchment in Brazil and asserted that WFDEI outperformed CFSR in their study area. Andersson *et al.* (2015) used ERA-Interim and WFDEI as input to drive the hydrological catchment model (HYPE) in Europe and Africa. They concluded that WFDEI improved streamflow simulation compared to Watch Forcing data methodology applied to ERA-40. Krogh *et al.* (2015) used CFSR and ERA-Interim to drive the Cold Regions Hydrological Model (CRHM) in the upper Baker river basin in Chile and concluded that CFSR simulated streamflow better than ERA-Interim. These numerous studies suggest that reanalysis datasets could be used for hydrological modelling in data scarce regions. Albeit widespread hydro-meteorological data scarcity in Africa in general and the Sudano-Sahel region in particular; the use of reanalyses datasets for hydrological modelling in this area remains largely unstudied.

The Logone catchment presents special attributes for the evaluation of reanalysis datasets because it is located at the transition zone between the Sudano and Sahel areas where rainfall is highly variable both in space and time (Nkiaka *et al.* 2016a). Furthermore, like most catchments in the region, the Logone suffers from acute observational data scarcity. Given that the performance of reanalysis products in hydrological modelling is largely determined by the quality of the precipitation estimates, (Krogh *et al.* 2015; Monteiro *et al.* 2015; Essou *et al.* 2016) recommend that the correlation between observed rainfall and reanalysis precipitation estimates should be assessed before the latter is used as input for hydrological modelling. In a previous study in the catchment, Nkiaka *et al.* (2016b) evaluated the quality of precipitation estimates from CFSR and ERA-Interim against observed monthly rainfall covering the period 1979-2002 and concluded that, precipitation estimates from both reanalyses products could reproduce the seasonal rainfall cycle in the catchment albeit significant variability in the data.

The objectives of this study were; (i) to evaluate the ability of two reanalysis datasets; CFSR and ERA-Interim and one bias corrected global meteorological forcing dataset WFDEI to be used as input to drive the SWAT model in the Logone catchment; and (ii) to evaluate the impact of reanalysis spatial resolution on the quality of simulated flows. This study will be useful in validating the use of reanalysis datasets in data scarce catchments subject to high spatial rainfall variability. In addition, Siam *et al.* (2013) have argued that, driving hydrological models with reanalyses datasets to reproduce observed streamflow represents one of the most accurate ways to evaluate how the hydrological cycle is simulated by reanalysis forecast models. Including WFDEI will permit us to assess the impact of bias correction on the performance of ERA-Interim. It is not our intention in this study to judge the quality of each reanalysis dataset or recommend the use of one product over another. This choice depends on personal preference because the performance of each reanalysis product varies from one region to another and one from climatic zone to another as mentioned earlier. A limitation of this study is the absence of daily rain gauge data that could also be used to drive SWAT to compare the performance of the reanalysis datasets against gauge data in simulating streamflow.

B.2 Materials and Methods

B.2.1 Study area

The Logone catchment (Figure B-1) is a transnational catchment shared by Cameroun, Chad and Central Africa Republic, with an estimated area of about 86,500 km^2 lying between latitude 6˚-12˚N and longitude 13˚-17˚E. There are two National Parks in the catchment (Waza and Kalamaloue), with high concentration of wildlife (Loth and Acreman 2004). The Logone River has its source in Cameroun through the Mbere and Vina rivers from the north eastern slopes of the Adamawa Plateau. In Lai, it is joined by the Pende River from Central Africa Republic and flows for about 1000km in a South-North direction with an elevational range from 300 masl in the north to about 1,200 masl in the south. The basin topography, apart from some local mountains in the south is very flat with an average slope of less than 1.3%. The catchment has a semi-arid climate in the north where annual rainfall varies between 600-900 mm/year and Sudano climate in the south where annual rainfall varies between 900-1400 mm/year. The climate is also characterized by high spatio-temporal variability in rainfall controlled by the oceanic regime from the south and the continental regime from the north (Nkiaka *et al.* 2016a). Almost all rain falls during the rainy season from May/June to September/October with high spatial and temporal variability and mean annual temperature is about 28°C (Loth and Acreman 2004).

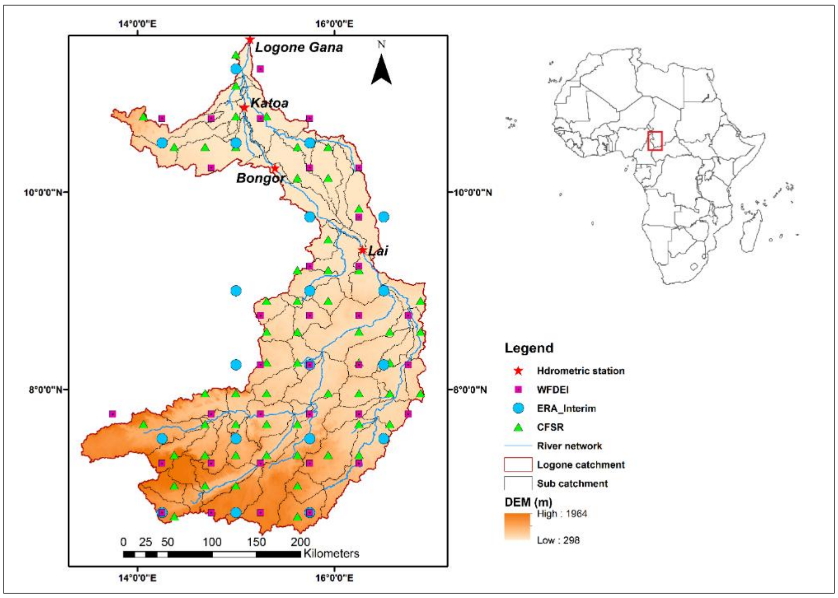


Figure B-1 Map of the study area showing the Logone river network, sub catchments and reanalysis grid points used for streamflow simulation

B.2.2 Data sources

B.2.2.1 Observed river discharge data

Daily river discharge measurements were obtained from the Lake Chad Basin Commission (LCBC) covering the period 1983-1997 at four discharge stations. Gaps in the river discharge data were filled using Artificial Neural Networks Self-Organizing Maps (ANN-SOM) (Nkiaka *et al.* 2016c).

B.2.2.2 Spatial datasets

Digital Elevation Model (DEM) data obtained from Shuttle Radar Topographic Mission (SRTM) at a spatial resolution of 90 m was used for catchment delineation. Land cover/use maps were obtained from Climate Change Initiative Land Cover (CCI-LC) at a spatial resolution of 300m. The land cover was reclassified in the ARCSWAT interface according to model input requirements. Soil data was obtained from the Food and Agricultural Organization (FAO), Harmonize World Soil Database (HWSD) at a spatial resolution of 1km.

B.2.3 Reanalysis data

A reanalysis project involves the reprocessing of observational data spanning an extended historical period. “It makes use of a consistent modern analysis system, to produce a dataset, that to a certain extent can be regarded as a "proxy" for observation with the advantage of providing coverage and time resolution often unobtainable with normal observational network” (Morse *et al.* 2013). It is generated with a data assimilation system combining observations with a numerical weather prediction model. For the entire reanalysis period, the model physics remain unchanged in the forecast model for consistency of the output data. The reanalysis consequently provides a physical picture of the global climate over a period during which observational data are available.

B.2.3.1 CFSR

The Climate Forecast System, NCEP version 2 is an upgraded version of CFS version one (CFSv1). It was first developed as part of the Climate Forecast System by NCEP in 2004 with quasi-global coverage, fully coupled atmosphere-ocean-land model used by NCEP for seasonal prediction (Saha *et al.* 2014). CFSR has a 3D-variational analysis scheme of the upper-air atmospheric state with 64 vertical levels with a horizontal resolution of 38km spanning the period 1st January 1979 to present day (Saha *et al.* 2014).

B.2.3.2 ERA-Interim

ERA-Interim is the latest global atmospheric reanalysis produced by the European Centre for Medium-Wave Forecasts (ECMWF) and covers the period from 1 January 1979 to present day (Dee *et al.* 2011). The core component of the ERA-Interim data assimilation system is the 12-h 4D-variational analysis scheme of the upper-air atmospheric state, which is on a spectral grid with triangular truncation of 255 waves (corresponding to approximately 80 km) spatial resolution and a hybrid vertical coordinate system with 60 vertical levels.

B.2.3.3 WFDEI

The WATCH Forcing Data methodology applied to ERA-Interim (WFDEI) dataset (Weedon *et al.* 2014) is produced from Watch Forcing Data (WFD) and ERA-Interim reanalysis via sequential interpolation to a 0.5° resolution, elevation correction and monthly-scale adjustments based on CRU TS3.1/TS3.21 and GPCCv5/v6 monthly precipitation observations for 1979–2012.

Details of the three products can be found in (Saha *et al.* 2014; Dee *et al.* 2011; Weedon *et al.* 2014) for CFSR, ERA-Interim and WFDEI respectively. For the Logone catchment, the reanalysis datasets were obtained for an area bounded by latitude 6°-12.0°N and longitude 13°-17.25°E from the Texas A&M University for CFSR, ECMWF for ERA Interim and Lund University for WFDEI. All variables were obtained at a daily time step with spatial resolution of 0.312° (~38 km), 0.50° (~55 km) and 0.75° (~80 km) for CFSR, WFDEI and ERA-Interim respectively hereafter referred to as high, medium and low resolution.

B.2.4 Model setup

River discharge at various locations along the Logone River was simulated using the SWAT (Gassman *et al.* 2014) in the ArcSWAT interface. SWAT is one of the most widely used river basin–scale models worldwide, applied extensively for solving a broad range of hydrologic and environmental problems (Gassman *et al.* 2014).

In this study, we focus only on water quantity simulation accomplished through two steps: (i) the land phase of the hydrological cycle which controls the amount of water transferred to the main channel from each sub catchment; and (ii) the routing phase which involves the movement of water through the channel network to the outlet. The hydrologic cycle in the land phase of the model is simulated using the water balance equation as:

$$SW_t = SW_0 + \sum_{i=1}^{n}(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}) \qquad (B.1)$$

SW_t is the final soil water content (mm), SW_0 is the initial water content (mm), R_{day} is the amount of precipitation on day i (mm) Q_{surf} is the amount of surface water runoff on day i (mm), E_a is the amount of actual transpiration on day i (mm), W_{seep} is the amount of water entering the vadose zone from the soil profile on day I (mm) and Q_{gw} is the amount of return flow on day i (mm).

Details of equations and methods used to estimate various hydrological components can be found in (Neitsch *et al.* 2011). During model development, SWAT divides a catchment into sub catchments using digital elevation model (DEM) data. The spatial distribution of hydrological processes over each sub catchment is represented through hydrologic response units (HRUs), used to further divide the sub catchments into smaller units. The HRU can be defined as a land area within a sub catchment with the same land use class, soil type, slope class and management combinations.

While building the model, an attempt was made to maximize the number of grid points used for streamflow simulation using CFSR as the reference dataset because of its high spatial resolution (0.312°) compared to the other two. Different threshold areas were tested for catchment delineation. Reducing the threshold area to 500 km^2 did not increase the number of reanalysis grid points selected while increasing it to 1000 km^2 reduced the number to only 45. An optimum threshold area of 750 km^2 was finally used to delineate the catchment into 66 sub catchments. Threshold values for creation of hydrological response units (HRUs) were set at 10%, 15%, and 15% for land use, soil and slope classes respectively creating 266 HRUs. A separate model was developed for each of the reanalysis datasets using the same threshold values.

The Hargreaves method for estimating potential evapotranspiration (PET) was applied owing to the less onerous data demands (minimum and maximum temperature) compared to the alternative Priestley-Taylor and Penman-Monteith methods. Surface runoff was calculated using the Soil Conservation Service's curve number (CN2) method while flow routing was accomplished through the variable storage method (Neitsch *et al.* 2011).

B.2.5 Model calibration and uncertainty analysis

The model was calibrated in the SWAT Calibration and Uncertainty Program software (SWAT-CUP) using the Sequential Uncertainty Fitting algorithm (SUFI-2) (Abbaspour 2008). During the calibration process in SUFI-2, parameters can be changed using either the relative or absolute parameter ranges. Each parameter value can be modified either by replacement of the initial value, addition of absolute change or multiplication by a relative change factor to obtain the optimum value. Given the multiple sources of uncertainties inherent in the use of hydrological models; the advantage of using SWAT-CUP is that these are taken into consideration during model calibration (Abbaspour 2008). As model parameters often depend on the input data used to drive the model which is susceptible to seasonal variation (Pathiraja *et al.* 2016); the calibrated parameter values in SWAT-CUP are given within a range to represent this variability. Model calibration consisted of running 500 simulations in each iteration with the parameter set shown in Table 1. The best parameter range obtained in the first iteration was then substituted and used in the next iteration for each of the five iterations performed. This was done for the three different datasets at daily and monthly time steps. To obtain the values of the different water balance components such as evapotranspiration, the simulation number that produced the best model output was used to calculate the water balance for the whole catchment.

Table B.1 Description of model parameters and parameter ranges used for calibration. The ranges are given for the three datasets used in the study

Parameter	Description	Model process	Parameter range used
CN2[a]	Curve number for moisture condition II	Surface runoff generation. High values lead to high surface flow	-0.5 – 0.15
GW_Delay	Groundwater delay	Groundwater (affects groundwater movement). It is the lag between the time water exits the soil profile and enters the shallow aquifer	30 – 250
GW_REVAP	Groundwater “revap” coefficient	Affects the movement of water from the shallow aquifer to the unsaturated soil layers. Low values lead to high baseflow	0.10 – 0.40
GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur	Groundwater (when reduced streamflow increases)	20 – 95
Revapmn	Threshold depth of water for "revap to occur" (mm)	Groundwater (when increased, base flow will increase)	0 – 20
Rchrg_DP	Deep aquifer percolation	Groundwater (the fraction of percolation from the root zone which recharges the deep aquifer. Higher values lead to high percolation).	0.05 – 0.50
Ch_K2	Hydraulic conductivity of main channel	Channel infiltration	1.69 – 6.0
ESCO	Soil evaporation compensation factor	Controls the soil evaporative demand from different soil depth. High values lead to low evapotranspiration	0.25 – 0.95
SOL-AWC[a]	Available Water Capacity or available is calculated as the difference between field capacity the wilting point	Groundwater, evaporation. When increased less water is sent to the reach as more water is retained in the soil thus increasing evapotranspiration	-0.04 – 0.04
ALPHA_BF	Base flow alpha factor	Shows the direct index of groundwater flow response to changes in recharge	0.3 – 0.9
Surlag	Surface runoff lag coefficient	Surface runoff	1.5 – 5.0

[a] Parameter value is multiplied by (1 + a given value). For example if CN2 = 85 then the calibrated CN2 value will be (1 +(-0.5)) * 85 = 0.5* 85 = 42.5

The model was evaluated using three different evaluation statistics: (i) the Nash Sutcliffe Efficiency (*NSE*); (ii) coefficient of determination (R^2); and (iii) Percent Bias (*PBIAS*). The *NSE* is used to assess the predictive capacity of the model and measures how well the observed and simulated flows match. Its value range from -∞ - 1 with values close to 1 indicating high model performance. The R^2 measures how well the observed data is correlated to the simulated data and varies from 0 - 1 with values closer to 1 also indicating high model performance. *PBIAS* indicates the average tendency of the simulated flows to be over/underestimated than observed flows with absolute low values indicating accurate model simulation. Positive values indicate model underestimation while negative values indicate overestimation. According to (Moriasi *et al.* 2007), the results of the calibrated model may be considered to be satisfactory if *NSE*>0.50, R^2>0.60 and *PBIAS* ±25%.

The degree of uncertainty in the calibrated model(s) was quantified using the *p-factor* and *r-factor*. The *p-factor* represents the percentage of observed streamflow bracketed by the 95% prediction uncertainty (95PPU) while the *r -factor* is the average width of the 95PPU. The 95PPU is calculated at the 2.5% and 97.5% confidence interval of observed streamflow obtained through Latin hypercube sampling. In SUFI-2, the goal is to minimize the width of the uncertainty band and enclose as many observations as possible because these observations are a result of all processes taking place in the catchment (Abbaspour 2008). The *p-factor* can vary between 0 and 1 while the ideal value for *r -factor* is 0 indicating that there is no uncertainty in the model outputs. However, an *r –factor* of 0 will indicate that fewer flow observations were included in the 95PPU band.

Given that the goal of this study was to evaluate how well each reanalysis dataset was able to simulate streamflow as closely as possible to the observed, all parameters that influence this process, were calibrated. Evapotranspiration (ESCO); surface runoff (CN2, Surlag, Ch_K2); groundwater exchange (Rchrg_DP, GWQMN, GW_REVAP, REVAPMN, GW_DELAY, ALPHA_BF) and infiltration (SOL_AWC). Furthermore, since this study objective did not include evaluation of alternative scenarios for which it would be necessary to establish the performance limits of different parameter sets e.g. by validating the parameter set(s) using independent observations, the entire period of the available streamflow record was used for calibration. The advantage of this approach is that, longer input time series are included in the simulation with the possibility of capturing long term trends and variability as simulated by reanalysis forecast models. Auerbach et al. (Auerbach *et al.* 2016) used a similar approach to evaluate the performance of CFSR dataset as input for hydrological modelling in the tropics. Furthermore, the parameters range obtained during model over this long time scale could be used for climate change impact assessment in the catchment. The model was calibrated from 1980 to 1997 at daily and monthly time steps using the first three years as warm-up period. This calibration was done at Logone Gana, Katao, Bongor and Lai hydrometric stations (Figure B-1).

B.3 Results

The optimum threshold area used for delineating the catchment into different sub catchments was 750 km^2. Using this area 57, 34 and 19 reanalysis grid points were selected for CFSR, WFDEI and ERA Interim respectively (Figure B-1).

Figure B-2 shows the variability in annual rainfall from the three datasets used in this study. It can be observed from the figure that the variability in the datasets is not the same because maximum and minimum rainfall occur in almost different years except in a few cases when all the datasets produced maximum/minimum rainfall in the same year e.g. 1985, 1988 and 1992. Annual rainfall from WFDEI varies between 1000 – 1300 mm/year, CFSR varies between 900 – 1550 mm/year and ERA-Interim varies between 750 – 1650 mm/year. Overall the analysis showed that the variability is highest for ERA-Interim followed by CFSR while WFDEI has lowest variability in annual rainfall. The annual average rainfall in the catchment as simulated by SWAT model for the three datasets was 1237 mm, 1240 mm and 1047 mm for WFDEI, CFSR and ERA-Interim respectively indicating that ERA-Interim recorded the lowest amount of rainfall in the catchment for the period under study.

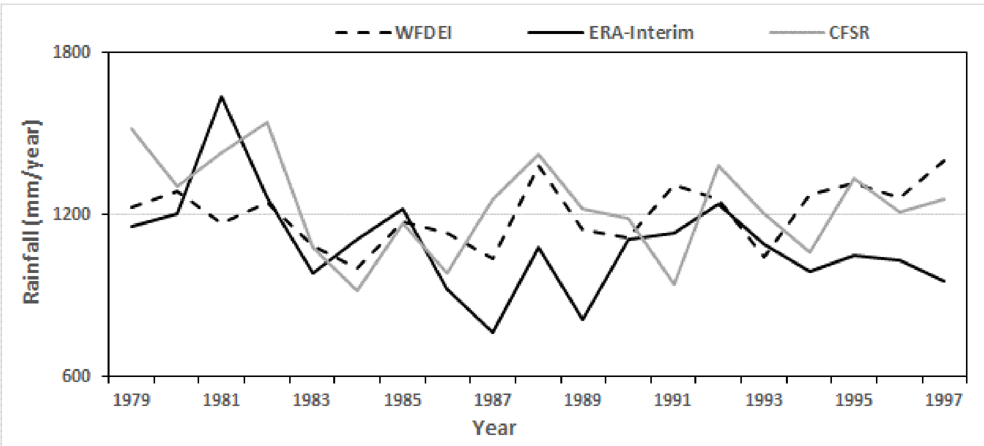


Figure B-2 Reanalysis annual rainfall variability in the Logone catchment

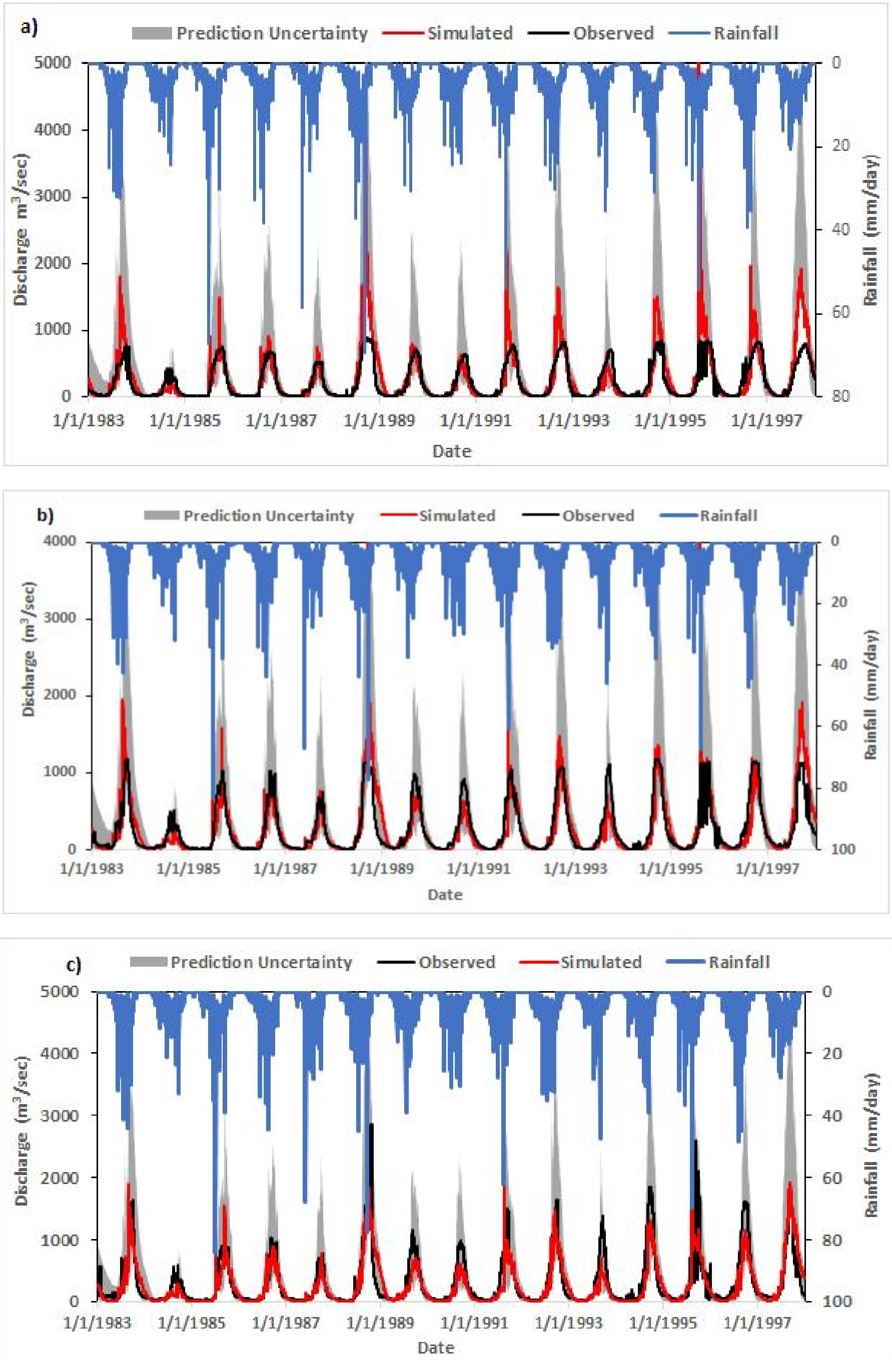
Results of model calibration are shown in Table B.2 for daily and monthly time steps respectively. It can be observed from the table that only WFDEI dataset produced *NSE* and R^2 values considered to be satisfactory according to Moriasi et al. (Moriasi *et al.* 2007) model evaluation criteria at both time steps for most hydrometric stations. CFSR and ERA-Interim both produced unsatisfactory results because most *NSE* values fall below the minimum threshold although the performance of the former was better compared to the latter. Generally, it was observed that there was a considerable improvement in *NSE* values at the monthly time step compared to daily for all datasets. For example, *NSE* values for WFDEI data improved from a range of 0.05 - 0.66 to 0.43 - 0.77 while that of CFSR improved from a range of -0.67 – 0.43 to -0.43 – 0.59. Despite a general under performance compared to WFDEI, CFSR registered negative *NSE* values at both time steps only at one hydrometric station (Logone Gana).

Table B.2 Results of model calibration ata daily and monthly time steps

Time step	Evaluation criteria	WFDEI				CFSR				ERA Interim			
		Gana	Katoa	Bongor	Lai	Gana	Katoa	Bongor	Lai	Gana	Katoa	Bongor	Lai
Daily	NSE	0.05	0.58	0.66	0.57	-0.67	0.17	0.43	0.31	-3.97	-1.54	-0.59	-0.56
	R2	0.64	0.68	0.68	0.6	0.65	0.62	0.57	0.51	0.47	0.44	0.38	0.31
	PBIAS (%)	-15.2	2.7	16.6	22.7	-74.5	-51.7	-32.3	-42.0	-146.1	-109.6	-81	-78.7
	p-factor	0.61	0.64	0.6	0.68	0.78	0.80	0.81	0.78	0.63	0.65	0.66	0.62
	r-factor	1.69	1.3	1.02	0.89	2.47	1.87	1.48	1.46	3.78	2.58	2.01	1.73
Monthly	NSE	0.43	0.75	0.77	0.67	-0.28	0.39	0.59	0.49	-3.12	-1.17	-0.38	-0.31
	R2	0.73	0.77	0.8	0.73	0.74	0.71	0.68	0.61	0.52	0.48	0.44	0.37
	PBIAS (%)	-16.2	3.5	17.7	23.6	-66.9	-45.4	-26.8	-36.6	-163.3	-125.5	-94.8	-91.4
	p-factor	0.86	0.88	0.81	0.83	0.68	0.73	0.78	0.74	0.64	0.66	0.67	0.63
	r-factor	1.65	1.26	1	0.87	2.04	1.55	1.25	1.23	3.41	2.6	2.09	1.86

The *PBIAS* values obtained also showed that only WFDEI was able to produce values that fall within the acceptable limits while results from the other two datasets show a consistent over estimation of annual discharge throughout the simulation period at all hydrometric stations.

Results further show that all the datasets were able to replicate the streamflow seasonal cycle at all hydrometric stations. This follows the finding of Nkiaka et al. (Nkiaka *et al.* 2016b) who showed that CFSR and ERA-Interim precipitation estimates could replicate the seasonal cycle of rainfall in the catchment. However, from the streamflow hydrographs shown in Figures (B-3 to B-6) it can be observed that WFDEI and CFSR were able to simulate low flows (baseflow) throughout the period under study while ERA-Interim overestimated low flows in most years during the same period. Apart from a few cases of overestimation, the WFDEI dataset was able to simulate peak discharges at Logone Gana hydrometric station but consistently underestimated at other stations. Although there were a few cases of overestimation and a general underperformance compared to WFDEI; CFSR was able to simulate peak flows at most hydrometric stations compared to WFDEI and ERA-Interim (Figure B-5). Only daily streamflow hydrographs for WFDEI are shown herein. Comparing the results of the other two reanalysis products showed that CFSR outperformed ERA-Interim. ERA-Interim consistently underestimated streamflow in 1987, 1989 and from 1994-1997 (Figure B-6). This underestimation of discharge by ERA-Interim follows the general underestimation of average rainfall in the catchment during these years.



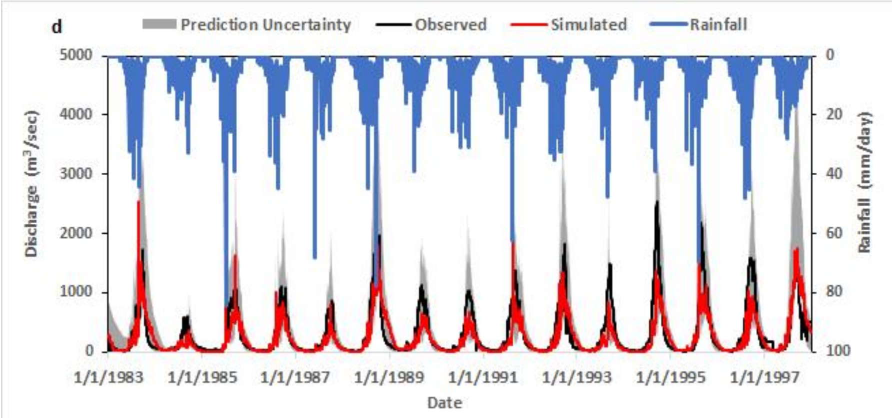
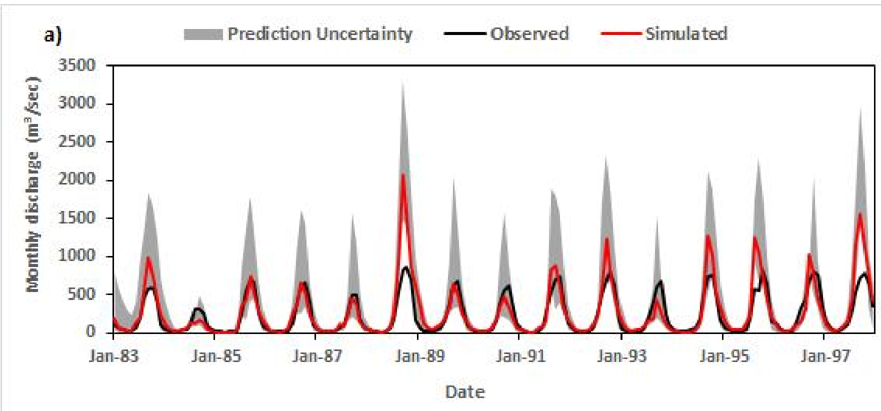


Figure B-3 WFDEI daily hydrographs for observed and simulated flows at (a) Logone Gana, (b) Katoa, (c) Bongor and (d) Lai

From Table B.2 and Figures B-3 to B-6, the *p-factor* values obtained indicate that more than 60% of observed streamflow values at all the hydrometric stations were bracketed within the 95PPU band at both time steps for all the datasets although CFSR outperformed WFDEI and ERA-Interim at daily time step. At the monthly time step, WFDEI outperformed the other two datasets with more than 80% of observed streamflow bracketed within the 95PPU band. Nevertheless, *r-factor* values obtained for CFSR and ERA-Interim as shown by Figures B-5, B-6 and Table B.2 indicate that the uncertainty band for these datasets was much wider compared to that of WFDEI. This suggest that streamflow simulated using WFDEI dataset had the lowest level of uncertainty followed by CFSR while ERA-Interim produced the highest uncertainty.



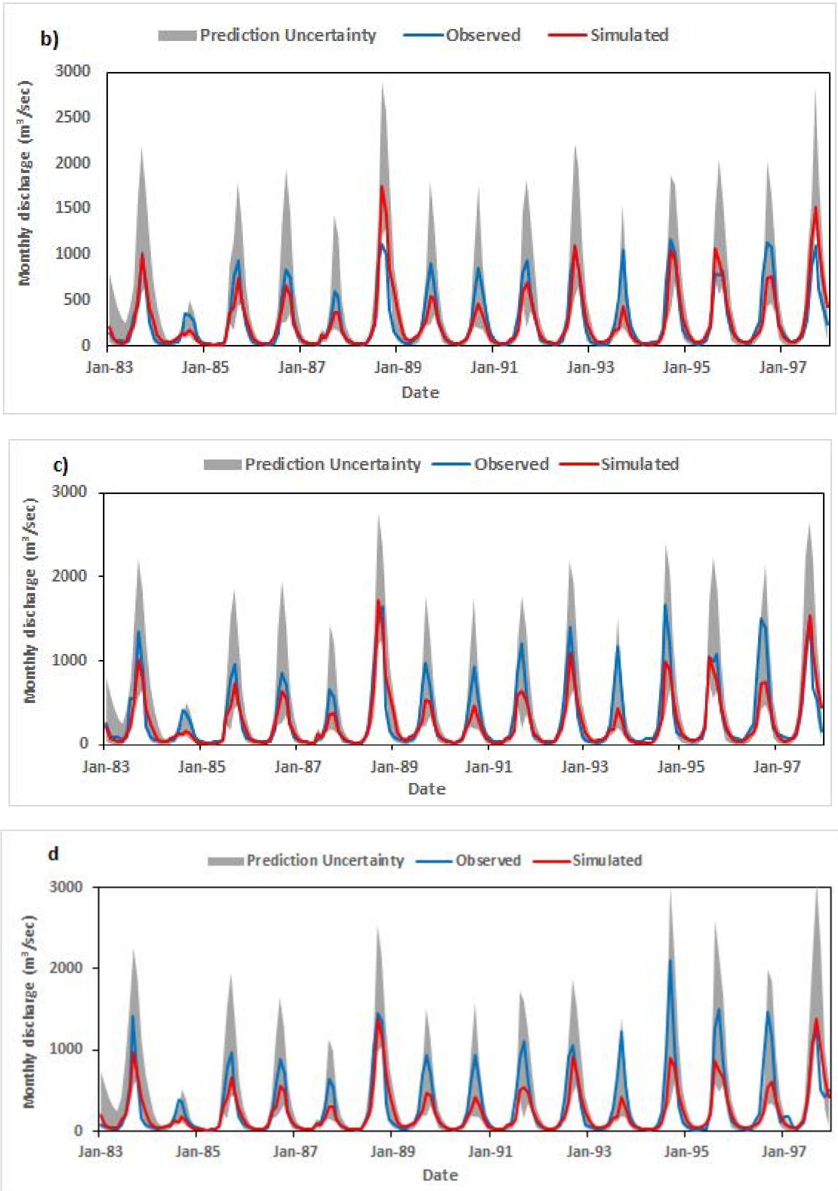


Figure B-4 WFDEI monthly hydrographs for observed and simulated flows at (a) Logone Gana, (b) katoa, (c) Bongor and (d) Lai

Regarding the impact of spatial resolution of reanalysis datasets on streamflow simulation, results showed that WFDEI which has a lower spatial resolution (0.5°) compared to CFSR (0.312°) performed better than the latter in streamflow simulation given that the calibration results produced by the WFDEI are better than those of CFSR. Furthermore, the PBIAS values showed that CFSR with fine resolution compared to WFDEI consistently overestimated simulated streamflow during the period under study.

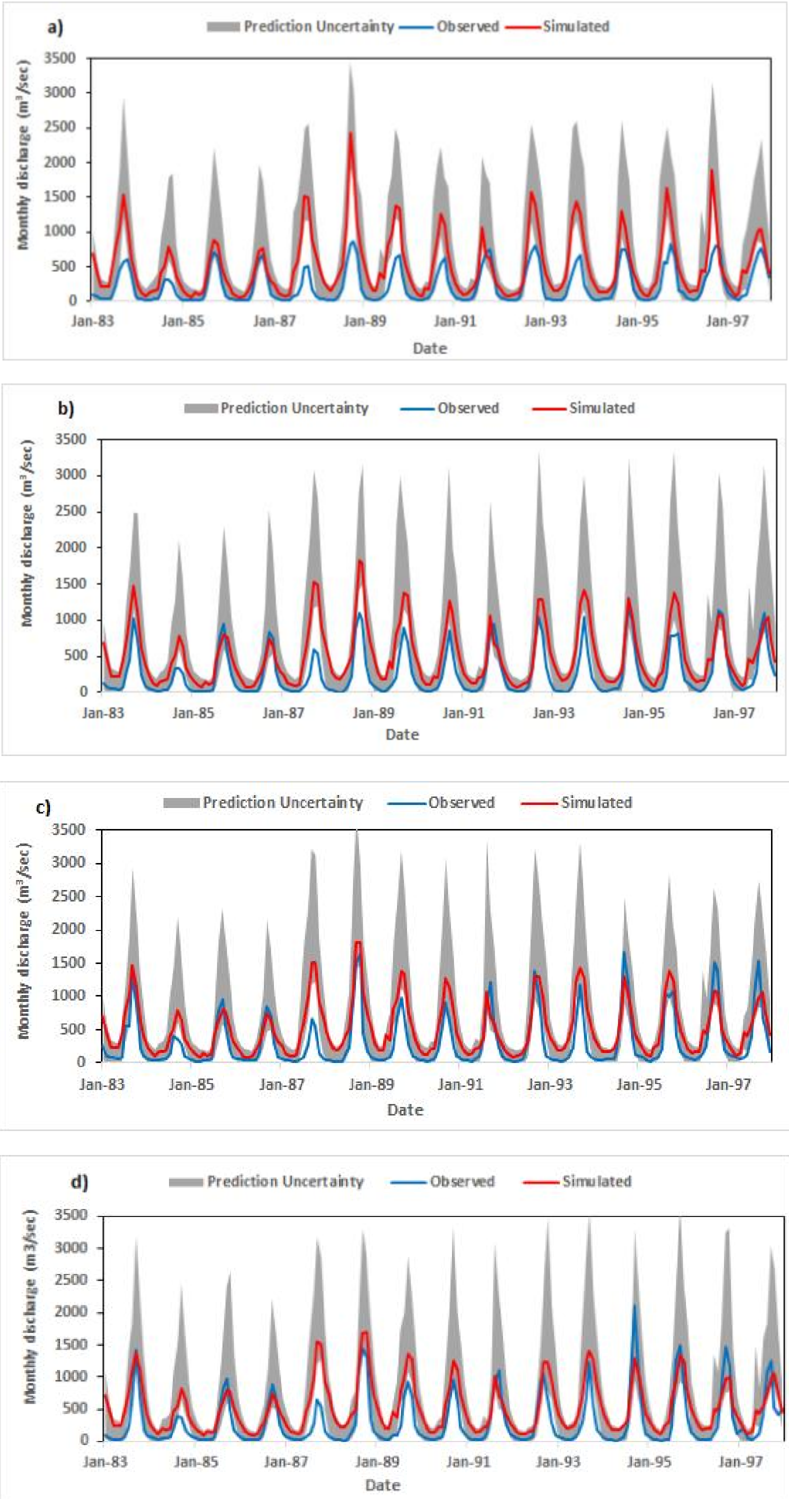


Figure B-5 CFSR monthly hydrographs for observed and simulated flows at (a) Logone Gana, (b) Katoa, (c) Bongor and (d) Lai

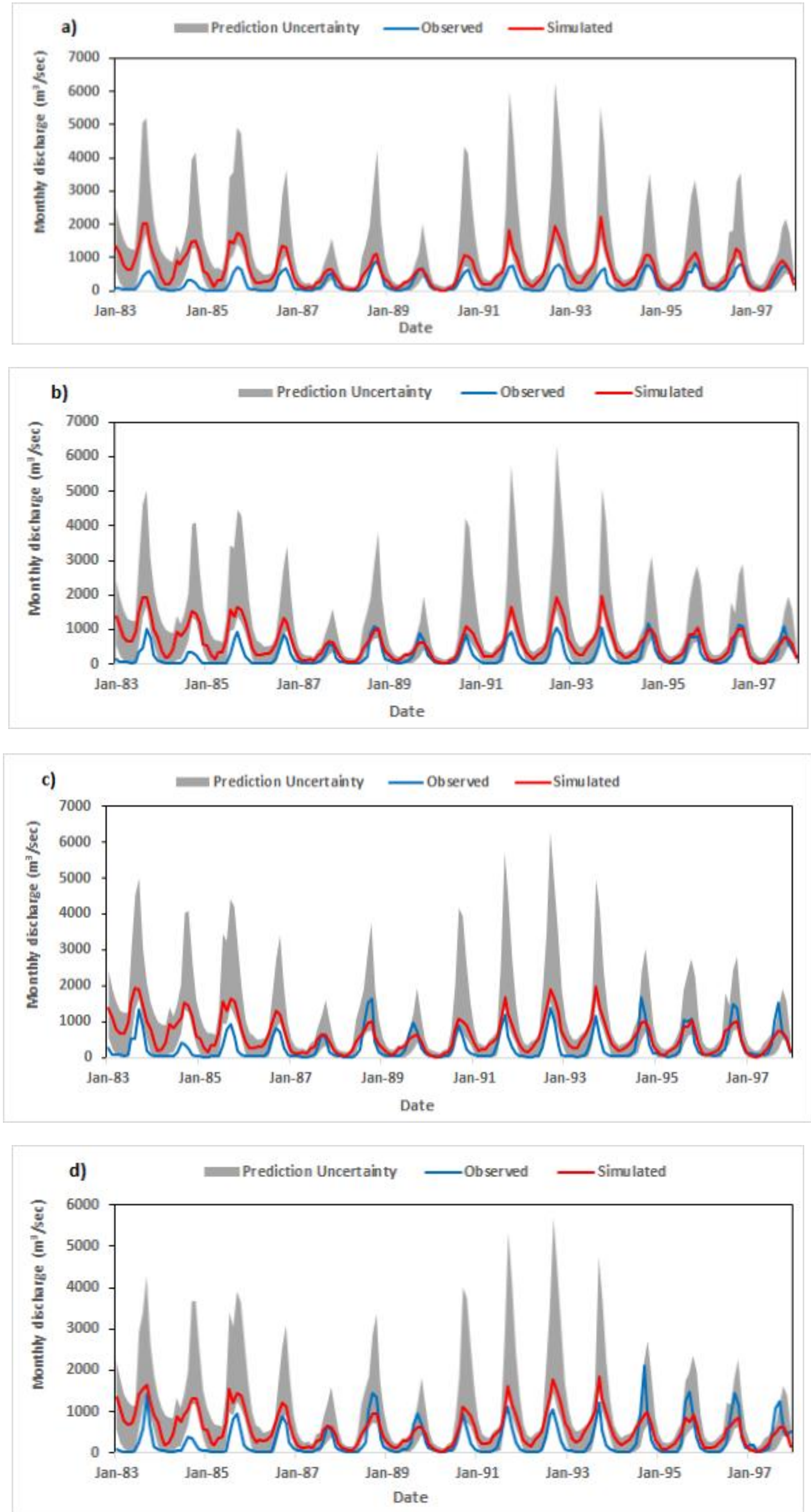


Figure B-6 ERA-Interim monthly hydrographs for observed and simulated flows at (a) Logone Gana, (b) Katoa, (c) Bongor and (d) Lai

Analysis of water balance components showed that 74%, 65% and 58% of total rainfall received in the catchment was lost through evapotranspiration for WFDEI, CFSR and ERA-Interim respectively. Compared to the amount of rainfall received in the catchment, the evapotranspiration estimates from WFDEI compare well with the results of (Ollivier *et al.* 2014; Giertz *et al.* 2006) obtained in the Ouemé river basin which is located in the same latitudinal zone with the Logone catchment.

B.4 Discussion

B.4.1 Selection of grid points

During the selection of grid points used as meteorological stations input in SWAT, the model selects each grid point depending on its proximity to the centroid of the sub catchment (Neitsch *et al.* 2011). When low resolution reanalysis data is used to drive SWAT, the possibility of the model locating a grid point in each sub catchment may be reduced. This explains why many grid points (57) were selected for CFSR because of its high spatial resolution which is almost two times that of WFDEI with (34) grid points and three times that of ERA Interim (19) grid points. Even so, not every sub catchment had a different grid point because only (57) grid points were selected for CFSR instead of 66 to correspond to the number of sub-catchments in the catchment.

B.4.2 Model evaluation

Results of model evaluation indices showed that WFDEI had the best performance among the three datasets. This is not surprising given that WFDEI had the best rainfall input among three datasets evaluated because of reduced variability in rainfall estimates. This demonstrates the importance of post-processing or bias correcting global reanalysis datasets before using them for hydrological modelling. The post-processing reduces the uncertainty in the rainfall data thus leading to better streamflow simulation. We therefore conclude that WFDEI outperformed the other two datasets (CFSR and ERA-Interim) in simulating streamflow in the Logone catchment due to reduced uncertainty in the rainfall estimates from this dataset as shown in Figure 2. These results are similar to those obtained by (Andersson *et al.* 2015; Krogh *et al.* 2015) who reported that WFDEI improved streamflow simulation compared to other global reanalysis datasets in their respective study areas. Meanwhile, Krogh *et al.* (2015) asserted that CFSR outperformed ERA-Interim in streamflow simulation in the Patagonia basin in South America.

Given that low flows and peak discharges were adequately simulated by WFDEI and CFSR datasets indicate that the parameter range(s) used to calibrate the model(s) can be considered to be satisfactory and cases of streamflow under/overestimation may be attributed to the uncertainty in the rainfall input used in calibrating the models or to parameter conditionality. This is because the same parameter set was used to calibrate the model in both semi-arid and Sudano areas; although the amount of rainfall received by each zone is different which has implications for parameter values used in calibrating the model.

The poor performance of ERA-Interim can be attributed to the high variability in annual rainfall produced by this dataset compared to the other two datasets. For example, Figure B-2 shows that annual rainfall produced by ERA-Interim was consistently lower compared to the other two datasets in 1987, 1989 and 1994-1997 leading to a systematic underestimation of simulated streamflow by ERA-Interim during these years. This high variability in ERA-Interim rainfall estimates may have offset the interaction among the different model parameters making it difficult to find a parameter range that could simulate streamflow above the minimum threshold limit. This suggest that rainfall input plays a significant role in model calibration because it has the potential to influence calibrated parameters as reported by (Pathiraja *et al.* 2016). Nevertheless, the significant variability in CFSR and ERA-Interim datasets in this study follow the findings of (Nkiaka *et al.* 2016b) in the Logone catchment.

B.4.3 Prediction uncertainty

The daily streamflow hydrographs with corresponding prediction uncertainty band and rainfall input shown in Figure 3 indicate that, as the variability in rainfall input increases, the values of *r-factor,* which measures the prediction uncertainty band increases as well. This indicates that rainfall input contributes significantly to increase the level of uncertainty in the simulated streamflow because as the variability in rainfall increases, the uncertainty band also increases. This suggests that, reducing the variability in the rainfall input or accurately estimating the rainfall data used for driving the model could lead to a significant improvement in simulated streamflow thereby reducing the level of uncertainty in the latter. This follows the findings of Essou *et al.* (2016) who asserted that performance of reanalysis datasets in hydrological modelling depends largely on the quality of the rainfall data.

The improved performance of model evaluation indices and improvement in model uncertainty at monthly time steps compared to daily can be attributed to the fact that, monthly rainfall is a cumulative measurement in which all the daily variability within the month is summed, thus reducing the variability in the input data which leads to an overall improvement in model performance.

Nevertheless, it is worth noting that the contribution of model parameters to the overall uncertainty in the simulated streamflow cannot be overlooked since it is difficult to decouple the uncertainty inherent in model parameters from that of input data (Saha *et al.* 2014). It should be noted that assessing the uncertainty of model parameters was not part of this study.

The high variability in rainfall estimates from the reanalysis datasets in the study area can be attributed to the low rain gauge density and few radiosonde coverages in Central Africa (Rienecker *et al.* 2011; Maidment *et al.* 2013) used for optimization and data-assimilation in the reanalysis forecast models thus increasing the forcing uncertainty. According to Weiland *et al.* (2015), when using global reanalysis datasets for hydrological modelling, the forcing uncertainty decreases with increasing number of sampling points available for optimization and data-assimilation, suggesting that a limited number of sampling points will lead to an increased level of forcing uncertainty. Although WFDEI has fewer grid points compared to CFSR, the improvement of WFDEI rainfall estimates compared to CFSR can be attributed to the fact that this dataset is bias corrected.

B.4.4 Effects of spatial resolution

The results obtained from this study also suggest that streamflow simulation may not represent an important factor to be used for evaluating the impact of spatial resolution of reanalysis datasets as long as the average rainfall over the modelled catchment is accurately estimated. This is because in moderate size catchments like the Logone, the model integrates rainfall data from a very large area which dampens and smooths the impact of rainfall spatial variability on the catchment outflow, hence limiting the effect of spatial resolution on streamflow. Under such circumstances, the ability of the reanalysis product to produce accurate rainfall estimates in the catchment is more important than its spatial resolution. Gascon *et al.* (2015) also demonstrated that the spatial resolution of rainfall datasets had no significant impact on streamflow simulation in the Ouémé basin. These authors used rainfall datasets at spatial resolutions of 0.05°, 0.1°, 0.25° and 0.5°. Results from this study also corroborate the findings of Fu *et al.* (2011), where the authors demonstrated that, the impact of rainfall spatial resolution was insignificant for catchment sizes above 250 km^2 and negligible for catchments larger than 1000 km^2. The impact of spatial resolution on flow simulation has been shown to be scale, catchment and event characteristic-dependent (Zhao *et al.* 2013). We conclude that, the ability of the reanalysis dataset(s) to accurately produce good quality rainfall estimates in the study area can significantly improve streamflow simulation compared to the spatial resolution of the rainfall. Nevertheless, Tramblay *et al.* (2011) have shown that spatial rainfall representation is important in the simulation of flood events.

B.4.5 Simulation of evapotranspiration

The values of actual evapotranspiration estimates obtained showed that there were significant differences in the values produced by the three models. These differences in actual evapotranspiration values from the different datasets can be attributed to the different amounts of rainfall input used in simulating each model. WFDEI and CFSR produced almost the same amount of rainfall during the simulation period but there is a significant discrepancy between the actual evapotranspiration values from the two datasets. This discrepancy can be attributed to the uncertainty inherent in each of the rainfall datasets. This is because precipitation estimates can strongly influence the parameter values that control the rates and threshold of hydrological processes taking place in the catchment (Remesan and Holman 2015). Furthermore, as pointed out by Remesan and Holman (2015) our results show that the uncertainty in the rainfall estimates is conserved and propagated into streamflow and other water balance components including evapotranspiration. Although ground data was not available to compare the evapotranspiration estimates in this study, the estimates from WFDEI are acceptable given that similar values have been obtained in other catchments the region (Giertz *et al.* 2006; Ollivier *et al.* 2014). We conclude that the estimation of actual evapotranspiration and other water balance components by the model is influenced by the rainfall and other input data used in driving the model. Furthermore, the importance of temperature in influencing actual evapotranspiration cannot be overstated implying that the minimum and maximum temperature estimates used in the simulations could also interact to strongly influence the results obtained.

B.5 Conclusion

The objectives were to evaluate the ability of two global reanalysis datasets; CFSR and ERA-Interim and one bias corrected global meteorological forcing dataset WFDEI to be used as input to drive the SWAT model in the Logone catchment and to evaluate the impact of reanalysis spatial resolution on the quality of simulated flows

The result of our study showed that WFDEI out-performed the other two datasets in simulating streamflow in the study area. This highlights the importance of bias correcting global reanalysis datasets before using them for hydrological modelling. As seen in the hydrographs of WFDEI, the bias correction reduces the uncertainty in precipitation estimates used to drive the hydrological model and consequently reducing the overall uncertainty in the simulated streamflow.

The results obtained in this study also showed that the ability of reanalysis dataset(s) to accurately produce precipitation estimates in the catchment is more important than its spatial resolution. This is because accurate streamflow simulation and hydrological modelling in general depend on accurate rainfall input.

From the result of evapotranspiration estimates obtained, we conclude that the estimation of actual evapotranspiration depends on the input data used in driving the model. This is because rainfall and temperature have significant impact on model parameters that interact to control hydrological processes in a catchment including actual evapotranspiration.

Finally, we conclude that in the absence of gauged hydro-meteorological data, WFDEI and CFSR could be used for hydrological modelling in data-scarce areas such as the Sudano-Sahel and other data scarce regions of the world.

This study is part of an on-going research aimed at understanding the hydrological dynamics of the Logone catchment with the aim of improving water resources management. Future research in the catchment will use the WFDEI dataset, which has been shown to out-perform the other two datasets in this study, for detailed hydrological analysis of the catchment to determine the main processes and feedback mechanisms driving the response of the catchment to natural and environmental changes.

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Appendix C: Research framework Matrix

Research theme and sub question	Methodology	Sources of data	Skills for analysis
Science – Policy Interface Which scientific method can be used to reveal different discourses in climate change in general and the relationship between science and policy and how it can be applied in hydro – climatic research?	**a)** Stakeholder analysis **b)** A review of existing documentation on climate change in Cameroun **c)** Semi-structure open ended interviews **d)** Q methodology	Data collected through face to face interviews and the application of Q methodology method in Yaoundé Cameroun and reading through policy documents.	Skills on how to conduct elite interviews. The use of Q methodology in discourse analysis in social science
Climatology **a)** Which most effective and less onerous technique for infilling missing observations in hydro-meteorological time series? **b)** How homogeneous is rainfall across the Logone catchment and do any discernible trends exist in rainfall time series in the catchment over the last half of the 20th century? **c)** How do the CMIP5 models simulate historical climate and project future precipitation and average surface temperature in the Lake Chad basin?	**a)** A review of existing methods for infilling missing observations in time series with particular attention to Artificial Neural Networks **b)** Use of the different statistical tests to determine homogeneity and trends in rainfall time series **c)** A brief review of existing methods for validating climate models with particular attention to the Reliability Ensemble Averaging (REA) techniques	**a)** Observed rainfall data obtained from www.hydrosciences.fr/sierem b) Observed climate data obtained from climate research unit (CRU) **c)** CMIP5 obtained from World Climate Research Program	Using Artificial Neural Networks-Self Organizing Maps (SOMs) toolbox in Matlab environment. How to conduct statistical tests using different statistical packages (R, SPSS, Excel, etc.).
Hydrology **a)** Compile datasets, develop, calibrate and validate a hydrological model of the Logone catchment using the SWAT model with the aim of understanding the hydrological behaviour of the catchment **b)** To what extent is the catchment vulnerable to floods and droughts and how does this vulnerability vary spatially across the catchment? Furthermore, use the SPI and SSI to assess the relationship between rainfall and streamflow in the Logone catchment	**a)** Use of different statistical methods for model evaluation b) Hydrological modelling **c)** The use of standardized indicators to assess the vulnerability of the catchment to drought/flood conditions	**a)** Reanalysis data obtained from CFSR, ERA-Interim and WFDEI. **b)** Streamflow data obtained from the LCBC c) DEM (90 m resolution) obtained from USGS/NASA SRTM **c)** Land cover/use data obtained from Climate Change Initiative (CCI) d) Soil data obtained from FAO Harmonized world soil database 2005.	**a)** Statistical analysis **b)** Hydrological model development, calibration, validation and uncertainty assessment **c)** The use of standardized indicators