Predictability of Seasonal Rainfall and Inflows for Water Resource Management at Lake Kariba

By

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Declaration

This is to declare that the research work presented here is entirely my own work, unless or otherwise explicitly acknowledged by citation of published and unpublished sources. Furthermore, I would like to state that, even if the work presented from chapter 2 to 4 has been co-authored with my promoter and other colleagues, the conceptualization of all these research works plus their scientific analysis and interpretations, article writings as well as the rebuttal during the peer-review processes were executed by me. This research has not been submitted for assessment in any form to the University of Pretoria or to any other institutions for any other purposes.

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List of abbreviations

2AFCs	Two-alternative Forced Choice
ACCESS	Applied Center for Climate and Earth System Science
BRT	Buishand Range Test
CCA	Canonical Correlation Analysis
CGCM	Coupled ocean-atmosphere general circulation model
CP	Cumulative Profit
CPT	Climate Predictability Tool
CRU	Climate Research Unit
CUSUM	Cumulative Summation
CWT	Cross Wavelet Transform
CWTs	Cross Wavelet Transform Coefficients
ENSO	El Niño–Southern Oscillation
EOF	Empirical Orthogonal Function
FSL	Full Supply Level
GCMs	General Circulation Models
IOD	Indian Ocean Dipole
IRI	International Research Institute for Climate and Society
ITCZ	Inter-tropical convergence zone
MOL	Minimum Operating Level
MOM3	Modular Ocean Model
MOS	Model Output Statistics
PT	Pettit Test
ROC	Relative operating characteristic
SNHT	Standard Normal Homogeneity Test

SOP	Standard Operating Procedure
SST	Sea-Surface Temperate
TTTs	Tropical Temperate Troughs
UEA	University of East Anglia's
VNRT	Von Neumann Ratio Test
WC	Wavelet Coherence
WMO	World Meteorological Organization
ZMS	Zimbabwe Meteorological Services
ZRA	Zambezi River Authority
ZRB	Zambezi River Basin

Contents

Abstract

The Lake Kariba catchment area in southern Africa has one of the most variable climates of any major river basin, with an extreme range of conditions across the catchment and through time. The study characterized rainfall variability across the Lake Kariba catchment area, followed by describing prediction models for seasonal rainfall totals over the catchment and for inflows into Lake Kariba. The thesis therefore improved our understanding of rainfall variations over central southern Africa and provided evidence on how seasonal forecasts can be applied in order to potentially improve decision making in dam management.

The prediction of the seasons in which floods or droughts are most likely to occur involves studying the characteristics of rainfall and inflows within these extreme seasons. The study started off by analyzing monthly rainfall data through statistical analysis. To determine the predictability of seasonal rainfall totals over the Lake Kariba catchment area, this study used low-level atmospheric circulation of a fully coupled ocean-atmosphere general circulation model over southern Africa, statistically downscaled to seasonal rainfall totals over the catchment. The verification of hindcasts showed that rainfall over the catchment is predictable at extended lead-times.

Seasonal climate forecasts need to be integrated into application models in order to help with decision-making processes. The use of hydro-meteorological models may be proven effective for reservoir operations since accurate and reliable prediction of reservoir inflows can provide balanced solution to the problems faced by dam or reservoir managers. In order to reliably predict reservoir inflows for decision-making, the study investigated the use of a combination of physical and empirical models to predict seasonal inflows into the Lake. Two predictions systems were considered. First, antecedent seasonal rainfall totals over the upper Zambezi catchment were used as predictors in a statistical model for estimating seasonal

inflows into Lake Kariba. The second and more sophisticated method used predicted low-level atmospheric circulation of a coupled ocean-atmosphere general circulation model downscaled to the inflows. Inflow hindcasts performed best during the austral mid-summer season of DJF (seasonal onset of inflows) and the autumn season of MAM (main inflow season).

Chapter 1: Introduction

1.1 Background

Southern Africa experiences precipitation at various spatial and temporal scales and is prone to serious drought and flood events e.g., (Tyson, 1986; Nicholson et al., 1987; Lindesay, 1998; Reason et al., 2000). The region is most sensitive to precipitation shifts and variability (IPCC, 2007; Reason et al., 2006). Despite the diverse climatic zones, rainfall in southern Africa is mainly observed during the austral summer between October and May. The future spatial and temporal rainfall distribution and variability is uncertain (Fauchereau et al., 2009; Vigaud et al., 2012). Its summer climate is mainly driven by oscillations of the inter-tropical convergence zone (ITCZ) (Beilfuss, 2012). The temporal and spatial distribution of convection is associated with evaporative losses that strains food and water resources (Jury et al., 1999; Lyon, 2009). The South Atlantic and Indian oceans, being the major sources of moisture for southern Africa, play a major role in determining the spatio-temporal variations of rainfall in the region (Matarira and Jury 1992; Levey and Jury 1996; Jury et al., 1999). These studies have identified the meteorological and provided ample evidence for regional forcing features of composite wet and dry spells by the atmospheric circulation. Harrison (1986); Harangozo (1989); Barclay et al., (1993) have found that seasonal cycle of convective spells over southern Africa during austral summer and the surrounding oceanic basins are characterized by equator-extra tropical temperature gradients. This is caused by differential solar heating between the equator and the mid-latitudes. A more recent study has determined how the external forcing of major wet spells over southern Africa varies through the summer (Fauchereau et al., 2009). The wet spells occur approximately at intervals of 20 to 35 d (Levey and Jury, 1996) and half of all the wet spells appear quasi-stationery from

November to March. Southern Africa is a predominantly semi-arid region with a high degree of interannual rainfall variability (Batisani and Yarnal, 2010).

1.1.2 Rainfall characteristics in southern Africa

Southern Africa is described as a predominantly semi-arid region with high intra-seasonal and inter-annual rainfall variability, with extreme events such as droughts and floods occurring frequently. The amount and seasonal distribution of rainfall are the most important factors to consider when looking at rainfall across southern Africa. Except for moist tropics, arid south-west and south cost rainfall over most of southern Africa is seasonal. Most of the rainfall in southern Africa occurs in the summer (October to March).

In general, southern Africa is dominated by summer rainfall with October to March being the main rainfall season. Southern Africa receives most of its rainfall between December and February when the rainy season reaches its peak (Hobbs et al., 1998). The occurrence of tropical cyclones on the Mozambican and South African coastlines normally brought significant rainfall and associated flooding to Mozambique, the northern parts of South Africa, and Zimbabwe. The characteristics of the rainy season are of considerable interest for water resource managers and other user groups.

Studies by Few (2003); Githeko et al. (200); Patz and Kovats, (2000) have indicated that rainfall variability brings droughts, floods, and other extreme events that negatively affect the people of southern Africa. Although much of the recent climate research has focused on the causes of drought events, the region has also experienced extremes of above average rainfall (Washington and Preston, 2006), the most recent examples being the major flooding episodes a result of persistent summer rainfall in the Zambezi River Basin catchment area devastated

Mozambique during 2010 and 2011 when many people were killed and nearly 200,000 people made homeless.

There is increasing changes in high rainfall events is some parts of the southern Africa region (Reason et al., 2014). The variability of such rainfall can have detrimental consequences to water resources, population and properties. This variability can affect the sustainability of major dams and reservoirs due to flood risks to the population and properties in the flood plains. The region's water resources, agriculture and rural communities are impacted considerably due to high rainfall variability (Cook et al., 2004). Rain-fed agriculture is the main backbone of sub-Saharan Africa as it produces about 90% food and feed (Rosegrant et al., 2002). It forms the bread-basket for at least 70% of the population (FAO, 2003). Many sectors, including the agricultural sector are affected negatively by climate variability, particularly through heat waves, droughts, floods, and other extreme weather events. Climate change is seen to be the main cause of frequencies of extreme events such as droughts and floods (Tompkins, 2005; Dougill and Taylor 2007; Hahn et al., 2009 ; Kotir, 2011).Changes in climate variability and average precipitation in time and space is as a result of the effects of climate change, including extreme events (Orlowsky and Seneviratne, 2012:). Subsequent modifications in rainfall patterns are already taking place on global (Zhou et al., 2005) and regional scales (e.g., Sachs et al., 2009). The effects of these modifications are more pronounced for areas already under climate-related stress, such as river basin catchments e.g. Lake Kariba (Muchuru et al., 2014). Batisani and Yarnal, 2010; Traore et al., 2013; Cooper et al., 2008) studies have shown an increase in the frequency of droughts in southern Africa on major river basins due to climate change.

The remote influence of the El Niño–Southern Oscillation (ENSO) events has seen to be contributing to major floods and drought events in Southern Africa e.g., Mason and Jury , 1997; Cook , 2000; Stott et al., 2002; Rosenthal and Broccoli , 2004 ; Reason and Rouault, 2002). The ENSO cycles also play a major great function in regards to inter-annual rainfall variability (Ngongondo, 2006). There is a strong relationship between the ENSO and precipitation in southern Africa (Ropelewski and Halpert, 1987; Matarira, 1990). The El Niño component of ENSO refers to temperature fluctuations in the eastern equatorial Pacific surface waters, and the Southern Oscillation is the associated change in sea-level pressure in the southern Pacific. ENSO influences climate worldwide because it brings about large changes in the heating of the tropical atmosphere that alter the global atmospheric circulation. Sea-surface temperatures and pressures in the Atlantic (Nicholson and Entekhabi, 1987) and the Indian Ocean (Jury et al., 1996) have also been found to correlate to varying degrees with precipitation patterns in Africa. There is a strong correlation of ENSO with seasonal precipitation in southern Africa, making it possible for applications of forecasts to agricultural and water resources management (Phillips et al., 1998).

Southern African precipitation shows high variability on all timescales (Mason and Jury, 1997). The proximity of the Agulhas, Benguela, and Antarctic circumpolar currents leads to complex and highly variable climate patterns around southern Africa (Shannon et al., 1990). The 1984 floods (Rouault et al., 2003) along the Namibian coast were associated with warm SST. The SST was anomalously warm in the South East Atlantic Ocean and several countries in the region experienced well above average rainfall and floods which led to significant loss of life and damage (Rouault et al., 2003). In the Angola/Benguela Front region typical of the Benguela Niño while the 2000 floods which hit Mozambique, eastern Zimbabwe and northeast South Africa could have been influenced by the tropical-temperate troughs (TTTs);

(Washington and Todd ,1999; Ratna et al., (2013) ;Tozuka et al., 2013), which have been previously linked to high rainfall intensities. The TTTs play an important role in determining the nature of the summer season over southern Africa (Reason et al., 2004). In addition, droughts in most of the southern part of southern Africa, on the other hand, have been linked to SST variations in tropical Indian Ocean and to ENSO (Manhique et al., 2011; Vigaud et al., 2012).

Southern African rainfall has a clear annual cycle with most of the rainfall occurring during austral mid-summer, therefore necessitating the assessment of the predictability of drought and flood seasons over the region For example, the identification of seasons in which floods are most likely involves studying characteristics of daily rainfall and streamflows (Kampata et al., 2008) within the seasons across the region. Annual cycles of rainfall are strongly determined by the position of the inter-tropical convergence zone (WCRP, 1999). It is useful to characterize spatio-temporal patterns of rainfall, its relationship with climatic variables and eventually linking them to streamflow variations in Southern Africa. This is important in order to assist in formulation of adaptation measures through appropriate strategies of water resources management (Kampata et al., 2008). In addition, a good understanding of seasonal variability patterns is of critical importance because of the highly unstable onset of the rainy season and the high frequency of dry spells (Traore et al., 2013). Such studies can assist in improving our understanding of hydro meteorological variability in southern Africa region and better management of water resources (Kenabatho et al., 2009). Better understanding of the relationships between rainfall and climatic variables is expected to be useful (Nsubuga et al., 2011) in improving the prediction skills of the operational general circulation models (GCMs) (Landman et al., 2012) on one hand and on the other, it will be possible to predict rainfall given that climatic variables are successfully predicted well in advance. Consequently, the impacts of floods and droughts can be significantly reduced.

1.1.3 Predictability of seasonal rainfall

Operational seasonal climate prediction has become an established practice, also in southern Africa, with far-reaching societal applications. In southern Africa, seasonal rainfall forecasts have been developed to improve the ability of users to cope with fluctuations in rainfall on a seasonal time scale. Seasonal climate forecasts are defined as probabilistic predictions of how much rain is expected during the season and they provide usable information about the probable conditions in the forthcoming season.

In fact, with the advent of state-of-the-art coupled ocean-atmosphere models, seasonal anomalies may be predicted with elevated levels of skill. Verification of a wide range of forecast models indicates that rainfall predictability over southern Africa is highest during the mid-summer period when tropical influences start to dominate the atmospheric circulation over southern Africa (Landman and Beraki, 2012; Landman et al., 2012),. Spring rainfall over the region is poorly predicted on a seasonal time scale, while higher skill is found for the autumn months. An ability to predict future climate fluctuations one or more seasons in advance would have measurable benefits for decision making in water resources and other sectors of society (Barnston et al., 2004). For example, it would allow for proactive and improved reservoir management (Cunha, 2003). Quantitative estimates of the impacts of climatic variability on hydrology are essential for both water resource management (Morin et al., 2009; Benito et al., 2010); flood risk planning (Milly et al., 2002) and decision making (McCartney et al., 2007). More recently, and largely as a result of better quantification of the climate effects of the ENSO phenomenon, prediction of precipitation have been clearly demonstrated to have skill in particular seasons, regions, and circumstances (Landman and Beraki, 2012; Landman et al., 2012).

1.1.4 Lake Kariba operation

Lake Kariba operation established, a flood control Rule Curve (RC) showing the levels below which the lake must be maintained throughout the year in order to avoid overtopping of the dam in the event of an extreme flood**.** The Kariba Lake was created and designed to operate between levels 475.5m and 483.5m, with 0.7m freeboard. The net inflow into Lake Kariba is accommodated by increase in storage, and/or spill through one or more of the six floodgates, and/or turbine discharge. According to media reports, in January 2011 southern Africa experienced flooding across the region, which saw Lake Kariba, open its spillway gates on 22 January 2011 as a result of high water levels in the lake. River authorities at Lake Kariba consider the maximum level for this time of the year to be 485 m, and the current water level in early 2011 was around 484.8 m. The Zambezi River Authority (ZRA) subsequently opened two spillway gates thereby increasing its discharge to around 3 000 m3/s. Opening of the spillway gates resulted in rising water levels and increased flooding further downstream.

1.2 Research problem statement

Seasonal rainfall and inflows are responsible for extreme droughts and related floods that occur over the ZRB (e.g. Reason et al., 2004). The variability of such rainfall can have detrimental consequences for water resources, population and property. This variability can affect the sustainability of major dams and reservoirs due to flood risks to the population and properties on the floodplain. Several of studies investigating climate variability in the Zambezi river basin have been reported in the literature. For example, Mazvidza et al., 2000 grouped the precipitation records of the Lake Kariba catchment using a number of Zambian weather stations into decadal means between 1960 and 1990 to determine climate change and variability. Records from 10 of the 15 examined stations showed the 1980-1990 decade experienced the lowest means of flows over the last 40 years, while 15 stations registered the lowest mean of flow for the past 30 years in the same decade. Mazvimavi and Wolski, 2006 analyzed the trends of rainfall, stream flow and long-term variations of annual flows of the Okavango and Zambezi Rivers for the period of Okavango River (1933–2004) and Zambezi River (1924–2004). Annual flows, annual maximum flows, and annual minimum flows of the Okavango River were analyzed and reported on the presence of identified change points in the annual flows of the Okavango River and Zambezi River. Furthermore, Wilk et al., 2006 evaluated the sensitivity of the rainfall fields to spatial interpolation techniques based on rainfall and water balance over the Okavango and Zambezi River Basin for using a combination of in-situ gauges and satellite data for the period 1955-1872 for hydrological applications. Kampata et al., 2008 analyzed long-term rainfall data in the headstream regions of the Zambezi River basin using the Cumulative Summation (CUSUM technique), step change analysis and Mann-Kendall-statistics to study the spatial-temporal variability of rainfall between 1935 and 2006 and reported that the rainfall data in the entire sub-basin belonged to a similar climate regime and rainfall data and the test for homogeneity in trend observed at different stations showed homogeneity between them. Predicting future climate fluctuations one or more seasons in advance is crucial for decision making in water resources and other sectors of society (Barnston et al., 2004). Operational seasonal climate prediction is an emerging practice with far-reaching societal applications.. Existing studies focusing on operational seasonal climate prediction (e.g. Barnston et al., 2004 and Landman et al., 2012) or take into account operational seasonal climate prediction (e.g. McCartney et al., 2007) without further elaborating societal applications. In fact, there is little publically available work taking into account operational seasonal climate prediction over Southern Africa for water resources management

A seasonal forecast model capable of producing useful forecasts of high probabilities of extreme rainfall and inflow totals to occur over the Lake Kariba Catchment area. While operational seasonal climate prediction is still an area of ongoing research (Muchuru et al., 2014), the Lake Kariba Catchment area may provide a study area where such forecasts could be useful and tested. Forecasts may be useful to Lake Kariba managers who need to plan months ahead of the rainy season, consequently leading to reduced losses suffered during flooding or drought seasons. The absence of any studies considering operational seasonal climate prediction with societal applications over the region however makes such undertakings challenging. Vulnerability in the Zambezi River Basin together with projections of rainfall variability (Reason et al., 2006) further compels and exacerbates extreme climatic impacts at longer time scales over the region. In relation to this, the Lake Kariba Catchment area has been singled out as an area where more needs to be done towards understanding and integrating seasonal climate forecasts into application models in order to help with decision-making processes.

3. Aim and objectives of the study

Given the research problem above, the aim of the project is to characterize and predict seasonal rainfall and inflow totals over the Lake Kariba Catchment in the Zambezi River Basin (ZRB), exploring the importance of seasonal forecast systems' ability to predict future climate fluctuations one or more seasons in advance for water resource management.

Hence the specific project objectives are:

- To investigate and characterize the inherent spatial-temporal rainfall variability over the Lake Kariba Catchment area using statistical analysis.
- To determine the predictability of seasonal rainfall totals over the Lake Kariba catchment area, using low-level atmospheric circulation (850 hPa geopotential height fields) of a state-of-the-art coupled ocean-atmosphere general circulation model (CGCM) over southern Africa, statistically downscaled to seasonal rainfall totals over the catchment.
- To develop and test a prediction system that is a combination of a physical and an empirical model to predict seasonal inflows into Lake Kariba in southern Africa at lead-times useful for decision makers in dam management.

4. Thesis outline

Chapter 2 provides, in the form of a journal paper *under review*, background information on characterizing the variability of rainfall across the Lake Kariba catchment area. Rainfall variability has been analyzed to characterize the inherent spatial-temporal variability crucial for water resources management and planning. Chapter 3 is in the form of an already *published peer reviewed journal paper*, which describes a seasonal rainfall prediction system, and then verifies retro-active rainfall forecasts produced with lead-times of several months.

Chapter 4 is in the form of a journal paper *under review*, investigates the use of a combination of physical and empirical models to predict inflows into Lake Kariba using two predictions systems. Chapter 5 is a summary, conclusions of the main findings of the thesis together with a list of recommendations for future modelling research.

Given that all figures and tables are specific to published and under review papers, a list is not provided in the contents section. Furthermore, each paper (Chapter 2 – 4) is followed by the reference list specific to that paper and journal requirements. The reference list for Chapter 1 is provided at the end of that chapter.

References

Barclay J, Jury MR and Landman WA (1993) Climatological and structural differences between wet and dry troughs over southern Africa in the early summer. *Meteorol. Atmos. Phys.* **51** 41–54.

Barlow M, Nigam S and Berbery, EH (2001) "ENSO, Pacific decadal variability, and US summertime precipitation, drought, and stream flow". *J. Clim.* **14** 2105-2128.

Barnston AG, Kumar AL, Goddard L and Hoerling MP (2004) Improving seasonal prediction practices through attribution of climate variability. *Bull. Am. Meteorol. Soc*. **86** 59–72.

Batisani N and Yarnal B (2010) Rainfall variability and trends in semi-arid Botswana: Implications for climate change adaptation policy. *Applied Geography* **30** 483–489.

Beilfuss RD (2012) A Risky Climate for Southern African Hydro. Hydrological Risks and Consequences for Zambezi River Basin Dams. International Rivers. Berkeley, CA.

Benito G, Thorndycraft VR, Rico M, Sánchez-Moya Y and Sopeña A (2008) Palaeoflood and floodplain records from Spain: evidence for long-term climate variability and environmental changes. *Geomorphology* **101** 68–77.

Block P and Strzepek K (2010) Economic analysis of large-scale upstream river basin development on the Blue Nile in Ethiopia considering transient conditions, climate variability, and climate change, *J. Water Resource*. **136** 156-166.

Cook C, Reason CJC and Hewitson BC (2004) Wet and dry spells within particularly wet and dry summers in the South African summer rainfall region. *Clim. Res.* **26** 17–31.

Cook KH (2000) The South Indian convergence zone and interannual rainfall variability over Southern Africa. *J. Clim*. **13** 3789–3804.

Cooper PJM, Dimes J, Rao KPC, Shapiro B, Shiferawa B and Twomlow S (2008) Coping better with current climatic variability in the rain-fed farming systems of sub-Saharan Africa: An essential first step in adapting to future climate change? *Agriculture, Ecosystems and Environment* **126** 24–35.

Cunha MD (2003) Water systems planning. The optimization perspective. *Eng. Optimiz.* **35** 255–266.

Dougill AJ, Reed MS and Taylor MJ (2007) Integrating local and scientific knowledge for adaptation to land degradation: Kalahari rangeland management options. *Land Degradation and Development* **18** 249-268

Engelbrecht FA, Landman WA, Engelbrecht CJ, Landman S, Bopape MM, Roux B, McGregor JL and Thatcher T (2011) Multi-scale climate modelling over Southern Africa using a variable-resolution global model. *Water SA* **37** 647-658 http://dx.doi.org/10.4314/wsa.v37i5.2.

FAO (2003) Responding to Agricultural and Food Insecurity Challenges Mobilizing Africa to Implement Nepad Programmes FAO. FAO, Maputo, Mozambique.

Fauchereau N, Pohl B, Reason CJC, Rouault M and Richard Y (2009) Recurrent daily OLR patterns in the Southern Africa/Southwest Indian Ocean region, implications for South African rainfall and teleconnections. *Clim. Dyn.* **32** 575–591.

Few R (2003) Flooding, vulnerability and coping strategies: local response to a global threat. *Progress in Development Studies* **3** 43–58.

Githeko AK, Lindsay SW, Confalonieri UE and Patz JA (2000) Climate change and vector-borne diseases: A regional analysis. *Bulletin of the World Health Organization* **78** 1136–1147.

Goddard L, Barnston AG and Mason SJ (2003) Evaluation of the IRI's "Net Assessment" seasonal climate forecasts, 1997-2001. *Bulletin of the American Meteorological Society* **84** 1761-1781.

Gordon C, Cooper, Senior CA, Banks H, Gregory JM, Johns TC, Mitchell JFB and Wood RA (2000) The simulation of SST, sea ice extents and ocean heat transports in a version of the Hadley Centre coupled model without flux adjustments. *Clim. Dyn.* **16** 147–168.

Hachigonta S, Reason R and Tadross M (2007) An analysis of onset date and rainy season duration over Zambia. *Theor. Appl. Climatol*. **91** 229–243.

Hahn MB, Riederer AM and Foster SO (2009) The Livelihood Vulnerability Index: a pragmatic approach to assessing risks from climate variability and change –a case study in Mozambique. *Global Environ. Change* **19** 74–88.

Hamlet AH, Huppert D and Letteinmaier DP (2002) Economic value of long-lead streamflow forecasts for Columbia River hydropower. *J. water resour. Plann. Manage.* **128** 91-101.

Hamlet AF, Lettenmaier DP and Kumar A (1999) Columbia River streamflow forecasting based on ENSO and PDO climate signals. *J. Water Resour.Plann.Manage.* **125** 333-341.

Harangozo SA (1989) Circulation characteristics of some South African rainfall systems. MSc thesis, Univ of the Witwatersrand. 341 pp.

Harrison MSJ (1986) A synoptic climatology of South African summer rainfall variations. PhD thesis, University of the Witwatersrand. 341 pp.

Harrison MSJ, Troccoli A, Anderson DLT and Mason SJ (2008) Introduction. In Troccoli, Harrison MSJ, Anderson DLT and Mason SJ (Eds), Seasonal Climate Variability: Forecasting and Managing Risk, Springer Academic Publishers, Dordrecht, 3-11.

Hartmann HC, Pagano TC, Sorooshian S and Bales R (2002) Confidence builders-Evaluating seasonal climate forecasts from user perspectives. *Bull. Am. Meteorol. Soc.* **83** 683-698.

Hellmuth ME, Moorhead A, Thomson MC and Williams J (Eds.): Climate Risk Management in Africa: Learning from Practice, 104 pp., International Research Institute for Climate and Society (IRI), Columbia University, New York, 2007.

Hobbs, J.E., J.A. Lindesay and H.A. Bridgman, 1998: Climates of the Southern Continents. Present Past and Future. Wiley and Sons, Chichester.

IPCC (INTERGOVERNMENTAL PANEL ON CLIMATE CHANGE) (2007) Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Solomon S, Qin D, Manning M, Chen Z, Marquis M, Averyt KB, Tignor M and Miller HL (eds.). Cambridge University Press, Cambridge.

Jamieson DG (1996) Decision Support System. *Journal of Hydrology* **177** 161-162

Jury MR (1998) Intra-seasonal convective variability over Southern Africa. Principal component analysis of Pentad outgoing-longwave radiation departures. *Theor. Appl. Climatol*. **62** 133–146.

Jury MR, Mulenga HM and Mason SJ (1999) Exploratory long-range models to estimate summer climate variability over southern Africa. *J. Clim.* **12** 1892–1899.

Jury RM, Pathack B, Rautenbach CJ DeW and Vanheerden J (1996) Drought over southern Africa and Indian Ocean SST: statistical and GCM results. *Global Atmosphere and Ocean System* **4** 47–63.

Kampata JM, Parida BP and Moalafhi DB (2008) Trend analysis of rainfall in the headstreams of the Zambezi River Basin in Zambia. *Phys. Chem. Earth* **33** 621–625.

Kenabatho PK, Mcintyre NR and Wheater HS (2009) Impacts of rainfall uncertainty on water resource planning models in the Upper Limpopo basin, Botswana. In: New Approaches to Hydrological Prediction in Data Sparse Regions. Proc. of Symposium HS.2 at the Joint IAHS & IAH Convention, Hyderabad, India, September 2009. IAHS Publ. 333. IAHS, Hyderabad, India.

Kotir JH (2011) Climate change and variability in Sub-Saharan Africa: Are view of current and future trends and impacts on agriculture and food security. *Environ. Dev. Sustain*. **13** 587–605.

Kovats RS (2000) El Niño and human health. *Bulletin of the World Health Organization* **78** 1127–1135.

Kumar AM, Hoerling MJI, Leetma AA and Sardeshmukh P (1996) Assessing a GCM's suitability for making seasonal predictions *J. Clim*. **9** 115–129.

Kuniyoshi T and Vanchai S (1995) Assessment of effectiveness of the use of inflow forecasts to reservoir management. Modelling and Management of Sustainable Basin-scale Water Resource Systems (Proceedings of a Boulder Symposium, July 1995). 1AHS Publ. no. 231, 1995.

Kyriakidis PC, Miller NL and Kim J (2001) Uncertainty propagation of regional climate model precipitation forecasts to hydrologic impact assessments". *J. Hydrometeorol.* **2** 140-160.

Landman WA, Mason SJ (2001) Retro-active skill of multi-tiered forecasts of summer rainfall over Southern Africa. *International Journal of Climatology* **21** 1-19: DOI: 10.1002/joc.592

Landman WA and Beraki A (2012) Multi-model forecast skill for mid-summer rainfall over Southern Africa. *International Journal of climatology* **32** 303-314, DOl: 10.1002/joc.2273.

Landman WA, DeWitt D, Lee DE, Beraki A and Lötter D (2012) Seasonal rainfall prediction skill over South Africa. 1- vs. 2-tiered forecasting systems. *Weather Forecast*. **27** 489–501.

Leung LR, Hamlet AF, Lettenmaier DP and Kumar A (1999) Simulations of Enso hydroclimate signals in the Pacific North-West Columbia River Basin." *Bull. Am. Meteorol. Soc.* **80** 2313-2329.

Levey KM and Jury MR (1996) Composite intra-seasonal oscillations of convection over southern Africa. *J. Clim.* **9** 1910-1920.

Lindesay JA (1998) South African rainfall, the Southern Oscillation and a Southern Hemisphere semi-annual cycle. *J. Climatol.* **8** 17–30.

Livezey RE (1990) Variability of skill of long-range forecasts and implications for their use and value. *Bull. Am. Meteorol. Soc.* **71** 300–309.

Lyon B (2009) Southern Africa summer drought and heat waves. Observations and coupled model behavior. *J. Clim.* **22** 6033–6046.

Maident DR (1992) Handbook of Hydrology. McGraw-Hill Inc., New York, USA, 1992.

Manhique AJ, Reason CJC, Rydberg LR and Fauchereau N (2011) ENSO and Indian Ocean Sea surface temperatures and their relationships with tropical temperate troughs over Mozambique and the southwest Indian Ocean. *Int. J. Climatol.* **31** 1–13.

Mason SJ and Jury MR (1997) Climate variability and change over Southern Africa: a reflection on underlying processes. *Progress in Physical Geography* **21** 23-50

Matarira CH and Jury MR (1992) Contrasting meteorological structure of intra-seasonal wet and dry spells in Zimbabwe. *Int. J. Climatol.* **12** 165–176.

Matarira CH (1990) Drought over Zimbabwe in a regional and global context. *Int. J. Climatol*. **10** 609–625.

Mazvidza DZ, Sakala W and Mukupe H (2000) Water transfer schemes due to uneven spatial distribution- Development projects. In M.J. Tumbare (edt). Management of River Basins and Dams: *The Zambezi River Basin.* A.A. Balkema, Rotterdam/Brookfields

Mazvimavi D and Wolski P (2006) Long-term variations of annual flows of the Okavango and Zambezi Rivers. *Physics and chemistry of the Earth* **31** 951-994.

McCartney MP (2007) Decision support systems for large dam planning and operation in Africa. Colombo, Sri Lanka: International Water Management Institute. *47 P. IWMI Working Paper 119*

McGregor JL (1996) Semi-Lagrangian advection on conformal-cubic grids. *Mon. Weather Rev*. **134** 1311-1322

Milly PCD, Wetherald RT, Dunne KA and Delworth TL (2002) Increasing risk of great floods in a changing climate. *Nature* **415** 514–517.

Mitchell TD and Jones PD (2005) An improved method of constructing a database of monthly climate observations and associated high-resolution grids. *International Journal of Climatology* **25** 693-712.

Morin E, Grodek T, Dahan O, Benito G, Kulls C, Jacoby Y, Van Langenhove G, Seely M and Enzel Y (2009) Flood routing and alluvial aquifer recharge along the ephemeral arid Kuiseb River, Namibia. *Journal of Hydrology* **368** 262–275.

Muchuru S, Landman WA, DeWitt D, Lötter D (2014) Seasonal rainfall predictability over the Lake Kariba catchment area. *Water SA* **40** 461-470 http://dx.doi.org/10.4314/wsa.v40i3.9.

Nicholson SE and Entekhabi D (1987) Rainfall variability in equatorial and southern Africa: relationships with sea surface temperatures along the southwestern coast of Africa. *J. Climate. Appl. Meteor*. **26** 561–578.

Nsubuga FWN, Olwoch JM and Rautenbach CJ (2011) Climatic trends at Namulonge in Uganda, 1947-2009. *J. Geogr. Geol.* **3** 119–131.

Orlowsky B and Seneviratne S (2012) Global changes in extreme events: Regional and seasonal dimension. *Clim. Change*, **110** 669–696.

Pagano TC, Hartmann HC and Sorooshian S (2001) Using climate forecasts for water management: Arizona and the 1997-1998 EL Nino. *J. AM. Water Resour. Assoc.* **37** 1139-1153.

Phillips JG, Cane MA and Rosenzweig C (1998) ENSO, seasonal rainfall patterns and simulated maize yield variability in Zimbabwe. *Agricultural and Forest Meteorology* **90** 39–50.

Piechota TC and Dracup JA (1996) “Drought and regional hydro-logic variation in the United States: Associations with the EL Nino Southern Oscillation”. *Water Resour. Res.* **32** 1359-1373.

Potgieter C (2009) Cut-Off Low Characteristics over South Africa in the Future Climate. ARC Technical Report No. GW/A/2009/26. Project GW/050/054. Agricultural Research Council, Pretoria, South Africa.

Ratna SB, Behera S, Ratnam JV, Takahashi K and Yamagata T (2013) An index for tropical temperate troughs over southern Africa. *Clim. Dyn.* **41** 421–441.

Reason CJC and Usman MT (2004) Dry spell frequencies and their variability over southern Africa. *Clim. Res.* **26** 199–211.

Reason CJC and Hachingonta S (2006) Interannual variability in dry and wet spell characteristics over Zambia. *Clim. Res*. **32** 49–62.

Reason CJC and Rouault M (2002) ENSO-like decadal patterns and South African rainfall. *Geophys. Res*. **29** 161–164.

Reason CJC and Weldon D (2014) Variability of rainfall characteristics over the South Coast region of South Africa. *Theor. Appl. Climatol*. **115** 177–185.

Reason CJC, Allan RJ, Lindesay JA and Ansell TJ (2000) ENSO and climatic signals across the Indian Ocean basin in the global context. Part 1 Interannual composite patterns. *Int. J. Climatol*. **20** 1285–1327.

Ropelewski CF and Halpert MS (1987) "Global and regional scale precipitation patterns associated with the El-Nino Southern Oscillation". *Mon. Weather Rev.* **115** 1601-1626.

Rosegrant MW, Cai X and Cline SA (2002) World water and food to 2025: dealing with scarcity. In: IFPRI-2020 Vision/International Water Management Book. IFPRI, Washington, DC.

Rosenthal Y and Broccoli AJ (2004) In search of paleo-ENSO. *Science* **304** 219–221.

Rouault M and Florenchie P (2003) South East tropical Atlantic warm events and southern African rainfall. *Geophysical Research Letters* 30 doi: 10.1029/2002GL014840.

Sachs JP, Sachse D, Smittenberg RH, Zhang ZH, Battisti DS and Golubic S (2009) Southward movement of the Pacific intertropical convergence zone AD 1400–1850. *Nature Geosci*. **2** 519–525.

SADC (2008) Draft Integrated Water Resource Management Strategy and Implementation Plan for the Zambezi River Basin. SADC-WD/ Zambezi River Authority SIDA/ DANIDA, Norwegian Embassy Lusaka

SADC (2010) Dam Synchronization and flood releases in the Zambezi River basin project. SADC Water Division (SADC WD), Zambezi Watercourse Commission (ZAMCOM)

Sankarasubramanian GKA and Devineni N (2009) Improved Management of Falls Lake Reservoir during the Summer Season using Climate Information based Monthly Streamflow Forecasts: Role of Restrictions in Water supply and Water Quality Management, *Journal of Water Resources Planning and Management* **135** 188-197.

Shannon LV, Lutjeharms JRE and Nelson G (1990) Causative mechanisms for intra-annual and interannual variability in the marine environment around southern Africa. *S. Afr. J. Sci.* **86** 356–373.

Steinemann AC (2006) Using climate forecasts for drought management. *J. Appl. Meteorol* **45** 1353-1361.

Stott L, Poulsen C, Lund S and Thunell R (2002) Super ENSO and global climate oscillations at millennial time scales. *Science* **297** 222–226.

Tompkins EL (2005) Planning for climate change in small islands: insights from national hurricane preparedness in the Cayman Islands. *Global Environmental Change* **15** 139–149.

Tozuka T, Abiodun BJ and Engelbrecht FA (2013) Impacts of convection schemes on simulating tropical-temperate troughs over southern Africa. *Clim. Dyn*. Doi: 10.1007/s00382-013-1738-4.

Traoré B, Marc C, Mark TV, Wijkc DM, Rufinod C and Giller KE (2013) Effects of climate variability and climate change on crop production in southern Mali. *Europ. J. Agronomy* **49** 115– 125.

Tyson PD (1986) Climate Change and variability in Southern Africa. Oxford University Press: Cape Town

Vigaud N, Pohl B and Cretat J (2012) Tropical-temperate interactions over southern Africa simulated by a regional climate model. *Clim. Dyn.* **39** 2895–2916.0

Washington R and Preston A (2006) Extreme wet years over southern Africa. Role of Indian Ocean sea surface temperatures. *J. Geophys. Res.* 111 DOI: 101029/2005JD006724.

Washington R and Todd M (1999) Tropical–temperate links in Southern Africa and Southwest Indian Ocean satellite-derived daily rainfall. *Int. J. Climatol.* **19** 1601–1616.

WCRP (1999) Climate Research for Africa. Informal Report No. 16/1999. World Climate Research Programme, International Clivar Project Office Publication Series No. 29. Southampton, United Kingdom.

Wilks DS (2006) Statistical Methods in the Atmospheric Sciences, 2nd and, Academic Press: San Diego, CA

Wilk J, Kniveton D, Andersson L, Layberry R, Todd MC, Hughes D, Ringrose S and Vanderpost C (2006) Estimating rainfall and water balance over the Okavango River Basin for hydrological applications, *Journal of Hydrology* **331** 18–29

Yao H and Georgakakos A (2001) Assessment of Folsom lake response to historical and potential future climate scenarios. 2-Reservoir management. *J. Hydro***.** **249** 176-196.

Yu B and Neil DT (1993) Long-term variations in regional rainfall in the south-west of Western Australia and the difference between average and high intensity rainfalls. *International Journal of Climatology* **13** 77–88.

Zhao H and Georgakakos A (2001) Assessment of Folsom Lake response to historical and potential future climate scenarios: 2. reservoir management, *J. Hydrol.* **249** 176-196.

Zhou TJ and Yu R C (2005) Atmospheric water vapor transport associated with typical anomalous summer rainfall patterns in China. *J. Geophys. Res. Atmos*. 110, D08104.

Chapter 2: Seasonal rainfall characteristics over Lake Kariba catchment in the Zambezi river basin, Zimbabwe*

Preface

*This chapter needs to be cited as:

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Towards reaching the first objective of the study, the average monthly and annual rainfall totals between 1970 to 2010 from a network of stations across Lake Kariba catchment of Zambezi River Basin were analysed to characterize spatial temporal variability. In the analysis, the data was separately subjected to intervention and homogeneity analysis using the Cumulative Summation (CUSUM) technique and step change analysis (using rank-sum test). Furthermore, seasonal rainfall was characterized by trend analysis across the Kariba catchment using the non-parametric Mann-Kendall statistic. In order to understand and track the inherent periodic components and the corresponding time evolution as well as the associated modes of spatial association, the rainfall series has been decomposed and the spectral characteristics derived using Cross Wavelet Transform (CWT) and Wavelet Coherence (WC) analysis. While the paper explores and characterizes rainfall variability over the Lake Kariba Catchment area, the predictability of seasonal rainfall totals over the catchment area was also investigated later on in the thesis.

The paper was co-authored with Joel O. Botai, W.A. Landman, Christina M. Botai and Abiodun M. Adeola. The conceptualization of the paper, collection of all the historical datasets plus their scientific analysis and interpretations and the actual article writing were done by me.

Seasonal rainfall charcteristics over Lake Kariba catchment in the Zambezi river basin, Zimbabwe

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ABSTRACT

The focus of this contribution is on the analysis of the variability of rainfall in the Lake Kariba catchment area in the Zambezi river basin, Zimbabwe. An understanding of rainfall variability and trends is needed in water resources management and planning and continue to be of a major concern to hydrologists and water managers. Average monthly and annual rainfall totals between 1970 to 2010 from a network of stations across Lake Kariba catchment of Zambezi River Basin is analysed to characterize the spatial-temporal variability. Basing in the analysis, all network stations in the Kariba catchment exhibited similar annual and seasonal (DJF) rainfall variability pattern. The annual and seasonal rainfall series demonstrated no apparent significant shifts were homogeneous and has non-significant positive and negative trends, and exhibit coherent oscillatory modes that are constantly locked in phase in the Morlet wavelet space. Moreover, there was no apparent significant shift in the annual and seasonal rainfall data in the Kariba catchment area based on the

CUSUM and rank-sum test analysis. Annual and seasonal rainfall data from most of the stations were homogeneous. The study is a step towards bridging the gap in rainfall variability characterization in the Kariba catchment area. In particular, these results would be valuable since local-scale rainfall variability can lead to sudden changes in water availability in surface and sub-surface hydrologic systems thereby significantly affecting agriculture, livestock, water supply and hydropower sectors: the social economic livelihoods over the study area. .

Key words: Lake Kariba catchment; Mann-Kendall; Rainfall variability; Cross wavelet Transform; Wavelet Coherence.

2.1 Introduction

Rainfall is one of the climatic variables that affect both the spatial and temporal patterns on water availability (De Luis et al. 2000; Kampata et al. 2008; Ngongondo 2006). In particular, the southern African region experiences significant rainfall variability at various spatial and temporal scales and is prone to serious drought and flood events (e.g., Tyson 1986; Nicholson & Entekhabi 1987; Lindesay 1998; Reason et al. 2000). There is increasing change in high rainfall events in some parts of the southern Africa region (Reason et al., 2014) and the region is sensitive to precipitation shifts and variability (IPCC 2007). One of the challenges posed by climate variability is ascertainment, identification and quantification of trends in rainfall and their implications on river flows in order to assist in decision-making through appropriate strategies of water resource management (Kampata et al. 2008). Spatial temporal variability analysis of rainfall can be useful in generating long sequences of rainfall data needed to support planning of the long-term water management strategies (Kenabatho et al. 2009).

The variability of rainfall over southern Africa can have detrimental consequences to economic development, disaster management, population, and hydrological planning of a particular country. Due to rainfall variability, major water resources and reservoirs are often at risk (e.g., due to flooding), and the population and properties in the basin are often impacted most. The region's water resources, agriculture and rural communities are impacted considerably due to high rainfall variability (Cook et al. 2004). It is imperative to perform spatial temporal variability analysis of rainfall at monthly or seasonal timescales to determine the likelihood of a drought or flood events. For example, the identification of seasons in which floods are most likely involves studying characteristics of monthly rainfall within the seasons across the region. Better understanding of the relationships between climatic variables is expected to be useful in water resource management and planning. It is therefore essential to closely monitor rainfall variability at monthly, seasonal and annual time scales in order to support the management of water resources (Nsubuga et al. 2013).

Southern African precipitation shows high variability at all timescales (Mason and Jury 1997). The South Atlantic and Indian Oceans, being the major sources of moisture for southern Africa, play a major role in determining the spatio-temporal variations of rainfall in the region (Levey and Jury, 1996; Jury et al. 1999). The proximity of the Agulhas, Benguela, and Antarctic circumpolar currents leads to complex and highly variable climate patterns around southern Africa (Toggweiler and Russell, 2008; Jury and Courtney, 1994). The 1984 floods along the Namibian coast were associated with extremely warm SST in the Angola/Benguela front region typical of the Benguela Niño while the 2000 floods which hit Mozambique, eastern Zimbabwe and northeast South Africa could have been influenced by the Tropical Temperate Troughs (TTTs) which have been previously linked to high rainfall intensities (Ratna et al., 2013; Tozuka et al., 2013). Further, the El Niño–Southern Oscillation (ENSO) has seen to be contributing to major floods and drought events in the southern African region (e.g., Cook 2000; Mason & Jury 1997, Reason & Rouault 2002).

Several of studies investigating rainfall variability in the Zambezi river basin have been reported in the literature. For example, Mazvidza et al. 2000 grouped the precipitation records of the Lake Kariba catchment using a number of Zambian weather stations into decadal means between 1960 and 1990 to determine climate change and variability. Records from 10 of the 15 examined stations showed the 1980-1990 decade experienced the lowest means of flows over the last 40 years, while 15 stations registered the lowest mean of flow for the past 30 years in the same decade. Mazvimavi and Wolski, 2006 analysed the trends of rainfall, stream flow and long-term variations of annual flows of the Okavango and Zambezi Rivers for the period of Okavango River (1933–2004) and Zambezi River (1924–2004). Annual flows, annual maximum flows, and annual minimum flows of the Okavango River were analysed. The study found that average annual discharges on the Okavango and Zambezi Rivers have in general similar variations over time and are closely correlated with a correlation coefficient of 0.70. Furthermore, Wilk et al. 2006 evaluated the sensitivity of the rainfall fields to spatial interpolation techniques based on rainfall and water balance over the Okavango and Zambezi River Basin for using a combination of in-situ gauges and satellite data for the period 1955-1872 for hydrological applications. The study has shown that for this data sparse region, a combination of spatial modelling of rain gauge readings and the satellite data based rainfall retrievals can provide a consistent rainfall database that forms the basis of further hydrological investigations. Kampata et al, 2008 analysed long-term rainfall data in the headstream regions of the Zambezi River basin using the Cumulative Summation (CUSUM technique), step change analysis and Mann-Kendall-statistics to study the spatial-temporal variability of rainfall between 1935 and 2006 and reported that the rainfall data in the entire sub-basin belonged to a similar climate regime and rainfall data and the test for homogeneity in trend observed at different stations showed homogeneity between them.

Notwithstanding the valuable contribution of the above studies towards our understanding of spatial-temporal variability of rainfall in the larger Zambezi river basin, analysis of the variability of rainfall in the Kariba catchment area remain inconclusive. This study focuses on the Lake Kariba catchment region in the Zambezi river basin since rainfall over this area is directly responsible for the water levels in the lake, runoff, erosion all important processes responsible for e.g., hydroelectricity, agriculture and livestock. Rainfall over the catchment is strongly seasonal. Lake Kariba catchment climatology is controlled mainly by the movement of air masses associated with the Inter-Tropical Convergence Zone (ITCZ), (Beilfuss 2012). Normally the rainy season extends from November to March. The entire catchment is highly susceptible to extreme droughts and floods that occur nearly every decade (Beilfuss 2012); but these has become more frequent and more pronounced with associated economic losses (Solomon et al. 2007). For example, during the severe 1991/1992 drought, reduced hydropower generation resulted in an estimated US102 million reduction in GDP, $36 million reduction in export earnings, and the loss of 3,000 jobs. Extreme floods have also resulted in considerable loss of life, social disruptions, and extensive economic damage. The purpose of this study to characterize rainfall variability across the Kariba catchment through intervention analysis, homogeneity tests, trend analysis as well as spatial and spectral correlation analysis using wavelet-based parameters. Characterizing rainfall variability and trends can be used for decision making and further hydrological modelling.

2.2 Study area

Lake Kariba is one of the largest artificial reservoirs (by volume) in the world – with a surface area of 5,577 km^2 and a live storage volume 564,800 mm^3. Lake Kariba regulates runoff from an upstream catchment area of 687,535 km^2, (see Figure 1) which is about 50% of the total Zambezi catchment area. Average annual rainfall for the Lake Kariba catchment (Beilfuss 2012) is about 1,000 mm, producing a mean annual discharge of 37,249 mm^3 (an average flow rate of 1181 m^3/s). Zambezi flows begin rising during the early rainy season months of December-January, increasing sharply from February to April. Flows recede steadily during the prolonged dry season, reaching an annual minimum during November. Approximately 50% of annual rainfall over the catchment, on average, contributes to Zambezi base flow (Sharma and Nyumbu 1985; Beilfuss 2012). During drought years, the magnitude and duration of average peak flows may be reduced by 70% or more. Runoff varies considerably from year to year (0.40 coefficient of variation, from a remarkable 72, 800 mm^3 in 1957/58 to as low as 12,300 mm^3 in 1995/96. The time series of annual flows reveals long-term cycles of high, medium, and low runoff. These cycles also influence runoff efficiency; a sequence of particularly low rainfall years in the catchment, such as the one occurred during the early 1900s and again during the period 1980-1998, can significantly reduce the proportion of annual rainfall that occurs as runoff (Beilfuss 2012).

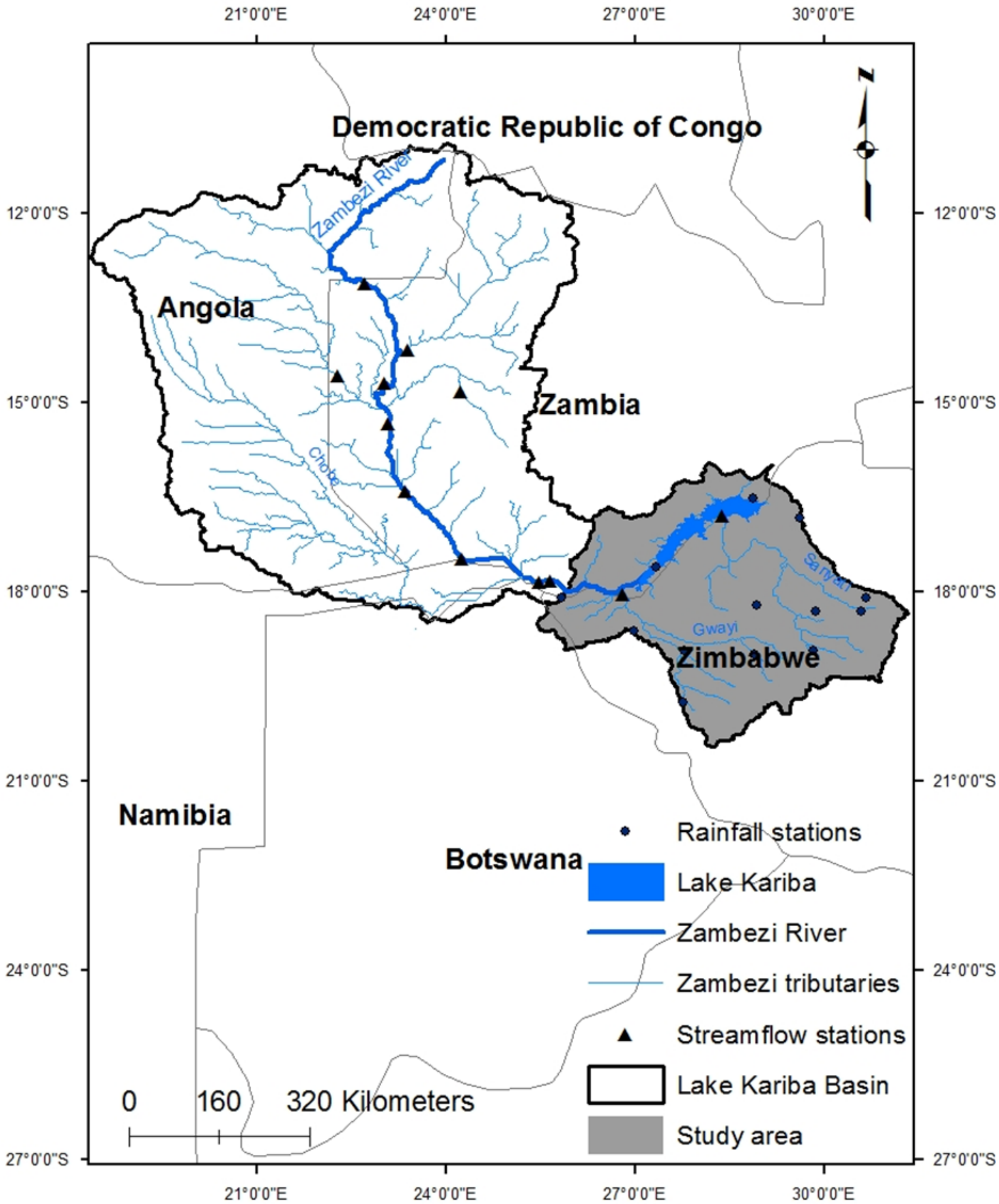

Figure 1. Location of the Kariba River Basin.

2.3 Data and Methodology

2.3.1 Data

The monthly total rainfall data (accumulated from daily totals) considered in the present study consists of observations from a network of thirteen stations which are distributed across the Lake Kariba Catchment area. These data sets were obtained from Zimbabwe Meteorological Services (ZMS). Furthermore, these monthly total rainfall data records spanned a period of 1970 to 2010 without any missing data sets. Table 1 summarizes the characteristics of the selected stations.

GEOGRAPHICAL LOCATION	NATIONAL NUMBER	STATION NAME	LATITUDE [degrees]	LONGITUDE [degrees]
MASHONALAND WEST	67891	Mhondoro Met	18 .19	30. 36
MASHONALAND WEST	67893	Chibhero Met	18. 09	30. 40
MASHONALAND WEST	67761	Kariba Airport Met	13. 31	28. 53
MATEBELELAND NORTH	67843	Victoria Falls Met	17.56	25.50
MIDLANDS	67865	Kwekwe Met	18.56	29.50
MASHONALAND WEST	67869	Kadoma Met	18.19	29.53
MASHONALAND WEST	67765	Karoi Met	16.50	29.37
MATEBELELAND NORTH	67853	Hwange Met	18.44	26.57
MIDLANDS	67861	Gokwe Met	18.13	26.56
MATEBELELAND NORTH	67755	Binga Met	17.37	27.20
MATEBELELAND NORTH	67857	Tsholotsho Met	19.45	27.46
MATEBELELAND NORTH	67855	Lupane Met	18.57	27.48
MATEBELELAND NORTH	67863	Nkayi Met	19.00	28.54

Table 1. Characteristics of the study network of stations.

2.3.2 Methodology

2.3.2.1 Intervention and homogeneity

Rainfall data collected at stations spanning a period of several years may not be homogeneous, i.e., the rainfall measurements may have inherent sudden changes or shifts in its mean and variance in relation to the original values. These in-homogeneities and inconsistencies may occur due to several causes, some of which are related to changes in; a) sensor instrumentation (malfunctioning, variation in the power supply and even replacements), b) observation practices (including changes in observation times, location of the instrument), c) modifications of the environmental conditions (overall changes in land cover and land use) of the site, and d) overall climate change and variability. As a result of these changes, observations made prior to the changes often exhibit different statistical properties than data collected after the change. As a first step towards understanding the variability of rainfall in a given area, it is necessary to apply appropriate techniques to evaluate whether a given data set can be considered to be homogeneous and, if not, introduce the appropriate corrections. In the present study, intervention and homogeneity analysis approaches are considered. In the intervention approach considered in the present study, a Cumulative Summation (hereafter CUSUM) technique reported in e.g., Parida et al. (2003) and Kampata et al. (2008) expressed in Equation (1) was used to decipher the inconsistencies and test for homogeneity across the network of thirteen stations of the Kariba catchment region depicted in Figure 1.

$$S_m = \sum_{i=1}^{m} \left(\bar{x} - \mu_0 \right) \tag{1}$$

In Equation 1, S_m is the CUSUM values while m and μ are the sample number and the 41 year climatological mean value respectively. Dates when the S_m values change between positive and negative values are used to split the data set into two periods i.e., the pre- and post-intervention periods. The resulting data groups are then subjected to a step change analysis using the rank-sum test (which is a non-parametric test, the median differences between two data subsets) reported in e.g., Helsel and Hirsch (2002). The relevant Equations for the rank-sum test statistic Z_{rs} have been summarized in Kampata et al. (2008) and re-written in Equations 2 for the purpose of completeness.

$$Z_{rs} = \begin{cases} \dfrac{S_m - 0.5 - \mu_t}{\sigma} & \text{if } S_m > \mu_t \\ 0 & \text{if } S_m = \mu_t \\ \dfrac{S_m - 0.5 - \mu_t}{\sigma} & \text{if } S_m < \mu_t \end{cases} \tag{2}$$

$$\mu_t = 0.5k\left(N+1\right)$$
$$\sigma = \sqrt{\frac{km\left(N+1\right)}{12}}$$

In Equation 2, S_m, μ_t and σ are the statistic (computed as the sum of ranks of the observations in the smaller group), the theoretical mean and standard deviation respectively of ranked data. Furthermore, N is the largest rank while k and m are the number of observations in the smallest and largest group respectively. When Z_{rs}<Z (this Z is the critical value of the Z-statistics obtained from the normal distribution table at a 5% significance level, Kampata et al. 2008), then the null hypothesis, H_0, is accepted suggesting that the two samples come from the same distribution.

It is seldom that long term rainfall measurements have been consistently performed by the same method, with the same undamaged instrumentation, at the same place and time, and the same environment. For this reason, such the rainfall records would exhibit inherent inhomogeneity. These in-homogeneities often bias e.g., climate time series and may lead to misinterpretations of the phenomena under investigation. As reported in Peterson et al. (1998), there are numerous methods used to assess the heterogeneity in a time series. It is however recommended that a combination of statistical and metadata information be considered during analysis of homogeneity in order to effectively track down any inherent heterogeneity in e.g., rainfall time series. Furthermore, homogeneity can be assessed by use of relative or absolute methods (Sahin and Cigizoglu, 2010). As reported in Sahin and Cigizoglu, (2010), relative methods of detecting homogeneity in a time series assume that the reference station is homogeneous and often require the series at each candidate stations to be correlated. In cases where the correlation is low, absolute methods (which often utilize individual station time series) are considered more tractable (Wijngaard et al. 2003).

Absolute statistical methods such as those reported in e.g., Bushland (1982), Peterson, et al. (1998), Alexanderson (1986), Costa, et al. (2009) and Ho, et al. (2012) have been widely used for homogeneity tests. These methods often vary in complexity and assumptions of the statistical properties of the data series. Refer to e.g., Wijngaard et al. (2003) for the detailed algorithm of these tests. In the present work, the four main absolute methods widely used for homogeneity test are considered and are summarised in Table 2. In the SNHT, BRT and PT, an inherent step-wise shift in the mean often designates an inhomogeneous series and the test is capable of locating the corresponding break-down time (i.e., these tests are location specific). Furthermore, a classification of the test results reported in Wijngaard et al. (2003) has also been considered to characterize the nature of homogeneity across the stations used in this study.

TYPE OF TEST	**NULL HYPOTHESIS**	**REMARKS**
STANDARD NORMAL HOMOGENEITY TEST (SNHT)	$H_{0:}$ The whole series is homogeneous, i.e., $z_i \in N(0,1);\ \mathrm{i} \in (1 \ldots n)$ $H_{1:}$ Series is inhomogeneous i.e., $z_i \in \begin{cases} N(\mu_1,1);\ \mathrm{i} \in (1 \ldots a) \\ N(\mu_2,1);\ \mathrm{i} \in (a+1 \ldots n) \end{cases}$	- Ref., Alexanderson (1986) and Alexandersson and Moberg (1997) - Can be used to account for more than one discontinuity, testing for inhomogeneous trends rather than just breaks, and inclusion of change invariance.
BUISHAND RANGE TEST (BRT)	$H_{0:}$ Precipitation follow one or more distributions that have the same mean $H_{1:}$ there exists a time t the precipitation changes the mean	-Ref., Buishand (1982) - Use adjusted partial sums: $S_0^* = 0$ $S_y^* = \sum_{i=1}^{y} \left(Y_i - \overline{Y}\right), \quad y = 1, 2 \ldots, n$ - When the value of S_y^* oscillate around zero, then the data is homogeneous - A rescaled range is computed as $R = \dfrac{\left(\max\limits_{0 \le y \le n} S_y^* - \min\limits_{0 \le y \le n} S_y^* \right)}{\sigma}$

PETTITT TEST (PT)	$H_{0:}$ Data are homogeneous, $H_{1:}$ A date at which there is change in the data exists	- Ref., Pettitt (1979) - This test is based on the rank, r_i of Y_i and ignores the normality of the series. $X_y = 2\sum_{i=1}^{y} r_i - y(n+1), \quad y = 1, 2, \ldots n$ - The break occurs in year k when $X_k = \max_{1 \le y \le n} \lvert X_y \rvert$
VON NEUMANN RATIO TEST (VNRT)	H_0: precipitation data sets are independent, identically distributed randomly and that for homogeneous precipitation, the mean of the ratio is two. $H_{1:}$ there is a date at which there is a change in precipitation.	-Ref., Von Neumann (1941) - It is a test that used the ratio of mean square successive (year to year) difference to the variance - Test statistic: $N = \frac{\sum_{i=1}^{n-1} (Y_i - Y_{i+1})^2}{\sum_{i=1}^{n} \left(Y_i - \bar{Y}\right)^2} \frac{N}{N-1}$

Table 2. Absolute statistical methods of homogeneity test.

2.3.3 Trend analysis

In this study, trend analysis was done using the non-parametric Man-Kendall (MK) test (Mann 1945; Kendall 1975). The trend magnitudes were computed by the Theil-Sen's estimator (Theil 1950; Sen's 1968). The MK test has been widely used in hydro-meteorological time series to detect significant trends (Yue and Hashino 2003b; Cannarozzo et al. 2006; Partal and Kalya 2006; Mazvimavi and Wolski 2006; Modarres and da Silva 2007; Kampata et al. 2008; Liu et al. 2008; Shang et al. 2009) and highly recommended by the World Meteorological Organization (WMO). The authors feel that it suffices just to mention the MK null hypothesis herein and the readers are encouraged to refer to the existing numerous literature for relevant equations of the MK test statistic.

2.3.4 Wavelet based coherence analysis

One practical application of wavelet analysis in interpreting multiscale, irregular, non-stationary and noisy time series as well as analysing the transient coupling between any two signals has been demonstrated and reported in numerous literature (see e.g., Torrence and Compo 1998; Grinsted et al. 2004; Maraun and Kurths 2004; Maraun 2007; Zhongwei and Jones 2008). Wavelet analysis permits local time-scale decomposition of the rainfall time series (i.e., estimating the spectral characteristics as a function time) therefore contributes towards understanding how the different scales are related to the inherent variability. In particular, wavelet cross-spectrum and coherency are vital parameters that aid in analysing dependencies of climate fluctuations across different locations or zones. Wavelet Coherence (WC) analysis is a robust technique that can be used to quantitatively depict time-scale-dependent correlations and phase shifts between time series records at various time scales (Grinsted et al. 2004; Liu et al. 2005).

In order to characterize the causal relationships (such as localized variability, dominant modes of variability and their time evolution) of precipitation across the study network in the Kariba catchment area (which are thought to be linked together by similar climatology), rainfall records at each station were decomposed into the time-frequency space based on the procedure described in Torrence and Compo (1998). In the present work, the continuous wavelet transform was used to expand the annual precipitation time series into the wavelet space (i.e., time-frequency) in order to detect and characterize any inherent intermittent variability (Torrence and Compo 1998; Grinsted et al. 2004; Maraun and Kurths 2004; Maraun 2007). In addition, the Cross Wavelet Transform coefficients (CWTs) were constructed from pairs of continuous wavelet transform coefficients (station-wise pairs). The CWTs are suitable for divulging common power and relative phases present in the time series in the wavelet space. In order to reveal significant coherence (even in cases of low common power) of the paired station-wise precipitation records, WC between any two CWT was computed and analysed using a methodology reported in e.g., Grinsted et al. (2004) and Maraun and Kurths (2004). Overall, the advantage of using wavelet-based parameters (i.e., CWT and WC) is that they vary in time and therefore can detect the association between different modes of climate fluctuation as well as provide the localized linear correlation of pairs of climate fluctuation at a specific frequency and time in the wavelet space. The statistical significance of the computed CWT and WC are estimated using Monte Carlo method as reported in Grinsted et al. (2004).

2.4 Results and discussion

2.4.1 Rainfall variability in the Kariba catchment area

Understanding and explaining the nature and causes of quasi-regular spatial-temporal variability in precipitation has been central in hydro-meteorology, climate and weather research. In the first phase of analysing rainfall variability in the Kariba catchment region, graphical visual examination of the data sets was carried out in order to flag any biases (this is determined statistically by use of standard deviation as the thresholds), and record the number of missing data sets. In general, the data sets used in the present study were good and the proportion of missing data was less than 0.5% in most of the stations. As shown in Figure

2, the pattern or structure of monthly and annual rainfall variability across the study network is strikingly similar albeit systematic differences in the amplitudes of the modes of variability.

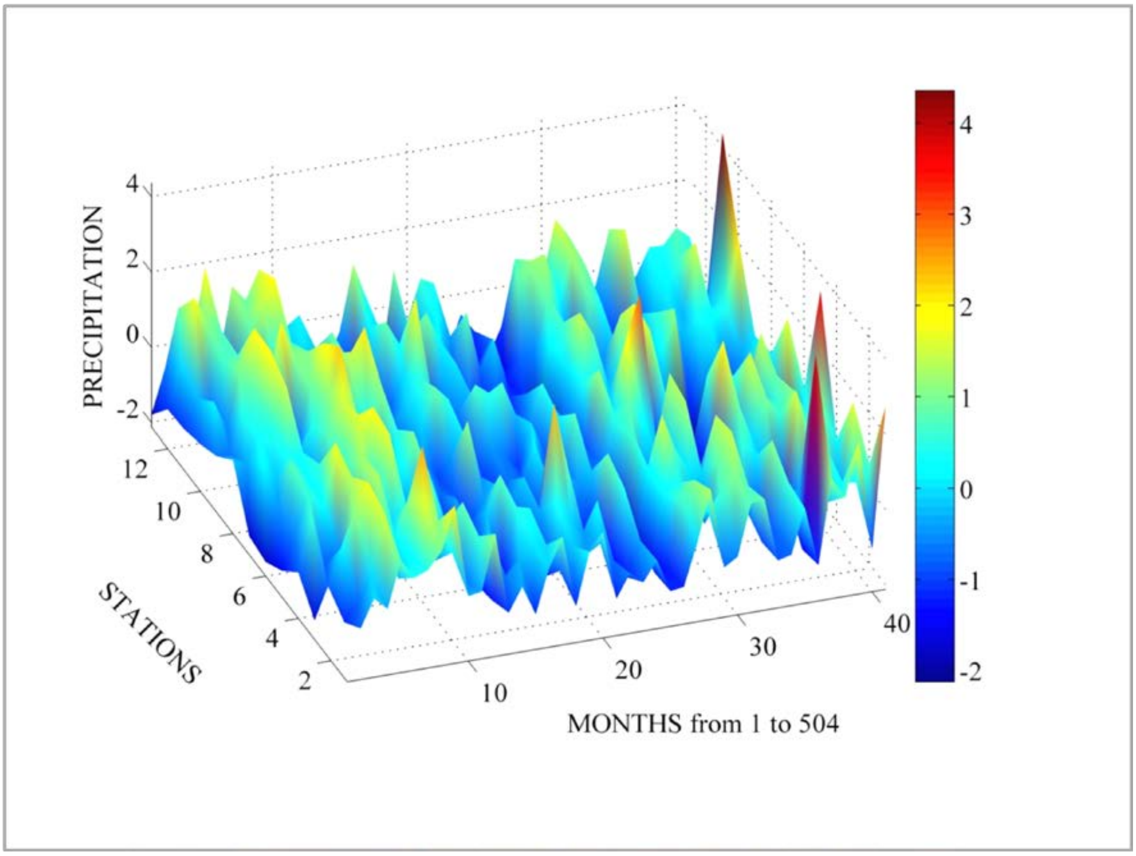

Figure 2. Visual inspection of rainfall variability.

Time Box-plots depicted in Figure 3 were used to analyze the characteristic variability of rainfall across all the stations. As illustrated in Figure 3, all the stations exhibit very similar decadal variability pattern as there are no noticeable differences in the decadal medians. The long upper whisker could be associated to the presence of extreme values and or outliers (biases) in the data sets. The seasonally averaged rainfall totals clearly depicts summer rainfall (DJF), is also 50% higher than winter (JJA) which, as expected, has the lowest rainfall. The variability during winter is at the minimum (short whickers). The seasonal pattern of rainfall in the Kariba catchment region is clearly demonstrated by the bottom panel of Figure 3. As shown in Figure 3, the Kariba catchment area receives rainfall between November and March with extreme rainfall events or suspected station dependent interventions recorded in across most the months except for January and November.

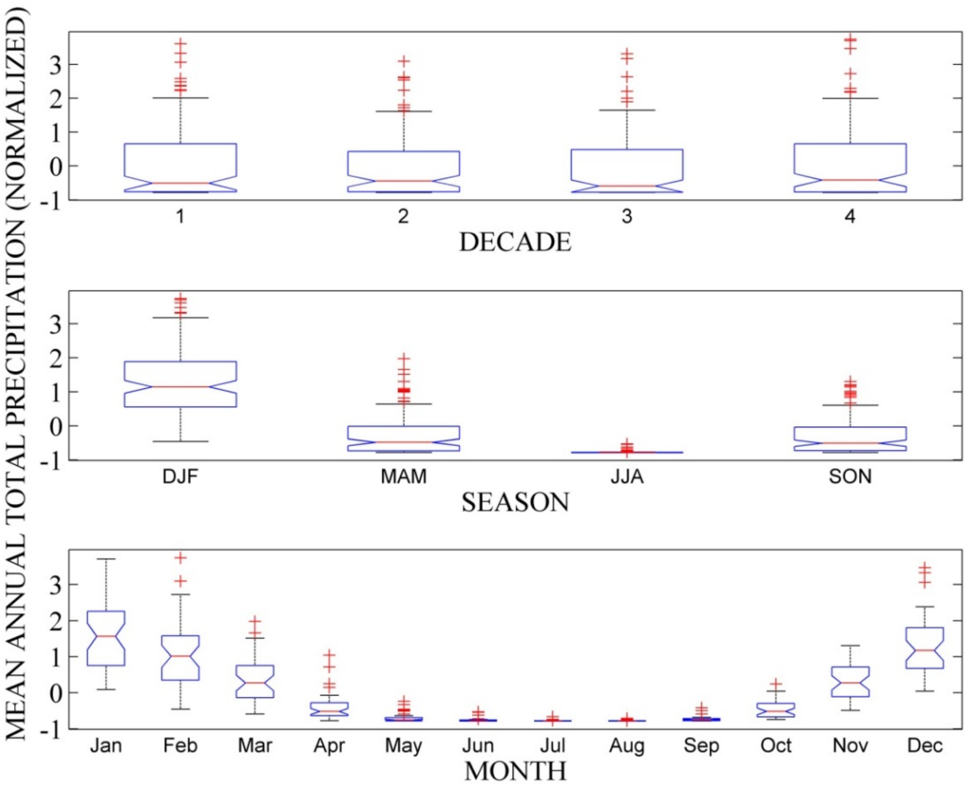

Figure 3. Box plot for showing rainfall variability.

Investigating whether the rainfall series exhibits a normal distribution is vital in order to determine whether parametric or non-parametric tests would be used for assessing the presence of interventions, homogeneities, trends and variability. In order to understand the underlying distribution characteristics of the monthly rainfall, DJF and annual averaged rainfall totals, four normality tests; Shapiro-Wilk (SW), Anderson-Darling (AD), Lillierfors (LF) and Jarque-Bera (JB) tests (see for example D'Agostino and Stephens 1986); Razali and

Wah 2011) were applied to the rainfall data sets. The results of these tests are given in Table 3. As illustrated in Table 3, the normality of rainfall data was confirmed by two and four tests only in Victoria Falls and Tsholotsho stations respectively. Data from six stations were confirmed normal distributed from all the tests. The percentage number stations confirmed to be normally distributed varied from test to test as follows: JB (85%), LF (81%), AD (81%) and SW (65%).

TYPE OF TEST AND PARAMETER OF INTEREST		KAROI	HWANGE	GOKWE	BINGA	TSHOLOTSHO	LUPANE	NKAYI	MHONDORO	CHIBHERO	KARIBA	VICTORIA FALLS	KWEKWE	KADOMA COTTON
SHAPIRO-WILK	ANNUAL	0.009	0.002	0.533	0.741	0.009	0.375	0.089	0.227	0.072	0.307	0.000	0.249	0.367
	DJF	0.210	0.322	0.483	0.447	0.026	0.231	0.439	0.008	0.174	0.922	0.045	0.134	0.647
ANDERSON-DARLING	ANNUAL	0.024	0.105	0.797	0.845	0.061	0.443	0.134	0.165	0.043	0.404	0.008	0.461	0.507
	DJF	0.282	0.478	0.574	0.214	0.055	0.308	0.683	0.206	0.214	0.974	0.017	0.038	0.476
LILLIEFORS	ANNUAL	0.074	0.358	0.936	0.700	0.017	0.518	0.139	0.391	0.100	0.508	0.096	0.462	0.275
	DJF	0.223	0.375	0.652	0.205	0.218	0.351	0.683	0.325	0.069	0.996	0.000	0.040	0.503
JACQUE-BERA	ANNUAL	0.153	0.000	0.630	0.648	0.000	0.551	0.080	0.843	0.287	0.560	0.000	0.377	0.455
	DJF	0.370	0.525	0.433	0.705	0.313	0.603	0.551	0.000	0.432	0.814	0.392	0.640	0.784
NUMBER OF PASSES		5	6	8	8	4	8	8	6	6	8	2	6	8

Table 3. Normality tests for annual, seasonal rainfall total.

2.4.2 Intervention and homogeneity analysis

2.4.2.1 Intervention analysis

The rainfall CUSUM values for twelve of the thirteen stations depicted in Figure 4 demonstrates that the monthly rainfall has been above the long-term mean for most of the time in 11 stations. Furthermore, there appears to have been interventions in most of the stations (about 8) from 1982, resulting in a generally downward trend. The most probable dates (months since January, 1970) for the observed interventions were determined and the step change analysis was carried to validate the observed intervention. The intervention dates and the corresponding step change analysis results are given in Table 4. It appears that the test statistic (Z-values) are less than the critical value of 1.96 (5%) in all the 12 stations suggesting that the CUSUM values cannot be confirmed. These results implies that the rainfall time series in Kariba catchment area come from the same climatological region and the area experiences an oscillatory hydro-meteorological signal that has no apparent shifts over the 40 year period.

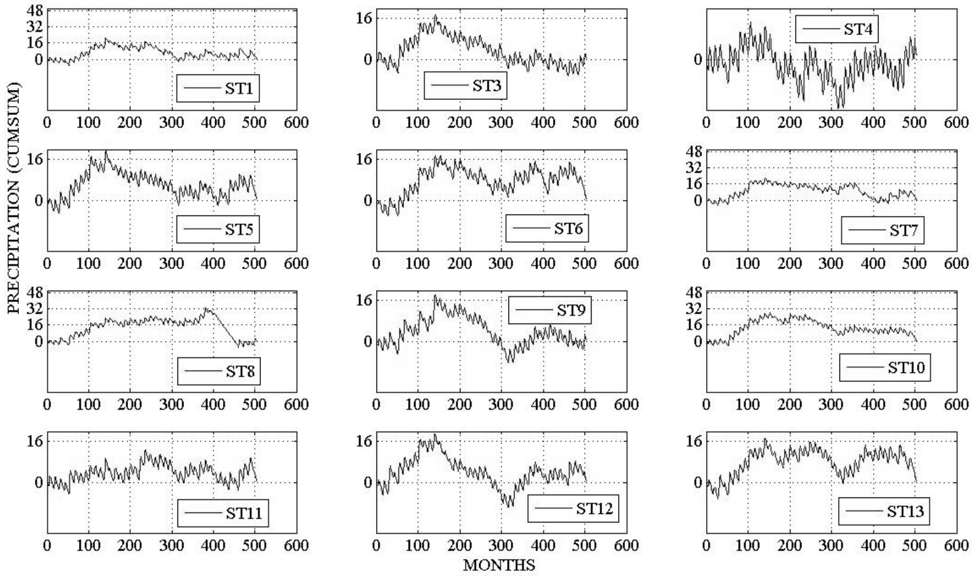

Figure 4. CUSUM plot for rainfall in 12 stations.

STATIONS	PARAMETER			
	BREAK-POINT (MONTH)	P-value	h-value	Z-value
KAROI	144	0.15	0	1.45
GOKWE	144	0.16	0	1.40
BINGA	112	0.22	0	1.24
TSHOLOTSHO	144	0.22	0	1.23
LUPANE	144	0.16	0	1.40
NKAYI	128	0.14	0	1.48
MHONDORO	384	0.09	0	-1.68
CHIBHERO	144	0.32	0	0.99
KARIBA	144	0.18	0	1.35
VICTORIA FALLS	240	0.19	0	1.30
KWEKWE	144	0.30	0	1.03
KADOMA COTTON	144	0.13	0	1.51

Table 4. Step change analysis using the rank-sum method.

2.4.2.2 Homogeneity tests

Annual total rainfall amounts at each of the thirteen stations was tested for homogeneity by the four absolute test methods reported in e.g., Wijngaard et al. (2003) i.e., SNHT, BRT, PT and VNT and the results are given in Table 5**.** As reported in e.g., Wijngaard et al. (2003), Feng et al. (2004) and Sahin and Ggizoglul (2010), the absolute tests considered here could have different sensitivities to changes in rainfall series. As a result, there are apparent differences in test results across the stations illustrated in Table 5**.** The VNT scored four in-homogeneities; SNHT scored two in-homogeneities while PT and BRT scored one in-homogeneities each. Additionally, based on the Wijngaard et al. (2003) classification, the present study distinguished the in-homogeneities across the stations by categorizing them depending on the number of absolute tests rejecting the null hypothesis at the 5% significance level i.e., a) class A: zero or one rejection, b) class B: two rejections, and c) class C: three or more rejections.

In Table 5, it is noticeable that only Mhondoro and Tsholotsho stations are suspect (class C) and doubtful (class B) respectively and all the other stations are useful (class A). This means that most of the stations considered in the present study seem to be homogeneous (and that the inherent heterogeneity amplitude that could be present is subtle) and therefore credible for trends and variability analysis. The heterogeneity present in Mhondoro suggest that any trends present in the Mhondoro rainfall data ought to be considered with caution or disregarded unless the magnitude of the trend is sufficiently large and this has to be supported with a priori information regarding the presence of climatic signal rather than artificial excursions. In Table 6, the results of the SNHT, BRT, PT and VNT test applied to DJF rainfall totals are given. The BRT and VNT characterize DJF rainfall at Hwange, Gokwe and Chibhero stations to be inhomogeneous. These stations are in close proximity to Mhondoro station. Similarly, the DJF rainfall at the thirteen stations has been characterized into two

TYPE OF TEST AND PARAMETER OF INTEREST		KAROI	HWANGE	GOKWE	BINGA	TSHOLOTSHO	LUPANE	NKAYI	MHONDORO	CHIBHERO	KARIBA	VICTORIA FALLS	KWEKWE	KADOMA COTTON
PETTITT	K	102	159.0	102.0	120.0	168.0	100.0	144.0	214.0	136.0	184.0	84.0	130.0	102.0
	P	0.63	0.13	0.63	0.44	0.11	0.65	0.24	0.02	0.30	0.07	0.83	0.35	0.62
SNHT	T_0	7.68	5.17	3.53	2.64	12.91	3.16	4.69	13.28	5.16	7.23	19.47	4.71	3.35
	P	0.10	0.25	0.49	0.74	0.04	0.61	0.30	0.001	0.22	0.08	0.001	0.28	0.55
BUISHAND	Q	5.29	6.51	5.21	4.66	7.25	4.21	6.77	9.78	6.70	7.93	5.85	5.83	4.19
	P	0.40	0.16	0.41	0.55	0.09	0.67	0.14	0.01	0.15	0.06	0.27	0.28	0.67
VON NEUMANN	N	1.92	1.88	1.83	2.04	1.38	1.87	1.72	1.04	1.59	1.24	1.67	1.37	1.66
	P	0.39	0.34	0.29	0.55	0.02	0.34	0.18	0.00	0.09	0.01	0.13	0.02	0.14
TEST CLASS		A	A	A	A	B	A	A	C	A	A	A	A	A

Table 5. Absolute homogeneity test for annual averaged rainfall totals.

TYPE OF TEST AND PARAMETER OF INTEREST		KAROI	HWANGE	GOKWE	BINGA	TSHOLOTSHO	LUPANE	NKAYI	MHONDORO	CHIBHERO	KARIBA	VICTORIA FALLS	KWEKWE	KADOMA COTTON
PETTITT	K	74.0	168.0	124.0	74.0	90.0	76.0	104.0	90.0	146.0	170.0	86.0	140.0	96.0
	P	0.94	0.14	0.45	0.93	0.81	0.92	0.65	0.81	0.26	0.13	0.84	0.32	0.74
SNHT	T_0	2.37	8.64	8.92	7.50	2.15	7.49	2.34	3.02	10.93	6.04	3.59	5.83	4.25
	P	0.78	0.03	0.04	0.10	0.84	0.10	0.82	0.59	0.01	0.15	0.55	0.17	0.37
BUISHAND	Q	4.57	8.21	5.39	3.74	4.11	3.69	4.53	5.15	5.41	6.79	3.42	5.26	4.25
	P	0.58	0.05	0.38	0.79	0.71	0.82	0.59	0.44	0.38	0.16	0.87	0.41	0.67
VON NEUMANN	N	2.38	1.41	1.44	2.22	2.71	2.04	1.96	2.36	1.43	6.90	2.14	2.10	1.87
	P	0.90	0.02	0.03	0.76	0.71	0.55	0.44	0.89	0.03	0.50	0.68	0.62	0.34
TEST CLASS		A	B	B	A	A	A	A	A	B	A	A	A	A

Table 6. Homogeneity tests for seasonal data.

nominal classes A and B. Furthermore, Hwange, Gokwe and Chibhero stations belong to class B category while the rest of the stations are class A category. These results suggest that trend and variability analysis of the DJF rainfall totals could be considered plausible e.g. Sexton et al, 2013).

2.4.3 Trend analysis

2.4.3.1 Annual trends

Results of the MK test for annual trends of precipitation in the Kariba catchment area, Zambezi basin, for the period 1970 to 2010 are shown in Table 7. All the stations with the exception of Mhondoro exhibit insignificant trends. As a result, our results

STATION NAME	MANN KENDALL TEST			SEN'S SLOPE		h_{values}
	KENDALL τ	P_{values} (2-tailed)	Z_{values}	P_{values} (2-tailed)	*b*	
KAROI	0.04	0.73	0.35	0.25	0.005	0
HWANGE	0.05	0.65	0.45	0.89	0.005	0
GOKWE	-0.02	0.87	-0.17	0.40	-0.002	0
BINGA	0.09	0.43	0.80	0.87	0.012	0
TSHOLOTSHO	0.10	0.38	0.89	0.54	0.013	0
LUPANE	0.00	1.00	0.00	0.45	0.000	0
NKAYI	0.08	0.49	0.69	0.75	0.009	0
MHONDORO	-0.25	0.02	-2.30	0.11	-0.027	1
CHIBHERO	-0.05	0.68	-0.42	0.45	-0.007	0
KARIBA	-0.03	0.80	-0.26	0.19	-0.008	0
VICTORIA FALLS	0.05	0.63	0.48	0.29	0.006	0
KWEKWE	-0.01	0.94	-0.08	0.67	-0.004	0
KADOMA COTTON	0.02	0.88	0.15	0.43	0.003	0

Table 7. Annual rainfall trend test statistics for significant trends at α=0.05

corroborate those reported in Kampata et al. (2008) who used non-intervened series of rainfall in the hind-stream of the upper Zambezi River Basin in Zambia. In particular, the study region reported in Kampata et al. (2008) belongs to the same climate regime as the current study region. Using the KM test, it can be noticed that both positive (~ 62%) and negative (~ 38%) trends were identified in annual precipitation data (this is illustrated in Figure 5) Based on the Theil-Sen's estimator, the magnitudes of the significant trends were determined to be in the range of about (-) 0.027 mm/year at Mhondoro station to (+) 0.013 mm per year at Tsholotsho station.

2.4.3.2 Seasonal trends

The existence of seasonal trends in rainfall trends was assessed by applying the MK test to the DJF rainfall time series spanning 1970 to 2010. As depicted in Table 8, all the stations did not have any significant trend at the 95% significance level. As shown in Table 8 and Figure 5, there exist both negative (~ 69%) and positive (31%) insignificant trends and this structure is a complete inverse compared to the annual distribution pattern. This means that the Kariba catchment region is becoming subtly drier. This scenario might impact negatively e.g., the agricultural and livestock production activities (especially those activities that are time critical) in the area. In addition, decisions related to water management will be impacted due to the associated reduction of water in Lake Kariba. This subtle declining DJF rainfall, high variability and the low statistical significance will often lead to underestimating the importance of climate signals (trends) that could be very catastrophic to society and the economy. The magnitude of the seasonal trends inherent in the DJF series in the Kariba catchment area ranges between (-) 0.022 mm per year Kariba station to (+) 0.013 at Nkayi station.

STATION NAME	MANN KENDALL TEST			SEN'S SLOPE		h_{values}
	KENDALL τ	P_{values} (2-tailed)	Z_{values}	P_{values} (2-tailed)	*b*	
KAROI	0.04	0.75	0.33	0.87	0.005	0
HWANGE	-0.18	0.28	-1.08	0.63	-0.016	0
GOKWE	-0.06	0.62	-0.51	0.46	-0.007	0
BINGA	-0.06	0.59	-0.54	0.40	-0.010	0
TSHOLOTSHO	0.01	0.91	0.11	0.91	0.001	0
LUPANE	-0.03	0.76	-0.30	0.91	-0.004	0
NKAYI	0.10	0.35	0.93	0.40	0.013	0
MHONDORO	-0.01	0.93	-0.09	0.66	-0.001	0
CHIBHERO	0.08	0.44	0.77	0.91	0.011	0
KARIBA	-0.17	0.12	-1.57	0.25	-0.022	0
VICTORIA FALLS	-0.03	0.76	-0.30	0.16	-0.003	0
KWEKWE	-0.07	0.50	-0.67	0.20	-0.012	0
KADOMA COTTON	-0.02	0.87	-0.16	0.43	-0.001	0

Table 8. Summer (DJF) rainfall trend test statistics for significant trends at α=0.05

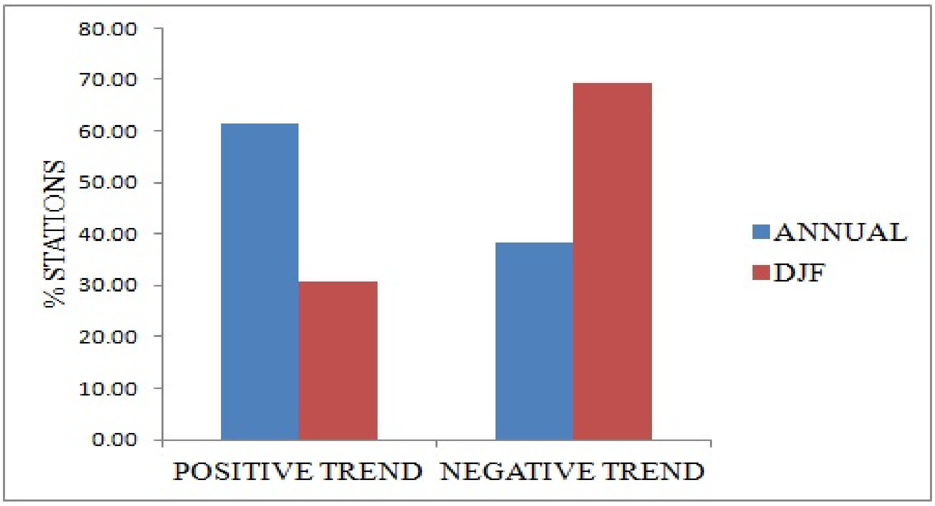

Figure 5. Distribution of positive and negative trends at the 95% confidence level using the Mann-Kendall test for the annual and seasonal rainfall mean totals (1970-2010).

2.5 Coherence of rainfall variability across stations

The CWT and WC derived from the Morlet continuous wavelet transform have been used to examine the nature of monthly total rainfall patterns across the Kariba catchment area by assessing the presence of common power and the relative phase in the time-frequency space. In particular, the phase relationships between standardized rainfall records are explored given that they have common climatology. The Monte Carlo method (using 1000 ensemble surrogate data set pairs of the red noise based on the lag-one autoregressive (AR1) model coefficients of the standardized rainfall data sets) were used to compute the statistical significance (5%) of CWT and WC.

In the wavelet space, the rainfall variability in the northern region of the Kariba catchment area is depicted in Figure 6. As illustrated in Figure 6, the CWT of the standardized rainfall records at Karoi and Chibhero stations have constant in-phase and high common power (at 5% significance level) during 1978-1983 and 1995-2003. There is however a larger area with phase-lock deviation outside the 5% significance level suggesting unreliable phase-lags in rainfall between the two northern stations. Furthermore, the WC depicts larger sections with 5% significance level exhibiting in-phase relationship suggesting causality in the rainfall fluctuations. Overall, the modes of rainfall variability in the northern region of the Kariba catchment area are wavelengths varying from about two to four years.

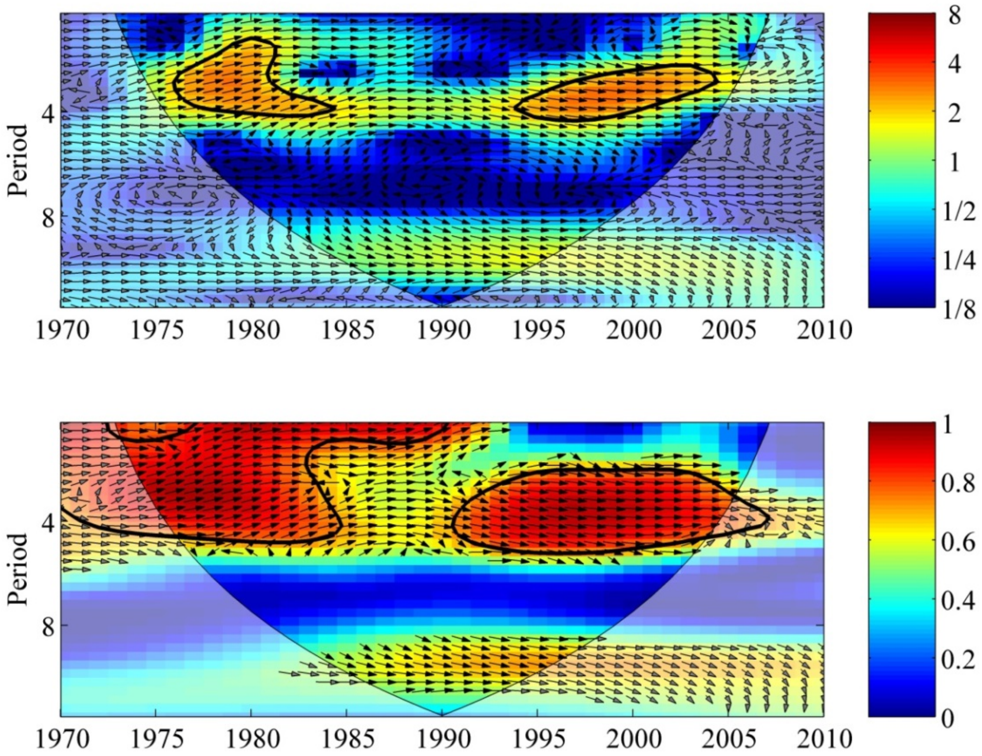

Figure 6. Cross wavelet transform (top) and squared wavelet coherence (below) for rainfall between Karoi and Chibhero stations. Colour codes from dark blue (low values) to dark red (high values). The thick black contour designates the 5% significance level again red noise and the lighter curve is the cone of influence (COI) delimits the region not influenced by edge effects.

As depicted in Figure 7, rainfall fluctuations in the southern part of the Kariba catchment area (Tsholotsho and Nkayi stations) do not show high common power (at 5% significance level) based on the CWT coefficients (top panel). However, the rainfall variability exhibit insignificant locked in-phase oscillatory modes at two wavelength bands varying from 2- 6 years and 8-11 years around 1975 to 1985 and 1985 to 2002 respectively.

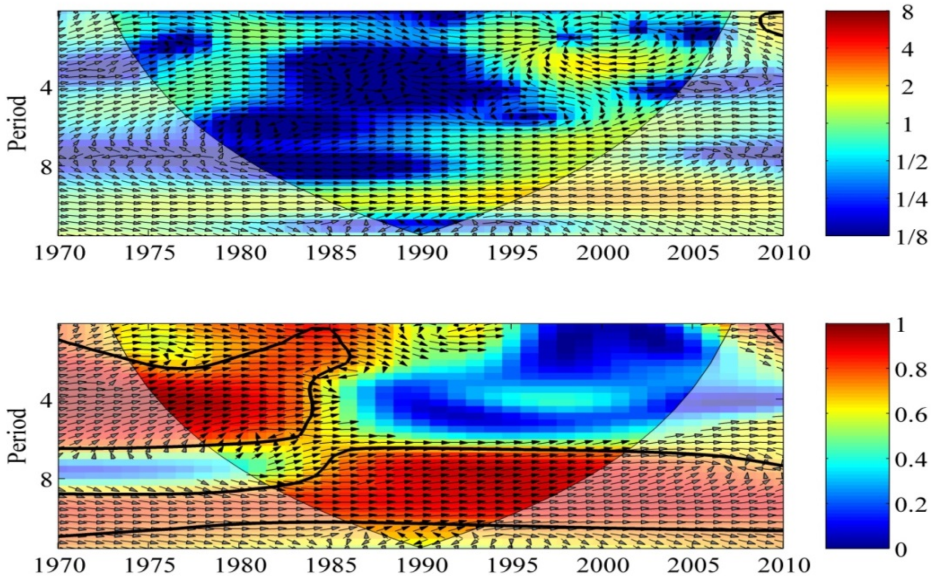

Figure 7. Same as Figure 6 but for rainfall between Tsholotsho and Nkayi.

The eastern part (Mhondoro and Chibhero stations) of the Kariba catchment area exhibits significant high power and constant in-phase around 1975-1985 and 1995-2002, see Figure 8. As shown in bottom panel of Figure 8, there is a larger section of the wavelet space with significant coherent oscillatory modes at varying wavelengths of 2-6 years and 10-12 years between 1975 and 1998. This suggests that the rainfall variability as recorded in Mhondoro mirror the rainfall records at Chibhero station.

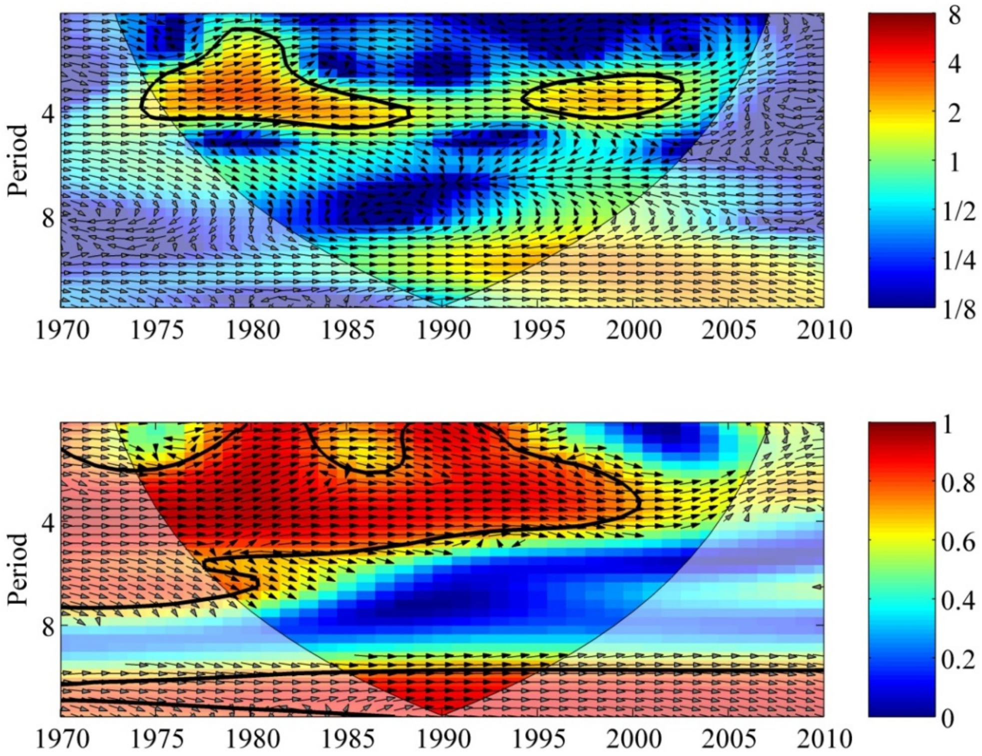

Figure 8. Same as Figure 6 but for rainfall between Mhondoro and Chibhero stations.

Rainfall variability for stations in the western part of Kariba catchment area i.e., Victoria Falls and Binga stations are depicted in Figure 9**.** The top panel illustrates that rainfall fluctuations at Victoria Falls and Binga stations have small sections in the wavelet space with significant common high power at timescales of 4 and 10 years. Sections with 5% significance level are in-phase locked. The coherency in oscillatory modes (see bottom panel of Figure 9.) occur at wavelengths above 8 years while the locked in-phase appear between 1982 and 1995.

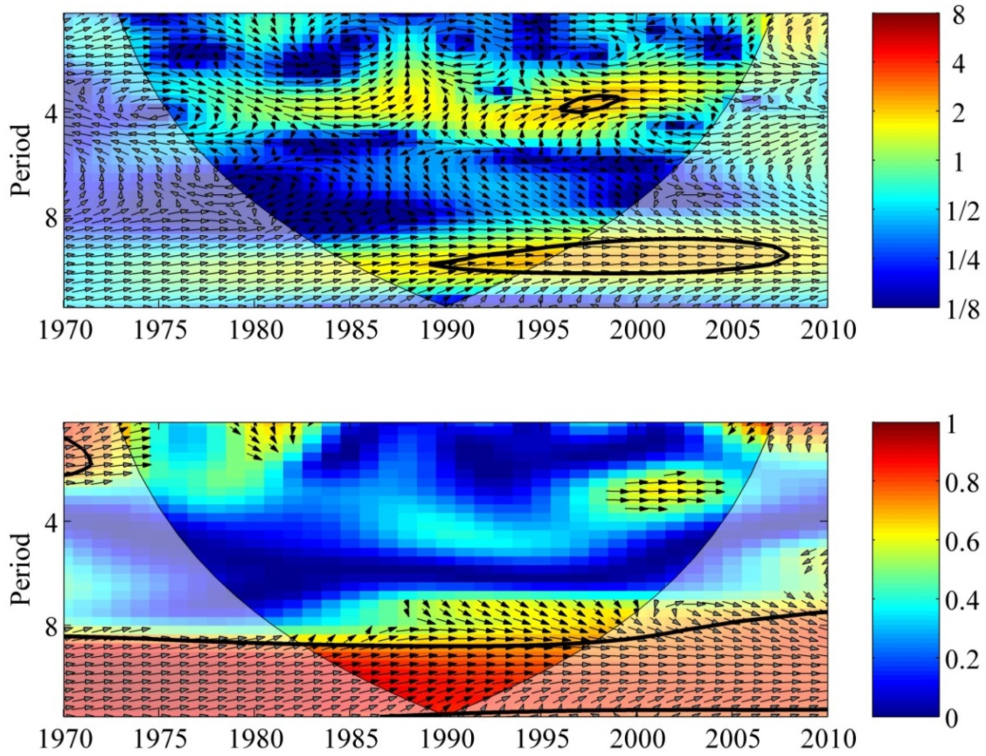

Figure 9. Same as Figure 6 but for rainfall at Victoria Falls and Binga stations.

Figure 10 depicts the CWT (top panel) and WC (bottom panel) for rainfall records in the central part (Gokwe and Kariba) of the Kariba catchment. According to CWT, areas of significant high common power occur at wavelength region of approximately 2-3 years centred around 1985. Furthermore, there is weak in-phase relationship between rainfall records at Gokwe and Kariba stations. Gokwe and Kariba stations have the shortest baseline implying that the fluctuations in the rainfall series ought to mirror each other. On the other hand, the WC of the rainfall at Gokwe and Kariba stations exhibit high coherence around 1985 (at a wavelength of 2-3 years) and between 1995 to 2005 (wavelength centred at 4 years). Compared to the short baseline, Karoi and Tsholotsho stations have a relatively long north-south baseline. The relationship between rainfall records at Karoi and Tsholotsho stations is depicted in Figure 11. The CWT (top panel in Figure 11) illustrate that the significant locked in-phase and common power with time-scale of four years occurred around 1998. Compared to CWT, the WC (bottom panel in Figure 11.) depicts a larger section of significant coherency with marked locked in-phase relationship suggesting that rainfall variability at the various stations across the Kariba catchment area exhibit spatially independent and temporally independent constant phases. Overall, the characteristic of rainfall variability in the Kariba catchment region based on the wavelet-based parameters can be summarized as in Table 9.

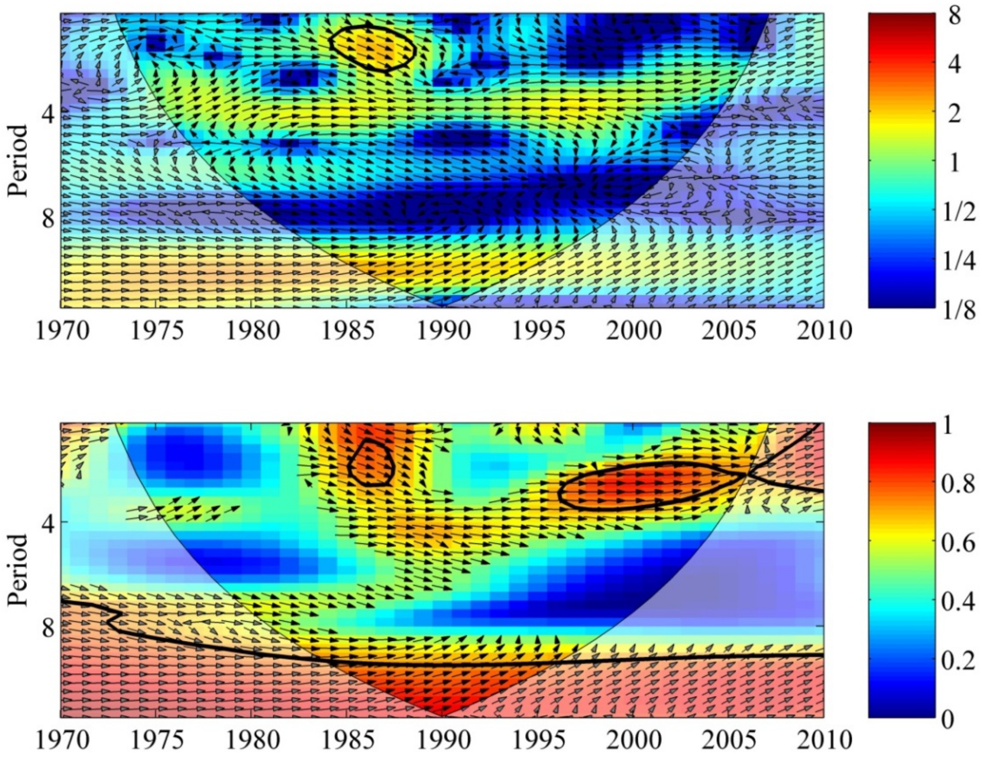

Figure 10. Same as Figure 6 but for rainfall between Gokwe and Kariba stations.

REGION	SIGNIFICANT COMMON POWER	SIGNIFICANT CONSTANT PHASE	WAVELENGTH (YEARS)	TIME SPAN
NORTH	Present	In-phase	2-4	1975-1983; 1995-2003
SOUTH	Absent	In-phase	2-6; 8-11	1975-1985; 1985-2002
EAST	Present	In-phase	2-6; 10-12	1975-1985; 1995-2002
WEST	Present	In-phase	4-10	1982-1995
CENTRAL	Present	In-phase	2-3	1985; 1995-2005

Table 9. Characteristic of rainfall variability based on wavelet-based parameters across the Kariba catchment region.

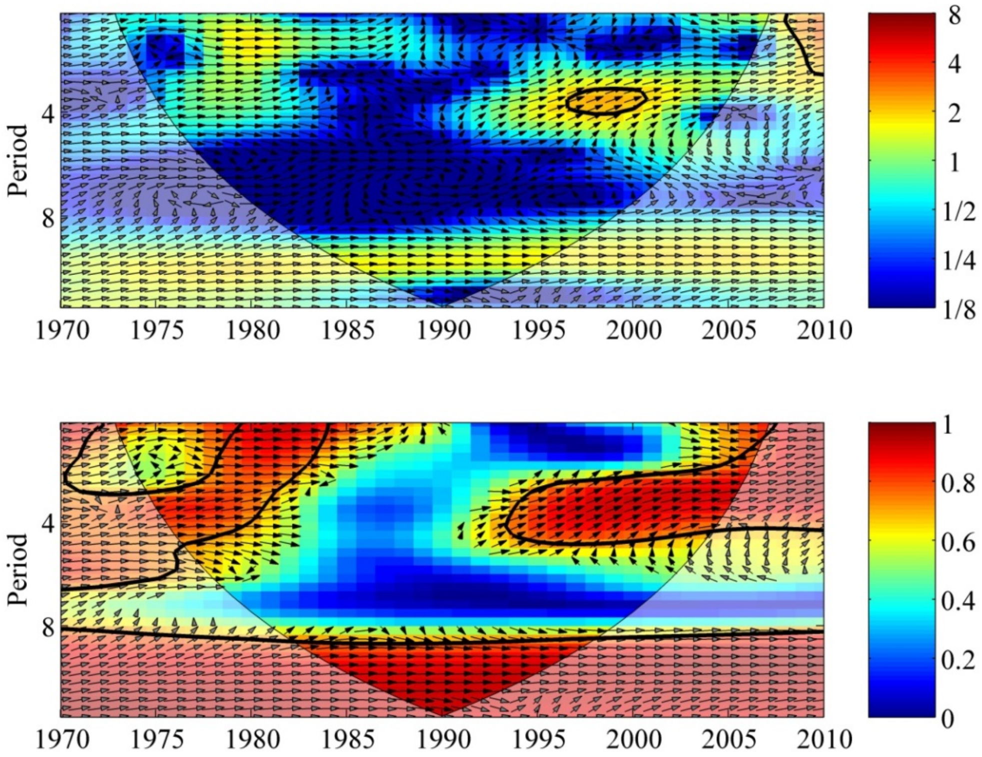

Figure 11. Same as Figure 6 but for rainfall between Karoi and Tsholotsho (long north-south baseline) stations.

2.6 Conclusions

The significance of analysing the variability of rainfall for weather and climate studies has been underscored by various researchers from diverse scientific community. In the present contribution, rainfall data from a network of thirteen stations across the Kariba catchment area in the Zambezi river basin has been analysed. Based on the four decades of rainfall data, the following conclusions can be drawn:

a) All network stations in the Kariba catchment exhibited similar annual and seasonal (DJF) rainfall variability patterns.

b) Annual and seasonal rainfall series across most (about 78%) demonstrated a normal distribution.

c) There were no apparent significant shifts in the annual and seasonal rainfall data in the Kariba catchment area based on the CUSUM and rank-sum test analysis.

d) Annual and seasonal rainfall data from most of the stations were homogeneous. Based on the Wijngaard et al (2003) classification, the network of station considered in the present study were category A (useful) and B (doubtful) stations implying that trend and variability analysis results using the station time series would be considered plausible.

e) The annual and seasonal rainfall series in the Kariba catchment area have non-significant positive and negative trends.

f) Most network stations considered in the present study exhibit coherent oscillatory modes that are constantly locked in phase in the Morlet wavelet space.

The current study is a step towards bridging the gap in rainfall variability characterization in the Kariba catchment area. In particular, these results would be valuable since local-scale rainfall variability can lead to sudden changes in water availability in the surface and sub-surface hydrologic systems thereby significantly affecting agriculture, livestock, water supply and hydropower sectors: the social economic livelihoods over the study area. Future studies focusing on investigating the a) occurrence of extreme events, and b) link between rainfall variability and tele-connection patterns such the Inter Tropical Convergence Zone (ITCZ), El-Niño and La-Niño (ENSO) and Indian Ocean Dipole (IOD) are recommended.

References

Alexandersson H., 1986. A homogeneity test applied to precipitation data. Journal of Climatology 6, 661–675.

Ana Cristina Costa, Amílcar Soares, 2009: Homogenization of Climate Data: Review and New Perspectives Using Geostatistics; Mathematical Geosciences April 2009, Volume 41, Issue 3, pp 291-305.

Beilfuss R.D., 2012. A Risky Climate for Southern African Hydro. Hydrological Risks and Consequences for Zambezi River Basin Dams. International Rivers. Berkeley, CA.

Buishand, T.A., 1982. Some methods for testing the homogeneity of rainfall records. Journal of Hydrology, 58, 11–27.

Cannarozzo, M.L.V. Noto, F. Viola, 2006: Spatial distribution of rainfall trends in Sicily (1921–2000). Physics and Chemistry of the Earth, Parts A/B/C Volume 31, Issue 18, 2006, Pages 1201–1211 Time Series Analysis in Hydrology.

Conway, D., 2005: From headwater tributaries to international river basin: Observing and adapting to climate change and variability in the Nile Basin. Global Environ. Change, 15, 99-114.

Cook, K..H., 2000: The South Indian Convergence Zone and Interannual Rainfall Variability over Southern Africa. J. Climate, 13, 3789-3804.

D'Agostino, R.B., Stephens, M.A., and Marcel D., 1986. Goodness-of Fit Techniques, "Smooth Tests of Goodness of Fit" Oxford Univ. Press, 1989.

De Luis, M., Raventos, J., Gonzalez-Hidalgo, J. R., Cortina, J., 2000. Spatial analysis of rainfall trends in Valencia (east of Spain), 2000. International Journal of Climatology 20 (12), 1451-1469.

Ebinger, J. and W. Vergara. 2011: Climate Impacts on Energy Systems, Key Issues for Energy Sector Adaptation. World Bank Energy Sector Management Assistant Program. Washington, D.C.

Feng S., Hu Q., Qian W., 2004. Quality control of daily meteorological data in China, 1951–2000: a new dataset. International Journal of Climatology, 24, 853–870.

Gordon, C., C. Cooper, C.A. Senior, H. Banks, J.M. Gregory, T.C. Johns, J.F.B. Mitchell, and R.A. Wood, 2000: The simulation of SST, sea ice extents and ocean heat transports in a version of the Hadley Centre coupled model without flux adjustments. Clim. Dyn. 16, 147-168.

Grinsted, J.C. Moore, and S. Jevrejeva, 2004: Application of the cross wavelet transform and wavelet coherence to geophysical time series. Nonlinear Processes in Geophysics (2004) 11, 561–566.

Haigh, M.J., 2004: Sustainable management of headwater resources: the Nairobi headwater declaration (2002) and beyond. Asian Journal of Water, Environment and pollution, 117-28.

Hans Alexandersson and Anders Moberg, 1997: Homogenization of SWEDISH Temperature Data. PART I: Homogeneity Test for Linear Trends; International Journal of Climatology, 17, 25–34.

Helsel, D.R., Hirsch, R.M., 2002. Statistical methods in water resources. United States Geological Survey, 524.

Intergovernmental Panel on Climate Change, 2007. Climate Change 2007: The Physical Science Basis. Cambridge, UK: Cambridge University Press. 6. Jury, M. R., and A. Makarau, 1996: Predictability of Zimbabwe summer rainfall. Int. J. Climatol. 17:1421-1432.

Jury, M.R. and Courtney, S., 1994: Climatic determinants of Benguela SST variability. Continental Shelf Research. 15, 1339-1354

Jury, M.R., Mulenga, H.M. and Mason, S.J., 1999: Exploratory long-range models to estimate summer climate variability over southern Africa. J. Clim. 12, 1892–1899.

Kampata, J.M., B.P. Parida and D.B. Moalafhi, 2008: Trend analysis of rainfall in the headstreams of the Zambezi River Basin in Zambia. Physics and Chemistry of the Earth, 33, 621-625.

Kenabatho, P.K.., N.R. McIntyre, and H.S. Wheater, 2009: Impacts of rainfall uncertainty on water resource planning models in the Upper Limpopo basin, Botswana. New approaches to Hydrological prediction in data sparse regions. Proc. of

Symposium HS.2 at the Joint IAHS & IAH Convention, Hyderabad, India, September 2009. IAHS Publ. 333.

Kendall, M., 1975: Rank Correlation methods. London: Charles Griffin.

Levey, K..M. and Jury M.R., 1996: Composite intra-seasonal oscillations of convection over southern Africa. J. Clim. 9, 1910-1920.

Lindesay, J.A., 1988: South African rainfall, the Southern Oscillation and a Southern Hemisphere semi-annual cycle. J. Climatol. 8,17-30.

Liu, J.P., J.A. Curry, W.B. Rossow, J.R. Key, and X. Wang, 2005: Comparison of surface radiative flux data sets over the Arctic Ocean. J. Geophys. Res., 110, C02015, doi: 10.1029/2004JC002381.

Liu, Y., K. Wang, C. Yu, Y. He, Y. Zhou, M. Liang, L. Wang, 2008: Regional homogeneity, functional connectivity and imaging markers of Alzheimer's disease: A review of resting-state fMRI studies.

Mann, H. - Econometrica, 1945: Nonparametric Tests Against Trend Vol. 13, No. 3 (Jul., 1945), pp. 245-259.

Maraun, D., Kurths, J. & Holschneider, M. 2007: Nonstationary Gaussian processes in wavelet domain: Synthesis, estimation, and significance testing. Physical Review E, 75.

Maraun. D. and J. Kurths, 2004: Cross wavelet analysis: significance testing and pitfalls. Nonlinear Processes in Geophysics 2004, 11, 505–514.

Mason, S.J. and A.M. Joubert, 1997: Simulated changes in extreme rainfall over southern Africa, Int. J. climatol. 17, 291 – 301.

Mason, S.J., and M.R. Jury, 1997: Climate variability and change over southern Africa: a reflection on underlying processes. Prog. Phys. Geog. 21,23–50.

Mazvidza, D.Z., W. Sakala and H Mukupe, 2000: Water transfer schemes due to uneven spatial distribution- Development projects. In M.J. Tumbare (edt). Management of River Basins and Dams: The Zambezi River Basin. A.A. Balkema, Rotterdam/Brookfields.

Mazvimavi, D., and P. Wolski, 2006. Long-term variations of annual flows of the Okavango and Zambezi Rivers. Physics and chemistry of the Earth, 31, 951-994.

Ngongondo, C.S., 2006: An analysis of long-term rainfall variability, trends and ground water availability in the Mulunguzi river catchment area, Zomba mountain, southern Malawi. Quat. Int. 148, 45-50.

Nicholson, S.E., and D. Entekhabi, 1987: Rainfall variability in equatorial and southern Africa: Relationships with sea-surface temperatures along south-western coast of Africa. J. Clim. Appl. Meteorol., 26,561–578.

Nsubuga, F.W.N., J.M. Olwoch, and C.J. Rautenbach, 2011: Climatic trends at Namulonge in Uganda: 1947- 2009. Journal of Geography and Geology, 3,119 -131.

Parida, B.P., Moalafhi, D.B., Kenabatho, P.K., 2003: Effect of urbanization on runoff coefficient: a case of Notwane catchment in Botswana. In: Proceedings of the International Conference on Water and Environment (WE-2003), Bhopal, “Watershed Hydrology”. Allied Publishers Pvt. Ltd., 123-131.

Partal, T, Kahya, E., 2006: Trend analysis in Turkish precipitation data. Hydrological processes, 20, 2011-2026.

Patrick Flandrin, Fellow, IEEE, Gabriel Rilling, and Paulo Gonçalvés, 2004: Empirical Mode Decomposition as a Filter Bank. IEEE Signal Processing Letters, VOL. 11, NO. 2, February.

Pettitt, A. 1979: A non-parametric approach to the change-point detection. Applied Statistics, 28, 126–135.

Ratna S.B., Behera S., Ratnam J.V., Takahashi K. and Yamagata T. (2013). An index for tropical temperate troughs over southern Africa. Clim, Dyn. 41, 421–441.

Razali, N.M., and Wah, Y.B, 2011: Power Comparisons of Shapiro-Wilk, Kolmogorov-Smirnov, Lillefors and Anderson Darling Tests, Journal of Statistical Modelling and Analytics, Vol 2, No 1, 21-33.

Reason, C.J.C., and M. Rouault, 2002: ENSO-like decadal patterns and South African rainfall. Geophys. Res. Lett. 29:10.1029/2002GL014663.

Reason, C.J.C., R.J. Allan, J.A. Lindesay, and T. J. Ansell, 2000: ENSO and climatic signals across the Indian Ocean basin in the global context: Part 1, Interannual composite patterns. Int. J. Climatol. 20:1285–1327.

Reason C.J.C. and Weldon D., 2014: Variability of rainfall characteristics over the South Coast region of South Africa. *Theor. Appl. Climatol*. **115** 177–185.

Reza Modarres and Vicente de Paulo Rodrigues da Silva, 2007: Rainfall trends in arid and semi-arid regions of Iran. Journal of Arid Environments Volume 70, Issue 2, July 2007, Pages 344–355.

Rousseeuw, P.J., 1984: Least Median of Squares Regression “Journal of the American Statistical Association, 79, 871-880.

Sen, P.K. 1968. Estimates of the regression coefficient based on Kendall's Tau, J. Am. Stat. Assoc., 1379-1389.

Sexton, J., Everinghama, Y. and Skocaja D, 2013: Regional climate change projections for the Tully sugar region. 20th International Congress on Modelling and Simulation, Adelaide, Australia, 1–6 December 2013 www.mssanz.org.au/modsim2013

Shannon, L.V., J.R.E. Lutjeharms, and G. Nelson, 1990: Causative mechanisms for intra-annual and interannual variability in the marine environment around southern Africa. South Afr. J. Sci., 86, 356-373.

Sharma, T.C., and I.L. Nyumbu, 1985: Some hydrologic characteristics of the Upper Zambezi Basin. Pages 29-43 in.L. Handlos and G.W. Howard, eds. Development Prospects for the Zambezi Valley in Zambia. Lusaka: Kafue Basin Research Committee of the University of Zambia.

Sheng Yue and Michio Hashimo, 2003b: Long Term Trends of Annual and Monthly Precipitation in Japan: JAWRA Journal of the American Water Resources Association Volume 39, Issue 3, pages 587–596.

Sinan Sahin and H. Kerem Cigizogl., 2010: Homogeneity analysis of Turkish meteorological data set. Hydrological Processes Hydrol. Process.

Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor, and H.L. Miller (eds.) 2007. Regional Climate Projections. In: Climate Change 2007: The Physical Science Basis. Contribution of Working Group 1 to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Theil, H. 1950:. "A rank-invariant method of linear and polynomial regression analysis. I, II, III", Nederl. Akad. Wetensch., Proc. 53: 386–392, 521–525, 1397–1412.

Thomas C. Peterson, David R. Easterling, Thomas R. Karl, Pavel Groisman, Neville Nicholls, Neil Plummer, Simon Torok, Ingeborg Auer, Reinhard Boehm, Donald Gullett, Lucie Vincent, Raino Heinof, Heikki Tuomenvirtaf, Olivier Mestreg, Tama´s Szentimreyh, James Salingeri, Eirik J. Førlandj, Inger Hanssen-Bauerj, Hans Alexanderssonk, Philip Jonesl and David Parker, 1998: Homogeneity Climate. Adjustments of In situ Atmospheric Data: A Review; International JOURNAL OF CLIMATOLOGY Int. J. Climatol. 18: 1493–1517.

Toggweiler, J.R., Russell, J., 2008: Ocean circulation in a warming climate. Nature, 451, 286-288.

Torrence, C. & Compo, G.P., 1998: A practical guide to wavelet analysis. Bulletin of the 45th American Meteorological Society, 79, 61-78.

Tozuka T., Abiodun B.J. and Engelbrecht F.A., 2013: Impacts of convection schemes on simulating tropical-temperate troughs over southern Africa. Clim. Dyn. Doi: 10.1007/s00382-013-1738-4.

Von Neumann, J., 1941. Distribution of the ratio of the mean square successive difference to the variance. Annals of Mathematical Statistics, 13, 367–395.

Wijngaard J.B., Klein Tank. A.M.G and Konnen G.P., 2003: Homogeneity of 20th century European daily temperature and precipitation series; International Journal of Climatology Volume 23, Issue 6, pages 679–692.

Synopsis

The characterization of the rainfall variability over the Lake Kariba Catchment area has now been demonstrated by analysing rainfall data from a network of stations across the Kariba catchment area in the Zambezi river basin. Specifically, the study is a step towards improving our understanding of rainfall variability characteristics in the Kariba catchment area. In particular, the results would be valuable since local-scale rainfall variability can lead to sudden changes in water availability in surface and sub-surface hydrologic systems. It is of great importance to predict future climate fluctuations one or more seasons in advance since such predictions would have measurable benefits in decision making for water resources management. To this end, a link needs to be established between characterizing rainfall variability and the actual prediction of the seasonal-to-interannual rainfall totals over the Lake Kariba Catchment area. This notion will be dealt with in the following chapter which addresses the second objective of the study.

Chapter 3: Seasonal rainfall predictability over the Lake Kariba catchment area

Preface

* This section consists of one peer reviewed paper as follows:

Muchuru S,, Landman W.A., DeWitt D., Lötter D., 2014: Seasonal rainfall predictability over the Lake Kariba catchment area. *Water SA*, **40:** 461-470 http://dx.doi.org/10.4314/wsa.v40i3.9

In this paper, the link between characterizing rainfall variability described in the previous chapter and the actual prediction of the seasonal rainfall totals over the Lake Kariba Catchment area is established. To determine the predictability of seasonal rainfall totals over the Lake Kariba catchment area, this study used the low-level atmospheric circulation (850 hPa geopotential height fields) of a coupled ocean-atmosphere general circulation model (CGCM) over southern Africa, statistically downscaled to seasonal rainfall totals over the catchment. The paper therefore addresses the second objective of the study and is seen as a necessary step towards potentially being able to provide an understanding of applied operational seasonal climate prediction.

My co-authors are W.A. Landman, DeWitt D. and Lötter D.I. conceptualized the paper, was responsible for all analyses and also the synthesis of the results.

Seasonal rainfall predictability over the Lake Kariba catchment area

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Abstract

The Lake Kariba catchment area in southern Africa has one of the most variable climates of any major river basin, with an extreme range of conditions across the catchment and through time. Marked seasonal and interannual fluctuations in rainfall are a significant aspect of the catchment. To determine the predictability of seasonal rainfall totals over the Lake Kariba catchment area, this study used the low-level atmospheric circulation (850 hPa geopotential height fields) of a coupled ocean-atmosphere general circulation model (CGCM) over southern Africa, statistically downscaled to gridded seasonal rainfall totals over the catchment. This downscaling configuration was used to retroactively forecast the 3-month rainfall seasons of September-October-November through February-March-April, over a 14-year independent test period extending from 1994. Retroactive forecasts are produced for lead times of up to 5 months and probabilistic forecast performances evaluated for extreme rainfall thresholds of the 25th and 75th percentile values of the climatological record. The verification of the retroactive forecasts shows that rainfall over the catchment is predictable at extended lead-times, but that predictability is primarily found for austral mid-summer rainfall. This season is also associated with the highest potential economic value that can be derived from seasonal forecasts. A forecast case study of a recent extreme rainfall season (2010/11) that lies outside of the verification period is presented as evidence of the statistical downscaling system's operational capability.

Keywords: Lake Kariba catchment, coupled ocean-atmosphere model, statistical downscaling, seasonal forecasting, economic value

3.1 Introduction

Southern Africa is a region of significant rainfall variability at a range of temporal and spatial scales and is prone to serious drought and flood events (e.g. Tyson, 1986); Nicholson et al., 1987; Lindesay, 1998; Reason et al., 2000). The region is also sensitive to precipitation shifts and variability (IPCC, 2007; Reason et al., 2006). Despite the diverse climatic zones, rainfall in southern Africa is mainly observed during the austral summer between October and May. The future spatial and temporal rainfall distribution and variability is uncertain (Gordon et al., 2000; Hachingonta et al., 2007). The region's summer climate is mainly driven by oscillations of the inter-tropical convergence zone (ITCZ) (Beilfuss, 2012). The temporal and spatial distribution of convection is associated with evaporative losses that strain food and water resources (Jury et al., 1999; Lyon B, 2009). The South Atlantic and Indian Oceans, being the major sources of moisture for southern Africa, play a major role in determining the spatio-temporal variations of rainfall in the region (Matarira and Jury, 1992; Levey and Jury, 1996; Jury et al., 1999). The aforementioned studies have provided ample evidence for regional forcing features of composite wet and dry spells caused by the atmospheric circulation. Harrison (1986), Harangozo, (1989) and Barclay et al. (1993) have found that the seasonal cycle of convective spells over southern Africa and the surrounding oceanic basins during the austral summer are characterised by equatorial extra-tropical temperature gradients. This is caused by differential solar heating between the equator and the mid-latitudes. A more recent study has determined how the external forcing of major wet spells over southern Africa varies through the summer (Fauchereau et al., 2009). The wet spells occur at intervals of approximately 20 to 35 d (Levey and Jury, 1996), and half of all of the wet spells appear quasi-stationery from November to March. Southern Africa is a predominantly semi-arid region with a high degree of interannual rainfall variability. Although much of the recent climate research has focused on the causes of drought events, the region has also experienced extremes of above-average rainfall (Washington and Preston, 2006), the most recent examples being the major flooding episodes that devastated Mozambique during 2010 and 2011 when many people were killed and nearly 200 000 people made homeless.

There is increasing change in high rainfall events in some parts of the southern Africa region (Conway, 2009). The variability of such rainfall can have detrimental consequences for water resources, population and property. This variability can affect the sustainability of major dams and reservoirs due to flood risks to the population and properties on the floodplain. The region's water resources, agriculture and rural communities are impacted considerably due to high rainfall variability (Cook et al., 2004). The remote influence of El Niño–Southern Oscillation (ENSO) events has been seen to be contributing to major floods and drought events in southern Africa (Mason and Jury, 1997; Cook, 2000 Reason and Rouault, 2002). Southern African precipitation shows high variability at all timescales (Mason and Jury, 1997). The proximity of the Agulhas, Benguela, and Antarctic circumpolar currents leads to complex and highly variable climate patterns around southern Africa (Shannon et al., 1990). The 1984 floods (Rouault et al., 2003) along the Namibian coast were associated with warm sea-surface temperatures (SST) in the Angola/Benguela Front region, typical of the Benguela Niño, while the 2000 floods which hit Mozambique, eastern Zimbabwe and northeast South Africa could have been influenced by tropical-temperate troughs (TTTs) (Washington and Todd, 1999; Ratna et al., 2013; Tozuka et al., 2013and Hart et al., 2010) which have previously been linked to high rainfall intensities. In addition, droughts in most of the southern part of southern Africa have been linked to SST variations in the tropical Indian Ocean and to ENSO (Manhique et al., 2011; Vigaud et al., 2012).

Southern African rainfall has a clear annual cycle with most of the rainfall occurring during austral mid-summer and the region is susceptible to drought and floods. The identification of the seasons in which floods are most likely involves studying the characteristics of daily rainfall and streamflows within the seasons experienced across the region (Kampata et al., 2008). It is useful to characterize the spatio-temporal patterns of rainfall, its relationship with climatic variables, and linkages to streamflow variations. This is important in order to assist in formulation of adaptation measures through appropriate strategies of water resource management (Kampata et al., 2008). Such studies can assist in improving our understanding of hydro-meteorological variability in the southern African region and result in better management of water resources (Kenabatho et al., 2009). Better understanding of the relationship between rainfall and climatic variables is expected to be useful in improving the predictive skills of the operational general circulation models (GCMs) ((Nsubuga et al., 2011; Landman et al., 2012). In addition, it will be possible to predict rainfall given that climatic variables are successfully predicted well in advance. Consequently, the impacts of floods and droughts can be significantly reduced.

Operational seasonal climate prediction is an emerging practice with far-reaching societal applications (Palmer and Räisänen, 2002; Meza et al., 2008). An ability to predict future climate fluctuations one or more seasons in advance would have measurable benefits for decision making in hydrology, agriculture, health, energy, and other sectors of society (Barnston et al., 2004). For example, it would allow for proactive and improved reservoir management (Cunha, 2003). More recently, and largely as a result of better quantification of the climate effects of the ENSO phenomenon, prediction of precipitation have been clearly demonstrated to have skill in particular seasons, regions, and circumstances (Wang et al., 2009; Kumar , 2010).

Many southern Africa populations depend largely on rain-fed subsistence agriculture, especially in rural areas (Booth et al., 1994), and are vulnerable to climate variability and extreme events. The population is dynamic and has been growing rapidly in recent decades. Increased population size has led to changes in the water use patterns in the region (Glantz et al., 1997). Financial and environmental gains can be realized if forecasts of rainfall are made more than one season in advance (Jury et al., 1998).

This study focuses on the Lake Kariba catchment since rainfall over this area is directly responsible for the water levels in the lake. Prior to the drought of 1982/83, which caused widespread environmental impacts in southern Africa, a regular cycle of seasonal and interannual precipitation was taken for granted, e.g., Jury and Makarau (1996). Rainfall over the catchment is strongly seasonal. The Lake Kariba catchment area’s climate is controlled mainly by the movement of air masses associated with the Inter-Tropical Convergence Zone (ITCZ) (Beilfuss, 2012). Normally the rainy season extends from November to March. The entire catchment is highly susceptible to extreme droughts and floods that occur nearly every decade (Beilfuss, 2012), but these have become more frequent and more pronounced (Beilfuss and Brown, 2010), with associated economic losses. For example, during the severe 1991/92 drought, reduced hydropower generation resulted in an estimated 102 million USD reduction in GDP, 36 million USD reduction in export earnings, and the loss of 3 000 jobs (Beilfuss, 2012). Extreme floods have also resulted in considerable loss of life, social disruptions, and extensive economic damage. For example, one of the biggest floods recorded in the Zambezi basin was in 2010/11 during mid-summer. Both Kariba and Cahora Bassa reservoirs were almost at full capacity when intense and prolonged rainfall over large areas of the basin resulted in a massive flood into Kariba. Due to the lack of knowledge and absence of forecasting there was poor communication between Lake Kariba dam managers and officials for Lake Cahora Bassa. Therefore, when Kariba successively opened the spillway gates, Cahora Bassa did not react in time to prepare for the arrival of the flood discharge from Kariba. The reaction was to open, almost immediately, all of the spillway gates of Cahora Bassa that were still closed, thus creating an enormous flood wave which, adding to the floodwaters of the tributaries located downstream of the dam, completely flooded the Lower Zambezi leading to the abovementioned catastrophes.

Lake Kariba is one of the largest hydro-electric dams in southern Africa and is the only bulk power supplier to Zambia and Zimbabwe. The generating capacity of the plant constitutes nearly 60% of the hydropower outputs for the riparian countries of Zambia and Zimbabwe. The creation of Lake Kariba offered opportunities for an inland fisheries industry that had not previously existed in southern Africa. Lake Kariba offers recreational/tourism facilities attracting tourists from all over the world. Communities in the Lake Kariba catchment engage in some crop production. The catchment area is also dominated by wildlife national parks, effectively creating a natural resource–based tourism belt stretching from Mana Pools in the lower Middle Zambezi Valley to the facilities in Namibia/Botswana and beyond. The combination of wildlife-based tourism and watersports has made Kariba an important hub in the region's tourist industry.

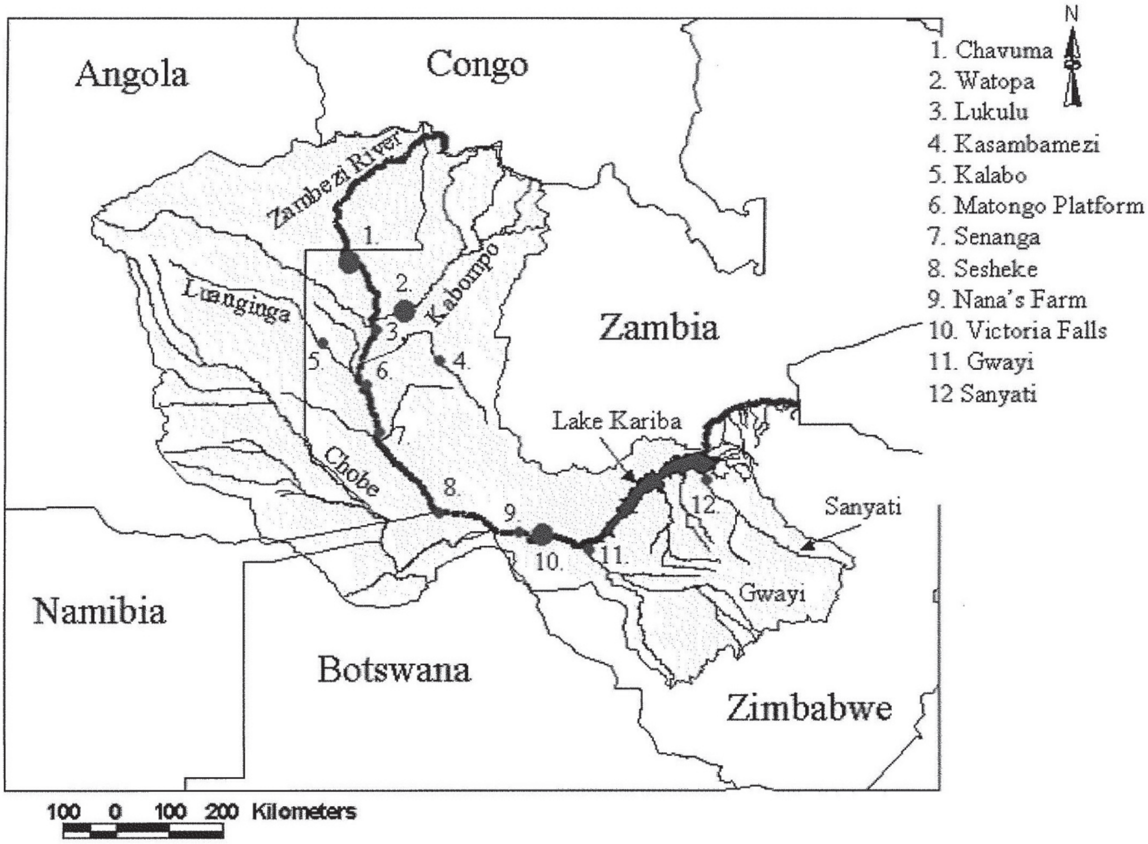

Figure 1. Lake Kariba catchment area (Source: Tumbare, 2000).

In the context of the importance of Lake Kariba as mentioned above, seasonal forecasts can increase water managers' preparedness and lead to better economic and environmental outcomes in the long run. A skillful seasonal forecast can be useful to Lake Kariba managers who needed to plan months ahead of the rainy season and can lead to reduced losses that can be incurred during the flooding season. Moreover, with seasonal forecast, water managers can adapt water management decisions to upcoming weather conditions.

This paper first describes a seasonal rainfall prediction system, and then verifies retro-active rainfall forecasts produced with lead-times of several months. Forecast assessment is followed by a demonstration of the potential economic impact of using such forecasts. Lastly, the paper describes a rainfall forecast for the flood season of 2010/11, i.e., that which would have been produced if the described forecast system was used operationally in late 2010.

3.2 Methods

3.2.1 The archived data of the general circulation model and gridded rainfall data

We investigated the predictability of 3-month seasonal rainfall totals over the Kariba catchment during the rainy season from September through April, by statistically downscaling the archived output of a state-of-the-art coupled ocean-atmosphere general circulation model (CGCM). The atmospheric model component is the ECHAM 4.5 (Roeckner et al., 1996) and the ocean model, directly coupled (DeWitt, 2005), is version 3 of the Modular Ocean Model MOM3 (Pacanowski and Griffies, 1998). The CGCM's archived hindcast data (12-member ensembles) used in this study was obtained from the data library of the International Research Institute for Climate and Society (IRI, 2013). Hindcast data for this CGCM are available from January 1982 to July 2012, and consist of 12 ensemble members. There are 7 one-month lead times available from the IRI's data library, of which only 5 forecast lead-times are to be considered here. The forecasts for the coupled model are produced near the beginning of the month. The following lead-time convention is used: A one-month lead time implies that there are about 3 weeks prior to the first forecast season. For example, a one-month lead-time forecast for the January-February-March (JFM) season is produced at the beginning of December, two-month lead-time forecasts in early November, etc.

The rainfall data used for downscaling and verification was the University of East Anglia's (UEA) Climate Research Unit (CRU) version TS3.1 seasonal precipitation data at a 0.5° x 0.5° resolution (Harris et al., 2013). Here, the CRU data from 1982/83 to 2008/09 are used. The focus area of our modelling study was from 21.25° E to 31.75° E, and 13.25° S to 19.75° S, and includes the major river system of the Zambezi river basin as shown in Fig. 1.

3.2.2 Statistical downscaling

The CGCM output has an approximate latitude–longitude resolution of 2.8°. As it is not possible to represent local sub grid features, rainfall over southern Africa is often overestimated by models, but it has been demonstrated that such biases can be minimized through statistical post-processing of the forecast data by applying corrections to the raw output of the model (e.g., Landman and Goddard, 2002; Robertson et al., 2012). In order to compensate for systematic errors in the global model, model output statistics (MOS) equations are developed between the hindcast variable of the CGCM and rainfall over the catchment (Wilks, 2011). MOS uses predictor values from the CGCM in both the development and forecast stages, subsequently reducing model errors. This notion of statistical post-processing has already been tested and successfully employed in studies of AGCM versus coupled model performance (Landman et al., 2012; Ndiaye et al., 2011). In addition, the post-processing will also have as a result model forecast data directly applicable over an area of interest, such as the 0.5° x 0.5° grid of the CRU data across the Lake Kariba catchment (e.g., Landman et al., 2012; Landman and Goddard, 2002; Shongwe et al., 2006). Such a forecast system could potentially be useful to a specific forecast user, such as a reservoir manager at Lake Kariba.

Since variables such as large-scale circulation are more accurately produced by global climate models than is rainfall, these variables should be considered instead in a MOS system for seasonal rainfall downscaling (Landman et al., 2012; Landman and Beraki, 2012; Landman and Goddard, 2002). Here, we use the 12-member ensemble mean geopotential height fields at the 850 hPa level as predictors in a canonical correlation analysis (CCA) model (e.g. Barnett and Preisendorfer, 1987), because atmospheric circulation at this level could be considered as low-level circulation since the area of interest is near the 850 hPa geopotential level. The software used for the statistical downscaling was the Climate Predictability Tool (CPT) of the IRI (2013). Before downscaling the CPT transforms the rainfall data into an approximate normal distribution. In order to capture the rain- or drought-producing synoptic systems of the model the domain from which the predictors are derived covers the sub-continent south of the equator and the adjacent oceans, specifically, from the Equator to 30°S, and from Greenwich to 50° E. Empirical orthogonal function (EOF) pre-filtering on both predictor and predictand fields is automatically done by the CPT software. Our objective was to test the MOS system using independent data, but also to make sure the CCA equations are reflecting a robust relationship between predictor and predictand fields (Landman and Goddard, 2002). Therefore, the MOS equations were first trained over 13 years from 1982–1994, followed by increasing the training period by 1 year for each season's downscaling (Landman et al., 2012). This incremental increase of the training period mimics a true operational forecast setting, and has as a result a 14-year period (from 1995) to be verified in order to determine the seasonal-to-interannual rainfall predictability over the target area.

3.2.3 Verification

We define extreme season thresholds as represented by the 75th (wet category) and 25th (dry category) percentile values of the climatological record. Verification results of the associated extreme rainfall categories are presented here. We have decided to use these particular thresholds because a reservoir manager at Lake Kariba may be more interested in the prediction of extreme seasons, since such seasons are more likely to affect the inflow and outflow of the reservoir than ‘normal’ rainfall seasons would (Sene, 2009). Moreover, the ‘normal’ category is also the least predictable (Van Loon and Toth, 1991). Such a category description has been used before and it has been shown that the prediction of such extreme rainfall seasons over southern Africa has skill (Landman et al., 2005; Landman et al., 2012).

The seasonal climate is inherently probabilistic, and so the downscaled retro-active forecasts are also judged probabilistically (Landman et al., 2001; Mason and Mimmack, 2002; Troccoli et al., 2008). Two of the main attributes of interest here for probabilistic forecasts are discrimination and reliability, because a reservoir manager may need to know whether or not a coming rainfall season is likely to be associated with extreme rainfall totals or with very low rainfall totals over the catchment, and may want to also know the reliability with which such probabilistic forecasts are made when they attempt to discriminate very wet seasons and very dry seasons from the rest of the seasons. The forecast verification measures presented here for testing these attributes of discrimination and reliability are, respectively, the relative operating characteristics (ROC); (Mason and Graham, 2002) and the reliability diagram (Hamill, 1997). These attributes have been tested extensively over parts of southern African before (Landman and Beraki, 2012; Landman et al., 2012), but not specifically focusing on the Kariba catchment, which is our area of study.

ROC applied to probabilistic forecasts indicates whether the forecast probability was higher when an event such as a flood season (defined by rainfall totals > the 75th percentile of the climatological record) or drought season (defined by rainfall totals < the 25th percentile of the climatological record) occurred compared with when it did not occur. The ROC curve is produced by plotting the forecast hit rates against the false alarm rates. The scores for the two extreme rainfall categories are represented by the respective areas beneath the ROC curve. For no-skill forecasts the area would be ≤0.5 and for perfect discrimination the ROC score is 1.0. When there is consistency between the predicted probabilities of the extreme rainfall categories and the observed relative frequencies of the observed rainfall being assigned to these categories, then the downscaled hindcasts are considered reliable (Yuan et al., 2014). We also performed some verification on deterministic downscaled hindcasts. For this purpose we use the Kendall ranked correlation coefficient or Kendall's tau. An advantage of using Kendall's tau is that it has close affinities with the area beneath the ROC curve (Jolliffe and Stephenson, 2012).

3.2.4 Retroactive forecast skill

3.2.4.1Relative operating characteristics

The ROC scores for the 3-month seasons from September-October-November (SON) through February-March-April (FMA) obtained by retroactively predicting extreme

(a) wet and (b) dry seasons over the retroactive years are shown in Fig. 2. Poor skill (ROC $\leq$ 0.5) is generally found over the catchment from SON through OND, but skill improves towards the main austral summer rainfall period from about November-December-January (NDJ) when most of the seasonal rainfall occurs. During this time, the reservoir starts to get most of its inflow from rivers within the catchment with a peak inflow by the austral autumn caused by mid-summer rainfall over the catchment. Moreover, Fig. 2 shows that during the seasons with high ROC scores these skill levels are found across all the lead-times presented, including lead-times of 4 months of NDJ and DJF when high ROC scores are found for both the extreme below- and above-normal rainfall categories. These skill levels and lead-times provide the potential for reservoir managers to make informed decisions regarding the likelihood of high or low rain-fed inflows into the reservoir during austral summer, several months ahead of time.

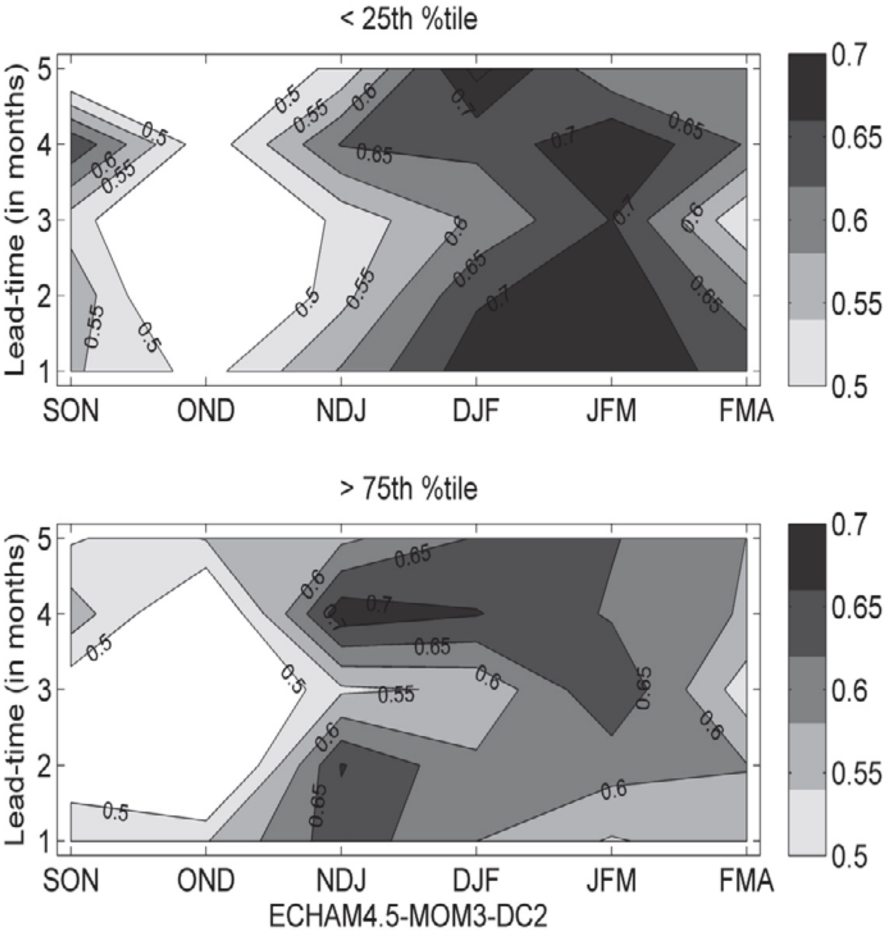

Figure 2. ROC scores obtained by retroactively predicting dry seasons (top panel; 25th percentile values of the climatological record) and wet seasons (bottom panel; 75th percentile of the climatological record) probabilistically over 14 years (1995/96–2008/09). The x-axes show the 3-month rainfall seasons for which the forecasts are made, and the y-axes show the lead-times in months.

3.2.5 Reliability

We have demonstrated the forecast system's ability to discriminate extremely wet or dry seasons from the rest of the seasons. Now we will assess if the confidence with which the probabilistic forecasts of extremely wet or dry seasons are made is warranted. As stated above, only the three seasons associated with the highest ROC scores are considered from now on, and at the useful lead-time of 4 months. Figure 3 shows the reliability and frequency diagrams for NDJ (left panels), December-January-February (DJF) (middle panels) and JFM (right panels). For perfect reliability (the forecast probabilities match the observed frequencies of respectively wet and dry seasons), the weighted regression lines (thin solid and dashed lines) will be on the diagonal line. When the slope of the regression line is shallower (/steeper) than the diagonal line, forecasts for the particular category tend to be over-(/under-)confident. Close to perfect reliability is seen for the prediction of DJF wet seasons (thin solid line almost on top of diagonal), but respectively under- and over-confident forecasts are seen for NDJ and JFM. For dry season prediction, however, forecasts tend to constantly be over-confident. The histograms in the reliability diagram of Fig. 3 show the frequencies with which wet–dry forecasts occur in probability intervals of 10%, and reveals how strongly and frequently the issued forecast probabilities depart from the climatological probabilities. The histograms generally show intermediate confidence and a general lack of sharpness (or plot number of events next to each point on reliability graph).

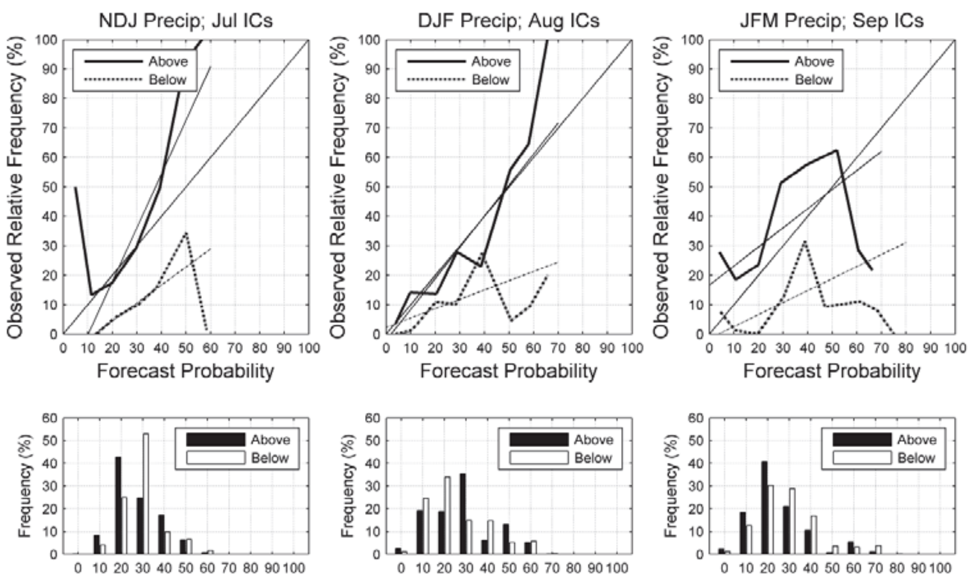

Figure 3. Reliability diagrams for NDJ, DJF and JFM, at a 4-month forecast lead-time.

3.2.6 Deterministic skill assessment

The deterministic forecast performance over the retro-active period is determined next, by considering a verification parameter that has a close relationship with the area under the ROC curve, i.e., Kendall's tau correlation statistic (Jolliffe and Stephenson, 2012; Wilks, 2011). Kendall's tau is a robust, less sensitive to outliers, simple, ease of interpretation and resistant alternative to the 'ordinary' or Pearson correlation. This statistic is calculated here between retro-forecasts and the observed seasonal rainfall anomalies at each CRU grid point. Figure 4 shows the Kendall's tau for the NDJ, DJF and JFM seasons, but only for a 1-month lead-time (there is a gradual decrease in skill for increasing lead-time). The dashed, stippled and solid lines on the figure respectively show the locations of the 90% (0.27), 95% (0.34) and 99% (0.47) levels for local significance testing. The significance levels are calculated with a re-randomisation or Monte Carlo test (Wilks, 2011). For all three seasons considered, skill was found for the upper Zambezi catchment. Large areas of positive correlation are also found, with the best performance of the forecast system for NDJ and DJF rainfall over an area west of Lake Kariba. Low skill is found for the larger part of the area for JFM rainfall, and generally over the northern part of the study area.

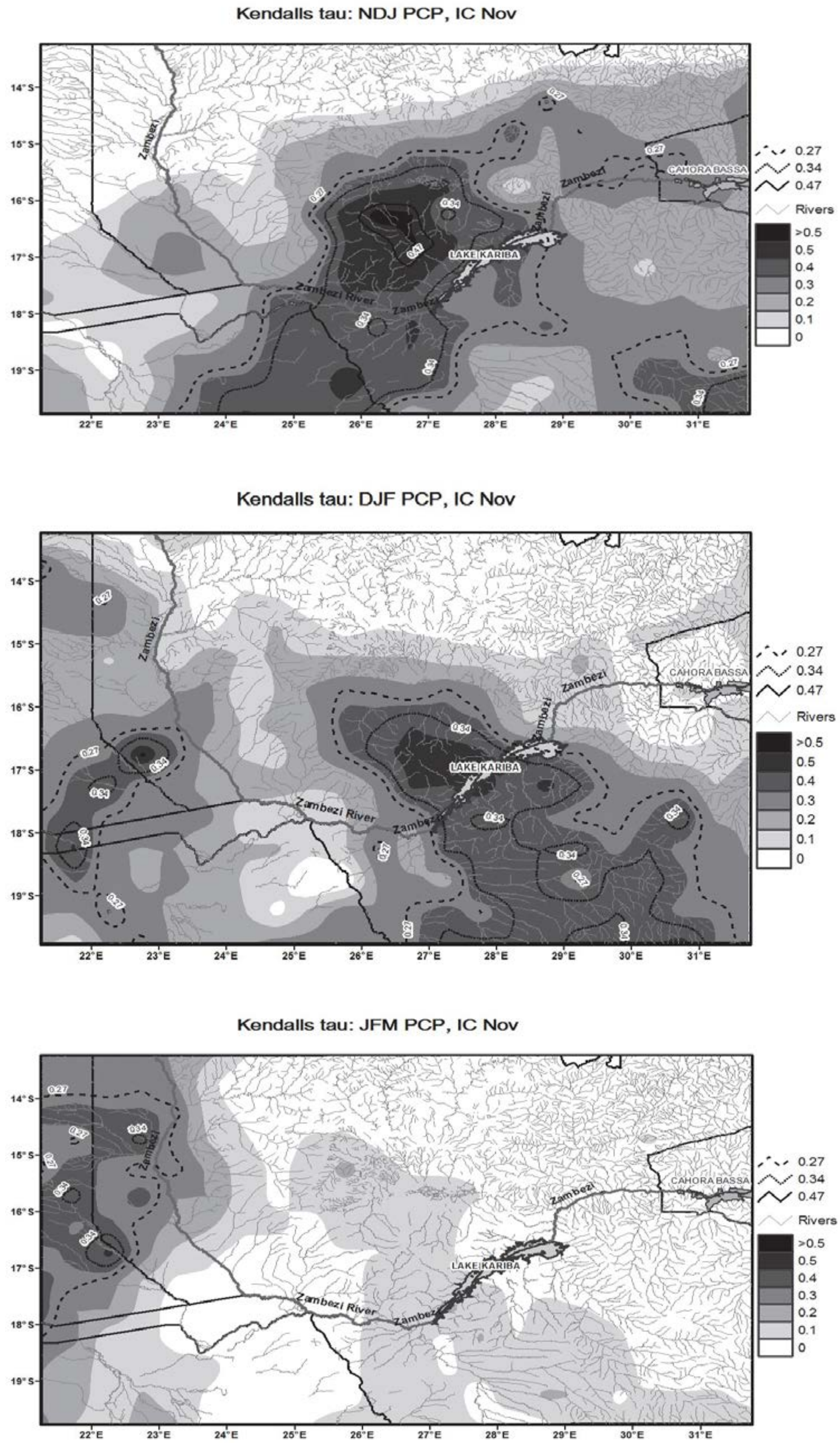

Figure 4. Kendall's tau between observed and retroactively predicted rainfall totals for the NDJ (top panel), DJF (middle panel) and JFM (bottom panel) seasons produced at a 1-month lead-time. See text for details.

3.3 Economic value of the probabilistic forecasts

The 14 years of downscaled retroactive forecasts, e.g., Landman et al. (2001) are evaluated next in terms of their potential economic value for an end-user such as the reservoir manager at Lake Kariba. In the past, such users used other techniques of forecasting systems (e.g., Hagedorn et al., 2008), such as the Brier Skill Score (Hagedorn et al., 2008; Wilks, 2006). Other techniques have been developed to illustrate the potential economic benefits of a forecast system (e.g. the costs/ loss approach of Richardson (2000) or the relative income of Roulston et al. (2003). Such scoring metrics are used to focus not only on the general skill of the forecasts per se, but also to reflect various aspects of the potential economic value of a forecast system (Hagedorn et al., 2008). Even if such diagnostics are well understood in the scientific community they often provide little intuitive insight for a forecast user and may prove ineffective in demonstrating to users that incorporating forecasts such as those presented above in their decision-making systems is worth the costs involved. For example, the cumulative profit (CP) graphs depicted in Fig. 5 indicate how an initial financial investment in the forecast would change in value over the 14-year verification period presented if it were invested in the forecasts and was paid fair odds on the outcome over the three seasons of NDJ, DJF and JFM. CP graphs can be interpreted as follows: If the CP value is 0.4 for a particular year, for example, it means that an initial investment of USD100 would now be worth USD140 for that year. One would subsequently invest all USD140 on the next year’s forecast, and so forth.

CP values increase the most during DJF (Fig. 5). Figure 5 shows how seasonal rainfall predictions for that season can bring about substantive financial rewards for users of such forecasts. Lower increases in profits are seen for NDJ and JFM with the latter showing only marginal economic value over the 14 test years. Take note of the association between the skill levels presented above (Figs. 2 and 3) for the three seasons and the corresponding cumulative profits (Fig. 5) – the higher the skill (ROC and reliability) the more profitable the use of the forecasts seems to become. This apparent association between skill and economic value should further motivate the use of forecast value assessment tools such as the CP presented above and the two-alternative forced choice test (Mason and Weigel, 2009). These tools will enable forecast producers to communicate the value of their probability forecasts to a wider user community. Reservoir managers, who are also decision makers, may not be experts on probabilistic forecast verification since they are more likely to be skilled in financial matters – they are largely interested in both profit making and value for money (Hagedorn et al., 2008), as well as optimized reservoir operations.

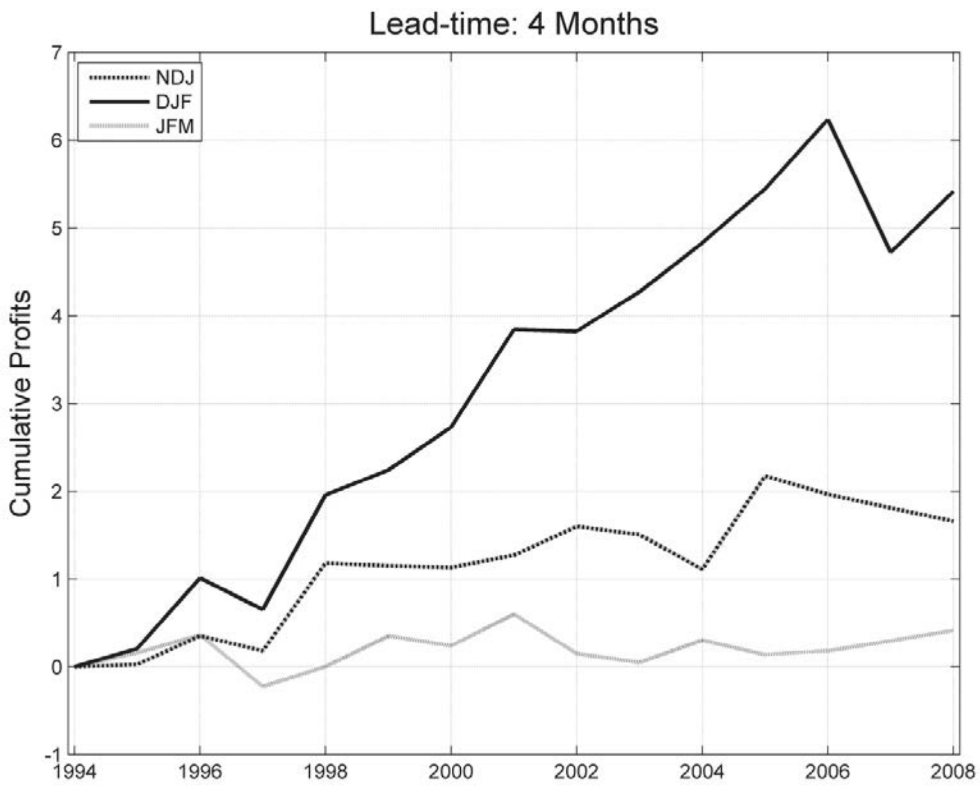

Figure 5. Cumulative profits over time if invested in the forecasts over the 14-year verification period. The years on the x-axis refer to the initialization month of the forecasts.

3.3.1 Predicting the 'flooding across Lake Kariba Basin'

According to media reports, in January 2011 southern Africa experienced flooding across the region, which saw Lake Kariba open its spillway gates on 22 January 2011 as a result of high water levels in the lake (Bulawayo News24, 2011). The high levels were a result of persistent summer rainfall in the Lake Kariba Basin catchment area (Siavonga News, 2011). River authorities at Lake Kariba consider the maximum level for this time of the year to be 485 m, and the current water level in early 2011 was around 484.8 m. The Zambezi River Authority (ZRA) subsequently opened two spillway gates thereby increasing its discharge to around 3 000 m3/s. Opening of the spillway gates resulted in rising water levels and increased flooding further downstream. The relevant government authorities of Zimbabwe and Zambia issued flood warnings to districts adjacent to the lower Lake Kariba Basin, with district disaster managers alerting downstream communities and preparing for possible major flooding. These actions notwithstanding, the resulting flooding downstream resulted in loss of life and property.

The question we want to address next is, assuming the prediction technology introduced here had been developed and operationalized before the 2010/11 flooding of our study area, whether the prediction system would have been able to issue a warning months ahead of time for the likelihood of a particularly wet mid-summer (DJF) rainfall season to occur. The ECHAM4.5-MOM3-DC large-scale DJF 2010/11 forecasts produced at a 4-month lead-time (i.e. issued in August 2010) are subsequently downscaled to DJF rainfall at the CRU resolution over the study area. Figure 6 shows the probabilistic DJF rainfall forecast for the above-normal (>75th percentile of the climatological record) and below-normal (<25th percentile of the climatological record) rainfall categories that would have been predicted if the prediction system introduced here had been used. The larger area of the catchment is associated with increased probabilities of above-normal rainfall occurring during DJF. This forecast of a high likelihood of rainfall inundation is evidence that the skillful forecast system introduced here would have been able to predict with high confidence, 4 months ahead of time, an extremely wet mid-summer season in 2010/11. This notion has been tested by Coelho, 2005; Landman and Beraki, 2012 studies showing skillful forecasts possible during La Niña. This forecast could have been useful to Lake Kariba managers who needed to plan months ahead of the rainy season, consequently leading to reduced losses suffered during the actual flooding season.

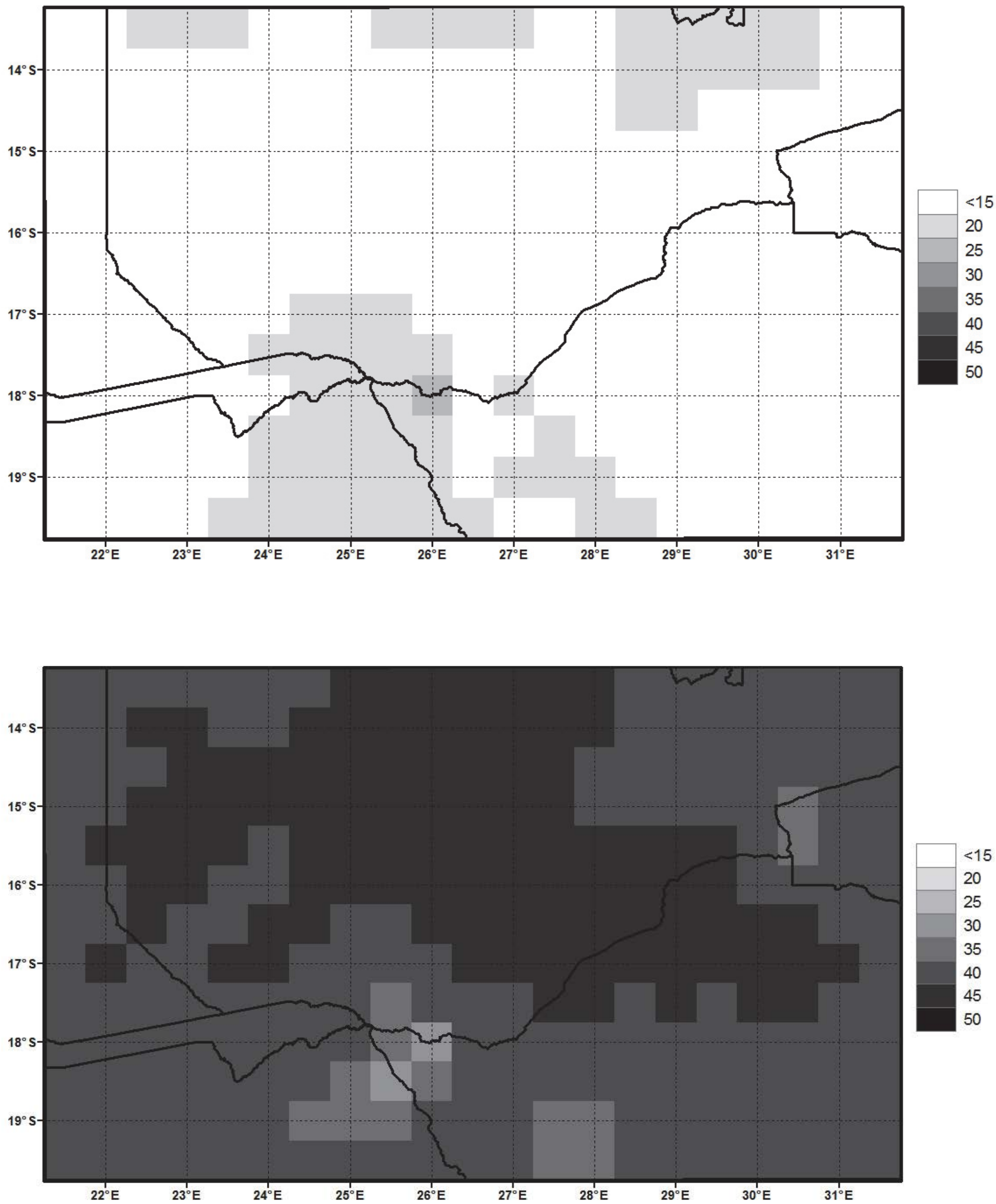

Figure 6. Predicted probabilities for extremely dry (top panel) and extremely wet (bottom panel) conditions to occur during the mid-summer season of 2010/11. The forecast is made at a 4-month lead time, i.e. issued in August 2010.

3.4 Discussion and conclusions

Lake Kariba is the world's largest artificial lake and reservoir by volume. The Lake Kariba catchment area has one of the most variable climates of any major river basin in Africa with an extreme range of conditions across the catchment and through time. The paper focuses on Lake Kariba due to its economic and social significance for the region. The importance of Lake Kariba motivated investigation of the predictability of seasonal rainfall totals over the catchment during the rainy season from September through April, by empirically downscaling the coarse-resolution output (~2.8°) of a state-of-the-art coupled ocean-atmosphere general circulation model (CGCM) to 0.5° resolution rainfall grids.

The seasonal rainfall forecast system produced retroactive forecasts for 14 years in a fashion that mimics a true operational setting, and the skill of the forecast system was subsequently determined over the independent period from 1995/96. The system has been found to be able to discriminate extremely dry/wet seasons from the rest of the seasons. Moreover, close to perfect reliability has been found for the DJF season due to high skill when predicting wet seasons (Landman et al., 2012). DJF is an important season since it is associated with the highest rainfall totals in the year. However, forecasts are for the most part over-confident, which is a common problem for seasonal forecasting, also in the region. A diagnostic other than the standard verification parameters has also been introduced to specifically address the potential economic benefits of the forecast system. The paper has shown how an initial financial investment would change in value over the 14-year verification time if it were invested in the forecasts and was paid fair odds on the actual outcome over the seasons considered. The highest profits have been found for the DJF season, which is the same season for which the best standard verification values were found – the higher the skill the more profitable the use of the forecasts becomes. The developed forecast system was also tested for the 2010/11 season associated with huge losses, especially downstream of Lake Kariba. The paper has demonstrated that the forecast system produced a potentially useful forecast of high probabilities of extremely high rainfall totals to occur during DJF. It will be useful if such a forecast model should become part of a decision support system for the Zambezi River. The demonstrated forecast system is a result of post-processing output from a highly sophisticated dynamical forecast model. The latter type of models are expensive to administer, but a good number of international centres, such as the IRI from which the model data for this research was obtained, are making their forecast outputs available for operational use. This data availability can further enable modellers in southern Africa to develop forecast systems specific to their interest and application without having to run expensive global models. This notion needs to be further developed, for example, for the actual streamflows into Lake Kariba.

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References

BARCLAY J, JURY MR and LANDMAN WA (1993) Climatological and structural differences between wet and dry troughs over southern Africa in the early summer. *Meteorol. Atmos. Phys.* **51** 41–54.

BARNET TP and PREISENDORFER R (1987) Origins and levels of monthly and seasonal forecast skill for United States surface air temperatures determined by canonical correlation analysis. *Mon. Weather Rev*. **115** 1825–1850.

BARNSTON AG, KUMAR AL, GODDARD L and HOERLING MP (2004) Improving seasonal prediction practices through attribution of climate variability. *Bull. Am. Meteorol. Soc.* **86** (1) 59–72.

BEILFUSS R and BROWN C (2010) 'Assessing environmental flow requirements and trade-offs for the Lower Zambezi River and Delta, Mozambique'. International Journal of River Basin Management, **8** 127-138.

BEILFUSS RD (2012) *A Risky Climate for Southern African Hydro. Hydrological Risks and Consequences for Zambezi River Basin Dams*. International Rivers. Berkeley, CA.

BOOTH A, MCCULLUM J, MPINGA J and MUKUTE M (1994) *State of the Environment in Southern Africa.* SARDC – Southern African Research and Documentation Centre in collaboration with IUCN and the Southern African Development Community, Harare. 332 pp.

BULAWAYO NEWS (2011) Heavy rains and widespread flooding: URL: http://bulawayo24.com/index-id-news-sc-national-byo-10638.html (Accessed 21 September 2013).

COELHO CAS, STEPHENSON DB, BALMASEDA M, DOBLAS-REYES FJ and VAN OLDENBORGH GJ (2005) Toward an Integrated Seasonal Forecasting System for South America. J. Clim. **19** 3704-3721.

COOK C, REASON CJC and HEWITSON BC (2004) Wet and dry spells within particularly wet and dry summers in the South African summer rainfall region. *Clim. Res*. **26** 17–31.

COOK KH (2000) The South Indian convergence zone and interannual rainfall variability over Southern Africa. *J. Clim.* **13** (1) 3789–3804.

CONWAY D (2009) The science of climate change in Africa: impacts and adaptation. Grantham Institute for Climate Change Discussion Paper 1. Imperial College, London, p. 24.

CUNHA MD (2003) Water systems planning. The optimization perspective. *Eng. Optimiz.* **35** 255–266.

DE WITT DG (2005) Retrospective forecasts of interannual sea surface temperature anomalies from 1982 to present using a directly coupled atmosphere–ocean general circulation model. *Mon. Weather Rev.* **133** 2972–2995.

FAUCHEREAU N, POHL B, REASON CJC, ROUAULT M and RICHARD Y (2009) Recurrent daily OLR patterns in the Southern Africa/Southwest Indian Ocean region, implications for South African rainfall and teleconnections. *Clim. Dyn.* **32** 575–591.

GLANTZ M, BESTILL M and CRANDALL K (1997) Food security in southern Africa. Assessing the use and value of ENSO information. NOAA Project Report. NCAR, Boulder. DOI: 10.1007/978-94-017-3010-5. 142 pp.

GORDON C, COOPER, SENIOR CA, BANKS H, GREGORY JM, JOHNS TC, MITCHELL JFB and WOOD RA (2000) The simulation of SST, sea ice extents and ocean heat transports in a version of the Hadley Centre coupled model without flux adjustments. *Clim. Dyn.* **16** (2–3) 147–168.

HACHIGONTA S, REASON R and TADROSS M (2007) An analysis of onset date and rainy season duration over Zambia. *Theor. Appl. Climatol.* **91** 229–243.

HAGEDORN R and SMITH LA (2008) Communicating the value of probabilistic forecasts with weather roulette. *J. Meteorol. Appl*. **16** 143–155.

HAMILLT M (1997) Reliability diagrams for multicategory probabilistic forecasts. *Weather Forecast.* **12** 736–741.

HARANGOZO SA (1989) Circulation characteristics of some South African rainfall systems. MSc thesis, Univ of the Witwatersrand 341 pp.

HARRIS I, JONES PD, OSBORN TJ and LISTER DH (2013) Updated high-resolution grids of monthly climatic observations. Int. J. Climatol. 34 623–642.

HARRISON M SJ (1986) A synoptic climatology of South African summer rainfall variations. PhD thesis, University of the Witwatersrand. 341 pp.

HART NCG, REASON CJC and FAUCHEREAU N (2010) Tropical Extratropical Interactions over Southern Africa: Three Cases of Heavy Summer Season Rainfall. Monthly Weather Review. **138** 2608-2623.

HUUG MVD and ZOLTAN T (1991) Why do forecasts for "Near Normal" often fail? *Weather Forecast.* **6** 76–85.

JOLLIFFE IT and STEPHENSON DB (2012) *Forecast Verification. A Guide in Atmospheric Science*. John Wiley and Sons Ltd, Chichester.

IPCC (INTERGOVERNMENTAL PANEL ON CLIMATE CHANGE) (2007) *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Solomon S, Qin D, Manning M, Chen Z, Marquis M, Averyt KB, Tignor M and Miller HL (eds.). Cambridge University Press, Cambridge.

IRI (INTERNATIONAL RESEARCH INSTITUTE FOR CLIMATE AND SOCIETY) (2013). The IRI/LDEO Climate Data Library. URL: http://iridl.Ideo.columbia.edu/ (Accessed 21 September 2013).

IRIN NEWS (2011) Humanitarian news and analysis. URL: http://www.irinnews.org/report/91698/southern-africa-heavy-rain-puts-relief-agencies-on-alert (Accessed 21 September 2013).

JURY MR (1992) A climatic dipole governing the interannual variability of convection over the SW Indian Ocean and SE Africa region. *Trends Geophys. Res.* **1** 165–172.

JURY MR (1998) Intra-seasonal convective variability over Southern Africa. Principal component analysis of Pentad outgoing-longwave radiation departures. *Theor. Appl. Climatol.* **62** 133–146.

JURY MR and MAKARAU A (1996) Predictability of Zimbabwe summer rainfall. *Int J. Climatol.* **17** 1421–1432.

JURY MR, MULENGA HM and MASON SJ (1999) Exploratory long-range models to estimate summer climate variability over southern Africa. *J. Clim.* **12** 1892–1899.

KAMPATA JM, PARIDA BP and MOALAFHI DB (2008) Trend analysis of rainfall in the headstreams of the Zambezi River Basin in Zambia. *Phys. Chem. Earth* **33** 621–625.

KENABATHO PK, McINTYRE NR and WHEATER HS (2009) Impacts of rainfall uncertainty on water resource planning models in the Upper Limpopo basin, Botswana. In: *New Approaches to Hydrological Prediction in Data Sparse Regions. Proc. of Symposium HS.2 at the Joint IAHS & IAH Convention, Hyderabad, India, September 2009.* IAHS Publ. 333. IAHS, Hyderabad, India.

KUMAR AM, HOERLING MJI, LEETMA AA and SARDESHMUKH P (1996) Assessing a GCM's suitability for making seasonal predictions *J. Clim.* **9** 115–129.

KUMAR AM (2010) Review on the assessment of the value of the seasonal forecast Information. Meteorol. Appl. 17 385–392. DOI: 10.1002/met.167.

LANDMAN WA (2001) Forecasts or near-global sea surface temperatures using canonical correlation analysis. *J. Clim.* **14** 3819–3833.

LANDMAN WA and BERAKI A (2012) Multi-model forecast skill for mid-summer rainfall over southern Africa. *Int. J. Climatol.* **32** 303–314.

LANDMAN WA and GODDARD L (2002) Statistical recalibration of GCM forecast over southern Africa using model output statistics. *J. Clim.* **15** 2038–2055.

LANDMAN WA, BOTES S, GODDARD L and SHONGWE M (2005) Assessing the predictability of extreme rainfall seasons over southern Africa. *Geophys. Res. Lett.* **32** L23818 DOI: 101029/2005GL023965.

LANDMAN WA, DE WITT D, LEE DE, BERAKI A and LöTTER D (2012) Seasonal rainfall prediction skill over South Africa. 1- vs. 2-tiered forecasting systems. *Weather Forecast.* **27** 489–501.

LEVEY KM and JURY MR (1996) Composite intra-seasonal oscillations of convection over southern Africa. *J. Clim.* **9** 1910-1920.

LINDESAY JA (1988) South African rainfall, the Southern Oscillation and a Southern Hemisphere semi-annual cycle. *J. Climatol.* **8** 17–30.

LIVEZEY RE (1990) Variability of skill of long-range forecasts and implications for their use and value. *Bull. Am. Meteorol. Soc.* **71** 300–309.

LYON B (2009) Southern Africa summer drought and heat waves. Observations and coupled model behavior. *J. Clim.* **22** 6033–6046.

MAKARAU A (1995) Intra-seasonal oscillatory modes of the Southern Africa summer circulation. PhD thesis, Oceanography Department, University of Cape Town.

MANHIQUE A J, REASON CJC, RYDBERG LR and FAUCHEREAU N (2011) ENSO and Indian Ocean Sea surface temperatures and their relationships with tropical temperate troughs over Mozambique and the southwest Indian Ocean. *Int. J. Climatol*. **31** 1–13.

MASON SJ and GRAHAM NE (2002) Areas beneath the relative operating characteristics (ROC) and levels (ROL) curves. Statistical significance and interpretation. *Q. J. R. Meteorol. Soc.* **128** 2145–2166.

MASON SJ and JOUBERTA M (1997) Simulated changes in extreme rainfall over southern Africa. *Int. J. Climatol.* **17** 291–301.

MASON SJ and WEIGEL AP (2009) A generic forecast verification framework for administrative purposes. *Mon. Weather Rev.* **137** (1) 331–349.

MASON SJ (1995) Sea surface temperature–South African rainfall associations, 1910–1989. *Int. J. Climatol.* **15** 119–135.

MASON SJ and JURY MR (1997) Climate variability and change over southern Africa. A reflection on underlying processes. *Prog. Phys. Geog.* **21** 23–50.

MATARIRA CH and FLOCAS AA (1989) Spatial and temporal rainfall variability over SE central Africa during extremely dry and wet years. *J. Meteorol.* **14** 3–9.

MATARIRA CH and JURY MR (1992) Contrasting meteorological structure of intra-seasonal wet and dry spells in Zimbabwe. *Int. J. Climatol.* **12** 165–176.

MEZA FJ, HANSEN JW and OSGOOD D (2008) Economic Value of Seasonal Climate Forecasts for Agriculture: Review of Ex-Ante Assessments and Recommendations for Future Research. J. Clim. Appl. Meteorol. 47 1269-1286.

NDIAYE O, WARD M N and THIAW W M (2011) Predictability of seasonal Sahel rainfall using GCMs and lead-time improvements through the use of a coupled model. *J. Clim.* **24** 1931–1949.

NICHOLSON SE and ENTEKHABI D (1987) Rainfall variability in equatorial and southern Africa. Relationships with sea surface temperatures along south-western coast of Africa. *J. Clim. Appl. Meteorol.* **26** 561–578.

NSUBUGA FWN, OLWOCH JM and RAUTENBACH CJ (2011) Climatic trends at Namulonge in Uganda, 1947-2009. *J. Geogr. Geol.* **3** 119–131.

PACANOWSKI RC and GRIFFIES SM (1998) MOM 3.0 manual. NOAA/Geophysical fluid dynamics. *J. Phys. Oceanogr.* **28** 831–841.

PALMER TN, ALESSANDRI A, ANDERSEN U, CANTELAUBE P, DAVEY M, DOBLAS-REYES FJ, FEDDERSEN H, GRAHAM R, HAGEDORN R, HOSHEN M and ROGEL P (2004) Development of a European multimodel ensemble system for seasonal-to-interannual prediction. *Bull. Am. Meteorol. Soc.* **85** 853–872.

PALMER TN and RÄISÄNEN J (2002) Quantifying the risk of extreme seasonal precipitation events in a changing climate. Nature 415 512-514. Doi: 10.1038/415512

RATNA SB, BEHERA S, RATNAM JV, TAKAHASHI K and YAMAGATA T (2013) An index for tropical temperate troughs over southern Africa. *Clim. Dyn.* **41** 421–441.

REASON CJC and HACHINGONTA S (2006) Interannual variability in dry and wet spell characteristics over Zambia. *Clim. Res.* **32** 49–62.

REASON CJC and WELDON D (2014) Variability of rainfall characteristics over the South Coast region of South Africa. *Theor. Appl. Climatol.* **115** 177–185.

REASON CJC, ALLAN RJ, LINDESAY JA and ANSELL TJ (2000) ENSO and climatic signals across the Indian Ocean basin in the global context. Part 1 Interannual composite patterns. *Int. J. Climatol.* **20** 1285–1327.

REASON CJC and ROUAULT M (2002) ENSO-like decadal patterns and South African rainfall. *Geophys. Res.***29** 161–164.

RICHARDSON DS (2000) Skill and economic value of the ECMWF ensemble prediction system. *Q. J. R. Meteorol. Soc.* **126** 649–668.

ROBERTSON AW, DIAN-HUA Q and MICHAEL KT (2012) Downscaling of seasonal rainfall over the Philippines. Dynamical versus statistical approaches. *Mon. Weather Rev.* **140** 1204–1218.

ROECKNER E, ARPE K, GIORGETTA M, SCHLESE U, SCHULWEIDA U, CLAUSSEN M, BENGTSSON L and CHRISTOPH M (1996) Simulation of present-day climate with the ECHAM4 model. Impact of model physics and resolution. *Max Planck Inst. Meteorol. Rep*. **93.** 171 pp.

ROUAULT M and FLORENCHIE P (2003) South east tropical Atlantic warm events and southern African rainfall. *Geophys. Res. Lett.* **30** DOI: 10.1029/2002GL014840.

ROULSTON MS and SMITH LA (2003) Combining dynamical and statistical ensembles. *Tellus Series A-Dyn. Meteorol. Oceanogr.* **55** 16–30.

SENE K (2009) Hydro-Meteorology. Forecasting and Applications. Springer, Dordrecht.

SHANNON LV, LUTJEHARMS JRE and NELSON G (1990) Causative mechanisms for intra-annual and interannual variability in the marine environment around southern Africa. *S. Afr. J. Sci.* **86** 356–373.

SHONGWE M E, LANDMAN WA and MASON SJ (2006) Performance of recalibration systems for GCM forecasts for southern Africa. Int. J. Climatol. 26 1567–1585.

SIAVONGA NEWS (2011) Spillway gates opened for the second time in 2011. URL: (http://www.siavonga-zambia.com/news-archive-2/spillway-gates-open-march-2011.html) (Accessed 21 September 2013).

CHRISTENSEN JH, HEWITSON B, BUSUIOC A, CHEN A, GAO X, HELD I, JONES R, KOLLI RK, KWON W-T, LAPRISE R, MAGAÑA RUEDA V, MEARNS L, MENÉNDEZ CG, RÄISÄNEN J, RINKE A, SARR A AND WHETTON P (2007) Regional Climate Projections. In: *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Solomon S, Qin D, Manning M, Chen Z, Marquis M, Averyt KB, Tignor M and Miller HL (eds.). Cambridge University Press, Cambridge.

TOZUKA T, ABIODUN BJ and ENGELBRECHT FA (2013) Impacts of convection schemes on simulating tropical-temperate troughs over southern Africa. *Clim. Dyn*. Doi: 10.1007/s00382-013-1738-4.

TROCOLLI AM, HARRISON D L, ANDERSON T and MASON SJ (2008) Seasonal Climate: Forecasting and Managing Risk. *NATO Science Series on Earth and Environmental Sciences* **82** 467 pp.

TYSON PD (1986) *Climatic Change and Variability in Southern Africa*. Oxford University Press, Cape Town.

VIGAUD N, POHL B and CRETAT J (2012) Tropical-temperate interactions over southern Africa simulated by a regional climate model. *Clim. Dyn*. **39** 2895–2916.0

WANG E, MCINTOSH P, JIANG Q and XU J (2009) Quantifying the value of historical climate knowledge and climate forecasts using agricultural systems modelling. 96 45-61. DOI; 10.1007/s10584-009-9592-4.

WASHINGTON R and PRESTON A (2006) Extreme wet years over southern Africa. Role of Indian Ocean sea surface temperatures. *J. Geophys. Res.* **111** DOI: 101029/2005JD006724.

WASHINGTON R and TODD M (1999) Tropical–temperate links in Southern Africa and Southwest Indian Ocean satellite-derived daily rainfall. *Int. J. Climatol.* **19** 1601–1616.

WILKS DS (2006) *Statistical Methods in the Atmospheric Sciences* (2nd edn). Elsevier, Amsterdam. 627 pp.

WILKS DS (2011) *Statistical Methods in the Atmospheric Sciences* (3rd edn). International Geophysics Series **100.** Academic Press, New York.

YUAN C, TOZUKA T, LANDMAN WA and YAMAGATA T (2014) Dynamical seasonal prediction of southern African summer precipitation. *Clim. Dyn*. **42** 3357-3374, DOI: 10.1007/s00382-013-1923-5.

Synopsis

The link between characterizing rainfall variability and the actual prediction of the seasonal-to-interannual rainfall totals over the Lake Kariba Catchment area has now been established. In addition, the skill levels have been presented and the potential economic value of such forecasts been demonstrated. The second objective of the study has therefore been addressed and the results provide the possibility to further develop and test a prediction system to directly predict seasonal inflows into Lake Kariba at lead-times useful for decision makers in dam management. In the following chapter, the use of a combination of physical and an empirical model to predict seasonal inflows into Lake Kariba in southern Africa is investigated.

Chapter 4: Prediction of inflows into Lake Kariba using a combination of physical and empirical models*

Preface

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In this chapter, two predictions systems are considered. The first uses antecedent seasonal rainfall totals over the upper Zambezi catchment as predictor in a statistical model for estimating seasonal inflows into Lake Kariba. The second and more sophisticated method uses predicted low-level atmospheric circulation of a coupled ocean-atmosphere general circulation model (CGCM) downscaled to the inflows. The predictability of 3-month seasonal rainfall totals over the Kariba catchment during the rainy season from September through April is investigated, by statistically downscaling the archived output of a state-of-the-art coupled ocean-atmosphere general circulation model (CGCM). The predictability of seasonal rainfall totals has been established in the previous chapter. This chapter addresses the third objective of the study, namely introducing linear prediction approaches to directly estimate inflows into Lake Kariba. The paper aims to potentially improve the overall management of water resources for Lake Kariba by supplying long-lead forecasts for the likelihood of high or low inflows into the dam to occur. In addition, the prediction system will provide key information on flood risk seasons to different stakeholders for example, hydropower production and water uses.

I conceptualized the paper and was responsible for data acquisition, analysis and interpretation as well as synthesis of results.

Prediction of inflows into Lake Kariba using a combination of physical and empirical models

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Abstract

Seasonal climate forecasts are operationally produced at various climate prediction centres around the world. However, these forecasts may not necessarily be objectively integrated into application models in order to help with decision-making processes. The use of hydro- meteorological models may be proven effective for reservoir operations since accurate and reliable prediction of reservoir inflows can provide balanced solution to the problems faced by dam or reservoir managers. This study investigates the use of a combination of physical and empirical models to predict seasonal inflows into Lake Kariba in southern Africa. Two predictions systems are considered. The first uses antecedent seasonal rainfall totals over the upper Zambezi catchment as predictor in a statistical model for estimating seasonal inflows into Lake Kariba. The second and more sophisticated method uses predicted low-level atmospheric circulation of a coupled ocean-atmosphere general circulation model (CGCM) downscaled to the inflows. Forecast verification results are presented for five run-on 3-month seasons; from September to June over an independent hindcast period of 14 years (1995/6 to 2008/9). Verification is conducted using the relative operating characteristic (ROC) and the reliability diagram. In addition to the presented verification statistics, the hindcasts are also evaluated in terms of their economic value as a usefulness indicator of forecast quality for bureaucrats and to the general public. The models in general perform best during the austral mid-summer season of DJF (seasonal onset of inflows) and the autumn season of MAM (main inflow season). Moreover, the prediction system that uses the output of the CGCM is superior to the simple statistical approach. An additional forecast of a recent flooding event (2010/11), which lies outside of the 14-year verification window, is presented to

further demonstrate the forecast system's operational capability during a season of high inflows that caused societal and infrastructure problems over the region.

Key Words: Lake Kariba, seasonal flows; downscaling; verification; water resource management

4.1 Introduction

River flows are sensitive to climatic variability and change. Rainfall and runoff are key drivers of reservoir inflow and vary considerably from year to year making prediction of inflows essential for effective water resource management (Ghosh et al., 2010). Reservoir operation is a multi-complex system which involves designing and operating to make informed decision on when and how much water to accommodate and release over time (Stedinger et al., 2001). Improved and reliable flow forecasts can reduce detrimental effects of floods, droughts and water supply for various users (Skotner et al., 2007; Cloke et al., 2009). Over the past years, dam managers often use traditional methods such as the design rule and water level fluctuation curves to guide and manage reservoir operation (Refsgaar et al., 1996). The traditional systems of predicting stream flow has its own shortcomings for example, they are not very reliable for balancing the demands from different users. However, the increase in the better understanding of atmospheric processes has resulted in the use and advancement of seasonal forecasts (Makarau and Jury, 1997). Reliable predictions of inflows in advance can improve the management of water resources systems. The ability to predict future climate fluctuations one or more seasons in advance would have measurable benefits for decision making, also in hydrology (Barnston et al., 2004; Schaake et al., 2010; Thielen et al., 2008; Schaake et al., 2007b).

Rainfall especially in the upper Zambezi catchment is the main driver of the inflows into Lake Kariba. The flow in the river results for the most part from rainfall over the upper catchment. There is a about a one-season delay between the main rainfall month (January) as measured at the inflow gauging station and the maximum inflows (March to May) as measured at the same station (Figure 1). Since rainfall is the main driver for inflows into Lake Kariba, we have previously investigated the prediction of 3-

month seasonal rainfall totals over the Kariba catchment and found good skill (Muchuru et al., 2014). Currently, there is in place a one-month look-ahead forecast model being used at Lake Kariba (ZRA, 2005). This forecast model is based on the Index-variable method for flows at Victoria Falls in the upper catchment of the Lake. The lead time between water arriving at the top of Victoria Falls and the water arriving at the Lake's inflow gauging system is approximately two weeks. Two-week lead time might not be adequate enough to effectively predict the flows at Victoria Falls and subsequently estimating inflows into the Lake. This lead-time is particularly crucial during the main inflow months of March and April when the largest flows from the upper catchment arrive. Moreover, the occurrence of exceptionally high flow volumes over the lower catchment tend to depend upon flows from the upper catchment reaching that area. Introducing a comprehensive set of model forecasts over a long lead-time might therefore be useful. The use of a longer lead-time can effectively reduce the risk of a possible underestimation of the flows into Kariba, particularly during high flow periods. For example, one of the biggest floods that occurred in the Zambezi basin was in 2010/2011 during the austral mid-summer. Lake Kariba reservoir was almost at full capacity when intense and prolonged rainfall over large areas of the basin originated a very big flood into Kariba. The enormous flood wave downstream resulted in loss of life and property. Extreme floods have also resulted in considerable loss of life, social disruptions, and extensive economic damage.

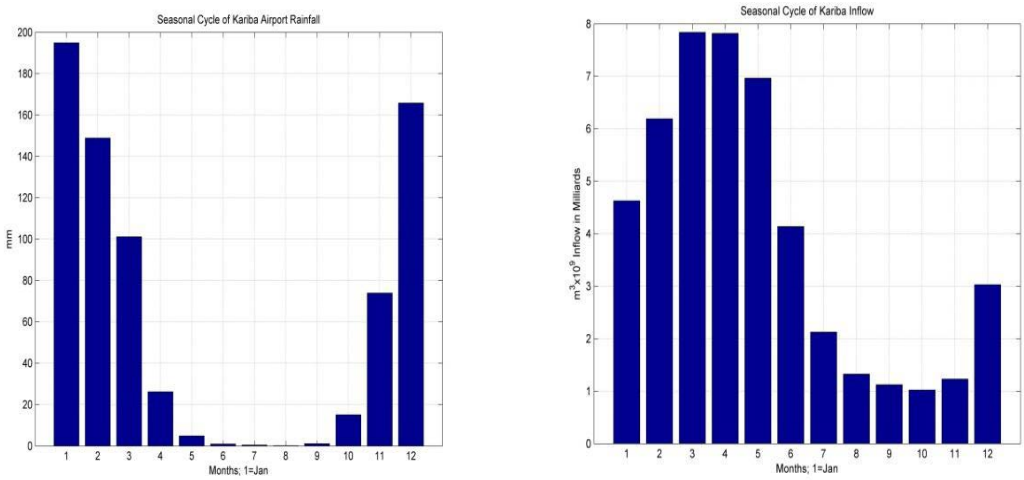


Figure 1. The seasonal cycles of the Kariba rainfall (left panel) and the inflow (right panel). Rainfall data was acquired from the Zambezi River authority.

The main reason for objectively predicting inflows is to better ascertain the uncertainty about the future and the need to reduce unforeseen catastrophes (Krzysztofowicz, 2001). The increase in the understanding of atmospheric processes has harnessed to improve the accuracy and reliability of forecasts for all climatic and hydrological variables (precipitation, temperature and runoff) (Cane et al., 1994; Hastenrath et al., 1995; Landman and Goddard, 2002). Forecasts still remain far from perfect, and may fall short of reaching society's expectations for timely and reliable warnings. Therefore, the need arises to improve prediction system by, for example, through combing physical and empirical models (Goetz et al., 2011; Ziervogel et al., 2005; Lessmann et al., 2012). Several studies of empirical modelling have been carried out to predict stream-flow (Opitz-Stapleton et al., 2007; Barnston et al., 1999; Tisseuil et al., 2010; Krzysztofowicz., 1999; Goetz et al., 2011; Maier et al., 2000); however most of these approaches still have short-comings to skilfully predict the flows. Therefore, the most common modelling approach is to use the combination of both physical and empirical techniques (Hansen, 2002). A reliable model should use both atmospheric and empirical prediction system, for both atmospheric and hydrologic predictions (Tong et al., 2012) in order to quantify and propagate uncertainty from various sources in the forecasting system. In general, this study will employ approaches to predicting inflow using both observed and predicted climate information. The prediction system will use both physical and empirical models with careful consideration of climatic predictors (Partington et al., 2012; Marco et al., 2010). Forecasts from ocean–atmosphere general circulation models GCMs will be used to translate seasonal forecasts into inflow forecasts using empirical downscaling approaches (Lazenby et al., 2014; Tong et al., 2012).

The study aims to potentially improve the overall management of water resources for Lake Kariba by supplying long-lead forecasts for the likelihood of high or low inflows into the dam to occur. In addition, the prediction system will provide key information on flood risk seasons to different stakeholders for example, hydropower production and water uses (Hamlet et al., 2002). However, forecasting can be performed deterministically or probabilistically (Yu et al., 2007). A deterministic forecast identifies a variable to be forecasted, while a probabilistic forecast specifies a probability distribution function pertaining to the predictand (Yu et al., 2007). Probabilistic forecasts can provide risk-based tools for flood alerts and watches, and can be used by dam managers in decision making (Krzysztofowicz, 2001; Stam et al., 1998; Yu et al., 2007; Krzysztofowicz, 1999). Dam managers are mainly concerned about keeping water levels between a Minimum Operating Level (MOL) and a Full Supply Level (FSL). However, this information might not be sufficient to optimize dam management. Probabilistic forecasts can reduce errors of potential misperception of responsibilities and decision making by reservoir operators (Krzysztofowicz, 2001). Since reservoirs have become the most important facilities for distributing water (Ncube et al., 2011), among various purposes, their management is crucial (Wei and Hsu, 2005 and Mujumdar et al., 2010). The inflow into Lake Kariba is mainly influenced by rainfall especially in the upper catchment of the Zambezi River Basin (Balek, 1971). Climate variations have an important impact on water supply in the southern Africa region (Rouault et al., 2003). Population increase and demand for water in southern Africa necessitates effective water management (Chidanti-Malunga, 2011). The need for forecast guidance for an approaching season has thus become necessary. Since the understanding of the predictability of the atmosphere at seasonal-to-interannual time-scales has improved considerably over southern Africa during the past decade (Landman, 2014), the provision of such forecasts has become a possibility (Carson, 1998; Palmer and Anderson, 1993). This notion will be tested here.

4.2 Study area

Lake Kariba was built in the late 1950’s mainly to provide water for hydro-power production. The Lake boasts a reservoir surface area of 5 580 km^2, a reservoir length of 280 km and width of 32 km at its widest point at full supply level. Lake Kariba’s upper and lower catchment areas drain from the five riparian states of Angola, Namibia, Botswana, Zambia and Zimbabwe. This drainage area covers some 815 000 km^2, or 60% of the whole Zambezi River basin area (Tumbare, 2000). Lake Kariba regulates runoff from an upstream catchment area of 687,535 km^2, which is about 50% of the total Zambezi catchment area. Lake Kariba is operated by both the Governments of the Republics of Zambia and Zimbabwe. Both authorities monitor, operate and maintain the Kariba Dam wall and manage the hydrology of Lake Kariba for hydropower generation and other stakeholder uses.

Average annual rainfall for the Lake Kariba catchment (see Figure 2) is about 1,000 mm, producing a mean annual discharge of 37,249 mm^3 (an average flow rate of 1181 m^3/s). Approximately 50% of the annual rainfall over the catchment, on average, contributes to the Zambezi base flow (Sharma and Nyumbu 1985). During drought years, the magnitude and duration of average peak flows may be reduced by 70% or more. Runoff varies considerably from year to year (0.40 coefficient of variation, from a remarkable 72, 800 mm^3 in 1957/58 to as low as 12,300 mm^3 in 1995/96). The time series of annual flows reveals long-term cycles of high, medium, and low runoff. These cycles also influence runoff efficiency; a sequence of particularly low rainfall years in the catchment, such as the one occurred during the early 1900s and again during the period 1980-1998, can significantly reduce the proportion of annual rainfall that occurs as runoff.

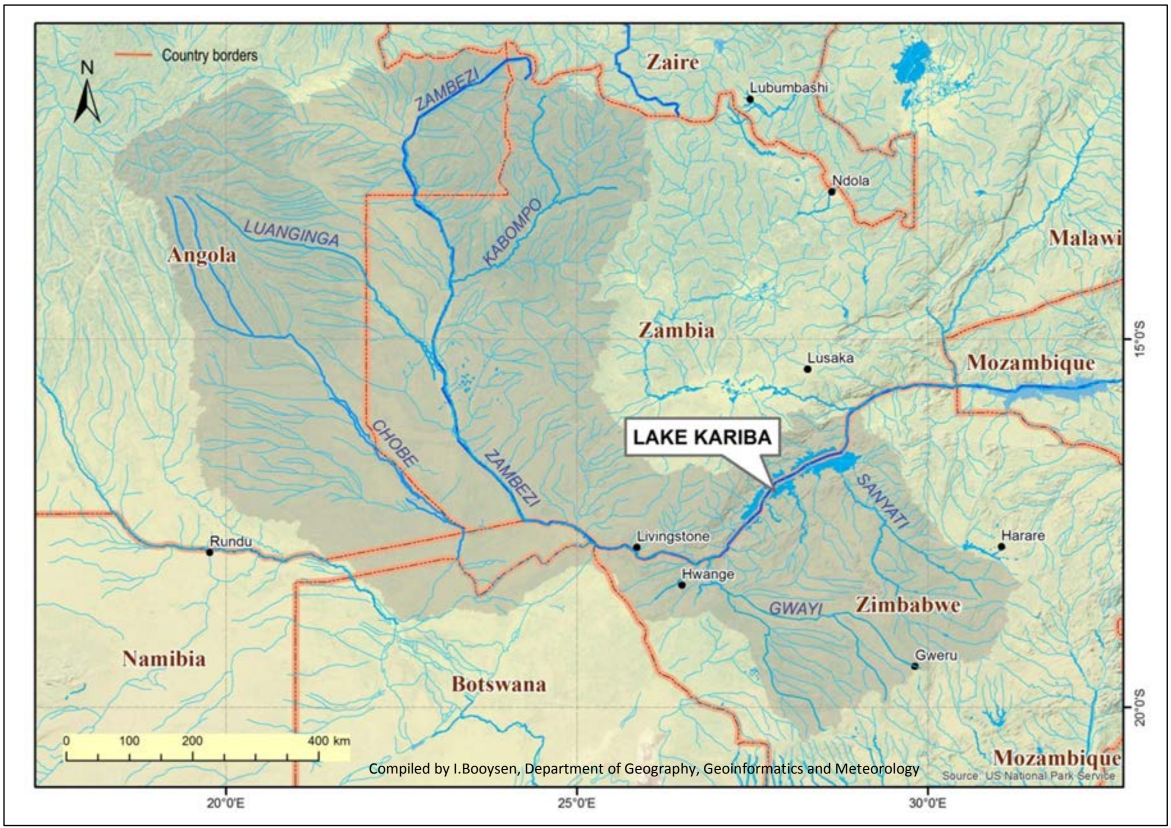


Figure 2. Lake Kariba catchment area (Source of basemap: www.arcgis.com, 2014).

4.3 Data

4.3.1 Rainfall data

The total seasonal rainfall over the upper Zambezi catchment is used as the predictors in a statistical model for estimating inflows into Lake Kariba. The rainfall data used for downscaling and verification is the University of East Anglia's (UEA) Climate Research Unit (CRU) version TS3.1 seasonal precipitation data at a 0.5°x0.5° resolution (Harris et al., 2013). Here, the CRU data from only 1982/83 to 2010/11are used. The CRU data represent one of the most comprehensive observational data sets available and have been used in former studies over southern Africa (e.g. Landman and Beraki, 2012).

4.3.2 ECHAM4.5-MOM3 coupled ocean–atmosphere model data

Statistical downscaling of the archived output of a state-of-the-art coupled ocean-atmosphere general circulation model (CGCM) is the second modelling system considered here for predicting inflows (the first system being the one using upper catchment rainfall as predictor). The CGCM's archived hindcast data used in this study were obtained from the data library of the International Research Institute for Climate and Society (IRI), (DeWitt, 2005). Only five forecast lead-times from the IRI's data library are to be considered. The forecasts for the coupled model are produced near the beginning of the month.

The atmospheric model used is the ECHAM4.5- an atmospheric general circulation model (GCM). The model uses spherical harmonics with a truncation at wavenumber 42 (T42) in the standard version (Roeckner et al., 1996), i.e. a mesh width of 2.8°. The Ocean Model, directly coupled, is version 3 of the Modular Ocean Model (MOM3; Pacanowski and Griffies, 1998). The ocean–atmosphere model used in this research is therefore the ECHAM4.5–MOM3 (DeWitt, 2005) and hindcast data for this fully coupled forecasting system are available from 1982 until July 2012.

4.4 Methodology

4.4.1 Statistical downscaling

Statistical downscaling, a procedure used as early as the 1970's for weather prediction (Glahn and Lowry, 1972), may also be used to assess local climate change impacts (e.g. Wilby et al., 2002) and for climate variability impacts (e.g. Landman and Goddard, 2002). Downscaling translates large-scale model output to a finer resolution (Muluye, 2011) or to a point of interest. The process involves deriving empirical relationships that transform large scale features of the GCM (predictors) to regional scale variables (predictands) such as precipitation (Mujumdar et al., 2008) and in this study, inflows into the Lake. The hindcasts of the coupled model at an approximate 2.8° x 2.8° resolution are downscaled statistically to the inflow at a gauging station at the inlet of the Lake for the selected seasons of SON through AMJ. The statistical downscaling procedure of model output statistics (MOS; Wilks, 2011) is used here. This procedure can minimize systematic errors of the coupled model (Wilks, 2011; Robertson et al., 2012) since the MOS equations are developed directly in the regression equations (Landman et al., 2012; Landman and Beraki, 2012; Landman and Goddard, 2002) and can thus reduce model errors in all stages of model development (Wilks, 2011). Moreover, the downscaled forecast should be able to enhance integrated simulation of the applicable variable, in this case inflows, in decision-making systems for effective reservoir operation (Braga et al., 2013). Downscaled retroactive forecasts, e.g., Landman et al. (2001), are evaluated in terms of their potential economic value for an end-user such as the reservoir manager at Lake Kariba. To quantify the potential value of a forecasting system, a concept of potential economic value, estimated using simple cost/loss models (Buizza, 2008). The simple cost/loss approach cconsiders a user who has access to a forecast, and who can take a protection action of cost (C) to avoid a loss (L) (note that L denotes only the avoidable losses not all the losses that a user can incur). According to this simple cost/loss decision model the potential economic value of a forecast system can be calculated by combining the outcomes of the decision-making process with an economic decision model like the static cost/loss model approach. In this cost/loss model, a hit and a false alarm are associated with a cost C, since an alarm causes the user to protect the environment against the event at a cost C. By contrast, if no alarm is given, no protective action is done: if the event is not observed, no loss occurs, but if the event occurs the user faces a loss L. In fact, the forecast system proposed here could potentially be of great value to a dam manager of reservoir operations and may be able to reduce risks in dam management decisions. In addition to this forecast system, antecedent rainfall totals over the upper Zambezi catchment are used as inflow predictors in a base-line model against which the more sophisticated forecast system is to be compared.

Since a major driver of seasonal-to-interannual flows in the Zambezi River is the associated rainfall observed over the catchment, a model forecast of the expected rainfall outcomes over the months ahead may aid in the predictions of flows downstream. However, large-scale circulation is more accurately produced by global climate models than rainfall and so circulation should be considered instead in the MOS system for seasonal inflow downscaling (Landman et al., 2012; Landman and Beraki, 2012; Landman and Goddard, 2002). Moreover, it has already been shown that predicted atmospheric circulation can successfully be used to downscale to seasonal rainfall totals over the catchment (Muchuru et al., 2014). The 12-member ensemble mean geopotential height fields at the 850 hPa level are used as predictors in order to obtain the downscaled flow forecasts. Atmospheric circulation at this atmospheric level could be considered as low-level circulation since the area of interest is near the 850 hPa geopotential level. The software to do the statistical downscaling is the Climate Predictability Tool (CPT) of the International Research Institute for Climate and Society (IRI; http://iri.columbia.edu). The procedure to create downscaled hindcasts follows Landman et al., (2012) and includes a number of steps from transforming the Zambezi flows at the inlet of Lake Kariba into an approximate normal distribution, prefiltering the predictors (850 hPa heights of the CGCM) through empirical orthogonal functions (EOFs) and subsequently producing downscaled inflow data using principal component regression (e.g. Malherbe et al., 2014). The model domain selected from which the downscaling is performed cover the area from Equator to 30° S, and from Greenwich to 50° E. MOS equations are first trained over 13 years from 1982-1994, followed by increasing the training period by one year. This incremental increase of the training period mimics an operational forecast setting. The resulting 14-year period for verification and comparison is from 1995/96 to 2008/09.

4.4.2 Verification

Forecasts produced by physical models are liable to systematic errors (Ebert et al., 2000) and may be exaggerated (Lazenby et al., 2014). The errors could be emanating from the initial conditions, errors in the prediction of atmospheric flow (dynamics), and inadequacies in the large-scale and convective rainfall parameterizations. Forecast verification can help to quantify these errors (Brown et al., 2010), to better understand the sources of predictive error and skill and to improve the model performance in order to make better forecast (Mesinger, 1996). In this study only extreme season inflows are considered. Extremes are here defined by the 75th (high inflow category) and 25th (low inflow category) percentile values of the climatological record. The reason to use extreme season thresholds is because a reservoir manager at Lake Kariba may be more interested in the prediction of extreme inflows that are more likely to affect the water level of the dam than "normal" rainfall seasons would (Sene, 2009). Moreover, the prediction of seasonal climate extremes over southern Africa has skill (Landman et al., 2005; Landman et al., 2012; Lazenby et al., 2014). Here we will attempt to test the predictability of extreme inflows into the Lake so that such forecasts may potentially be able to feed into decision support systems that can be used by reservoir managers at the Lake.

For seasonal time scales especially, probabilistic forecasts (i.e. the likelihood of a particular flow outcome to occur) are preferred over deterministic forecasts (e.g. the inflow will be high this coming season) since deterministic forecasts can be misinterpreted if they are portrayed as the only possible future outcome. Moreover, probability forecasts are in fact required in order to enable users to make optimal decisions since predicted uncertainty is a key element in the decision-making process (Troccoli et al., 2008). This notion has also been adopted in water resource management since a reservoir manager needs information available on the likelihood of a coming season to be associated with extreme rainfall totals over the catchment that may lead to high flow volumes into the dam. Reservoir managers may want to also know the reliability with which such probabilistic forecasts are made when they attempt to discriminate high inflow seasons from the rest of the seasons and very low inflow seasons from the rest. Therefore, discrimination and reliability are two attributes of interest here for probabilistic forecasts. Discrimination and reliability are tested using forecast verification measures of the Relative Operating Characteristics (ROC; Mason and Graham, 2002) and the reliability diagram (Hamill, 1997).

4.5 Results

The two forecast systems' – respectively using upper Zambezi rainfall and CGCM low-level circulation as predictors – discrimination and reliability are assessed next by first considering ROC scores over various lead-times and 3-month seasons and then assessing reliability. Five forecast lead-times are considered and are defined by the number of months between forecast issuance and the first month of the season being forecast. For example, a 1-month lead-time forecast for DJF inflows are for forecasts issued in early November, a 2-month lead-time with forecasts issued in early October, etc. Furthermore, using upper Zambezi rainfall as predictor, a 1-month lead-time forecast would be for rainfall totals over the 3-month season of ASO since this season's totals can only be obtained near the beginning of November. For the CGCM, 1-month lead-time forecasts are those initialised near the beginning of November.

4.5.1 Inflow hindcasts

Relative operating characteristic (ROC) scores can demonstrate a forecast system's ability to discriminate high (or low) flow events from non-events. Here we are interested in extreme seasons as defined by the seasonal inflows greater than the 75th percentile of the climatological record (high inflows) or less than the 25th percentile (low inflows) of the climatological record. Perfect discrimination is found when the ROC score is 1.0, but no skill forecasts are associated with scores $\leq$0.5. The ROC score in this study are shown in Figure 3 for both modelling systems, for five lead-times and for eight run-on 3-month seasons.

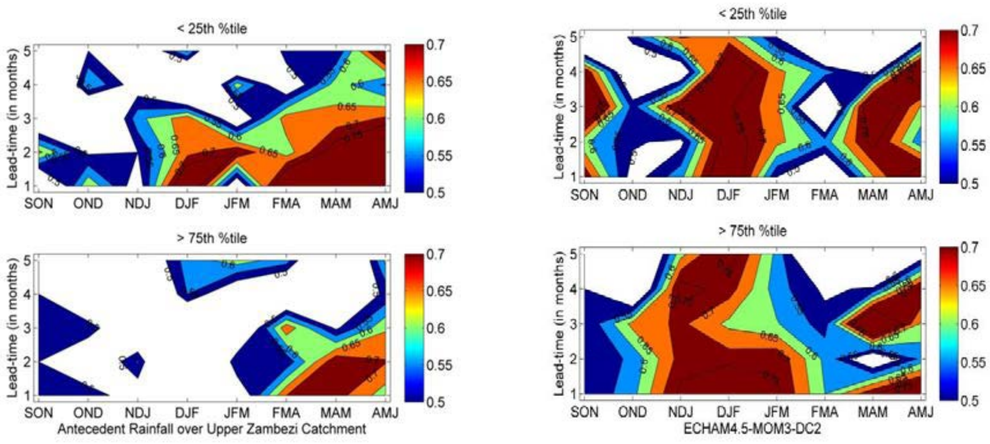
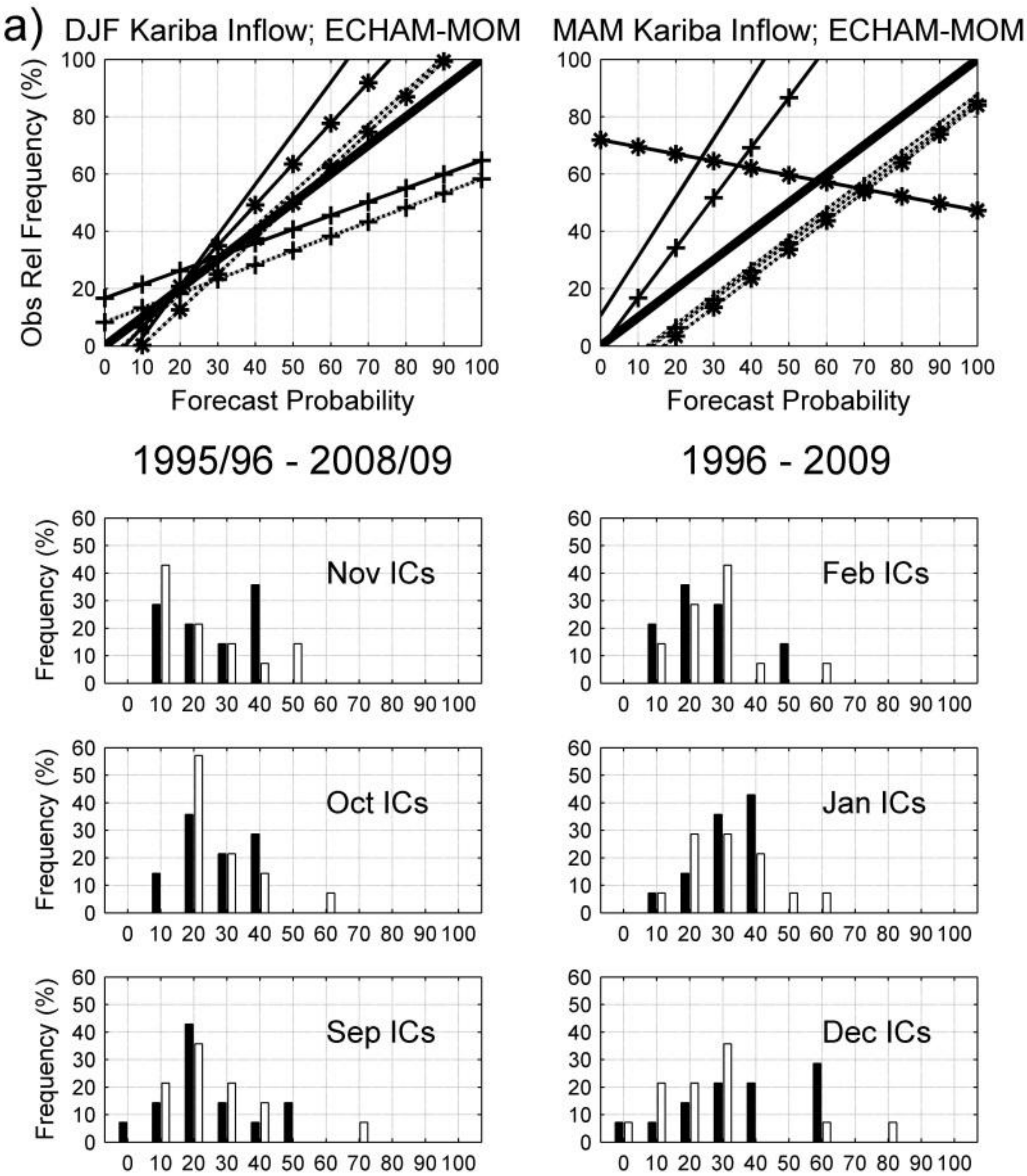


Figure.3. ROC scores of both the CGCM (right panel) and antecedent seasonal rainfall over the upper Zambezi catchment (left panel) obtained by retroactively generated probabilistic hindcasts for low inflow seasons (top panel; less than the 25th percentile values of the climatological record) and high inflow seasons (bottom panel; greater than the75th percentile of the climatological record) over 14yr (1995/96-2008/09). The x-axes show the 3-month seasons for which the inflow forecasts are made, and the y-axes shows the five lead-times.

The ROC scores in Figure 3 are for the 3-month inflow seasons from SON through AMJ when using respectively the CGCM output (right panels) and the antecedent rainfall over the upper Zambezi catchment (left panels) as inflow predictors. Figure 3 demonstrates that for MAM, peak flow season, there is good skill at 1-2 month lead-time in the 75 % category using antecedent seasonal rainfall whereas in the GCM-MOS model there is poor skill at these lead times. However, at a 3-4 month lead-time there is good skill in GCM-MOS model but no skill in the antecedent rainfall model. These eight run-on seasons sufficiently cover the main inflow period as shown in Figure 1. The ROC scores are calculated from retroactively generated hindcasts of extremely high and low seasonal inflows. The better discrimination is obtained when using CGCM output as predictors since more seasons and more lead-times are associated with ROC scores higher than 0.5. Moreover, although both prediction systems produce high ROC scores during the main inflow period (c.f. Figure 1) it is only the CGCM that enables the prediction of seasonal inflow onset (i.e. DJF inflow predictions) across all lead-times and for both inflow categories. This relatively high skill associated with DJF may be attributed to the finding that some CGCMs are best at predicting the DJF circulation over southern Africa that is related to the rainfall variability over the region (Landman et al., 2012). High skill DJF onset predictions for inflows should also help with decisions Lake Kariba managers need to make at the start of the main inflow time of the year. However, such managers certainly also want to know well ahead of time what to expect during the main inflow season of MAM (Figure 1). During this time, the reservoir starts to get most of its inflow from rivers and tributaries. High ROC scores are indeed found for both predictions systems for MAM, but the scores are somewhat lower than for DJF and also only high for shorter lead-times. Notwithstanding, for both the onset and for the main inflow period, ROC scores suggest useable forecast discrimination may be possible at lead-times far exceeding the 2-week lead time as described in the Standard Operating Procedure (SOP) manual (ZRA, 2005). Therefore, these skill levels and their associated lead-times presented here provide evidence that a decision support tool for reservoir managers, in order to make informed decisions regarding the likelihood of high or low rain-fed inflows into the reservoir during several months ahead of time, may well be feasible.

ROC scores' measure of forecast performance is sometimes questionable due to its insensitivity to reliability (Troccoli et al., 2008). Therefore, it is imperative to assess the confidence with which the probabilistic forecasts of extremely high or low seasonal flows are made. Only the DJF and MAM seasons are considered from now on since they are for both forecast systems (CGCM output and the antecedent rainfall over the upper Zambezi catchment) associated with the highest ROC scores. Figure 4 (a, b) shows the 1- to -3month lead reliability plots and frequency histograms for DJF and for MAM, as well as for both forecast systems. For perfect reliability (the forecast probabilities exactly match the observed frequencies of respectively high and low seasonal flows) the weighted least squares regression lines of the reliability curves (not shown for the sake of clarity) will occur on top of the thick diagonal line. When the slope of a regression line is shallower (steeper) than the diagonal lines of perfect reliability, forecasts for a particular category are said be over- (under-) confident. DJF 1- and 2-month lead-time verification of the CGCM (the thin solid and dashed lines and lines with asterisks of Figure 4a, left panel) shows under-confidence for both categories since these regression lines are for the most part steeper than the diagonal line of perfect reliability. On the other hand, 3-month lead-time forecasts for DJF as produced by the CGCM (solid and dashed lines with plus signs) show under-confidence because these lines are found to be shallower than the diagonal. For MAM inflows predicted by the CGCM reliability is lower than found for DJF since the regression lines are further removed from perfect reliability. Even lower reliability is found for using antecedent rainfall as predictor (Figure 4b). Figures 4 a and b show in general that the probability hindcasts of the DJF season seem more reliable than the MAM season, and using the CGCM output to downscale to the inflows are superior to using antecedent seasonal rainfall as predictor of the flows. The same result is found for the ROC scores. One may ask then why did rainfall totals over the upper catchment not turn out to be as skilful predictor of the flows as opposed to using predicted atmospheric circulation. One likely explanation is that, especially for DJF inflows, is that by the time DJF inflows are predicted with the simple statistical approach (at best, observed rainfall up to October is used as predictor) not much rain has actually fallen over the catchment (to drive the flows) as seen by the annual rainfall cycle depicted in Figure 1. However, short lead-time (1 to 2 months) forecasts using rainfall as predictor did perform reasonable well for MAM inflows (Figure 3).



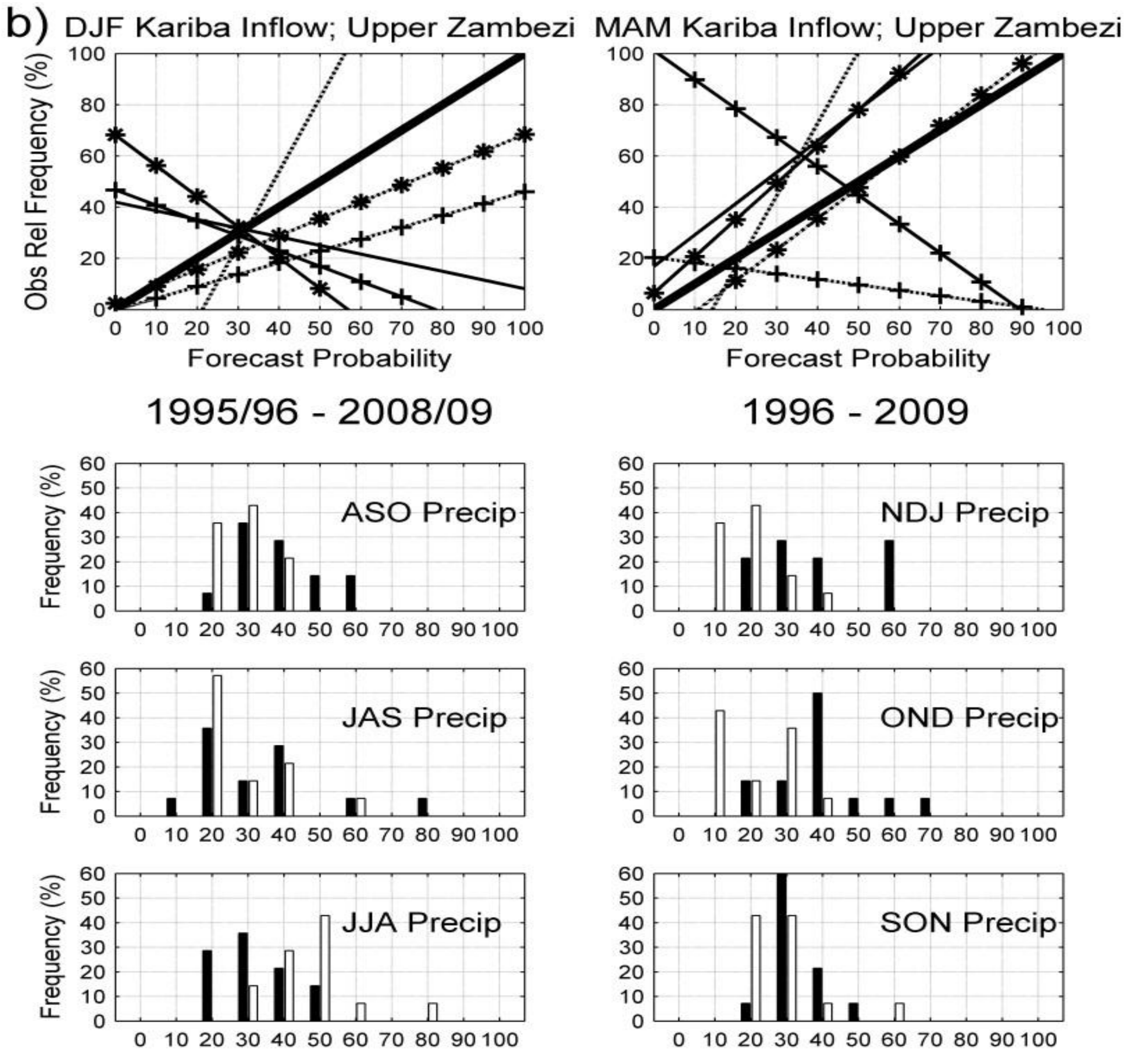


Figure 4a and b. Reliability diagrams (top panels) and frequency histograms for above- (>75th percentile) and below- (<25th percentile) normal DJF (left panels) and MAM (right panels) 1- to 3-month lead-time forecasts produced by a) downscaling the 850 hPa geopotential heights of the ECHAM4.5-MOM3-DC2 coupled model to inflows into Lake Kariba, and by Figure b) using the antecedent seasonal rainfall totals over the upper Zambezi catchment as predictors of Lake Kariba inflows. The thick black line of the reliability diagrams represents perfect reliability of the forecasts, while the rest of the lines represent weighted least-squares regression lines of reliability: Solid and dashed lines respectively represent the above- and below-normal categories for 1-month lead-times; solid and dashed lines with asterisks are for 2-month lead-times; solid and dashed lines with plus signs are for 3-month lead-times. For the frequency histograms the black bars represent above-normal flows and the white bars represent below-normal flows. Also shown on the frequency histograms are the Figure 4a) initialization month and Figure 4b) the rainfall season used as predictor.

4.5.2 Value of the probabilistic inflow forecasts

Reservoir managers, who are also decision makers, are largely interested in both profit making and value for money (Hagedorn and Smith, 2008) as well as optimized reservoir operations (Alemu et al., 2011). In the past, such managers may have mostly been presented with technical verification parameters describing the skill of probabilistic forecast systems (e.g. Hagedorn and Smith, 2008) through scoring metrics such as the Brier skill score (Hagedorn and Smith, 2008; Wilks, 2011) and those presented above. However, in addition to be presented with measures of skill such forecast users may in fact want to know whether or not spending a high amount of capital on forecasts from a forecast system that is reliable is indeed leading to higher profits or return of investment as opposed to not using any forecast information. (Richardson, 2000; Roulston et al., 2003 and Muluye, 2011) assessed forecast systems on a simple optimal decision-making, cost–loss analysis technique. Here we similarly attempt to evaluate both our forecast systems in terms of the economic gain they promise to a user (Hagedorn and Smith 2008) as expressed through effective interest rates. These rates are typically calculated over a relatively long period of time spanning several years. Here the economic value of Kariba inflow forecasts are assessed over the same 14yr verification period described above.

Effective interest rates are positive when the investment made in the forecasts have produced positive outcomes, while negative values suggest that money may have been lost by the investors during the evaluation period. The effective interest rate values presented in Figure 5 show positive values during spring (SON), mid-summer (DJF) and autumn (MAM) when the CGCM output is used as predictor (top panel), but is only positive from the JFM season onwards for the case of using antecedent seasonal rainfall as predictors (bottom panel). These results are in strong agreement with the

ROC graphs of Figure 3 and show that seasons associated with high skill over the catchment are likely to be those associated with the best chance of financial gain (e.g. Muchuru et al., 2014). Both the ROC scores (Figure 3) and the rates of Figure 4 similarly suggest that inflows predicted by the output of the CGCM may have the best chance for the Kariba Lake manager to gain the most financially. Owing to the strong association with the ROC scores, effective interest rates may be considered as a user-oriented verification parameter to communicate the value of probability forecasts to a wider user community.

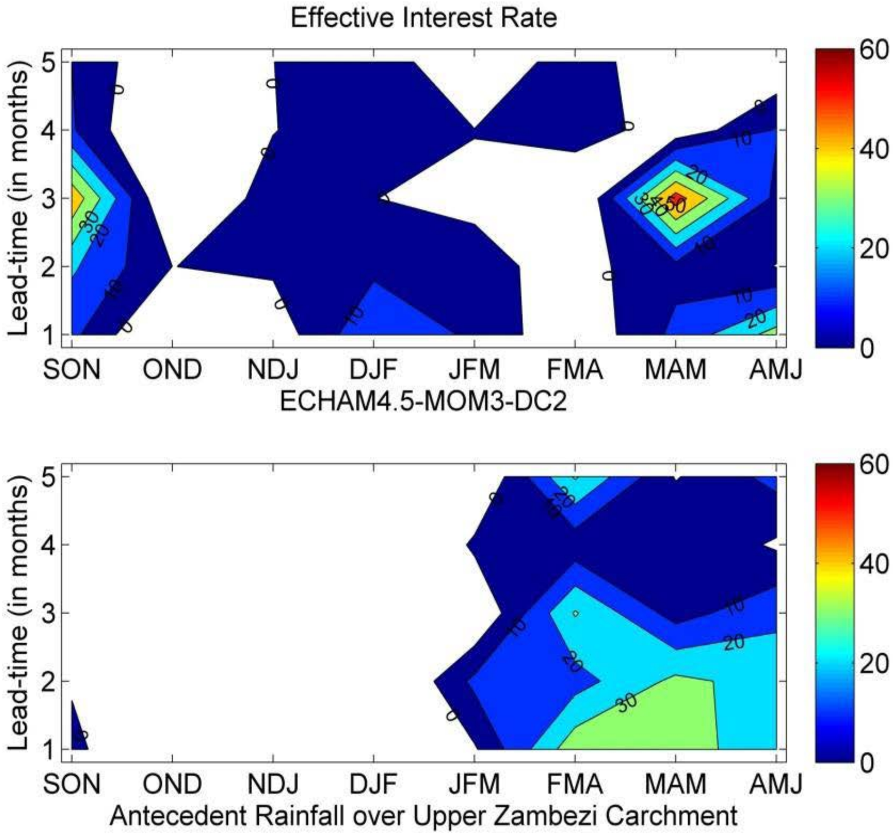


Figure 5. Effective interest rates associated with the CGCM (top panel) and with the antecedent rainfall over upper Zambezi catchment as predictor (bottom panel) from SON to AMJ.

An additional approach to communicate forecast value may be achieved through the so-called two-alternative forced choice test (2AFC; Mason and Weigel, 2009). The

2AFC is a scoring procedure that is generic to be usable on forecasts ranging from simple yes–no forecasts of dichotomous outcomes, to forecasts of continuous variables. 2AFC scores have broad intuitive appeal in that the expected score of an unskilled set of forecasts (random guessing or perpetually identical forecasts) is 50%, and is interpretable as an indication of how often the forecasts are correct, even when the forecasts are expressed probabilistically and/or the observations are not discrete. Figure 6 a and b, shows the 2AFC scores for both forecast systems and as was the case for the effective interest rates, the graphs show strong similarities to the ROC scores of Figure 3.

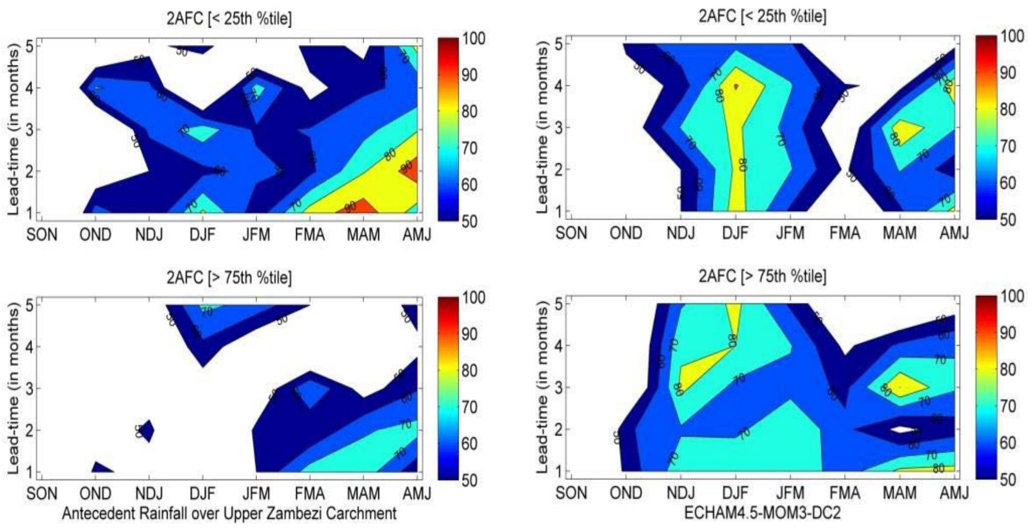


Figure 6. 2AFC Scores associated with the antecedent rainfall (right panel) over upper Zambezi catchment as predictor (left panel) and the CGCM.

To summarise the results, ROC scores suggest skilful forecasts to be possible during onset and during the main inflow seasons. Moreover, the better modelling approach is to use the atmospheric circulation from the CGCM as predictor. In general, the same conclusions regarding best season and best practice are also found when assessing the economic value of forecasts and when demonstrating forecast quality to the general public (2AFC scores).

4.5.3 Year-by-year hindcasts

The above sections have demonstrated the various skill levels of the forecasting systems presented here. The verification work, both from a scientific and from a forecast user's perspective, resulted in the following conclusions being drawn. Antecedent seasonal rainfall over the upper Zambezi catchment is not as skilful in predicting inflows into the Lake as opposed to using as predictor the coupled ocean-atmosphere's model output of low-level atmospheric circulation; the 3-month seasons of highest inflow predictability is DJF and MAM; and although MAM is the peak inflow season, its associated forecast skill levels are inferior to DJF inflow forecast skill. To provide a statement that may be best interpreted by a user of these forecasts is that we have demonstrated our ability to predict for the seasonal onset and peak seasonal inflows into Lake Kariba by using output of a state-of-the-art climate model, although more modest skill levels are associated with the peak inflows.

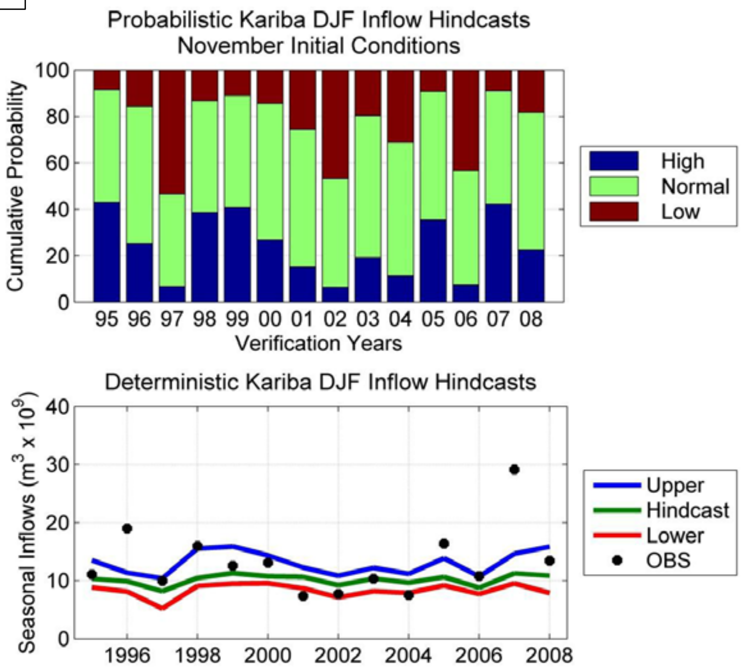
In this section we will show and discuss some of the actual downscaled hindcasts, season by season, over the 14-year verification period for DJF and for MAM. The value in presenting these hindcasts could provide information regarding the prediction of particular seasons of high and low inflows, the potential value of probabilistic over deterministic forecasts, and also to provide independent forecasts that may be assimilated into decision support systems. Both probabilistic and deterministic inflow forecasts are presented. The former forecasts show the likelihood of inflows being below (above) the 25th (75th) percentile of the climatological record, while the latter shows a forecast by inflow volumes ($m^3 \times 10^9$) and forecast limits as defined by the 1-

standard deviation of the forecasts. Figure 7a and b shows only the 1-month lead forecasts for DJF and the 3-month lead forecasts for MAM since good verification skills have been found for these lead-times and that with such lead-times decisions regarding optimal dam management and operations can be made before the end of the calendar year preceding the main inflow period.

The DJF (Figure 7a) high probability forecasts for high (low) inflows are usually associated with La Niña (El Niño) years. For example, the five highest probability forecasts for high inflows are associated with the La Niña seasons of 1995/96, 1998/99, 1999/2000, 2005/06 and 2007/08, while the four highest probability forecast years for low inflows during the 1997/98, 2002/03, 2004/5 and 2006/07 are associated with El Niño years. So the forecasts seem to be responding to ENSO years, as has been found to be the case for DJF rainfall predictions over the region (Landman and Beraki, 2012; Landman et al., 2012). Moreover, this ENSO link is also seen for the most part in the observed inflows where the five highest observed inflow years of 1996/97, 1998/99, 2000/01, 2005/06 and 2007/08 are associated with La Niña years. Also, some of the lowest inflow years are on the other hand found during the El Niño years of 1997/98, 2002/03, 2004/05 and 2006/07.

For the MAM forecasts presented in Figure 7b there is a good agreement between some of the high-probability forecast seasons (for both high and low volume inflows) and the deterministic estimates. For example, with increased seasonal flows towards 1999 and 2000, from 2002 to 2004, and from 2005 towards 2009, the forecast probabilities increased in accordance with the deterministic forecast ranges. Regarding the observed and predicted flows and their association with ENSO, this link seem to be weaker as was found for DJF – low inflows during the 1996 La Niña and high inflows during the 2007 El Niño.

7a



7b

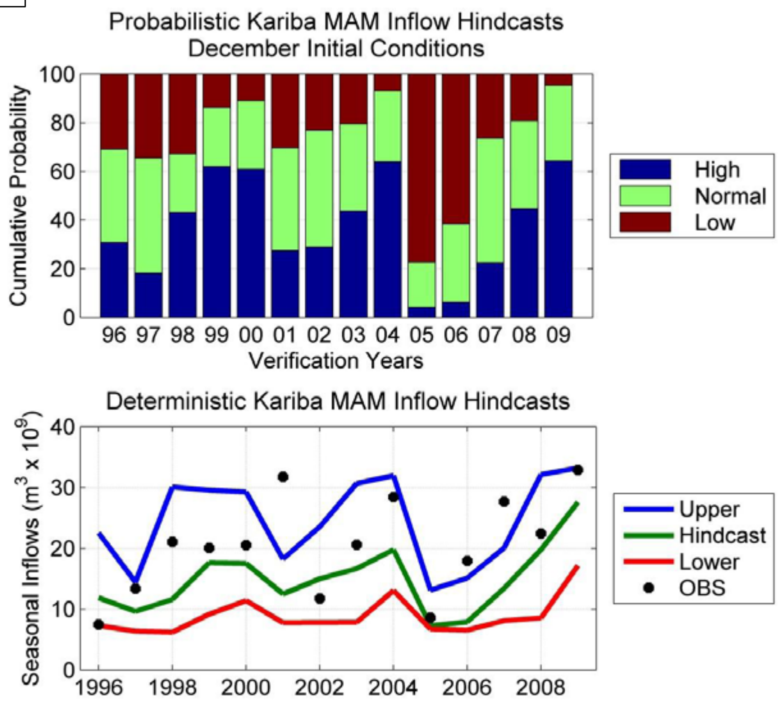


Figure 7a (top) and 7b (bottom). Probabilistic and determinisitic hindcasts of inflow totals for the DJF (top) and MAM (bottom) seasons. The categories of the probability hindcasts (top panels) are associated with the 25th and 75 percentile thresholds of the climatological record, while the upper and lower ranges of the deterministic hindcasts (bottom panels) represent 1-standard deviations of the hindcasts.

4.6 Independent case study: The flood season of 2010/11

This research was to a large extent motivated by the flooding season of 2010/11 when persistent summer rainfall over the Zambezi River Basin catchment area resulted in high water levels of Lake Kariba. Opening of the spillway gates resulted in rising water levels and increased flooding further downstream. The resulting flooding downstream resulted in loss of life and property. A skilful forecast could have been useful to Lake Kariba managers who needed to plan months ahead of the rainy season, consequently leading to reduced losses suffered during the actual flooding season. Owing to this extreme event that caused severe flooding over the catchment and associated high flows into the dam, we will attempt to next find out if the CGCM-based prediction system could have been able to issue a warning of the observed flooding several months ahead of time. Figure 8 a and b, shows the DJF (onset) and MAM (main season) inflow probabilistic forecasts and their corresponding deterministic forecasts. The latter also shows the 25th and 75th percentile values defining respectively the low and high inflow thresholds for each season. Here one can see the predicted high probabilities for DJF inflow across all presented lead-times, and the enhanced probability MAM high inflow forecast at 3- and at 4-month leads. These 2010/11 forecasts provide evidence that the CGCM-based forecast system introduced here would have been able to predict with high confidence well ahead of time for extremely high flows to occur during the inflow onset season, but was less successful in predicting high flows during the peak season since enhanced probabilities of high inflows are only found for longer lead-times. Notwithstanding, these forecasts may have been useful to Lake Kariba managers who needed to plan months ahead of the rainy season, consequently leading to reduced losses suffered during the actual flooding season.

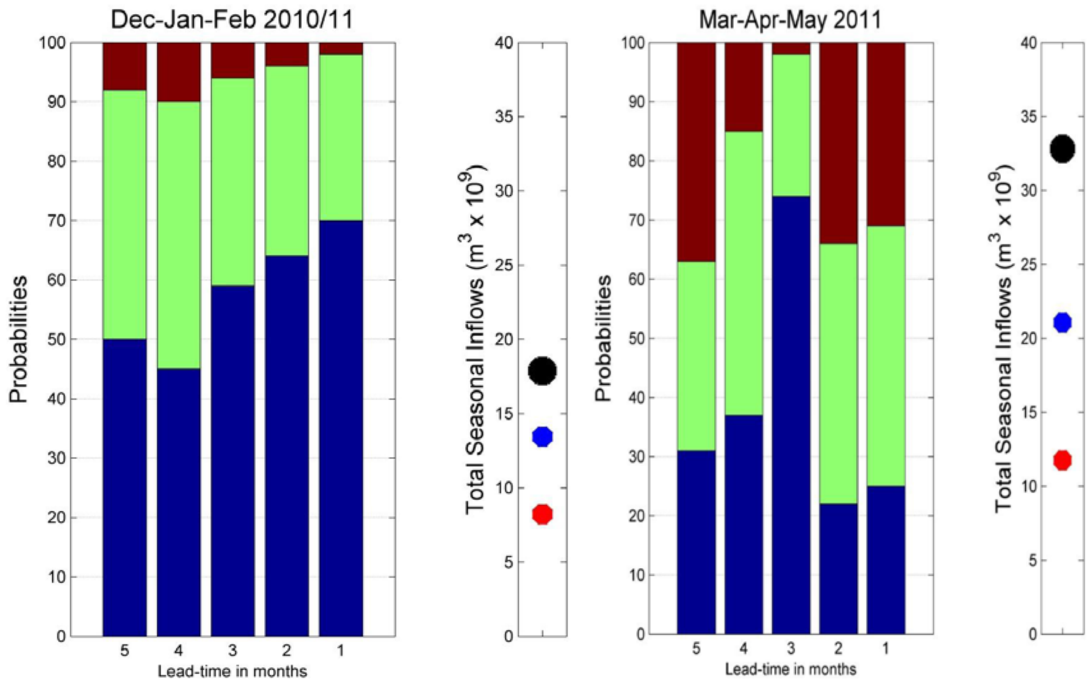


Figure 8: DJF (onset, left panel) and MAM (peak, right panel) inflow forecasts for the 2010/11 season, made at lead-times from 1 to 5 months. The bars represent probabilities predicted for three categories of above- (blue), near- (green) and below-normal (red) seasonal inflow. On the right of the probability bars, the below- (red dot) and above-normal (blue dot) thresholds are shown along with the actual observed inflows (black dot).

4.7 Conclusion and discussion

Lake Kariba is one of the largest sources of hydro-electric power in southern Africa. In addition, the Lake's catchment area is dominated by various agricultural activities, tourist attraction, fisheries and wildlife. In this regards, the water management system of the reservoir is crucial and would benefit from getting long-lead forecasts of the expected flow volumes into the Lake. The study therefore aims to provide such forecasts of high or low inflows into the dam to occur and their associated uncertainties. Such a prediction system should be able to provide key information on coming flood risk seasons to different stakeholders involved with, for example, hydropower production and water uses. Moreover, predictions for inflows into Lake

Kariba should help reservoir managers to improve decisions to be made at the start of the main inflow time of the year regarding the likelihood of high or low rain-fed inflows into the reservoir to occur.

Two prediction systems have been presented and rigorously tested in this study. The first was based on using the antecedent seasonal rainfall over the upper Zambezi as a predictor in a simple statistical approach. The second is a more sophisticated system that involves a hybrid physical-empirical model that uses predicted low-level atmospheric circulation generated by a state-of-the-art climate model as a predictor in a statistical model. It was discovered that the more sophisticated modelling system presented superior levels of skill over the simple statistical model. This hybrid model demonstrated the ability to predict seasonal onset of inflows (DJF), but more modest albeit useable skill levels were found for the peak inflows (MAM). As demonstrated in Figure 3 that for MAM, peak flow season, there is good skill at 1-2 month lead-time in the 75 % category using antecedent seasonal rainfall whereas in the GCM-MOS model there is poor skill at these lead times. However, at a 3-4 month lead-time there is good skill in GCM-MOS model but no skill in the antecedent rainfall model. The skill was calculated over an independent test period of 14 years by testing the models in a true representation of an operational forecasting environment. Forecasts skilful in terms of discrimination and reliability were also found to be associated with the best guidance for users (e.g. improved profits associated with skilful forecasts). The higher skill associated with DJF inflows may be attributed to the fact the austral mid-summer circulation is skilfully captured by most general circulation/climate models. This time of the year is also when tropical influences start to dominate the atmospheric behaviour over southern Africa.

Next it was shown what actual forecasts may look like for some of the lead-times considered here. For DJF a 1-month lead-time and for MAM a 3-month lead-time set of forecasts were shown as both probabilistic and deterministic outcomes. Not only were good verification results found for these lead times, but such lead-times potentially enable decisions to be made regarding optimal dam management and operations before the end of the calendar year proceeding the main inflow period. The probabilistic forecasts show the likelihood of inflows being below (above) the 25th (75th) percentile of the climatological record (in other words, extremes), while the deterministic forecasts are shown as inflow volumes (m^3 x 10^9) with accompanying forecast limits. Both types of forecasts may have to be assimilated into appropriate decision support systems in order to determine their relative value for dam management.

The DJF high probability forecasts for high (low) inflows are usually associated with La Niña (El Niño) years. For examples, the five highest probability forecasts for high inflows are associated with the La Niña seasons of 1995/96, 1998/99, 1999/2000, 2005/06 and 2007/08, while the four highest probability forecast years for low inflows during the 1997/98, 2002/03, 2004/5 and 2006/07 are associated with El Niño years. For the MAM forecasts presented, there is a good agreement between some of the high-probability forecast seasons (for both high and low volume inflows) and the deterministic estimates. For example, with increased seasonal flows towards 1999 and 2000, from 2002 to 2004, and from 2005 towards 2009, the forecast probabilities increased in accordance with the deterministic forecast ranges. Regarding the observed and predicted flows and their association with ENSO, this link seem to be weaker as was found for DJF – low inflows during the 1996 La Niña and high inflows during the 2007 El Niño.

This research was to a large extent motivated by the flooding season of 2010/11 when persistent summer rainfall in the Zambezi River Basin catchment area resulted in high water levels of Lake Kariba. Opening of the spillway gates resulted in rising water levels and increased flooding further downstream of Lake Kariba as well as jeopardizing effective reservoir management at Cahora Bassa downstream in Mozambique. Moreover, the resulting flooding downstream resulted in loss of life and property. The hybrid prediction system was also used to predict inflows during this season, and it was found that in particular for the DJF (onset) season high probabilities and above-normal deterministic outcomes were predicted, thus providing evidence that the abovementioned societal and management problems could have at least been to some extent alleviated had these long-lead forecasts of extreme flooding been released in late 2010. The paper has demonstrated that the hybrid prediction system has the potential to produce forecasts that may benefit decision making under certain conditions (i.e. onset of inflows, ENSO seasons, etc.) and therefore has demonstrated the value of applying seasonal forecasts of skill to a particular application.

References

Balek J. 1971. Water balance of the Zambezi Basin. Technical Report 15. Lusaka, Zambia: National Council for Scientific Research.

Barnston AG., He Y., Glantz MH. 1999. Predictive skill of statistical and dynamical climate models in SST forecasts during the 1997–98 El Ni˜no episodes and the 1998 La Niña onset. Bull. Am. *Meteorol. Soc*, **80** 217–244.

Barnston AG, Kumar A, Goddard L, Hoerling MP. 2004. Improving seasonal prediction practices through attribution of climate variability. *Bull. Amer. Meteor. So.*, **86:** 59-72.

Buizza R. 2008. The value of probabilistic prediction. Special Issue Article – HEPEX Workshop: Stresa, Italy, June 2007. *Atmospheric Science Letters*, 9: 36-42. DOI: 10.1002/asl.170.

Brown JD, Demargne J, Seo D-J, Liu Y. 2010. The Ensemble Verification System (EVS): A software tool for verifying ensemble forecasts of hydro meteorological and hydrologic variables at discrete locations. *Environmental Modelling & Software,* **25:** 854-872.

Cane MA, Eshel G and Buckland RW. 1994. Forecasting Zimbabwean maize yield using eastern Pacific sea surface temperatures. *Nature* **370**: 204-206.

Chen S-T, Yu P-S.2007: Real-time probabilistic forecasting of flood stages. *Journal of Hydrology* **340:** 63-77.

Chidanti-Malunga J. 2011. Adaptive strategies to climate change in Southern Malawi. *Physics and Chemistry of the Earth* **36:** 1043-1046.

Chiew FHS, McMahon TA. 2002. Global ENSO–streamflow teleconnection, streamflow forecasting and interannual variability. *Hydrol. Sci*. **47**: 505-522.

Cloke HL, Pappenberger F. 2009. Ensemble flood forecasting: A review. *Journal of Hydrology* **375:** 613-626.

David RI, Kazimierz A S. 2004: The operation of Lake Kariba: A Bayesian Analysis. *Journal of Multi-Criteria Decision Analysis.* **4**: 203-222. DOI: 10.1002/mcda.4020040402.

Dettinger MD, Cayan DR, McCabe GJ, Marengo JA. 2000. Multiscale streamflow variability associated with El Nino/ Southern oscillation. In: Diaz, H.F., Markgraf, V. (Eds.), El Nino and the Southern Oscillation: Multiscale Variability and Global Regional Impacts. *Cambridge University Press*, Cambridge, pp. 113-147.

DeWitt D G. 2005. Retrospective forecasts of interannual sea surface temperature anomalies from 1982 to present using a directly coupled atmosphere–ocean general circulation model. *Mon. Wea. Rev*. **133**: 2972–2995. doi: http://dx.doi.org/10.1175/

MWR-D-11-00177.1

Ebert EE, McBride JL.2000. Verification of precipitation in weather systems: determination of systematic errors. *Journal of Hydrology* **239:** 179-202.

Faber BA, Stedinger J R. 2001. Reservoir Optimization using sampling SDP with ensemble streamflow prediction (ESP) forecasts. *Journal of Hydrology* **249:** 113-133.

Ghosh S, Mujumdar PP. 2008. Statistical downscaling of GCM simulations to streamflow using relevance vector machine. *Advances in Water Resources* **31:** 132-146.

Glahn H, Lowry R.1972. The use of model output statistics (MOS) in objective weather forecasting. *J. Appl. Meteor*. **11**: 1203-1211.

Goetz JN, Guthrie RH, Brenning A. 2011.Integrating physical and empirical landslide susceptibility models using generalized additive models. *Geomorphology***129:** 376-386.

Hagedorn R Smith LA. 2008. Communicating the value of probabilistic forecasts with weather roulette. *Meteorol. Appl.* 1-13. DOI: 10.1002/met.

Hamill TM. 1997. Reliability diagrams for multicategory probabilistic forecasts. *Wea. Forecasting* **12**: 736-741.

Hamlet AF, Huppert D, Lettenmaier DP. 2002. Economic value of long-lead streamflow forecasts for Columbia River hydropower, *Journal of Water Resources Planning and Management* **128:** 91-101.

Hansen JW. 2002. Applying seasonal climate prediction to agricultural production (preface). *Agricultural Systems* **74:** 305-307.

Harris I, Jones PD, Osborn TJ, Lister DH. 2013. Updated high-resolution grids of monthly climatic observations. *Int. J. Climatol*. **34**: 623–642, Doi: 10.1002/joc.3711.

Hastenrath S, Greischar L, van Heerden J. 1995. Prediction of summer rainfall over South Africa. *J. Clim* **8**: 1511-1518.

Jolliffe IT, Stephenson DB. 2012. Forecast Verification: A Guide in Atmospheric Science. John Wiley & Sons Ltd. The Atrium, Southern Gate, Chichester, West Sussex PO19 8SQ, England. ISBN 0-471-49759-2.

Jury MR, Makarau A. 1996. Predictability of Zimbabwe Summer Rainfall. *Int J. Climatol.* **17**:1421-1432.

Kashid SS, Ghosh S, Maity R. 2010. Streamflow prediction using multi-site rainfall obtained from hydroclimatic teleconnection. *Journal of Hydrology***395:** 23-38.

Krzysztofowicz R. 1999. Bayesian theory of probabilistic forecasting via deterministic hydrologic model. *Water Resources Research* **35**: 2739-2750.

Krzysztofowicz R. 2001. The case of probabilistic forecasting in hydrology. *Journal of Hydrology* **249:** 2-9.

Landman WA. 2014. How the International Research Institute for Climate and Society has contributed towards seasonal climate forecast modelling and operations in South Africa. Earth Perspectives, 1:22, DOI: 10.1186/2194-6434-1-22.

Landman WA. 2001. Forecasts or near-global sea surface temperatures using canonical correlation analysis. *J. Climate***14**: 3819-3833.

Landman WA and 4 co-authors. 2012. Seasonal rainfall prediction skill over South Africa: One- versus two-tiered forecasting systems. *Weather and Forecasting***27**: 489-501.

Landman WA, Beraki A. 2012. Multi-model forecast skill formid-summer rainfall over southern Africa. Int. *J. Climatol*. **32:** 303-314.

Landman WA, Goddard L. 2002. Statistical recalibration of GCM forecast over southern Africa using model output statistics. *J. Climate* **15**: 2038-2055.

Lazenby MJ, Landman WA, Garland RM, DeWitt DG. 2014. Seasonal temperature prediction skill over Southern Africa and human health. *Meteorological Applications DOI: 10.1002/met.1449.*

Lessmann S Sung M-C, Johnson J EV, Ma T. 2012. A new methodology for generating and combining statistical forecasting models to enhance competitive event prediction. *European Journal of Operational Research* **218:** 163-174.

Madeiros-Braga ACF, Da Silva RM, Guimarães S C A, Stam A, Salewicz K A, Aronson J E. 1998. An interactive reservoir management system for Lake Kariba. *European Journal of Operational Research* IO7 119-136.

Maier HR, Dandy GC. 2000. Neural networks for the prediction and forecasting of water resources variables: a review of modelling issues and applications. *Environmental Modelling & Software***15:** 101-124.

Makarau A, Jury MR. 1997. Predictability of Zimbabwe summer rainfall. *Int. J. Climatol*, **17**: 1421-1432.

Marco B, Fausto T, Alberto P. 2010: Development and testing of a physically based, three-dimensional model of surface and subsurface hydrology *Adv. Water Resour*, **33:** 106-122.

Mason SJ, Graham NE. 2002. Areas beneath the relative operating characteristics (ROC) and levels (ROL) curves: Statistical significance and interpretation. *Quart. J. Roy. Meteor. Soc*. **128:** 2145-2166.

McMahon TA, Finlayson BL, Haines AT, Srikanthan R. 1992. Global Runoff—Continental Comparisons of Annual Flows and Peak Discharges.Catena: Cremlingen-Destedt, Germany. P.166.

Mesinger F.1996. Improvements in quantitative precipitation forecasts with the eta regional model at the National Centers for Environmental Prediction: the 48-km upgrade. *Bull. Am. Meterol. Soc*, **77**: 2637-2649.

Mitchell TD, Jones PD. 2005. An improved method of constructing a database of monthly climate observations and associated high-resolution grids. *International Journal of Climatology* **25**: 693-712.

Muchuru S, Landman WA, DeWitt D, Lötter D. 2014. Seasonal rainfall predictability over the Lake Kariba catchment area. *Water SA*, **40:** 461-470 http://dx.doi.org/10.4314/wsa.v40i3.9

Muluye GY. 2011. Implications of medium-range numerical weather model output in hydrologic applications: Assessment of skill and economic value. *Journal of Hydrology* **400:** 448-464.

Ncube SP, Makurira H, Kaseke E, Mhizha A. 2011.Reservoir operation under variable climate: Case of Rozva Dam, Zimbabwe. *Physics and Chemistry of the Earth* **36:** 1112-1119.

Ndiaye O Ward MN, Thiaw WM. 2011. Predictability of seasonal Sahel rainfall using GCMs and lead-time improvements through the use of a coupled model. *J. Climate* **24**: 1931-1949.

Opitz-Stapleton S, Gangopadhyay S, Rajagopalan B. 2007. Generating streamflow forecasts for the Yakima River Basin using large-scale climate predictors. *Journal of Hydrology* **341**: 13finis1-143.

Pacanowski RC, Griffies SM. 1998. MOM3.0 Manual. A Technical Guide to MOM4 GFDL Ocean Group Technical Report NO. 5. NOAA/ Geophysical Fluid Dynamics Laboratory. Princeton, NJ; 608.

Palmer T N and Coauthors. 2004. Development of a European Multimodel Ensemble System for Seasonal-to-Interannual Prediction (DEMETER). *Bull. Amer. Meteor. Soc*, **85:** 853-872.

Palmer TN, Anderson DLT. 1993. Scientific assessment of the prospects for seasonal forecasting a European perspective. ECMWF Tech. Report No. 70, Reading, UK.

Partington D, Brunner P, Simmons CT. 2012. Evaluation of outputs from automated baseflow separation methods against simulated baseflow from a physically based, surface water–groundwater flow model. *J. Hydrol*, **458-459:** 28-39.

Pedersen CB, Madsen H, Skotner C. 2007. Real-Time Optimization of Dam Releases Using Multiple Objectives. Application to the Orange-Fish-Sundays River Basin, South Africa; 13th SANCIAHS Symposium, 6-7 September, 2007, Cape Town, South Africa.

Raje D, Mujumdar PP. 2010: Reservoir performance under uncertainty in hydrologic impacts of climate change. *Advances in Water Resources* **33:** 312-326.

Refsgaard JC, Knudsen J. 1996. Operational validation and intercomparison of different types of hydrological models. *Water Resources Research* **32**: 2189-2202.

Richardson DS. 2000. Skill and economic value of the ECMWF ensemble prediction system. *Quarterly Journal of the Royal Meteorological Society* **126**: 649-668.

Robertson AW, Dian-Hua Q, Michael KT. 2012. Downscaling of Seasonal Rainfall over the Philippines: Dynamical versus Statistical Approaches. *Mon. Wea. Re.* **140**: 1204-1218.

Roeckner E, and Coauthors.1996. Regional climate simulation with a high resolution GCM: Surface hydrology. *Climate Dyn*, **12**: 755-774

Rouault M and Florenchie P. 2003. South east tropical Atlantic warm events and southern African rainfall. *Geophys. Res. Lett*. 30 DOI: 10.1029/2002GL014840.

Roulston MS, Smith LA. 2003. Combining dynamical and statistical ensembles. *Tellus Series A-Dynamic Meteorology and Oceanograph*y **55**: 16-30.

Schaake J and Coauthors. 2010. Summary of recommendations of the first workshop on Post processing and Downscaling Atmospheric Forecasts for Hydrologic Applications held at Météo-France, Toulouse, France, 15–18 June 2009. *Atmos. Sci. Let*t, **11**: 59-63.

Schaake JT, Hamill M, Buizza R. 2007b. Hepex: The Hydrological Ensemble Prediction Experiment. *Bull. Amer. Meteor. Soc,* **88**: 1541-1547.

Sharma TC, Nyumbu I L. 1985. Some hydrologic characteristics of the Upper Zambezi Basin. Pages 29-43 in.L. Handlos and G.W. Howard, eds. Development Prospects for the Zambezi Valley in Zambia. Lusaka: Kafue Basin Research Committee of the University of Zambia.

Shongwe ME, Landman W A., Mason SJ. 2006. Performance of recalibration systems for GCM forecasts for southern Africa. *Int. J. Climatol*, **26**: 1567-1585.

Solomon SD. Qin M, Manning Z, Chen M, Marquis K, Averyt B, Tignor M , Miller H L. (eds.) 2007. Regional Climate Projections. In: *Climate Change 2007: The Physical Science Basis. Contribution of Working Group 1 to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Thielen J, Schaake J, Hartman R, Buizza R. 2008. Aims, challenges and progress of the Hydrological Ensemble Prediction Experiment (HEPEX) following the third HEPEX workshop held in Stresa 27 to 29 June 2007. *Atmos. Sci.* Lett, **9**: 29-35.

Tisseuil C, Vrac M, Lek S, Wade AJ. 2010. Statistical downscaling of river flows. *Journal of Hydrology* **385:** 279-291.

Tong STY, Sun Y, Ranatunga T, He J, and Yang YJ. 2012. Predicting plausible impacts of sets of climate and land use change scenarios on water resources. *Applied Geography* **32:** 477-489.

Troccoli A, Harrison M, Anderson DLT, Mason SJ. 2008. Seasonal Climate: Forecasting and Managing Risk. *NATO Science Series on Earth and Environmental Sciences*, **82**: Springer, 467 pp.

Tumbare MJ. 2000. Management of River Basin and Dams: The Zambezi River Basin, AA Balkema, Rotterdam/Brookfields.

Tumbare MJ. 2000. Mitigating floods in Southern Africa, in 1st WARFSA/WaterNet Symposium: sustainable use of water resources, pp. 1-8, Maputo, Mozambique.

Wei CC, Hsu, NS. 2005. A real-time optimization model for flood control. In: 2005 AGU Fall Meeting, San Francisco, CA.

Welsh WD, Vaze J, Dutta D, Rassam D, Rahman JM, Jolly ID, Wallbrink P, Podger GM, Bethune M, Hardy MJ, Teng J, Lerat J.2012. An integrated modelling framework for regulated river systems. *Environmental Modelling & Software*. http://dx.doi.org/10.1016/j.envsoft.2012.02.022**.**

Wilby RL, Dawson CW, Barrow EM. 2002. SDSM – a decision support tool for the assessment of regional climate change impacts. *Environ. Model. Software***17**: 147-159.

Wilks D. 2006a. Statistical Methods in the Atmospheric Sciences, 2nd edn. Academic Press: New York, 2nd edition, 627, see chapter 7 (255-332).

Wilks, DS. 2006. Statistical Methods in the Atmospheric Sciences. 2nd ed. Academic Press, 627 pp.

Wilks, DS. 2011. Statistical Methods in the Atmospheric Sciences.3nd ed. International geophysics series, Vol.100.

Yu, CK, Jorgensen, DP and Roux F. 2007. Multiple precipitation mechanisms over mountains observed by airborne Doppler radar during MAP IOP5, *Mon. Weather Rev*., **135**: 955-984, doi:10.1175/MWR3318.1.

Ziervogel G, Bithell M, Washington R, Downing T. 2005. Agent-based social simulation: a method for assessing the impact of seasonal climate forecast applications among smallholder farmers. *Agricultural Systems* **83:** 1-26.

ZRA. 2005. Report on the Standard Operating Procedures (SOP) for Zambezi River Authority on Kariba Dam and Reservoir, November, 2005.

Chapter 5: Summary, conclusions and future perspectives

While there have been accounts of floods and drought over southern Africa and in particular the Zambezi River Basin related to the influence of seasonal rainfall variations and associated flows, the current study provided insights into the rainfall variability over central southern Africa and described prediction systems that can be used by reservoir managers to predict seasonal rainfall variations and associated flows in one of the region's biggest river systems, the Zambezi. Additionally, it demonstrated the potential economic value of applying real-time seasonal climate prediction in the region. This variability and modelling research was strongly motivated by the devastating flooding season of 2010/11 when persistent summer rainfall over the Zambezi river basin catchment area resulted in high water levels of Lake Kariba.

This thesis started off by characterizing rainfall with the main aim of showing the significance of its variability for water resource management. Identification and quantification of trends in rainfall and their implications on river flows assist in decision-making by water managers for improved water resource management. In this contribution, rainfall data from a network of stations across the Kariba catchment area in the Zambezi river basin were analyzed in order to develop and improve understanding of the variability of seasonal rainfall over Lake Kariba Catchment area. To achieve this objective, appropriate techniques were applied to evaluate whether a given data set can be considered to be homogeneous and, if not, introduce the appropriate corrections. The aim was to characterize rainfall variability across the

Kariba catchment through intervention analysis, homogeneity tests, trend analysis as well as spatial and spectral correlation analysis using wavelet-based parameters. Additionally, spatial temporal variability analysis of rainfall can be useful in generating long sequences of rainfall data needed to support planning of the long-term water management strategies e.g. the Lake Kariba water management system. It is essential to identify and quantify trends in rainfall since variability of rainfall over southern Africa can have detrimental consequences to economic development, disaster management, population, and hydrological planning of a particular country. Due to rainfall variability, major water resources and reservoirs are often at risk (e.g., due to flooding), and the population and properties in the basin are often impacted most e.g. *"The flooding season of 2010/11 when persistent summer rainfall over the Zambezi River Basin catchment area resulted in high water levels of Lake Kariba. Opening of the spillway gates resulted in rising water levels and increased flooding further downstream"*. The resulting flooding downstream resulted in loss of life and property. It is imperative to perform spatial temporal variability analysis of rainfall at monthly or seasonal timescales to determine the likelihood of a drought or flood events. For example, the identification of seasons in which floods are most likely involves studying characteristics of monthly rainfall within the seasons across the region. Better understanding of the relationships between rainfall and climatic variables is expected to be useful for water resource management and planning.

An important contribution of this study was towards understanding of spatial-temporal variability of rainfall over the Kariba catchment area. In particular, these results would be valuable since local-scale rainfall variability can lead to sudden changes in water availability in surface and sub-surface hydrologic systems thereby significantly affecting agriculture, livestock, water supply, hydropower sectors and the social economic livelihoods over the study area. Studies focusing on investigating the occurrence of extreme events through predicting seasonal rainfall totals and inflows by linking these with tele-connection patterns such as El Niño and La Niña (ENSO) are therefore recommended.

Operational seasonal climate prediction has become an established practice, also in southern Africa, with far-reaching potentially positive societal implications. This thesis further provided information on the predictability of seasonal rainfall fluctuations one or more seasons in advance since predictions made at such lead-times would have measurable benefits for decision making, also for water resource management. This new knowledge of operational or real-time seasonal climate prediction for both seasonal rainfall and inflows in the region can be used together with characterizing rainfall variability and trends for decision making and further hydrological modelling. For example, it would allow for proactive and improved reservoir management. This thesis described a seasonal rainfall and inflow prediction system, and then verified retro-active forecasts (i.e. hindcasts) of rainfall and inflows produced at lead-times of several months. Forecast assessment was followed by a demonstration of the potential economic impact of using such forecasts. Since the study was motivated by the 2010/11 flood season, the study provided evidence of potentially successful rainfall and inflow forecasts for that season that would have been produced if the described forecast systems were operational in late 2010.

Major results of this study are summarized as follows:

- Regarding rainfall variability in the Kariba catchment area:

- All network stations in the Kariba catchment exhibited similar annual and seasonal rainfall variability patterns.

- Annual and seasonal rainfall time series across the Lake Kariba catchment area (about 78%) were found to be normally distributed.

- There were no apparent significant shifts in the annual and seasonal rainfall data in the Kariba catchment area based on the CUSUM and rank-sum test analysis.

- Annual and seasonal rainfall data from most of the stations were homogeneous. Based on the Wijngaard et al (2003) classification, the network of station considered in the present study were category A (useful) and B (doubtful) stations implying that trend and variability analysis results using the station time series would be considered plausible.

- The annual and seasonal rainfall series in the Kariba catchment area have non-significant positive and negative trends.

- Most network stations considered in the present study exhibit coherent oscillatory modes that are constantly locked in phase in the Morlet wavelet space.

Southern African rainfall has a clear annual cycle with most of the rainfall occurring during austral mid-summer. The region is susceptible to drought and floods and so the identification of the seasons in which these extremes occur and subsequently attempting to predict them involves studying the characteristics of seasonal-to-interannual rainfall variability and then modelling these variations.

- For predictability of seasonal-to-interannual rainfall totals over the Lake Kariba catchment area:
    - The seasonal rainfall forecast system produced retroactive forecasts for 14 years in a fashion that mimics a true operational setting, and the skill of the forecast system was subsequently determined over the independent period from 1995/96.
    - The system was found to be able to discriminate extremely dry/wet seasons from the rest of the seasons.
    - Poor skill (ROC $\leq$ 0.5) was generally found over the catchment from SON through OND, but skill improves towards the main austral summer rainfall period from about NDJ when most of the seasonal rainfall occurs.
    - Close to perfect reliability was found for the prediction of DJF wet seasons, but respectively under- and over-confident forecasts are seen for early (NDJ) and late (JFM) summer.
    - A diagnostic other than the standard verification parameters was also introduced to specifically address the potential economic benefits of the forecast system. The study showed how an initial financial investment would change in value over the 14-year verification time if it were invested in the forecasts and was paid fair odds on the actual

outcome over the seasons considered. The highest profits were found for the DJF season, which is the same season for which the best standard verification values were found – the higher the skill the more profitable the use of the forecasts becomes.

- The developed forecast system was also tested for the 2010/11 season which was associated with huge losses, especially downstream of Lake Kariba. The study demonstrated that the forecast system produced a potentially useful forecast of high probabilities of extremely high rainfall totals to occur during DJF.
- Global forecast models can be very expensive to administer but international centres, such as the IRI from which the model data for this research was obtained, are making their forecast outputs available for use in operational forecast systems such as those demonstrated here.

The use of hydro-meteorological models may be proven effective for reservoir operations since accurate and reliable prediction of reservoir inflows can provide balanced solutions to the problems faced by dam or reservoir managers.

- The study has demonstrated the ability to discriminate high (or low) flow events from non-events. Two prediction systems were presented and tested, the antecedent seasonal rainfall over the upper Zambezi as a predictor in a simple statistical approach and a more sophisticated system that involved a hybrid physical-empirical model that used predicted low-level atmospheric circulation generated by a state-of-the-art climate model as a predictor in a statistical model.

- The more sophisticated modelling system presented superior levels of skill over the simple statistical model. This hybrid model demonstrated the ability to predict seasonal onset of inflows (DJF), but more modest albeit useable skill levels were found for the peak inflows (MAM).

- Forecasts skillful in terms of discrimination and reliability were also found to be associated with the best guidance for users (e.g. improved profits associated with skillful forecasts). The higher skill associated with DJF inflows may be attributed to the fact the austral mid-summer circulation is usually skillfully captured by most general circulation/climate models. This time of the year is also when tropical influences start to dominate the atmospheric behavior over southern Africa.

- The DJF high probability forecasts for high (low) inflows were found to be associated with La Niña (El Niño) years. For examples, the five highest probability forecasts for high inflows were associated with the La Niña seasons of 1995/96, 1998/99, 1999/2000, 2005/06 and 2007/08, while the four highest probability forecast years for low inflows during the 1997/98, 2002/03, 2004/5 and 2006/07 were associated with El Niño years.

- For the MAM forecasts presented, there was a good agreement between some of the high-probability forecast seasons (for both high and low volume inflows) and the deterministic estimates. For example, with increased seasonal flows towards 1999 and 2000, from 2002 to 2004, and from 2005 towards 2009, the forecast probabilities increased in accordance with the deterministic forecast ranges. Regarding the observed and predicted flows and their association with ENSO, this link seems to be weaker as was found for DJF – low inflows during the 1996 La Niña and high inflows during the 2007 El Niño. The GCM-MOS system does well at a particular lead time over the rainfall onset season but the deterministic system is superior at longer a lead time in MAM.

Several new findings regarding rainfall variability, prediction of seasonal rainfall and inflows for water resources management have emerged during the study, and the following key recommendations are made with the view on future research:

- The study demonstrated and provides an understanding of spatial-temporal variability of rainfall over the Kariba catchment area. In particular, these results would be valuable since local-scale rainfall variability can lead to sudden changes in water availability in surface and sub-surface hydrologic systems thereby significantly affecting agriculture, livestock, water supply and hydropower sectors: the social economic livelihoods over the study area. Future studies should continue to focus on investigating the a) occurrence of extreme events, and b) link between rainfall variability and teleconnection patterns such the El Niño/Southern Oscillation (ENSO), North Atlantic Oscillation (NAO) and the Pacific Decadal Oscillation (PDO) are highly recommended.

- Seasonal hydrological forecasting is not being done routinely in the region and plays an important role in transitioning the scientific advances from the climate research community to the end users of society. The study managed to demonstrate the ability to predict future seasonal rainfall fluctuations one or more seasons in advance would have measurable benefits in decision making for water resources management. Similar approaches as followed in the current study may yield further benefits in the area of water resources management

- Skillful inflow forecasts are possible during onset and during the main inflow seasons. Moreover, the better modelling approach is to use the atmospheric circulation from the CGCM as predictor. In general, the same conclusions regarding best season and best practice are also found when assessing the economic value of forecasts and when demonstrating forecast quality to the general public (2AFC scores).

The study has provided a demonstration on how current seasonal forecast systems can be applied to improve water management decisions. This notion was demonstrated through improved understanding of the rainfall variability over the Lake Kariba catchment, followed by predicting seasonal rainfall extremes over several years, and then finally applying similar prediction methodologies to actual inflows into the Lake. In addition to the skill levels been presented and the potential economic values of such forecasts been demonstrated, the forecast lead-times with which inflow predictions are currently made have substantially been increased from a couple of weeks to several months. In summary, the thesis has demonstrated that a reservoir manager as seasonal forecast user should be able to take advantage of current seasonal forecasting capabilities.