

**Hydrological and water resources modelling under
uncertainty and climate change: An application to
the Limpopo basin, Botswana**

by

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Declaration of own work

I declare that this thesis

“Hydrological and water resources modelling under uncertainty and climate change: An application to the Limpopo basin, Botswana”

is my own work and that where any material could be construed as the work of others, it is fully cited and referenced, and/or appropriate acknowledgement is given.

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Abstract

The application of water resources planning models to semi-arid or arid areas is expected to be particularly challenging because of the high variability of rainfall and streamflow, highly limited historic observations, sparse rain gauge and flow networks with significant periods of missing rainfall and potential data quality issues. These lead to high uncertainty in rainfall and hydrological models which need to be explicitly represented in model predictions. These uncertainties are expected to increase when considering future predictions associated with the effects of climate change. This has presented an opportunity for this thesis to develop a framework of uncertainty analysis in hydrological and water resources modelling. The framework consists of multi-site continuous time stochastic rainfall model to (1) identify suitable rainfall predictors, (2) infill the missing values in the historic rainfall data, (3) extend the limited rainfall observations, and (4) generate rainfall under climate change scenarios by downscaling global climate models outputs. The stochastically infilled rainfall data allows calibration of a hydrological model under input uncertainty. The rainfall model together with the uncertain hydrological model are then used to generate multiple realisations of reservoir inflows over a 100-year period, first assuming a stationary climate and secondly under a changed climate. This framework is applied to the upper Limpopo basin in Botswana, using 25 years of observed daily rainfall and flow data for model calibration. A Generalised Linear Model was used for the rainfall and a semi-distributed version of the IHACRES model was used for the hydrology. A proposed 382 Mm³ reservoir at the outlet of this basin, which is part of Botswana's national water resource strategy, is re-evaluated in light of the extended inflow data and the estimated uncertainty.

Analysis within this thesis revealed that the effects of data and model parameter uncertainty on water resources planning models can be high, and thus should not be ignored. The thesis advocates a shift from deterministic to stochastic ways of infilling missing rainfall values, and for consideration of hydrological model uncertainty, climate model and climate scenario uncertainties. Given the high uncertainty in the semi arid case study, priority areas can be identified, which may include acquiring and expanding the gauge networks, building efficient and robust data collection processing and achieving to improve the existing database so as to support and enable quality research.

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List of Papers

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CHAPTER ONE

1 Introduction

This section provides a summary of background information about semi arid hydrology and water resources situation in these areas. It also provides an outlook on the projected climate change related to these areas, and how that is likely to impact upon future water resources of semi arid areas. Areas which need further investigations are identified to set the scope and aims of this thesis.

1.1 Background and motivation

There is an urgent need to provide fresh water to many countries of the world in order to meet the ever increasing water demand. The situation is more critical in developing countries, where about 1.1 billion people have no access to potable water (World Health Organization and UNICEF, 2005). This is even worse in arid and semi arid areas, where rainfall is usually insufficient to meet the water demand and the rates of evaporation from water storages such as rivers and dams are high (Jain, 2010). Although the scientific understanding of arid and semi arid areas is developing rapidly, and new tools and management information are becoming more available (Wheater, 2006), most of these areas are yet to benefit from these developments largely due to insufficient resources and lack of trained personnel.

This means that water resources planners and managers in these areas are still faced with a mammoth task of managing scarce water under the complex hydrological processes associated with arid and semi arid areas. These processes, evident in the literature (Pilgrim et al., 1988, Cordery et al., 1983, Wheeler et al., 1997) include (1) highly variable rainfall both in space and time, which often result from highly localised convective storms; (2) insufficient measuring instruments (for rainfall and streamflow), making it difficult to accurately represent spatial rainfall needed in hydrological modelling; (3) extended periods of missing rainfall and streamflow records as well as poor data quality, which compromise the performance of many models especially those which require unbroken data records as input ; (4) unpredictable flash floods, which negatively impact upon people's livelihood such as crops and livestock; (5) high rates of evapotranspiration, which reduce water levels from storages such as dammed reservoirs. In some areas it has been found that on a monthly basis the rates of evaporation from reservoirs can exceed that of abstraction. For example, the Water Utilities

Corporation in Botswana (which is responsible for supplying water to urban areas) reports that evaporation from reservoirs can account for up to 2% of water losses in a month compared to 1% which is due to abstractions (Senai, 2005). Most of the challenges discussed above have been recognised in the literature as significant sources of uncertainty in model predictions. For example, the challenges (1) to (3) are usually associated with natural uncertainty and data uncertainty (Melching and Singh, 1995, Guo et al., 2004). The natural uncertainty refers to uncertainty resulting from natural random effects which includes the random temporal and spatial fluctuation that affects the physical process of runoff generation. Data uncertainty relates more to the quality and type of data, particularly rainfall data which is widely used as input to many hydrological models. These and other sources of uncertainty are discussed in detail in section 2.4.3.2 .

1.2 Impacts of climate change on water availability in semi arid areas: with emphasis on southern Africa

Projections regarding future water resources in these areas are even more worrisome. For example, it is projected that even in the absence of climate change the present population trends and patterns of water use indicate that more African countries may exceed the limits of their “economically usable, land-based water resources before 2025” (Ashton, 2002).

Coupled with these are the potential effects of climate change due to global warming. Recent studies suggest that overall, there is a likelihood of an increase in longer dry seasons, frequent extreme events, including droughts, and more uncertain rainfall patterns and magnitude in southern Africa due to the effects of climate change (Arnell et al., 2003, Fauchereau et al., 2003, Tadross, 2006). Regarding annual and seasonal rainfall, the literature projects contrasting change in rainfall within southern Africa. For example, summer rainfall which contributes more than 80% of annual rainfall in this region may drop by about 20% in some areas by the year 2100 while other

areas may experience rainfall increase of up to 43% particularly those with relatively low temperature changes (Hulme et al., 2001, Zhao et al., 2005, Christensen et al., 2007, Tadros et al., 2005). Consequently, areas which are likely to experience rainfall deficits may experience a runoff decrease of up to 40% by the end of the century (Arnell et al., 2003, Matondo et al., 2004, Andreasson and Rosberg, 2006, deWit and Stankiewicz, 2006, Boko et al., 2007). Similarly, due to an increase in temperature, potential evaporation estimated for major River basins in southern Africa (including the Limpopo, Zambezi, and Orange Rivers) may rise by 25% by the year 2100 (IPCC, 2001b). Clearly these changes may have significant impacts on future water supply sources in semi arid areas of southern Africa.

However, in order to assess climate change impact on water resources, long sequences of rainfall and streamflow data are needed. For example, good rainfall data is required in order to identify a rainfall-runoff model, which includes adequate representation of processes, of useful accuracy for the current climate. The fitted rainfall and hydrological models can then be used to simulate future hydrological response based on future climate scenarios obtained mainly from global climate models or general circulation models (GCMs). However, to start with, observed rainfall data are rarely available at desirable temporal and spatial scales in many areas of the world, and particularly in semi arid areas. For this reason, there is need to develop appropriate rainfall simulation tools which can generate rainfall sequences at these scales (Wheater et al., 2005). In order to address these concerns, stochastic models are commonly used to generate synthetic sequences of rainfall that are statistically consistent with the observed record (Mehrotra and Sharma, 2007).

However, there are limitations related to most of these models as summarised below and also detailed in Chapter 2 of this thesis. Firstly, most of these models require complete rainfall records for model fitting, which may limit their applications in data sparse areas with extended periods of missing data. Secondly, they often need a large number of

parameters in order to satisfactorily reproduce observed rainfall, potentially creating high uncertainty in simulations. Thirdly, most of them lack the ability to represent seasonal rainfall variability parametrically, but rather the models are often fitted to individual months independently which also increases model complexity. Fourthly, they often use more computationally intensive algorithms to fit and assess the performance of different models. And fifthly, few models realistically represent the inter-dependence of rainfall between gauged sites. However, other rainfall simulation tools have been developed recently which are aimed at overcoming some of the limitations cited above. These models are reviewed in chapter 2 in order to identify those which could be applicable under potentially more challenging semi-arid and data-sparse conditions-i.e. the difficulty of using rainfall records with extended periods of missing data given high rainfall variability and yet limited rainfall gauges.

Furthermore, it is evident from the reviews above (and those of chapter 2) that projections of the impacts of climate change on water availability in southern Africa show contrasting results, i.e. some predict severe decline in rainfall and runoff while others predict the opposite. There is, therefore an opportunity to investigate the impacts of climate change in data limited areas in light of the extended data and associated uncertainty produced by stochastic rainfall models and hydrological models.

1.3 Aims and Objectives of the study

The overall purpose of this work is to provide guidance for assessing the impacts of uncertainty and climate change impacts on water resources planning in data limited semi arid areas. This includes uncertainty resulting from limited rainfall data, hydrological model parameter uncertainty, climate change models and scenarios. This framework is applied to the upper Limpopo basin in north-eastern Botswana.

Specific aims of the proposed work can be summarised as follows:

- 1.3.1 To evaluate the quality of rainfall data in the upper Limpopo basin, and determine how the quality may affect rainfall modelling results.
- 1.3.2 To develop a rainfall simulation model (RSM) suitable to the study area and possibly to other data sparse semi arid areas.
- 1.3.3 To identify the parameters of the (RSM) model and uncertainty, including uncertainty arising from rainfall data (in particular missing data).
- 1.3.4 To explore the applicability of RSM as a downscaling tool in generating rainfall sequences under scenarios of climate change for the study area.
- 1.3.5 To identify suitable rainfall-runoff models (RRMs) and time-scales for water resources assessment.
- 1.3.6 To develop a calibration strategy for a RRM based on the spatial-temporal rainfall obtained from the RSM.
- 1.3.7 To generate multiple realisations of rainfall and reservoir inflows using the RSM and RRM.
- 1.3.8 Assess reservoir performance under uncertain rainfall and hydrological response, under both baseline and changed climate.

1.3.9 To make recommendations on making the uncertainty framework more comprehensive

The following methods will be used to achieve these aims:

- To use data quality assessment methods, including double mass plots, box plots and correlation methods for assessing data quality.
- To use the generalised linear models (GLMs) as RSM for simulating spatial-temporal rainfall in the study area.
- To test the sensitivity of GLM when used with adjusted rainfall data.
- To identify suitable rainfall predictors that can be used to drive a GLM for the purpose of simulating future rainfall sequences under scenarios of climate change and rainfall uncertainty.
- To bench-mark performance of GLMs against simpler downscaling methods such as the delta change method.
- To use the GLM results to drive a rainfall-runoff model under rainfall and parameter uncertainty
- To use reservoir performance indices for evaluating the sustainability of a reservoir located in the study area under scenarios of climate change and uncertainty.

1.4 The study area

The upper Limpopo basin in the north-eastern part of Botswana (see details in Chapter 3) has been selected for this study based on the following

reasons:

- Botswana's recent national water resource strategy has recommended the construction of a water supply dam on the Shashe River within the study area. The proposed dam, when complete will be the largest in the country with an active capacity of 382,000 ML.
- Like most semi arid areas, the upper Limpopo basin has limited rain gauges and flow gauges. There are only 16 rain gauges and 5 flow gauges in a 7600 km² catchment. This translates to very low gauge density which may lead to increased uncertainty in model predictions.
- The rainfall data is characterised by extended periods of missing values (with some gauges having 11% of missing daily values, see (Table 3-1). This is a potential source of data uncertainty.
- The quality of data (particularly rainfall) is very low, with evidence of suspicious daily values (see discussion in section 3.3.1)-*another source of uncertainty*.
- There are no published studies on how climate change will affect water resources within the basin.

1.5 Organisation of the thesis

In order to achieve the above objectives, the thesis is organised into 8 chapters (including the current) as follows:

Chapter 2 presents a review of multi-site stochastic rainfall models and rainfall-runoff models for use in data sparse areas in the context of climate change impact assessment.

Chapter 3 presents an introduction to the study area as well as justification of its choice. The historic data is also presented and analysed in this chapter.

Following this, chapter 4 presents a methodology for multi-site rainfall modelling in the study area.

Chapter 5 builds on the results of chapter 4 to calibrate a hydrological model under rainfall and model parameter uncertainty.

Chapter 6 is about downscaling of rainfall in the study area using a rainfall model and outputs from a suite of global climate models (GCMs) and scenarios. The results are used to generate rainfall and streamflow under stationary and climate change scenarios.

Chapter 7 considers a proposed reservoir at the outlet of the study area to begin to assess its performance under stationary and future climate scenarios.

Chapter 8 presents conclusions and recommendations for future research areas.

CHAPTER TWO

2 A review of literature on rainfall and rainfall-runoff modelling

This chapter provides an extensive literature review on spatial-temporal daily rainfall models which are potentially useful in augmenting the commonly limited rainfall information in data sparse semi arid areas. In this context, models which are potentially useful in providing future rainfall series to aid in assessing the impacts of climate change on water resources are identified. Following this, a number of hydrological models are reviewed to seek those with potential for use in semi arid data sparse areas to investigate the effects of climate change on hydrology and water resources in these areas when driven by rainfall outputs.

2.1 Introduction

Long sequences of rainfall data are required as inputs for many water resource and flood management applications. However observed rainfall data are rarely sufficient to characterise the full range of rainfall variability at the temporal and spatial scales of interest. To overcome this, stochastic models are commonly used to generate synthetic sequences of rainfall that are statistically consistent with the observed record at one or more gauged sites. Stochastic models also have the potential to quantify uncertainty due to missing values in the observed record (Yang et al., 2005), and to downscale the outputs of global climate models (Leith, 2005b, Charles et al., 2007, Burton et al., 2008, Chiew et al., 2010). Many applications require a model which incorporates spatial structure, so that simultaneous rainfall at multiple sites can be generated. For example, regional water resource studies routinely employ distributed hydrological models driven by spatially distributed rainfall time-series. The challenge of representing rainfall in space as well as time continues to attract considerable interest, and various models have been proposed and tested to a limited extent (see review below). A particular challenge for these models is the application to arid and semi-arid regions because of the generally high variability in rainfall, sparse networks of rain gauges and potential data quality problems, including the presence of extended periods of missing records. Yet these regions are often the most in need of models to supplement observed records and to help address water management issues associated with climate change. These models are reviewed below with the aim of identifying models potentially applicable to data sparse areas in the context of climate change.

2.2 Multi-site stochastic rainfall models

Probably the most widespread family of daily rainfall models in use today is

based on Markov-chains (Richardson and Wright, 1984). In these models, the probability of rainfall occurrence on a particular day depends on the previous days' occurrence/non-occurrence. Rainfall amounts may then be modelled for any wet days assuming a suitable distribution function. However, most Markov-chain models generate rainfall at single sites whereas regional scale water resource applications generally require spatial rainfall information. Moreover, the models have a tendency to underestimate the frequency of long wet and dry spells and to underestimate the variability of rainfall aggregated to monthly and seasonal time scales (e.g. (Katz and Parlange, 1998). For this reason, recent studies have applied more sophisticated multi-site models (Segond et al., 2006). Among the available multi-site stochastic models are spatial-temporal Neyman–Scott rectangular pulse (STNSRP) models (Burton et al., 2008); non-homogeneous hidden Markov models (NHMMs) (Charles et al., 1999a); models based on semi-parametric stochastic frameworks (Mehrotra and Sharma, 2007); and generalised linear models (GLMs) (Chandler and Wheeler, 2002).

2.2.1 The spatial-temporal Neyman–Scott rectangular pulse (STNSRP)

STNSRP models (Cowpertwait, 1995) are discussed in detail by Burton et al. (2008). In these models a rain event consists of a collection of storms. Storms originate as a Poisson process in time and are assumed to cover the entire catchment. Each storm generates a number of circular rain cells randomly located within the storm with exponentially distributed radii. During each cell's lifetime rainfall occurs with a uniform intensity across its spatial extent and throughout its duration. The process is spatially stationary; as a result a non-uniform scaling factor based on mean rainfall is used to account for orography. However, the assumption of spatial stationarity remains a limitation particularly for larger catchments which may experience multiple storm origins, and those which may have substantial topographic variations (Wheeler et al., 2005, Burton et al., 2008, Leonard et al., 2008). They may also require long records of observed sub-

daily data to characterise storm evolution patterns, and this may limit their application in data sparse areas. The model has been applied extensively in Europe; experience in semi-arid areas includes applications in central Spain and Palestine. However, it is not recommended for catchments larger than 5000 km² (Burton et al., 2008).

2.2.2 The Non-homogeneous hidden Markov models (NHMMs)

The NHMMs (Charles et al., 1999a, Hughes et al., 1999, Charles et al., 2007) assume that daily rainfall occurrence patterns are driven by a finite number of unobserved weather states that evolve according to a first-order Markov process as a function of observed or modelled atmospheric variables. The joint multi-site conditional distributions of daily rainfall amounts are defined by regressions of transformed amounts at a given site against amounts at selected neighbouring sites. The introduction of the extra unobservable stochastic state is the primary difference between this and other multi-site methods, potentially allowing a more flexible structure for linking atmospheric variables to rainfall temporal and spatial patterns (Mehrotra et al., 2006). The model has been applied widely in Australian catchments over a range of climates for different purposes, including water resources assessment and climate change analysis (Charles et al., 1999b, Charles et al., 2004, Charles et al., 2007, Mehrotra et al., 2004, Robertson et al., 2006), and has been found capable of reproducing the magnitude and inter-annual variability of rainfall during dry and wet periods. As with most multi-site models, NHMMs may need a large number of parameters in order to satisfactorily reproduce observed rainfall, potentially creating high uncertainty in simulations. For example, Mehrotra et al (2006) found that for 30 raingauges 132 parameters were needed. Most of the applications of these models have been at large spatial scales (tens of thousands of km²) where the weather patterns can be interpreted in terms of synoptic-scale structures. However, at smaller spatial scales it may not be easy to find such meaningful distinct patterns of rainfall spatial variability. A further

potential problem is that NHMMs are typically fitted using complete records with no missing values (Charles et al., 2007, Charles et al., 1999a), which may limit their application in data sparse areas with extended periods of missing data.

2.2.3 Semi parametric stochastic models (SPSMs)

Other multi-site models include semi-parametric stochastic models (Mehrotra and Sharma, 2007), where rainfall occurrence is modelled using a two state first-order Markov model, and “historical wetness states” for each site aggregated over a specified period. The transition probabilities of the first-order Markov model are functions of aggregated variables from longer-term predictors which define how wet it has been over a period of time. The addition of these predictors aims to capture the inter-annual variability and low-frequency features such as droughts, although the basis for this is empirical rather than physical. For wet days, rainfall amounts are modelled using a first-order Markov model combined with a nonparametric kernel density approach (Harrold et al., 2003, Mehrotra and Sharma, 2007). The spatial dependence model is based on observed correlations between sites as described by Mehrotra and Sharma (2007). This model has been used successfully in a number of catchments in Australia for different applications, including climate change studies (Mehrotra et al., 2004, Mehrotra and Sharma, 2006). As with the NHMMs, these models require complete records for model fitting (Mehrotra and Sharma, 2007).

2.2.4 Generalised Linear Models

Generalised linear models (GLMs) have been applied widely in the UK to multi-site rainfall modelling (Yang et al., 2005, Segond et al., 2006, Wheeler et al., 2006). They were first used for single-site daily rainfall modelling in the early 1980s (Coe and Stern, 1982, Stern and Coe, 1984) and Chandler and Wheeler (2002) extended that work to multi-site rainfall. GLMs are an

extension of linear regression methods, in which variables of interest are considered to be drawn from specified families of probability distributions. The means of these distributions are written as linear or non-linear functions of relevant predictors. These parameter values will in general vary from day to day and, for multi-site modelling, also from site to site. Spatial predictors may include, for example, elevation and/or grid coordinates, while temporal predictors may include previous days' rainfall, annual trends and seasonal cycles. A particular potential advantage of GLMs is the ability to represent seasonal variability parametrically instead of fitting to data from individual months independently as done by the models reviewed above. Also, missing values can be infilled within the GLM framework by determining the distribution of the missing values conditional upon the observed values (Yang et al., 2005). Predictors may also be included to represent the effects of large-scale climate variables, for example those available from climate re-analysis data set (e.g. (Charles et al., 2004, Frost et al., 2006, Chiew et al., 2010). GLMs may achieve satisfactory results with few parameters, for example Segond et al (2006) used 14 and 7 predictors for the occurrence and amounts models respectively, to simulate rainfall in a 1400 km² catchment over a network of 21 rain gauges in the UK. Furthermore, efficient and stable numerical algorithms are available for finding the maximum likelihood estimates and associated standard errors, which avoids the need for approximating solutions with more computationally intensive methods (e.g. Burton et al., 2008). While UK applications have led to the conclusion that GLMs can provide a rigorous framework to evaluate and simulate the space-time variability of rainfall, they have not been tested significantly under potentially more challenging semi-arid and data-sparse conditions.

2.2.5 Summary and conclusions on multi-site modelling in data limited areas

The models reviewed above are summarised in Table XX, and do have potential for providing spatially and temporally varying rainfall fields which

are needed for distributed continuous-time modelling, particularly when the aim is to predict hydrological variables (i.e. streamflow) at interior points and outlet of the catchment. This is because most of these rainfall models use catchment climatic/atmospheric properties (i.e. previous days' rainfall) and physiographic properties (such as elevation) to define rainfall storm evolution patterns over the catchment. These are able to generate simultaneous rainfall at multiple sites which are statistically consistent with the observed rainfall records. However, most of these models require complete rainfall records for model fitting, which may limit their applications in data sparse areas with extended periods of missing data. It has also emerged that models such as the NHMMs often need a large number of parameters in order to satisfactorily reproduce observed rainfall, potentially creating high uncertainty in simulations. Models such as the STNSRP lack the ability to represent seasonal rainfall variability parametrically, but rather the models are often fitted to individual months independently which also increase model complexity (Leonard et al., 2008). Fourthly, they often use more computationally intensive algorithms to fit and assess performance of different models.

Drawing from the above discussions, GLMs might be suitable for application in semi-arid areas because of their ability to represent a wide range of rainfall structures (spatial and temporal) and the computational tractability which makes it relatively straightforward to fit and compare different models. An added advantage of GLMs for application to data sparse areas is the ability to quantify uncertainty due to missing values in the observed data. Also, the models could be useful in identifying significant external climate predictors driving rainfall variability in these areas, which so far has received limited attention particularly in data sparse semi arid areas.

Table 2-1: A summary of the main strengths and weaknesses of the rainfall models reviewed in this chapter.

Model	Strengths	Weakness
STNSRP	-Can simulate continuous spatial-temporal rainfall (Gupta and Waymire) -Sub-daily rainfall can be simulated. -Can be used for climate change analysis when conditioned on atmospheric predictors (Burton et al., 2010)	-Rain cells contribute rainfall uniformly distributed in space and time (Burton et al., 2008; Leonard et al., 2008); -Not suitable for application to larger catchments (i.e. >5000 km²)
NHMMs	-Use of weather state and atmospheric data to condition rainfall occurrence potentially capturing temporal persistence (Charles et al, 2007) -Evolution of storms is not assumed homogeneous as with the STNSRP (Hughes et al., 1999; Charles et al., 2007).	-Requires large number of parameters -Application with extended periods of missing data is computationally intractable (Charles et al., 2007; Hughes and Guttorp)
SPSMs	-Historical wetness state can be used to condition rainfall occurrence like the NHMMs to capture temporal persistence. -Spatial dependence is accounted using correlations based on distance between the gauges	-It requires complete rainfall data with no missing values (Mehrotra and Sharma, 2007). -Requires long data records to capture long-term temporal persistence
GLMs	-Missing data can be infilled and its uncertainty quantified easily (Yang et al., 2005) - Computationally tractable - A wide range of rainfall structures (spatial and temporal) can be accommodate -Allows for the use of atmospheric variables to characterise rainfall variability potentially useful for climate change analysis.	-Cannot be applied at sub-daily time scales (Chandler and Wheeler, 2002)

2.3 Generating rainfall for climate change impact assessment.

The effects of climate change on hydrology and water resources have become an important subject of research and discussion over the past few decades. These investigations are driven by the recognition that climate change as a result of global warming is a complex issue, which involves the interactions and feedback between atmosphere, oceans and land surfaces. These have significant implications for the environment, ecosystems, water resources and all aspects of human life (Jiang et al., 2007). In hydrology, possible effects of global warming include the magnitude and timing of rainfall and runoff, the frequency and intensity of extreme events such as droughts and floods, as well as the quality and quantity of water (Nakicenovic and Swart, 2000, IPCC, 2007a). The Intergovernmental Panel on Climate Change (IPCC) is providing guidance and directions by way of developing possible future scenarios using global climate models (or general circulation models) (GCMs). GCMs offer physical models for assessing climatic change as a result of increase in greenhouse gases and aerosols over time. They are considered to be the most comprehensive models for investigating the physical and dynamic processes of the earth-atmosphere system and they provide plausible patterns of global climate change (Arnell, 2002, Jiang et al., 2007).

However, there are major limitations associated with GCMs, primarily regarding the coarse spatial and temporal scales associated with them (von Storch et al., 1993, Xu et al., 2005). The GCMs have crude spatial resolutions, often around 3° latitude and 4° longitude (i.e. more than 65 000 km²). But for hydrological and water resources purposes information is usually needed at finer scales far less than 1000 km² (Arora, 2001). GCMs are also unable to represent local sub grid-scale features and dynamics, such as convective cloud processes (Prudhomme et al., 2002), and therefore greatly simplify the hydrologic cycle (Arora, 2001, Jiang et al., 2007). At that scale, the regional and local details of the climate are lost. Regarding the temporal scale, the GCMs are currently not considered reliable at time

scales shorter than one month (Prudhomme et al., 2002, Arnell, 2002).

Another problem inherent in GCMs is that they calculate rainfall with large errors compared to other climate variables like sea-level pressure and temperature (Prudhomme et al., 2002, Arnell, 2002, Xu et al., 2005). For example, it was observed that when using a total of 21 climate models for simulating rainfall over Africa, 90% of these models overestimated rainfall over southern Africa, by more than 20% on average (and in some cases by as much as 80%) over a wide area extending into equatorial Africa (Christensen et al., 2007). This is because GCMs cannot explicitly represent the processes controlling rainfall (Leith, 2005b), such as the feedback mechanisms due to vegetation, for instance (Christensen et al., 2007). On the other hand, Christensen et al. (2007) observed that temperature biases over land were not large enough to directly affect the credibility of the model projections over these regions. As a result most studies tend to use other atmospheric variables (predictors) that are well simulated by the GCMs to generate rainfall (predictand) at local scale rather than using rainfall directly obtained from the GCMs (Frost et al., 2006, Randall et al., 2007).

For these reasons, many studies now focus on methods which can downscale GCM outputs so as to make them applicable to finer scales of interest (Leith, 2005b, Chen et al., 2006, Semenov, 2007). This information is highly needed in impact assessment studies such as those related to climate variability and water resources. Downscaling is the process of transforming information from climate models at coarse resolutions to a fine spatial resolution (Maurer and Hidalgo, 2008).

2.3.1 Downscaling Methods

There are two broad categories of downscaling: dynamic (which simulates physical processes at fine scales) and statistical (which transforms coarse-scale climate projections to a finer scale based on observed relationships

between the climate at the two spatial resolutions) (Christensen et al., 2007, Maurer and Hidalgo, 2008).

2.3.1.1 Dynamical downscaling

This approach uses regional climate models (RCMs) which are nested within a GCM to give estimates at finer resolutions, typically of the order of $0.5 \times 0.5^\circ$, or approximately 2500km^2 (Wilby et al, 1999; Prudhomme et al, 2002; Arnell, 2002). The RCMs use GCM output as the boundary condition to calculate variables at detailed scale and inherently depend on the reliability of the parent GCM used (Prudhomme et al., 2002). For example, the parent GCM is used to simulate the response of the global circulation to large scale forcing and the RCM is used to (i) account for sub-GCM grid scale forcing (e.g. complex topographical features and land cover non-homogeneity) in a physically-based way, and (ii) enhance the simulation of atmospheric circulations and climatic variables at fine spatial scales (Mearns et al., 2003). However, it has been recognised that even at finer scales, many RCMs fail to adequately represent the rainfall processes particularly in mountainous and vegetated areas. For example, Christensen et al (2007) argue that vegetation feedbacks and feedback from aerosols are not represented in many RCMs. As a result, the extent to which current RCMs can successfully downscale precipitation over these areas, particularly in Africa is unclear (Christensen et al., 2007).

Another limitation for RCMs is that they are computationally intensive, and are generally run only for short periods with limited realisations (Arnell, 2002, Mearns et al., 2003). Hence their usage in impact studies is very limited (Maurer and Hidalgo, 2008).

2.3.1.2 Statistical downscaling

Statistical downscaling (SD) methods use relationships between the

atmospheric variables provided by the GCM (i.e. sea level pressure) (known as predictors) and locally measured variables such as rainfall (known as predictands) (Prudhomme et al., 2002) to transform coarse-scale climate projections to a finer scale (Christensen et al., 2007). The results will depend on the quality and length of the data series used for calibration, and on the performance of the regression model used in capturing the variability of the observed data (Prudhomme et al., 2002, Xu et al., 2005). The main assumption of all SD methods is that statistical relationships between the predictors and predictands will hold even under changed climates (time invariance) (Wilby, 1997, Evans and Schreider, 2002b, Wilby et al., 2004). However, this assumption is not guaranteed under changed climate, which is the main criticism of all the SD methods. SD methods used for downscaling daily rainfall can be broadly categorised as follows (Wilby et al., 2004, Charles et al., 2004, Leith, 2005a):

2.3.1.2.1 Transfer functions or regression methods

These involve establishing statistical relationships between local or station-based rainfall and continuous large scale predictors mainly by using linear or non-linear regression functions. Commonly used methods include multiple regression, canonical correlation analysis (CCA) and artificial neural networks. The problem with transfer functions is that they do not adequately predict the magnitude of extreme events and under represent variability particularly when downscaling daily rainfall (Wilby et al., 2004, Linderson et al., 2004). This is because they are simply estimating the mean and so they are guaranteed to under represent variability (Leith, 2005a).

2.3.1.2.2 Weather typing

They involve grouping days into a number of finite discrete weather types or “states” according to their synoptic similarity (Charles et al., 2004) and associate either a rainfall mean or a complete rainfall distribution with each

of these types. Unlike the transfer functions, weather typing methods do not assume a continuous relationship between large scale atmospheric structure and precipitation (Leith, 2005a). But, it has been observed that downscaling methods using discrete weather classifications have a conflict between maintaining the uniqueness of rare events and simultaneously grouping sufficient data to secure statistical integrity (Wilby, 1997).

Typically, weather states are defined objectively by applying cluster analysis methods such as the principal component analysis to the atmospheric fields (Huth, 2000). The local-scale predictand at a particular time is a function of the prevailing weather state at that time, and it is replicated under changed climate by resampling or regression functions (Linderson et al., 2004, Wilby et al., 2004, Charles et al., 2004). The main limitation of these methods is that they often fail to reproduce autocorrelation and persistence between the daily observations during wet or dry conditions (Zorita and von Storch, 1999, Wilby et al., 2004).

2.3.1.2.3 Weather generators

Weather generators (WGs) are models that replicate the statistical attributes of a local climate variable but not the observed sequences of events (Wilks and Wilby, 1999, Wilby et al., 2004). They are usually stochastic models and therefore can be used to simulate long sequences of daily rainfall data, explicitly representing both dependence of rainfall upon atmospheric structure and its persistence over successive days, (Chandler, 2005). The principle behind the weather generators is that the occurrence of rain on a given day is assumed to have a major influence on secondary variables such as wet-day amounts, temperature and solar radiation for the day (Richardson and Wright, 1984). As a result, the weather generators independently calculate daily precipitation first and then use this information to guide the generation of other weather variables depending on whether a wet day or dry day was previously generated (Richardson and

Wright, 1984, Sentelhas et al., 2001).

For generating daily rainfall at individual sites, weather generators usually use first or second order two-state (wet or dry) Markov chains models to generate the probability of rainfall *occurrence* on a given day conditioned on whether there was rainfall during the previous day (Richardson and Wright, 1984). When a wet day is generated, a distribution is fitted, say a 2-parameter gamma distribution (Richardson and Wright, 1984), or mixed distributions (Semenov and Barrow, 1997) and used to generate the precipitation *amount* for that day. The same procedure is followed for subsequent days. For multi-site rainfall generation, the daily probabilities at individual sites are normally linked by specifying a suitable spatial dependence structure (Mehrotra and Sharma, 2007). The main limitation of the WGs is that many of them (particularly those which are based on first-order Markov chains) are unable to reproduce all of the features relevant in hydrological problems, mainly temporal variability and persistence of rainfall (Mehrotra and Sharma, 2007). However, recent developments show that other forms of WGs generators are able to reproduce this variability, for example those based on the generalised linear model approach (GLMs) (Chandler and Wheater, 2002, Yang et al., 2005, Wheater et al., 2005) as discussed in section 2.2.4. Here they are only discussed in comparison to the other WGs for downscaling purposes.

2.3.2 Application of weather generators for downscaling rainfall

WGs are adapted for statistical downscaling by conditioning their parameters on large-scale atmospheric predictors, weather states or rainfall properties (Semenov and Barrow, 1997, Wilby et al., 2004). This is achieved for example, by linking the parameters of a stochastic WG to the values of atmospheric variable from the GCMs/RCMs. By conditioning on atmospheric variables, the WGs are able to represent the way in which local rainfall distributions respond to large-scale atmospheric conditions. Leith

(2005a) noted that there are a number of different techniques for conditioning the parameters of a weather generator on large scale atmospheric structure, and in some of these techniques there is a degree of overlap with the previous two downscaling categories. For example, Busuioc and von Storch (2003) used a two-state first order Markov chain to model rainfall occurrence and a gamma distribution to model rainfall amount if wet. They linked the observed NCEP (reanalysis data) large scale sea level pressure to the seasonal empirical transition probabilities and gamma distribution parameters using canonical correlation analysis (Busuioc and von Storch, 2003). They compared the conditional model to the unconditional one (where the parameters were not conditioned on sea level pressure) and noted that the conditional model better captured the trend and the inter-annual variability in the seasonal precipitation amount. However they did not use the models to simulate future rainfall but they noted that the ability of a conditional model to capture changes in the local seasonal rainfall induced by changes in large-scale sea level pressure makes it useful for the construction of climate change scenarios.

Recently, Leith (2005b) and Frost et al (2006) used a generalised linear model framework conditioned on observed (NCEP data) and future (GCMs/RCMs) large scale atmospheric variables (sea level pressure, temperature and humidity) to simulate multi-site rainfall sequences under scenarios of climate change. Their findings were consistent with those of Busuioc and von Storch (2003) in that conditional models better represented the inter-annual variability of observed annual amounts than the unconditional model (Frost et al., 2006).

Frost et al. (2006) also assessed the effect of temporal resolution of the atmospheric variables on the simulated rainfall sequences. They concluded that the simulated extremes increased when moving from monthly to daily atmospheric variables, although in absolute terms those effects were small to justify the use of daily variables, which increase model complexity. Furthermore, they noted that there are problems in reconciling the 360-day

climate model years with calendar dates. In general, realistic rainfall simulations were obtained even when using monthly time series of atmospheric variables as predictors in GLMs.

Similarly, they assessed the effect of standardisation of the atmospheric variables on simulated rainfall. Standardisation is routinely applied in climatology and is an attempt to adjust for climate model bias (Charles et al., 2007, Leith, 2005b). In this way, the atmospheric variables are standardised separately by month with respect to the mean and standard deviation of the control period. They noted that for the control period, the properties of GLM simulations conditioned on standardised climate model output were indistinguishable from those simulations conditioned on the NCEP reanalysis data. From this, they concluded that regardless of the atmospheric sequences used in the control period, any differences between the properties of control and future rainfall simulations can reasonably be ascribed to changes over time, rather than to intrinsic differences between simulations driven by observations and by climate models. This is very important for simulating future rainfall under scenarios of climate change.

Regarding, the uncertainty of climate models, it is widely recommended that an ensemble of more than one climate models (GCMs/RCMs) should be used as one of the ways to incorporate uncertainty from these models which usually give very different projections for future climate (Leith, 2005b, Wilby and Harris, 2006). For example, in the case of weather generators, an ensemble of rainfall simulations can be generated conditioned on the outputs from different climate models (Leith, 2005b), or from different downscaling methods (Chiew et al., 2010). This is a simple and straight forward way of incorporating uncertainty in future rainfall sequences.

2.4 Rainfall-runoff modelling

This section introduces issues related to the classification of rainfall-runoff models, and how they represent different aspects of processes perceived to be important at different scales and climatic conditions. Furthermore, issues of model selection, calibration and validation are discussed in light of model complexity and data availability. Examples showing how these models are used across different climatic conditions, with more emphasis placed in arid areas, are also given. Their potential for use in climate change studies is also explored.

2.4.1 Classification of rainfall-runoff models

There are many classifications of rainfall-runoff models found in the literature. Perhaps the most widely used is the one by Beck, (1991) in (Wheater et al., 1993) that there are three broad generic model types (although such classifications have significant overlaps), which are the (i)metric, (ii)conceptual and (iii) physics based models. Within these classes, several names have emerged, such as: data-based, empirical or black box for the metric models; parametric, explicit soil-moisture accounting or grey box for the conceptual models; and the mechanistic or white box for the physics-based models (Wheater et al., 1993, Ye et al., 1998, Masopha, 2001, Wheeler, 2002, Wagener et al., 2004, Lee, 2006). Other classifications include those into lumped and distributed models (Refsgaard and Knudsen, 1996, Beven, 2001, Reed et al., 2004b, Moreda et al., 2006, Lee, 2006) and into deterministic and stochastic models (Refsgaard and Knudsen, 1996, Beven, 2001).

2.4.1.1 Metric models

Wheater et al., (1993) give a detailed account of these models, dating back to the development of a well known unit hydrograph theory, which is based primarily on observations seeking to characterise hydrologic system response from the available data. According to Shaw (1994), a unit

hydrograph is the hydrograph of surface runoff resulting from effective rainfall falling in a unit of time such as 1 hour or 1 day and produced uniformly in space and time over the catchment area. The streamflow is separated into quick hydrograph (resulting from effective rainfall) and slow response component (base flow which may contribute to groundwater storage) (Shaw, 1994). The main criticism of the unit hydrograph theory is that the mechanism of hydrograph separation is purely subjective, and as a result prone to errors. The assumption of uniform rainfall over the catchment is also far from reality since rainfall tends to vary from one storm to the other, or even within the duration of a single storm. Furthermore, the unit hydrograph theory considers only event response, thus eliminating complexities associated with continuous moisture accounting, evaporation and long-term complexities (Wheater et al., 1993). Other issues that cripple the use of a unit hydrograph are the inherent assumptions of linearity and time invariant. Young et al., (2006) observed that when using the metric models (including the unit hydrograph), physical meanings can only be attached to the input (rainfall) and the output (runoff), while model parameters are merely fitted empirical values that do not relate to real world measurements of physical characteristics.

Despite these criticisms, the unit hydrograph concept has some strength, particularly where data is a limiting factor. With regards to the linearity assumption inherent in the unit hydrograph theory, Raudkivi (1979) in (Ye et al., 1998) noted that comparative studies have shown that the combined effects of non-linearity can be relatively small, and as a result the unit hydrograph continue to be used widely for catchment rainfall-runoff studies, especially in relation to the modelling of short-term (single storm event) scenario, where the long term non-linearity in the rainfall-runoff relationships is not so apparent. However, the issue of non-linearity still remains a challenge to modellers particularly in dry climate conditions as discussed sections 2.4.2 and 2.4.3.

Wheater et al., (1993) argue that the major strength of the unit hydrograph

concept is in the way hydrologic analyses are made. For example, once the stormflow and effective rainfall components of an observed response have been separated, a unit hydrograph can be derived, characterising the event response, which can be used to analyse data from a range of events. In the UK, the unit hydrograph has been extensively used as a regional design tool (Natural Environmental Research Council (NERC), 1975), and the Flood Studies Handbook (Institute of hydrology (IH), 1999). These studies employed a slight modification of the original unit hydrograph, by characterising the systems through linear analysis and linking the catchment response with catchment physiographic and climatological characteristics (i.e. regionalisation approach). The regionalisation approach has further enhanced the strength of the unit hydrograph, making it applicable to ungauged catchments. The unit hydrograph time to peak, percentage runoff and baseflow can be estimated by using regression analysis and physical/climatic descriptors of the catchment, Robson and Reed (1999) in (Lee, 2006).

Besides the unit graph concept, there are other forms of metric models, which relate the output (runoff) to the input (rainfall). One of these models is artificial intelligence models (e.g. artificial neural networks), which are widely used in rainfall-runoff modelling (Zealand et al., 1999, Uvo et al., 2000, Riad et al., 2004, Parida et al., 2006) Such networks usually comprise many layers arranged in series, each layer containing one or group of neurons, each of which have the same pattern of connections to the neuron in the other layer (s) (Shamseldin, 1997). The first and last layers are used for input and output variables (i.e. rainfall and runoff, respectively), while the intermediate layers are known as the hidden layer (s). Mathematical functions, known as transfer functions are used to transform the input to output for each neuron through hidden layers (Parida et al., 2006). Through the process of training and weighting, neurons are able to learn and recognise patterns and find solutions, and even forecast future events. Neural networks are therefore not necessarily modelling the physical process but only the relationship between input and output and therefore can be

classified as improved form of metric models (Lee, 2006).

2.4.1.2 Conceptual Models

These models seek to represent important component processes as perceived by the modeller, and as a result the model structure is specified a priori (Wheater et al., 1993). They typically conceptualise the catchment water balance using series of interconnected storages that do have a physical interpretation, but usually employ empirically parameterised equations to describe the movement of water between the storages (Young et al., 2006). While some of the parameters in the equations in some conceptual models do have a physical interpretation, they usually only represent lumped, spatially averaged catchment characteristics, and so are not directly measurable (Ye et al., 1998).

Parameter adjustment through calibration is therefore required against a reasonable period of observed streamflow (Wheater et al., 1993, Young et al., 2006). One of the early conceptual (lumped) rainfall-runoff model is the Stanford Watershed Model (SWM), Crawford and Linsley (1966) in (Wheater et al., 1993), which attempts to represent all the dynamic aspects of rainfall-runoff processes in the model structure. The complexities of these models make them data demanding and highly parameterised which eventually affect model optimisation and performance. Over the last three decades, several investigators seem to agree that the use of simple modelling approaches, by using as few parameters as possible to represent the key identifiable catchment runoff processes is a promising strategy in rainfall-runoff modelling (Nash and Sutcliffe, 1970, Beven, 1989, Jakeman et al., 1990, Young and Beven, 1991, Beven, 1993, Young and Beven, 1994, Jakeman and Hornberger, 1993, Wheeler et al., 1993, Ye et al., 1998, Masopha, 2001, Wagener et al., 2004, Lee, 2006, McIntyre and Al-Qurashi, 2009, Pechlivanidis et al., 2010). This is normally achieved by matching model complexity with spatial scale and data availability (Young et al.,

2006).

However, these investigators also caution that when the model is too simple, it may not reflect the complexity of the rainfall-runoff response. This may shift the model structure towards a metric structure. On the other hand, when the model structure is too complex it may not be supported by the available data, and will lead to problems of parameter identifiability (Beven, 1989, Jakeman and Hornberger, 1993, Ye et al., 1998, Perrin et al., 2001)

Another problem that is associated with conceptual models is called equifinality (Beven, 1993), which means that different combinations of parameter values give equally good results. This makes it difficult to identify a uniquely optimised parameter set from the available data. This becomes even more difficult when the model is over parameterised, which results in complex interaction of parameters within the modelling environment. Despite the challenges advanced above, conceptual models are probably the most widely used of all model types in rainfall-runoff studies. However, some recent studies point towards the use of hybrid models, which in a way borrow from the metric and conceptual models.

2.4.1.3 Hybrid metric-conceptual models

These models combine the use of relationships between observed rainfall and streamflow (i.e. the metric approach) with a conceptualisation of the catchment response (conceptual models) (Jakeman et al., 1990, Wheater et al., 1993, Ye et al., 1998). Perhaps the most well documented example of this type is the Identification of Hydrographs and Components from Rainfall, Evaporation and Streamflow data model (IHACRES) (Jakeman et al., 1990, Jakeman and Hornberger, 1993, Post and Jakeman, 1996, Ye et al., 1998, Croke and Jakeman, 2004, Croke et al., 2005, Croke et al., 2006a, Littlewood et al., 2007, McIntyre and Al-Qurashi, 2009).

The IHACRES model generally has two modules; a conceptual non-linear loss function (i.e. the soil moisture accounting module which produce effective rainfall) and a linear routing component (i.e. which transfers effective rainfall to streamflow). The underlying concept of the original IHACRES model is that after accounting and adjusting appropriately for the antecedent conditions, the response of a catchment is predominantly linear over a wide range of climatological regimes and catchment scale (Ye et al., 1998). Improved versions of the model have been reported elsewhere (Evans and Jakeman, 1998, Croke and Jakeman, 2004, Ye et al., 1998, Croke et al., 2005, Croke et al., 2006a). The IHACRES model has been applied to a wide variety of catchment scales and climates; For example, in Australia (Chiew et al., 1993, Ye et al., 1997a, Schreider et al., 2002, Evans and Schreider, 2002a, Croke and Jakeman, 2004, Croke et al., 2006b) in the USA (Evans, 2003), in France (Andreassian et al., 2001) in the UK (Sefton and Howarth, 1998, Littlewood, 2002), and southern African catchments (Masopha, 2001), and in South Africa (Dye and Croke, 2003).

The success of IHACRES model and its improved variants means that it can be used in rainfall-runoff modelling particularly where only rainfall and temperature are available, as is usually the case in most semi arid and arid areas. Recently Croke et al (2006) applied the method to a large scale data-limited catchment in Australia and concluded that the model was capable of producing estimates of flow on unregulated rivers including situations where no flow gauge exists. This is an indication that IHACRES can be used in ungauged sub catchments within the entire catchment being modelled.

Perhaps the wide application of the model in Australia points towards its potential for use in similar arid environments, such as in Botswana, in which the case study is located. Recent studies also suggest that the model can be applied with success to even more arid areas. For example, McIntyre and Al-Qurashi (2009) applied the IHACRES model in both lumped and semi distributed modes to an arid catchment in Oman. The main findings were that parsimonious versions of the semi distributed IHACRES model

performed better than complex versions of the same model, as well as other models they used. The authors attribute good performance to better representation of spatial rainfall, and ability to compensate for systematic rainfall and flow observation errors yet with simple model structure.

When used with regional climate models in the USA (Evans, 2003), IHACRES was able to simulate streamflow events under different climate change scenarios. This also indicates that IHACRES can be used with success in water resources and climate change studies.

2.4.1.4 Physics-based models

Physics-based models attempt to take full account of the spatial variability of various hydrological parameters by using a suite of physically/mathematically based equations that govern surface and subsurface water flow (Wheater et al., 1993, Ye et al., 1998, Young et al., 2006). These equations are solved numerically using finite difference or element discrete grids (Wheater et al., 1993). Two examples of these models are the Systeme Hydrologique Europeen (SHE) model and the Institute of Hydrology Distributed Model (IHDM) (Abbot et al., 1986; Bathurst, 1986; Beven et al., 1987 (in Wheater et al., 1993), both of which account for the surface and subsurface processes (Sahoo et al., 2006). The SHE model is a grid based finite difference scheme, while the IHDM solves the Richards' equation for unsaturated flow using a 2-dimensional finite element scheme to represent a hillslope processes.

In principle, these types of models are superior to the other models discussed above, mainly because of their ability to represent the physics behind the spatial hydrological processes within the interiors of a catchment, leading to a better understanding of catchment processes. This means that detailed spatial data is needed in order to use these types of models. However, it is not always possible to have sufficient data required to

adequately satisfy the data demands of these models (Young et al., 2006). Klemes (1983) observed that the details required by these models exceed those measured in the field. For this reason, the models usually need to be calibrated (Calver, 1988), which may result in unidentifiable parameters because of a very large parameter space (Beven and Binley, 1992, Wheater et al., 1993).

Furthermore, in reality catchments are structured and heterogeneous which makes it even more difficult to fully represent them in the model structure particularly when issues of scale are taken into consideration (Beven, 1989, Wheater et al., 1993, Andersen et al., 2001, Guntner and Bronstert, 2004). It has also been argued that these models are based on equations that describe small-scale spatially homogeneous processes that do not necessarily apply to large heterogeneous catchments (Young et al., 2006, Moreda et al., 2006). For all these reasons physics-based models are difficult to apply, and may at best provide slightly improved predictions over simpler conceptual models in small data-rich catchments (Ye et al., 1998, Young et al., 2006).

Despite the complexities associated with physically based models, the models are still used in rainfall-runoff studies. Andersen et al (2001) applied the modified version of the physics -based distributed MIKE SHE model to the 375,000 km² Senegal River basin in the western part of Sahel, in Africa. The model was built on a 4 x 4 km² grid scale with the aim of representing field conditions at the subcatchment scale. However, the model gave poor validation results, which were attributed to lack of good quality spatial data. These include precipitation data, which had many gaps and were derived from coarse rain gauge network resolution (Andersen et al., 2001). Andersen et al noted that the non-uniform distribution of topography, geology, soil types, vegetation types and potential evapotranspiration introduces heterogeneity within the modelling environment, which subsequently affect the model output. In their study they observed that soil depth distribution was responsible for a substantial part of heterogeneity. This is also

supported by Guntner and Bronstert (2004) who observed that the spatial variability of landscape features such as topography, soils and vegetation define the spatial pattern of hydrological state variables like soil moisture. Thus spatial variability controls the functional behaviour of the landscape in terms of its runoff process.

Perhaps the value of physics based models is their ability to represent complex interactions, such as between ground water, surface water, physical and climatic conditions of the catchment (Joris and Feyen, 2003), where they can be used as operational tools to assess the effect of changes in catchment properties and climatic variables on hydrological regimes (Droogers et al., 2008). This is expected to be particularly useful when the purpose is to account for land-surface-climate interactions and their feedback mechanisms to predict future hydrological responses informed by these interactions (Brouyère, et al., 2004; Kunstmann et al., 2004; Mauser and Bach, 2009), and the current conceptual hydrological models are limited in this respect.

2.4.1.5 Distributed versus lumped modelling

Another approach to classification concerning hydrological models is that of lumped models (which are associated with conceptual models) versus distributed models (associated with physically-based models). Many hydrologists differ in their definition of distributed models. Reed et al. (2004) defines a distributed model as any model that explicitly accounts for spatial variability inside a basin and has the ability to produce simulations at interior points without explicit calibration at these points. According to Moreda et al (2006) the advantages of distributed models extend beyond the potential for better flow simulation at basin outlets and providing flow simulation at interior points. Distributed models may also allow streamflow prediction at interior locations of the basin where no streamflow observation

exist (Koren et al., 2004). Hence distributed models can be used as a foundation for environmental modelling, including water quality and sediment transport, among others.

However, despite these advantages, there are challenges that affect performance of distributed models. These are summarised by Moreda et al (2006) as *what spatial and temporal resolutions of distributed hydrologic modelling are appropriate when considering (a) The need for minimum violation of physical/conceptual assumptions of the model structure (b) The lack of high space/time resolution model inputs such as precipitation which in most cases is aggregated over a catchment or subcatchment? (c) The difficulties associated with calibration of large numbers of distributed model parameters, and (d) The lack of sufficient data to evaluate the performance of distributed models.*

For these reasons, some investigators are contending that depending on the basin characteristics, the application of a distributed or semi-distributed model may not improve flow simulations over lumped simulations at the catchment outlet (Reed et al., 2004b, Zhang et al., 2004, Koren et al., 2004). This normally applies when there is insufficient spatial data of good quality to calibrate these models. Johnson (1993) in (Zhang et al., 2004) compared the lumped and distributed simulation results from a small Goodwin Creek catchment (21 km²). They concluded that a distributed model performs better than a lumped model when there are accurate data describing soil and land use characteristics: and, if there are insufficient sub-basin stream gauge data for calibration, then lumped simulations are comparable to distributed simulations.

From this conclusion, Zhang et al., (2004) argued that since the study was based on a small catchment, Johnson's findings may not necessarily be transferable to larger catchments where hydrological processes are known to be more complex. However, recent studies continue to show the value of distributed models especially when high quality spatial data is available.

Reed et al (2007) used a distributed model to forecast flash floods in the USA, and compared its performance with the lumped model used for flood studies. Their findings were that indeed distributed models improve upon the performance of lumped models in small interior basins when driven by high quality rainfall data, such as radar based data. Other studies are also advocating for the use of semi distributed models particularly when the aim is to represent catchment spatial heterogeneity and to generate outputs at interior points through the use of spatially variable inputs (mainly rainfall). For example, the study by McIntyre and Al-Qurashi (2009) mentioned in 2.4.1.3 lead to a similar conclusion that semi distributed representation of rainfall may outperform a lumped representation. These findings are supported by more recent studies. For example, Pechlivanidis et al. (2010) applied a semi distributed and a lumped version of the PDM model using hourly data to the upper Lee catchment in the UK to investigate the models' ability in generating flows at interior locations and catchment outlet. The general conclusion was that a semi distributed version usually (but not always) performed better than a lumped version at gauged points (yet with poor predictions at ungauged points).

2.4.1.6 Deterministic versus stochastic models

Deterministic models produce only one outcome from a simulation with one set of input data and parameter values (Refsgaard and Knudsen, 1996, Beven, 2001). Stochastic models are those which allow for some randomness, variance, and uncertainty in the possible outcomes due to uncertainty in the input data, boundary conditions or model parameters (Beven, 2001). However, there are some overlaps in the way these models are used. For instance, Beven (2001) noted that a vast majority of rainfall-runoff models are used in a deterministic way although some do have a stochastic error function, while some stochastic models do make predictions in a deterministic way. Whether a model structure should take on a deterministic or stochastic formulation depends on the conceptualisation of

the processes under investigation.

For example, Gottschalk and Weingartner (1998) studied the distribution of peak flow derived from a distribution of rainfall volume, runoff coefficient and a unit hydrograph in Switzerland. In their model structure, they represented the unit hydrograph as a deterministic function, while the runoff coefficient and the rainfall volume were regarded as random variables. In view of these overlaps, it is suggested that if the model output variables are associated with some variance or other measure of predictive dispersion the model can be considered stochastic; if the output values are single values at any time step the model can be considered deterministic, regardless of the nature of the underlying calculations (Corradini et al., 1998, Gottschalk and Weingartner, 1998).

2.4.2 Model complexity and data availability

Several investigators observed that recently there has been a tendency to move away from fully distributed, physically based models back to conceptual or lumped models (Masopha, 2001, Wheeler, 2002, Nutzmann and Mey, 2007). This is due to several reasons, for instance, the physics-based models are data-demanding while these data are often not available (Andersen et al., 2001, Nutzmann and Mey, 2007). Secondly, it is argued that small-scale physics may not be appropriate at the scale of model applications and as such it is difficult to accurately determine physical parameters *a priori* (Seibert and McDonnell, 2002). On the other hand, less complex models which use few parameters to represent important catchment hydrological processes tend to perform similar to (or even better than) complex models particularly in data sparse areas (Littlewood et al., 2007, Masopha, 2001, Young and Beven, 1994, Beven, 1989).

This has led to various view points among hydrologists. Harremoes and Madsen (1999) argued that the best approach often lies somewhere between

distributed and lumped hydrological modelling, while others (Jakeman and Hornberger, 1993, Littlewood et al., 2007, Masopha, 2001, Wheater, 2002) argue that the hybrid conceptual rainfall runoff modelling is often the way forward when considering the fact that data availability remains a limiting factor in hydrological modelling (Chandimala and Zubair, 2007). And some studies have preferred semi-distributed versions of metric-conceptual models where the rainfall spatial variability is important (e.g. McIntyre and Al-Qurashi 2009).

However, the literature reflects that when data is available, physics-based model should may be beneficial, particularly when the purpose is to account for land-surface-climate interactions and their feedback mechanisms (Brouy`ere, et al., 2004; Kunstmann et al., 2004; Mauser and Bach, 2009), to which the current conceptual hydrological models are limited.

2.4.3 Model identification, sources of uncertainty, calibration and validation

2.4.3.1 Model identification

In light of the above discussion, it can be seen that the most challenging part of rainfall-runoff modelling is to identify a suitable model structure for use in hydrologic applications. Beven (2001) gives the following advice for selecting a suitable model: (i) preparation of a list of the models under consideration (those readily available or to be developed), (ii) preparation of a list of variables predicted by each model (output) and those required (input), (iii) preparation of assumptions made by the model, (iv) consideration of available data and its quality, and (v) definition of the modelling task.

From the above points it can be seen that a lot of issues have to be overcome before a suitable model can be selected. The next step deals with the

identification (estimation) of an appropriate parameter set within the chosen model structure (Wagener et al., 2004). This is a challenging task due to a range of uncertainties involved in the modelling exercise.

2.4.3.2 Sources of uncertainty

Several investigators have identified the sources of these uncertainties (Melching and Singh, 1995, Beven, 2001, Wagener et al., 2004) as data uncertainty, model parameter uncertainty, model structural uncertainty and natural uncertainty.

2.4.3.2.1 Data uncertainty

It is recognised in the literature that the performance of hydrological models is mainly affected by data uncertainty (Chiang et al., 2007). This uncertainty arises from errors in the observed data, particularly data used for model calibration. The errors may be linked to the quality of data which depends on the type and conditions of measuring instruments as well as data handling and processing (Melching and Singh, 1995, Wagener et al., 2004). Rainfall and runoff are usually major sources of input and output data uncertainty (Kavetski et al., 2006).

2.4.3.2.2 Model parameter uncertainty

Known also as model specification uncertainty, this relates to the inability to converge to a single best parameter set using available data, which leads to parameter identifiability problems (Beven, 2001, Wagener et al., 2004).

2.4.3.2.3 Model structural uncertainty

This uncertainty is introduced through simplifications and/or inadequacies in the representation of real world processes using a given model. It also originates from inappropriate assumptions within the modelling procedure (Efstratiadis and Koutsoyiannis, 2010), inappropriate mathematical description of these processes (Beven, 2000), and the scale at which processes are represented in the model (Koren et al., 1999). However, no matter how precise the model is calibrated, there always exists discrepancy between model outcome and observed data (Chiang et al., 2007, Beven, 2006) because in modelling more attention is given only to the dominant processes perceived to be important by the modeller thereby ignoring other processes, which may nevertheless affect model prediction results. This type of uncertainty is usually identified through assessing the model's ability to represent properties of the hydrograph (Butts et al., 2004) and can be quantified (in a summary way) using goodness-of-fit methods during model calibration such as the Nash-Sutcliffe efficiency (NSE) (Chiang et al., 2007).

2.4.3.2.4 Natural uncertainty

Natural uncertainty arises due to the randomness of natural processes (Beven, 2001). This uncertainty can therefore be linked to data uncertainty, where by the quality and type of data plays a significant role in determining the amount of uncertainty. For example, the spatial and temporal randomness of rainfall can somewhat be represented explicitly when using good rain gauge networks and radar rainfall data (Segond, 2006; Pechlivanidis 2009).

2.4.3.3 Uncertainty identification, estimation and quantification

Beven (2001) argues that an optimum parameter set gives only a single prediction, while multiple acceptable parameter sets give the range of prediction uncertainty. The latter therefore allows for uncertainty analysis in predictions, which could be used as part of the decision-making process

arising from a modelling project. For this reason, methodologies that favour the concept of equifinality rather than the concept of an optimum parameter set have been proposed.

2.4.3.3.1 Uncertainty estimation techniques

The most widely used in the literature is the generalised likelihood uncertainty estimation (GLUE) by Beven and Binley (1992). GLUE is based on the estimation of probabilities of different outcomes using likelihood measures. In the GLUE methodology, a prior distribution of parameter values is used to generate random parameter sets. Each sampled set is used to drive the model to produce a sample result (i.e. a Monte Carlo simulation framework (Melching and Singh, 1995)). Each result is compared with the available calibration data using a quantitative (likelihood) measure of performance.

A likelihood measure in the GLUE approach can be any measure of performance so long as better performing models attain higher values and the sum taken over all sampled parameter sets is unity (Wagener et al., 2004) such that non-behavioural parameter sets have a likelihood of zero (i.e. for those parameter sets that fall below a given threshold value). Only the simulations with a likelihood measures greater than zero are used for predictions, and these predictions are weighed by the likelihood measure associated with that simulation (Beven, 2001; Wagener et al., 2004).

Uncertainty in the parameter values and input data are propagated and represented in the model output in the form of confidence limits at specified percentiles (Wagener et al., 2004). The GLUE methodology thus requires sets of decisions to be made, i.e. (i) the model or models to be included in the analysis, (ii) a feasible range for each parameter, (iii) a sampling strategy for the parameter sets, and (iv) an appropriate likelihood measure.

As GLUE essentially explores how model performance varies over the

parameter space, results may be used for parameter sensitivity analysis. This seeks to identify sensitive parameters, i.e. those which most govern whether a model result is behavioural or non-behavioural (or high-likelihood or low likelihood). A quantitative measure such as the nonparametric Kolmogorov-Smirnov (KS, or d) statistic is normally used to assess the significance of the differences between the behavioural and non-behavioural parameter values.

The main criticism of GLUE is that the selection of the threshold used in separating acceptable (behavioural) and unacceptable (non-behavioural) simulations is purely subjective. In addition, most applications of GLUE use an informal likelihood function, does not attempt to find the maximum likelihood estimate of the parameters to benchmark the performance of the model (inconsistent with the formal Bayesian applications) which does not properly account for the number of measurements used to condition the parameter estimates (Mantovan and Todini, 2006; Mantovan et al., 2007; Vrugt et al., 2009).

Other methods include those based on formal Bayesian theory such as Markov Chain Monte Carlo (MCMC), which are a slight deviation from the GLUE methodology. One of them is the differential evolution adaptive metropolis (MCMC-DREAM) (Vrugt et al., 2009). Unlike GLUE, MCMC DREAM simulation uses a formal likelihood function based on maximum likelihood theory, appropriately samples the high-probability-density region of the parameter space, and separates behavioural from non-behavioural solutions using a cut-off threshold that is based on the sampled probability mass, and thus underlying probability distribution (Vrugt et al., 2009).

Other techniques based on the Bayesian theory are also available in the literature. These include particle filter algorithm (Smith et al., 2008.). In this approach, the model parameters are assumed to vary in time, and filtering process is used to identify a unique parameter distribution needed at each time to reproduce the observed data in an iterative way. The treatment of

model parameters as varying in time is another difference between this approach and other approaches such as GLUE mentioned above.

2.4.3.4 Model calibration

Since most of the parameters used in the conceptual models do not have a direct physical interpretation, they have to be estimated through calibration against observed data so as to improve the model fit (Wagener et al., 2004). Calibration is defined as the process of adjusting parameter values in order to optimise model performance according to predefined criteria (Watts, 1997). This is normally achieved by optimisation of parameter values by comparing the results of repeated simulations with available data. The parameter values are adjusted between each run of the model, either manually by the modeller or by computerised optimization scheme until some best fit parameter set has been found (Beven, 2001). These optimization schemes involve measures of goodness of fit or objective functions. The idea is to find the highest peak in the parameter space response surface defined by one or more objective functions (Beven, 2001). However, as noted above, better practice is considered to be the identification of, not just the parameter set associated with the peak, but a sample of equifinal parameter sets.

2.4.3.5 Model validation

In the literature, model validation or verification means a process of demonstrating that a given site-specific model is capable of making acceptable predictions for periods outside a calibration period (Refsgaard and Knudsen, 1996), usually in the form of a split-sampling test where a data set is divided into two periods of calibration and validation (Klemes, 1986, Wagener et al., 2004). However, there are many reservations expressed concerning the use of the words 'validation ' or 'verification', which come from Latin, meaning some degree of truth in the model (Oreskes

et al., 1994; Popper, 2000) in (Wagener et al., 2004) and (Beven, 2001). These investigators argue that no theory or hypothesis or model could ever be taken as a final truth, and there is no model structure nor the data necessary to identify that complex, unique, 'true' single realization that is the real catchment. Hence the concept of model validation should be replaced by model evaluation (Beven, 2001). And the definition of validation (or evaluation) as given by Refsgaard and Knudsen (1996) above, seems to support these views. Klemes (1986) proposed a rigorous hierarchical scheme of model evaluation, which contain four stages in which the model's performance to predict the output is tested, as summarised in Wagener et al. (2004):

- (i) A simple split-sample test, in which a data set is divided into two, one set used for calibration and another separate, non-overlapping set used to check the performance of the model (validation).
- (ii) A proxy basin test, where the model's capability to predict flow in a hydrologically similar catchment is tested. In this test the model is calibrated for one catchment, and validated by running the model using data for the other catchment.
- (iii) A differential split sampling test, where the two data periods selected have different hydrological characteristics (e.g. dry and wet periods), i.e. the model is calibrated for dry periods and validated using wet period data set.
- (iv) A proxy-basin differential split sampling test, i.e. combining tests (ii) and (iii).

2.4.3.6 Model performance and objective functions

Objective functions (OF) are measures of model performance, and often based on either measures derived from statistics or based on hydrological aspects of the model performance (Wagener et al., 2004). This is usually done in combination with visual inspection of the calculated output (i.e.

hydrograph). There are several OFs used in rainfall-runoff modelling. These include the Root Mean Square Error (RMSE) method (or the normalised RMSE), the Nash and Sutcliffe Efficiency (NSE) method (Nash and Sutcliffe, 1970), among others. The former has the advantage of being in the same units as the observed system output while the latter allows for the comparison of a model performance over different catchments. The aim of these OFs is to minimise the magnitude of the residuals.

The RMSE takes the following form:

$$RMSE = \sqrt{\frac{1}{N} \left(\sum_{i=1}^N (o_i - c_i)^2 \right)} \quad (2.1)$$

Where N is the number of data points, o_i and c_i are observed and simulated flows at month i .

The NSE is shown in Equation 2.2.

$$NSE = 1 - \frac{\sum_{i=1}^N (o_i - c_i)^2}{\sum_{i=1}^N (o_i - \bar{o})^2} \quad (2.2)$$

Where $\bar{o}$ is the mean of observed flows.

The above OFs have some limitations. By using the squared residuals or variance, they tend to exaggerate the influence of larger errors, which tends to be equivalent to exaggerating the influence of higher events (peak flows), and putting relatively little weight on lower events (low flows) (Perrin et al.,

2001, Wagener et al., 2004). Chiew and McMahon (1994) in (Perrin et al., 2001) used a slightly different criterion which was obtained by using root-square transformed streamflow as shown in Equation 2.3.

$$OF(\%) = 100 \left(1 - \frac{\sum_{i=1}^N (\sqrt{Q_{obs,i}} - \sqrt{Q_{calc,i}})^2}{\sum_{i=1}^N (\sqrt{Q_{obs,i}} - \sqrt{\overline{Q_{obs}}})^2} \right) \quad (2.3)$$

Where $Q_{obs,i}$ and $Q_{calc,i}$ are the observed and calculated streamflows at time step i , respectively. There are other OFs found in the literature, see (Perrin et al., 2001, Wagener et al., 2004) for detailed reviews.

Some investigators suggest the importance of studying the characteristics of the residual distribution in evaluating the suitability of a model structure, e.g. (Yapo et al., 1996, Mroczkowski et al., 1997, Wagener et al., 2004). This is based on the fact that if a fit produces residuals consistent with the random error assumptions, then the model has extracted all useful information from the data leaving only noise in the residuals (Wagener et al., 2004). This includes assessing: (i) whether the variance of the residuals increase with increasing flow values (which is known as heteroscedascity), (ii) whether the residuals reveal long term effects (trends) or dependency in time, (iii) how close the residual distribution is to a normal distribution, and (iv) how the residuals are correlated in time.

The question of which OF to use normally depends on the objective of the study. However, it is evident from the literature that using only one OF to judge the calibration of a model will lead to results which fail to simulate the hydrograph shape in a satisfactory way, hence the use of many OFs to assess the suitability of the model and its performance is recommended (Littlewood et al., 2003, Littlewood, 2002).

However, there is always a trade-off between different OFs such that by improving one OF may lead to a change in the other OF. As an example, Littlewood (2002) used two OFs, the D_c and %ARPE (in the IHACRES module to model low flows and high flows). The D_c was used to assess difference between observed flow and modelled flow (i.e. some form of an NSE OF), with a higher value of D_c representing a good model fit. The %ARPE (percentage average relative parameter error) OF was used to assess how well the model represents the unit hydrograph parameters identified in their previous studies (Littlewood and Jakeman, 1994), with a low %ARPE value representing a good model fit. He found that one model structure (model #1) which gave high D_c and low %ARPE values overestimated the low flows (i.e. when studying the flow duration curve for the study area). On the other hand, another model structure (model #2) was able to represent low flows very well, but yielded lower D_c and higher %ARPE values compared to those produced by model #1.

This example shows that it is not usually easy to have a single OF that adequately represent the entire hydrograph (i.e. such as when the aim is to represent both the high and low flows) but that a combination of different OFs may yield results that are acceptable within the limit of the study objectives.

2.4.4 Optimisation methods and parameter adjustment strategy

The search for suitable parameter sets can be manual, i.e. trial and error, which is often time consuming and labour intensive. Manual calibration therefore requires comprehensive understanding of catchment response behaviour and the model structure. Also the termination of the calibration process and the results thereof are subjective, and as a result the modelling expertise is not transferable to the next person (Wagener et al., 2004). For these reasons, and due to the increase in computer power and technology, automatic optimization approaches are available and utilised in hydrologic

modelling. These include local optimisation (search) and global optimisation schemes.

The local search schemes start at a single point (i.e. single parameter set in the feasible parameter space), and follow a programmed set of rules to find steps of improvement until a specified termination criterion is satisfied. These include (i) direct search methods (downhill simplex, pattern search and rotating directions methods, among others (Wagener et al., 2004), (ii) gradient approaches that use derivatives of the response surface in an iterative manner until convergence (Sorooshian et al., 1995, Wagener et al., 2004). The major problems associated with local search schemes is that they are often hindered by the presence of multiple response surface optima, and tend to get stuck at the local optima.

Also due to problems of large discontinuous and complex parameter spaces local search are often inefficient in finding the optimal parameter values. Global search schemes are seen as a solution to overcome the above problems.

An example is the evolutionary type of algorithm (which includes the Genetic Algorithms and the Shuffled Complex Evolution Algorithms (Wagener et al., 2004), and are widely used in rainfall runoff modelling search schemes (Wagener et al., 2004, Muleta and Nicklow, 2005, Cooper et al., 2007). The Shuffled Complex Evolution (SCE) algorithm in particular is esteemed for its ability to use complexes that share information, thereby ensuring that the search is really global (Wagener et al., 2004).

From the above discussion, it is clear that the challenges of rainfall-runoff modelling include selecting the appropriate OFs and the search for optimum parameter sets. Similarly, as discussed earlier there is a drawback associated with using a single-criterion. In order to overcome these shortcomings, a multi-criteria approach was proposed by Gupta et al. (1998), which seeks to (i) find the parameter population necessary to fit all

aspects of the observed output time series, (ii) increase the identifiability of the model parameters, and (iii) assess the suitability of the model structure to represent the natural system (Gupta et al., 1998, Boyle et al., 2000, Wagener et al., 2004).

2.5 Application of rainfall-runoff models in arid and semi arid areas (with major emphasis on southern Africa).

A considerable number of rainfall-runoff models of various degrees of complexity are available and have been applied in southern Africa. These include the Pitman model (Hughes et al., 2006), the IHACRES model (Dye and Croke, 2003), and the U.S. Soil Conservation Service (SCS) (Masopha, 2001). These models are reviewed below:

The Pitman model is a conceptual, monthly time step model which is widely used in the region, mainly in South Africa (Hughes et al., 2006). It is one of the old hydrological models developed in the early 1970s (Pitman, 1973) mainly to represent a wide range of hydrological processes such as interception, surface runoff, soil moisture storage, evapo-transpiration losses and routing at sub-basin scales of 10-1000s of km² (Hughes et al., 2010). It has undergone several improvements since its development to incorporate groundwater discharge and recharge (Hughes, 2004), and a spatially semi-distributed component in which sub-basins are classified based on model input and parameter set (Hughes et al., 2006, Hughes et al., 2010).

However, the main problems of the model are that it cannot be used for shorter time-steps such as daily, particularly when the aim is to account for non-linearity of hydrological response which naturally occur at these small time scales. Secondly the model is considered over parameterised (i.e. around 18 parameters to be estimated (Hughes et al., 2010)) and this may

affect calibration and identifiability procedures leading to poor performance especially in areas where these parameters cannot be supported by the data available (SMEC, 1991, Tsheko, 2006). However, the model has shown great potential for use in wetter catchments, such as the Okavango basin in Botswana (Hughes et al., 2006, Wilk et al., 2006).

The SCS model (also known as SCS-CN for Curve Number) model is also commonly used in the region (Andersen et al., 1998, Mocke, 1998, Masopha 2001). The model uses rainfall as input to compute runoff using curve numbers (CN). The non-dimensional curve number is an index which relates hydrological processes with catchment characteristics such as land use and cover, soil groups and soil moisture conditions. Higher CN values indicate higher runoff factor. Masopha (2001) used the SCS-CN model for some catchments in southern Africa and found that the model performed poorly for the drier catchments (Masopha, 2001). This was attributed mainly to the structure of the model, which only uses rainfall as input without any climate data such as temperature or potential evaporation. But runoff processes are more complex in drier catchments, and these complexities are not adequately represented in simpler models such as SCS-CN.

However, other investigators have reported that the SCS-CN model has potential for use in drier catchments. For example, Mocke (1998) used the semi-distributed version of SCS-CN in modelling recharge in the sand rivers of Botswana and found that the model gave better results when catchment average rainfall was used than when using rainfall obtained from other methods such as the Thiessen Polygon method. Secondly, he found that there was a strong relationship between proportional curve numbers (PCN, i.e. the curve numbers which are scaled by area) and drainage density. The latter was found to be the major physical factor which controls runoff processes in this area. This relationship was regarded as a step towards regionalisation since the PCN can be determined from the drainage density of any basin in the study area to compute runoff. The SCS-CN method used by Mocke (1998) provides an alternative for modelling the sand rivers of

Botswana. However, its utility in climate-change related studies may be limited in that only rainfall is used explicitly as input while evaporation is implicitly represented through the curve number (Mocke, 1998). In this way, it is difficult to incorporate explicitly, climatic changes resulting from variables such as evaporation and/or temperature.

The daily extended IHACRES model (discussed in 2.4.1.3) seems to offer great potential for use in arid areas, mainly because of its ability to represent the physical processes of arid hydrology even with fewer parameters (i.e. between 5 and 6 parameters depending on the type of catchment). The other advantage is that it uses climate data, i.e. rainfall, temperature/potential evaporation as input parameters to produce streamflow, making it useful in climate related studies. The non-linearity of rainfall-runoff processes in arid areas, and soil moisture storage which controls runoff generation processes is potentially well represented in the extended IHACRES model (e.g. McIntyre and Al-Qurashi, 2009).

Perhaps the most important aspect of the IHACRES model is that it uses climate data as input to generate streamflow, unlike the SCN-CN model reviewed above, which uses only rainfall as a climate variable. This may provide a platform for assessing the effects of climate variability on streamflow generation and water resources, which are the subject of the proposed study. This potential was also highlighted by Evans (2003), who found that IHACRES (CMD-IHACRES) was able to simulate runoff well when used with the regional climate models (Evans, 2003). Secondly, with the IHACRES model, processes can be represented on a daily time step unlike the Pitman model, whose highest time resolution is at monthly time step.

Thirdly, the model has undergone valuable modifications to account for essential processes that characterise arid hydrology, and for that reason it has been used in many areas of different hydroclimatic conditions, including areas similar to the proposed study area. The model is also efficient and easy to use compared to complex spatially distributed models that are

available in the literature.

2.6 Summary and conclusions on rainfall-runoff modelling

Hydrological models and their level of complexities have been reviewed. Simple models fall under the metric group classification, where the level of details required is less. On the far end of the spectrum are the more complex physics based models, which require detailed information to account for spatial variability and physical processes taking place. Between these extremes lie the conceptual group of models whose complexities can be pitched depending on the nature of the model task and supporting data.

It has emerged from the above discussion, and from the literature cited therein that while ideally the physics based models present an upper hand in the way they represent the physics behind the processes taking place at finer scales, such processes are not easily represented at larger scales due to huge amount of data required by these models. As a result, most of the parameters need to be calibrated. The interaction of parameters often makes calibration a difficult task, especially when observational data are not available at the desired scale. At best they tend to marginally improve upon conceptual model performances. At worst they will underperform against the conceptual models (less precision with higher uncertainty) at higher expense. For these reasons most researchers have not adopted the physics-based type of models-except when the purpose is to represent the land-surface-climate interactions and their feedback mechanisms based on the availability of extensive good quality data.

Metric models have been criticised for being too simple to capture the physical processes inherent in hydrological cycle. However, their simplicity compared to more process-based models has been appreciated especially in areas where data are limited, for example when only rainfall is available for hydrological modelling. The use of the classical unit hydrograph approach in

many hydrological studies speaks volumes about the value of metric models in data poor areas.

The most widely used group of models are the conceptual rainfall-runoff models. The dominant processes as perceived by the modeller are defined *a priori*, and hence the complexity of the model is informed by the key processes to be represented and the amount of data available. Calibration is therefore an important part of the modelling exercise, where the parameters are tuned to improve the model performance based on the observed data as well as performance criteria used to judge the model performance (i.e. by using objective functions). For this reason, there is need for sufficiently long data records to be used for calibration, evaluation (or validation) as well as simulations.

The issues of parameter interaction, lack of parameter identifiability and equifinality were also highlighted as problems associated with highly parameterised model structures encountered in both conceptual and physics based models. It was therefore highlighted that model parameters need to be kept as few as possible, i.e. typically not more than 6 parameters in order to strike a balance between model complexity and parameter interaction.

It also emerged that some models, called the hybrid metric-conceptual models do possess the merits of both metric and conceptual models. Furthermore, they tend to use few parameters while accounting for dominant hydrological processes. An example of these models is the well known IHACRES model, which has been used for about two decades across different climatic conditions and catchment scales. These models use only rainfall and temperature/evaporation as input, and therefore can be useful in areas where data is limited, such as in arid areas. They are also viewed as suitable potential candidates for dealing with ungauged catchments.

It was also observed that a lot of decisions need to be taken when selecting

the model structure, optimisation schemes as well as objective functions and the thresholds defining which model parameters yield acceptable results.

CHAPTER THREE

3 Case study description, data presentation and analysis

In this chapter the study area is described and justification is provided for the choice of the study area. Data sets used in this study are presented, analysed and discussed. This includes data quality, its completeness as well as its spatial and temporal coverage. The main findings are that: (1) there are indications of data quality problems at some gauges, such as N9, N11 and N13. Following this analysis, some data quality procedures were established. These include removal of suspicious data and treating them as missing values; applying a threshold to the data set to define a wet day; (2) An analysis of site-to-site daily rainfall showed low correlation between sites, ranging from 0.14 to 0.6 over radii of 140 and 20 km respectively. However the closeness of gauges was found not to be the only indication of inter-site correlation-rather, orographic effects were also found to affect inter-site correlation; (3) An analysis of annual rainfall revealed that rainfall in the upper Limpopo basin is poorly correlated with the El Nino teleconnection (i.e. $r^2=0.07$) despite numerous literature which suggest a strong relationship in most parts of southern Africa; (4) This relationship was weak when compared to that between temperature and rainfall (i.e. $r^2=0.22$) possibly indicating that temperature and other climatic variables could be the main drivers of inter-annual rainfall variability in the study area.

3.1 Introduction

3.2 The upper Limpopo basin

The case study basin (hereafter called “the catchment”) has an area of 7660 km² and is located within the Limpopo basin in north eastern Botswana, as shown in Figure 3-1. The Limpopo basin, shared between Botswana, South Africa and Zimbabwe, is critical in terms of water resources in Botswana since all the major dams used for water supply are located within it. Botswana’s recent national water resource strategy (Snowy Mountains Engineering Corporation and Engineering Hydrological Environmental Management Consultants, 2006) includes development of new reservoirs, including one at the outlet of the case study catchment, to increase security of water supply. The catchment is gauged at five locations leading to five sub-catchments with the outlet located in sub-catchment 5 in Figure 3.1.

All the sub-catchments have flow data, except for sub-catchment 4 (gauged at Shashe Bridge, see also (Table 3-4) where only the water level data are available. The area consists of gently undulating to highly variable altitude with lowest and highest points at about 850 and 1400 m above sea level (Table 3-5).

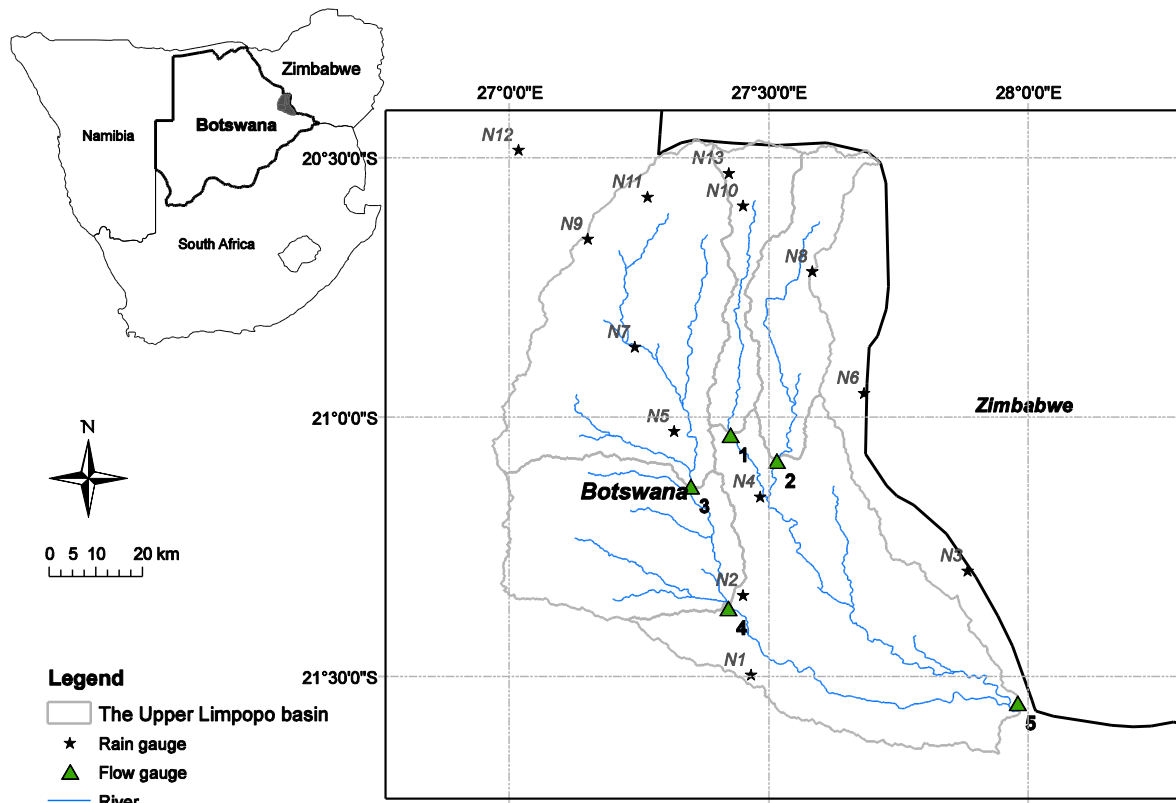


Figure 3-1: The upper Limpopo study area

Mean annual rainfall is about 450 mm and mean annual runoff at the catchment outlet is about 70 mm. Rainfall and runoff occur mainly between November and April. Annual rainfall in the study area varies from year to year. This variability may be partly associated with ENSO phases which are often linked with droughts and seasonal rainfall variability over southern Africa (Reason et al., 2005). However, recent studies suggest that ENSO may be poorly associated with rainfall in some parts of southern Africa (Manatsa et al., 2008) including the Limpopo basin (Kenabatho et al., 2010). Figure 3-2 shows the relationship between ENSO and rainfall for a selected gauge (N4) at an annual scale. N4 was chosen based on its long record length of 44 years. The rainfall values were standardized (zero mean and unit standard deviation) to make them comparable to the standardized ENSO values. It was found that there is a weak relationship between the two, with an r^2 of 0.07 (bottom plot). This was done in order to determine whether some of the

historical El Nino years are reflected in the rainfall records of the N4 gauge. It was found that only a few El Nino years are reflected in the rainfall records. For example, there is a strong agreement between ENSO and rainfall deficit in 1965, and a moderate agreement between 1990 and 1994. However, strong El Nino years such as 1982/83, 1987 and 1997 are not reflected at all in the rainfall records, which further indicate a weak relationship between the ENSO and rainfall in the upper Limpopo basin. This relationship will be investigated further in chapter 4 to determine whether ENSO has a bearing on the inter-annual variability of rainfall in this basin. A relationship between annual temperature and annual rainfall was also investigated using standardised values as shown in Figure 3-3. This plot shows that rainfall in the study area is inversely related to temperature, and the relationship is much stronger ($r^2=0.22$) when compared to that between rainfall and ENSO. This observation might be of interest particularly when considering issues such as climate change where temperature is generally expected to increase due to global warming. Further investigations regarding rainfall and temperature in the study area are carried out at monthly scale in section 3.4.3.

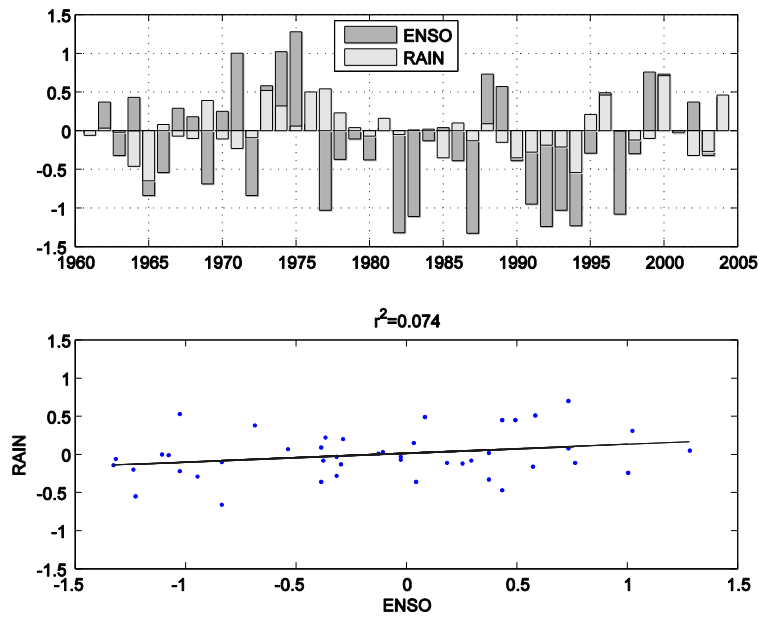


Figure 3-2: The relationship between ENSO and rainfall obtained from the N4 rain gauge.

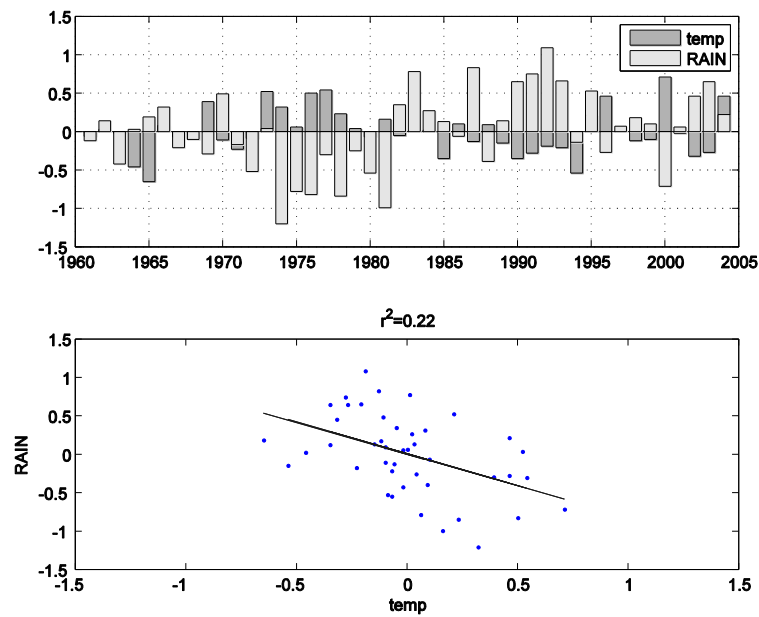


Figure 3-3 : The relationship between temperature and rainfall obtained from the N4 rain gauge.

Table 3-1: Summary of rainfall data used in this study

Station code	Station name	Data Source	Record period	Years in record	% missing data
N1	Tonota	DMS	1961–1996	36	1
N2	Shashe Dam	DMS	1973–1994	22	6
N3	Matsiloje	DWA	1980–1990	10	3
N4	Francistown	DMS	1961–2004	44	0
N5	Mathangwane	DWA	1969–2000	32	0
N6	Jackalasi No.2	DMS	1985–2002	18	9
N7	Sebina	DMS	1968–2004	37	1
N8	Tshesebe	DMS	1968–1994	27	1
N9	Ntondola	DWA	1973–2002	30	0
N10	Masunga	DWA	1973–2002	30	0
N11	Kalakamati	DWA	1973–2002	30	0
N12	Tutume	DWA	1972–2002	31	0
N13	Zwenshambe	DMS	1980–1995	16	1
V1*	Senyawwe	DMS	1981-1994	14	10
V2*	Siviya	DMS	1981-1992	12	9
V3*	Jackalasi No.1	DMS	1981-1994	14	11

* *Gauges whose data were reserved for model validation in chapter 4*

Seasonal rainfall in the area is generally affected by two trade winds, the south east trade winds of the Atlantic Ocean and the north east trade winds of the Indian Ocean. The boundary between the two trade winds is the Inter-tropical Convergence Zone (ITCZ). The movement and location of the ITCZ is

the major factor which is responsible for rainfall over much of southern Africa, including Botswana (Ramothwa and Minja, 2001). For example, during the summer (rainy) season (November-April) the south east trade winds move over the Atlantic Ocean collecting moisture from the ocean. The air mass then moves through the rain forests of the Congo where they reach near saturation. This air mass is commonly referred to as the “Congo Air mass Boundary (CAB) and are associated with the summer rainfall in southern Angola and Botswana (Ramothwa and Minja, 2001, Hudson and Jones, 2002, Nicholson, 2000).

The highest mean monthly maximum temperatures are generally recorded in the months of October and November. The highest maximum temperature ever recorded in the study area is 41.1°C (November 1951). Mean monthly minimum temperatures are generally recorded in July, and can drop to about 5°C. The estimated potential evaporation is about 2000 mm per annum.

3.2.1 Population and demand projections

The city of Francistown, which is the second largest city in Botswana, is located within the catchment. The population of Francistown alone is about 84 000 and it is projected to increase to about 90 000 by 2035 (CSO, 2001). The current average annual demand for major cities, including Francistown is estimated to be 77 ML, and it is projected to reach 190 ML by 2035 due to population growth, increased industrialisation and agricultural activities (Snowy Mountains Engineering Corporation and Engineering Hydrological Environmental Management Consultants, 2006).

3.2.2 Geology , hydrogeology, soils and vegetation of the basin

The Limpopo basin is characterised by bed rock exposures, mainly metamorphosed rocks known as gneissic granitoids, which have been

deformed over time (Mapeo et al., 2001). These are driven by the Limpopo mobile belt, which lies between the Zimbabwe and Kaapvaal craton. The belt is also known for its mineral deposits, i.e. nickel and copper as well as some gold deposit in the basin.

The main aquifer within the basin is known as the Archean Crystalline rocks, which are fractured, and have fair to good yielding aquifers (Gieske and Gabaake, 2001). Ground water is generally deep, which in some cases reach 80 m beneath the surface. However, shallow aquifers are found within the sand-dominated rivers in the basin (Mocke, 1998). Recharge varies from as low as 2 mm/year to 20 mm/year) in the basin compared to an average of 1.5 mm per year across the country (Gieske and Gabaake, 2001).

Limpopo falls within the hardveld of Botswana, which is characterised by 5 major soil types (Moganane et al., 2001). These are Arenosols (sandy, deep and low moisture soils), Regosols (stony, shallow soils with low water holding capacity), Leptosols (shallow and low moisture soils found mainly in the hilly areas of the catchment), Cambisols (young and fertile soils found) and Acrisols (acidic soils, with clayey materials).

The dominant vegetation type in the basin is known as Tree and Bush Savanna consisting mainly of *Colophospermum Mopane* trees and grassland (Moganane et al., 2001). Vegetation resources in this basin are mainly used for (1) livestock farming (e.g. free range livestock farming in communal areas, private commercial livestock farming in lease-held ranches); (2) firewood, which in recent years has become a major source of income to rural communities; and (3) fencing ranches and agricultural fields.

3.2.3 Land use

The dominant land use activities within the Limpopo basin are (1) agriculture (i.e. arable and pastoral farming) in communal areas and privately-owned ranches; (2) Mining (large-scale mining, which include Gold, Copper and Nickel mining); and (3) Residential (including towns and rural villages) (Mmolawa and Richard, 2001; Moganane et al., 2001; Kgomotso et

al., 2001). From these authors, 80% of the population is involved in agriculture, although these farmers are subsistence farmers, with only a few involved in commercial farming. Pastoral agriculture (mainly livestock rearing) takes place in communal areas, where livestock have free movement within the area and this often leads to overgrazing because of poor land management system (Moganane et al., 2001). Arable farming involves crops and vegetables farming. The main crops in the basin are sorghum, maize and millet. Although this type of farming has been mainly for subsistence purposes, the situation is likely to change in the future. For example, the government of Botswana is currently promoting commercial agriculture as one of the major economic diversification options and citizen empowerment initiatives (Khama, 2010). These initiatives are likely to encourage many people to venture into agriculture, which may put pressure on land and vegetation leading to changed catchment dynamics in the basin, as well as increase in water demand. Even without these interventions, a problem of overgrazing due to livestock overstocking is reported in the basin (Moganane et al., 2001). This problem has lead to soil erosion and land degradation in some parts of the basin, particularly in areas adjacent to ephemeral streams and down slope from adjacent plateaus. For example, the authors found that land degradation (i.e. the increase of bare soils as a result of vegetation and grassland loss) has occurred between 1984 and 1994, ranging between 10 to 30% across the cathment between these years.

Regarding future vegetation projections, other studies indicate degeneration of major vegetation types (between -15 to -40%) by the year 2050 in the basin due to agricultural related activities (Ringrose et al., 2002). These problems may affect river morphology in the basin which in turn, may affect flow regimes in the basin. For example, Parida et al (2006) shows that runoff coefficient in the Notwane catchment, which is in the upstream of the Limpopo case study has increased marginally (about 3% per year) for the period 1978-2000 due to land use land cover contributions and climatic

factors. In their study, they found that while 48% contribution came from climatic factors, 52% came from land use/land cover changes.

3.3 Rainfall data

Daily data for 16 rain gauges were obtained from two sources, the Department of Meteorological Services (DMS) and the Department of Water Affairs (DWA). The data extent and completeness are presented in Table 3-1, and the locations of the gauges are shown in Figure 3-1. It is clear from Table 3-1 and Figure 3.1 that most rain gauges have extended periods of missing data and that the gauges are sparsely distributed. Data from thirteen rain gauges (N1-N13) were retained for further analysis while those from the other 3 stations (V1-V3) were only reserved for future model validation purposes due to their high proportion of missing values.

3.3.1 Data quality assessment

It is well known that the quality of rainfall data in semi arid regions is generally poor mainly because of lack of resources available for collection and maintenance of instrumentation, insufficient rain gauge networks, and problems of accessibility to rain gauge sites during wet seasons (Mocke, 1998). Botswana is no exception, and the following problems have been noted regarding the collection and processing of data (Mocke, 1998):

- Periods of non operational gauges could be recorded as zero rainfall.
- Schoolteachers, who may occasionally leave the village over some weekends, generally operate rain gauges in the surrounding villages resulting in unusually high readings on Monday mornings due to weekend accumulation.
- During summer holidays in December and January often no

recordings are taken during this time which results in accumulated total recorded at the end of January.

- Gauge readers are sometimes unsure of when to record the readings. The standard practice is to read the gauge at 8:00am and record the rainfall as the previous day's readings. However, often it may be recorded as that day's reading.
- Occasionally the incorrect number of days in a month is used when the data is digitised so rainfall is registered on an incorrect day.

Clearly, these are potential sources of error and anyone of these will affect the quality of rainfall data for modelling applications in this area. In order to investigate this, the data from the thirteen rainfall gauges were subjected to quality checks using the following approaches:

1. Removal of suspicious rainfall values.
2. Dealing with inconsistencies due to presence of small values.
3. Establishing correlations of daily rainfall amounts with distance.
4. Box plots.
5. Double mass plots.

These are widely used as data quality checks in hydro-meteorological studies and rainfall modelling (Chandler and Wheater, 1998, Wheater et al., 2006, Yang et al., 2006).

3.3.1.1 Removal of suspicious values

Figure 3-4 shows annual rainfall data for all the stations during the period 1961-2004. Some values which appeared to be suspicious were removed from the data base. For example, during the years 1982-83 station N9 recorded values close to zero, while in 1983 N10 recorded no rainfall at all

(but reported zero rainfall), presumably meant to be a period of missing values. These values are inconsistent with the rest of the values recorded by other stations. Further assessment of daily records revealed that some values appeared suspicious, which were probably meant to be recorded as monthly totals. These were also removed from the database and reported as missing values.

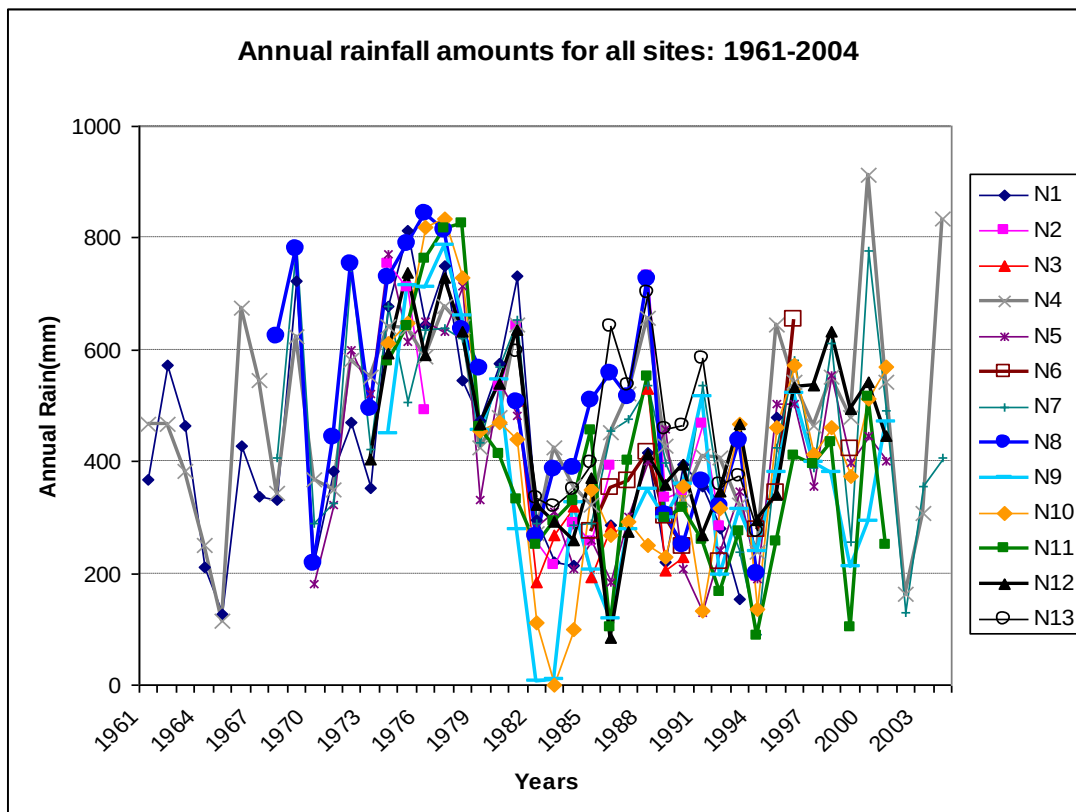


Figure 3-4 : Annual rainfall amounts for all the thirteen gauges

3.3.1.2 Inconsistencies due to the presence of small values

It is possible that inconsistencies in spatial rainfall amounts may also arise due to differences in recording instruments, among others. For example some rain gauges may be read manually while others are automated. This normally causes discrepancies in rainfall amounts particularly during periods of light rains (Yang et al., 2006). The situation becomes even more complicated when data sources are obtained from various sources, such as in the work reported here (see Table 3-1). These inconsistencies are normally corrected by applying a threshold to the data set provided the threshold is small enough, and is based on the precision level of the measuring instrument. In the work reported here, a threshold of 0.5 mm was used and this value is used by the Department of Meteorological Services (DMS), and is also consistent with the values used by many researchers (Yang et al., 2005, Wheater et al., 2006). To illustrate the importance of applying a threshold to rainfall data, two stations which are highly correlated (i.e. r^2 is 0.6) are used to plot cumulative rainfall for both occurrences and amounts, with and without a threshold Figure 3-5. The two stations have a separation distance of 21 km, and have an elevation difference of 5 m. The plots on the left show cumulative wet days while those on the right show cumulative rainfall amounts. The top plots have no threshold while the bottom plots have threshold. The 45° line shows what is expected if the two stations behave in the same way.

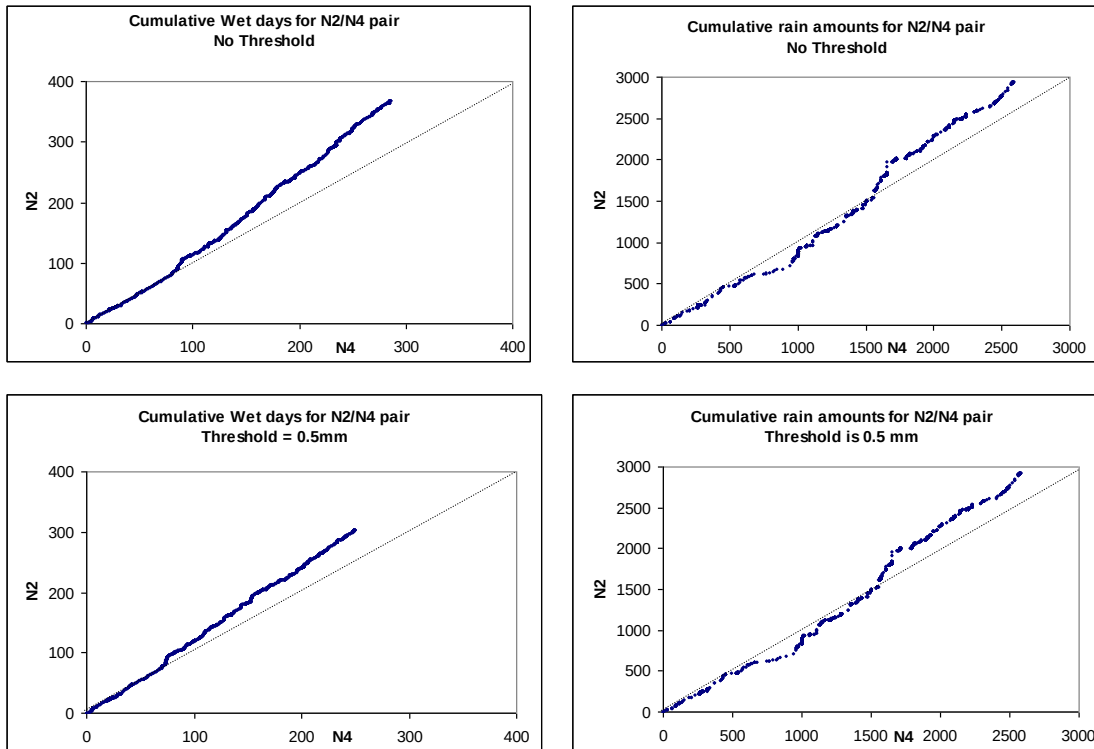


Figure 3-5: Threshold using N2 and N4 stations

The effect of thresholding is more evident on the plot which shows cumulative wet days (left plots) since the magnitude of discrepancy is reduced when a threshold of 0.5 mm is applied. It was also found that the numbers of wet days were reduced by about 1% and 3 % for N2 and N4, respectively when a threshold was applied. Thresholding does not show any effects when it comes to the rainfall amounts (right plots). From Figure 3-5 it can be concluded that thresholding affects rainfall occurrences and has little effects on rainfall amounts. Furthermore, it can be seen from the same figure that thresholding is not the only cause of inconsistencies. Other possible factors could be data quality issues at one or both gauges.

3.3.1.3 Correlations of daily rainfall with distance and elevation

An analysis of site-to-site daily rainfall showed low correlation between sites (Figure 3-6), ranging from 0.14 to 0.6 over radii of 140 and 20 km respectively. However the closeness of gauges was not a good indication of inter-site correlation, for example the correlation between daily rainfall at sites N10 and N13 (10 km apart) was only 0.37. The reason for this could be related to topography - N13 is located at a higher altitude and may be more subject to orographic influences. In order to investigate this hypothesis, stations which show higher site-to-site correlations were pooled for further analysis. It was found that the stations located around the centre of the basin (approximately) are highly correlated as shown in Table 3-2 and Figure 3-7. This indicates that rainfall is more uniform over this part of the catchment where topography is relatively flat compared to elsewhere in the catchment.

Regarding the variation of mean annual rainfall with altitude, marginal increasing trends were observed for rainfall amounts ($r^2=0.3$) and mean number of wet days ($r^2=0.14$) in Figure 3-8. Given the apparently complex spatial correlation structure, conventional deterministic methods of infilling the missing data are likely to mis-represent the rainfall field and will not represent the associated uncertainty.

3.3.1.4 Box plots

Box plots are usually used to assess the distribution of rainfall amounts or the spread of rainfall values using quartiles. The quartiles include Q_0 (Normally the minimum); Q_1 (the 0.25 percentile); Q_2 (the median); Q_3 (the 0.75 percentile) and Q_4 (normally the maximum). They also indicate possible outliers within the data set. Daily rainfalls for each station were used to construct the box plots. A threshold of 0.5mm was applied to all the daily rainfall data meaning that only rainfall values higher than the threshold

were considered for the box plots. Only non-zero rainfalls were considered for the box plots. This was necessary because if zero rainfall values are included, all the quartiles are almost zero except the higher quartiles. The results are shown in Figure 3-9.

In general the stations show some variability regarding the higher quartiles, mainly the maximum rainfalls. Secondly, there is a slight increasing trend regarding the median quartile. For example the stations that are located at higher altitudes show high median values (see Figure 3-8 which shows the - station altitudes). Also, it appears that in general the stations which receive high rainfalls (e.g. N8, N7, N12 and N13) tend to have high spread of values than the rest of the stations. However, N6 tends to have a high spread although the mean annual rainfall and the number of wet days are relatively low. This might be a data quality problem for this station. Besides this observation, the box plots do not show any major inconsistencies regarding the remaining data sets.

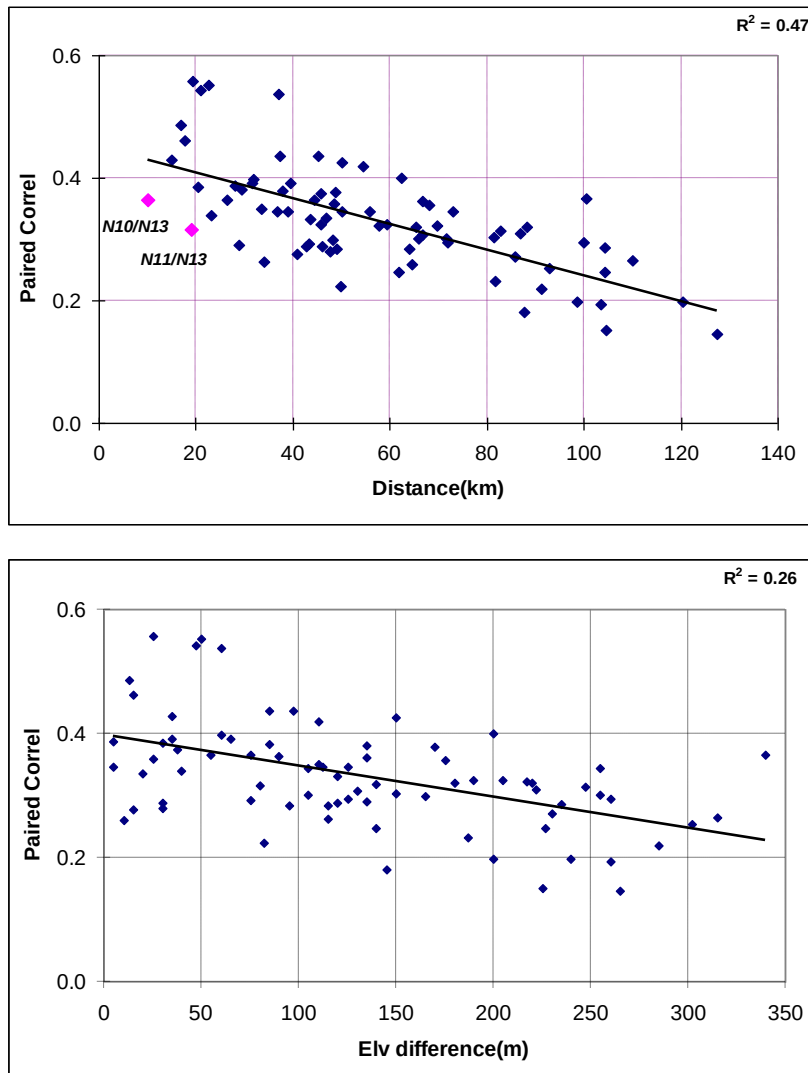


Figure 3-6: Correlation between pair of stations using rainfall amounts. The top plot shows correlation of rainfall with distance, while the bottom plot shows correlation of rainfall with elevation.

Table 3-2: Pooled pairs of sites which show high correlations between daily rainfall and distance

Station A	Station B	Correlation	Dist (km)	Difference in Elevation (m)
N10	N11	0.56	19	25
N4	N5	0.55	23	50
N2	N4	0.54	21	47
N1	N4	0.54	37	60
N1	N2	0.49	17	13
N5	N7	0.46	18	15
N2	N5	0.44	37	97
N3	N4	0.44	45	85
N9	N11	0.43	15	35
N5	N10	0.42	50	150
N1	N5	0.42	55	110
N4	N10	0.40	62	200
N9	N10	0.40	32	60

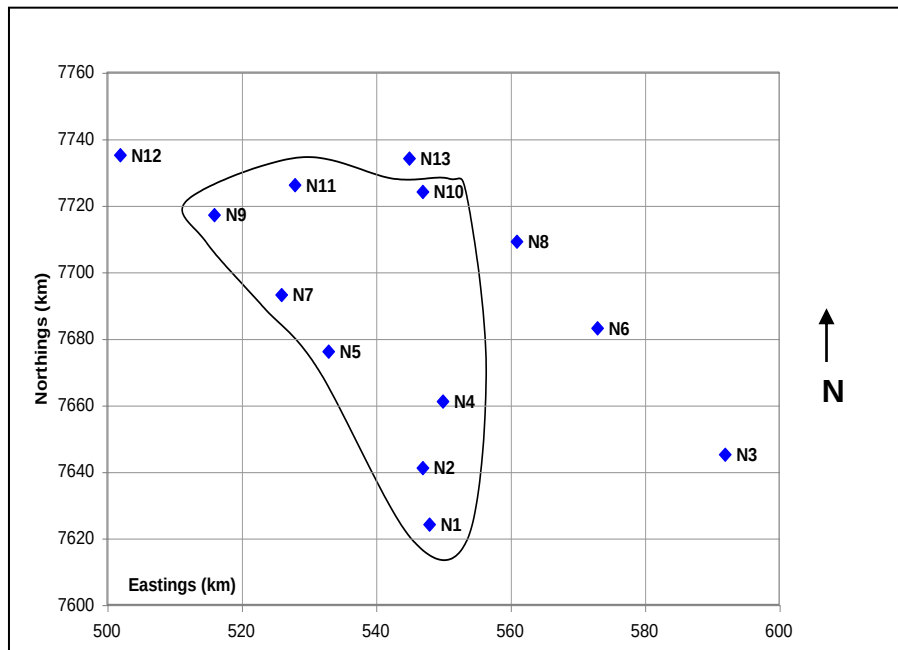


Figure 3-7 : A map showing rainfall stations in the basin. The circled stations show high correlations between rainfall and distance

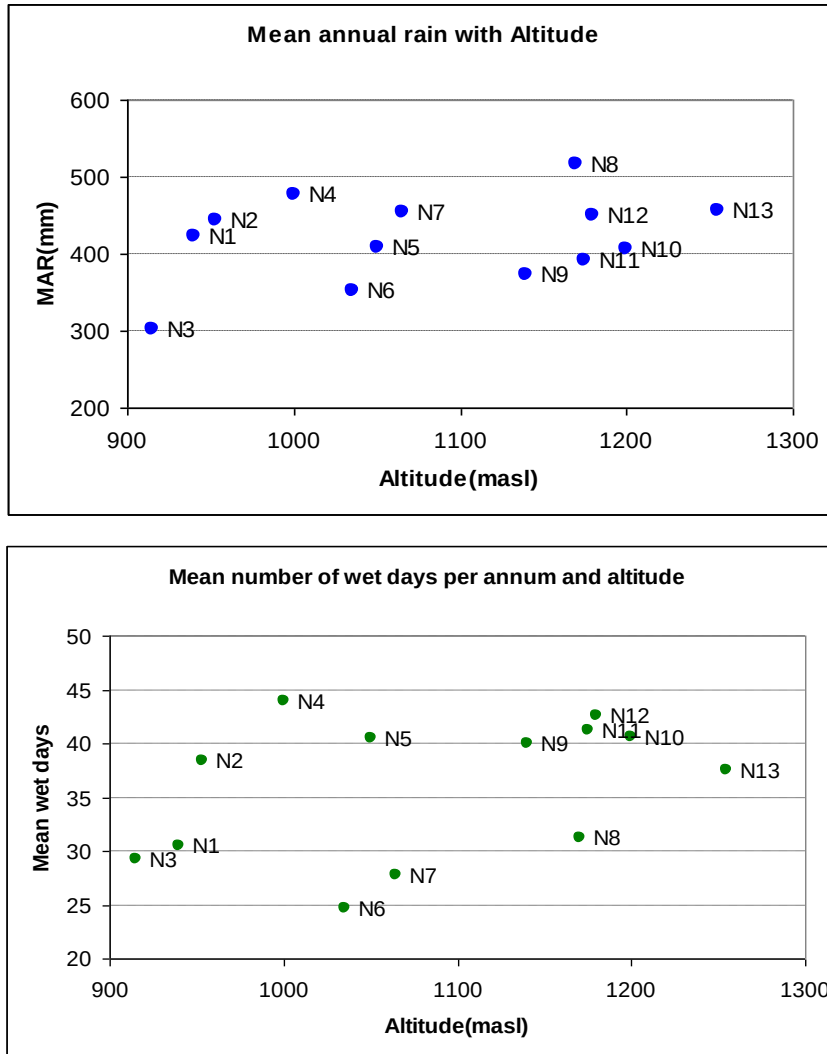


Figure 3-8 : Mean annual rainfall and wet days plotted against altitude

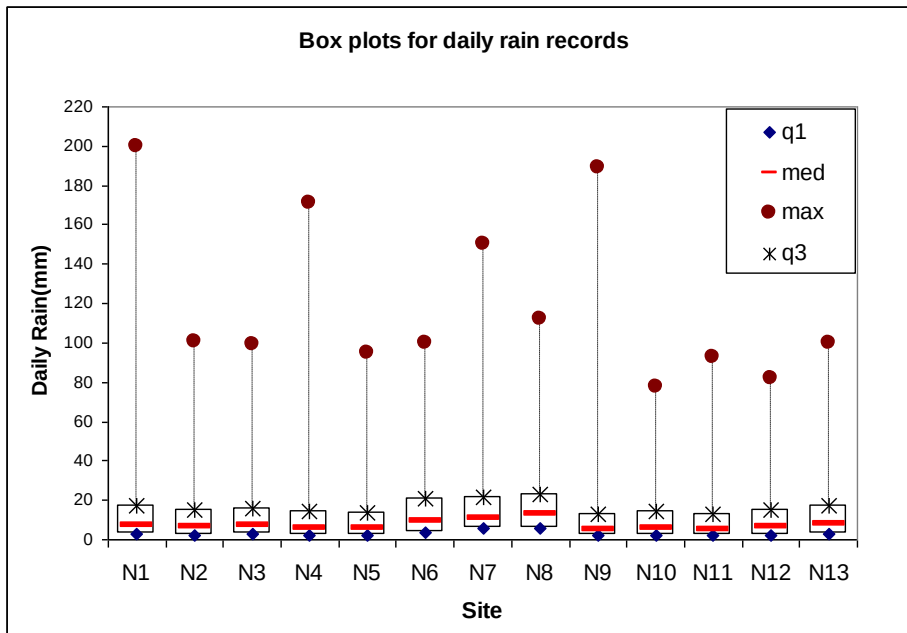


Figure 3-9: A box plot showing the spread of values for each site

3.3.1.5 Double mass plots

The final data quality check was through the use of double mass plots (Figure 3-10). The double mass curve/plot is a graph of cumulative rainfall for the station of interest against those for the neighbouring stations. The underlying assumption is that there is no change in the relationship between rainfall from the test station and that from the other stations. If the test station is consistent with the rest of the stations then the plot should appear linear without significant break in slope. The closest stations are N10 and N13, located about 10 km from each other while the furthest stations are N3 and N12, with a separation distance of about 128 km (see also Figure 3-7). The double mass technique has been criticised for not being as applicable in semiarid and arid regions due to the spatial variation in rainfall in these regions (Mocke, 1998). This was kept in mind during the analysis process and only those gauges that showed very large deviations from the average values were considered to have significant data quality

problems.

Double mass plots for some of the gauges used here were undertaken by Mocke (1998), but only for 5-years, between October 1990 and September 1995. The reason for choosing this period for analysis was to incorporate the calibration year considered for a rainfall-runoff model used (Mocke, 1998). Gauges were subdivided into groups of three neighbouring stations and double mass plots were derived for these groups of stations. Based on this, stations were classified as shown in Table 3-3. Data quality was assessed based on the proportion of missing values (as these were included when constructing double mass plots), presence of dubious values and whether the stations showed large deviations from the average rainfall in each group, and the results are summarised in Table 3-3.

Table 3-3 : Summary of data quality as obtained from Mocke (1998)

Classification	Gauges	Performance
Best gauges	N4, N5, N8, N9, N10,	Good performance, match average
Good gauges	N11	Good performance, higher/lower than average
Average gauges	N6, N13 (some dubious values)	Poor performance, match average
Poor gauges	N7 (no rain between 24/12/92 and 30/12/93)	Poor performance, higher/lower than average

(Adopted from Mocke (1998) and slightly modified to include codes used in Table 3-1: N1-N3 and N12 were not among the stations used by Mocke).

A few points can be said about Mocke's findings:

- That these results are only valid for the period October 1990-September 1995 and may not give a true picture when considering longer records outside this 5 year period.
- The inclusion of periods with missing values in the double mass plot is problematic since there will be no distinction between zero records and missing records.
- Dividing the stations into groups of neighbouring stations might be a good idea when assessing the mean rainfall for each sub-basin but might be limiting if the ultimate aim is to explore spatial relationships between the stations over the entire basin.

However, these findings provide a basis for understanding the nature and type of data quality issues for rainfall data in this area. In particular, the extended periods of missing values as well as the presence of dubious values. Station 7 was classified under poor gauges on the basis that there was no rainfall during the period 1992-1993. However, from our records this is not true since this station has complete records during the same period. The reason for this discrepancy is unknown, but it could be that the database was not updated during the time when his study was undertaken.

In the work reported here, double mass plots were constructed only for days with rainfall records. Periods with missing values were not considered and as a result the records lengths were reduced for stations with missing values. It can be seen from Figure 3-10 that in general the double mass plots do not show unusual changes in the slopes except for few stations, principally N6, N9, N10, N11 and N13 which might indicate that there is a data quality problem at one or both of these stations. For this reason, data from these stations were excluded when computing the mean rainfall shown in the x-axis of Figure 3-10. However, this did not make any discernible difference from the plots obtained when data from these stations were included in computing mean basin rainfall. However, for any model applications, a sensitivity study on the quality of data to model performance

may need to be investigated (see Chapter 4).

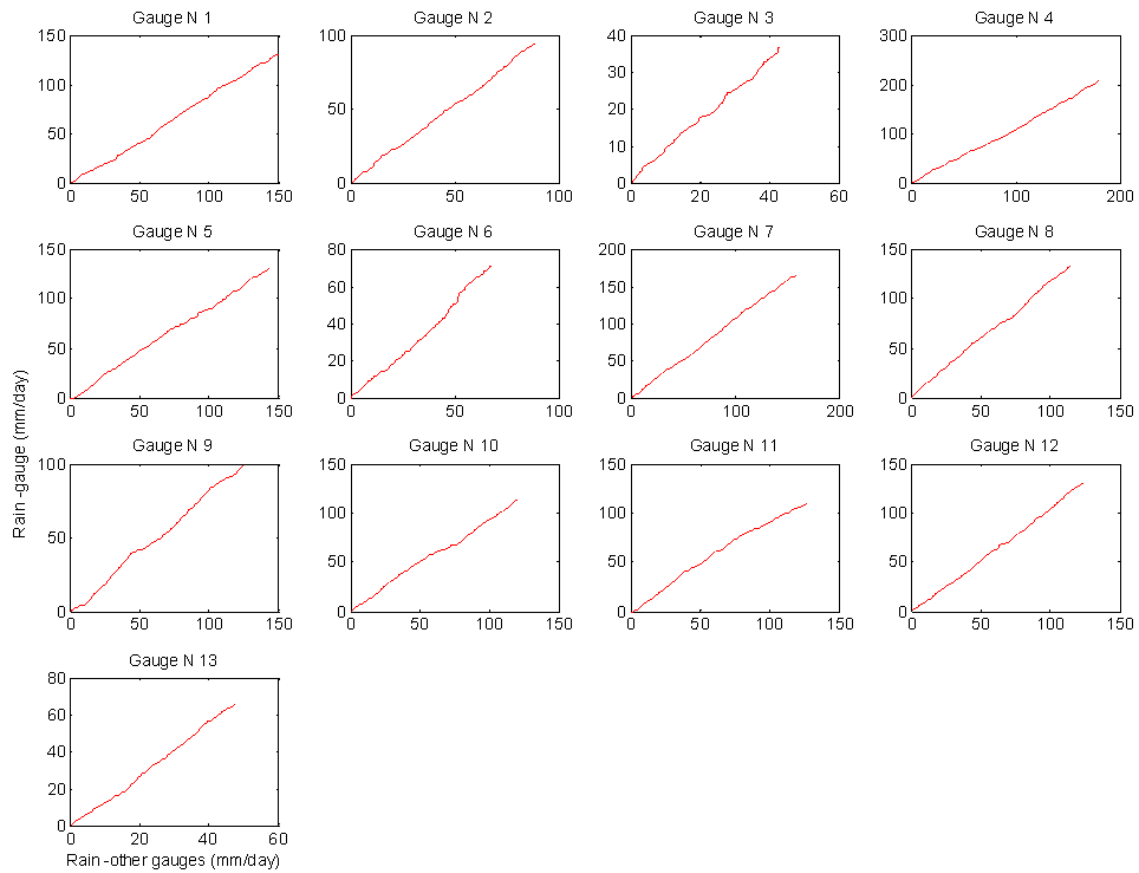


Figure 3-10: The double mass plots constructed using daily data for all the stations used for model fitting. Rainfall is in the units of $\text{mm} \cdot 10^2$. The y-axes represent cumulated daily rainfall for each gauge while the x-axes are the cumulated mean rainfall for other gauges. A visually linear plot shows consistency between the test gauge and the rest of the gauges.

3.4 Additional data analysis

3.4.1 Distribution of annual rainfall amounts and occurrence

Prior to rainfall modelling, some additional data analyses were undertaken in order to gain more insight into the general rainfall properties in the study area. Figure 3-11 shows rainfall amounts and occurrence in the Limpopo basin. It can be seen that in general the two plots show high inter-annual variability, with more rainfall amounts and occurrences high during the period 1976-1979 than any other period. The period 1997-2000 also has higher rainfall frequency.

However, some observations can be made regarding the individual stations. For example, station N4 shows the highest rainfall amounts in 2000, followed by N7 and N12. But station N12 recorded the highest number of wet days during this year, followed by N4, while N7 recorded small numbers of wet days during the same year. This possibly indicates that more wet days do not necessarily translate into higher rainfall amounts in this basin. This is certainly due to the fact that the wet days observed may constitute only smaller rainfall amounts. Similarly, one rainfall event might be an equivalent of monthly total rainfall possibly due to the fact that rainfall in arid and semi arid areas is largely convective.

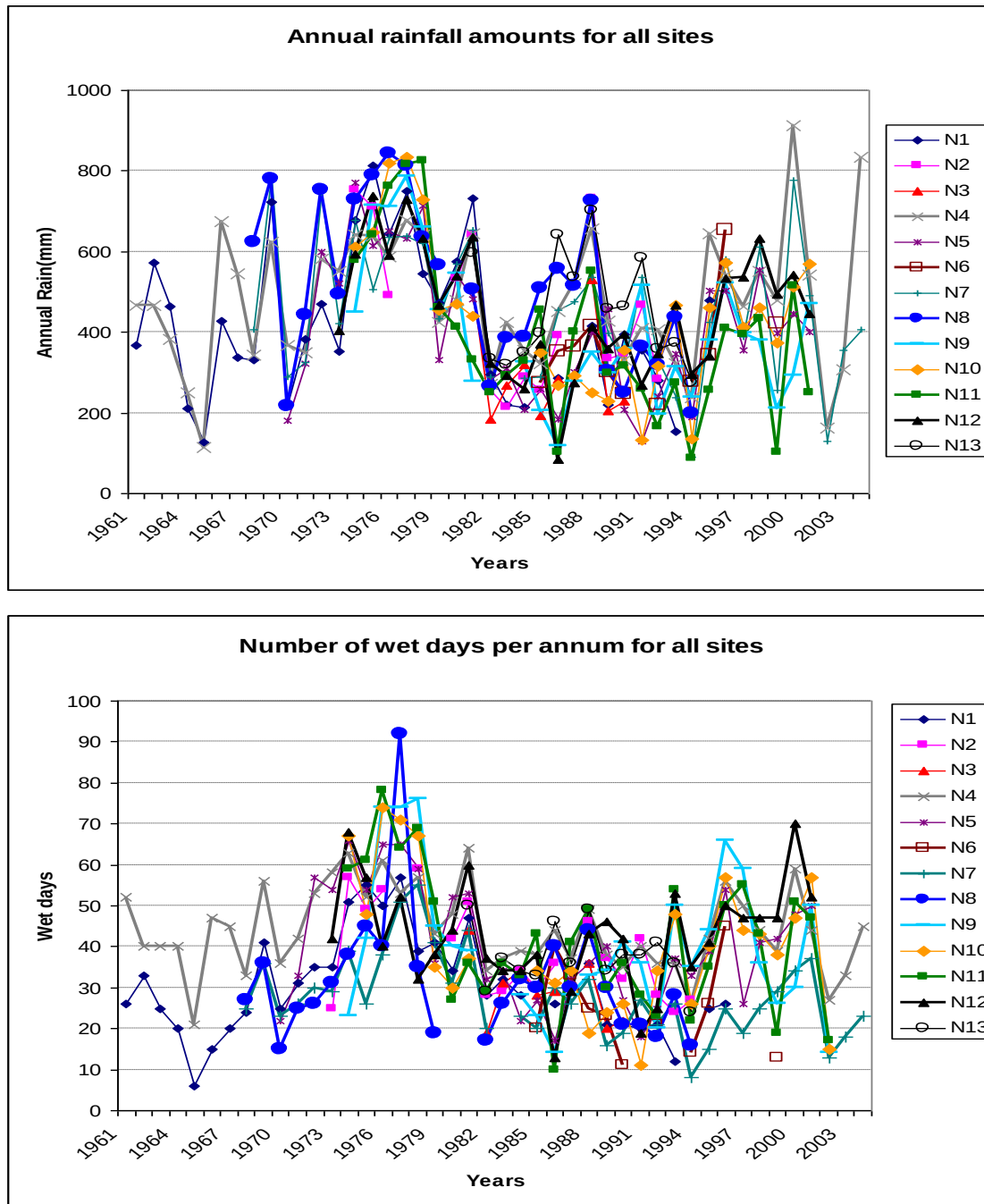


Figure 3-11: Distribution of rainfall amounts and occurrences in the Limpopo basin

3.4.2 Distribution of monthly rainfall amounts and occurrence

Figure 3-12 shows that intra-annual rainfall in the Limpopo basin follows some U-shaped cycle, with more rainfall occurring during the months of October-April (wet season). The remaining period of May-September represents the dry season. The bottom plot shows the proportion of wet days for each station in each month, and they follow the same distribution as the mean rainfall and wet days. It is also observed that on average the proportion of wet days in a month in the Limpopo basin does not exceed 30% even during the wet season.

3.4.3 Relationship between monthly rainfall and temperature

Figure 3-13 shows the relationship between monthly temperature and rainfall in the study area. Maximum temperatures (i.e. monthly averages) and mean monthly rainfalls were used to study these relationships. The data used here are for station N4, which is located at the centre (approximately) of the catchment, and was considered representative of the entire catchment. Secondly, this is the only station which has temperature data within the catchment. Thirdly, the station has long and complete records, from 1961 to 2004 for both temperature and rainfall. However, this issue is revisited in Chapter 4, where more representative spatial temperature data is used. Only the results for the wet period are shown (Figure 3-13). It can be seen that in general there is an inverse relationship between temperature and rainfall as was observed in section 3.3. However, these relationships vary from month to month, and from season to season, and are generally stronger when compared to those at annual scale reported in section 3.3. For example, during the wet season, a stronger relationship is observed during the month of January (r^2 is 0.43), followed by March (r^2 is

0.34), October and February (r^2 is 0.26 and 0.23, respectively), then December (r^2 is 0.21). A weak correlation is observed for the month of November (r^2 is 0.03). This correlation is the weakest compared to the rest of the months (including the dry period). This is surprising and the reason for this is unknown. The same trend was observed when the mean temperature was used instead (not shown).

The temperature-rainfall relationship could be an indication that temperature is an important climatic factor which influences rainfall in the study area. As such, any significant changes in temperature could have negative impact on rainfall in the study area. For example, Figure 3-12 shows that more rainfall occurs during the period October-March (which is the wet and hottest period), and this is the period in which stronger temperature-rainfall relationships were observed. Although the physical basis for rainfall-temperature relationship is not known in this basin, other studies elsewhere show that where this relationship exists, it is mainly because of large scale thermal advection dynamically induced by anomalous tropical heating associated with convective rainfall (Liu and Yanai, 2001).

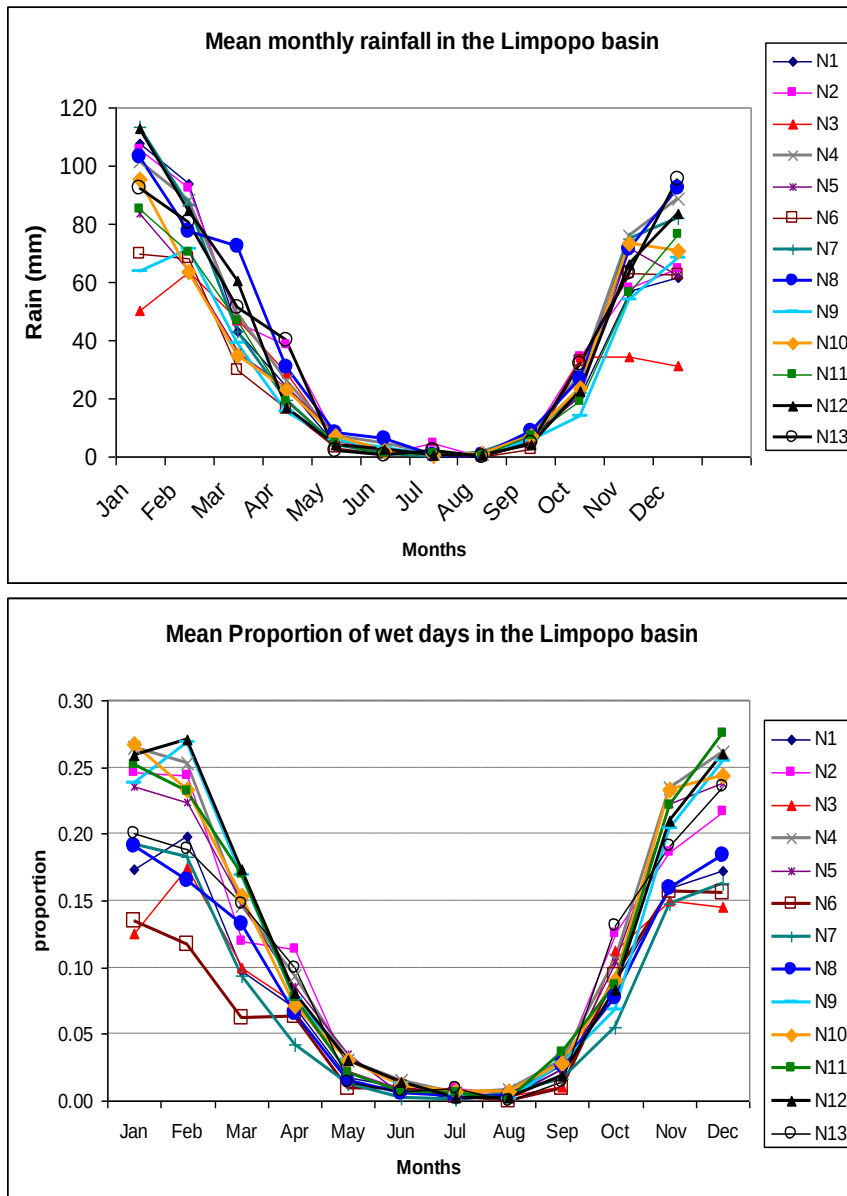


Figure 3-12: Mean monthly rainfall and proportion of wet days in the Limpopo basin.

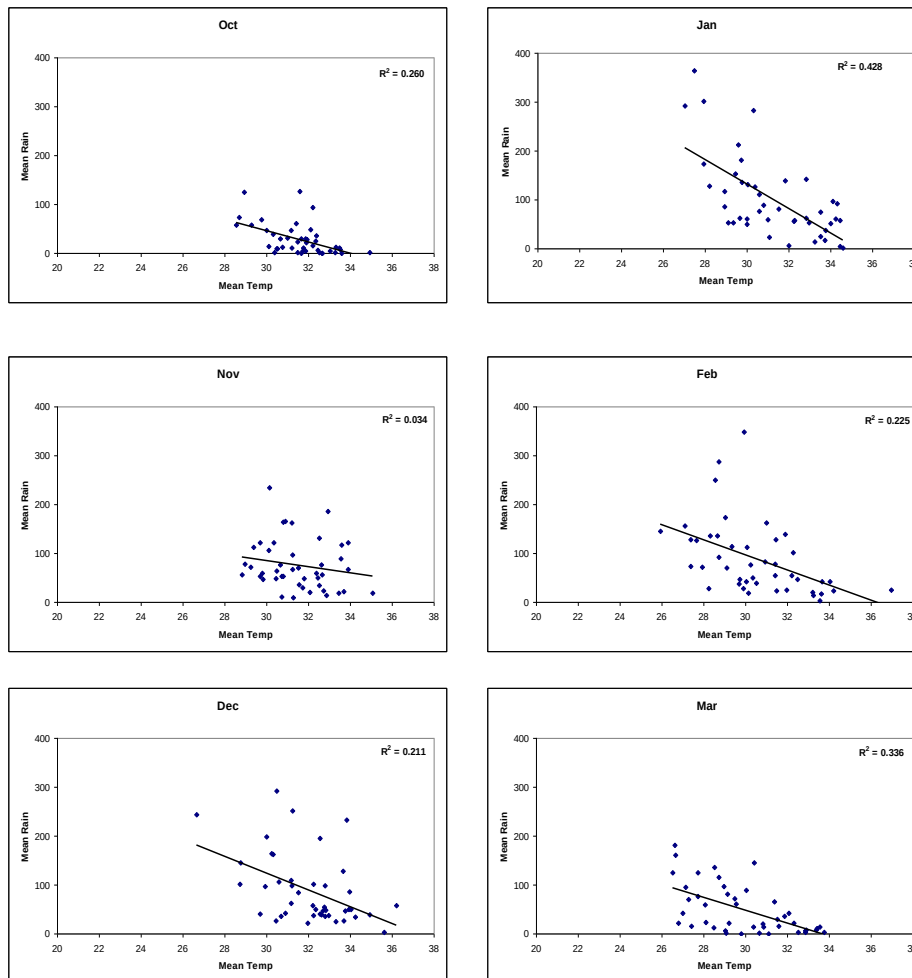


Figure 3-13: Relationship between Monthly maximum temperature and rainfall in the Limpopo basin (rainfall unit is mm, and temperature unit is °C)

3.5 Conclusions

In this chapter, preliminary data quality checks were undertaken using different approaches in order to identify unusual features of the rainfall data. It was suspected that the data had some dubious values which were removed from the data set. The issue of inconsistency in rainfall amount as a result of the presence of small values was investigated. It was found that this was one of the contributing factors in spatial rainfall inconsistencies. By using a threshold the inconsistency was reduced particularly for the rainfall occurrences. This intervention is necessary, for example if stochastic models are used for simulating daily rainfall occurrences. This is because these models simulate rainfall amounts based on rainfall occurrences. So, the presence of unnecessary trace values will count as wet days, which in turn may affect the simulated rainfall amounts. From this observation it can be concluded that for purposes of rainfall modelling studies, the models should be fitted to thresholded data in order to minimise errors due to trace rainfall values.

The box plots did not show any worrisome inconsistencies for most gauges except the high spread of values associated with N6. The double mass plot for this station did not reveal any anomaly. In his analysis, Mocke (1998) noted that N6 recorded low rainfall values between 24/11/92 and 10/01/93. However, in this work it was found that other stations recorded lower values during this period as well, with some stations recording values which were lower than those of N6. So it is not clear why N6 shows high spread of values in the box plots. However, this will be treated as an indication of a data quality problem-which was kept in mind when interpreting the rainfall model results. The main finding from the box plot was that the stations located at higher altitudes, which in general experience high rainfalls tend to have high spread of values.

Regarding the daily rainfall correlations, it was also established that in

general rainfall correlations between stations decrease with distance. This shows that stations which are located close to each other are more likely to experience similar rainfall amounts on some days than those which are located far away. However, it was also found that the closeness of gauges was not a good indication of inter-site correlation; since some gauges which are located close to each other were poorly correlated. Topography was also found to be an indicator of inter-site correlation, where gauges which were located at relatively same elevations (particularly those located at the centre of the basin) were more correlated with each other than those located at highly variable topography. From the double mass plots, it was found that stations N6, N9, N10, N11 and N13 show some inconsistencies in relation to the mean rainfall of other stations, and this could be a data quality problem at one or both of the gauges. It will be interesting to see how the discrepancies shown by these stations affect the performance of a stochastic rainfall model.

Another major finding from this chapter is that rainfall in the upper Limpopo is poorly correlated with the El Nino teleconnection despite numerous literatures which suggest a strong relationship in most parts of southern Africa. It was also observed that monthly (and annual) temperatures have an inverse relationship with rainfall in the study area. The relationship is stronger during the wet season compared to the dry season. These findings are very important and may be useful when undertaking rainfall modelling for this basin. For example, ENSO, temperature and other atmospheric variables could be considered to determine the main drivers of inter-annual rainfall variability in the upper Limpopo basin, which is the subject of chapter 4.

3.6 Streamflow data and catchment delineation

Tables 3-4 and 3-5 show the streamflow data for the basin, and some catchment characteristics derived from catchment delineation exercise.

There are no streamflow records for the Shashe Bridge gauge-the gauge water levels are available but have not been processed to obtain flow values. The rest of the stations have flow values as shown in Table 3-4. The station with highest percentage of missing values is Ntshe Weir (3.4%) while the lowest is Tati Weir (0.04%). The Lower Shashe gauge which is located at the catchment outlet has the highest MAR (69mm) while the gauge with lowest MAR is Shashe Mooke (32mm). An analysis of annual streamflow variability shows that streamflow in this basin is highly variable (with coefficient of variation ranging between 0.87 (Mooke catchment) to 1.43 (the catchment outlet). The high variability is typical of semi arid regions and the values reported here are comparable to those of other semi arid areas within the neighbouring countries in southern African. For example, the Vis River at Harderug South Africa (with coefficient of variation of 1.27) (McMahon et al., 2006). The Upper Limpopo basin has 5 sub-catchments as shown in Table 3-4, Table 3-5 and Figure 3-1. However, for modelling purposes only four subcatchments with flow data will be used as detailed in chapter 5. Streamflow time series for the four subcatchments are shown in Figure 3-14, indicating high flows observed at the catchment outlet. Further, more detailed, analyses of streamflows are provided in chapter 5.

There are three main rivers in the basin, namely Tati, Ntshe and Shashe Rivers, which all drain to the catchment outlet. The catchment was delineated based on the flow gauges. The catchment characteristics are presented in Table 3-5. These data indicate a heterogeneous basin, in which subcatchments differ mainly in terms of slope, stream length and basin elevation-potentially indicating non-uniform hydrological processes within the basin. These variations therefore may need to be accounted for when calibrating hydrological models for this basin, which is the subject of chapter 5.

Table 3-4

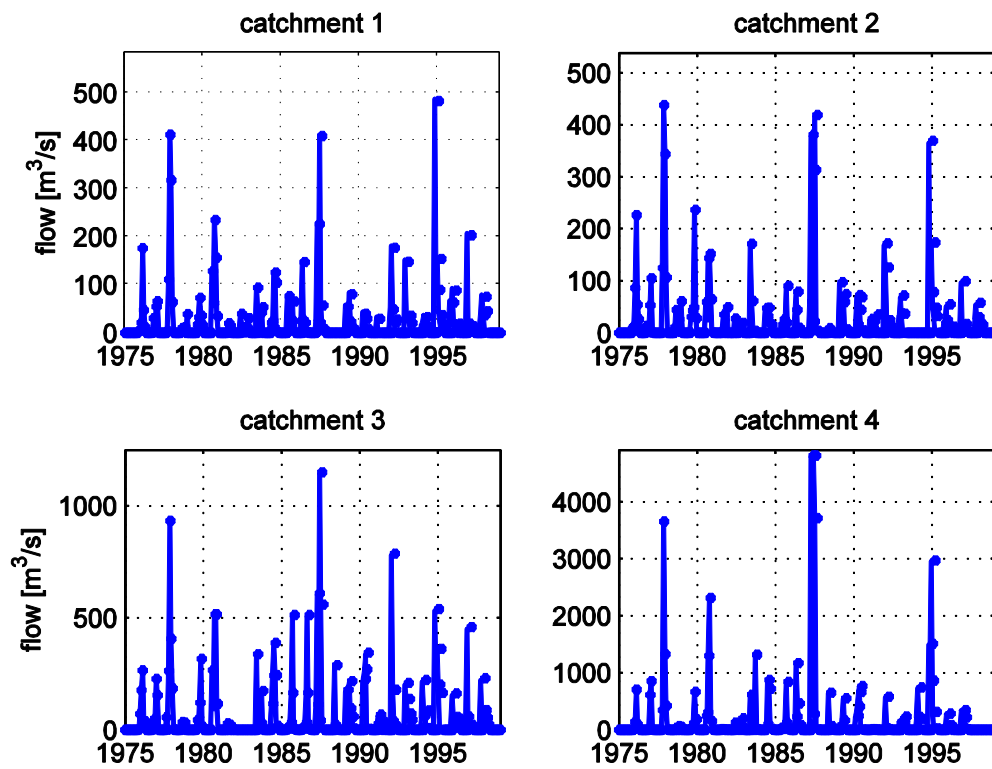


Figure 3-14: Monthly streamflow data for the subcatchments, including the catchment outlet (catchment 4).

Table 3-4 : Streamflow data for the Upper Limpopo basin in Botswana

River	Location	Code in Figure 3- 1	Area (km ²)	MAR ^[*] (mm)	CV of annual flows	Record	Years	%Dry	%Gaps
Tati	Tati Weir	1	539	48	1.31	(1970-1999)	30	83	0.04
Ntshe	Ntshe Weir	2	788	37	1.04	(1970-1999)	30	80	3.4
Shashe	Mooke Weir	3	2245	32	0.87	(1968-1999)	32	85	0.1
Shashe	Shashe Bridge	4	1409	-	-	-	-	-	-
Shashe	Lower Shashe	5	2680	69	1.43	(1970-1997)	28	84	1.8
	Total area		7661						

[*]MAR is the mean annual runoff

Table 3-5 : Catchment characteristics derived from catchment delineation

River	Sub catchment	BS ^[1]	MSS ^[2]	MSL ^[3] (Km)	AVEL ^[4] (m.a.s.l.)	Sinuosity ^[5]
Tati	Tati Weir	0.0019	0.003	58.5	1174.9	0.93
Ntshe	Ntshe Weir	0.0213	0.003	68.9	1158.7	1.01
Shashe	Mooke Weir	0.0130	0.002	78.9	1114.0	1.07
	Shashe Bridge	0.0125	0.002	55.1	1049.2	1.17
Shashe	Lower Shashe	0.0159	0.002	115.5	965.8	

^[1]BS is Basin Slope (average basin slope); ^[2]MSS is Maximum Stream Length (MSL) Slope; ^[3]MSL is Maximum Stream Length (maximum distance travelled by flow from upstream to the point where the stream exit the basin); ^[4]AVEL is the Mean Basin Elevation.^[5] gives indication on how straight or bending the river channel is: a sinuosity of 1 indicates that in general the river channel is straight.

CHAPTER FOUR

4 Multi-site rainfall modelling

The application of spatial-temporal stochastic rainfall models to semi-arid or arid areas is expected to be particularly challenging because of the high variability of rainfall, sparse rain gauge networks with significant periods of missing rainfall and potential data quality issues. In this chapter, a spatial-temporal rainfall model, the Generalised Linear Model (GLM) has been identified and fitted to daily rainfall data from the period 1975-1999 at 13 gauges in a 7660 km² sub-basin of the Limpopo basin, with the objective of exploring applicability of the GLM to (1) infill the missing values in the historic rainfall data; (2) identify suitable rainfall predictors in the study area; (3) extend the limited rainfall observations and for (4) climate change analysis.

Several relevant statistics of rainfall space-time variability were used to analyse the model performance against the observations, including use of a validation period and sites which were not used in the fitting. The GLM was considered to simulate rainfall adequately for the purpose of sub-basin scale water resources studies although the model uncertainty is high. The main factors affecting rainfall space-time variability were found to be seasonality, autocorrelation of daily rainfall, altitude, latitude and longitude. Addition of large-scale drivers of rainfall (temperature, pressure and humidity) further improved representation of inter-annual variability, and this link to large-scale climate potentially facilitates downscaling of global climate model outputs. Although the model was locally sensitive to data quality issues, there was no evidence that these issues affected sub-basin scale analysis.

4.1 Introduction

A suite of stochastic multi-site rainfall models has been presented and reviewed in chapter 2 with the aim of identifying models for application in data sparse semi arid areas. The review led to the selection of generalised linear models (GLMs) as potential rainfall models mainly because of the following reasons (summarised from chapter 2):

- (1) Their ability to quantify uncertainty due to missing values in the observed data.
- (2) Their potential for using external climate predictors deemed important as drivers of rainfall variability, which can be extended to rainfall downscaling using outputs of GCMs.
- (3) Their ability to represent a wide range of rainfall structures (spatial and temporal).
- (4) Their computational tractability which makes it relatively straightforward to fit and to compare different models.

In this chapter, the GLMs are developed for the study area to represent the observed rainfall records in the upper Limpopo basin.

4.2 Description of GLMs of multi-site rainfall

4.2.1 Basic structure

A detailed description of rainfall GLMs can be found in Chandler and Wheater (2002) and Yang et al (2005). Here only a brief description relevant to this application is provided. A GLM for daily rainfall is specified in two parts: a distribution defining the probability of rainfall occurrence, and a distribution defining the amount of rainfall for non-zero occurrences. The pattern of wet and dry days (rainfall occurrence) at a site is typically

modelled using logistic regression. If p_i denotes the probability of rain for the i^{th} case in the data set conditional on a vector x_i of predictors, then the occurrence model is given by

$$\ln\left(\frac{p_i}{1-p_i}\right) = x_i' \beta \quad (4.1)$$

where β is a coefficient vector. Secondly, a distribution function is fitted to the amount of rainfall on each wet day. A gamma distribution is typically assumed, whereby,

$$\ln u_i = \xi_i' \gamma \quad (4.2)$$

Where u_i is the mean of the gamma distribution on the i^{th} wet day, ξ_i is a predictor vector and γ is a coefficient vector. The distribution's shape parameter v is commonly assumed to be constant so that, conditional on the covariates, daily rainfall values have a constant coefficient of variation. In general, the values of the predictors will change over days and over sites. The use of gamma distribution is preferred over other distributions such as mixed exponential distributions, mainly because each day has a different gamma distribution fitted to the observed data-implying that the amount model used here corresponds to the use of "*mixed gamma*" which is more general and flexible to characterise the observed data than the mixed exponential distributions (Yang et al., 2005). If the influence of one predictor is thought to depend upon the value of one or more other predictors, then the predictors are said to interact: this can be accommodated by including the product of the interacting predictors as an additional predictor.

4.2.2 Model fitting and spatial dependence representation

Model fitting involves identifying an appropriate set of predictors x and ξ in Equations (4.1) and (4.2) and then estimating the corresponding coefficient vectors β and γ . In the work reported here, the GLIMCLIM software (Chandler, 2002) was used to fit the occurrence and amounts models independently. Estimation of model coefficients is done using maximum likelihood under the assumption that observations from different sites are independent; standard errors and likelihood ratio statistics are subsequently adjusted for spatial dependence (Chandler and Bate, 2007). As one objective is to produce a model for interpolating and extrapolating the observed record, predictors that do not have a credible physical basis were avoided.

By defining suitable dependence structures between sites, it is possible to build a multivariate GLM, which captures the general characteristics of rainfall over a network of sites (Yang et al., 2005). For the occurrence model, a beta-binomial distribution was used for the number of wet sites on any day (Z_t) to define the spatial dependence. Following Yang et al. (2005), the distribution of Z_t is modelled via the flexible beta-binomial distribution,

$$P(Z_t = z) = \binom{S}{z} \frac{\Gamma(\phi\theta_t + z)\Gamma(S + \phi(1 - \theta_t) - z)\Gamma(\phi)}{\Gamma(\phi + S)\Gamma(\phi\theta_t)\Gamma(\phi(1 - \theta_t))} \quad (4.3)$$

For $z = 0, 1, 2, \dots, S$, and where Γ is the gamma function. The distribution has two parameters - the *mean* (θ_t) (which varies in time and is estimated from the probabilities derived from the occurrence model) and a *shape parameter* (ϕ) (which is assumed constant for all days and is estimated using the method of moments), a small value of which indicates strong inter-site dependence. This approach has the flexibility to capture strong local dependence structures and may yield a range of distributions of numbers of wet sites as illustrated in Figure 1 of Yang et al., (2005). For the amounts model the inter-site correlation structure of the Anscombe residuals was used: these are rainfall values transformed in such a way that under the fitted model, their distribution is approximately normal (Yang et al., 2005). In order to remove potential inconsistencies associated with trace rainfall

values, which tend to vary with observer and instrument type, a threshold value is usually subtracted from the data before modelling (Chandler and Wheeler, 2002). Here a threshold of 0.5 mm was applied (implying that a wet day is defined only for rainfall values greater than 0.5 mm).

4.2.3 Representation of regional variability

It is possible to encounter situations where rainfall (occurrence or amount) is associated with a particular predictor in such a way that the relationship is best thought of as between rainfall and some non-linear transformation of the predictor. For example, regional variability of rainfall is not generally best explained by linear functions of coordinates and altitude. Instead, for example, exponential increases in rainfall may be associated with altitude gain and/or the rainfall may rise then fall (or vice versa) across the region (Chandler and Wheeler, 2002, Chandler, 2005). To overcome this, Chandler and Wheeler (2002) proposed an approach whereby site effects can be represented over a fixed range of the underlying predictor using orthogonal series representation (Priestley, 1981). Instead of using the underlying predictor directly in Equations (4.1) and (4.2), the corresponding values of the orthogonal basis functions are used as predictors, thereby reducing the problem to linearity (Chandler, 2005). For example, if an effect is likely to be monotonic (such as an increase of rainfall with altitude) this might be represented parsimoniously using a polynomial basis such as Legendre polynomials whereas oscillatory patterns may be represented using Fourier series. Clearly some caution is needed when using these orthogonal series to represent variability between the gauged sites and more so if extrapolating beyond the gauged area, particularly when using the oscillatory series or higher order polynomials.

4.2.4 Simulation and imputation

The logistic and gamma models can be used jointly to simulate sequences of

rainfall at multiple sites. As the model is stochastic, multiple realisations will produce an envelope of simulations to represent uncertainty. Also, the models used here are constructed in such a way that if any data values are missing, their conditional distribution can be determined from the values observed at other locations. Missing values can be simulated from these conditional distributions to yield complete time series with no missing values (known as imputation) (Yang et al., 2005) so that uncertainty envelopes for historical data can be generated.

4.2.5 Model performance evaluation

Model performance can be assessed using simple but informative tests, such as Pearson residuals (McCullagh and Nelder, 1989). The Pearson residual for an observation Y_i can be represented as

$$r_i^{(P)} = \frac{Y_i - u_i}{\sigma_i} \quad (4.4)$$

where u_i and σ_i are the modelled mean and standard deviation on day number i . If the fitted model is correct, any set of Pearson residuals will come from a distribution with mean 0 and variance 1. The residuals are then used to check that the seasonal, regional and annual structures are well captured by plotting the mean and variance of the corresponding sets of residuals and checking whether they fall within analytically derived confidence limits. The sign of residuals is also informative as it indicates whether the model is over or under-predicting.

Since the idea is to generate sequences of rainfall data that are statistically consistent with the observed data, the statistics of the simulated and observed data are compared in order to evaluate the performance of the model. Depending on the purpose of the study, a range of statistics can be computed. It is expected that if the infilled observed data are well simulated then the statistics of the infilled observed data should appear to be samples from the simulated distributions.

4.3 Application to the study area

Daily data for 16 rain gauges (see Table 3-1) were obtained from two sources, the Department of Meteorological Services and the Department of Water Affairs as discussed in Chapter 3. Thirteen rain gauges were used for model fitting. The remaining 3 stations were only used for model validation due to their higher proportion of missing values.

An analysis of data quality in chapter 3 revealed that there are possible data quality issues. As a result, the sensitivity of the model to data quality adjustments will be investigated (4.4.7). The period 1975-1999 was identified as suitable for model fitting because it is relatively well covered by the data set and contains both exceptionally wet and dry years, as well as wet and dry inter-annual sequences. The selection of potential external predictors was guided by the literature (Hewitson and Crane, 2006, Cavazos and Hewitson, 2005). Large-scale gridded climate data from the European Centre for Medium-range Forecasts re-analysis data (1957 to 2002), known as the ERA-40 re-analysis data (Uppala et al., 2005) were obtained from the British Atmospheric Data Centre (<http://badc.nerc.ac.uk>). From this re-analysis data, 11 potential predictors were identified. These include relative humidity, specific humidity, air temperature, dew point temperature, sea level pressure, and geo-potential heights (i.e. heights above sea level of given pressures). ENSO data were obtained from the Climate Prediction Centre website (www.cpc.noaa.gov).

Indices considered were the Southern Oscillation Index based on sea level pressure at Tahiti and Darwin, Darwin sea level pressure and the Nino 3.4 sea surface temperature (SST). The time resolution for the external predictors is monthly. For each of the 12 months of the year, each set of predictor values was standardised to a distribution with zero mean and unit variance (after Frost et al., 2006). This removes seasonality so that the

external predictors only have inter-annual effects (seasonality is already represented in the GLM). Also, removing seasonality in this way reduces the influence of seasonal scale errors in climate model outputs where these are used as predictors.

4.4 Results and discussion

4.4.1 Spatial and temporal predictors

The predictors identified as significant are listed in Table 4-1 together with coefficient values and standard errors. Constructing the models involved adding one predictor at a time and testing each for significance as discussed in 4.2. In the occurrence model there were 20 predictors including the constant. To represent seasonality, the annual cycle and its first harmonic were needed, particularly to capture the length of the wet season. Temporal dependence was accounted for using indicators for each wet site for the previous two days. In order to account for site effects, the first two trigonometric terms of the Fourier series along the easting and northing were used. In addition, a third order Legendre polynomial was used to account for topographic variation. The number of predictors in the amounts model was 13, largely the same ones which were used in the occurrence model although there was no evidence of the first harmonic of the annual cycle in amounts.

From the candidate external predictors, relative humidity at sea level (*RHS*), mean air temperature (*TMP*) and mean sea level pressure (*SLP*) were used in the occurrence model (Table 4-1). This was based on their statistical significance, physical significance and the absence of strong correlation between the three sets of standardised values. Relative humidity reflects how close to saturation the atmosphere is. Neither temperature nor pressure was significant in the amounts model. Although the ENSO indices were expected to be important based on the literature (Richard et al., 2000,

Mulenga et al., 2003, Reason et al., 2005, Manatsa et al., 2008) none of these indices were within the eight most statistically significant external predictors.

Consequently, none of the ENSO indices led to improved model fit or simulation results when used alone or with any of the top eight predictors in the model. It should be noted that likelihood ratio tests are known to be more powerful than any other procedure for detecting weak signals (Chandler and Bate, 2007), so the failure to find significant ENSO relationships in this case study is not thought to be due to methodological limitations. Many investigators point to the weakening ENSO-Africa teleconnections in recent years (Landman and Mason, 1999, Sewell and Landman, 2001), and some authors have suggested that they should not be used as rainfall predictors particularly for downscaling purposes (Hewitson and Crane, 2006).

The spatial structure of occurrence was specified using a beta-binomial distribution for the number of wet sites on any day. The value of the shape parameter ϕ was 5.18, corresponding to a low inter-site dependence and indicating that there might be limited scope for transferring information between sites for imputation purposes. The spatial dependence structure for the amounts model was specified using the correlation between the Anscombe residuals equal to 0.27 for all site pairs. The simulation results obtained from this assumption of uniform correlation compared well with those obtained when using correlations specific to each site pair. The simpler model was adopted so that the model could easily be applied to generate rainfall at the validation sites and other ungauged sites.

Table 4-1: The occurrence and amounts models

	Occurrence model				Amounts model			
	Predictor	Value	SE ^[d]	ID	Predictor	Value	SE ^[d]	ID
Site effects	Constant	-3.53	0.05		Constant	1.99	0.05	
	Fourier sine 1 for Easting	0.12	0.02	1	Fourier sine 1 for Easting	0.04	0.06	1
	Fourier cosine 1 for Easting	-0.09	0.02	2	Fourier cosine 1 for Easting	0.11	0.02	2
	Fourier sine 1 for Northing	0.27	0.05	3	Fourier sine 1 for Northing	-0.32	0.06	3
	Fourier cosine 1 for Northing	-0.39	0.08	4	Fourier cosine 1 for Northing	0.39	0.07	4
Temporal effects	Legendre polynomial 3 for Altitude	-1.30	0.22	5	Legendre polynomial 3 for Altitude	1.41	0.17	5
	Daily half-year cycle, cosine	-0.28	0.05	6	-			
	Daily half-year cycle, sine	-0.27	0.04	7	-			
	Daily seasonal effect (full year), cosine	1.97	0.07	8	Daily seasonal effect (full year), cosine	0.31	0.04	6
	Daily seasonal effect (full year), sine	0.34	0.05	9	Daily seasonal effect (full year), sine	0.12	0.03	7
Atmospheric Predictors	I (Y[t-1]>0)	1.96	0.08	10	Mean of I (Y[t-1]>0)	0.60	0.06	8
	I (Y[t-2]>0)	0.56	0.04	11	-			
	RHS ^[a]	0.55	0.04	12	RHS ^[a]	0.06	0.02	9
	TMP ^[b]	0.14	0.04	13	-			
	SLP ^[c]	-0.08	0.03	14	-			
Interactions	1 and 5	-0.35	0.09	15	1 and 4	0.65	0.16	10
	2 and 5	-0.38	0.08	16	1 and 5	2.00	0.31	11
	4 and 5	-0.31	0.12	17	2 and 5	0.46	0.07	12
	8 and 10	-0.72	0.10	18				
	9 and 10	0.17	0.07	19				
Threshold	`Soft' threshold (mm)	0.50			`Soft' threshold (mm)	0.5		
Spatial dependence	Beta-binomial distribution.	5.18			Constant correlation	0.27		
Dispersion parameter	-					0.66		

^a Relative humidity (surface),

^b Mean Temperature,

^c Mean sea level pressure

^d Standard error

4.4.2 Interactions and their interpretation

It can be seen from Table 4-1 that the interaction terms involved mostly the location coordinates and altitude. This presumably suggests a more complex spatial variability within the catchment. However, there was no apparent physical significance of these spatial interactions in terms of rainfall mechanisms in this catchment although removing them from the models lead to poor fit in the spatial models and simulation results. Other interactions are between the seasonal predictors and the previous days' rainfall. Both the sine and cosine terms for interaction with successive days' rainfall were used because the phase of the seasonal cycle is not known *a priori*. It is expected that during wet periods, particularly in summer, greater dependence between successive days' rainfall will exist. In this application, it was found that previous two days' rainfall has an influence in rainfall occurrence. This short memory was presumed to be because of the short-lived convective rainfalls associated with semi arid areas as opposed to more frontal systems in temperate climates. For example, Chandler and Wheeler (2002) identified rainfall of up to 5 previous days to be significant for rainfall occurrence in west Ireland. Furthermore, only the interaction between previous one day's rainfall and seasonal cycle was found significant which further confirms the weakening signal between successive previous days' rainfalls and seasonality in this basin.

4.4.3 Assessment using Pearson residuals

The means of the Pearson residuals for the occurrence and amounts model are presented in Figure 4-1 along with the analytically derived 95% confidence intervals. These statistics were computed after grouping the data into months, years and sites. In the annual plots it can be seen that some years have residuals placed outside the confidence interval indicating that these years may not be well represented by the models (however, results in

Figure 4-6 show that observed annual and seasonal rainfall in these years are within the simulated bounds implying that the combined occurrence and amounts models produce reasonable annual totals even within these extreme years). Also, there seems to be a decreasing trend in the occurrence model residuals shown in Figure 4-1. To check this, a linear trend was added as an additional predictor in the occurrence model. The trend was found significant at the 95% level (mean is -0.07, standard error is 0.03) and led to an improved fit for the annual residuals. However there is no physical justification for including the trend in the model and if the model were to be used for extrapolation to future climate, this downward trend is likely to yield results that are biased. The trend can be partially removed by introducing more interactions between predictors; however this could not be justified on a physical basis and prefer to maintain the more parsimonious model. Instead, the residuals associated with the apparent trend will add to the model variance and imputation/simulation uncertainty.

The residuals for the sites are plotted in Figure 4-2. It is expected that if the regional variation due to site effects is well accounted for in the model, the residuals should appear randomly distributed over the study area. Figure 4-2 shows that the residuals in general appear random over the catchment except for a cluster of negative values in the middle of the area for the occurrence model. Although these residuals (from N6, N7 and N8) are not significant when assessed independently, together they are more significant and the model is expected to over-predict the occurrence of rainfall around this area. Only one gauge (N11) has an occurrence residual which is significant at the 95 % level.

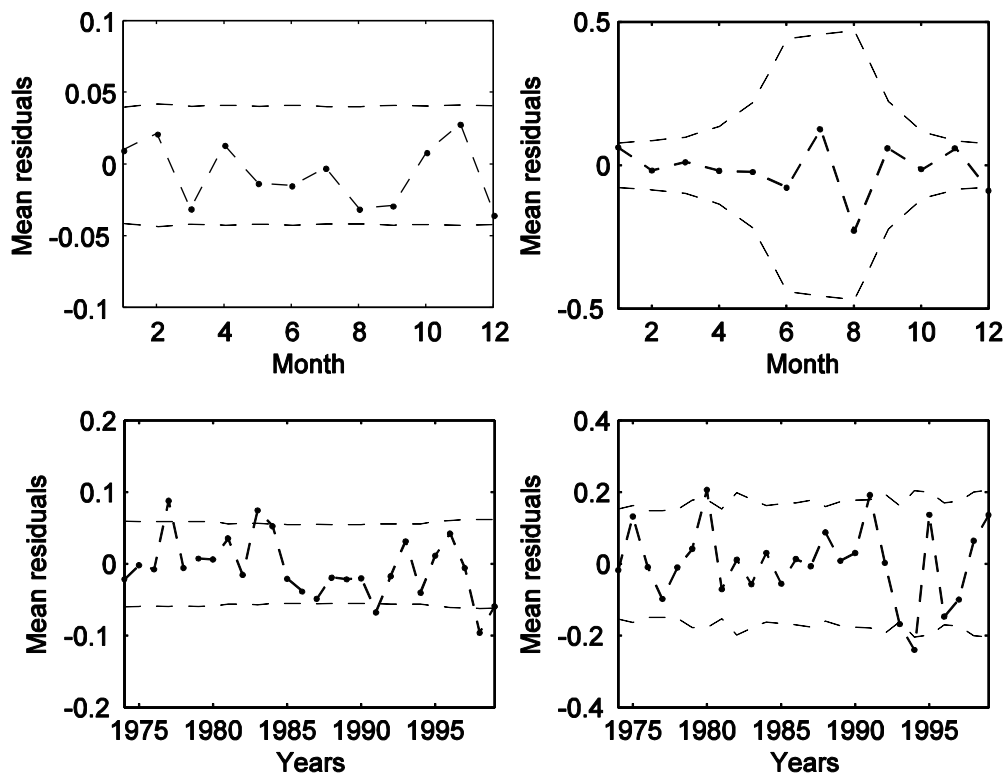


Figure 4-1: Pearson residuals plotted by months (top plots) and years (bottom) for the occurrence (left plots) and amounts models (right plots). Dotted lines indicate the 95% confidence levels

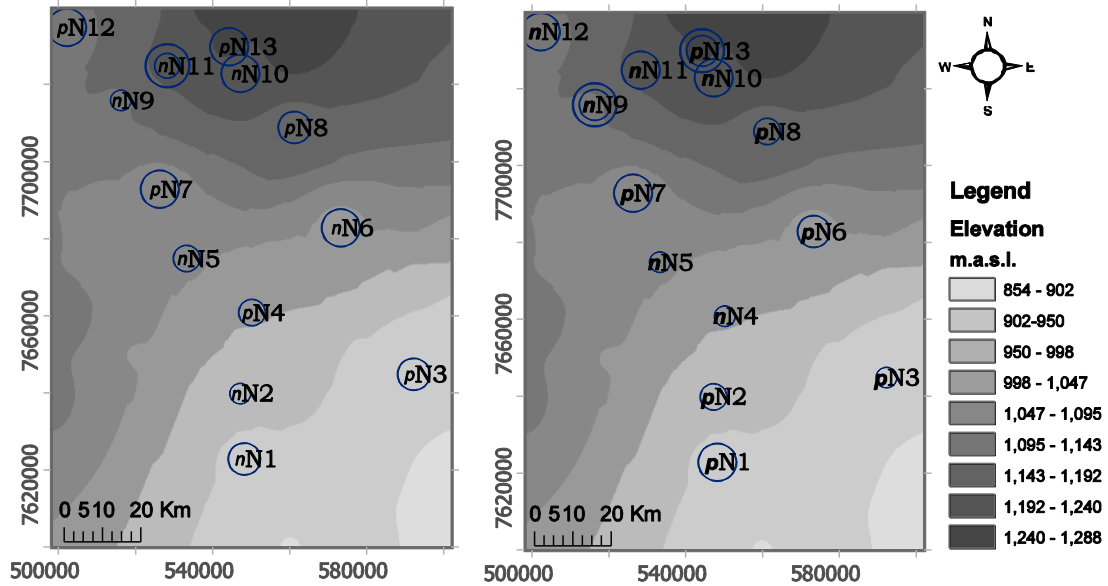


Figure 4-2: Bubble map showing mean Pearson residuals from the occurrence (left) and amounts (right) models plotted by site. Circle areas are proportional to standardised residuals. Double circles represent residuals that differ significantly from zero at 5% significance level and p and n indicate positive and negative residuals. The background grey-scale shows the topography of the area with darker shading corresponding to higher ground. Altitude ranges from 850 to 1400 metres above sea level. The x and y axes are Easting and Northing in meters

For the amounts, the plot shows that the modelled rainfall at sites N9 and N13 have errors which are significant at the 95 % level. Although this does not necessarily mean the model is incorrect at these sites (5 % of sites are expected to have errors beyond the 95 % significance bound), it is speculated that the lack of good fit for these sites may be associated with data quality issues, and this is explored later in 4.4.7.

It is worth noting that representing regional variation with only a few gauges at the spatial scale of the study area is not easy. For example, it can be seen from Table 4-1 that eight spatial predictors (including interactions) were used for both occurrence and amounts models on the basis of data from only 13 sites. Using a large number of spatial predictors compared to the number of sites can lead to over-fitting the model. This possibility is investigated in sections 4.4.5 and 4.4.6.

4.4.4 Assessment using imputation and simulation

The models were used for imputation (infilling) of missing rainfall for the period 1975-1999 using information from the 13 rain gauges. Ten sets of imputations were generated for the period 1975-1999. Then, 100 sets of simulations were generated for the same period. Two cases were considered during simulations. The first case involved running the model without external atmospheric predictors (*RHS*, *TMP* and *SLP*) while in the second case they were included. The statistics of the simulated daily data were compared with those of the infilled observed data for each month of the year. This was done for each individual site and by averaging the daily series from all sites. The statistics considered were the mean and standard deviation, the mean and standard deviation for wet days only, the proportion of wet days, daily maxima and lag-1 and lag-2 autocorrelations.

The results, obtained by averaging the daily series from all sites, are shown

in Figure 4-3 for the model which incorporates external atmospheric predictors. The range of each set of statistics of the infilled observed data is represented by thick black lines. These ranges of statistics arise due to missing data - the wider the gap between these black lines, the higher the uncertainty due to stochastically imputed values. The grey scale represents percentiles of the simulated distributions. Figure 4-3 shows that in general the model results are consistent with the observed rainfall properties across all the statistics investigated.

The results for individual sites are presented in Appendix A. In this section only the results for two stations are presented in Figures 4-4 and 4-5. The two stations are N4, which has complete data during the period selected for modelling, and N6 which has high proportion of missing values. From these results, it can be seen that the model simulates the observed data well, even for the station that has high proportion of missing values (N6)-although the uncertainty is high due to missing data at this gauge. The results for the rest of the stations look almost similar to those presented here as shown in Appendix D (Figures D-1 to D-3)

The time series of observed and simulated data, averaged over sites to annual and seasonal scales, are plotted in Figure 4-6, including results obtained with and without the use of external atmospheric predictors. It can be seen that in general the observed rainfall appears to be reasonably well simulated by the model when the external predictors are included. The uncertainty is high, but realistic since the observations span the range of the simulations. Importantly, the simulated distributions track the observations when the atmospheric predictors are included. Even the years which are exceptionally wet (such as 1976 and 1996) or dry (1994) are reasonably represented.

4.4.5 Model validation tests: temporal and spatial validation

To further check whether the GLM developed for this basin has captured the temporal structure of the observed data, the GLM was used to simulate rainfall at sites N1, N4, N7 and N8 for the period 1962-1974, which is outside the fitting period. These particular sites were chosen on the basis of data availability prior to the period used for fitting. For spatial validation, rainfall data were simulated for the period 1982-1994 at stations V1, V2 and V3, which were not used at all for fitting. The results are presented in Figure 4-7. Again, from this plot, it can be seen that in general the GLM seems to adequately simulate the observed data including exceptionally dry years like 1965. There is no evidence that the linear trend (which was omitted on the basis that it could not be safely extrapolated) extends into this period. The summary statistics for both validation tests were also well represented and look like those presented in Figure 4.3.

4.4.6 Spatial rainfall infilling

As a check on the spatial stability of the model, 92 hypothetical rain gauges were placed at regular grid intervals of 10 kilometres over the entire basin, and rainfall was simulated for these gauges using the fitted GLM with the purpose of spatially infilling the rainfall. The resulting (annual) rainfall values were then interpolated using the inverse distance weighting method in order to produce a rainfall surface over the basin as shown in Figure 4-8. This test helps to assess the ability of the model to generate reasonable spatial rainfall over the basin. In particular, if the spatial model was over-fitted, due to the use of too many spatial predictors, this test is expected to expose instability over the basin. The results analysed at annual, seasonal and weekly time-scales showed that the model gave reasonable spatial rainfall surface only over areas where the topography is relatively flat but not at exceptionally high or low altitude, where the model gave either very high or low rainfall values. For example, the mean annual rainfall (MAR) towards the catchment outlet estimated by spatially infilling rainfall using the GLM is as low as 220 mm whereas none of the existing nearby

raingauges has a MAR less than 300 mm. The implication of this is that where spatial features of rainfall fields are needed for a catchment that has a large variation in topography such as this case study (as shown in the left panel of Figure 4-8), the spatial rainfall fields generated by the GLM may give erroneous results. This issue is discussed further in chapter 5, where an alternative method of estimating the spatial rainfall field is considered. However, it is emphasised that the lack of good performance reported here is expected since the points where the model fails fall outside the range covered by the available gauges.

4.4.7 Sensitivity of model results to data quality

Double mass plots (Figure 3-10) indicate that there may be data quality issues, in particular at gauges N9 and N13 (discussed in section 3.3.1), and this was supported by the model residuals shown in Figure 4-1. Subsequent to the analysis presented above, periods of data at these gauges were scaled so that the double mass plots were a visually satisfactory straight line. This involved scaling up 14% of the data at gauge N9 (from 01/01/1984 to 10/03/1988) and scaling down 14% of the data at gauge N13 (from 25/02/1986 to 15/02/1988). In the case where the test gauge showed extended periods of zero rainfall while the other gauges recorded some rainfall values, data from the test gauge were treated as missing values and therefore excluded from the fitting. It is not presumed that this corrects the record, but it represents a reasonable adjustment that may in practice be made as part of a quality control procedure. The initial GLM structure (i.e. the predictors in Table 4-1) was refitted using the adjusted data. The Pearson residuals for the initial and adjusted amounts models are presented in Figure 4-9. This result shows that the adjusted data leads to a closer fit to the observed rainfall amounts (i.e. generally reduced Pearson residuals). Because the adjustment primarily affected amounts, there was comparatively little change in the occurrence fit. The simulation results show small differences for the conditional means at the two affected sites

(corresponding to the differences in Pearson residuals), but do not show discernible differences in other statistics or for any of the statistics when considering basin aggregated rainfall. These sensitivity tests indicate that localised data quality issues of the magnitude considered here do not affect regional rainfall estimation.

4.5 Summary and conclusions

The aim of this chapter was to investigate the potential applicability of a generalised linear model (GLM) for stochastic simulation of multi-site daily rainfall in semi arid areas; and to develop a model which can be used to infill and extend historical rainfall data sets for water resource applications in a 7660 km² sub-basin of the River Shashe in the Limpopo basin, Botswana. The GLM model is an extension of linear regression to allow for non-linearity and non-Gaussian distributions. In this application, logistic regression was used to simulate rainfall occurrence and two-parameter Gamma distributions were used to simulate amounts on wet days. Inter-site dependence models were included for both occurrence and amounts. The modelling procedure requires a set of statistically and physically significant predictors of rainfall parameters to be identified, associated coefficients to be optimised using maximum likelihood, and a series of tests to assess model accuracy.

The main predictors of rainfall in the Limpopo case study were found to be location effects, seasonality, and temporal dependence. Humidity, temperature and sea level pressure from ERA-40 re-analysis data were significant external predictors. Analysis of model residuals showed that in general the model captured the seasonal, annual and spatial structure of rainfall in the basin. However, there were a few cases where the residuals indicated that the model could not fully capture the annual variability (during the especially wet and dry years) and spatial rainfall structure (particularly but not only at stations which were suspected to have data

quality problems). Despite these local problems, the simulation results indicated that in general the model results were consistent with the observed rainfall properties.

Spatial and temporal validation tests showed that the GLM adequately simulated rainfall for the periods and gauges not used during model fitting. However, the uncertainty was high particularly at gauges with high proportion of missing values. The inter-annual variability evident in the observed data was well simulated by the model when the external atmospheric predictors were included, but not without them. As the external predictors have both physical and statistical significance, and are simulated by global climate models, the model may be used in conjunction with climate model outputs to make tentative extrapolations of the historic daily rainfall patterns to future climate. ENSO indices which are generally considered to influence rainfall variability in southern Africa were not found to be significant drivers of rainfall variability in the study area. This supports the view that the influence of ENSO in southern Africa may previously have been overestimated, or is regionally variable. Sensitivity tests which were performed to assess sensitivity of model results to data quality showed that while the amounts model showed locally improved model fit as a result of data adjustment, there were no significant changes in the basin scale simulation results. When the model was used for spatial infilling, it was observed that it gave reasonable spatial rainfall surface only at areas where the topography is relatively flat but not at exceptionally high or low altitude, where the model gave either very high or low rainfall values. This might limit its use for spatial interpolation particularly where topography is highly variable.

It can be concluded that the GLM provides a useful tool for simulating multi-site rainfall in the semi-arid Limpopo basin in Botswana for water resources purposes and may potentially be applicable to climate change analysis and to other semi-arid regions. It is of interest to test sensitivity of hydrological model outputs to the rainfall input uncertainty and

assumptions used in the GLM application, which is covered in chapter 5.

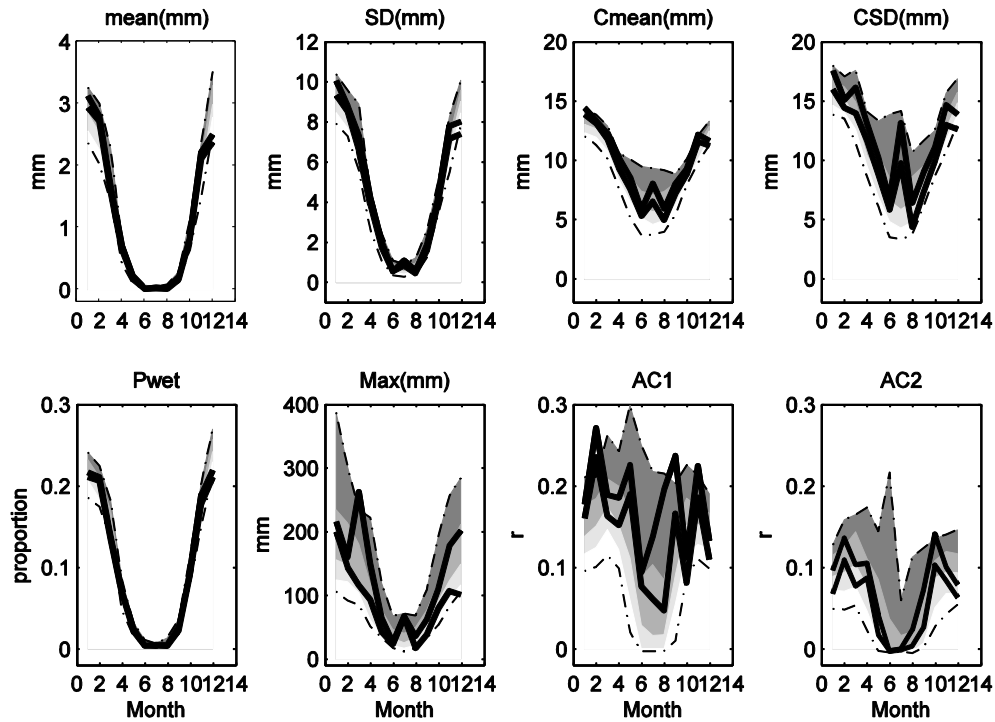


Figure 4-3: Monthly statistics including data from all 13 sites. The black lines indicate observed data (with uncertainty due to missing values). The grey scale indicates percentiles of the simulated data (10, 50 and 90 percentile) enveloped within the dashed minimum and maximum bounds. SD is standard deviation, Cmean and CSD is mean and standard deviation for wet days, Pwet is proportion of wet days, Max is daily absolute maximum values, AC1 and AC2 are autocorrelations lags 1 and 2.

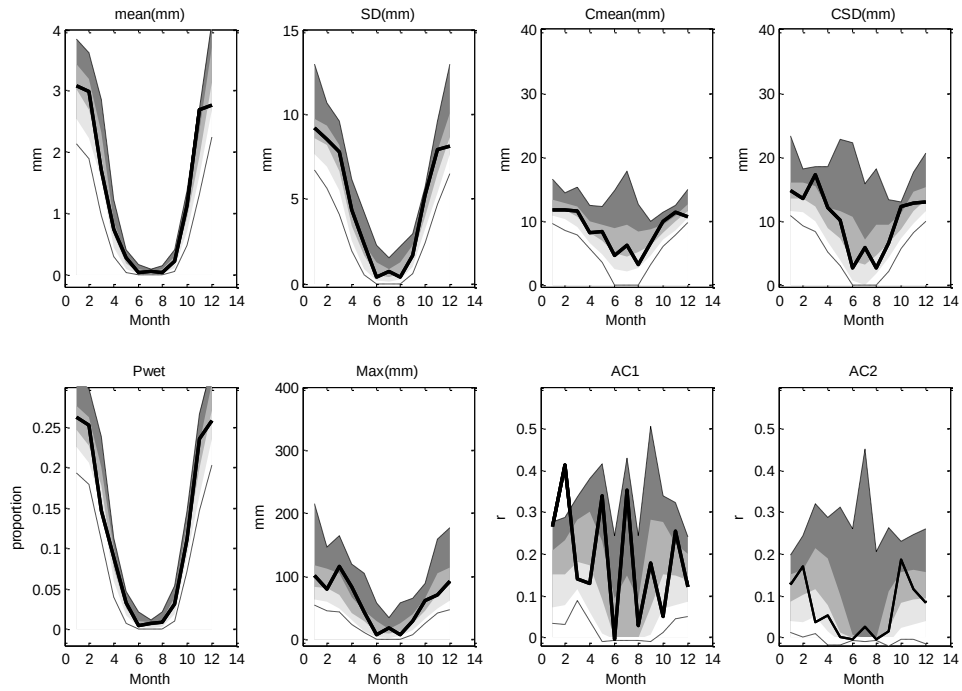


Figure 4-4: Monthly summary statistics for gauge N4, which does not have any missing values. The black lines indicate observed data (with uncertainty due to missing values). The grey scale indicates percentiles of the simulated data as shown in Figure 4-3.

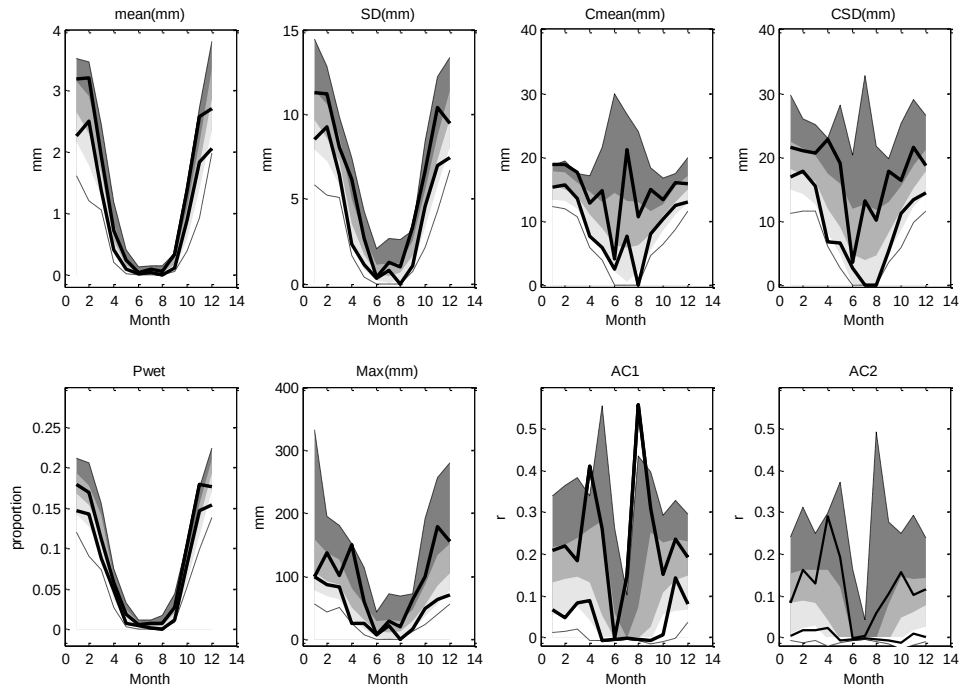


Figure 4-5: Monthly summary statistics for gauge N6, which has missing daily rainfall values. The black lines indicate observed data (with uncertainty due to missing values). The grey scale indicates percentiles of the simulated data as shown in Figure 4-3.

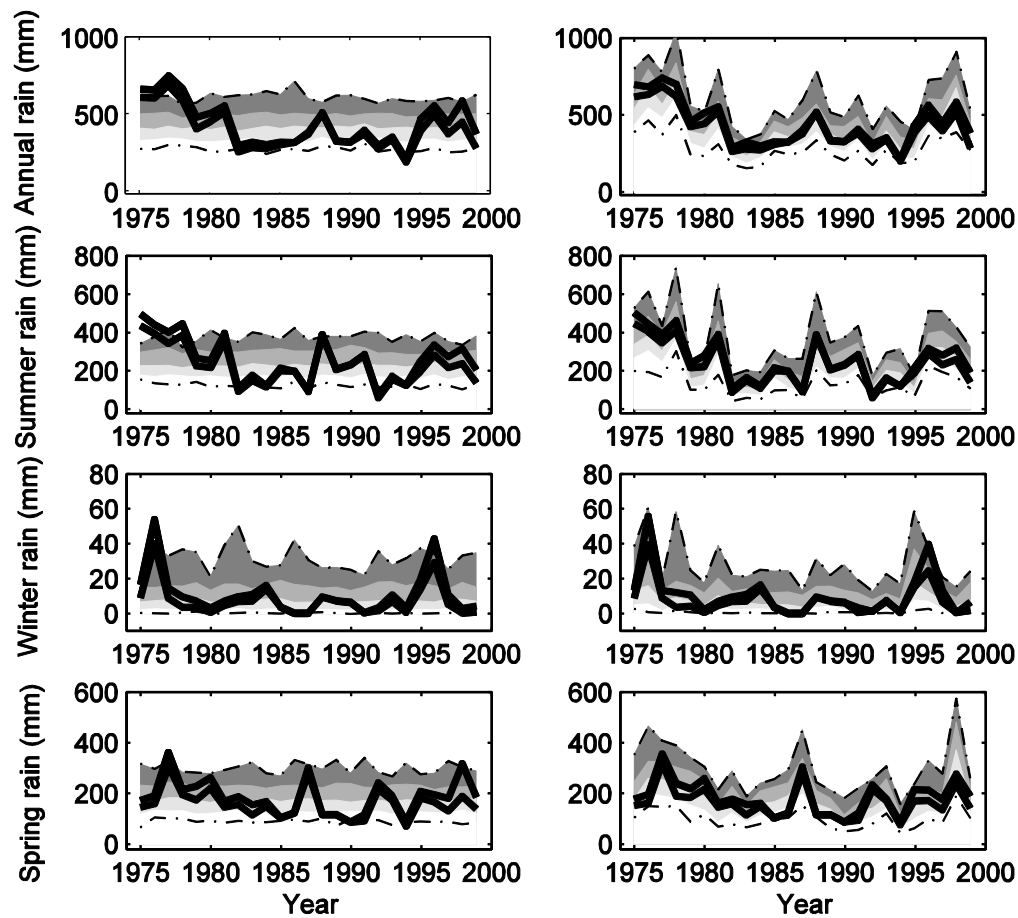


Figure 4-6: Annual and seasonal rainfall for all the 13 sites obtained from the models without external predictors (left plot) and with them (right plot). The black line indicates imputed observed data (and double lines show uncertainty due to missing values). The grey scale indicates percentiles of the simulated data. Seasons are summer (January-April), winter (May-August) and spring (September-December).

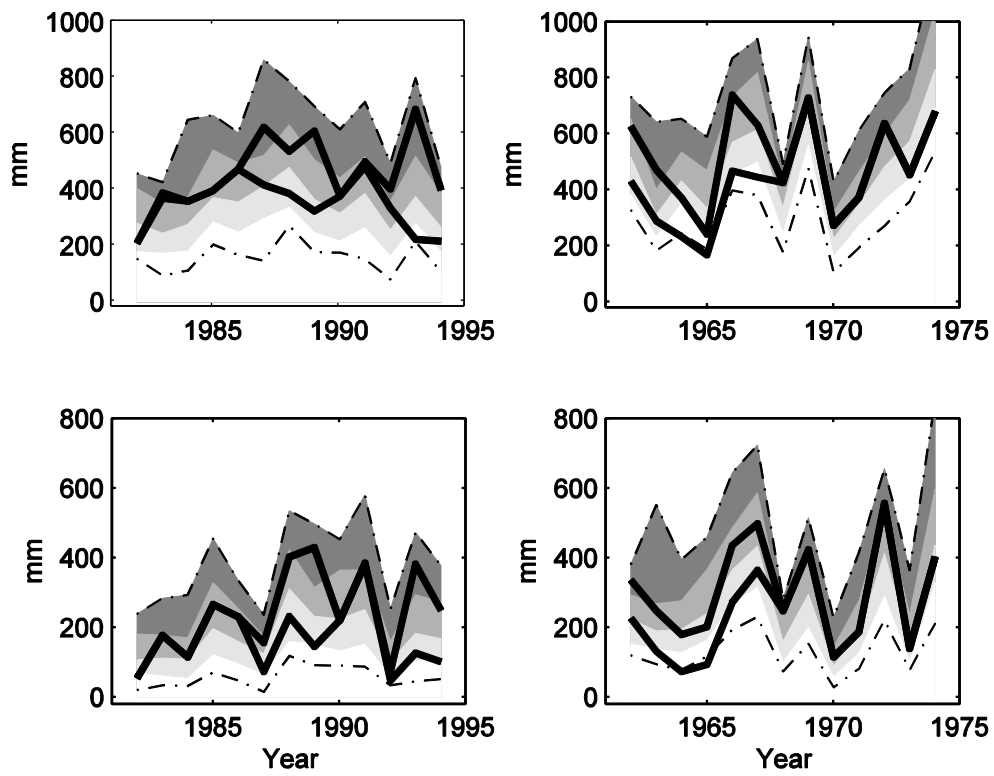


Figure 4-7: Annual and summer rainfall for temporal validation (left plot) and spatial validation (right plot).

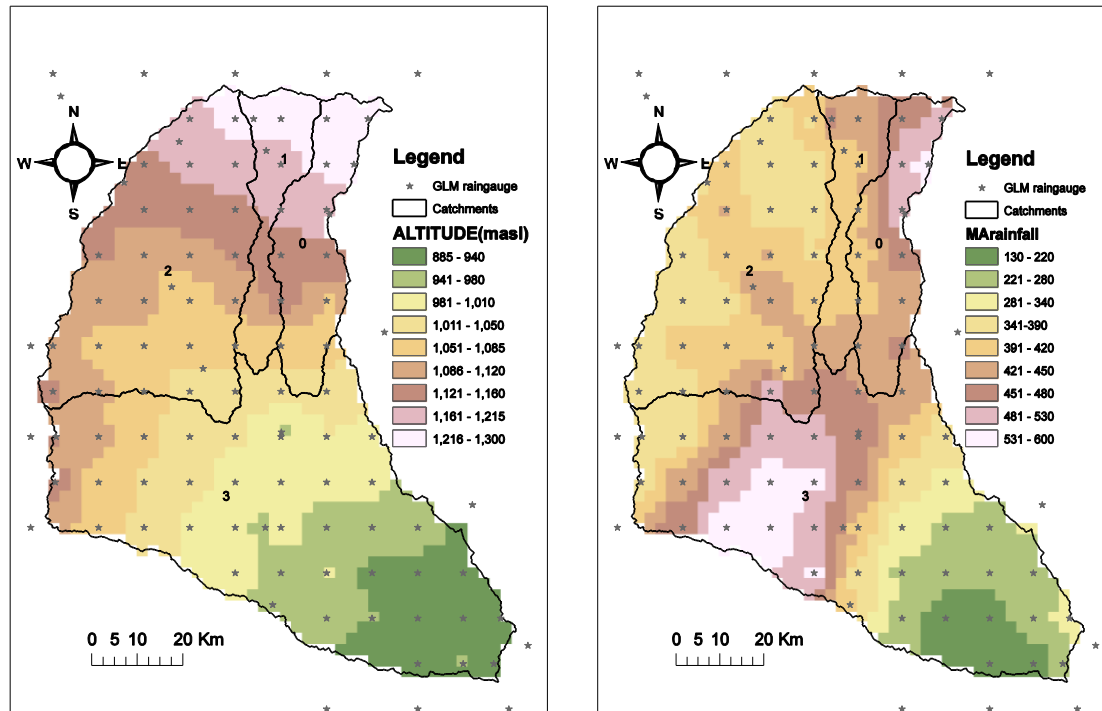


Figure 4-8: Topographic surface for the study area obtained using data from the Digital Elevation Model (DEM) (the left plot) and spatial rainfall surface (mean annual rainfall) generated from the GLM (the right plot).

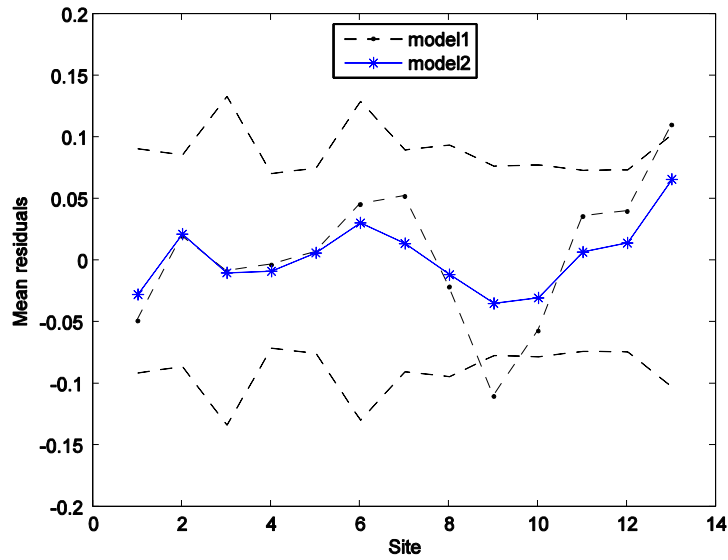


Figure 4-9: The Pearson residuals for the amounts model showing the results from the model fitted to the unadjusted data (model_1) and for the model with adjusted data (model_2). Both models incorporate atmospheric predictors.

CHAPTER FIVE

5 Calibration of a hydrological model under uncertainty

It is increasingly becoming important to represent spatial features in hydrological modelling, in particular rainfall. To achieve this, distributed hydrological models have become essential modelling tools within which spatial variability of rainfall and/or parameters can be effectively represented. However, uncertainty issues arise mainly due to limitations in historic observations and uncertainty in hydrological models, which need to be considered in model calibration. Focussing on rainfall and hydrological uncertainty, this chapter outlines a framework of uncertainty analysis, which allows such consideration to be given. The framework consists of multi-site continuous time stochastic rainfall modelling to infill historic rainfall data (discussed in chapter 4). The stochastically infilled rainfall data allows calibration of a hydrological IHACRES model under input uncertainty. In addition, uncertainty resulting from equifinal parameter values is considered. The resulting effects of uncertainty on model prediction are then explored. Sensitivity analysis is used to identify suitable model structures for this basin.

The main findings in this chapter are that (1) when considering the uncertainty arising from model parameters, it was found that the confidence limits for the equifinal parameters for each rainfall realisations were wide; (2) the optimal parameter values varied highly from one rainfall realisation to the other, particularly during the periods where gauged rainfall data is quite incomplete and much of the data was infilled using the GLM. Regarding the model simulations: (3) the model was able to explain the observed flows during the calibration period although the uncertainty was high (resulting from rainfall and parameter uncertainty); however, (4) during the validation period the model was, except at the smallest subcatchment and during exceptionally wet years, unable to explain the observations when using either of the two independent calibration periods. As a result, it is suggested that future hydrological scenarios be developed based on both sets of calibration periods used in this work and the simulated flows should consider the effects of parameter and rainfall uncertainty.

5.1 Introduction

Hydrological models are important tools for use in water resources planning and management. Their practical use includes for example, flood and drought prediction, water resources assessment for reservoir design and operation as well as climate change and land use impacts assessment. Because of limited availability of the spatial data required to satisfy the demands of distributed physically-based hydrological models, many studies have in the past focused more on conceptual lumped models. This is particularly true in data sparse semi arid areas where, as well as limitations in flow data for calibration, lack of complete rainfall data of good quality and lack of good rain-gauge networks to capture the spatial variability limits the benefits of using a distributed model. However, stochastic spatial-temporal rainfall models are increasingly becoming important tools for characterising rainfall in space and time which can be used to drive distributed hydrological models (Segond et al., 2006). Of particular importance to data sparse areas, some of these models, such as the generalised linear model (GLM) used in Chapter 4, have the potential to quantify uncertainty due to missing values in the observed records (Yang et al., 2005). This provides opportunity to explicitly consider rainfall uncertainty in the calibration and application of a distributed hydrological model.

The aim of this chapter is to calibrate a rainfall-runoff model of the upper Limpopo basin and test its performance under input and parameter uncertainty. This is achieved by calibrating a semi-distributed IHACRES model which is driven by spatial rainfall obtained from the GLM. The results are then used to assess the implications for reservoir design and operations within Botswana's national water resource strategy as detailed in chapter six.

5.2 Semi distributed modelling toolbox

Owing to the widely known problems of fully distributed rainfall runoff models-mainly the problem of overparameterisation and increased parameter uncertainty during model identification (Madsen et al., 2002) (see Chapter 3) - recent modelling efforts seem to be concentrating on semi distributed (SD) models (Pechlivanidis, 2009, McIntyre and Al-Qurashi, 2009, Orellana et al., 2008, Khakbaz et al., 2009). This is because distributed models are designed to account for spatial variability of (1) hydrological processes, (2) basin physiographic properties, and (3) input data (mainly rainfall), in order to predict streamflow at interior points as well as at the catchment outlet (Reed et al., 2004a, Smith et al., 2004). Models with high spatial resolution (often called fully distributed models) inevitably require a lot of input data of high quality which is usually not available at fine scales to support the demand of fully distributed models (Nouh, 2006). In view of this, SD models are alternative group of hydrological models which are aimed at relaxing the data requirements without compromising the need to consider the spatial features of input meteorological variables and (sub) catchment properties. This is achieved mainly by conceptualising the catchment as comprising of different lumped subcatchments, where the forcing data and the modelled hydrological processes are treated as homogeneous within each subcatchment (Khakbaz et al., 2009, Pechlivanidis, 2009, Ajami et al., 2004). Flows from one subcatchment to the other are usually integrated through a channel routing model (McIntyre and Al-Qurashi, 2009) to obtain accumulated flow at the basin outlet. It is argued by these researchers that SD models combine the advantages of lumped and distributed models, such as ability to strike a balance between matching model complexity with the availability and quality of data, and the importance of making use of the spatial features of rainfall data to estimate flows at spatial units smaller than the catchment area.

The semi distributed rainfall runoff modelling toolbox (RRMT-SD) used in this thesis was developed at Imperial College London (Orellana et al., 2008), and has a generic structure as shown in Figure 5-1. The reader is referred to Orellana et al. (2008) for a full description of the RRMT-SD. Here only a brief introduction relevant to this thesis is provided, with the application detailed in section 5.3. RRMT-SD is an extension of the Rainfall Runoff Modelling Toolbox (RRMT) (Wagener et al., 2002) developed previously to produce parsimonious lumped model structures to estimate streamflow at the catchment outlet. The RRMT-SD is used to model continuous time streamflow at points along the river system defined by the subcatchment outlets. A selected parsimonious model structure is applied to each subcatchment. Each subcatchment is considered as lumped and the modelled processes are treated as homogeneous within each subcatchment. The degree of spatial distribution is represented through the number of subcatchments, and a channel routing module is used to route the flow from the subcatchments to the catchment outlet.

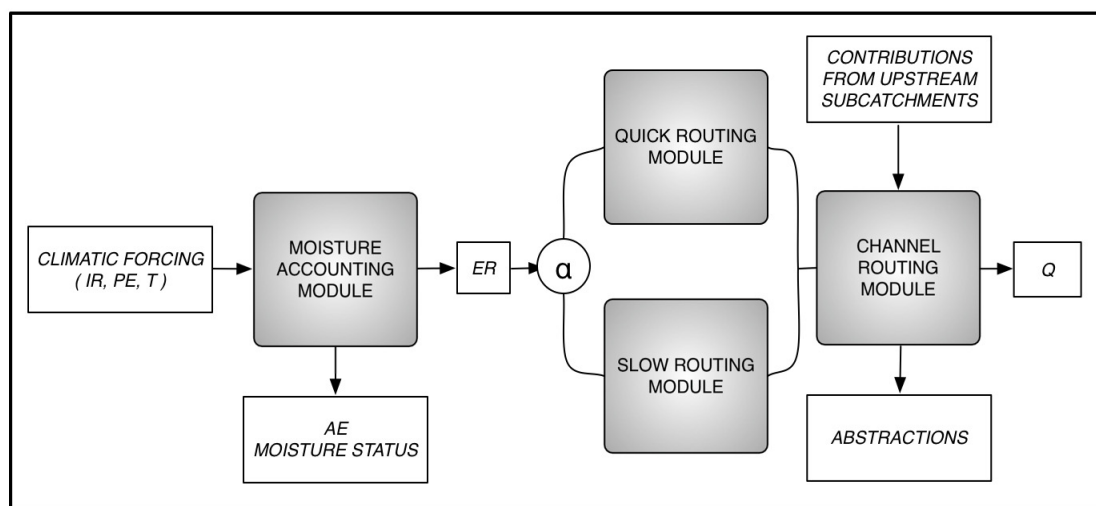


Figure 5-1: An SD modeling toolkit showing subcatchment module structure (source, Orellana et al., 2008).

5.3 Hydrological modelling using the semi-distributed IHACRES model

5.3.1 Description of the IHACRES model

The IHACRES model, initially developed by Jakeman *et al.* (1990) for application in temperate catchments, has undergone several modifications to suit various applications. For example, it has been modified for use in ephemeral catchments (Ye *et al.*, 1997b), and for application in semi-distributed modelling (Croke *et al.*, 2006b). The model has two modules, one nonlinear and the other linear. The nonlinear module converts rainfall (r) into effective rainfall (u), while the linear module converts effective rainfall into streamflow (q). This flow can be routed through any configuration of storages, in parallel or series (e.g. quick and slow flow) depending on the underlying hydrological processes of the area under investigation. The effective rainfall at each time step (k) is usually assumed to be proportional to catchment wetness index (w) as follows:

$$u_k = w_k r_k \quad (5.1)$$

The evolution of w with time can be represented as a proportion (a) of the rainfall in that time step (i.e. which acts to increase w), and the loss is a proportion ($1/b$) of the preceding estimate of w :

$$w_k = ar_k + w_{k-1} \left(1 - \frac{1}{b}\right) \quad (5.2)$$

where b is usually estimated as an empirical function of air temperature T :

$$b = b' e^{g(T-T')} \quad (5.3)$$

where b' is a reference value of b at air temperature $T = T'$, and g is the temperature modulation parameter. For application to low yielding ephemeral rivers, the model was modified by introducing a threshold l , and

a non-linearity (an exponent) parameter p (Ye et al., 1995, Schreider et al., 1996):

$$u_k = (w_k - l)^p r_k \quad \text{if } w_k > l, \text{ otherwise } u_k = 0 \quad (5.4)$$

The flow routing is represented by a linear transfer function usually corresponding to two linear reservoirs in parallel, i.e. the quick and slow flow responses with residence times kq and ks , respectively. However, for application to ephemeral rivers, a single reservoir may be adequate (Ye et al., 1997b).

In the Limpopo application a semi distributed version of IHACRES is used, where IHACRES is applied to each sub-catchment, and then the runoff from all the sub-catchments is integrated with a channel network model. McIntyre & Al-Qurashi (2009) used a channel routing model with constant celerity parameter (c) to integrate the simulated runoff from 20 sub-catchments of the arid Wadi Ahin basin in The Sultanate of Oman. The same channel routing model is applied to the main channels of the Limpopo case study where the channel within each subcatchment receives the distributed runoff from that subcatchment (q) and the accumulated flow from the upstream catchments (U) to yield flow at the catchment outlet (Q) according to

$$Q_t = U_{t-L/c} + \int_{x=0}^{x=L} q_{t-x/c} dx \quad (5.5)$$

Where L (m) is the channel length in the subcatchment, x (m) is distance from the downstream end of the channel towards the upstream end, and c (ms^{-1}) is a celerity parameter. As the model operates on discrete daily time-steps, whereas L/c and x/c are real numbers, $U_{t-L/c}$ and $q_{t-x/c}$ are estimated by linear interpolation between the values at the two surrounding time-steps (McIntyre and Al-Qurashi, 2009). In this application, channel transmission losses were not represented explicitly in the channel routing model, rather

they are implicitly accounted by the parameter b according to Equation 5.2 consistent with the approach by other researchers (e.g. McIntyre and A-Qurashi, 2009). The argument is that the lumping of all losses in this way is consistent with the empiricism of the IHACRES model, and that hillslope and channel routing models are linear and so whether or not the losses come before or within them is inconsequential, except they are functions of only subcatchment areas rather than also channel lengths.

5.3.2 Justification for the use of the IHACRES model

The IHACRES model and its recent improved variants as stated above are amongst the widely used rainfall-runoff models particularly in semi arid areas mainly for 3 reasons. Firstly, IHACRES requires few input data, i.e. only rainfall, temperature or evapotranspiration time-series are required to predict streamflow given a calibrated model. These datasets are often available in semi arid areas, including the case study under investigation. Secondly, the dominant hydrological processes known to occur in ephemeral rivers of semi arid catchments (see Equation (5.4) are thought to be well represented in the IHACRES model by the empirical wetness index model (Ye et al., 1998, Ye et al., 1997b). Thirdly, it has the potential for use in climate change assessment studies because of the fact that it uses key climate variables, precipitation and temperature or evapotranspiration, as inputs. However, it has been argued in the literature that one of the sources of uncertainty is through the choice of a model structure (Brutts et al., 2004, Beven, 2001). Traditionally, this uncertainty is identified by analysing different runoff properties (such as flow volumes, time to peak, peak discharge and flow duration curves, among others) to determine if the model gives reasonable results, within an acceptable limit of accuracy, based on the purpose of investigation.

5.4 Spatial-temporal rainfall representation using the GLMs

Daily rainfall was stochastically generated using GLMs (as detailed in Chapter 4 (and Kenabatho et al., 2008, Kenabatho et al., 2009, Kenabatho et al., 2010) from the 13 rain gauges presented in Chapter 4 (Table 4-1). In summary, the GLMs were applied to the Limpopo case study in these stages:

1. Identification of suitable predictors and coefficient values for the occurrence and amounts models (see Table 4-2, Chapter 4). This included sea-level pressure and humidity taken from ERA-40 reanalysis data for the grid square which overlies the catchment.
2. The stochastic generation of 10 sets of temporally infilled rainfall data for the period 1974–1999, to give a complete set of inputs for calibration of the hydrological model under uncertainty.
3. In principle, the GLM could be used to infill spatially as well as temporally. This was demonstrated in Chapter 4 (section 5). The conclusion from there was that the GLM gave satisfactory results for temporal infilling. However, for spatial infilling it was observed that the model gave reasonable spatial rainfall surface only at areas where the topography is relatively flat but not at exceptionally high or low altitude, where the model gave either very high or low rainfall values (Figure 5-2, the left plot). For example, the mean annual rainfall (MAR) towards the catchment outlet estimated by spatially infilling rainfall using the GLM is as low as 220 mm whereas none of the existing nearby raingauges has a MAR less than 300 mm. The implication of this problem is that where spatial features of rainfall fields are needed for a catchment that has a large variation in topography such as this case study (see Figure 4-8), the spatial rainfall fields generated by the GLM may give erroneous results compared to when the catchment is relatively flat. For this reason the Thiessen polygons (Figure 5-2, right plot, Table 5-1) were used to generate the spatial field over the

catchment for use with the semi distributed hydrological model.

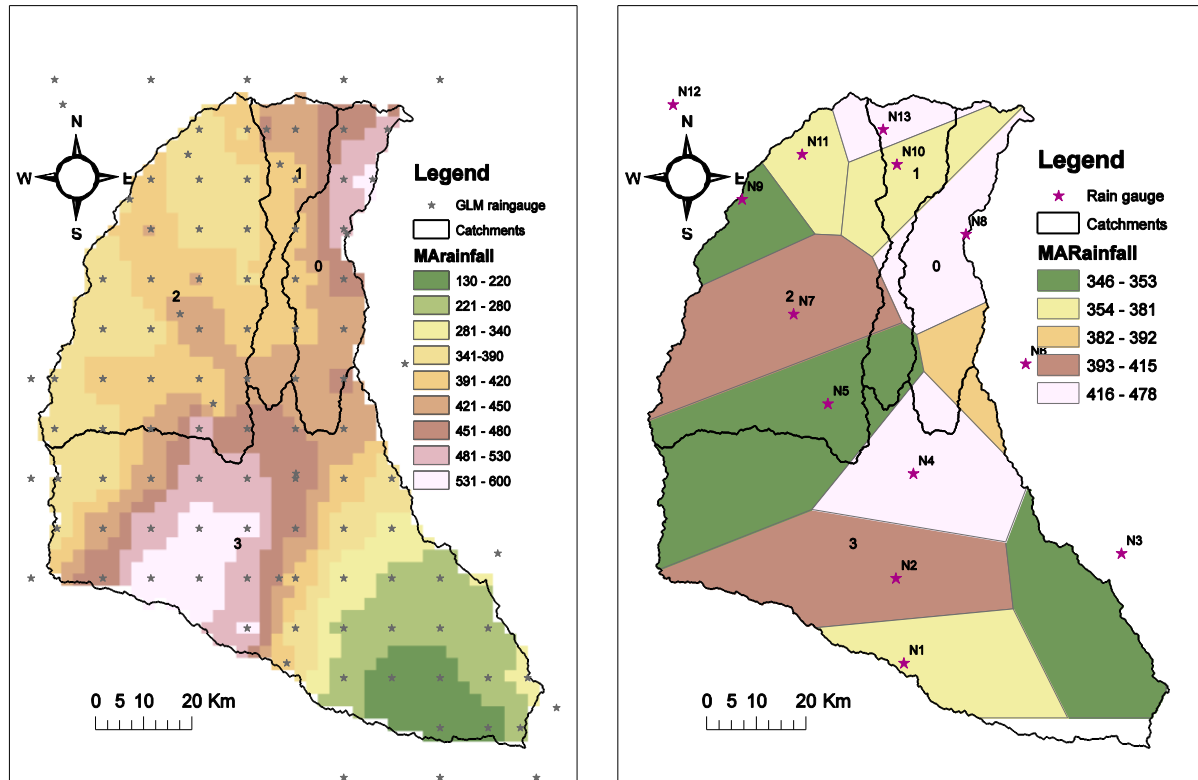


Figure 5-2 Spatial rainfall surface (mean annual rainfall) generated from the GLM (left plot, reproduced from Figure 4-8 to ease comparison) and the Thiessen Polygon method for the upper Limpopo basin.

Table 5-1: Areas of Thiessen polygons used for computing spatial rainfall shown in Figure 5-2, right plot.

Subcatchment Number (Name)	Gauge Number	Polygon Area (km ²)	Total Area (km ²)
1 (Tati)	N13	112.6	534.8
	N10	201.6	
	N8	64.9	
	N7	29.0	
	N5	126.8	
0 (Ntshe)	N13	10.1	784.9
	N10	99.2	
	N8	430.6	
	N5	15.1	
	N6	153.5	
	N4	76.4	
2 (Mooke)	N13	82.9	2245.2
	N10	144.9	
	N8	10.8	
	N7	934.3	
	N5	528.4	
	N11	274.9	
	N9	266.2	
	N4	2.7	
3 (Outlet)	N6	70.5	4094.1
	N4	713.1	
	N5	723.0	
	N2	1080.8	
	N1	625.4	
	N3	881.2	
Basin area (km²)			7659.0

5.4.1 Review of the calibration data

Before calibrating the model, an attempt was made to review the data used (further to the review in Chapter 3). This was done by evaluating the runoff coefficient for the subcatchments to help understand the variability of the hydrological responses over the years. The results (Figure 5-3) showed that significant variations in runoff coefficients occurred over the years (considering a hydrological year, October–September). For example, the runoff coefficients for the catchment outlet are very high in 1987 and 1988. In addition, there is an increasing trend between 1982 and 1988. In order to understand the causes of these anomalies, a plot showing temperature and rainfall for the same period (Figure 5-4) was undertaken. Figure 5-4 shows that warmer and wetter years often experience higher runoffs. This may perhaps be related to the convectional rainfall mechanisms associated with warm air which cause relatively intense storms with high runoff. IHACRES is designed to represent this runoff non-linearity through Equation 5.4. However, there are years where this mechanism is not evident. The period 1986-87 experienced a higher than average runoff coefficient even though rainfall was lower than average. Note that these two years followed a four year dry spell potentially indicating reduced evapotranspiration due to reduced vegetation cover.

This phenomenon has been observed by other investigators of semi arid hydrology. For example, in western New South Wales, Australia, Cordery et al., (1983) noted that during the period 1973-1975 rainfall was high and vegetation dense, and the following 2 years no runoff was recorded even though several appreciable rainfalls occurred, yet after several dry years, runoff was recorded following virtually every rainfall greater than 5mm. This mechanism cannot be simulated by IHACRES because the loss parameters

are stationary in time. However, the limited evidence of this effect in Figure 5-4 cannot be considered conclusive and cannot justify development of a more complex model. Instead, the calibration data was split into two sets: 1975-1987, and 1987-1991. Although these two periods do not have distinctly different hydrological regimes (two such continuous periods of suitable length for calibration data sets are not identifiable from Figure 5-4) they provide some representation of sensitivity to the calibration period.

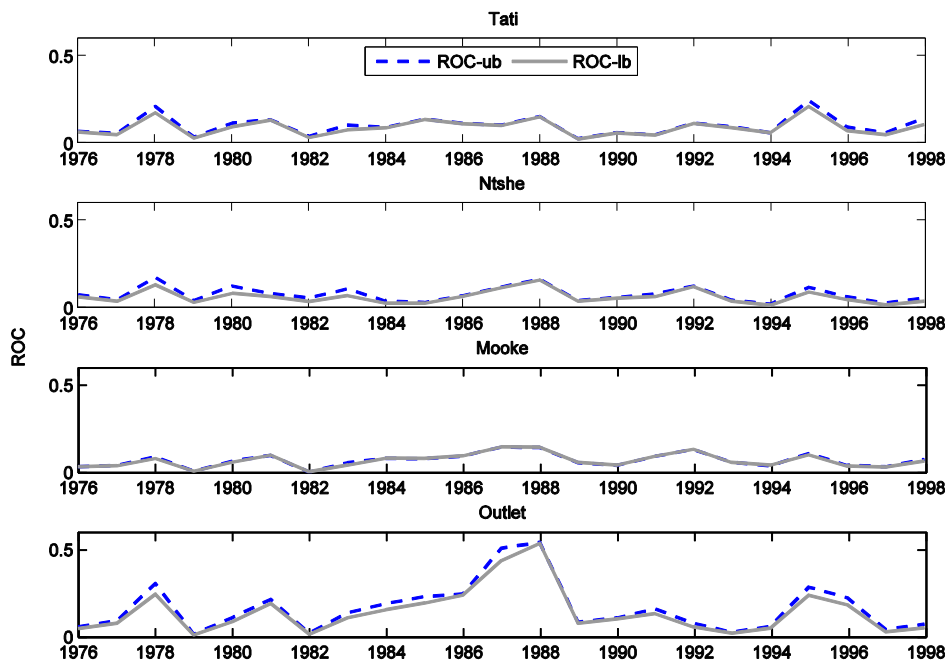


Figure 5-3: Runoff coefficients (ROC) for the three subcatchments and the catchment outlet. The ROC are plotted with their lower bound (lb) and upper bound (ub) derived from 10 rainfall realisation.

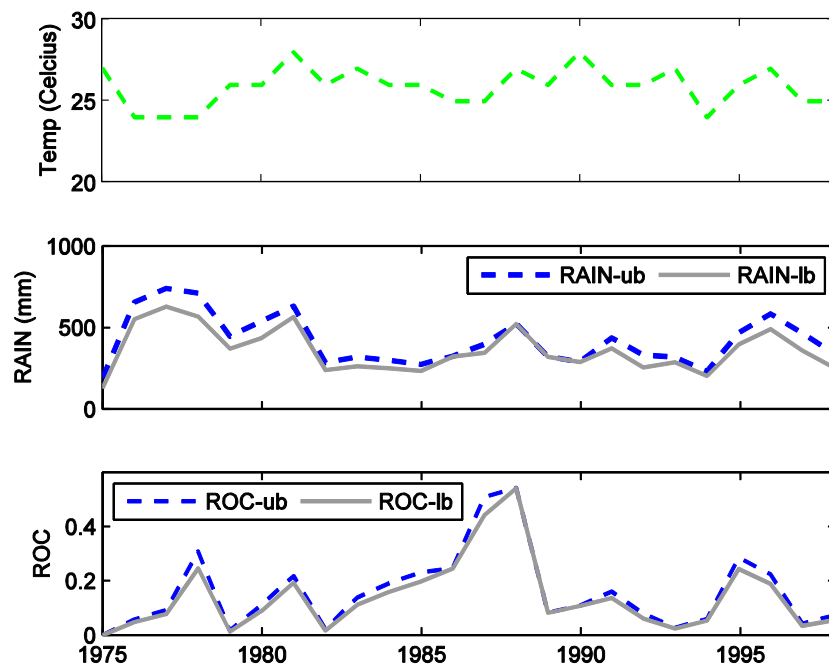


Figure 5-4: Temperature, rainfall and runoff coefficients for the catchment outlet plotted with their lower (lb) and upper (ub) bounds derived from 10 rainfall realizations. The third plot repeats the last plot in the previous figure for comparison with the rainfall and temperature plots.

5.4.2 Calibration strategy

The IHACRES model was run with a daily time-step using the four sub-catchments with flow data (Figure 4-1) for the calibration period 1975-1987. The upper catchments were calibrated individually and their behavioural parameter sets were fixed prior to calibrating the downstream catchment. Uniform random sampling was used as the calibration search method, with 10 000 samples. Two main sources of uncertainty were considered during the calibration; (i) uncertainty arising from 10 in-filled rainfall realisations obtained from the GLM, and (ii) uncertainty due to parameter equifinality, whereby, irrespective of rainfall uncertainty, many parameters sets may give equally optimal objective function values. The equifinality was assessed by considering the best 100 parameter sets from each of the three upstream

catchments to feed into the calibration of the outlet catchment. From these parameter sets (with the potential for 100^3 different combinations), 100 were selected at random for calibrating the downstream catchment. Using each of these 100 parameter sets in turn, the downstream catchment was then calibrated by taking 10000 samples, so ultimately there were 1 million parameter sets to choose from. The best 100 parameter sets of these were chosen. This calibration procedure was repeated 10 times - using each of the 10 rainfall realisations - giving a total of 1000 parameter sets considered to be equally optimal.

Various objective functions (Table 5-2, Appendix B) were tested during the initial stage of modelling, and given the main ultimate task is to analyse reservoir behaviour from flow volumes under input uncertainty, the cumulative absolute relative monthly volume error was selected as performance measure:

$$VE_{abs} = \frac{\sum_{i=1}^N (|o_i - c_i|)}{\sum_{i=1}^N o_i} \quad (5.6)$$

Where N is the number of data points, o_i and c_i are observed and simulated flow volumes in month i . The model was run at a daily time step, but the VE_{abs} was assessed at a monthly scale. This monthly assessment was thought to be appropriate given the large capacity of the reservoir whereas daily simulations are appropriate because of the high variability of the rainfall and the nonlinearity of the response.

5.4.3 Parameter identifiability and sensitivity

Initially, the model defined in Eq.(5.4) was used together with two linear stores in parallel. The reference air temperature T^* in Eq. (5.3) was fixed at

the average temperature of 26°C leading to 9 parameters to estimate (a , b , g , l , p , f , kq , ks , c). This enables the catchment water loss to be controlled primarily by the temperature modulation parameter g , on the basis that evapotranspiration losses are expected to be linked to temperature (Jakeman et al., 1990, Post and Jakeman, 1999, McIntyre and Al-Qurashi, 2009).

Following the approach used by McIntyre and Al-Qurashi (2009), where the model parameters which are thought to be non-identifiable and insensitive are eliminated (i.e. by either fixing them or removing them to check if their presence or absence affect model performance and simulations), the final model was reduced to a 6-parameter model (without ks , and by fixing c and f to 1, with only one routing store (kq) used). The ks parameter, which represents groundwater storage, was removed because groundwater is usually deep in this basin as discussed in section 3 (i.e. on average 60 m beneath the surface).

The limitation of this sensitivity analysis approach is that there is no formalised way of determining the point/value at which a parameter is fixed, the decision is rather subjective. Also, it is not guaranteed that an insensitive parameter will remain so, even during the validation or simulation period, which may affect predictive performance.

The prior parameter ranges are listed in Table 5-3. The dotted plots, Figure 5-5, are a scatter plot of model parameter values for the catchment outlet and their corresponding objective function values (Wagener et al., 2002), and these were used to assess parameter identifiability and sensitivity.

Of the remaining 6 parameters, the non-linearity (p) parameter is the most identifiable as evident in Figure 5-5 followed by the volume balance (a) and the fast flow residence time (kq) parameters. The least identifiable and sensitive parameter is the wetness threshold (l), however, this parameter was retained as the predictive performance of the model deteriorated when it was eliminated. It is important to note from Equation (5.4) that p controls

the distribution of losses over time, and kq parameter controls the runoff routing hence affecting monthly runoff, hence it is not surprising that they are sensitive when the water balance (volumetric error, VE) objective function is used. This is consistent with the findings from other semi arid areas (see (McIntyre and Al-Qurashi, 2009)). Similarly, the volume balance parameter controls the overall water balance such that the volume of effective rainfall matches that of observed streamflow during the calibration period (Littlewood, 2002).

Table 5-2 Objective functions used during the calibration

Objective function	Acronym	Formulae	Remarks
Nash-Sutcliffe Efficiency	1. NSE*	$NSE = 1 - \frac{\sum_{i=1}^N (o_i - c_i)^2}{\sum_{i=1}^N (o_i - \bar{o})^2}$	o_i and c_i are observed and simulated flows at time steps i , $\bar{o}$ is the mean of observed flows. N is the number of data points. $NSE^* = 1 - NSE$
Root mean square error	2. RMSE	$RMSE = \sqrt{\frac{1}{N} \left(\sum_{i=1}^N (o_i - c_i)^2 \right)}$	o_i and c_i are observed and simulated flows at time steps i
Root mean square error for low flows	3. RMSEL	$RMSEL = \sqrt{\frac{1}{NL} \left(\sum_{i=1}^{NL} (o_i - c_i)^2 \right)}$	NL is the number of data points below a threshold of observed flow L , o_i and c_i are observed and simulated flows at time steps i for which $c_i < L$.
Water balance (Volumetric) error	4. VE	$VE_{abs} = \frac{\sum_{i=1}^N (o_i - c_i)}{\sum_{i=1}^N o_i}$	o_i and c_i are observed and simulated flows at time steps i
10% Tolerance	5. TOL _{0.1}	$TOL_{0.1} = Num(o_i - c_i) - \{Num(abs(o_i - c_i)) < Num(0.1 * o_i)\}$	o_i and c_i are observed and simulated flows at time steps i , Num is the number of elements of the array in the parenthesis

Table 5-3 Model parameters used and their ranges

Parameter	Description	Units	Lower Limit	Upper Limit
b	Control on loss rate	-	1	40
g	Temperature dependence	$^{\circ}\text{C}^{-1}$	0.1	0.5
l	Wetness threshold	-	0	2
p	Non-linearity of response	-	0.5	1.5
a	Volume balance	dmm^{-1}	0.0001	0.02
kq	Fast residence time	d	1	25

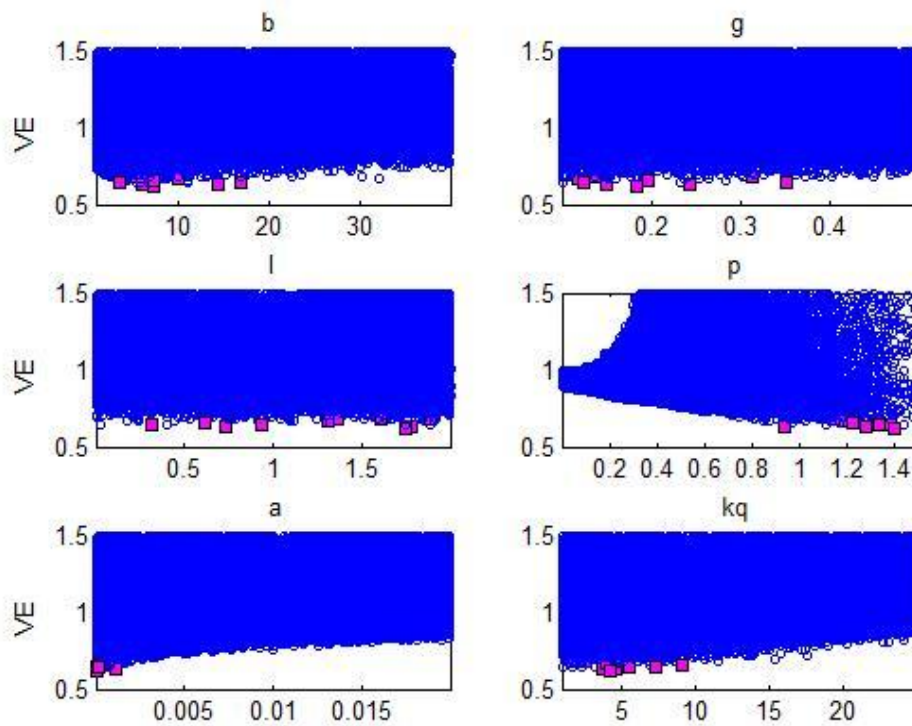


Figure 5-5: Parameter identifiability for VE fit at catchment outlet using dotty plots. The plots include the parameter samples across all 10 rainfall realisations. In each plot the optimum parameter values for each rainfall realisation are shown by a pink box.

In addition to the dotty plots in Figure 5-5 parameter values corresponding to each rainfall realization were plotted for each subcatchment as shown in Figures 5-6 to 5-9. These were produced by taking the 100 parameter sets considered optimal to define parameter uncertainty bounds as well as selecting the optimal parameter values for each rainfall realization. These plots show that optimum parameters and their uncertainty can vary widely over the different rainfall realizations. This is also evident in Figure 5-5, indicating the significance of rainfall uncertainty on model parameters as well as over the individual catchments, indicating the importance of the properties of the catchments such as vegetation cover and soil types. Also,

the uncertainty bounds for most parameters are wide, indicating high uncertainty resulting from the equifinality of parameter sets.

A similar plot was done when using a different calibration period (1981-1991) (Figure 5-10 and Appendix C). When considering the catchment outlet, it is evident (Figures 5-6 and 5-10) that model parameters are sensitive to the calibration period chosen. For example, the optimal values and parameter uncertainty bounds for the non-linearity parameter (p) are less variable from one rainfall realisation to the other when using the 1981-1991 period (possibly because of completeness of rainfall data during this period, see Figure 4-6 in Chapter 4, see also Figure 5-4), and the optimum values for this parameter are pushed towards the maximum (1.5) for most of the rainfall realisations (possibly indicating a change in runoff generation presumably because of changes in vegetation cover/land use as discussed in section 5.4.1).

Another parameter worth assessing is the temperature modulation parameter (g), which as discussed above controls the water loss assuming that evapotranspiration losses are linked to temperature. During the first calibration period (1975-1987), the g parameter values for the catchment outlet appear to be pushed towards the lower values (around 0.2), but are highly variable during the second calibration period (at times attaining the highest value of 0.5). In both cases uncertainty due to equifinality is high. The results for this parameter show that it is difficult to link losses in the upper Limpopo basin to temperature although in some periods (1981-1991) there is stronger evidence than in others. The implication of this problem is that losses may be controlled principally, at least in some periods, by infiltration or abstractions; however estimation of future flow volumes without including temperature dependency may lead to erroneous results particularly when considering climate variability/change.

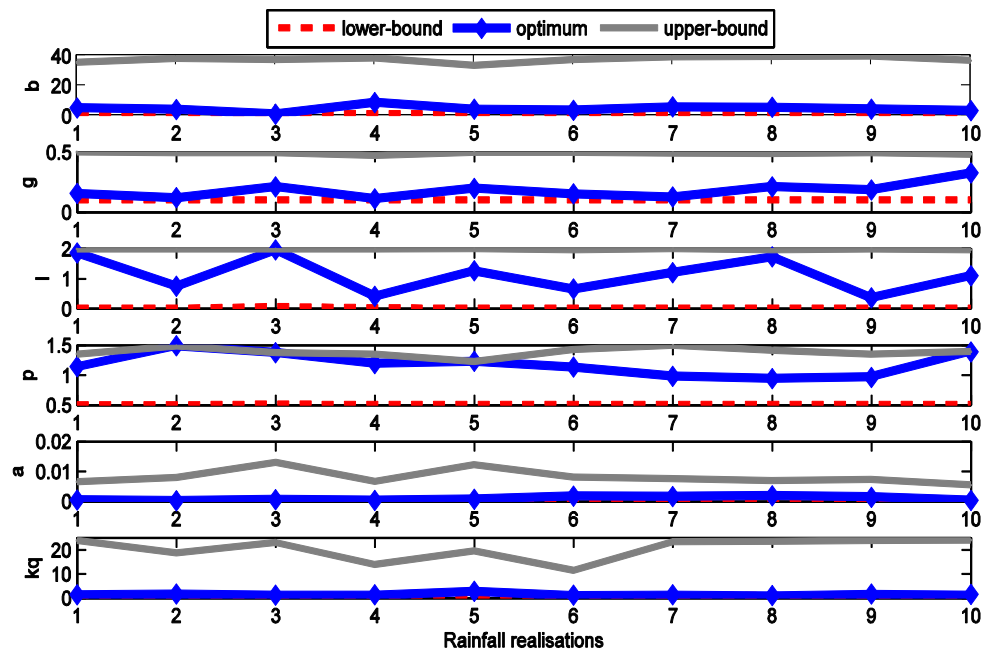


Figure 5-6: Parameter variability for the Outlet catchment plotted for each rainfall realization using the 1975-87 calibration period. The upper and lower bounds were computed from the best 100 parameters.

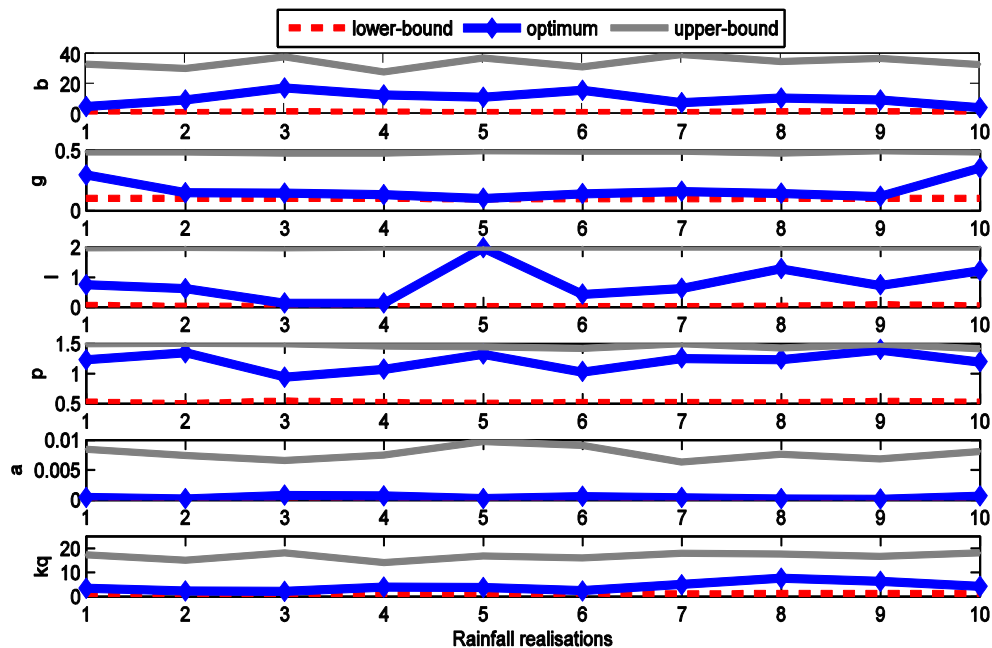


Figure 5-7: Parameter variability for Mooke catchment plotted for each rainfall realization using the 1975-87 calibration period. The upper and lower bounds were computed from the best 100 parameters.

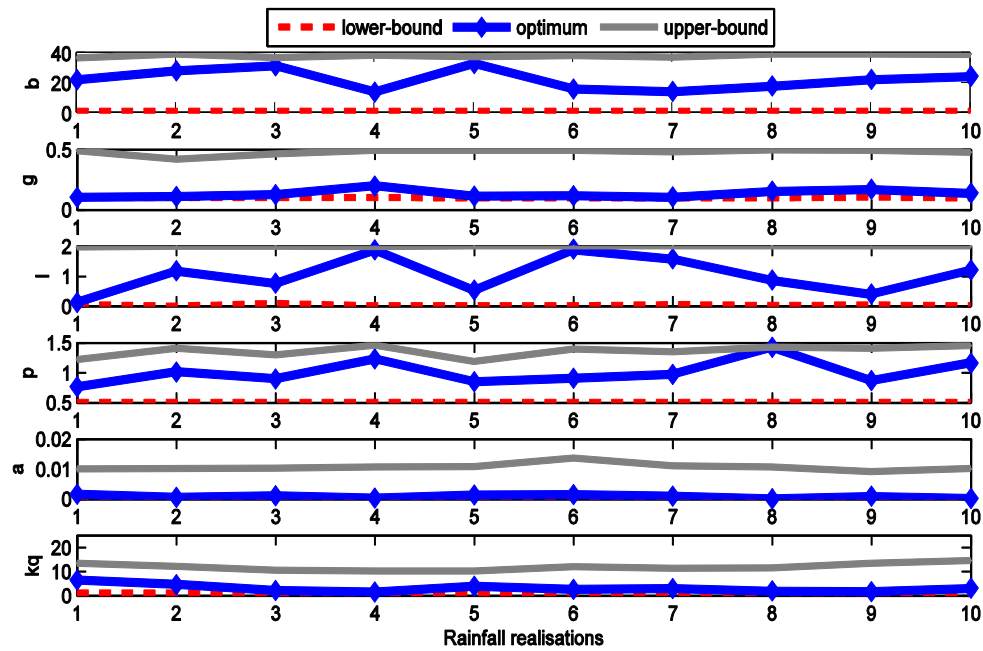


Figure 5-8: Parameter variability for Ntshe catchment plotted for each rainfall realization using the 1975-87 calibration period. The upper and lower bounds were computed from the best 100 parameters.

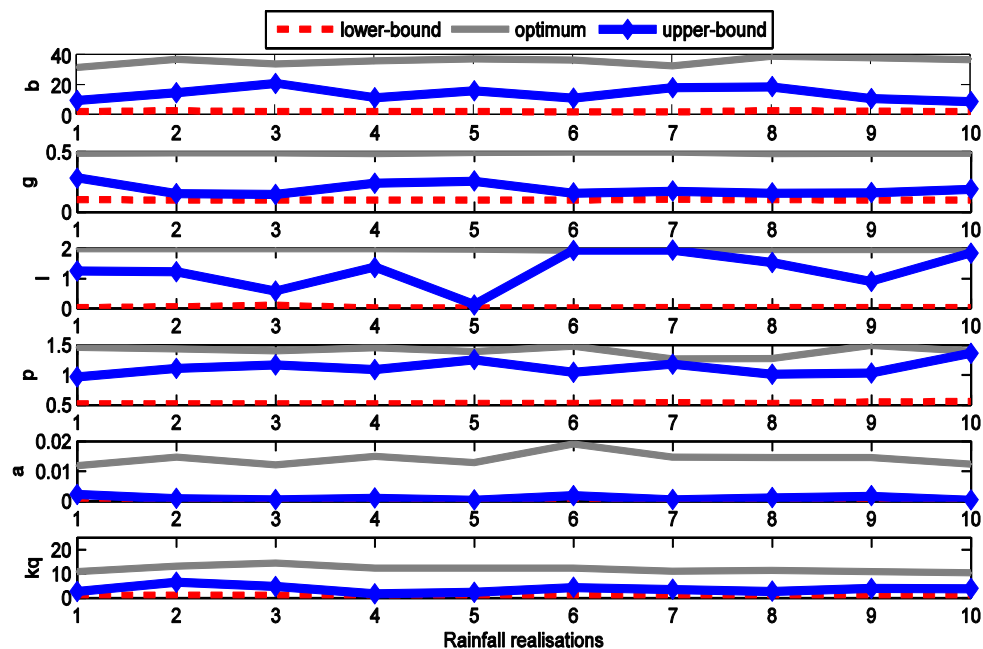


Figure 5-9: Parameter variability for Tati catchment plotted for each rainfall realization using the 1975-87 calibration period. The upper and lower bounds were computed from the best 100 parameters.

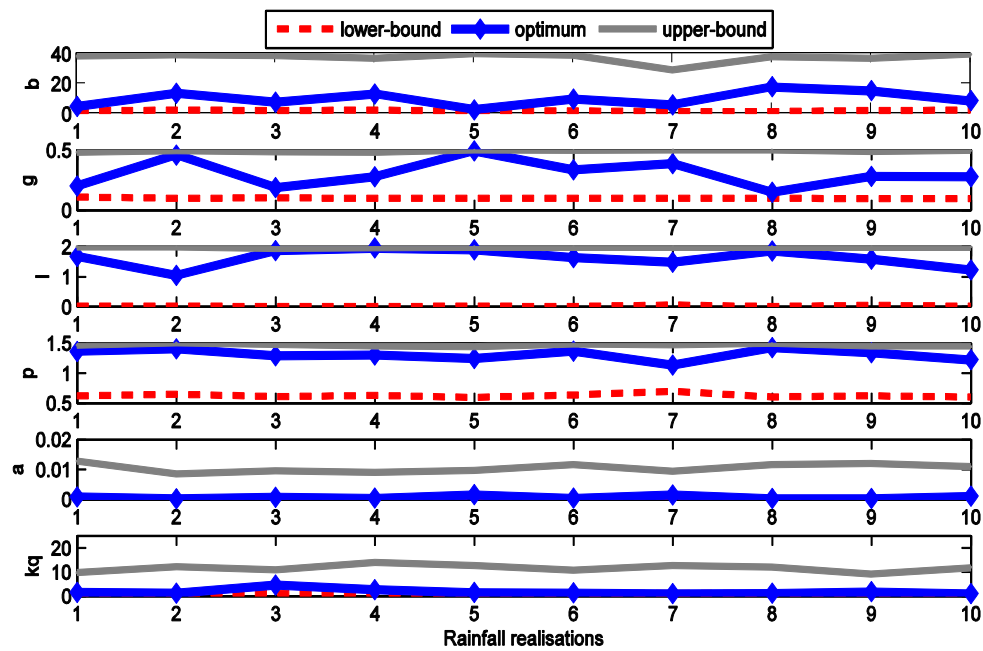


Figure 5-10: Parameter variability for the Outlet catchment plotted for each rainfall realization using the 1981-91 calibration period. The upper and lower bounds were computed from the best 100 parameters.

5.4.4 Calibration and validation results

In line with the review in section 5.4.1, the difficulty of modelling this set of rainfall-runoff data is evident in the model results. Figure 5-11 shows the simulated uncertainty bounds for the flow time series and the flow residuals for the calibration period 1975-1987 and the validation period 1988-1997, for the catchment outlet. For the calibration period, the confidence limits are wide due to rainfall and parameter uncertainty, but the observations fall within the limits. However, the same model is unable to explain the observations for exceptionally wet periods (i.e. 1987/88 and 1995/96-as shown by high residuals in the validation period), where the observations are highly underestimated by the model. The same observation is made when considering the results for the individual subcatchments in Figures 5-13 to 5-15. Clearly, a major source of uncertainty is the unpredictable variability of the hydrological response.

To investigate this further, the 1981-1991 data was used for model calibration (Figure 5-16, and Appendix D). Similarly, the model is able to explain the observations during the calibration (with the exception of the problem years: 1987/88) but not during the validation period (mainly after 1995/96 period) where the model highly overestimates the observed flows. The results from these two cases (see also Figure 5-12 which shows model efficiency results for the two calibration periods) support the view that the model parameters in this catchment vary significantly over time.

Similarly, a close look at Figure 5-12 (top plots) indicates that during the first case, where the model was calibrated using the period 1975-1989, the validation results for the Mooke catchment improved significantly (i.e. the VE during the validation is very small-see also Figure 5-15, where the residuals are also minimal). On the other hand, when using the second calibration period, the model performance at the catchment outlet deteriorated (as shown by an increase in VE). The simulated results (Figure

5-16) also show reduced performance for the catchment outlet when using the second calibration period. These findings indicate that the model is sensitive to the calibration period used, and that model parameters are not stationary in this basin.

The parameter variability found here could be a result of land use/cover changes over time in this catchment as supported by results from other studies in this basin. For example, a study by Parida et al., (2006) which looked at the effects of runoff changes in the Notwane catchment-a catchment located some 300 km in the upstream of the study area, found that land use/land cover changes (mainly as a result of urbanisation) contributes about 52% of the runoff changes, compared to 48% from climatic factors. Studies conducted elsewhere also confirm that land use/land cover changes have effects on runoff changes (e.g. Zhi et al., 2009). The implication of this is that future hydrological responses cannot be represented using any one of these calibration periods. To overcome this, it is thought that developing a range of scenarios of flows based on a combination of the parameter sets from both the calibration periods will produce a better representation of the true uncertainty than using either one or the other.

Figures 5-13 to 5-15 (presented in order of increasing catchment scale) also show that the smallest catchment, Tati shows relatively good model performance during both calibration and validation periods as the observed streamflows are well within the uncertainty bounds. The performance deteriorates as the catchment size increases, particularly during the validation period where the model underestimates the observed flows in some years, particularly during 1987/88 and 1995/96 as shown by the results at the catchment outlet. One of the possible reasons for the errors could be related to sensitivity of the model to catchment characteristics at different scales. Smaller catchments in this basin may display relatively homogeneous characteristics compared to the larger catchments, which may be highly heterogeneous-hence the difficulty in calibrating the latter

considering that processes are assumed homogeneous in each subcatchment.

Additional catchment data derived from the DEM, which are shown in Table 3-5 were used to add on to the catchment characteristics presented in chapter 3. From this table, it is evident that smaller catchments, i.e. Tati and Ntshe generally have similar key characteristics such as slope (basin and flow), sinuosity (which gives indication on how straight or bending the river channel is: a sinuosity of 1 indicates that in general the river channel is straight). These similarities could imply similar or related bio-physical characteristics as well as fluvial processes between these catchments (Camporeale and Ridolfi, 2010).

The results obtained using another calibration period of 1981-1991 (Appendix D) show a similar pattern with those obtained using the calibration period of 1975-1987 (Figures 5-13 to 5-15, where smaller catchments are well represented by the models).

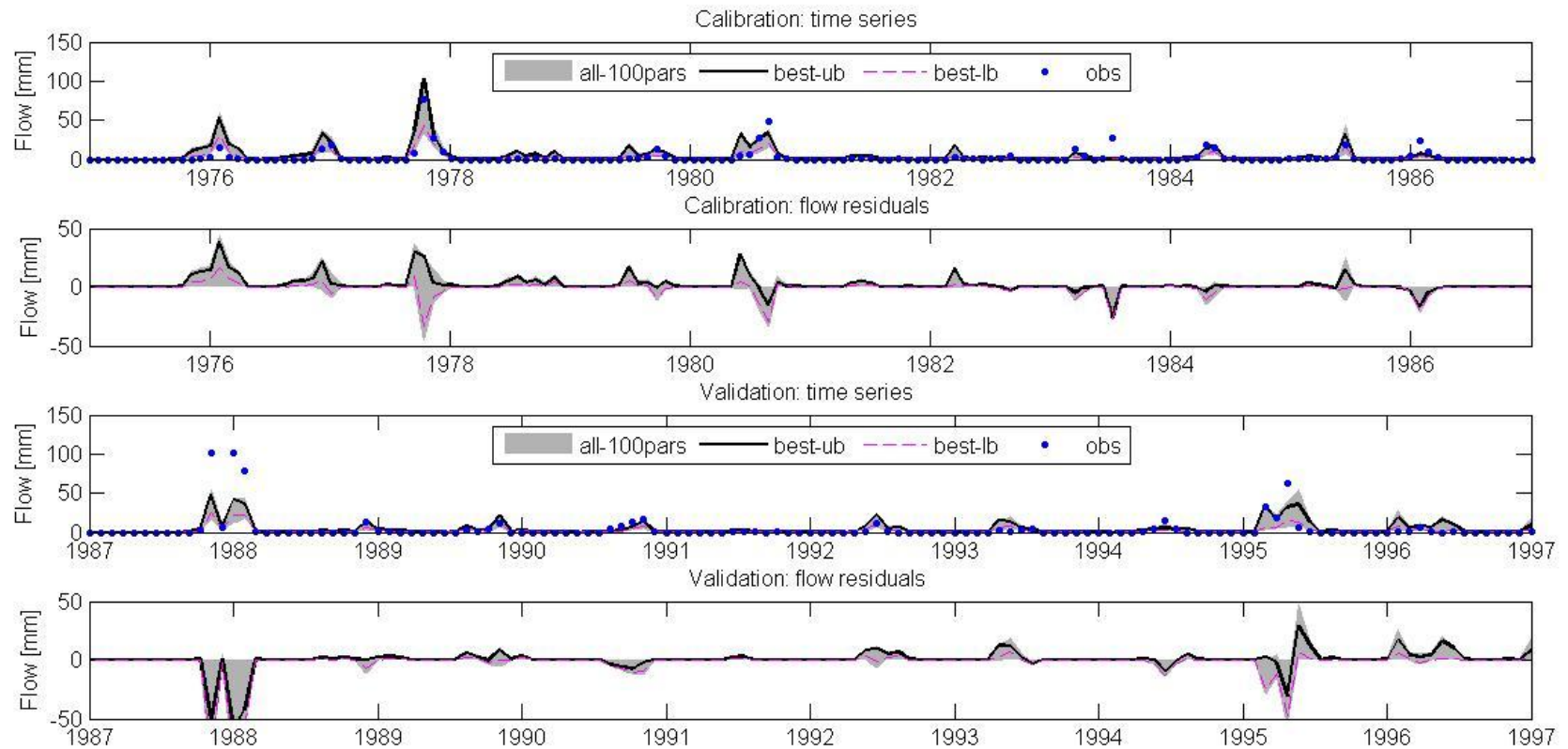


Figure 5-11: Calibration (top two plots) and validation (bottom two plots) results for the outlet catchment. The blue dots show observed flow data. The solid and dashed lines represent the upper and lower bounds of the best simulated flows from the 10 rainfall realizations. The grey area represents uncertainty arising from the top 100 parameter sets from all the rainfall realizations.

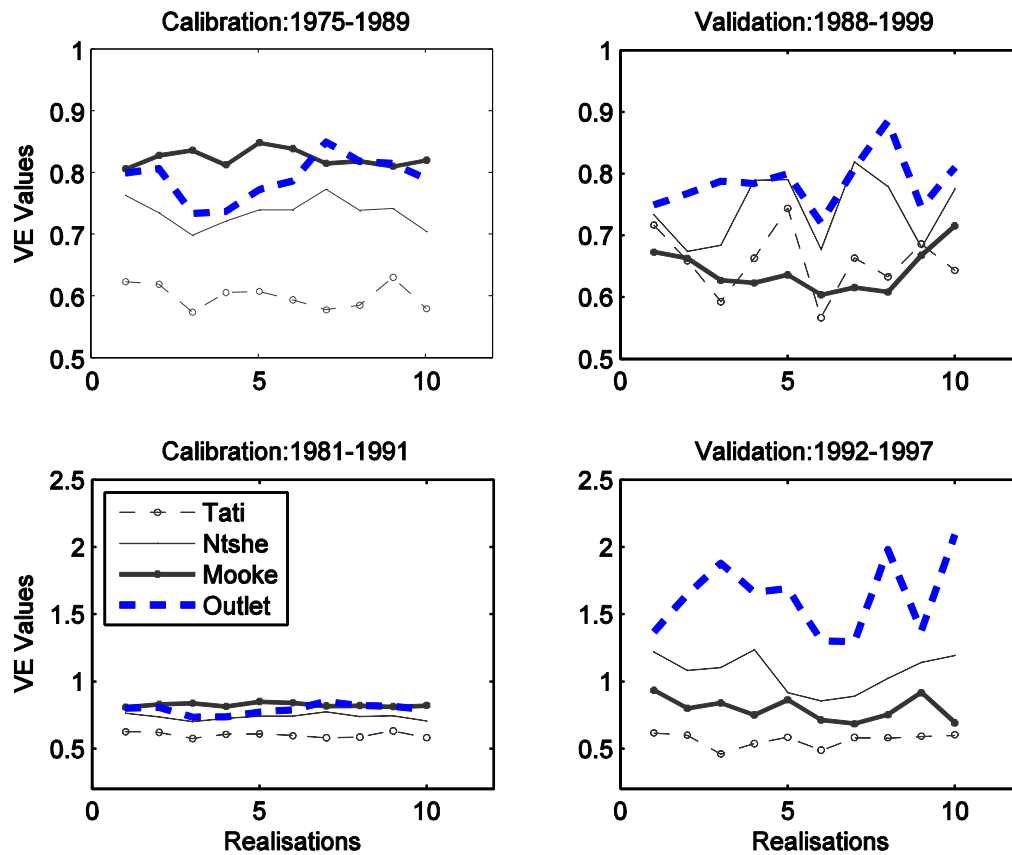


Figure 5-12: Model efficiency in terms of the volumetric errors (VE values) for the two calibration periods and the corresponding validation periods in the study area.

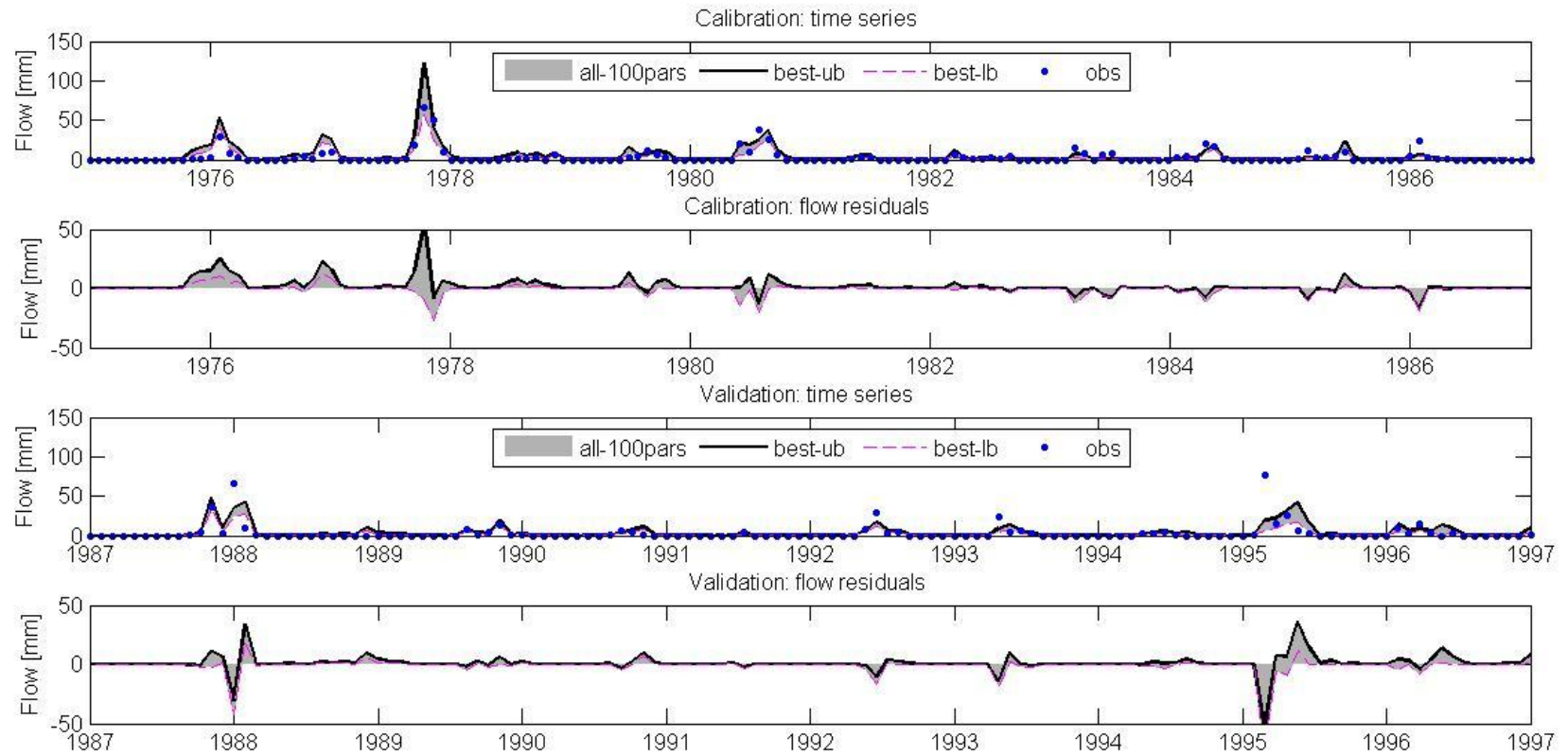


Figure 5-13: Calibration (top two plots) and validation (bottom two plots) results for Tati subcatchment. The legend is same as Figures 5-11.

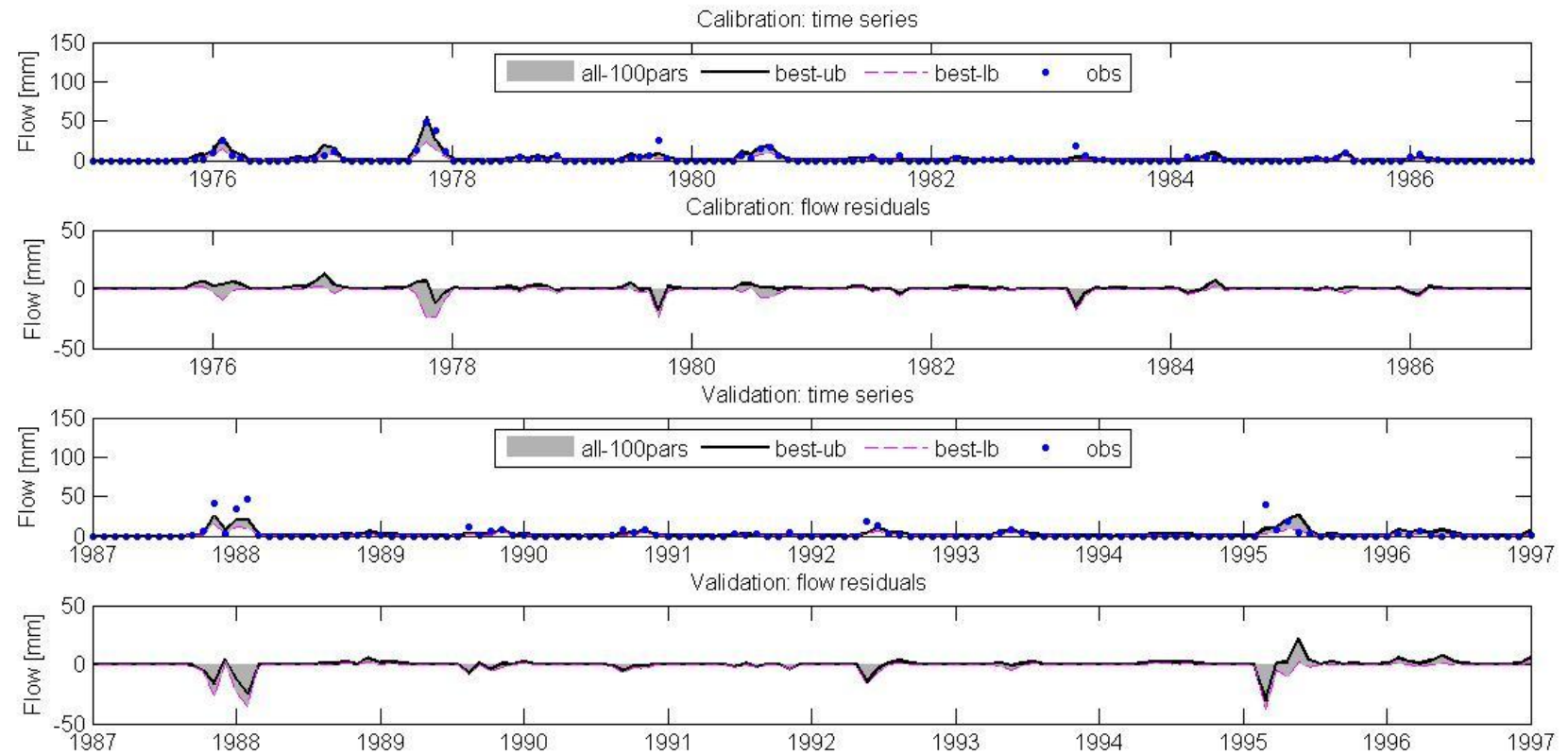


Figure 5-14: Calibration (top two plots) and validation (bottom two plots) results for Ntshe subcatchment. The legend is same as Figures 5-11.

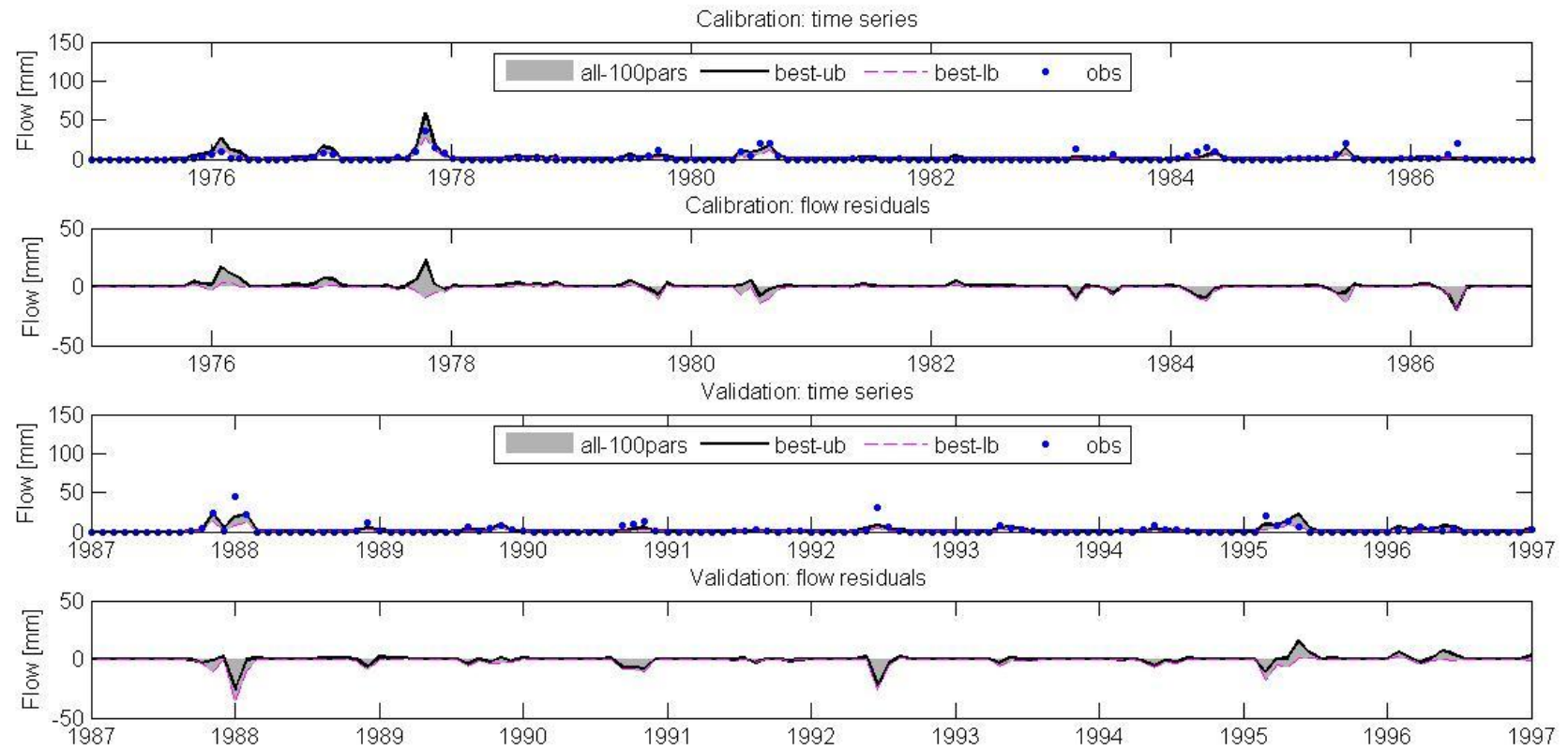


Figure 5-15: Calibration (top two plots) and validation (bottom two plots) results for Mooke subcatchment. The legend is same as Figure 5-11 .

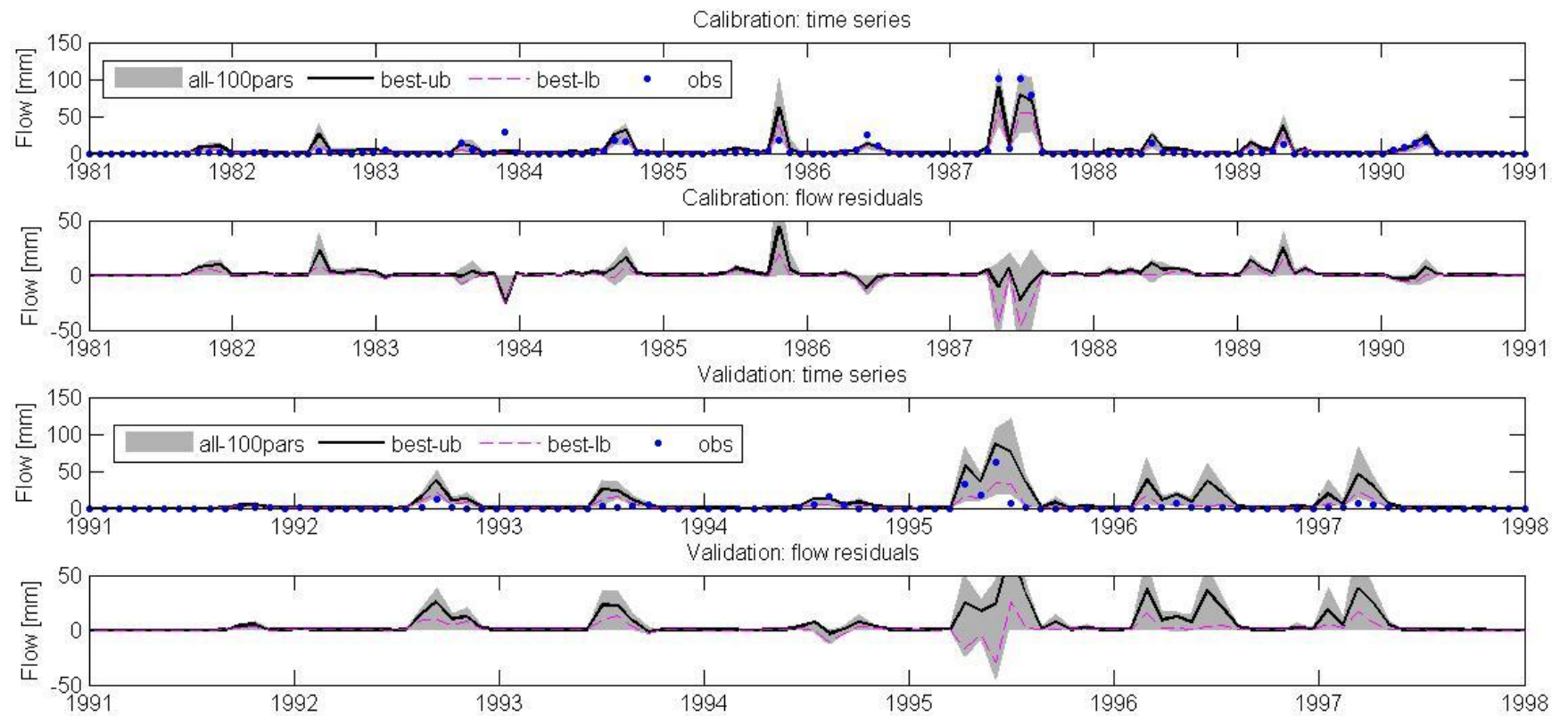


Figure 5-16: Calibration (top two plots) and validation (bottom two plots) results for the outlet catchment (using the second calibration period). The legend is same as Figure 5-11.

5.5 Conclusions

The focus of this chapter was to demonstrate the importance of incorporating uncertainty in hydrological models. Three major sources of uncertainty have been presented in this chapter. These were: (1) Uncertainty resulting from multiple rainfall realisations. This was addressed by infilling the observed rainfall data using a stochastic Generalised Linear Model (GLM). (2) Uncertainty arising from multiple 'equifinal' parameter sets. This has been addressed by using a semi distributed hydrological model which was calibrated using each of 10 rainfall realisations, and for each realisation best 100 parameter sets from each of the three gauged upstream catchments fed into the calibration of the outlet catchment to obtain ensemble model results. (3) Uncertainty arising from the unpredictable variability of the hydrological response. This has been addressed by calibrating the hydrological model using different and independent sets of hydro-climatic data as input to the model. The combined effects of these uncertainties have been presented: (1) when considering the model parameters, it was found that the confidence limits for the equifinal parameters for each rainfall realisations were wide; (2) the optimal parameter values varied highly from one rainfall realisation to the other, particularly during the 1975-87 period where gauged rainfall data is quite incomplete and much of the data was infilled using the GLM. Regarding the model simulations: (3) the model was able to explain the observed flows during the calibration period (except during some years such as 1987/88- which were considered problem cases) although the uncertainty was high (resulting from rainfall and parameter uncertainty); however, (4) during the validation period the model was, except at the smallest subcatchment and at exceptionally wet years, unable to explain the observations. This behaviour was also observed when using a different calibration period leading to a conclusion that model parameters varied significantly over time in this catchment presumably due to land cover/land use changes-clearly

indicating (5)high non-stationarity of response which the rainfall-runoff model could not match. As a result, it is suggested that future hydrological scenarios be developed based on both sets of calibration period used in this work and the simulated flows should consider the effects of parameter and rainfall uncertainty.

As a way of comparison, it is proposed that a change factor approach also be used, i.e. using relative changes instead of the actual flows. This will be implemented by considering the predicted flows under the baseline and changed climate obtained using all the equifinal parameters. From these flows, a large sample of change factors for each month can be determined and then applied to the historic flows to yield changed future flows. This idea is based on speculation that the rainfall-runoff model is more suitable for predicting relative changes to flow under climate change than it is for estimating flow time-series, for which observed records should be used. These approaches are addressed in detail in chapter six.

CHAPTER SIX

6 Rainfall downscaling and flow generation under climate change

The potential impacts of climate change on water resources include unprecedented variability in rainfall patterns, extended periods of droughts as well as high frequency and magnitude of flood events. However, the expected impacts of climate change and the associated uncertainty vary widely from one location to the other which often necessitates catchment scale impact studies. Models which are currently used to assess the impacts of climate change, i.e. the global (general) circulation models (GCMs) and regional climate models (RCMs) are considered too coarse to give feasible results at catchment scale. Furthermore, rainfall, which is of paramount importance in water resources development, is not accurately simulated by the present generation of GCMs and RCMs. To resolve this, statistical downscaling methods are normally used to ensure that climate predictions are consistent with historical evidence of catchment scale variability over space and time. Focusing on this aspect, this chapter outlines a methodology for downscaling rainfall for the upper Limpopo basin. The methodology includes the use of a statistical rainfall model (the GLM) and the outputs of 5 GCMs (BCM2, CSMK3, HADCM3, INCM3 and MPEH5) to generate rainfall series under baseline and 3 climate change scenarios (i.e. scenarios B1, A1B and A2). The results are then used together with the calibrated hydrological model to generate flow series to quantify the impacts of uncertainty on streamflows in the upper Limpopo basin.

The main findings from this chapter are that (1) rainfall will generally decrease in the upper Limpopo basin (i.e. ranging between 40 to 80% by the year 2100), leading to; (2) a decrease in runoff by the end of the century; (3) the magnitudes of change vary widely across the models; (4) and across the scenarios. The results from an alternative flow estimation approach (i.e. the change factor (CF) method also gave rainfall and runoff changes which are similar to the approach used here, with the exception of spring runoff which was underestimated when using the actual flows rather than relative flow changes estimated from the CF method.

6.1 Introduction

Unprecedented variability in rainfall and flow patterns, extended periods of droughts as well as high frequency and magnitude of flood events will probably constitute major future global environmental problems mainly as a result of global warming and climate change. For example, on a global scale, recent studies suggest that climate change is likely to alter seasonal flow regimes by more than 10% for 90% of the global land area as early as 2050 (Doll and Zhang, 2010). In Africa alone, it is projected that mean air temperature may increase in general by between 3 and 4 °C by the end of the century compared with the 1980-1999 period, with less warming in equatorial and coastal areas (Boko et al., 2007, Christensen et al., 2007), and increased warming in other areas such as North Africa and Southern Africa, which may reach 9 °C and 7 °C, respectively (Ruosteenoja et al., 2003).

In many semi-arid regions global warming is expected to increase evaporative losses and increase the variability of rainfall in both space and time, potentially leading to reduced and more variable river flows (IPCC, 2001a). For example, mean annual flow in the Okavango basin in the north-western part of Botswana may decrease by up to 26% by 2100 using the A2 IPCC emission scenarios (Andersson et al., 2006), considering data from five different GCMs. In the southern part of Botswana, rainfall is expected to decrease by up to 11% by 2050 on the basis of data from two GCMs (HadCM3 and CSIRO MK2) and three IPCC scenarios (A1B, A1FT and A1T) (Masike and Urisch, 2008). Other studies in southern Africa predict contrasting effects of climate change. Using two regional climate models (RCMs) Tadros et al (2005) found that some areas should expect increased temperatures and decreased rainfall by 2070 while other areas will experience increased seasonal rainfall particularly those with relatively low temperature changes. Other studies suggest a change in average annual

rainfall in most parts of southern Africa ranging from -8 to 43% by the year 2100 (Christensen et al., 2007).

To keep up with the ever-escalating water demand in Botswana, in particular the major cities in Botswana, including the capital Gaborone, there is currently significant investment towards constructing artificial reservoirs in the semi-arid Limpopo basin. The upper Limpopo basin, discussed in chapter 3 (Figure 3-1), is critical in terms of water resources in Botswana, and all the major dammed reservoirs are located in it. Botswana's recent national water resource strategy (Snowy Mountains Engineering Corporation and Engineering Hydrological Environmental Management Consultants, 2006) includes development of new reservoirs to increase security of supply. In particular, a 382,000 ML reservoir is proposed at the case study catchment outlet. However, knowledge of how uncertainty in future climate projections will affect water resources systems in the Limpopo basin is currently poor, and there have been no published studies on how climate change will affect the supply of water into the proposed reservoirs.

Three particular hydrological challenges are considered in this chapter:

- 1) Estimation of the variability of future climate. There are several global climate models (GCMs) and regional climate models (RCMs) which estimate responses of future climate to CO₂ emissions scenarios. In many semi-arid regions, results vary widely between models and between scenarios particularly under long planning horizons such as 50 or 100 years (Tadross, 2006, Andersson et al., 2006, Toews and Allen, 2009, Driessen et al., 2010). This introduces uncertainty which must be explicitly considered in hydrological assessment.
- 2) Estimation of rainfall and evaporation at relevant scales. GCMs and RCMs typically produce outputs on grids (e.g. 200km and 25km respectively) which are too large to accurately represent climate within the catchment of proposed reservoirs. Furthermore, the single most important climate variable for reservoir design, rainfall, is not

accurately simulated by the present generation of GCM and RCM models. This problem is addressed by the use of statistical downscaling methods which ensure that climate predictions are consistent with historical evidence of catchment scale variability over space and time (Chiew et al., 2010, Burton et al., 2010).

- 3) The challenge of considering hydrological model uncertainty, model structure and parameter uncertainty, especially when supporting rainfall-runoff data are limited. The issue of non-stationary response is also critical, which may demand that alternative methods of flow estimation be used to compare with the flow results obtained directly from hydrological models which assume stationarity.

These issues are considered in this chapter by using a statistical downscaling model (the GLM introduced in chapter 4) to downscale rainfall to the upper Limpopo basin in Botswana, and thereafter use a rainfall runoff model (from Chapter 5) and the change factor method to estimate streamflow, which in Chapter 7 will be used to assess reservoir reliability.

6.2 Climate modelling and rainfall downscaling tools

6.2.1 Generalised linear models

Generalised linear models (GLMs) have three roles in this thesis. Firstly, they have been used to infill missing rainfall data in the historic records to allow calibration of the hydrological model (chapters 4 and 5); secondly they are used to generate long records (100 years) of local scale rainfall under stationary climate; and thirdly they are used to generate rainfall under climate change scenarios. This is explained below (the reader is referred to chapter 4 for an introduction to the structure of GLMs).

As discussed in chapter 4, suitable climate variables (or indices) in the predictor vectors x and ξ in Eqs. 4.1 and 4.2 were identified. This included temperature, sea-level pressure and humidity taken from ERA-40 reanalysis data for the grid square which overlies the catchment. Assuming that the identified historical dependencies will also apply under future climate, sea-level pressure, temperature and humidity predicted by GCMs under various scenarios were then used as input to generate daily local scale rainfall under stationary and changed climate.

6.2.2 Global climate models (GCMs)

GCMs are the only physics-based models which provide estimates of future climate variables in response to emissions scenarios, and hence were used to support the downscaling. The GCM outputs were obtained from the IPCC data distribution centre (www.ipcc-data.org) for the grid squares which overlie the study catchment. Only the GCMs which have both variables identified as suitable predictors were considered for use in downscaling. The selected GCMs are presented in Table 6-1. To reduce errors associated with GCMs while maintaining the temporal variability from each GCM, the monthly bias in the GCMs' historical sea-level pressure, temperature and humidity outputs (relative to the ERA-40 data, Figure 6-1) was used to adjust the predicted future GCM values. This approach (hereafter called the GLM rainfall downscaling approach (GLMRDA) was preferred to the so called "change factor (CF)" approach (Fowler and Kilsby, 2007, Minville et al., 2008, Buytaert et al., 2010, Diaz-Nieto and Wilby, 2005), where the observed daily values for a variable of interest-e.g. rainfall are scaled using the differences between the predicted future GCM monthly values and the baseline GCM monthly values of that variable. This is because in its original form, the CF yields uniform changes to all precipitation series as the temporal structure of the future climate scenario is unchanged from that of the historical record (Kilsby et al., 2007, Prudhomme et al., 2010). Whereas using the bias adjustment allows the GCM to define changes in the temporal

structure, albeit assuming that the future bias is the same as the historic bias, which is preferred in this case. However, to complete our analysis, we will also evaluate the CF approach for downscaling rainfall to allow comparison with the GLMRDA.

Seasonality was removed from the GCM data (Kenabatho et al., 2010) since seasonality is represented by other predictors in the stochastic rainfall model, such as those presented in Table 4-1 (under temporal effects).

6.2.3 Construction of climate change scenarios

Three IPCC greenhouse gas emission scenarios (B1, A1B and A2) from the fourth assessment report (IPCC, 2007b) were used to construct future climate scenarios. The A1 scenario group assumes a world of very rapid economic growth with a population that peaks in mid-century, and rapid introduction of new and more efficient technologies. This is divided into three categories that describe alternative directions of technological change: fossil intensive (A1F), non-fossil energy resources (A1T) and a balance across all sources (A1B). B1 describes a convergent world, with the same global population as A1, but with more rapid changes in economic structures toward a service and information economy inclined towards reducing material intensity, and introducing clean and resource-efficient technologies. The A2 scenario describes a very heterogeneous world with high population growth, slow economic development and slow technological change. Thus, among these three groups, the A2 is regarded as high CO₂ emission scenario, followed by A1B and B1 scenarios. In addition, four 25 year periods of non-stationary climate from each GCM were considered: 2001-2025, 2026-2050, 2051-2075 and 2076-2100 which we call 2025s, 2050s, 2075s and 2100s horizons. These were used together with the GCMs presented in Table 6-1 to complete the GLMRDA.

Table 6-1: Global climate models used

GCM name	Spatial resolution	Country of origin
HadCM3	3.75° x 2.5°	UK
CSMK3	1.875° x 1.85°	Australia
MPEH5	2.75° x 3.5°	Germany
INCM3	2.5° x 3.5°	Russia
BCM2	2.5° x 3.5°	Norway

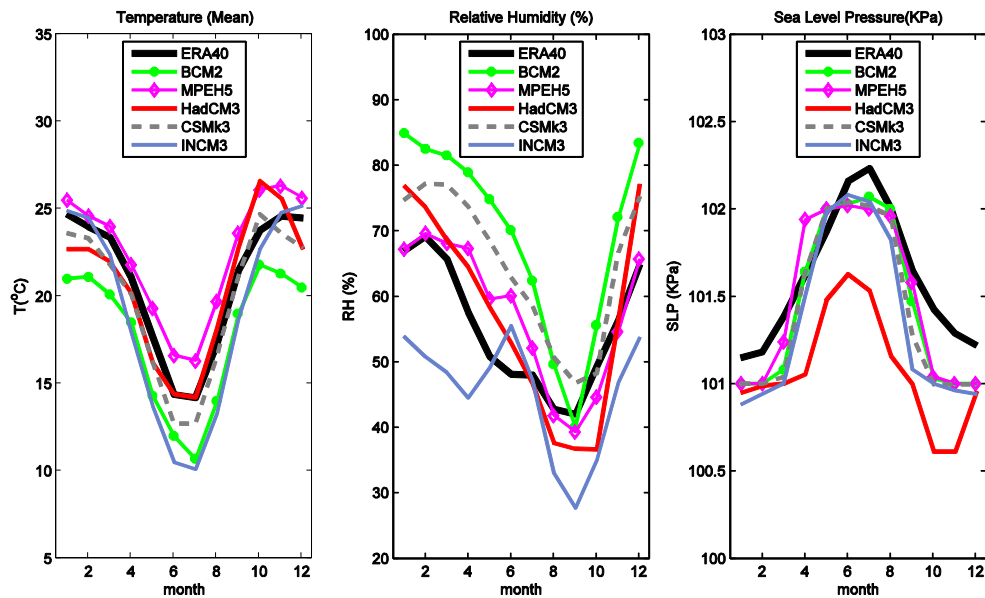


Figure 6-1: GCM results for 1975-1999 relative to the 1975-1999 re-analysis climate (ERA40) (representing the observed climate-the black line) for temperature, humidity and sea level pressure.

6.3 Results: Rainfall and temperature predictions

6.3.1 Baseline Predictions: GCM verification

Before using the GCMs to predict future climate, the five GCMs were used to predict the current baseline rainfall (1975-1999). This was implemented by using the fitted GLM (Table 4-1)–but conditioned on the atmospheric predictors of each GCM after bias correction. The rainfall statistics derived from the GCMs and those from the ERA40 data (representing observed climate) are presented in Table 6-2, while the annual rainfall series are shown in Figure 6-2 and the summer rainfall series in Figure 6-3. The annual and summer rainfall series in these figures are summed over all the 13 gauges used in the basin. Results from Table 6-2 indicate that in general the GCMs are able to simulate the current climate well since the rainfall statistics across the bias-corrected GCMs are comparable to the observed records. However, the rainfall plots shown in Figure 6-2 show that the annual rainfall prior to 1978 is not well represented by most climate models. Beyond this period the rainfall patterns (including the inter-annual variability) are well simulated by the models possibly indicating that prior to 1978 the models were not well adapted to the fitted data particularly that this period appears exceptionally wet. This particular challenge may indicate that the GLM model could struggle to give reasonable rainfall predictions for cases where future climate falls outside the range of observations.

In addition to plotting the results of individual GCMs, the simulations pooled from all the 5 climate models were plotted with the rainfall data derived from ERA40 (i.e. the 6th plot in Figures 6-2 and 6-3). This shows that the observed rainfall is well represented when the combined prediction uncertainty of the 5 GCMs is considered, as the ERA40-based rainfall is now enveloped by the GCM uncertainty bounds.

Table 6-2: Rainfall statistics for the bias-adjusted baseline climate: rainfall generated using the GCM data against rainfall generated using the ERA40 data.

	ANNUAL				JFMA				SOND			
	MIN ⁽ⁱ⁾	MEAN	MAX ⁽ⁱ⁾	SD	MIN	MEAN	MAX	SD	MIN	MEAN	MAX	SD
ERA40	277	415	606	65	124	230	394	50	99	175	291	38
BCM2	272	417	582	64	121	227	369	49	101	178	289	39
MPEH5	266	404	581	63	121	221	364	49	98	172	291	38
HadCM3	281	417	604	63	132	227	373	48	101	178	297	39
CSMK3	274	421	596	66	129	229	382	51	96	178	292	41
INCM3	274	409	602	65	128	225	373	49	94	175	292	39

⁽ⁱ⁾ Min and ⁽ⁱ⁾ Max are defined as the minimum and maximum rainfalls obtained from the 10 rainfall imputations (based on the ERA40 variables) and 100 rainfall simulations (based on the GCM outputs).

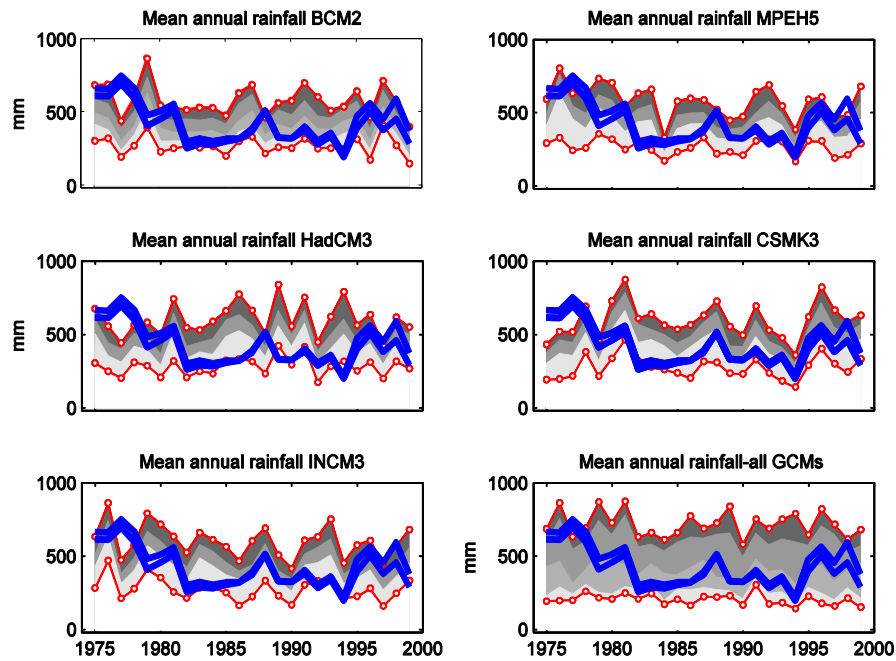


Figure 6-2: Mean annual rainfall for the five GCMs plotted with the ERA40-based rainfall imputations (blue band). The grey scale indicates percentiles of the simulated data (10, 50 and 90 percentile) enveloped within the dashed minimum and maximum bounds.

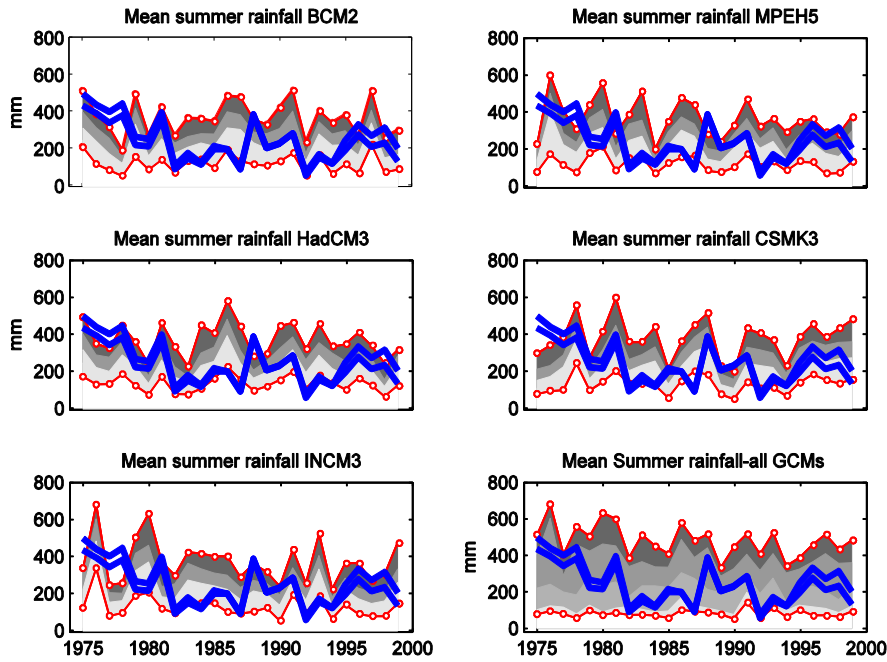


Figure 6-3: Mean summer rainfall for the five GCMs plotted with the ERA40-based rainfall imputations (blue band). The grey scale indicates percentiles of the simulated data (10, 50 and 90 percentile) enveloped within the dashed minimum and maximum bounds.

6.3.2 Future rainfall predictions

Three approaches were used here to generate future rainfall fields. Firstly, 100 years of continuous daily rainfall were generated at each of the 13 gauges using the fitted GLM (Table 4-1) conditioned on the external predictors assuming a stationary climate, which is called stationarity (note that this uses the ERA40 variables, and does not include the use of GCM variables). This was implemented by assuming that the observed atmospheric predictors, i.e. humidity, temperature and sea level pressure from the ERA-40 data for the period 1975-1999 will repeat in the future. Secondly, the bias-corrected GCMs used in section 6.2.2 were used together with the IPCC climate scenarios, and the four horizons to predict 100 years of daily rainfall at the 13 gauges under a changed climate. Thirdly, the CF

approach referred to in section 6.2.2 was used to construct changed climate using the bias-corrected GCMs and IPCC scenarios to predict 100 years of rainfall at the 13 gauges.

6.3.2.1 Rainfall predictions under stationary climate

Table 6-3 shows predicted changes in annual and seasonal rainfall statistics under stationary climate for the 4 horizons (i.e. the 1975-1999 climate repeated four times). As expected, all horizons show only marginal changes in the mean rainfall, i.e., an increase of 3 and 8% in annual and spring rainfall, and a reduction of up to 9% in summer rainfall. The changes reflected here are mainly due to natural variability of input data and the stochastic component from the rainfall model. These results are also plotted in Figure 6-4 to show the inter-annual variability of future rainfall series under this scenario, which is comparable to the observed rainfall variability in Figure 6-2 despite a remarkable peak in the early 2050s.

Table 6-3: Seasonal simulated rainfall statistics showing % changes from the observed data when assuming a stationary climate. JFMA is a core rainy season (summer) compared to the SOND rainy season (the spring season).

	ANNUAL				JFMA				SOND			
	Min ⁽ⁱ⁾	Mean	Max ^(j)	SD	Min	Mean	Max	SD	Min	Mean	Max	SD
2025s	-3	2	1	5	-3	-9	-2	4	7	3	7	6
2050s	0	3	-1	4	0	-4	-2	0	5	8	8	6
2075s	-2	2	1	7	-2	-5	-2	4	7	4	8	8
2100s	2	3	-1	2	2	-4	-1	-1	3	3	8	7

⁽ⁱ⁾ Min and ^(j) Max are defined as the minimum and maximum rainfalls obtained from the 10 rainfall imputations (for the ERA40) and 100 rainfall simulations (for the stationary climate).

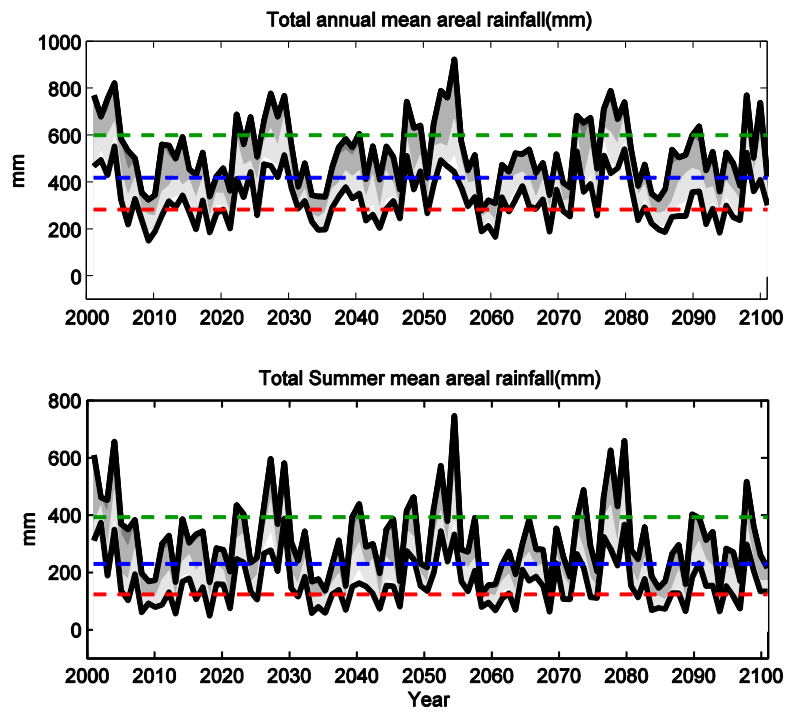


Figure 6-4: Rainfall predictions under a stationary climate. The dashed lines represent the minimum (red), mean (blue) and maximum (green) annual average rainfall of 10 imputations for 1975-1999 period.

6.3.2.2 Temperature and rainfall predictions under changed climate

Figure 6-5 shows monthly temperatures as predicted by the five GCMs for the four time-slices and three IPCC scenarios. The results indicate increased monthly temperature changes of up to 6 °C by 2100 particularly for the A2 scenario, with the MPEH5, HadCM3 and INCM3 models also predicting hotter conditions. Rainfall (as simulated using the GLMs) and temperature (annual and seasonal) changes are displayed in Figure 6-6 for the same scenarios. All models predict that mean rainfall will dramatically decrease (up to 80%) coinciding with increased temperatures (up to 5.4 °C) under the three scenarios for the 2100 horizon, with the HadCM3 and MPEH5 models giving drier conditions for annual, summer (JFMA) and spring (SOND) rainfall under the A1B and A2 scenarios. Furthermore, the model and scenario uncertainty is largest during the 2100 horizon, where annual temperature and rainfall changes range from +2 to +5.4 °C and -40 to -80%, respectively.

Considering the near future (the 2025 horizon), mean annual rainfall values could decrease on average by between 0 (CSMK3-B1) to 40% (MPEH5-A2), with the majority of the models and scenarios clustered around 20%. The highest rainfall changes under the 2025 horizon are evident in summer rainfall ranging from 0 to 50% decrease. Spring rainfall shows some marginal rainfall increase of up to 10% (INCM3-A1B) and some decrease of up to 35% mainly from the A2 and A1B scenarios.

Figures 6-7 to 6-9 show the rainfall time series for the 2001-2100 period (one 25 year simulation period for each time-slice) under the three scenarios. These are plotted with the 50th percentile rainfall obtained from the approach which assumes a stationary climate. It is evident from these plots that mean annual rainfall will decrease by the end of the century as

predicted by all the 5 GCMs. The A2 scenario depicts very dry future conditions compared to the B1 scenario. In all the scenarios drought conditions could worsen by mid century (as shown by the differences in rainfall series between the stationary and GCMs results), with a possible decrease of up to 50% in mean annual rainfall during drought years. When considering the combined results of all the 5 GCM models (the 6th plot in Figures 6-7 to 6-9), it is still evident that drier conditions will recur beyond the mid century as shown by the lack of models to represent the rainfall predicted under a stationary climate, even under an ensemble of GCM uncertainty bounds.

As mentioned in section 6.2.2, the rainfall results obtained using the change factor approach for rainfall generation (Figure 6-10, Figures E-1 to E-2) are reported. The results are in agreement with those obtained using the first approach, indicating that rainfall will dramatically decrease beyond the mid century. However, as expected with this approach, the results from each GCM show a uniform inter-annual variability pattern spanning a 25-year period-further corroborating the findings of other researchers mentioned in section 6.2.2 that the temporal structure of future climate scenarios is unchanged when using the CF approach to generate rainfall. This approach was not considered further, rather for downscaling future rainfall, only the GLMRDA was used under a stationary and a changed climate.

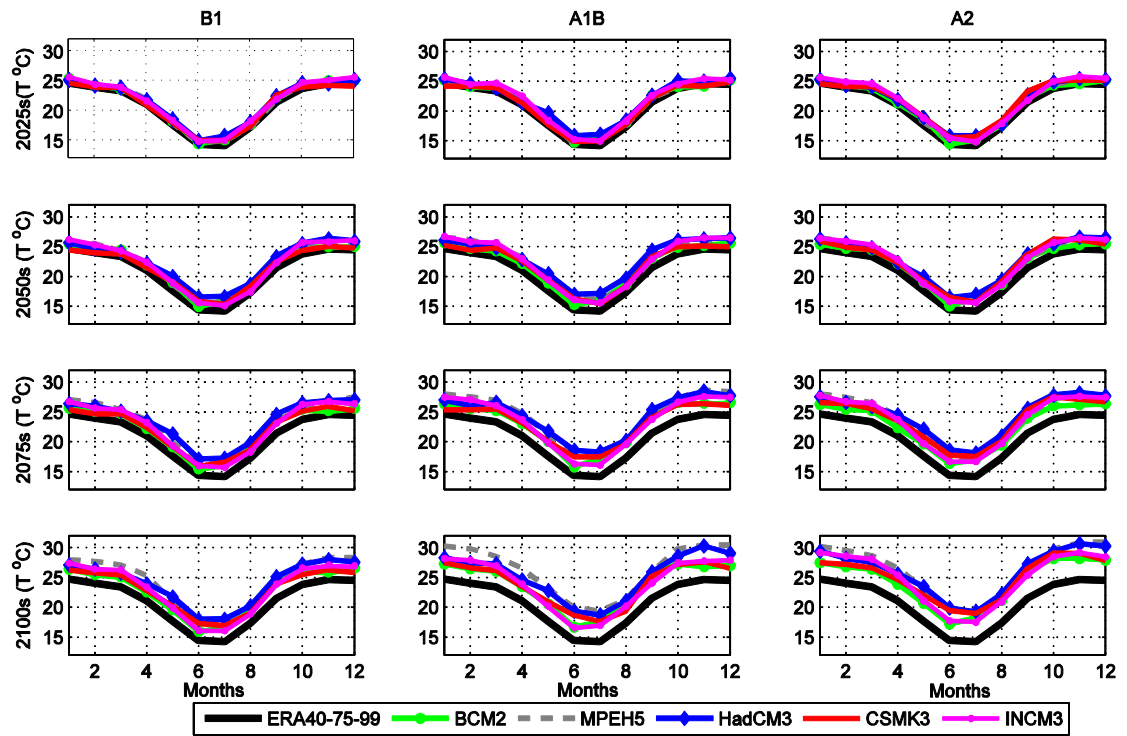


Figure 6-5: Temperature changes for the four horizons and three IPCC scenarios for the five GCMs.

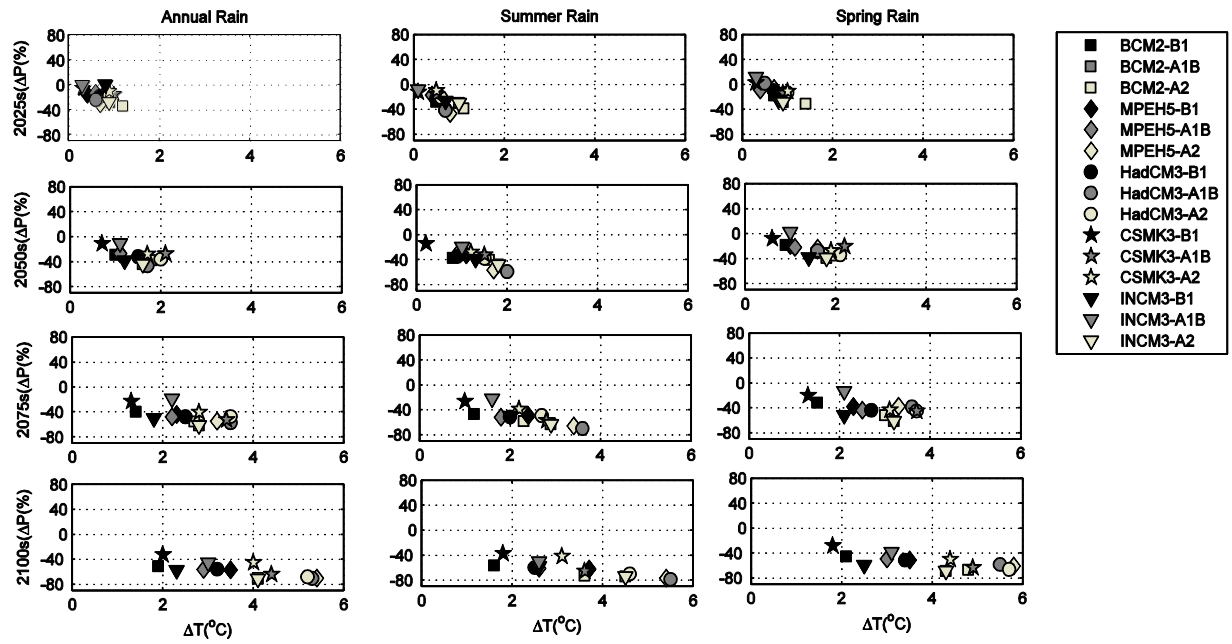


Figure 6-6: Mean annual and seasonal rainfall changes for the four horizons based on five GCMs and three IPCC scenarios.

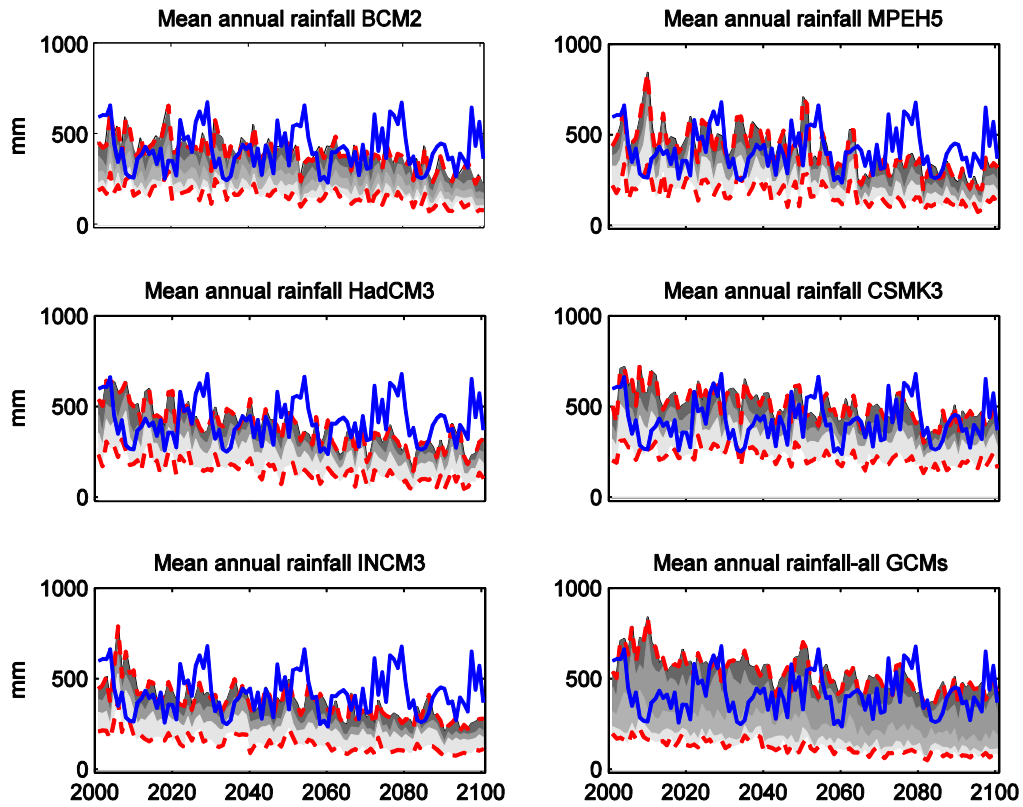


Figure 6-7: Annual rainfall predictions from the 5 GCMs under the B1 scenario. The dashed red lines represent the minimum and maximum uncertainty limits while the blue line represents the 50th percentile rainfall from the stationary climate.

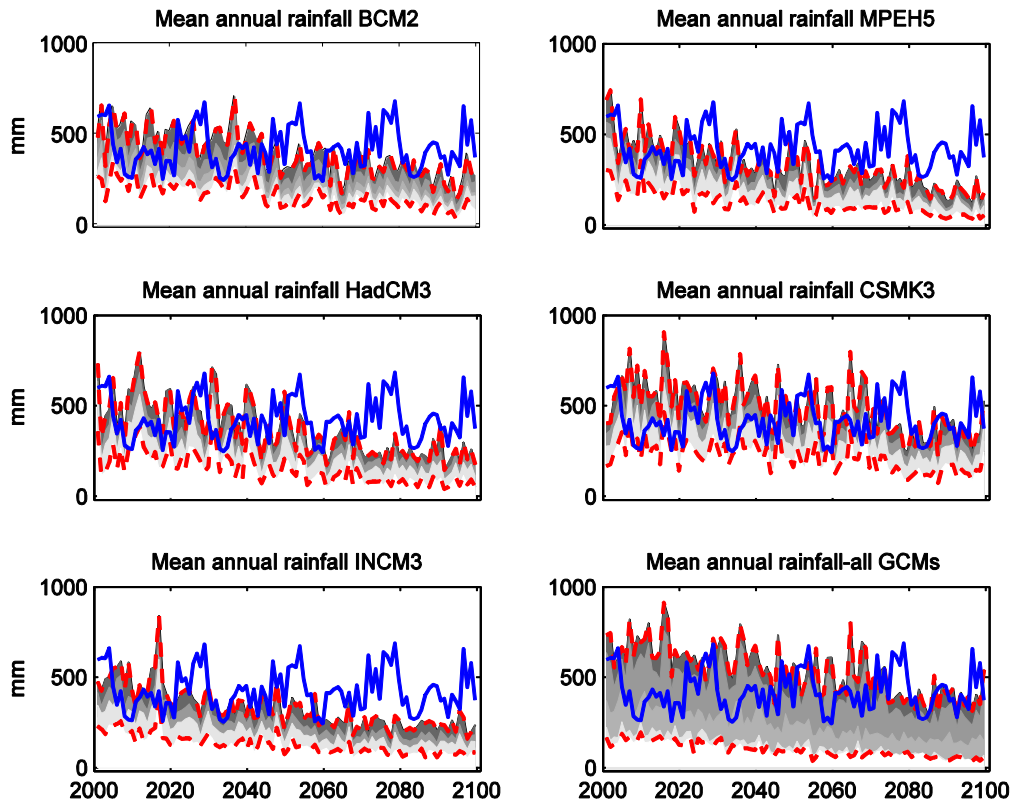


Figure 6-8: Annual rainfall predictions from the 5 GCMs under the A1B scenario. The dashed red lines represent the minimum and maximum uncertainty limits while the blue line represents the 50th percentile rainfall from the stationary climate.

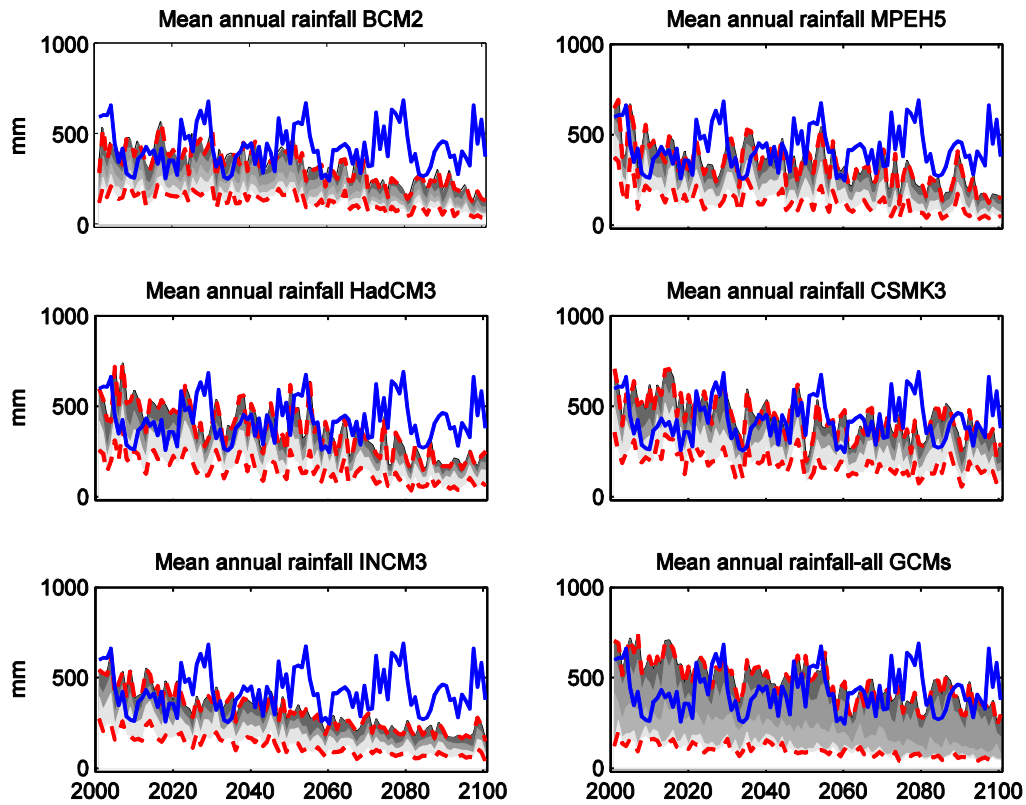


Figure 6-9: Annual rainfall predictions from the 5 GCMs under the A2 scenario. The dashed red lines represent the minimum and maximum uncertainty limits while the blue line represents the 50th percentile rainfall from the stationary climate.

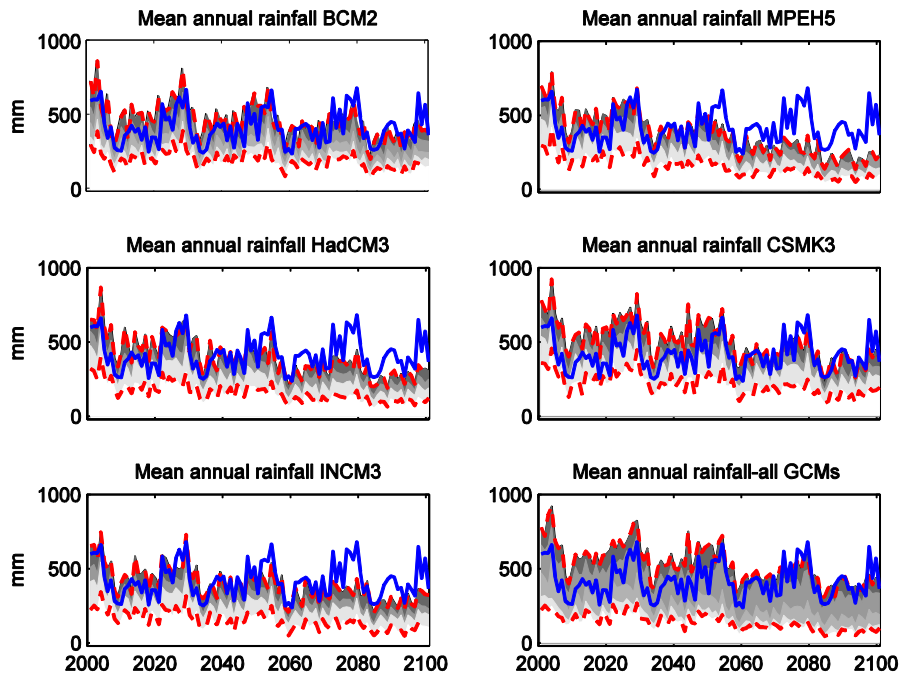


Figure 6-10: Annual rainfall predictions from the 5 GCMs under the B1 scenario. The results are based on the change factor approach. The dashed red lines represent the minimum and maximum uncertainty limits while the blue line represents the 50th percentile rainfall from the stationary climate.

6.4 Runoff generation under climate change

This section deals with runoff generation under the stationary and changed climate. Under the stationary climate we assume that the current climate (i.e. the ERA40 data) will repeat up to the end of the century as discussed in 6.3.2. The climate change scenarios will employ those used in sections 6.2 and 6.3. The predicted rainfall and temperature series were used to drive a calibrated hydrological model (IHACRES model) to produce runoff scenarios under the stationary and climate change scenarios. The IHACRES model used here is described in chapter 5, in which a 6-parameter model (Table 5-3) was identified as a preferred model. This model was applied to the whole

catchment within the upper Limpopo basin using 100 parameter sets considered optimal to define parameter uncertainty bounds as detailed in Chapter 5. The outlet catchment coincides with the location of the proposed reservoir referred to in section 6.1. To represent the stochastic component of rainfall, 1000 rainfall realisations were used together with the hydrological model to generate flow simulations.

6.4.1 Results: Runoff changes

Figures 6-11 to 6-14 show the runoff results based on the five GCMs under the three IPCC climate scenarios for the four horizons. The runoff predictions were based on rainfall obtained from the GLMRDA. As expected the results show that runoff will decrease dramatically by the end of the century, with all the climate models and scenarios predicting drier conditions ranging between a 40 to 80% reduction in annual runoff for the 2100 horizon simulation (Figure 6-11). The small decreases are predicted under the B1 scenario (where the CSMK3 and BCM2 models predict about 40% decrease in runoff). Drastic decreases are predicted under the A2 and A1B scenarios (where the MPEH5 predicts about 86% and 88% decrease in annual runoff).

For the 2025 horizon simulation, models are predicting heterogeneous runoff regimes where some models and scenarios predict an increase in runoff while others show runoff decrease. For example, the CSMK3 predicts up to 44% increase in annual runoff and 59% increase in spring runoff during this period (These results are analysed further under section 6.5.1). This pattern is consistent with the rainfall changes where some models predict an increase in spring rainfall as shown in Figure 6-6. However, the magnitude of increase in spring runoff is huge compared to those of rainfall during the same season, where only a marginal increase of <10% was reported. An analysis of the runoff coefficient (RC) for the spring season

during the 2025 horizon did not indicate that the positive change is plausible as the RC was below 1 throughout the 2025 horizon (i.e. 2001-2025). Furthermore, when the RC for this horizon was compared with the RC for the period 1975-1999, the two sets of RCs were almost similar (i.e. the RC for the 1975-1999 period was 0.149 whereas that of 2001-2025 was 0.146)-with no indication of any huge increase in runoff. It is therefore thought that this huge increase in runoff could be linked to the non-linearity of response evident in the rainfall-runoff model results in chapter 5.

The flow time series are shown in Figures 6-12 to 6-14, and they are plotted with the 50th percentile flow generated under the stationary climate. As expected, there is a clear evidence of runoff reduction over the years which vary across the models and scenarios. The high emission scenario, A2 (Figure 6-14) predicts very dry conditions compared to other scenarios.

6.5 The change factor approach for flow generation

As an alternative method for estimating future flows, a change factor approach is used to make comparison with the above scheme. In the change factor approach, relative changes are used instead of the actual flows. This is implemented by considering the predicted flows of each GCM under the baseline and changed climate (i.e. using each of the 3 IPCC scenarios and time slices/horizons) obtained using each of the equifinal parameters. For each time-series of flow, a change factor for each month is determined according to Equation (6.1) and is used to multiply the historic flows to yield a time-series of future flows (Prudhomme and Davies, 2009b). This idea is based on speculation that the rainfall-runoff model is more suitable for predicting relative changes to flow under climate change than it is for estimating flow time-series, for which observed records should be used, due to problems with the hydrological model performance, as explained in Section 5.4.

$$CF_{g,m,h,p} = \overline{f_{utr,g,m,h,p}} / \overline{f_{base,g,m,h,p}} \quad (6.1)$$

Where $CF_{g,m,h,p}$ is a change factor for a GCM g , month m , horizon h , and parameter set number p ; $\overline{f_{utr,g,m,h,p}}$ and $\overline{f_{base,g,m,h,p}}$ represent the mean monthly simulated future and baseline flows for a GCM g , for the month m , and horizon h . The change factors were determined for all K parameter sets for all g , m and h thus allowing uncertainty limits to be derived.

6.5.1 Results

Results from the change factor approach are plotted in Figure 6-15 (annual and seasonal changes) to Figure 6-19 (monthly flows). These results are also summarised in Tables 6-4 to 6-6 together with runoff changes obtained from the previous approach, as well as rainfall and temperature changes. Comparing the runoff changes in Figure 6-11 with those in Figure 6-15, it can be seen that the two approaches yield different results (principally for the CSMK3 model). For example, in the 2025 horizon, the change factor approach does not indicate any positive changes compared to the previous approach, where up to 59% increase (from the CSMK3 model under the B1 scenario) was reported for the spring runoff (Figure 6-11). To make the comparison much easier, the results for the two approaches are discussed using Tables 6-4 to 6-6, in light of the rainfall and temperature results reported earlier in sections 6.3. Starting with the magnitude of runoff decrease, it appears from Table 6-4 that the change factor approach in general predicts drier conditions particularly during the 2025 and 2050 horizons. During the 2100 horizon, the GLMRDA predicts drier conditions when compared with the CF method. These patterns are also observed for the summer rainfall (Table 6-5) and spring rainfall (Table 6-6). The results from Tables 6-5 and 6-6 also show that the CF method consistently predicts drier conditions for the B1 scenario across all the 4 horizons, while the results for the other scenarios and horizons show apparent differences in

the magnitude of change.

Predictions for the near future (particularly the 2025 horizon) show differences in the direction of runoff changes where, for example, most of the models predict an increase in spring runoff under the GLMRDA, with the CSMK3 (A1B) model predicting 59% increase in runoff compared to -11% by the CF method under the same scenario and horizon. The apparent differences between the results obtained from these two approaches add to the uncertainties in climate impacts modelling, whereby the degree and direction of future changes may be dependent upon the approach. This would not have been achieved without the use of an alternative approach for estimating future flow changes.

When considering the runoff changes from these two methods in comparison with rainfall and temperature changes from Table 6-4, it can be seen that in general, a reduction in annual rainfall causes larger reductions in runoff. For example, irrespective of the runoff estimation method used, the runoff changes (i.e. reductions) are very high particularly during the 2100 horizon coinciding with huge reductions in rainfall and high increase in temperature. However, during the 2025 horizon, it is observed that reduction in rainfall does not always lead to reduced runoff particularly when using runoff generated from the GLMRDA. For example, the results from the CSMK3 model, under the A2 scenario indicate a rainfall reduction of 15% against a runoff increase of 10% (see also a case where runoff increased by 44% for the same model under the A1B scenario despite no changes in rainfall). These inconsistencies are also observed for the summer and spring rainfall in Tables 6-5 and 6-6 (particularly during the 2025 horizon). This further confirms the non-linearity in the rainfall-runoff model as demonstrated earlier in section 6.4.1. However, when considering the runoff prediction results from the CF method, it can be seen that in general, the direction of change are consistent with that of rainfall across the models, scenarios, and horizons for both annual, summer and spring runoff and rainfall (Table 6-4 to 6-6). It is thought that the use of the CF method is justified given that the rainfall-runoff model could not match the non-stationarity of response as evident from the above discussions.

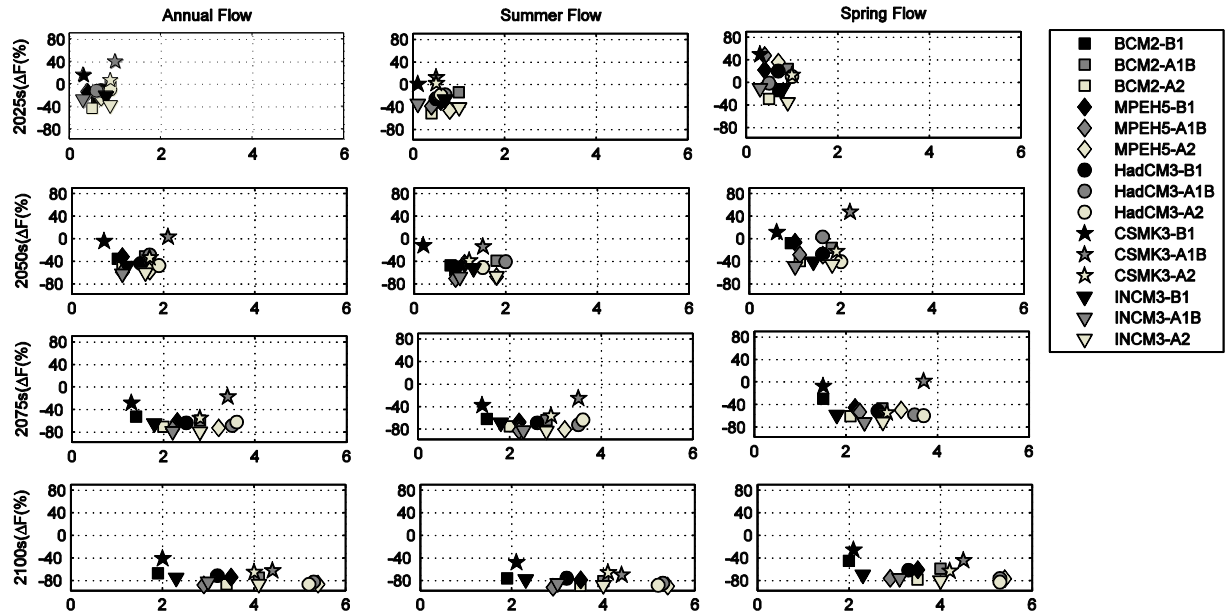


Figure 6-11: Mean annual and seasonal runoff changes for the four horizons based on five GCMs and three IPCC scenarios. The runoff results were generated using rainfall from the GLMRDA. The x-axis is same as that in Figure 6.6 (i.e. ΔT ($^{\circ}\text{C}$)).

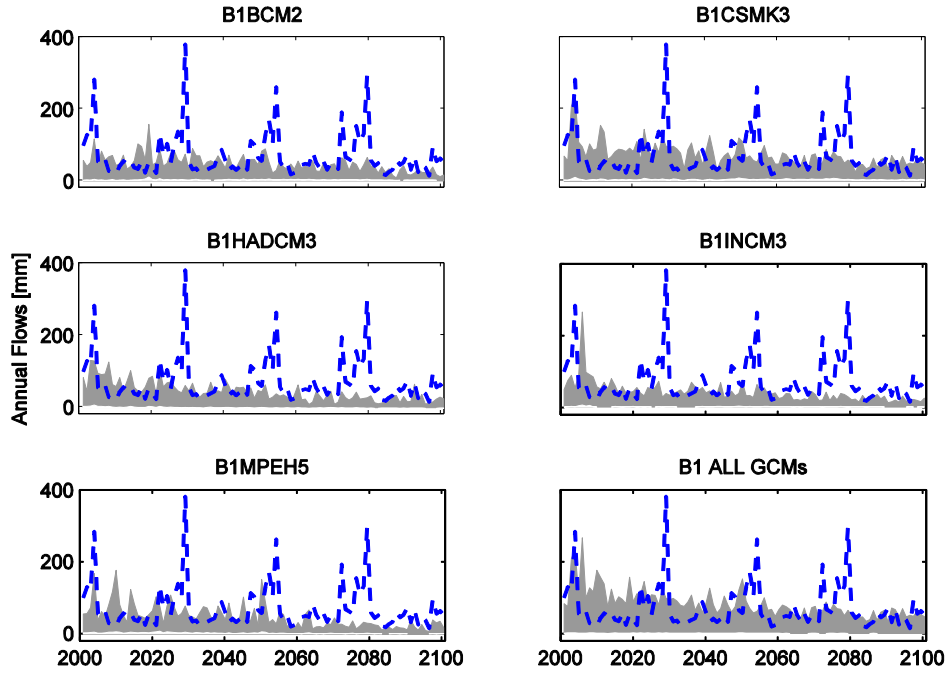


Figure 6-12 : Runoff predictions from the 5 GCMs under the B1 scenario. The grey scale represents the ensemble runoff generated from all the equifinal parameters and rainfall realisations while the blue line represents the 50th percentile runoff obtained using the stationary climate.

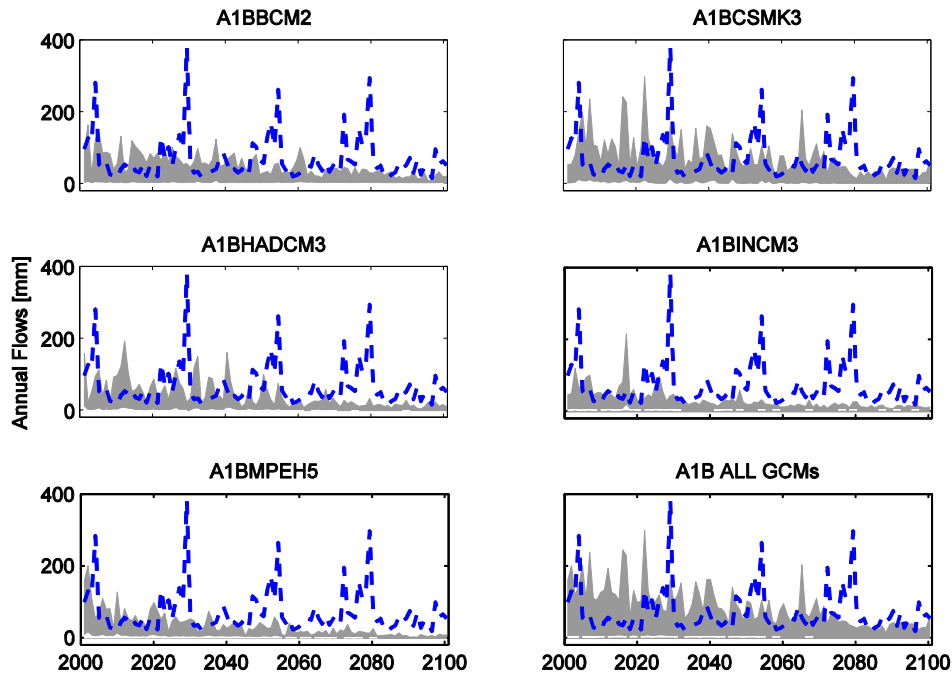


Figure 6-13: Runoff predictions from the 5 GCMs under the A1B scenario. The grey scale represents the ensemble runoff generated from all the equifinal parameters and rainfall realisations while the blue line represents the 50th percentile runoff obtained using the stationary climate.

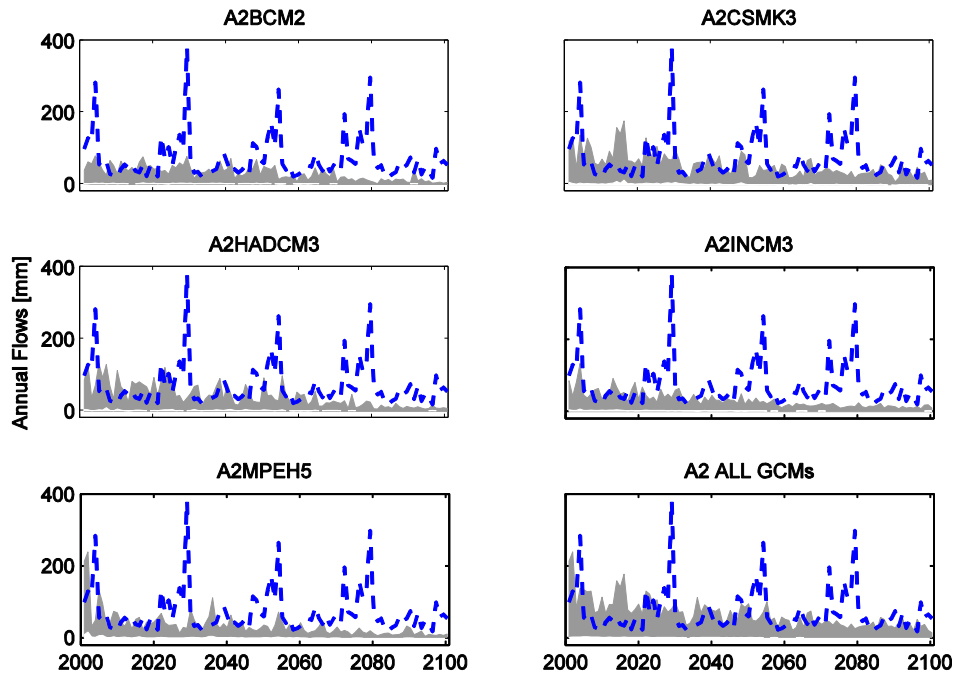


Figure 6-14: Runoff predictions from the 5 GCMs under the A2 scenario. The grey scale represents the ensemble runoff generated from all the equifinal parameters and rainfall realisations while the blue line represents the 50th percentile runoff obtained using the stationary climate.

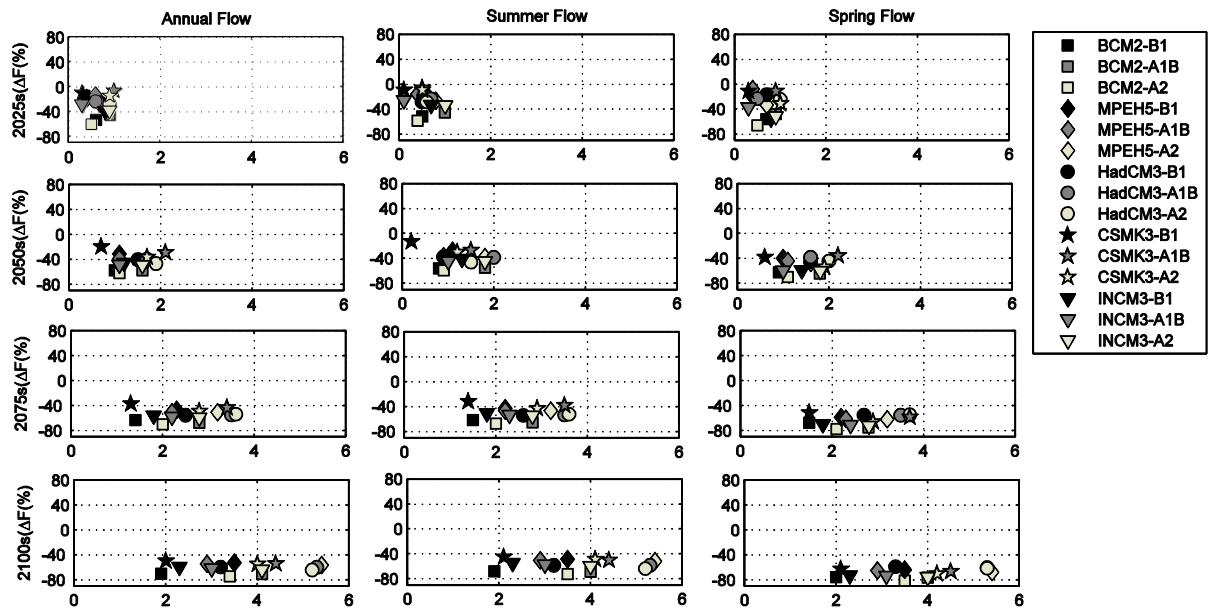


Figure 6-15: Mean annual and seasonal runoff changes for the four horizons based on five GCMs and three IPCC scenarios obtained using the change factor approach. The x-axis is same as that in Figure 6.6 (i.e. ΔT ($^{\circ}\text{C}$)).

In addition to the summary results presented above, the monthly runoff depths simulated using the change factor method (including parameter uncertainty and the rainfall uncertainty due to the stochastic component of the GLM model) are presented in Figure 6-16 to 6-19, compared to the historic observations. The 2025 horizon simulations show a wide range of flow changes, so that the observed flows are enveloped within the uncertainty bounds (though the observed flows are generally underestimated by most models). Again, the high emission scenario (A2) shows greater rainfall decreases across the models. Drier conditions are estimated during the 2100 horizon where the prediction uncertainty narrows dramatically towards the minimum values.

Table 6-4: Annual runoff predictions using the GLMRDA and the CF approaches shown with annual rainfall predictions (from the GLMRDA) and temperature changes (from GCMs)

scenario	A2					A1B					B1				
HORIZ	BCM2	MPEH	HADC	CSMK	INCM3	BCM2	MPEH	HADC	CSMK	INCM3	BCM2	MPEH	HADC	CSMK	INCM3
GL-2025	-42	-22	-7	+10	-36	+1	-13	-10	+44	-25	-24	-11	-9	+19	-18
CF-2025	-61	-28	-28	-15	-38	-46	-14	-24	-7	-29	-53	-18	-26	-10	-39
R-2025	-18	-41	-17	-15	-11	-13	-23	-15	0	-23	-23	-11	-14	+2	-23
T-2025	1.2	0.7	0.9	0.9	0.9	0.6	0.6	1.0	0.3	0.9	0.6	0.4	0.7	0.3	0.8
GL-2050	-49	-56	-46	-31	-59	-29	-58	-26	+6	-61	-34	-30	-42	-2	-46
CF-2050	-62	-41	-47	-36	-49	-57	-38	-39	-29	-49	-58	-31	-40	-20	-46
R-2050	-24	-53	-36	-36	-27	-27	-46	-28	-9	-46	-33	-27	-28	-8	-43
T-2050	1.8	1.7	2.0	1.7	1.6	1.1	1.7	2.1	1.1	1.8	1.0	1.1	1.5	0.7	1.2
GL-2075	-70	-71	-61	-54	-78	-58	-74	-67	-15	-78	-51	-60	-63	-26	-64
CF-2075	-70	-51	-54	-49	-59	-68	-50	-55	-43	-58	-63	-47	-56	-37	-56
R-2075	-46	-65	-48	-55	-42	-48	-57	-53	-19	-59	-46	-50	-48	-23	-57
T-2075	2.7	3.2	3.5	2.8	2.8	2.2	3.5	3.4	2.2	2.6	1.4	2.3	2.5	1.3	1.8
GL-2100	-86	-86	-86	-64	-86	-74	-88	-82	-62	-82	-67	-73	-71	-40	-75
CF-2100	-75	-56	-64	-55	-64	-71	-54	-60	-54	-62	-70	-53	-60	-50	-60
R-2100	-65	-76	-69	-67	-49	-57	-71	-65	-45	-67	-60	-66	-60	-36	-66
T-2100	4.1	5.4	5.2	4.0	4.1	2.9	5.3	4.4	3.0	3.1	1.9	3.5	2.2	2.0	2.3

Table 6-5: Summer runoff predictions using the GLMRDA and the CF approaches shown with summer rainfall predictions (from the GLMRDA) and temperature changes (from GCMs)

scenario	A2					A1B					B1				
HORIZ	BCM2	MPEH	HADC	CSMK	INCM3	BCM2	MPEH	HADC	CSMK	INCM3	BCM2	MPEH	HADC	CSMK	INCM3
GL-2025	-49	-45	-17	+5	-39	-12	-37	-16	+16	-33	-30	-29	-23	+4	-25
CF-2025	-59	-27	-29	-9	-34	-45	-16	-24	-6	-34	-52	-17	-28	-10	-33
R-2025	-18	-51	-19	-18	-11	-15	-39	-14	-7	-26	-25	-13	-12	-1	-22
T-2025	1.1	0.8	0.6	0.5	1.0	0.4	0.7	0.5	0.1	1.1	0.5	0.6	0.5	0.1	0.7
GL-2050	-55	-66	-50	-37	-66	-37	-70	-39	-12	-67	-45	-42	-50	-10	-51
CF-2050	-60	-38	-46	-30	-45	-55	-36	-39	-27	-45	-56	-28	-38	-13	-41
R-2050	-22	-59	-37	-40	-31	-29	-57	-31	-17	-48	-40	-30	-22	-6	-40
T-2050	1.6	1.7	1.5	1.2	1.8	0.9	2.0	1.5	1.0	2.0	0.8	1.1	0.9	0.2	1.3
GL-2075	-74	-80	-63	-55	-83	-63	-82	-72	-23	-82	-61	-67	-68	-36	-68
CF-2075	-67	-47	-52	-43	-54	-65	-47	-53	-38	-53	-62	-43	-54	-32	-51
R-2075	-45	-67	-49	-57	-45	-51	-69	-56	-20	-59	-51	-52	-46	-22	-53
T-2075	2.3	3.4	2.7	2.2	2.9	1.8	3.6	2.8	1.6	2.8	1.2	2.4	2.0	1.0	2.0
GL-2100	-89	-90	-88	-66	-89	-81	-92	-85	-69	-85	-76	-79	-76	-47	-78
CF-2100	-72	-52	-64	-49	-59	-69	-51	-58	-50	-57	-68	-48	-58	-45	-55
R-2100	-66	-78	-71	-70	-51	-61	-78	-66	-48	-68	-63	-68	-60	-37	-64
T-2100	3.6	5.4	4.6	3.1	4.5	2.6	5.5	3.6	2.6	3.5	1.6	3.7	2.5	1.8	2.6

Table 6-6: Spring runoff predictions using the GLMRDA and the CF approaches shown with spring rainfall predictions (from the GLMRDA) and temperature changes (from GCMs).

scenario	A2					A1B					B1				
HORIZ	BCM2	MPEH	HADC	CSMK	INCM3	BCM2	MPEH	HADC	CSMK	INCM3	BCM2	MPEH	HADC	CSMK	INCM3
GL-2025	-26	+42	+15	+18	-32	+30	+54	+3	+59	-6	-11	+28	+26	+31	-6
CF-2025	-66	-34	-24	-31	-51	-48	-8	-23	-11	-37	-56	-20	-17	-11	-55
R-2025	-18	-27	-15	-13	-13	-11	+1	-15	+9	-20	-23	-11	-16	+5	-27
T-2025	1.4	0.7	1.0	1.0	0.9	0.4	0.5	0.9	0.3	0.8	0.7	0.4	0.7	0.3	0.8
GL-2050	-37	-26	-38	-19	-43	-12	-25	+8	+54	-47	-4	-2	-24	+16	-38
CF-2050	-70	-47	-45	-38	-36	-60	-64	-44	-38	-36	-62	-40	-46	-38	-59
R-2050	-26	-44	-37	-31	-23	-24	-28	-23	+2	-45	-24	-25	-36	-10	-46
T-2050	2.0	1.6	2.1	1.9	1.8	1.1	1.6	2.2	1.0	1.9	0.9	1.0	1.6	0.6	1.4
GL-2075	-59	-47	-58	-53	-69	-44	-51	-56	+6	-70	-26	-43	-49	-3	-56
CF-2075	-78	-62	-55	-66	-72	-75	-61	-56	-58	-71	-68	-59	-55	-52	-70
R-2075	-47	-62	-48	-53	-39	-45	-42	-47	-16	-61	-40	-49	-53	-27	-65
T-2075	3.0	3.3	3.7	3.1	3.2	2.5	3.6	3.7	2.1	2.8	1.5	2.3	2.7	1.3	2.1
GL-2100	-77	-76	-82	-62	-79	-57	-75	-76	-42	-75	-43	-60	-60	-23	-68
CF-2100	-81	-68	-62	-70	-75	-76	-65	-61	-67	-74	-76	-64	-59	-63	-73
R-2100	-65	-74	-68	-64	-48	-51	-61	-65	-40	-66	-57	-64	-60	-36	-69
T-2100	4.8	5.8	5.7	4.4	4.3	3.0	5.5	4.9	3.1	3.2	2.1	3.5	3.4	1.8	2.5

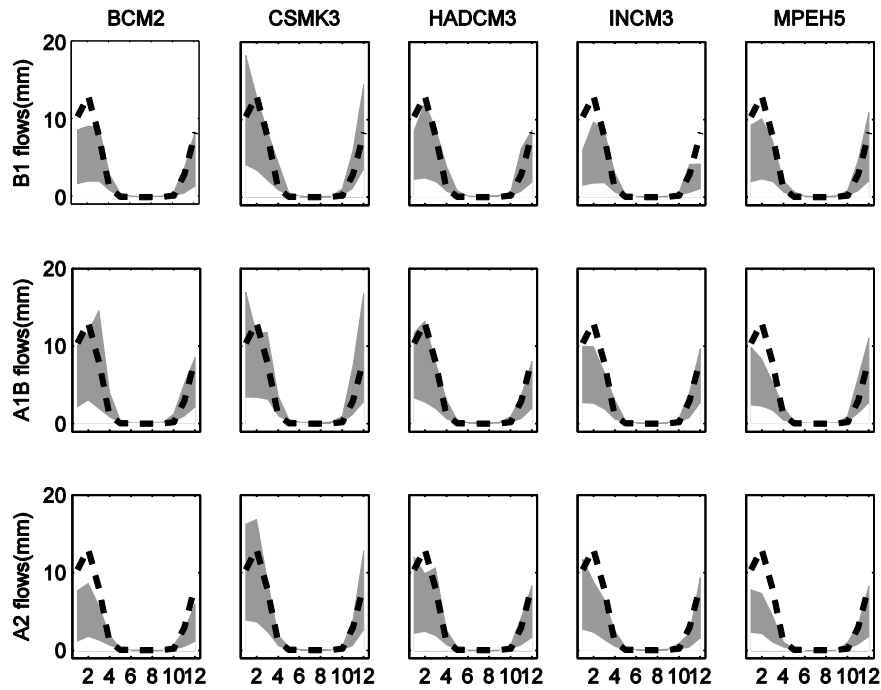


Figure 6-16: Monthly flow results obtained using the change factor approach for the 2025s time slice. The black dashed line represents the observed flows (1975-1999) while the grey scale shows the ensemble changed future flows (2001-2025) obtained from all the equifinal parameters.

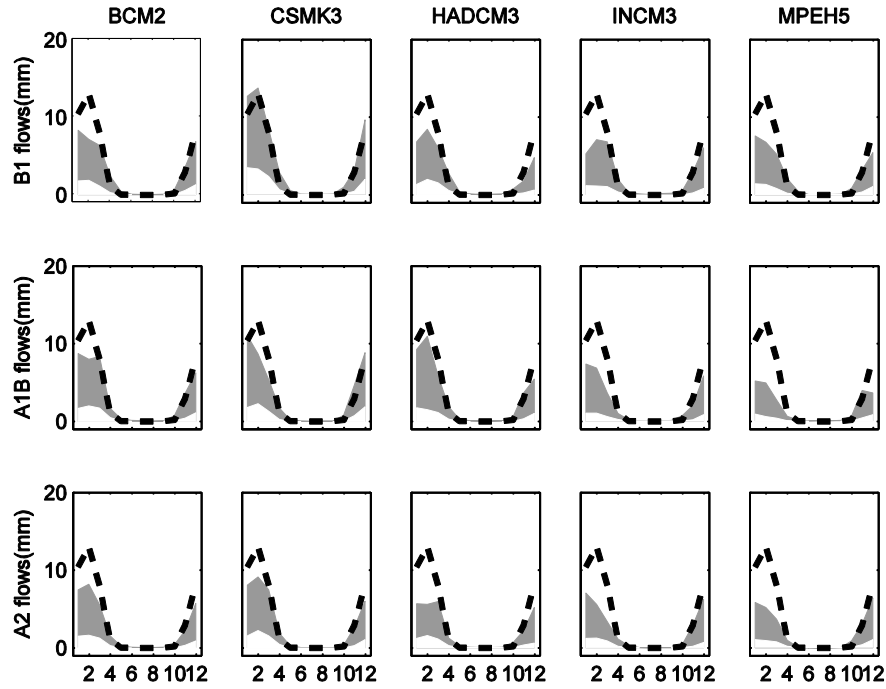


Figure 6-17: Monthly flow results obtained using the change factor approach for the 2050s time slice. The black dashed line represents the observed flows (1975-1999) while the grey scale shows the ensemble changed future flows (2026-2050) obtained from all the equifinal parameters.

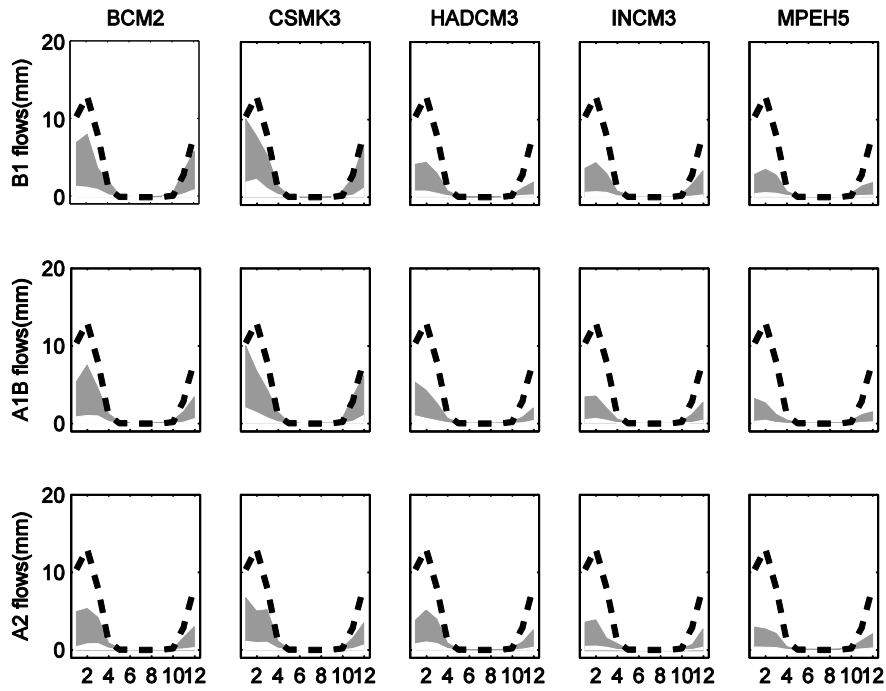


Figure 6-18: Monthly flow results obtained using the change factor approach for the 2075s time slice. The black dashed line represents the observed flows (1975-1999) while the grey scale shows the ensemble changed future flows (2051-2075) obtained from all the equifinal parameters.

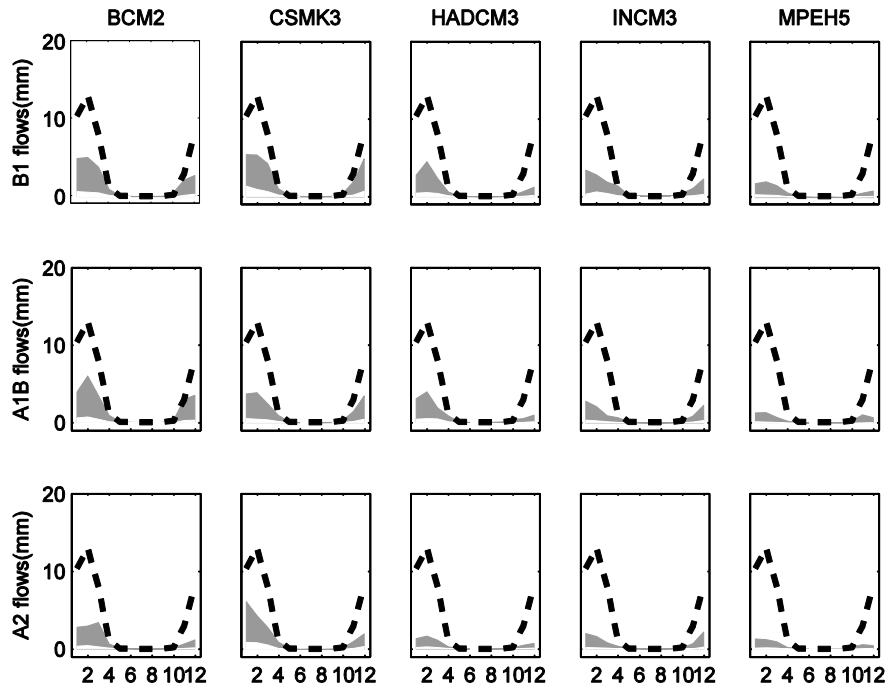


Figure 6-19: Monthly flow results obtained using the change factor approach for the 2100s time slice. The black dashed line represents the observed flows (1975-1999) while the grey scale shows the ensemble changed future flows (2076-2100) obtained from all the equifinal parameters.

6.6 Summary and conclusions

In this chapter, climate change was assessed using 5 GCMs (BCM2, MPEH5, HadCM3, CSMK3 and INCM3) and 3 IPCC scenarios (B1 A1B and A2) for the 4 horizons (2025s, 2050s, 2075s and 2100s). These were applied within a framework where a stochastic rainfall model and a hydrological model were used to predict future rainfall and streamflow under uncertainty (rainfall and parameter uncertainty) in the upper Limpopo basin. Within this framework, future rainfall and streamflow have been estimated under a stationary climate assuming that the observed (or reanalysis) atmospheric predictors will repeat in the future. A change factor approach was also used as an alternative model for estimating flow changes under uncertainty based on the speculation that the rainfall-runoff model is more suitable for predicting relative changes to flow under climate change than it is for estimating the variability of the flow time-series. This analysis represents a more comprehensive treatment of uncertainty than has previously been attempted in water resources climate change impact studies.

The main findings from this chapter are that (1) rainfall will generally decrease while rainfall will increase in the upper Limpopo basin, leading to a decrease in runoff by the end of the century; (2) the magnitudes of change vary widely across the models and across scenarios used; (3) the non-linearity in the rainfall-runoff model lead to some inconsistencies in the direction and magnitude of rainfall and runoff changes; (4) an alternative method of runoff estimation is necessary to overcome the problem of non-stationarity of response in the rainfall-runoff model. In addition to these findings, projections indicate that as early as 2025s annual and winter rainfall may decrease by up to 40% while the decrease in summer rainfall will be slightly higher. At the close of the century, all the climate models are predicting very dry conditions, ranging from 40 to 80% decrease in annual and seasonal rainfall. The high CO₂ emission scenario (A2) generally gives

highest rainfall changes compared to the low and intermediate emission scenarios (B1 and A1B).

Runoff will also decrease dramatically by the end of the century regardless of which runoff estimation approach is used. This is shown by an agreement between the models, which suggest between 40-80% decrease in annual and seasonal runoff during the 2100 horizon. However, in the near future (2025 horizon), some models (CSMK3) and scenarios (B1 and A1B) predict positive runoff changes (i.e. up to 59% for annual and spring rainfall) particularly when using the flow time series obtained directly from a rainfall-runoff model. When using alternative runoff estimation approach-i.e. the change factor approach, all the models predict flow reduction across the scenarios and time horizons. These changes were in general, consistent with those of rainfall unlike when using the flow time series generated from the GLMRDA. This would not have been achieved without the use of alternative runoff estimation as an attempt to resolve the problem of non-stationarity inherent in the rainfall-runoff model.

However, the magnitude of change at the close of the century as estimated using the two approaches is generally comparable (ranging from -40 to -80%). These results may have significant implications for water resources planning in the upper Limpopo basin where a 382,000 ML reservoir is proposed as part of Botswana's national water resource strategy to meet the current and future water demand in the country. The implication is that with the projected rainfall and runoff decrease, both in the near (2025s) and distant (2100s) future, the performance of the proposed reservoir may be drastically affected, leading to reduced water supply in the country. The extent of these effects depends not only on the overall reduction in incoming flow, but also on the temporal properties of the flow such as inter-seasonal and inter-annual droughts, and the changes in evaporation losses. The extent of these supply-side effects will be assessed by re-evaluating the proposed reservoir's performance in light of the extended rainfall and inflow data and the estimated uncertainty (i.e., uncertainty arising from missing

rainfall data; hydrological model parameter uncertainty; climate models uncertainty as well as scenario uncertainty) in chapter 7.

CHAPTER SEVEN

7 Evaluation of reservoir performance under climate change

Increasing water demand from cities, together with more variable supply under climate change, calls for effective water supply strategies. In many cases this includes reservoir development. The reservoirs are usually designed with a specified reliability in order to meet the target demand for water supply purposes. A reservoir with high reliability is often desired in order to minimise incidences of failure during the lifespan of a reservoir. However, in many areas, due to ever increasing water demand as a result of population growth, industrial developments, reservoirs become over burdened leading to increased failure events. This is expected to worsen particularly under climate change where evaporative losses are expected to increase as a result of increased temperatures. Using a case study of water resources planning in the upper Limpopo basin in Botswana we present a strategy for assessing reservoir design under supply-side uncertainty, focussing on impacts of climate change. The strategy follows from previous chapters, where a rainfall model, together with the hydrological model, are used to generate multiple realisations of reservoir inflows over a 100 year period first assuming a stationary climate and then a changed climate. A proposed 382,000 ML reservoir, which is part of Botswana's national water resource strategy, is re-evaluated in light of the extended inflow data and the estimated uncertainty. The main performance indices used here are reservoir reliability, resilience and vulnerability.

The main findings from this chapter are that (1) the prediction uncertainty range found in the reservoir performance indicators is wide as a result of incorporating a suite of possible uncertainty sources; (2) there is evidence of decreases in reservoir volumes and performance, which indicate the possible effect of climate change as a result of increased temperature, reduced rainfall and evaporative losses within the basin; and (3) these decreases vary across the models and scenarios under a changed climate; (4) The degree of decrease in reservoir volumes is more pronounced by 2050, where in general, the predicted reservoir volumes do not reach full capacity beyond the mid century. These findings lead to the conclusion that uncertainty and climate change have significant effects on water resources planning models and water supply systems in the study area- as such they should be fully incorporated in order to make informed planning decisions particularly in data limited and semi arid areas such as the upper Limpopo basin.

7.1 Introduction

Increasing water demand, especially from cities, is a growing global problem. In particular, countries undergoing rapid economic development tend to have both increasing urban populations and increasing per capita demand for water. This is occurring coincidentally with the impacts of climate change on water availability, particularly in many semi-arid regions where global warming is expected to increase evaporative losses potentially leading to increased number of failure events (Jain, 2010). The potential for increasing water demand from cities together with more variable natural supply calls for a combination of effective demand and supply side management measures. On the supply side, an attractive solution is to develop systems of reservoirs which will store surplus water from the uplands and allow controlled release of this water to the cities. The design of reservoirs for water supply purposes is a traditional hydrological and civil engineering problem, and design methods are well established. However, two major particular hydrological challenges remain, which will be considered in this chapter:

- (1) How will uncertainty in future climate projections affect water resources systems in the Limpopo basins. This includes effects on reservoir performance indices such as reservoir reliability, resilience and vulnerability.
- (2) The challenges of representing sources of uncertainty other than climate projections, i.e. uncertainty arising from input data, model parameter uncertainty, model structure uncertainty

These issues are addressed by evaluating the performance of a proposed 382,000 m³ reservoir in light of the extended rainfall and flow data generated under stationary and changed climate and also focusing on input

(rainfall) and hydrological parameter uncertainty.

7.2 Representation of uncertainty in water supply systems

While it is increasingly becoming common to explicitly represent uncertainty in hydrological studies (Beven, 2001, Chiang et al., 2007, McMillan et al., 2010, Beven and Freer, 2001, Li et al., 2009, Hughes et al., 2010, Wagener and Wheater, 2006), so far it appears that in reservoir performance studies model uncertainty has received limited attention. Rather, most researchers usually adopt the strategy of using auto-regressive models to stochastically generate synthetic annual streamflows which match the statistical properties of historical flows (Srikanthan and McMahon, 1982, McMahon et al., 2006, Jain, 2010, Stedinger and Taylor, 1982). For example, McMahon et al (2006) used a lag-one autoregressive model to generate annual flows under parameter uncertainty. The annual flows were then disaggregated into monthly flows using Method of Fragments (MOF) (Srikanthan and McMahon, 1982) from which reservoir performance was evaluated. There are problems with these methods, (1) the parameters used are basically derived only from the historical flows, as such the uncertainty used relates purely to the stochastic component of the model. This is in contrast to the more comprehensive treatment of uncertainty which is sometimes done in hydrological modelling, for example chapters 4-6 of this thesis, where a suite of uncertainty sources can be explicitly represented (i.e. uncertainty arising from input data, model parameter uncertainty, model structure uncertainty) (Wilby and Harris, 2006, Krueger et al., 2009); (2) The use of a disaggregation technique such as the MOF has not so far allowed parameter uncertainty to be propagated into the monthly flows (McMahon et al., 2006), because their disaggregation theory was not extended to estimating uncertainty in more structure and parameters.

To my knowledge, only studies by Xiang et al., (2010), Lowe et al., (2009), and Davies et al., (2005) have attempted to explicitly represent uncertainty

specific to reservoir operation studies, and water resources systems. Xiang et al (2010) used a dynamic flood control model applied to the China's three gorges reservoir (TGR) to evaluate reservoir operation for flood management by representing inflow uncertainty, which they considered the primary risk source of reservoir control operation (Xiang et al., 2010). In their research, they defined inflow uncertainty as uncertainty arising from the inflow forecasting error (i.e. the difference between the predicted and historical inflows scaled by the observed flows) and uncertainty of the flood hydrograph shape (i.e. the hydrograph shape at each stage of reservoir operation). These were incorporated into the dynamic flood control model implemented within Monte Carlo (MC) framework to simulate reservoir water levels under inflow uncertainty. Lowe et al. (2009) evaluated evaporation from water supply reservoirs using three reservoirs in the Werribee catchment in Australia with the view to quantify the uncertainty arising from reservoir evaporation estimates using a Bayesian approach within the MC framework. In their approach, they focused on estimating the uncertainty in evaporation which arises from using the evaporation pan method. Sources of uncertainty include, among others (1) uncertainty associated with the type and characteristics of evaporation pan, precision of measurement instrument and the characteristics of the surrounding environment; (2) uncertainty arising from rainfall measurements, based on manual and automated rain gauges; (3) uncertainty associated with birds and animals which may drink water from the evaporation pan; (4) uncertainty arising from pan location with respect to water supply reservoir (spatial transposition factor); (5) uncertainty arising from temporal estimation of evaporation coefficient (i.e. whether at monthly or annual scale). These multiple sources of uncertainty were combined within the MC framework and assessed individually to estimate individual and overall evaporation uncertainty. Conclusion from this study showed that the largest contributors to the uncertainty in reservoir evaporation are the spatial transposition factor (mentioned above) and the annual evaporation pan coefficient, which ranged between 21% and 40% of the median in favour of the latter.

The study by Davies et al. (2005) focused on quantifying uncertainty from GCM scenarios, which were propagated through climate downscaling models, rainfall-runoff models and a water resource model in 13 UK catchments. Uncertainties were considered at all stages: 3 GCMS were considered (HadCM3, CCGCM, CSIRO-ML2), each with 2 carbon emission scenarios. 3 downscaling methods were used (HADRM3H, SDSM, Change Factors), providing daily time-scale climate data for input to rainfall-runoff models. 2 rainfall-runoff model structures were used (both based on conceptual PDM model). Uncertainty was considered by using resampling of historic rainfall records to fit the downscaling models; and sampling parameter uncertainty in rainfall runoff models. The resource systems were small, simple, hypothetical resource zones. The main conclusions from their study, were that GCMs are the main source of uncertainty, the 2020 emission scenarios have very small uncertainty, but uncertainty is significant for 2080s, and downscaling uncertainty is small but significant. However, Davies et al, (2005) cautioned that their report does not intend to provide climate change impact assessment results. Rather, it only provides a set of illustrations of potential uncertainty sources. The two companion studies (Prudhomme and Davies, 2009a, Prudhomme and Davies, 2009b) used the same methodologies and sources of uncertainty, but focused on only 4 catchments to provide climate change impact assessment results for baseline and future climate. The conclusions were similar to those of Davies et al., (2005) but went further to conclude that the bias in GCMs must be correctly accounted for since it affects future rainfall predictions, and they also highlighted the need to consider more than one GCM and downscaling technique in impact studies.

The above studies show the importance of explicitly quantifying uncertainty related to individual sources in water supply systems as this may help in concentrating the resources where they are needed most to improve management of these water resources systems particularly in semi arid areas.

In this application, the focus is on quantifying the effects of uncertainty in reservoir performance. These uncertainties (identified from chapters 4 and 5) arise from rainfall (specifically, the missing data and short record length) and hydrological model parameters (equifinal parameters). Furthermore, it is widely accepted that climate change will affect many hydrological variables such as rainfall and streamflow (see reviews and prediction results discussed in chapter 6 of this thesis), where in many cases these effects were predicted to be severe (Andersson et al., 2006, Masike and Urisch, 2008). In reservoir design and operation studies, these variables are mainly used as input to water resources planning models, such as when computing volumetric storage contents and reservoir performance. As such, it is important to know how these changes will affect water resources systems under climate change. Apparently, there are only limited studies that have gone a step further to quantify the effects of climate change on water supply systems, particularly reservoir performance (Christensen and Lettenmaier, 2007), and under harsh climate conditions such as in semi arid areas. This is another gap that this thesis seeks to address by using prediction results from selected GCMs and climate scenarios to evaluate the performance of a proposed reservoir.

7.3 Reservoir performance under stationary and changed climate

The results obtained in Chapter 6 indicate that rainfall and streamflow will decrease in the future, reaching unprecedented levels by the end of the century. To investigate the possible effects of climate change on Botswana's water resources, a proposed reservoir in the study area is used as a case study. The reservoir includes a dam on the Shashe River, which is the main tributary after the confluence of Tati and Shashe Rivers (see Figure 3.1). The calibrated model is used to simulate flows at the catchment outlet (coinciding with the location of the proposed reservoir) using the 100 years

of rainfall generated by the GLM. The generated ensemble of flows was subsequently used to assess performance of the proposed reservoir under baseline conditions and the three climate change scenarios.

The proposed reservoir will have an active storage of $382 \times 10^6 \text{ m}^3$ (Snowy Mountains Engineering Corporation and Engineering Hydrological Environmental Management Consultants, 2006). The simulation of the reservoir is based on a simple monthly volume balance (McMahon and Adeloye, 2005):

$$Z_{t+1} = Z_t + Q_t - D_t - EV_t - L_t \quad (7.1)$$

Where Z_{t+1} and Z_t are the contents of the storage at months $t + 1$ and t ; Q_t is the inflow to the storage; L_t is the release in volume units; EV_t is the net evaporation loss; and D_t is the abstraction for input to the water supply system. Infiltration losses are neglected here. Evaporation losses (EV_t) are estimated using the reservoir surface area-storage relationships, as well as estimates of monthly open water evaporation for the catchment (Snowy Mountains Engineering Corporation and Engineering Hydrological Environmental Management Consultants, 2006). The contents of the reservoir were not allowed to exceed the active storage (i.e. the excess is spilled) and the abstraction for supply is turned off when Z reaches zero to avoid the condition $Z < 0$. Additionally, a simple control rule is imposed whereby only 20% of the demand will be abstracted whenever the storage drops below 25% of capacity. The unrestricted demand is estimated to be $65 \times 10^6 \text{ m}^3$ per year (this is the 2005 estimate—although this is expected to reach $190 \times 10^6 \text{ m}^3$ by 2035, the reservoir in question is designed to meet the 2005 demands). However, these figures are expected to increase in the future (see sections 3.21. to 3.2.3) which may affect future water supply, including reliability of the reservoir under study. The environmental flow

release is 5% of the inflow. The reservoir is assumed full at the beginning of the assessment.

7.4 Description of reservoir performance indices

There are many performance indices that are used to evaluate performance of water supply systems, particularly reservoirs used for water supply purposes. However, the literature seems to concentrate on the three main indices, which are reliability, resilience and vulnerability (McMahon and Adeloye, 2005, McMahon et al., 2006, Adeloye et al., 2003, Fowler et al., 2003, Montaseri and Adeloye, 1999, Jain, 2010). The common definitions of these indices according to these studies are as follows:

7.4.1 Time-based reliability

Reliability is defined as the probability that the system can meet the target demand. One reliability metric is the probability that a reservoir will be able to meet the unrestricted demand in any particular time interval (usually a year) within the simulation period. This can be represented as follows:

$$R_t = \frac{N_s}{N} \quad (7.2)$$

Where R_t is the time-based reliability, N_s is the total number of intervals during which the unrestricted demand was met, and N is the total number of time intervals in the simulation. In general, the monthly time-based reliability is preferred to annual reliability since each month of failure (i.e. when the unrestricted demand is not met) will be recognised in its own right (McMahon and Adeloye, 2005).

7.4.2 Volumetric reliability

Another reliability index, based on volume, is computed as the total quantity

of water actually supplied divided by the total quantity of water demanded during the entire simulation period. It can be expressed as follows:

$$R_v = 1 - \frac{\sum_{j \in f} (D_j - D'_j)}{\sum_{j \in N} D_j} \quad (7.3)$$

Where R_v is the volumetric reliability, f is the number of failure periods for which $D' < D$ ($= N - N_s$), D'_j is the actual supply from the reservoir system during the j^{th} period (which is different from the demand) and N is the number of periods in the simulation. ($R_v \rightarrow 1$ if demand is 100% satisfied, i.e. $D'_j = D_j$)

7.4.3 Resilience

This is used as an indicator of how fast a reservoir will recover following a failure period. It is defined as the probability that a reservoir system will recover following a failure within one month (Hashimoto et al., 1982), i.e.

$$\varphi = \frac{f_s}{f_d} \quad f_d \neq 0, 0 < \varphi \leq 1 \quad (7.4)$$

Where φ is resilience, f_s is the number of individual continuous sequences of failure periods (in units of months) and f_d is the total duration of all the failures (also in units of months), i.e. $N - N_s$.

7.4.4 Vulnerability

This measures the severity or extent of the failure itself. This is defined as the average of the maximum shortfalls occurring in each of the continuous

failure periods, i.e.,

$$\eta' = \frac{\sum_{k=1}^{f_s} \max.(sh_k)}{f_s} \quad (7.5)$$

Where η' is the vulnerability index, $\max.(sh_k)$ is the maximum shortfall during the k^{th} continuous failure sequence, and f_s is the number of continuous failure sequences in the simulation. Vulnerability is often expressed in dimensionless units by dividing by the target demand during the failure period, denoted as follows,

$$\eta = \frac{\eta'}{D} \quad (7.6)$$

Where D is the target demand during a failure period.

Equation (7.6) ensures that the vulnerability falls in the range $0 \leq \eta \leq 1$.

7.4.5 Additional indices considered

In addition to these standard indices, two other indices are used: the severity of failure and mean reservoir volume.

7.4.5.1 Severity of failure

The first one is used to assess the severity of failure, i.e. if failure occurs, what is the probability that it occurs as a result of an empty reservoir. This is represented in Equation (7.7). This is based on the definition of failure provided in 7.3, where failure occurs whenever the storage level drops below 25% of capacity.

$$SF = \frac{\sum_{t=1}^N (Z_t = 0)}{f_s} \quad (7.7)$$

Where f_s is the number of continuous sequences of failure periods, including when the reservoir is empty.

7.4.5.2 Mean reservoir volume

As a final performance index, the mean reservoir volume, in Equation (7.8), is used to indicate the mean status of the reservoir contents during the entire simulation period.

$$V_m = \frac{1}{N} \sum_{i=1}^N Z_t \quad (7.8)$$

Where V_m is the mean reservoir volume during each simulation.

These performance indicators were all computed considering rainfall and parameter uncertainty, and the range of uncertainty in performance is indicated in Table 7-1.

7.5 Results

7.5.1 Reservoir performance under stationary climate

Figure 7-1 shows the simulated reservoir volume under stationary climate, using all the 100 equifinal parameter set from each of the 10 rainfall realisations used in the calibration (see chapter 5). The plot shows the importance of accounting for a full range of uncertainty during model calibration. For example, when considering only rainfall uncertainty (the grey scale, derived using the single best parameter set for each rainfall realisation), the uncertainty is narrow and underestimated compared to when adding the hydrological parameter uncertainty (the dotted lines showing uncertainty bounds). To illustrate this, the reservoir reliability indicator was used. The reliability (in terms of the percentage of months for which the target demand is satisfied) varies from 60% to 100% (Table 7-1) (or 98% when averaged across all the 1000 simulations representing rainfall and hydrological uncertainty). However, when considering only rainfall uncertainty, the reliability ranges from 81% to 100%, averaging to 96% (not shown in Table 7-1). Although the underestimation of the average reliability is rather small, this underestimation of uncertainty may have far reaching implications for reservoir performance, which may lead to an underestimation of frequency of failure events leading to poor decision making, for example regarding the reservoir operation rules mentioned in section 7.3.

When considering other performance indices in Table 7-1, it is notable that time-based reliability and volumetric reliability for this reservoir are similar- the only slight differences being in the lower uncertainty bound, where the values are relatively high for the volumetric reliability. Regarding the reservoir resilience, it is notable that once a failure occurs, the reservoir does not quickly recover to a satisfactory state as shown by low resilience

values (with an average of 0.19 across all the simulations, and a range of 0.03 to 1). When the severity of failure (SF) is considered, it can be seen from Table 7-1 that the values are quite low (a range of 0 to 0.03, and an average of 0), indicating that in general the failures do not occur as a result of an empty storage, but rather when the volume is below 25% of the capacity. In fact, when assessing the mean reservoir volume under a stationary climate, it is observed that the volumes are relatively high, i.e. 65% of the capacity when averaged across all the simulations, and a range of 43% to 92%. Another performance index of interest is reservoir vulnerability. These values are quite high, with an average of 0.98 across all the simulations (and a range of 0.8 to 1). This indicates that once a failure occurs, the shortfall could be very high, translating to 98% of the target demand.

7.5.1.1 Comparison of results with the findings from other studies in southern Africa

The results presented above are evaluated in light of other studies conducted in similar environments. There are a limited number of published studies on reservoir performance in southern Africa. A study by McMahon et al. (2006) investigated performance of hypothetical reservoirs from selected catchments, including a semi arid catchment in South Africa. In their research, they evaluated performance measures using streamflow from four rivers – the Earn river at Kinkell (United Kingdom), the Hatchie river at Bolivar (USA), the Richmond river at Casino (Australia) and the Vis River at Harderug (South Africa), covering a wide range of streamflow variability (with the CV (coefficient of variation) of annual flows ranging from 0.16 in the UK to 1.27 in South Africa). These hypothetical reservoirs were evaluated assuming no evaporation, which is in contrast to the present study. Synthetic flow data of 1000 years and 1000 replicates representing stationary climate (no climate change) were generated using a stochastic

auto-regressive model as discussed in section 7.2. While the interest of this study is mainly the semi arid catchment, for completeness we summarise their findings for both a humid area with low annual streamflow CV (UK) and a semi arid area with high CV (South Africa). For the UK catchment, reliability varied from 98 to 100%; resilience varied from 0.58 to 1; and vulnerability varied from 0 to 0.34. For a semi arid catchment, the indices are as follows: reliability (52 to 97%); resilience (0.1 to 0.52); vulnerability (0.71 to 0.96) (McMahon et al., 2006). These results are for a range of hypothetical reservoirs (i.e. each reservoir was assessed assuming a combination of reservoir capacities and demand, both as a fraction of mean annual flow) averaged over 1000 simulations (Table 8-(McMahon et al., 2006). The authors concluded that reservoirs in humid areas (and with low annual streamflow CV) are less vulnerable and more resilient during failure periods, and also in general are more reliable compared to those in semi arid areas (with high CV). Although these authors used hypothetical case studies with different climate inputs and different demands from this case study, and thereby representing uncertainty which is different from the one considered in this thesis, it is noted that the results for the semi arid South African catchment are comparable to the findings in Table 7-1, presumably because streamflows in this catchment are also highly variable, (with annual streamflow CV of 1.43).

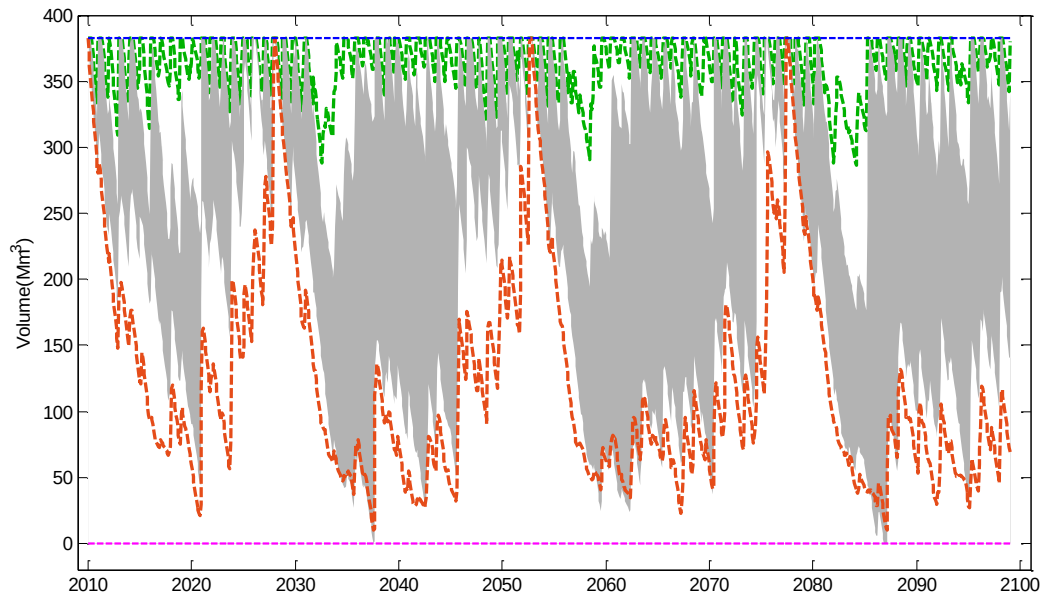


Figure 7-1: Simulated reservoir volumes under baseline climate for the period 2010-2100: ten realisations (the grey scale) and 100 equifinal parameters bounded between the lower bound (red colour) and the upper bound (green colour). The pink colour represents zero storage level while the blue colour represents full capacity of 382,000 Million M³.

Table 7-1: Reservoir performance indicators for stationary climate, GCMs and climate scenarios during the period 2010-2100 computed using the actual flow time series.

	^[1] Time Reliab.		^[2] Vol. Reliab		^[3] Sev.Fail	^[4] Mean Vol.		^[5] Resil.		^[6] Vuln.
	(%)		(%)			(10⁶ m³)				
Stationary	60-100	(98)	64-100	(98)	0-0.03 (0.00)	43-92	(65)	0.03-1	(0. 19)	0.80-1 (0.98)
BCM2-B1	7-98	(51)	9-98	(51)	0-0.53 (0.04)	8-75	(29)	0.01-1	(0.07)	0.91-1 (0.99)
CSMK3-B1	15-100	(82)	19-100	(82)	0-0.29 (0.00)	19-88	(47)	0.02-1	(0.24)	0.86-1 (0.99)
HADCM3-B1	4-91	(37)	5-91	(37)	0-0.64 (0.12)	4-62	(22)	0.00-1	(0.07)	0.93-1 (0.99)
INCM3-B1	4-91	(26)	4-91	(26)	0-0.69 (0.11)	5-59	(18)	0.00-1	(0.09)	0.94-1 (0.99)
MPEH5-B1	7-89	(45)	7-89	(45)	0-0.55 (0.16)	8-63	(25)	0.00-1	(0.06)	0.91-1 (0.99)
BCM2-A1B	8-92	(47)	10-92	(47)	0-0.58 (0.15)	8-67	(28)	0.00-1	(0.07)	0.92-1 (0.99)
CSMK3-A1B	25-100	(73)	31-100	(73)	0-0.47 (0.03)	18-80	(45)	0.01-1	(0.22)	0.90-1 (0.99)
HADCM3-A1B	10-70	(40)	10-70	(40)	0-0.71 (0.34)	10-52	(23)	0.00-1	(0.02)	0.94-1 (0.99)
INCM3-A1B	7-62	(21)	7-62	(21)	0-0.85 (0.30)	6-43	(14)	0.00-1	(0.02)	0.97-1 (1.00)
MPEH5-A1B	4-65	(25)	4-65	(25)	0-0.73 (0.36)	7-45	(16)	0.00-0.02	(0.00)	0.95-1 (1.00)
BCM2-A2	4-71	(23)	4-71	(23)	0-0.75 (0.31)	5-46	(15)	0.00-0.14	(0.02)	0.95-1 (1.00)
CSMK3-A2	13-100	(47)	15-100	(47)	0-0.55 (0.03)	14-67	(29)	0.00-1	(0.22)	0.91-1 (1.00)
HADCM3-A2	7-75	(36)	7-75	(36)	0-0.68 (0.35)	9-53	(21)	0.00-0.38	(0.02)	0.94-1 (1.00)
INCM3-A2	4-54	(18)	4-54	(18)	0-0.83 (0.37)	6-40	(12)	0.00-0.10	(0.01)	0.97-1 (1.00)
MPEH5-A2	4-69	(22)	4-69	(22)	0-0.75 (0.32)	6-47	(15)	0.00-0.02	(0.10)	0.96-1 (1.00)

^[1] Time reliability based on Eqn. (7.2). ^[2] Volumetric reliability based on Eqn. (7.3). ^[3] Severity of failure is obtained using Eqn.(7.7).^[4] Mean volume is computed from all the simulations as a percentage of the reservoir capacity based on Eqn. (7.8). ^[5] Resilience is computed using Eqn. (7.4). ^[6] Vulnerability of Eqn. (7.6). The ranges are for 1000 simulations while the values in parenthesis represent values averaged across all the 1000 simulations.

Table 7-2: Reservoir performance indicators for 5 GCMs, climate scenarios during the period 2010-2100 computed using the actual flow time series.

	^[1] Time Reliab.		^[2] Vol. Reliab		^[3] Sev.Fail	^[4] Mean Vol.		^[5] Resil.		^[6] Vuln.
	(%)		(%)			(10⁶ m³)				
BCM2-B1	15-100	(69)	18-100	(69)	0-0.47 (0.01)	12-81	(38)	0.01-1	(0.56)	0.89-1 (0.99)
CSMK3-B1	23-100	(79)	28-100	(80)	0-0.38 (0.00)	19-85	(47)	0.00-1	(0.05)	0.88-1 (0.99)
HADCM3-B1	15-91	(44)	17-91	(44)	0-0.60 (0.12)	13-63	(27)	0.00-1	(0.08)	0.92-1 (0.99)
INCM3-B1	8-94	(42)	11-94	(42)	0-0.59 (0.08)	7-65	(25)	0.00-1	(0.11)	0.92-1 (0.99)
MPEH5-B1	7-78	(45)	9-75	(45)	0-0.68 (0.29)	7-59	(26)	0.00-1	(0.03)	0.94-1 (1.00)
BCM2-A1B	18-100	(57)	20-100	(57)	0-0.50 (0.02)	16-74	(34)	0.01-1	(0.36)	0.90-1 (0.99)
CSMK3-A1B	23-100	(67)	26-100	(67)	0-0.48 (0.09)	18-76	(40)	0.01-1	(0.16)	0.90-1 (0.99)
HADCM3-A1B	10-83	(43)	12-83	(40)	0-0.62 (0.18)	11-58	(26)	0.00-1	(0.06)	0.93-1 (0.99)
INCM3-A1B	6-73	(34)	11-82	(34)	0-0.71 (0.19)	9-53	(21)	0.00-1	(0.05)	0.94-1 (1.00)
MPEH5-A1B	8-62	(30)	10-62	(30)	0-0.77 (0.42)	7-46	(19)	0.00-0.02	(0.01)	0.96-1 (1.00)
BCM2-A2	10-82	(39)	12-82	(39)	0-0.64 (0.15)	10-61	(23)	0.01-1	(0.07)	0.93-1 (1.00)
CSMK3-A2	18-95	(52)	20-95	(52)	0-0.54 (0.05)	15-68	(33)	0.01-1	(0.19)	0.91-1 (1.00)
HADCM3-A2	10-79	(36)	12-79	(36)	0-0.65 (0.29)	9-54	(22)	0.00-0.16	(0.02)	0.93-1 (1.00)
INCM3-A2	9-82	(34)	6-73	(34)	0-0.71 (0.30)	8-52	(21)	0.00-1	(0.02)	0.94-1 (1.00)
MPEH5-A2	7-65	(30)	9-65	(30)	0-0.82 (0.40)	7-47	(18)	0.00-0.10	(0.01)	0.97-1 (1.00)

^[1] Time reliability based on Eqn. (7.2). ^[2] Volumetric reliability based on Eqn. (7.3). ^[3] Severity of failure is obtained using Eqn.(7.7)).^[4] Mean volume is computed from all the simulations as a percentage of the reservoir capacity based on Eqn. (7.8). ^[5] Resilience is computed using Eqn. (7.4). ^[6] Vulnerability of Eqn. (7.6). The ranges are for 1000 simulations while the values in parenthesis represent values averaged across all the 1000 simulations.

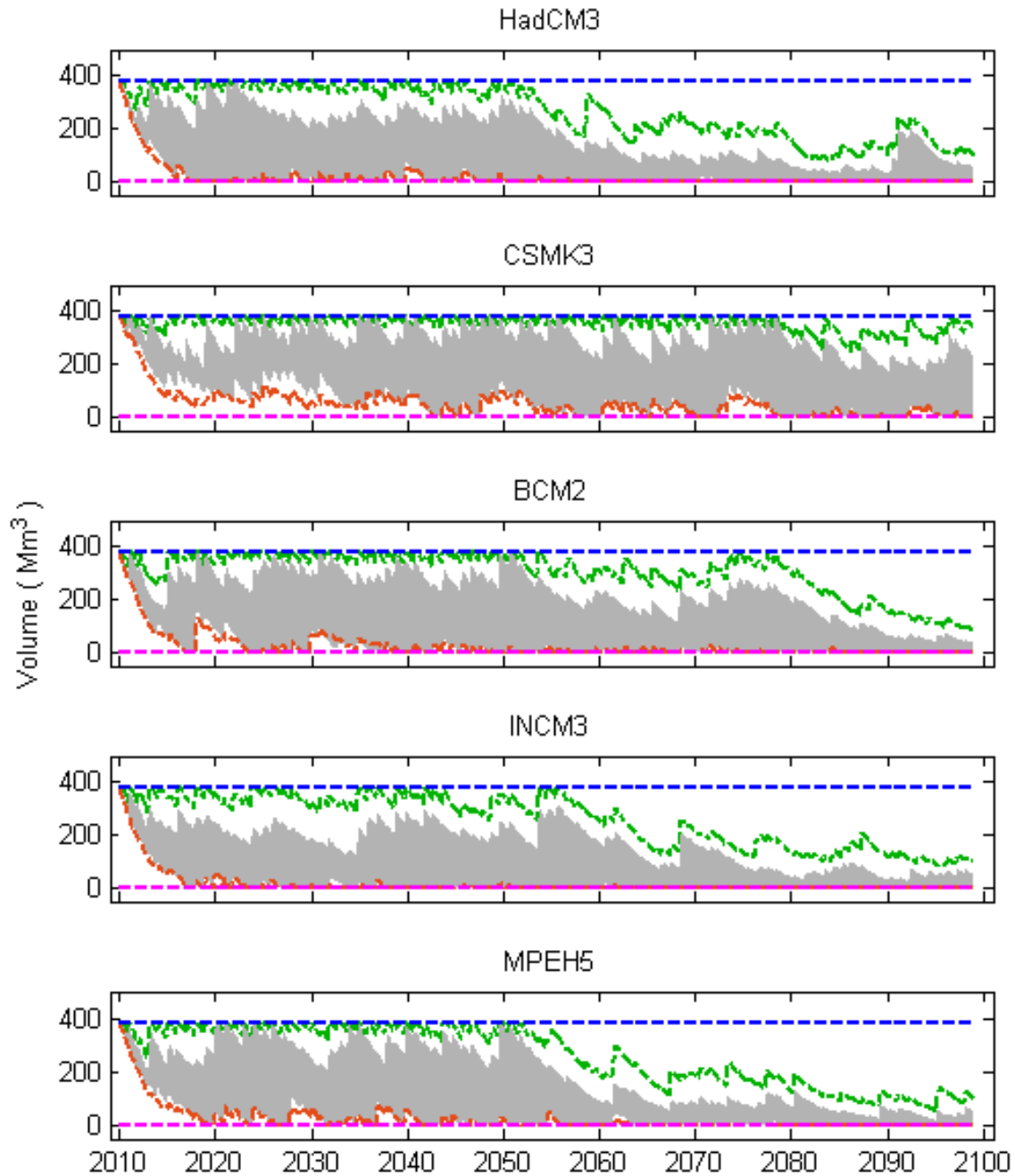


Figure 7-2: Simulated reservoir volumes under the B1 climate change scenarios for the 5 GCM models using the actual flow time series. The results are obtained from 10 rainfall realisations (the light grey scale) as well as best 100 parameters sets of the catchment outlet (the dotted lines). The pink colour represents zero storage level while the blue colour represents full capacity of 382,000 Million M³.

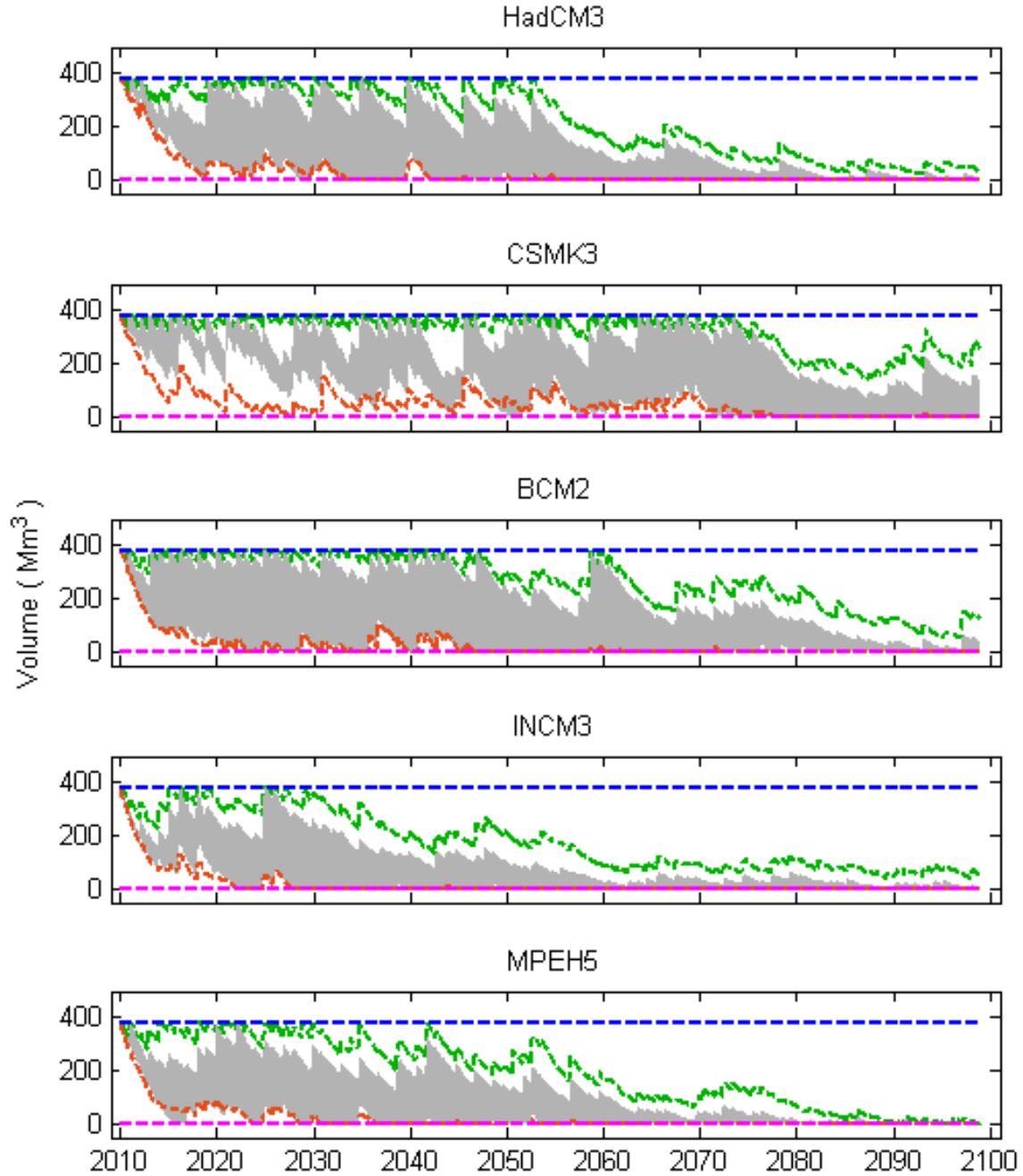


Figure 7-3: Simulated reservoir volumes under the A1B climate change scenario for the 5 GCM models using the actual flow time series. The results are obtained from 10 rainfall realisations (the light grey scale) as well as best 100 parameters sets of the catchment outlet (the dotted lines). The pink colour represents zero storage level while the blue colour represents full capacity of 382,000 Million M³.

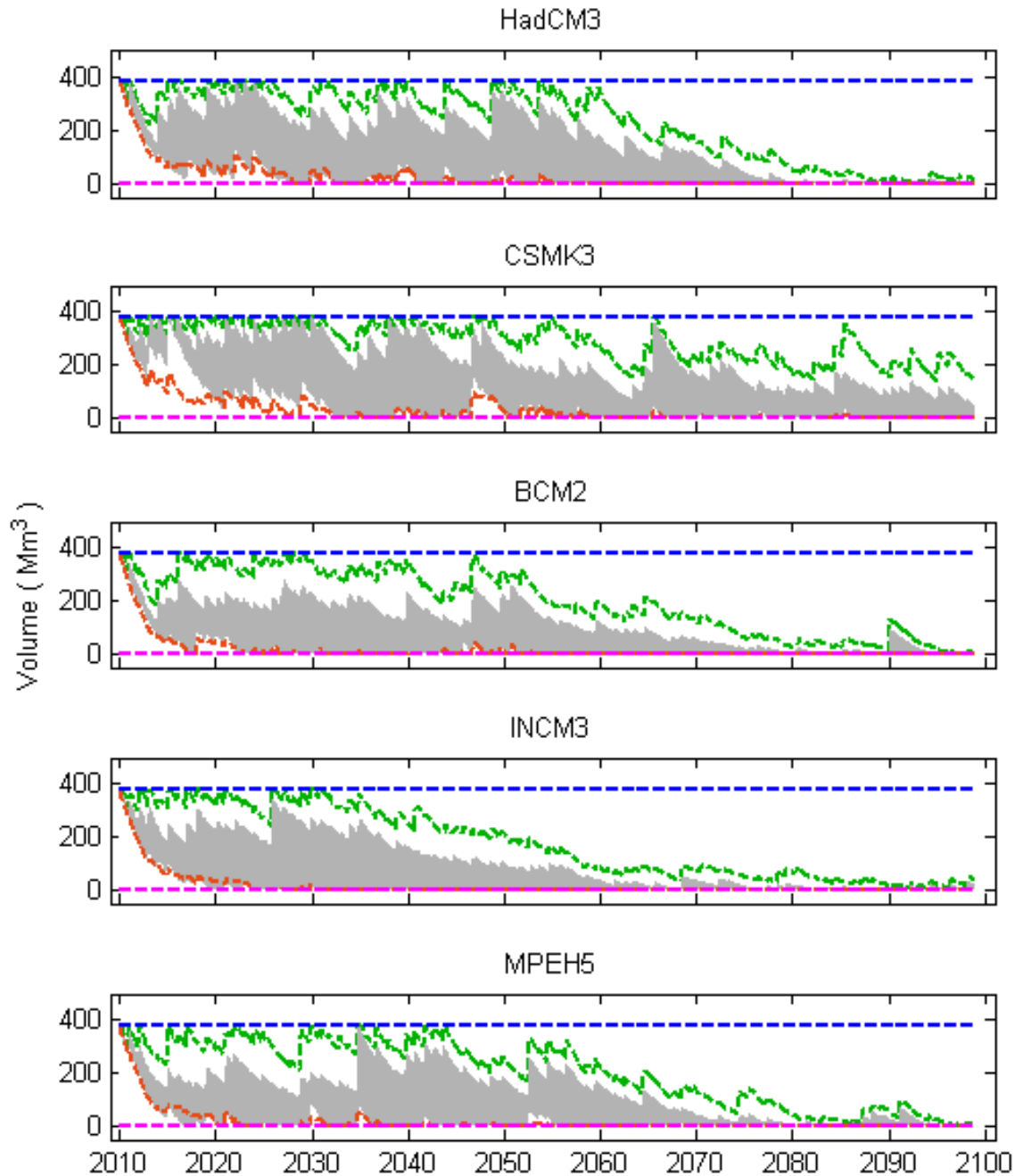


Figure 7-4: Simulated reservoir volumes under the A2 climate change scenario for the 5 GCM models using the actual flow time series. The results are obtained from 10 rainfall realisations (the light grey scale) as well as best 100 parameters sets of the catchment outlet (the dotted lines). The pink colour represents zero storage level while the blue colour represents full capacity of 382,000 Million M³.

7.5.2 Reservoir performance under changed climate

7.5.2.1 Reservoir performance using the actual flows generated from the GLMRDA

Figures 7-2 to 7-4 show the future results based on the climate variables generated by 5 GCM models and 3 IPCC climate scenarios (from chapter 6) run through the hydrological model (chapter 5). This includes temperature (taken directly from the GCMs) and rainfall (downscaled). The results are also presented for both rainfall uncertainty (the grey scale) and equifinal parameter sets (the dotted lines). In general, the following observations are made about the results from these 3 plots:

(1) the uncertainty range is wide as a result of including all the 100 equifinal parameter sets; (2) the results show evidence of decline in reservoir volumes across the models and scenarios; (3) results from the CSMK3 model display smaller changes compared to other models for all the scenarios; (4) greater changes are observed for the MPEH5 and INCM3 models, while HADCM3 and BCM2 models give intermediate changes; (5) the B1 scenario predicts lower changes, followed by A1B and A2 scenarios; (6) The reservoir volumes predicted by the GCM models struggle to reach a full state mainly beyond 2050 (with an exception of the CSMK3 model), even for the B1 low emission scenario.

Considering the results from the individual GCMs, and comparing across the scenarios, it can be seen from Figure 7-2 that for the CSMK3 model, the reservoir begins to fail in 2040 and does not regularly reach full capacity after 2078. For the A1B scenario (Figure 7-3) failure begins as early as 2022 and the reservoir never fills to capacity after 2075. The rainfall uncertainty is very narrow before 2050 in this scenario, presumably due to random effects as only 10 samples of rainfall were used. For the A2 scenario (Figure 7-4) the reservoir begins to fail in 2028, does not fill up often thereafter, with

only 2 cases of full capacity after 2050. The results for MPEH5 (which is among the models which predict drastic decreases in rainfall) show that the reservoir begins to fail in 2018 but never reaches full capacity after 2050; while for the A1B and A2 scenarios, failure begins in 2012 and the reservoir does not fill to capacity after 2042. Results for the INCM3 model also display dramatic decreases in performance particularly for the A1B and A2 scenarios, where the reservoir never recovers to full capacity after 2030.

Results also highlight the importance of considering the uncertainty due to equifinality of model parameters. For example, looking at the prediction results from the HADCM3 and INCM3 models under the B1 scenario (Figure 7-2), it is observed that the reservoir never fills to capacity after 2025 (for the HADCM3 model) and 2011 (for the INCM3 model) when using only the rainfall uncertainty.

Table 7-1 shows the performance indices obtained for the GCMs and scenarios. Considering the reservoir reliability (time and volume), it can be seen that the reliability is relatively high under the B1 scenario (between 26 and 82% across the GCM models), followed by the A1B (21-73%) and A2 (18-47%) scenarios. From these results, and those reported in section 7.5.1, it is observed that in general the reservoir reliability declines with time as a result of climate change. The inter-model (GCM) uncertainty and scenario uncertainty are high compared to simulation uncertainty (i.e. uncertainty arising from a combination of rainfall and parameter uncertainty). For example, the CSMK3 model predicts the highest reliability values in all the scenarios while the INCM3 model predicts the lowest values. This confirms the value of using more than one GCM in climate change assessment studies.

As discussed in 7.5.1, the SF values are generally low. However, they have increased when compared to those reported under a stationary climate, indicating that more failures are associated with an empty storage under changed climate than under stationary climate. The values of SF are

generally low under the B1 scenario compared to the A2 scenario, implying that the reservoir empties quite often under the A2 scenario. When considering the mean reservoir volumes, it is clear that these values have dropped under a changed climate. In addition, these values are low for the low emission scenarios B1 and A1B compared to the high emission scenario A2.

Regarding the resilience indicator, it is observed that in general the values are low compared to those predicted under a stationary climate with the exception of CSMK3 (where the resilience is relatively high, up to 0.24 under the B1 scenario), which suggest that in general the reservoir loses the ability to recover fast under changed climate. This scenario may arise when the inflows from the peak of the rainy season, such as during the summer (JFMA) are significantly reduced. In fact, it was found in chapter six (refer to Figures 6-6 and 6-11) that in general, summer rainfall and flows are more affected by climate change than other seasons.

7.5.2.2 Reservoir performance using the CF method

This section presents the results of reservoir performance based on the CF method. These results are presented in Figures 7-5 to 7-7, and Table 7-2. In general, the results from these figures follow a similar trend identified earlier when using the flows generated from the GLMRDA approach. For example, the six main observations made in 7.5.2.1 can also be made here. However, a closer look at these plots shows that the CSMK3 model predicts relatively dry conditions (particularly after the 2080, see Figures 7-2 and 7-5) under the B1 scenario when using the CF method, where the reservoir rarely fills to capacity. On the other hand, for the same climate scenario, it is observed that predictions by the BCM2 and INCM3 models suggest wetter conditions when using the CF method compared to the other approach. Other than these differences, (which are also evident in other climate scenarios) the

effects of uncertainty resulting from these runoff estimation methods are small compared to other uncertainties. For example, when using statistics summarised in Tables 7-1 and 7-2 the reservoir reliability simulated by the CSMK3 model under the B1 scenario is 79% when using the CF method compared to 82% when using the other approach (which are quite close). When considering other performance indicators across the climate scenarios, the inter-model mean volume results range from 18% (MPEH5) to 33% (CSMK3) under the A2 scenario when using the CF method, compared to a range of 12% (INCM3) to 29% (CSMK3) under the same scenario. Although these uncertainties are small (compared to GCM uncertainty, scenario uncertainty, rainfall and model parameter uncertainty) these findings are consistent with the conclusion made in chapter 6 (6.4.1), that the extent of runoff changes and the associated effects on reservoir performance may also depend on the runoff estimation method used.

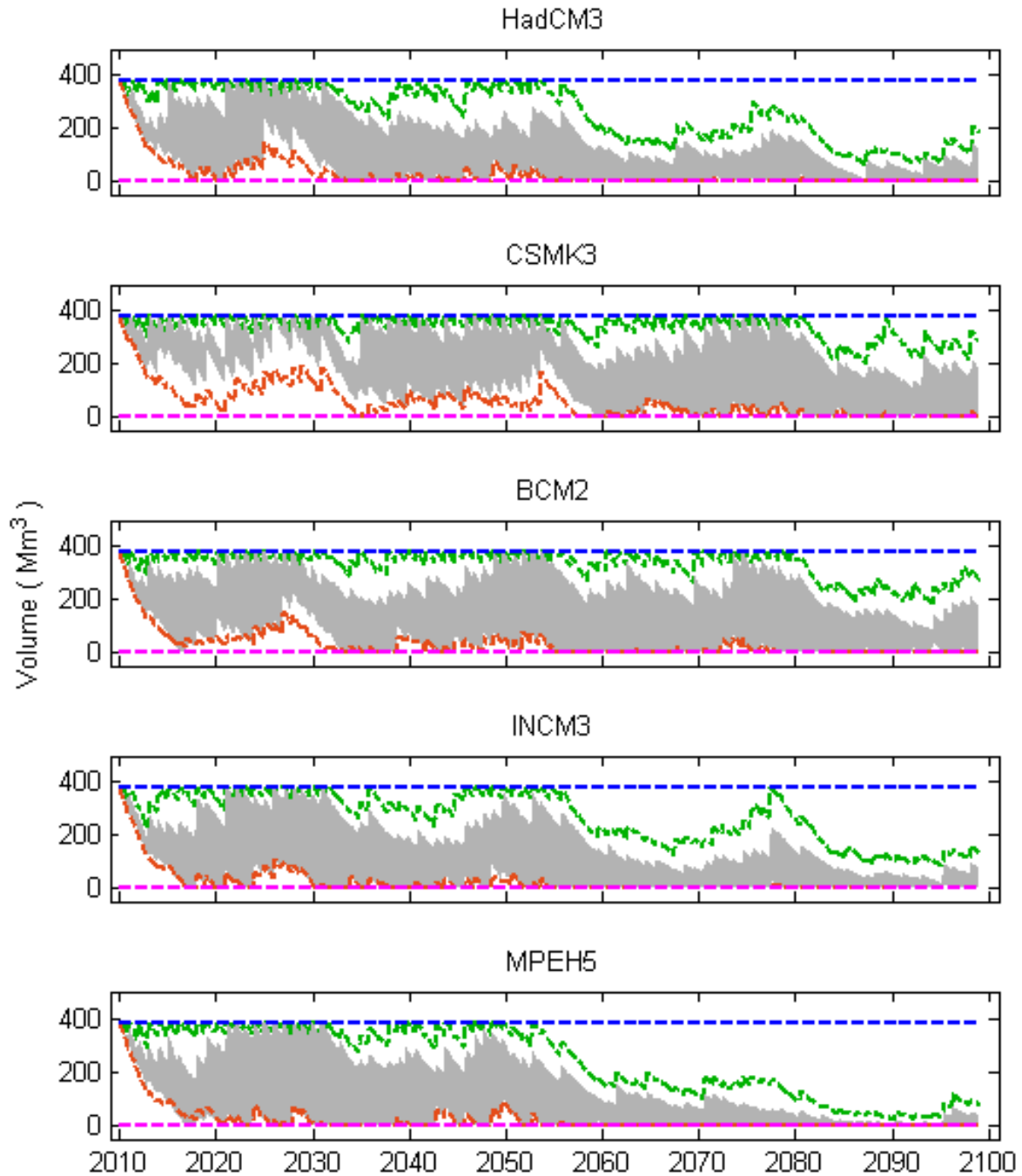


Figure 7-5: Simulated reservoir volumes under the B1 climate change scenarios for the 5 GCM models using the relative flow changes from the CF method. The results are obtained from 10 rainfall realisations (the light grey scale) as well as best 100 parameters sets of the catchment outlet (the dotted lines). The pink colour represents zero storage level while the blue colour represents full capacity of 382,000 Million M³.

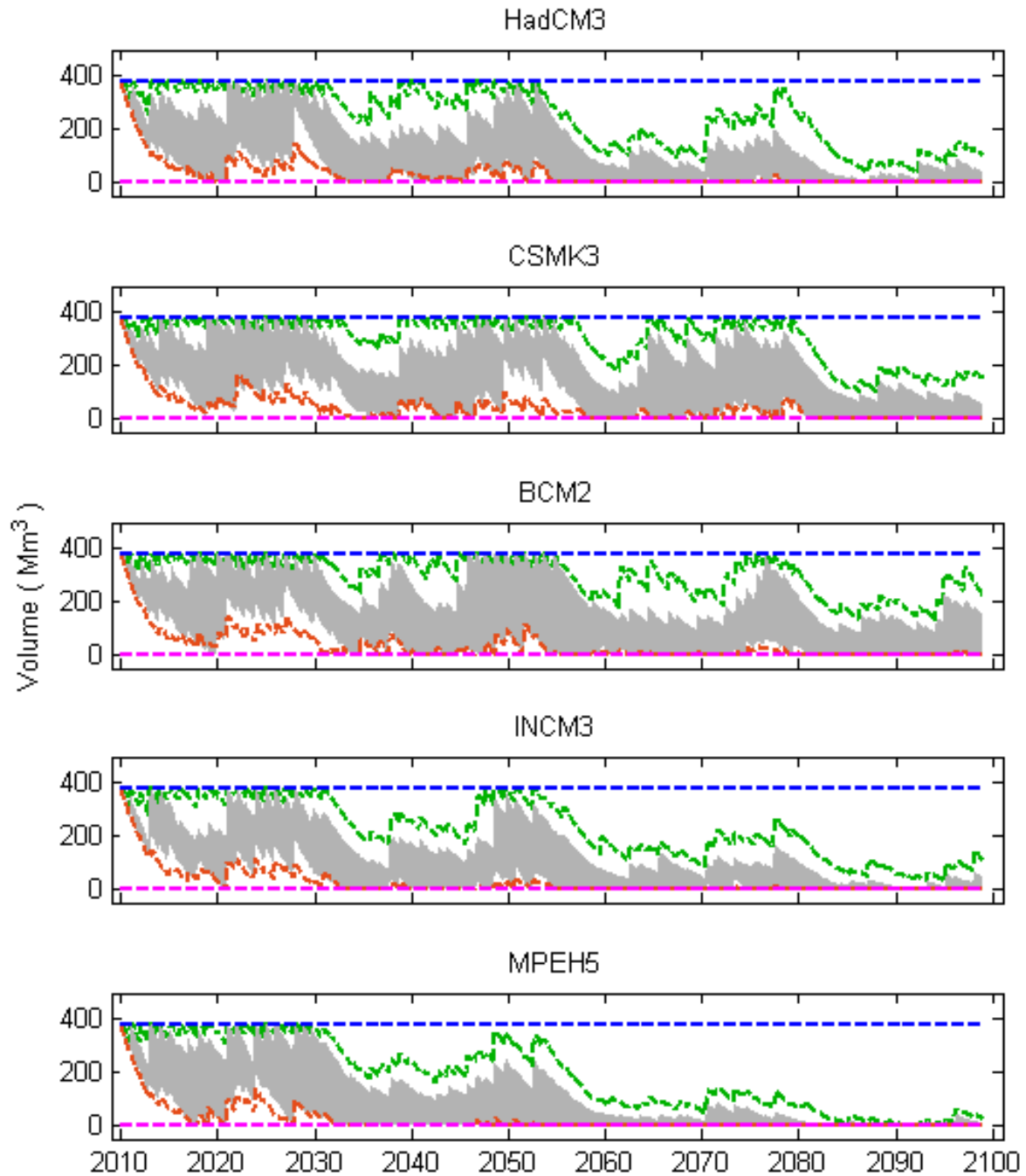


Figure 7-6: Simulated reservoir volumes under the A1B climate change scenarios for the 5 GCM models using the relative flow changes from the CF method. The results are obtained from 10 rainfall realisations (the light grey scale) as well as best 100 parameters sets of the catchment outlet (the dotted lines). The pink colour represents zero storage level while the blue colour represents full capacity of 382,000 Million M³.

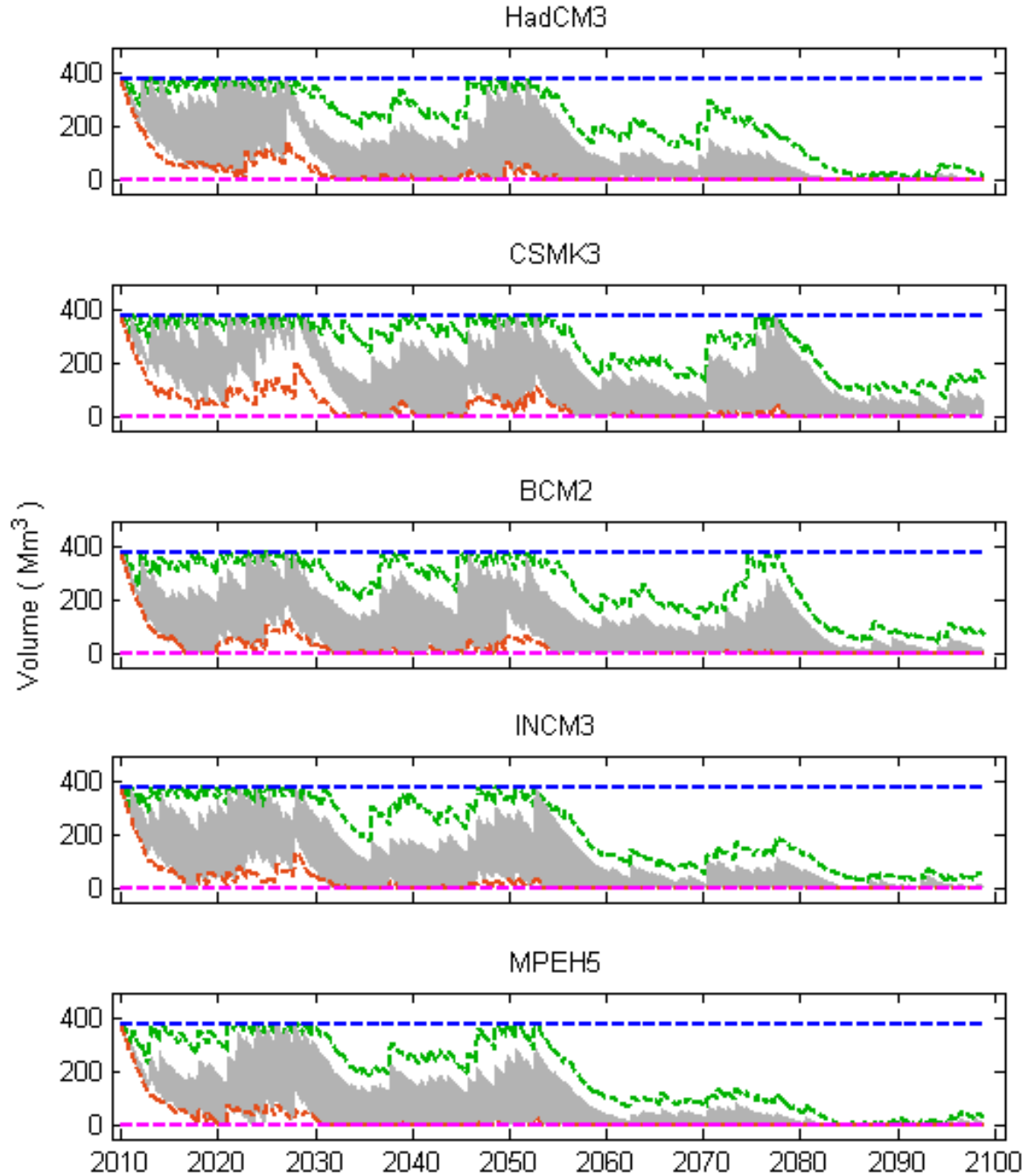


Figure 7-7: Simulated reservoir volumes under the A2 climate change scenarios for the 5 GCM models using the relative flow changes from the CF method. The results are obtained from 10 rainfall realisations (the light grey scale) as well as best 100 parameters sets of the catchment outlet (the dotted lines). The pink colour represents zero storage level while the blue colour represents full capacity of 382,000 Million M³.

7.6 Summary and conclusions

The main conclusions from this chapter are that: (1) The prediction uncertainty range found in the reservoir performance indicators is wide as a result of incorporating a suite of possible uncertainty sources. These include uncertainty arising from rainfall and hydrological equifinal parameters; uncertainty from climate models and from climate scenarios. Another source of uncertainty arises from the runoff estimation method used. However, this latter source of uncertainty was found to be small compared to the other sources of uncertainty.

With this approach, it was demonstrated that at times the reservoir reliability may be under estimated when only rainfall uncertainty is used (but assuming no hydrological uncertainty), which may ultimately affect decision making regarding reservoir operation and water supply activities. This would not have been achieved without representing a wide range of rainfall and hydrological uncertainties which are often ignored in reservoir performance studies; (2) There is evidence of decreases in reservoir volumes and performance, which indicate the possible effect of climate change as a result of increased temperature, reduced rainfall and increased evaporative losses within the basin; (3) These decreases vary across the climate models and scenarios under a changed climate. These two sources of uncertainty dominate uncertainty from rainfall and hydrological model parameter uncertainty. For example, the decrease was found to be larger under the high emission scenario, A2, where, for example the mean reservoir reliability dropped from 98% (assuming a stationary climate) to 18% (using the INCM3 model and A2 scenario); the mean severity of failure increased from 0 to 0.37 when moving from the stationary climate to changed climate using the INCM3 model and A2 scenario; the mean rate of recovery (resilience) also

dropped in general (with the exception of the CSMK3 model), for example from 0.19 under a stationary climate to 0 under a changed climate (using the MPEH5 and A1B scenario); (4) The degree of decrease in reservoir volumes is more pronounced by 2050, where in general, the predicted reservoir volumes do not reach full capacity beyond the mid century. From these results, it can be concluded that uncertainty and climate change have significant effects on water resources planning models - as such they should be duly taken into consideration in order to make informed planning decisions. Moreover, given that the demand pattern may change in the future (i.e. following the discussion in section 3)-mainly due to population growth, increased industrial and agricultural activities, increased access to water, the effects of uncertainty and climate change assessed in this chapter are likely to escalate dramatically.

The approach adopted by this thesis has evidently demonstrated a framework in which uncertainty arising from different sources can be quantified. This is deemed important as it can help identify priorities for reducing uncertainty to better manage water supply systems. The utility of this framework also extends to quantifying the effects of climate change on reservoir performance. There are of course, several limitations to the methods used, which would ideally be addressed in further research, and this is covered in Chapter 8.

CHAPTER EIGHT

8 Conclusions and Recommendations

This chapter presents the main conclusions from the discussions in the preceding chapters. The objectives of the thesis are recalled in this chapter in order to put the conclusions in perspective. The methodologies adopted are summarized and the main findings from these are stated. From these, the limitations of the study are highlighted leading to the recommendations to direct the future work.

8.1 Introduction

This thesis has been motivated by the fact that while water is a scarce resource in semi-arid Africa and comparable regions, the application of water resources planning models in these areas is highly challenging. The challenges arise because (1) rainfall and streamflow, which are the most important variables to many hydrological and water resources planning models, are highly variable in these areas, (2) yet the relevant measuring instruments for these variables (rain gauges and flow gauges) are in most cases sparsely distributed in space, which makes it difficult to capture these high spatial variability. Furthermore, where these measurements are available, they (3) are often very limited, (4) of questionable quality (5) and characterised by significant periods of missing data. These data issues (6) may limit the use of models requiring unbroken rainfall and streamflow data-potentially leading to (7) difficulties in capturing the temporal variability in the historic observations, as well as leading to (8) poor model predictions with (9) high uncertainty. These uncertainties are expected to (10) increase when considering future predictions associated with the effects of climate change. Indeed, the issue of representing, quantifying and reducing uncertainty in environmental models continues to attract attention to most researchers (e.g. Liu and Gupta, 2007, Montanari, 2007, Efstratiadis and Koutsoyiannis, 2010). However, due to the challenges presented above, (11) consideration of uncertainty and climate change analysis is still very limited in semi arid areas, and (12) where it is given, it does not always extend to the performance of water storage systems-such as dams which have become the last hope (besides groundwater) for many semi arid areas.

With these in mind, a framework of uncertainty and climate change analysis has been developed through this thesis to guide hydrological and water resources modelling in semi arid areas. Specifically, the framework sought to address the following tasks as summarised in chapter 1:

- To evaluate the quality of rainfall data in the upper Limpopo basin, and determine how the quality may affect rainfall modelling results.
- To develop a rainfall simulation model (RSM) suitable to the study area and possibly to other data sparse semi arid areas.
- To identify the parameters of the (RSM) model and quantify uncertainty, including uncertainty arising from rainfall data (in particular the missing data).
- To explore the applicability of RSM as a downscaling tool in generating rainfall sequences under scenarios of climate change for the study area.
- To identify suitable rainfall-runoff models (RRMs) and time-scales for water resources assessment under uncertainty (mainly the model parameter uncertainty).
- To develop a calibration strategy for a RRM based on the spatial-temporal rainfall obtained from the RSM.
- To generate multiple realisations of rainfall and reservoir inflows using the RSM and RRM under uncertainty and climate change.
- Assess reservoir performance under uncertain rainfall and hydrological response, under both baseline and changed climate.
- To make recommendations on making the uncertainty framework more comprehensive.

The framework was applied to the upper Limpopo basin in Botswana, using 25 years of observed daily rainfall and flow data. The framework begins with multi-site continuous time stochastic rainfall modelling to infill historic rainfall data and to identify the main drivers of rainfall in the study area (chapter 4). The stochastic infilling of rainfall data allows calibration of a continuous-time semi-distributed hydrological model under input uncertainty and model parameter uncertainty (chapter 5). The rainfall model, together with the uncertain hydrological model, is then used to generate multiple realisations of rainfall and streamflows over a 100-year period under climate change (chapter 6) to begin to evaluate the performance of a proposed reservoir in the study area in light of the extended rainfall and streamflow data under uncertainty and climate change (chapter 7). Discussions from these chapters are then picked up and summarised as conclusions and recommendations for future work (this chapter).

8.2 Rainfall modeling in data limited and semi arid areas

8.2.1 Exploring the potential application of GLMs in semi arid areas

A review provided in chapter 2 indicates that there are many rainfall models that are used to simulate multi-site daily rainfall. These models vary in the way they represent storm evolution patterns over space and time, how they incorporate spatial rainfall structure, as well as linking rainfall to the predictors which are deemed important in driving rainfall for a given area. However, most of these models require complete rainfall records for model fitting, which may limit their applications in data sparse areas with extended periods of missing data such as in the upper Limpopo basin. It was also found that they often need a large number of parameters (which are not supported by the available data) in order to satisfactorily reproduce observed rainfall, potentially creating high uncertainty in simulations. Furthermore, most of them lack the ability to represent seasonal rainfall variability parametrically, but rather the models are often fitted to individual

months independently, which increases model complexity in terms of the number of parameters to be estimated.

These reviews, and the case study selected here, lead to selection of the Generalised Linear Models (GLMs) as a potentially applicable tool, and the applicability was explored in Chapter 4. This included exploring applicability for infilling missing records, while quantifying uncertainty arising specifically from the presence of missing values; the value of large scale atmospheric variables as external predictors of rainfall in recognition of the realities of climate change; testing sensitivity to rainfall data quality as well as the issue of extending the limited rainfall observations in time and space.

8.2.2 Major findings from chapter 4

The GLM model is an extension of linear regression to allow for non-linearity and non-Gaussian distributions. In this application, logistic regression was used to simulate rainfall occurrence and two-parameter Gamma distributions were used to simulate amounts on wet days. Inter-site dependence models were included for both occurrence and amounts. The modelling procedure requires a set of statistically and physically significant predictors of rainfall parameters to be identified, associated coefficients to be optimised using maximum likelihood, and a series of tests to assess model accuracy.

The main predictors of rainfall in the Limpopo case study were found to be location effects, seasonality, and temporal dependence. Humidity, temperature and sea level pressure from the ERA-40 re-analysis data were significant external predictors. Analysis of model residuals showed that in general the model captured the seasonal, annual and spatial structure of rainfall in the basin. However, there were a few cases where the residuals indicated that the model could not fully capture the annual variability (during the especially wet and dry years) and spatial rainfall structure (particularly but not only at stations which were suspected to have data quality problems). Despite these local problems, the simulation results

indicated that in general the model results were consistent with the observed rainfall properties.

Spatial and temporal validation tests showed that the GLM simulated rainfall for the periods and gauges not used during model fitting with reasonable accuracy. However, when the model was used for spatial infilling (i.e. by simulating rainfall using hypothetical gauges distributed over the basin), the predictions were not thought to be realistic, especially at exceptionally high or low altitude, where the model gave either very high or low rainfall values-potentially indicating that the model may not be suitable for estimating spatial rainfall where there are no rain gauges particularly at areas with highly variable topography. In the case study, this led to the use of Thiessen polygons for estimating spatial rainfall rather than using the GLM.

The inter-annual variability evident in the observed data was well simulated by the model when the external atmospheric predictors were included, but not without them. As the external predictors have both physical and statistical significance, and are simulated by global climate models, the model may be used in conjunction with climate model outputs to make tentative extrapolations of the historic daily rainfall patterns to future climate. ENSO indices which are generally considered to influence rainfall variability in southern Africa were not found to be significant drivers of rainfall variability in this study area. This supports the view that the influence of ENSO in southern Africa may previously have been overestimated, or is regionally variable (Manatsa et al., 2008). Sensitivity tests which were performed to assess sensitivity of model results to data quality showed that while the amounts model showed locally improved model fit as a result of data adjustment, there were no significant changes in the basin scale simulation results, indicating that localised data quality issues of the magnitude considered here do not affect regional rainfall estimation in this basin.

In general, it is concluded that the GLM provides a useful tool for simulating multi-site rainfall in the semi-arid Limpopo basin in Botswana for water resources purposes and may potentially be applicable to climate change analysis and to other semi-arid regions. This conclusion stimulated an interest, within this thesis, to test sensitivity of hydrological model outputs to the rainfall input uncertainty and assumptions used in the GLM application-whose summary results are presented in section 8.3.

8.3 The importance of incorporating uncertainty in hydrological models

It has been argued in this thesis (chapter 2 and chapter 5) that issues of uncertainty can no longer be ignored in hydrological modelling. In addition to data (rainfall) uncertainty, the uncertainty framework was extended to include hydrological model parameter uncertainty.

8.3.1 Results from the calibration of a semi distributed model under uncertainty

The focus of chapter 5 was to demonstrate the importance of incorporating uncertainty in hydrological models. Three major sources of uncertainty have been presented in that chapter. These were: (1) uncertainty resulting from multiple rainfall realisations, which was addressed by infilling the observed rainfall data using a stochastic GLM; (2) uncertainty arising from multiple 'equifinal' parameter sets, which was catered for by ensemble simulation using a continuous-time semi distributed IHACRES model. The model was calibrated using each of 10 rainfall realisations (referred to as imputations in chapter 5), and for each realisation best 100 parameter sets from each of the three gauged upstream catchments fed into the calibration of the outlet catchment to obtain ensemble model results; (3) uncertainty arising from the unpredictable variability of the hydrological response. This has been addressed by calibrating the hydrological model using different and

independent sets of hydro-climatic data as input to the model.

8.3.2 Major findings from chapter 5

The combined effects of these uncertainties have been evaluated in that chapter, leading to the following conclusions:

- (1) When considering only the model parameter uncertainty, the confidence limits for each rainfall realisation were wide.
- (2) The optimal parameter values varied highly from one rainfall realisation to the other, particularly during the 1975-87 period where gauged rainfall data is quite incomplete and much of the data was infilled (i.e. infilled temporally) using the GLM.
- (3) The model was able to explain the observed flows during the calibration period although the uncertainty was high (resulting from rainfall and parameter uncertainty).
- (4) During the validation period the model was, except at the smallest subcatchment and during exceptionally wet years such as 1987/88 and 1995/96, unable to explain the observations presumably owing to the high non-linearity of response and the non-stationarity evident in the observed flow response, not captured by the rainfall-runoff model. This behaviour was also observed when using a different calibration period leading to a conclusion that model parameters varied significantly over time in this catchment presumably due to land cover/land use changes, which lead to the suggestion that future hydrological scenarios be developed based on both sets of calibration periods used in this work and the simulated flows should consider the effects of parameter and rainfall uncertainty.

Because of the apparent high non-stationarity of the response, this chapter

proposed that a change factor approach also be used as a way of comparison to the more traditional simulation approach. The idea was based on speculation that the rainfall-runoff model is more suitable for predicting relative changes to flow under climate change than it is for estimating flow time-series, for which observed records should be used. While the variability of parameters due to the non-stationarity is represented using parameter sets from different calibration periods, no parameter set can capture the observed inter-annual dynamics (e.g. Figs 5.11, 5.12 and 5.16).

8.4 Rainfall and streamflow predictions under climate change

With the insights gained from chapter 4 and 5, the uncertainty framework was then extended to include climate change as demonstrated in chapter 6. This was implemented using 5 GCMs (BCM2, MPEH5, HadCM3, CSMK3 and INCM3) and 3 IPCC scenarios (B1 A1B and A2) for the 4 horizons (2025s, 2050s, 2075s and 2100s). These were applied within a framework where an uncertain stochastic rainfall model, together with an uncertain semi distributed hydrological model were used to predict future rainfall and streamflow under uncertainty (rainfall, parameter uncertainty) and climate change (climate model uncertainty and climate scenario uncertainty) in the case study area.

Within this framework, future rainfall and streamflows were estimated, first under a stationary climate (i.e. assuming that the observed atmospheric predictors used in this thesis (chapter 4) will repeat in the future), and secondly under a changed climate (i.e. using the atmospheric predictors from the GCMs can be used to drive the GLM to generate rainfall under climate change models and scenarios). The change factor approach was also used to add to the uncertainty framework. This framework represents a more comprehensive treatment of uncertainty than has previously been attempted in water resources climate change impact studies.

8.4.1 Major findings from chapter 6

The main findings from this chapter are that (1) rainfall will generally decrease while temperature will increase in the upper Limpopo basin, leading to; (2) a decrease in runoff (from most models and across the horizons) reaching unprecedented levels by the end of the century. Projections indicate that as early as 2025s annual and winter rainfall may decrease by up to 40% while the decrease in summer rainfall will be slightly higher. During this horizon, some models (mainly the CSMK3, MPEH5) predict increased runoff while there was no evidence of increased rainfall. This inconsistency was thought to be due to the non-linearity of response in the rainfall-runoff model, which was discussed in chapter 5 and section 8.3). At the close of the century, all the climate models are predicting very dry conditions, ranging from 40 to 80% decrease in annual and seasonal rainfall. The high CO₂ emission scenario (A2) generally gives highest rainfall changes compared to the low and intermediate emission scenarios (B1 and A1B); (3) the magnitudes of change vary widely across the GCM models and across scenarios, which dominate other sources of uncertainty.

In general, runoff is expected to decrease dramatically by the end of the century regardless of which runoff estimation approach is used. This is shown by an agreement between the GCM results, which suggest between 40-88% decrease in annual and seasonal runoff during the 2100 horizon. However, in the near future (2025 horizon), some models (CSMK3) and scenarios (B1 and A1B) predict positive runoff changes (i.e. up to 59% for annual and spring rainfall) particularly when using the flow time series obtained directly from a rainfall-runoff model. When using alternative runoff estimation approach-i.e. the change factor approach, all the models predict flow reduction across the scenarios and time horizons. The direction of change was in general, consistent with those of rainfall unlike when using the flow time series generated from the GLMRDA. This would not have been

achieved without the use of alternative runoff estimation as an attempt to resolve the problem of non-stationarity inherent in the rainfall-runoff model.

8.5 Effects of uncertainty and climate change on reservoir performance

At this point, this thesis has established a framework in which a wide range of uncertainty can be represented and quantified in rainfall and hydrological models, and through which the effects of climate change can be evaluated. It has been found in chapter 7 that while the issues of uncertainty are extensively addressed in many hydrological models, their consideration in water supply systems performance is still very limited, particularly in semi arid areas. This important gap was addressed in chapter 7, where the framework developed in this thesis was extended to evaluating the performance of a proposed dammed reservoir in the study area in light of the extended data under uncertainty and climate change. The location of the proposed water supply reservoir coincides with the catchment outlet along the Shashe River within the upper Limpopo basin, whose rainfall and streamflows have been modelled and extended using the framework developed here. The reservoir was evaluated using a monthly reservoir volume balance model in light of the extended rainfall and flow series. This was addressed by using some performance indicators such as reservoir reliability, resilience, vulnerability and severity of failure under a stationary and changed climate assuming some reservoir operation rules for demand management.

8.5.1 Major findings from chapter 7

The main conclusions emanating from this chapter were that:

- (1) The prediction uncertainty range found in the reservoir performance

indicators is wide as a result of incorporating a suite of possible uncertainty sources. It was demonstrated that at times the reservoir reliability may be over estimated when only rainfall uncertainty is used (but assuming no hydrological uncertainty), which may ultimately affect decision making on reservoir operation and water supply activities. This thesis contends that the above insights on reservoir reliability would not have been achieved without representing a wide range of rainfall and hydrological uncertainty which are often ignored in reservoir performance studies.

(2) There is evidence of decreases in reservoir volumes and performance, which indicate the possible effect of climate change as a result of increased temperature, reduced rainfall and increased evaporative losses within the basin.

(3) These decreases vary across the climate models, climate scenarios, and runoff estimation method under a changed climate. The decrease was found to be more under the high emission scenario, A2, where, for example: the mean reservoir reliability dropped from 98% (under a stationary climate) to 18% (using the INCM3 model and A2 scenario); the severity of failure increased from 0 (under stationary climate) to 0.37 (using the INCM3 model and A2 scenario); the rate of recovery (resilience) also dropped (in general, with the exception of the CSMK3 model) from 0.19 (under a stationary climate) to 0 (using the MPEH5 and A1B scenario).

(4) The degree of decrease in reservoir volumes becomes pronounced by 2050, after which, in general, the predicted reservoir volumes do not reach full capacity.

From these results, it can be concluded that uncertainty and climate change have significant effects on water resources planning models - as such they should be fully incorporated in order to make informed planning decisions

8.6 New insights and contributions of this thesis

The main achievements of this thesis are summarised as follows:

1. Development of a framework through which the challenges related to data in semi arid areas (mainly the missing rainfall values, the limited historic observations, the data quality issues) can be accommodated more comprehensively in rainfall and hydrological models.
2. This framework includes representing and quantifying uncertainty arising from input data (mainly rainfall, and specifically missing rainfall values) during the development of rainfall runoff models and when calibrating hydrological models.
3. The framework extends to identifying and linking significant external atmospheric predictors which influence rainfall with outputs of global climate models to generate future rainfall predictions under climate change.
4. Explicit representation of hydrological model input and parameter uncertainty, to provide flow inputs to water supply systems such as reservoir design and performance assessment.
5. The new insight that inter-annual rainfall variability in the study area and perhaps in other similar environments in southern Africa is not influenced by ENSO, but rather, it is influenced by humidity, temperature and sea level pressure.
6. That even with limited input data, it is not impossible to effectively evaluate the impacts of climate change in data limited areas, particularly in semi arid areas such as the case study used here-

which to my knowledge there are no published documents in which the effects of climate change on water supply systems have been quantified.

7. The uncertainty evaluated in this work is high, including uncertainty arising from the missing rainfall data. This uncertainty could be reduced by concentrating the resources on acquiring and expanding the gauge networks, building efficient and robust data collection processing and achieving to improve the existing database.
8. Other contributions follow below, where recommendations for future work is provided.

8.7 Direction for future work

The rainfall and hydrological modelling in this thesis focused on quantifying uncertainty arising from input data (mainly rainfall) and model parameters as the two main sources of uncertainty. This was based on the understanding that data uncertainty is the most influential and over-rides other sources of uncertainty (Chiang et al., 2007), and that since the advent of the ‘equifinality’ concept-the model parameter uncertainty has become another major subject of ongoing research (Montanari, 2007, Efstratiadis and Koutsoyiannis, 2010). However, this thesis did not address the (1) uncertainty arising from model structures (Chiang et al., 2007, Montanari, 2007, Beven, 2001) except as implicitly represented by parameter uncertainty, and (2) uncertainty arising from streamflow data quality (McMillan et al., 2010). The consideration of these could further widen the uncertainty limits reported here. It is also highlighted that during the calibration of a hydrological model in chapter 5, it was found that the hydrological model parameters in this basin were not stationary, presumably due to land use and/or land cover changes in the basin. However, when generating the future inflows under climate change the

hydrological model parameters were assumed stationary. This was mainly due to lack of historical land cover and land use data to sufficiently characterise the non-stationarity of response. This is another limitation which could be addressed in future research, particularly when land cover data of sufficient spatial and temporal resolution become available. In this application, an attempt was made to partly address this limitation (i.e. the inability of the rainfall-runoff to accommodate the historical non-stationarity) by employing a change factor method, where relative runoff changes were used instead of the actual flows as detailed in chapter 6.

Focusing on rainfall modelling, the generalized linear model (GLM) was used assuming that the spatial and temporal rainfall structures in the basin are adequately represented. During the analysis presented in chapter 4, it was found that the GLM was able to quantify uncertainty due to missing data as well as providing simulations that were consistent with the observed data. However, the model did not give satisfactory results when it was used to infill rainfall spatially, particularly in highly variable topography. This could be an indication of structural short-comings of the GLM which may have been overcome by using an alternative model structure, or it could just be due to low rain gauge coverage at those poorly modelled elevations. One area that could be explored to investigate this problem further would be to test the predictive spatial performance of the GLM (and any other alternative rainfall models) against spatial rainfall obtained from satellite products (Asadullah et al., 2008). As a result of poor spatial rainfall representation by the GLM, and using the case study with highly variable topography, the Thiessen polygon method was used to generate the spatial field over the catchment for use with the semi distributed hydrological model (chapter 5). The use of this method may have simplified spatial rainfall representation in the study area, and other alternative spatial rainfall estimation methods such as kriging could lead to improved spatial rainfall fields (Shrestha et al., 2007).

Another assumption regarding rainfall modeling was that rainfall model

parameters can be extrapolated to changed climate, indicating that the relationship between predictors (temperature, humidity and sea level pressure) and predictand (rainfall) will not change. This is the major limitation and criticism of all the stochastic rainfall modeling techniques (Wilby et al., 2004) (including the one used here, see chapter 2). It would have been more interesting to compare the results of this work (particularly with regards to climate change) with those obtained directly from regional climate models (RCMs), whose added advantage include high spatial resolution compared to the GCMs used here. However, the RCMs are still computationally intensive to be applied to a large ensemble of GCM output to characterize uncertainties associated with inter-GCM variability and different emission scenarios (Maurer et al., 2010) as they are usually based on just one or two driving GCMs (Buytaert et al., 2010), which may limit the uncertainty analysis. For example, for the 5 GCMs used here, only the HADCM3-based RCM (the HADGEM1 model) was available within the IPCC database where outputs of the GCMs were obtained.

Another limitation in this thesis is that the GLMs have been used as the only rainfall downscaling technique, which may have underestimated uncertainty. It is recommended that multiple rainfall downscaling techniques be used in future research to make uncertainty analysis more comprehensive (Chiew et al., 2010).

This work has also not addressed the common need to predict flows in ungauged basins (Huang and Liang, 2006), the use of regionalisation to improve parameter estimates (Lee, 2006). The multi-site stochastic rainfall model developed in this work could provide spatial rainfall information, to be used together with parsimonious semi distributed models (such as the one used in this work) to address the issues of ungauged basins and regionalization of model parameters particularly in data limited semi arid areas while considering uncertainty issues.

8.8 Concluding statement

This thesis has presented a comprehensive framework of uncertainty analysis including rainfall, hydrological and water resources models. Analysis within this thesis revealed that the effects of data and model parameter uncertainty on water resources planning models can be high, and thus should not be ignored. This thesis advocates a shift from deterministic to stochastic ways of infilling missing rainfall values, and for consideration of hydrological model uncertainty, climate model and climate scenario uncertainties. This thesis complements other ongoing research discussions on the need to adequately define, quantify, and handle uncertainty in hydrological modeling (Montanari, 2007, Jin et al., 2010), as well as in climate change assessment studies (Prudhomme and Davies, 2009b, Buytaert et al., 2010) and in water supply systems (Xiang et al., 2010). Given the high uncertainty in the semi arid case study, priority areas may include acquiring and expanding the gauge networks, building efficient and robust data collection processing and achieving to improve the existing database so as to support and enable quality research.

References

- ADELOYE, A. J., LALLEMAND, F. & MCMAHON, T. A. 2003. Regression models for within-year capacity adjustment in reservoir planning. *Hydrological Sciences Journal* 48, 539-552.
- AJAMI, N. K., GUPTA, H., WAGENER, T. & SOROOSHIAN, S. 2004. Calibration of a semi-distributed hydrologic model for streamflow estimation along a river system. *Journal of Hydrology*, 298, 112-135.
- ANDERSEN, J., REFSGAARD, J. C. & JENSEN, K. H. 2001. Distributed hydrological modelling of the Senegal River Basin -- model construction and validation. *Journal of Hydrology*, 247, 200-214.
- ANDERSEN, N. J., WHEATER, H. S., TIMMIS, A. J. H. & GAONGALELWE, D. 1998. Sustainable development of alluvial groundwater in sand rivers of Botswana. In Sustainability of Water resources under increasing uncertainty. *IAHS Pubn*, 240, 367-376.
- ANDERSSON, L., WILK, J., TODD, M. C., HUGHES, D. A., EARLE, A., KNIVETON, D., LAYBERRY, R. & SAVENIJE, H. H. G. 2006. Impact of climate change and development scenarios on flow patterns in the Okavango River. *Journal of Hydrology*, 331, 43-57.
- ANDREASSIAN, V., PERRIN, C., MICHEL, C., USART-SANCHEZ, I. & LAVABRE, J. 2001. Impact of imperfect rainfall knowledge on the efficiency and the parameters of watershed models. *Journal of Hydrology*, 250, 206-223.
- ANDREASSON, J. & ROSBERG, J. 2006. Moving on from Delta change towards direct use of RCM output by scaling – A method for transient impact simulations. *Geophysical Research Abstracts*, 8, 03820.
- ARNELL, N. W. 2002. Hydrology and Global Environmental Change. *Harlow, Pearson*.
- ARNELL, N. W., HUDSON, D. A. & JONES, R. G. 2003. Climate change scenarios from a regional climate model: Estimating change in runoff in southern Africa. *JOURNAL OF GEOPHYSICAL RESEARCH*, 108, ACL 9.1-9.17.
- ARORA, V. K. 2001. Streamflow simulations for continental-scale river basins in a global atmospheric general circulation model. *Advances in Water Resources*, 24, 775-791.

- ASADULLAH, A., MCINTYRE, N. & KIGOBE, M. 2008. Evaluation of five-satellite-based products for estimation of rainfall over Uganda. *Hydrological Sciences Journal*, 53, 1137-1150.
- ASHTON, P. J. 2002. Avoiding conflicts over Africa's water resources. . *Ambio*, 31, 236-242.
- BEVEN, K. 1989. Changing ideas in hydrology -- The case of physically-based models. *Journal of Hydrology*, 105, 157-172.
- BEVEN, K. J. 1993. Prophecy, reality and uncertainty in distributed hydrological modelling. *Advances in Water Resources Research*, 16, 41-51.
- BEVEN, K. J. 2001. Rainfall-runoff modelling: The Primer. *John Willey and Sons, Chichester, UK*. pp 360.
- BEVEN, K. J. 2006. A manifesto for the equifinality thesis. *Journal of Hydrology* 320, 18-36.
- BEVEN, K. J. & BINLEY, A. 1992. Future of distributed models. Model calibration and uncertainty prediction. *Hydrological Processes*, 6, 279-298.
- BEVEN, K. J. & FREER, J. 2001. Equifinality, data assimilation, and uncertainty estimation in mechanistic modelling of complex environmental systems using the GLUE methodology. *Journal of Hydrology* 249, 11-29.
- BOKO, M., NIANG, I., NYONG, A., VOGEL, C., GITHEKO, A., MEDANY, M., OSMAN-ELASHA, B., TABO, R. & YANDA, P. 2007. Africa: Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, M.L. Pary, O.F. Canziani, J.P. Palutikof, P.J. van der Linden and C.E. Hanson, Eds,. *Cambridge University Press, Cambridge UK*, 433-467.
- BOYLE, D. P., GUPTA, H. V. & SOROOSHIAN, S. 2000. Toward improved calibration of hydrological models: combining the strengths of manual and automatic methods. *Water Resources Research*, 36, 3663-3674.
- BRUTSS, M. B., PAYNE, J. T., KRISTENSEN, M. & MADSEN, H. 2004. An evaluation of the impact of model structure on hydrological modelling uncertainty for streamflow simulation. *Journal of Hydrology*, 298, 242-266.
- BROUYERE, S., CARABIN, G., & DASSARGUES, A. 2004. Climate change impacts on groundwater resources: modelled deficits in a chalky aquifer, Geer basin, Belgium. *Hydrogeology Journal*, 12, 123-134.

- BURTON, A., FOWLER, H. J., BLENKINSOP, S. & KILSBY, C. G. 2010. Downscaling transient climate change using a Neyman-Scott Rectangular Pulses stochastic rainfall model. *Journal of Hydrology*, 381, 18-32.
- BURTON, A., KILSBY, C. G., FOWLER, H. J., COWPERTWAIT, P. S. P. & O'CONNELL, P. E. 2008. RainSim: A spatial-temporal stochastic rainfall modelling system. *Environmental Modelling & Software*, 23, 1356-1369.
- BUSUIOC, A. & VON STORCH, H. 2003. Conditional stochastic model for generating daily precipitation time series. *Climate Research*, 24, 181-195.
- BUTTS, M. B., PAYNE, J. T., KRISTENSEN, M. & MADSEN, H. 2004. An evaluation of the impact of model structure on hydrological modelling uncertainty for streamflow simulation. *Journal of Hydrology*, 298, 242-266.
- BUYTAERT, W., VUILLE, M., DEWULF, A., URRUTIA, R., KARMALKAR, A. & C'ELLERI, R. 2010. Uncertainties in climate change projections and regional downscaling in the tropical Andes: implications for water resources management. *Hydrology and Earth System Sciences*, 14, 1247-1258.
- CALVER, A. 1988. Calibration, sensitivity and validation of a physically-based rainfall-runoff model. *Journal of Hydrology*, 103, 103-115.
- CAMPOREALE, C. & RIDOLFI, L. 2010. Interplay among river meandering, discharge stochasticity and riparian vegetation. *Journal of Hydrology*, 382, 138-144.
- CAVAZOS, T. & HEWITSON, B. C. 2005. Performance of NCEP-NCAR reanalysis variables in statistical downscaling of daily precipitation. *Climate Research*, 28, 95-107.
- CHANDIMALA, J. & ZUBAIR, L. 2007. Predictability of stream flow and rainfall based on ENSO for water resources management in Sri Lanka. *Journal of Hydrology*, 335, 303-312.
- CHANDLER, R. E. 2005. On the use of generalized linear models for interpreting climate variability. *Environmetrics*, 16, 699-715.
- CHANDLER, R. E. & BATE, S. 2007. Inference for clustered data using the independence loglikelihood. *Biometrika*, 94, 167-183.

- CHANDLER, R. E. & WHEATER, H. S. 1998. Climate change detection using Generalised Linear Models for rainfall-a case study from West of Ireland: Preliminary analysis and modelling of rainfall occurrence. *Research Report No. 194*. London: University College of London.
- CHANDLER, R. E. & WHEATER, H. S. 2002. Analysis of rainfall variability using generalized linear models: A case study from the west of Ireland. *Water Resources Research*, 38, 1192, doi:10.1029/2001WR000906, 2002.
- CHARLES, S. P., BARI, M. A., KITSIOS, A. & BATES, B. C. 2007. Effect of GCM bias on downscaled precipitation and runoff projections for the Serpentine Catchment, Western Australia *International Journal of Climatology*, 27, 1673–1690.
- CHARLES, S. P., BATES, B. C. & HUGHES, J. P. 1999a. A spatiotemporal model for downscaling precipitation occurrence and amounts. *Journal of Geophysical Research*, 104, 31657-31669.
- CHARLES, S. P., BATES, B. C., SMITH, I. N. & HUGHES, J. P. 2004. Statistical downscaling of daily precipitation from observed and modelled atmospheric fields. *Hydrological Processes*, 18, 1373-1394.
- CHARLES, S. P., BATES, B. C., WHETTON, P. H. & HUGHES, J. P. 1999b. Validation of downscaling models for changed climate conditions: case study of southwestern Australia. *Climate Research*, 12, 1-14.
- CHEN, Y. D., CHEN, X., XU, C.-Y. & SHAO, Q. 2006. Downscaling of daily precipitation with a stochastic weather generator for the subtropical region in South China. *Hydrol. Earth Syst. Sci. Discuss.*, 3, 1-39.
- CHIANG, S., TACHIKAWA, Y. & TAKARA, K. 2007. Hydrological model performance comparison through uncertainty recognition and quantification. *Hydrological Processes*, 21, 1179-1195.
- CHIEW, F. H. S., KIRONO, D. G. C., KENT, D. M., FROST, A. J., CHARLES, S. P., TIMBAL, B., NGUYEN, K. C. & FU, G. 2010. Comparison of runoff modelled using rainfall from different downscaling methods for historical and future climates. *Journal of Hydrology*, 387, 10-23.
- CHIEW, F. H. S., STEWARDSON, M. J. & MCMAHON, T. A. 1993. Comparison of six rainfall-runoff modelling approaches. *Journal of Hydrology*, 147, 1-36.

- CHRISTENSEN, J. H., B. HEWITSON, A. BUSUIOC, A. CHEN, X. GAO, I. HELD, R. JONES, R.K. KOLLI, W.-T. KWON, R. LAPRISE, V. MAGAÑA RUEDA, L. MEARNES, C.G. MENÉNDEZ, J. RÄISÄNEN, A. RINKE, SARR, A. & WHETTON, P. 2007a. 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., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L. Miller (eds.)*. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
- CHRISTENSEN, N. S. & LETTENMAIER, D. P. 2007. A multimodel ensemble approach to assessment of climate change impacts on the hydrology and water resources of the Colorado River basin. *Hydrology and Earth System Sciences*, 11, 1417–1434.
- COE, R. & STERN, R. D. 1982. Fitting models to daily rainfall data. *Journal of Applied Meteorology*, 21, 1024–1031.
- COOPER, V. A., NGUYEN, V. T. T. & NICELL, J. A. 2007. Calibration of conceptual rainfall-runoff models using global optimisation methods with hydrologic process-based parameter constraints. *Journal of Hydrology*, 334, 455–466.
- CORDERY, I., PILGRIM, D. H. & DORAN, D. G. 1983. Some hydrological characteristics of arid western New South Wales. *The Institution of Engineers, Australia, Hydrology and Water Resources Symp. Nov.*
- COWPERTWAIT, P. S. P. 1995. A generalized spatial-temporal model of rainfall based on a clustered point process. *Proceedings of the Royal Society of London* 450, 163–175.
- CROKE, B. F. W., ANDREWS, F., JAKEMAN, A. J., CUDDY, S. M. & LUDDY, A. 2005. Redesign of the IHACRES rainfall-runoff model. *Engineers Australia. 29th Hydrology and Water Resources Symposium.*, February, 2005.
- CROKE, B. F. W., ANDREWS, F., JAKEMAN, A. J., CUDDY, S. M. & LUDDY, A. 2006a. IHACRES Classic Plus: A redesign of the IHACRES rainfall-runoff model. *Environmental Modelling & Software*, 21, 426–427.
- CROKE, B. F. W. & JAKEMAN, A. J. 2004. A catchment moisture deficit module for the IHACRES rainfall-runoff model. *Environmental Modelling & Software*, 19, 1–5.

- CROKE, B. F. W., LETCHER, R. A. & JAKEMAN, A. J. 2006b. Development of a distributed flow model for underpinning assessment of water allocation options in the Namoi River Basin, Australia. *Journal of Hydrology*, 319, 51-71.
- CSO 2001. Central Statistics Office: Population and Housing Census: Population of towns, villages and associated localities. *Ministry of Finance and Development Planning, Gaborone, Botswana*.
- DAVIES, H., OSBORN, T., PIPER, B. & PRUDHOMME, C. 2005. Climate Change Uncertainty in Water Resource Planning. *Centre for Ecology and Hydrology Report*, Ref: 05/CL/04/4, ISBN 1 84057 389 9, 81pp.
- DEWIT, M. & STANKIEWICZ, J. 2006. Changes in water supply across Africa with predicted climate change. *Science*, 311, 1917-1921.
- DIAZ-NIETO, J. & WILBY, R. L. 2005. A comparison of statistical downscaling and climate change factor methods: impacts on low flows in the River Thames, United Kingdom. *Climatic Change* 69, 245-268.
- DOLL, P. & ZHANG, J. 2010. Impact of climate change on freshwater ecosystems: a global-scale analysis of ecologically relevant river flow alterations. *Hydrology and Earth System Sciences Discussions*, 7, 1305-1342.
- DRIESSEN, T. L. A., HURKMANS, R. T. W. L., TERINK, W., HAZENBERG, P., TORFS, P. J. J. F. & UIJLENHOET, R. 2010. The hydrological response of the Ourthe catchment to climate change as modelled by the HBV model. *Hydrology and Earth System Sciences*, 14, 651-665.
- DROOGERS, P., VAN LOON, A., IMMERZEEL, W.W. 2008. Quantifying the impact of model inaccuracy in climate change impact assessment studies using an agro-hydrological model. *Hydrology and Earth System Sciences*, 12, 669-678.
- DYE, P. J. & CROKE, B. F. W. 2003. Evaluation of streamflow predictions by the IHACRES rainfall-runoff model in two South African catchments. *Environmental Modelling & Software*, 18, 705-712.
- EFSTRATIADISA, A. & KOUTSOYIANNIS, D. 2010. One decade of multi-objective calibration approaches in hydrological modelling: a review. *Hydrological Sciences Journal*, 55, 58-78.
- EVANS, J. & SCHREIDER, S. 2002a. Hydrological impacts of climate change on inflows to Perth, Australia. *Climatic Change*, 55, 361-393.

- EVANS, J. & SCHREIDER, S. 2002b. Hydrological Impacts of Climate Change on Inflows to Perth, Australia. *Climatic Change*, 55, 361-393.
- EVANS, J. P. 2003. Improving the characteristics of streamflow modeled by regional climate models. *Journal of Hydrology*, 284, 211-227.
- EVANS, J. P. & JAKEMAN, A. J. 1998. Development of a simple, catchment-scale, rainfall-evapotranspiration-runoff model. *Environmental Modelling and Software*, 13, 385-393.
- FAUCHEREAU, N., TRZASKA, S., RICHARD, Y., ROUCOU, P. & CAMBERLIN, P. 2003. Seasurface temperature co-variability in the southern Atlantic and Indian Oceans and its connections with the atmospheric circulation in the southern hemisphere. *Int. J. Climatol.*, 23, 663-677.
- FOWLER, H.J., KILSBY, C.G. & O'CONNELL, P.E. 2003. Modeling the impacts of climatic change and variability on the reliability, resilience, and vulnerability of a water resource system. *Water resources research*, 39, 1222, doi:10.1029/2002WR001778.
- FOWLER, H. J. & KILSBY, C. G. 2007. Using regional climate model data to simulate historical and future river flows in northwest England. *Climatic Change*, 80, 337-367.
- FROST, A. J., CHANDLER, R. E. & SEGOND, M.-L. 2006. Multi-site downscaling for the Blackwater catchment. *FD2113 project report, no. 4* (December 2006), Available from <http://www.ucl.ac.uk/Stats/research/Rainfall/reports.html>.
- GIESKE, A. & GABAAKE, G. 2001. Hydrogeology of Botswana. Botswana National Atlas. *Department of Surveys and Mapping, Botswana*.
- GUNTNER, A. & BRONSTERT, A. 2004. Representation of landscape variability and lateral redistribution processes for large-scale hydrological modelling in semi-arid areas. *Journal of Hydrology*, 297, 136-161.
- GUO, J., LIANG, X. & RUBY LEUNG, L. 2004. Impacts of different precipitation data sources on water budgets. *Journal of Hydrology*, 298, 311-334.
- GUPTA, H. V., SOROOSHIAN, S. & YAPO, P. O. 1998. Toward improved calibration of hydrologic models: multiple and noncommensurable measures of information. *Water Resources Research*, 34, 751-763.
- HARROLD, T. I., SHARMA, A. & SHEATHER, S. J. 2003. A nonparametric model for stochastic generation of daily rainfall occurrence. *Water Resources Research*, 39, 1300, doi:10.1029/2003WR002182.

- HASHIMOTO T., STEDINGER, J.R., & LOUCK, D.P. 1982. Reliability, resiliency and vulnerability criteria for water resource system performance evaluation. *Water Resources Research*, 18(1), 14-20.
- HEWITSON, B. C. & CRANE, R. G. 2006. Consensus between GCM climate change projections with empirical downscaling: precipitation downscaling over South Africa. *International Journal of Climatology*, 26, 1315-1337.
- HUANG, M. & LIANG, X. 2006. On the assessment of the impact of reducing parameters and identification of parameter uncertainties for a hydrologic model with applications to ungauged basins. *Journal of Hydrology*, 320: 37-61.
- HUDSON, D. A. & JONES, R. G. 2002. Simulations of present-day and future climate over southern Africa using HadAM3H. *Hadley Centre technical note* 38.
- HUGHES, D. A. 2004. Incorporating groundwater recharge and discharge functions into an existing monthly rainfall-runoff model. *Hydrological Sciences-Journal-des Sciences Hydrologiques*, 49, 297-311.
- HUGHES, D. A., ANDERSSON, L., WILK, J. & SAVENIJE, H. H. G. 2006. Regional calibration of the Pitman model for the Okavango River. *Journal of Hydrology*, 331, 30-42.
- HUGHES, D. A., KAPANGAZIWIRI, E. & SAWUNYAMA, T. 2010. Hydrological model uncertainty assessment in southern Africa. *Journal of Hydrology*, 387, 221-232.
- HUGHES, J. P., GUTTORP, P. & CHARLES, S. P. 1999. A non-homogeneous hidden Markov model for precipitation occurrence. *Journal of the Royal Statistical Society: Series C. Applied Statistics*, 48, 15-30.
- HULME, M., DOHERTY, R., NGARA, T., NEW, M. & LISTER, D. 2001. African climate change: 1900-2100. . *Climate Research*, 17, 145-168.
- HUTH, R. 2000. A circulation classification scheme applicable in GCM studies. *Theoretical and applied climatology*, 67, 1-18.
- INSTITUTE OF HYDROLOGY (IH) 1999. Flood Estimation Handbook, Wallingford, UK.
- IPCC 2001a. Climate Change 2001-the scientific basis. *Third Report of the Intergovernmental Panel on Climate Change*.
- IPCC 2001b. Climate Change 2001: Impacts, Adaptation, and Vulnerability: Chapter 10: Africa. *Contribution of Working Group II to the Third Assessment Report of the Intergovernmental Panel on Climate Change*.

- IPCC 2007a. Climate Change 2007: Impacts, Adaptation and Vulnerability- Working Group II Contribution to the Intergovernmental Panel on Climate Change Fourth Assessment Report. *UNEP, WMO*.
- IPCC 2007b. Climate Change 2007: Synthesis Report. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change[Core Writing Team, Pachauri, R.K and Reisinger, A. (eds.)]. IPCC, Geneva, Switzerland 104 pp.
- JAIN, S. K. 2010. Investigating the behavior of statistical indices for performance assessment of a reservoir. *Journal of Hydrology*, doi: 10.1016/j.jhydrol.2010.07.009.
- JAKEMAN, A. J. & HORNBERGER, G. M. 1993. How much complexity is warranted in a rainfall-runoff model? *Water Resources Research*, 29, 2637-2649.
- JAKEMAN, A. J., LITTLEWOOD, I. G. & WHITEHEAD, P. G. 1990. Computation of the instantaneous unit hydrograph and identifiable component flows with application to two small upland catchments. *Journal of Hydrology*, 117, 275-300.
- JIANG, T., CHEN, Y. D., XU, C., CHEN, X., CHEN, X. & SINGH, V. P. 2007. Comparison of hydrological impacts of climate change simulated by six hydrological models in the Dongjiang Basin, South China. *Journal of Hydrology*, 336, 316-333.
- JIN, X., XU, C-Y., ZHANG, Q., SINGH, V.P. 2010. Parameter and modelling uncertainty simulated by GLUE and a formal Bayesian method for a conceptual hydrological model. *Journal of Hydrology* 383, 147-155.
- KATZ, R. W. & PARLANGE, M. B. 1998. Overdispersion phenomenon of stochastic modeling of precipitation. *Journal of Climate*, 11, 591-601.
- KAVETSKI, D., KUCZERA, G. & FRANKS, S. W. 2006. Bayesian analysis of input uncertainty in hydrological modelling: 1. Theory. *Water Resources Research*, 42, W03407, doi:10.1029/2005WR004368.
- KENABATHO, P. K., MCINTYRE, N. R., CHANDLER, R. E. & WHEATER, H. S. 2010. Stochastic simulation of rainfall in the semi arid Limpopo basin. *International Journal of Climatology*, (In Press).
- KENABATHO, P. K., MCINTYRE, N. R. & WHEATER, H. S. 2008. Application of generalised linear models for rainfall simulations in semi arid areas: a case study from the Upper Limpopo basin in northeast Botswana. . In: *Sustainable Hydrology for the 21st Century, Proc. 10th BHS National Hydrology Symposium (Exeter), British Hydrological Society, ISBN 1903741165*, 437-444.

- KENABATHO, P. K., MCINTYRE, N. R. & WHEATER, H. S. 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, 2009.
- KGOMOTSO, A., WILLIAMS, S., MATHIBA, M. 2001. Botswana National Atlas: Minerals and mining. *Department of Surveys and Mapping, Botswana*.
- KHAKBAZ, B., IMAN, B., HSU, K. & SOROOSHIAN, S. 2009. From lumped to distributed via semi-distributed: Calibration strategies for semi-distributed hydrologic models. *Journal of Hydrology*, doi:10.1016/j.jhdrol.2009.02.021.
- KHAMA, I.K.S. 2010. State of the Nation Address: Delivering people centred development. *Republic of Botswana, Gaborone*.
- KILSBY, C. G., JONES, P. D., BURTON, A., FORD, A. C., FOWLER, H. J., HARPHAM, C., JAMES, P., SMITH, A. & WILBY, R. L. 2007. A daily weather generator for use in climate change studies. *Environmental Modelling & Software*, 22, 1705-1719.
- KLEMES, V. 1986. Operational testing of hydrological simulation models. *Hydrological Sciences Journal*, 31, 13-24.
- KOREN, V.I., FINNERTY, B.D., SCHAAKE, J.C., SMITH, M.B., SEO, D.J., DUAN Q-Y. 1999. Scale dependencies of hydrologic models to spatial variability of precipitation. *Journal of Hydrology*, 217: 285-302.
- KOREN, V., REED, S., SMITH, M., ZHANG, Z. & SEO, D.-J. 2004. Hydrology laboratory research modeling system (HL-RMS) of the US national weather service. *Journal of Hydrology*, 291, 297-318.
- KRUEGER, T., QUINTON, J. N., FREER, J., MACLEOD, C. J. A., BILOTTA, G. S., BRAZIER, R. E., P., B. & HAYGARTH, P. M. 2009. Uncertainties in Data and Models to Describe Event Dynamics of Agricultural Sediment and Phosphorus Transfer. *Journal of Environmental Quality* 38, 1137-1148.
- KRZYSZTOFOWICZ, R. 2002. Bayesian system for probabilistic river stage forecasting. *Journal of Hydrology* 268, 16-40.
- KUNSTMANN, H., SCHNEIDER, K., FORKEL, R., KNOCH, R. 2004. Impact analysis of climate change for an Alpine catchment using high resolution dynamic downscaling of ECHAM4 time slices. *Hydrology and Earth System Sciences*, 8(6), 1030-1044.

- LANDMAN, W. A. & MASON, S. J. 1999. Change in the association between Indian Ocean sea-surface temperatures and summer rainfall over South Africa and Namibia. *International Journal of Climatology*, 19, 1477-1492.
- LEE, H. 2006. Regionalisation of Rainfall-Runoff models in the UK. *PhD Thesis, Department of Civil and Environmental Engineering, Imperial College, London*.
- LEITH, N. 2005a. Forecasting local scale precipitation under scenarios of global climate change: A literature review. *FD2113 project report, no. 1 (July 2005). University College of London*.
- LEITH, N. 2005b. Using generalised linear models to simulate daily rainfall under scenarios of climate change. *Technical Report UCL. University College of London*.
- LEONARD, M., LAMBERT, M. F., METCALFE, A. V. & COWPERTWAIT, P. S. P. 2008. A space-time Neyman-Scott rainfall model with defined storm extent. *Water Resources Research*, 44, W09402, doi:10.1029/2007WR006110.
- LI, Z., XU, Z., SHAO, Q. & YANG, J. 2009. Parameter estimation and uncertainty analysis of SWAT model in upper reaches of the Heihe river basin. *Hydrological Processes*, 23, 2744-2753.
- LIU, X., & YANAI, M. 2001. Relationship between the Indian monsoon rainfall and the tropospheric temperature over the Eurasian continent. *Quarterly Journal of the Royal Meteorological Society*, 127: 909-937.
- LINDERSON, M., ACHBERGER, C. & CHEN, D. 2004. Statistical downscaling and scenario construction of precipitation in Scania, Southern Sweden. *Nordic Hydrology*, 35, 261-278.
- LITTLEWOOD, I. G. 2002. Improved unit hydrograph characterisation of the daily flow regime (including low flows) for the River Teifi, Wales: towards better rainfall-streamflow models for regionalisation. *Hydrology and Earth System Sciences*, 6, 899-911.
- LITTLEWOOD, I.G. & JAKEMAN, A.J., 1994. A new method of rainfall-runoff modelling and its applications in catchment hydrology. In: *Environmental Modelling (Volume II)*, P. Zannetti (Ed.). Computational Mechanics Publications, Southampton, UK, 143-171.

- LITTLEWOOD, I. G., CLARKE, R. T., COLLISCHONN, W. & CROKE, B. F. W. 2007. Predicting daily streamflow using rainfall forecasts, a simple loss module and unit hydrographs: Two Brazilian catchments. *Environmental Modelling & Software*, 22, 1229-1239.
- LITTLEWOOD, I. G., CROKE, B. F. W., JAKEMAN, A. J. & SIVAPALAN, M. 2003. The role of top-down modelling for Prediction in Ungauged Basins (PUB). *Hydrological Processes*, 17, 1673-1679.
- LIU, Y. & GUPTA, H. V. 2007. Uncertainty in hydrologic modeling: Toward an integrated data assimilation framework. *Water Resources Research*, 43, W07401, doi:10.1029/2006WR005756.
- MADSEN, H., WILSON, G. & AMMENTORP, H. C. 2002. Comparison of different automated strategies for calibration of rainfall-runoff models. *Journal of Hydrology*, 261, 48-59.
- MANATSA, D., CHINGOMBE, W., MATSIKWA, H. & MATARIRA, C. H. 2008. The superior influence of Darwin sea level pressure anomalies over ENSO as a simple drought predictor for southern Africa. *Theoretical and applied climatology*, 92, 1-14.
- MANTOVAN, P. & TODINI, E. 2006. Hydrological forecasting uncertainty assessment: Incoherence of the GLUE methodology. *Journal of Hydrology*, 330(1-2):368-381.
- MANTOVAN, P. & TODINI, E., & MARTINA M.L.V. 2007. Reply to comment by Keith Beven, Paul Smith and Jim Freer on "Hydrological forecasting uncertainty assessment: Incoherence of the GLUE methodology". *Journal of Hydrology*, 338: 319-324.
- MAPEO, R., ATLHOPHENG, J., NTSIMANYANA, M., CHATUPA, J., TSIMAKO, J., SIAMISANG, T., RAMONYANE, P. 2001. Botswana National Atlas: Geology and geomorphology of Botswana. *Department of Surveys and Mapping, Botswana*.
- MASIKE, S. & URISCH, P. 2008. Vulnerability of traditional beef sector to drought and the challenges of climate change: The case of Kgatleng District, Botswana. *Journal of Geography and Regional Planning* 1, 012-018.
- MASOPHA, M. M. F. 2001. Development and regionalisation of rainfall-runoff models for the semi-arid Southern African catchments. *PhD thesis, Department of Civil and Environmental Engineering, Imperial College, London*.

- MATONDO, J. I., PETER, G. & MSIBI, K. M. 2004. Evaluation of the impact of climate change on hydrology and water resources in Swaziland: Part I. *Physics and Chemistry of the Earth, Parts A/B/C*, 29, 1181-1191.
- MAURER, E. P. & HIDALGO, H. G. 2008. Utility of daily vs. monthly large-scale climate data: an intercomparison of two statistical downscaling methods. *Hydrol. Earth Syst. Sci*, 12, 551-563.
- MAUSER, W., & BACH, H. 2009. PROMET-Large scale distributed hydrological modelling to study the impact of climate change on the water flows of mountain watersheds. *Journal of Hydrology*, 376, 362-377.
- MCCULLAGH, P., & NELDER, J.A. 1989. Generalized Linear Models, 2nd ed., Chapman and Hall, New York, 1989.
- MCINTYRE, N. R. & AL-QURASHI, A. 2009. Performance of ten rainfall-runoff models applied to an arid catchment in Oman. *Environmental Modelling & Software*, 24, 726-738.
- MCMAHON, T. A. & ADELOYE, A. J. 2005. *Water resources yield*, Colorado, USA, Water Resources Publications, LLC.
- MCMAHON, T. A., ADELOYE, A. J. & ZHOU, S.-L. 2006. Understanding performance measures of reservoirs. *Journal of Hydrology*, 324 359-382.
- MCMILLAN, H., FREER, J., PAPPENBERGER, F., KRUEGER, T. & CLARK, M. 2010. Impacts of uncertain river flow data on rainfall-runoff model calibration and discharge predictions. *Hydrological Processes*, 24, 1270-1284.
- MEARNS, L. O., GIORGI, F., WHETTON, P., PABON, D., HULME, M. & LAL, M. 2003. Guidelines for Use of Climate Scenarios Developed from Regional Climate Model Experiments. *DDC of IPCC TGCIA: Final Version*.
- MEHROTRA, R. & SHARMA, A. 2006. A nonparametric stochastic downscaling framework for daily rainfall at multiple locations. *Journal of Geophysical Research*, 111, D15101, doi:10.1029/2005JD006637.
- MEHROTRA, R. & SHARMA, A. 2007. A semi-parametric model for stochastic generation of multi-site daily rainfall exhibiting low-frequency variability. *Journal of Hydrology*, 335, 180-193.

- MEHROTRA, R., SHARMA, A. & CORDERY, I. 2004. Comparison of two approaches for downscaling synoptic atmospheric patterns to multisite precipitation occurrence. *Journal of Geophysical Research*, 109, D14107, doi:10.1029/2004JD004823.
- MEHROTRA, R., SRIKANTHAN, R. & SHARMA, A. 2006. A comparison of three stochastic multi-site precipitation occurrence generators. *Journal of Hydrology* 331, 280-292.
- MELCHING, C. S. & SINGH, V. P. 1995. Reliability estimation. In Computer models of watershed hydrology. *Water Resources Publications, USA*.
- MINVILLE, M., BRISSETTE, F. & LECONTE, R. 2008. Uncertainty of the impact of climate change on the hydrology of a nordic watershed. *Journal of Hydrology*, 358, 70-83.
- MMOLAWA, N., RICHARD, S. 2001. Botswana National Atlas: Land use and planning. *Department of Surveys and Mapping, Botswana*.
- MOCKE, R. 1998. Modelling the sand-rivers of Botswana-Distributed modelling of runoff and groundwater recharge processes to assess the sustainability of rural water supplies. *University of London, Imperial College of Science, Technology and Medicine, Dept of Civil and Env Eng. MSc dissertation*.
- MOGANANE, B., TOTOLLO, O., MAFOKO, T., RINGROSE, S., KWEREPE, R., 2001. Botswana National Atlas: Soils and vegetation. *Department of Surveys and Mapping, Botswana*.
- MONTANARI, A. 2007. What do we mean by ‘uncertainty’? The need for a consistent wording about uncertainty assessment in hydrology. *hydrological Processes*, 21, 841-845.
- MONTASERI, M. & ADELOYE, A. J. 1999. Critical period of reservoir systems for planning purposes. *Journal of Hydrology*, 224, 115-136.
- MOREDA, F., KOREN, V., ZHANG, Z., REED, S. & SMITH, M. 2006. Parameterization of distributed hydrological models: learning from the experiences of lumped modelling. *Journal of Hydrology*, 320 218-237.
- MROCZKOWSKI, M., RAPER, G. P. & KUCZERA, G. 1997. The quest for more powerful validation of conceptual catchment models. *Water Resources Research*, 33, 2325-2335.
- MULENGA, H. M., ROUAULT, M. & REASON, J. C. 2003. Dry summers over northeastern South Africa and associated circulation anomalies. *Climate Research*, 25, 29-41.

- MULETA, M. K. & NICKLOW, J. W. 2005. Sensitivity and uncertainty analysis coupled with calibration for a distributed watershed model. *Journal of Hydrology*, 306, 127-145.
- NAKICENOVIC, N. & SWART, R. 2000. Emissions scenarios. 2000 Special Report on the Intergovernmental Panel on Climate Change. Nakicenovic N, & Swart, R (eds). *Cambridge University Press*.
- NASH, J. E. & SUTCLIFFE, J. V. 1970. River forecasting through conceptual models, 1. a discussion of principles. *Journal of Hydrology*, 10, 282-290.
- NATURAL ENVIRONMENTAL RESEARCH COUNCIL (NERC) 1975. Flood Studies Report. Wallingford, UK.
- NICHOLSON, S. E. 2000. The nature of rainfall variability over Africa on time scales of decades to millenia. *Global and Planetary Change* 26, 137-158.
- NOUH, M. 2006. Wadi flow in the Arabian Gulf states. *Hydrological Processes* 20, 2393-2413.
- NUTZMANN, G. & MEY, S. 2007. Model-based estimation of runoff changes in a small lowland watershed of north-eastern Germany. *Journal of Hydrology*, 334, 467-476.
- ORELLANA, B., PECHLIVANIDIS, I. G., MCINTYRE, N. R., Wheeler, H.S. & WAGENER, T. 2008. A Toolbox for the Identification of Parsimonious Semi-Distributed Rainfall-Runoff Models: Application to the Upper Lee Catchment. In: *Integrating Sciences and Information Technology for Environmental Assessment and Decision Making.*, 670-677.
- PARIDA, B. P., MOALAFHI, D. B. & KENABATHO, P. K. 2006. Forecasting runoff coefficients using ANN for water resources management: The case of Notwane catchment in Eastern Botswana. *Physics and Chemistry of the Earth, Parts A/B/C*, 31, 928-934.
- PECHLIVANIDIS, I. G. 2009. The significance of spatial variability of rainfall on runoff generation. *PhD thesis. Department of Civil and Environmental Engineering, Imperial College London*.
- PECHLIVANIDIS, I. G., MCINTYRE, N. R. & WHEATER, H. S. 2010. Calibration of the semi-distributed PDM rainfall-runoff model in the Upper Lee catchment, UK. *Journal of Hydrology*, 386, 198-209.
- PERRIN, C., MICHEL, C. & ANDREASSIAN, V. 2001. Does large number of parameters enhance model performance? Comparative assessment of common catchment model structures on 429 catchments *Journal of Hydrology*, 242, 275-301.

- PILGRIM, D. H., CHAPMAN, T. G. & DORAN, D. G. 1988. Problems of rainfall-runoff modelling in arid and semiarid regions. *Hydrological Sciences*, 33, 379-400.
- PITMAN, W. V. 1973. A Mathematical model for generating river flows from meteorological data in South Africa. . *Report No.2/73. Hydrological Research Unit, University of Witwatersrand, Johannesburg, South Africa.*
- POST, D. A. & JAKEMAN, A. J. 1996. RELATIONSHIPS BETWEEN CATCHMENT ATTRIBUTES AND HYDROLOGICAL RESPONSE CHARACTERISTICS IN SMALL AUSTRALIAN MOUNTAIN ASH CATCHMENTS. *Hydrological Processes*, 10, 877-892.
- POST, D. A. & JAKEMAN, A. J. 1999. Predicting the daily streamflow of ungauged catchments in S.E. Australia by regionalising the parameters of a lumped conceptual rainfall-runoff model. *Ecological Modelling*, 123, 91-104.
- PRIESTLEY, M. B. 1981. Spectral Analysis and Time Series. *Academic, San Diego, California.*
- PRUDHOMME, C. & DAVIES, H. 2009a. Assessing uncertainties in climate change impact analyses on the river flow regimes in the UK. Part 1: baseline climate. *Climatic Change*, 93, 177-195.
- PRUDHOMME, C. & DAVIES, H. 2009b. Assessing uncertainties in climate change impact analyses on the river flow regimes in the UK. Part 2: future climate. . *Climatic Change*, 93, 197-222.
- PRUDHOMME, C., REYNARD, N. & CROOKS, S. 2002. Downscaling of global climate models for flood frequency analysis: where are we now? *Hydrological Processes*, 16, 1137-1150.
- PRUDHOMME, C., WILBY, R. L., CROOKS, S., KAY, A. L. & REYNARD, N. S. 2010. Scenario-neutral approach to climate change impact studies: Application to flood risk. *Journal of Hydrology*, doi:10.1016/j.jhydrol.2010.06.043.
- RAMOTHWA, G. & MINJA, W. 2001. Botswana National Atlas: Weather and Climate. *Department of Surveys and Mapping, Botswana.*
- RANDALL, D. A., WOOD, R. A., BONY, S., COLMAN, R., FICHEFET, T., FYFE, J., KATSOV, V., PITMAN, A., SHUKLA, J., SRINIVASAN, J., STOUFFER, R. J., SUMI, A. & TAYLOR, K. E. 2007. Climate Models and Their Evaluation. In Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K. B., Tignor, M., and Miller, H. L., editors, Climate Change 2007. *Working Group I: The Physical Science Basis, chapter 8. Cambridge University Press.*

- REASON, C. J. C., HACHIGONTA, S. & PHALADI, R. F. 2005. Interannual variability in rainy season characteristic over the limpopo region of southern Africa. *International Journal of Climatology*, 25, 1835–1853.
- REED, S., KOREN, V., SMITH, M., ZHANG, Z., MOREDA, F., SEO, D.-J. & DIMPPARTICIPANTS 2004a. Overall distributed model intercomparison project results. *Journal of Hydrology*, 298, 27–60.
- REED, S., KOREN, V., SMITH, M., ZHANG, Z., MOREDA, F. & SEO, D. J. 2004b. DMIP Participants, 2004. Overall distributed model intercomparison project results. *Journal of Hydrology* 298, 27–60.
- REFSGAARD, J. C. & KNUDSEN, J. 1996. Operational validation and intercomparison of different types of hydrological models. . *Water Resources Research*, 32, 2189–2202.
- RIAD, S., MANIA, J., BOUCHAOU, L. & NAJJAR, Y. 2004. Predicting catchment flow in a semi arid region via an artificial neural network technique. *Hydrological Processes* 18, 2387–2393.
- RICHARD, Y., TRZASKA, S., ROUCOU, P. & ROUAULT, M. 2000. Modification of the Southern African rainfall variability/ENSO relationship since late 1960's. *Climate Dynamics* 16, 883–895.
- RICHARDSON, C. W. & WRIGHT, D. A. 1984. WGEN: A model for generating daily weather variables. *US Department of Agriculture, Agricultural Research Service, ARS-8. USDA, Washington, DC.*
- RINGROSE, S., CHIPANSHI, A.C., MATHESON, W., CHANDA, R., MOTOMA, L., MAGOLE, I., JELLEMA, A. 2002. Environmental Assesment: Climate-a human induced woody vegetation changes in Botswana and their implications for human adaptation. *Environmental Management*, 30: 98–109.
- ROBERTSON, A. W., KIRSHNER, S., SMYTH, P., CHARLES, S. P. & BATES, B. C. 2006. Subseasonal-to-interdecadal variability of the Australian monsoon over North Queensland. *Quarterly Journal of the Royal Meteorological Society*, 132, 519–542.
- RUOSTEENOJA, K., CARTER, T. R., JYLHÄ, K. & TUOMENVIRT, H. 2003. Future climate in world regions: an intercomparison of model-based projections for the new IPCC emissions scenarios. *Finnish Environment Institute* No. 644, Helsinki, 83 pp.
- SAHOO, G.B., RAY, C. & CARLO, E.H. 2006. Calibration and validation of a physically distributed hydrological model, MIKE SHE, to predict streamflow at high frequency in a flashy mountainous Hawaii stream. *Journaal of Hydrology*, 327: 94–109.

- SCHREIDER, S. Y., JAKEMAN, A. J., LETCHER, R. A., NATHAN, R. J., NEAL, B. P. & BEAVIS, S. G. 2002. Detecting changes in streamflow response to changes in non-climatic catchment conditions: farm dam development in the Murray-Darling basin, Australia. *Journal of Hydrology*, 262, 84-98.
- SCHREIDER, S. Y., JAKEMAN, A. J. & PITTOCK, A. B. 1996. Modelling rainfall-runoff from large catchment to basin scale: the Goulburn Valley, Victoria. *Hydrological Processes*, 10 863-876.
- SEFTON, C. E. M. & HOWARTH, S. M. 1998. Relationships between dynamic response characteristics and physical descriptors of catchments in England and Wales. *Journal of Hydrology*, 211, 1-16.
- SEGOND, M.L. 2006. Stochastic modelling of space-time rainfall and the significance of spatial data for flood runoff generation. *PhD thesis. Department of Civil and Environmental Engineering, Imperial College London.*
- SEGOND, M. L., ONOF, C. & WHEATER, H. S. 2006. Spatial-temporal disaggregation of daily rainfall from a generalized linear model. *Journal of Hydrology*, 331, 674-689.
- SEIBERT, J. & MCDONNEL, J. J. 2002. On the dialog between experimentalist and modeler in catchment hydrology: Use of soft data for multicriteria model calibration. *Water Resources Research*, 38, 1241, doi:10.1029/2001WR000978.
- SEMENOV, M. A. 2007. Development of high-resolution UKCIP02-based climate change scenarios in the UK. *Agricultural and Forest Meteorology*, 144, 127-138.
- SEMENOV, M. A. & BARROW, E. M. 1997. USE OF A STOCHASTIC WEATHER GENERATOR IN THE DEVELOPMENT OF CLIMATE CHANGE SCENARIOS. *Climatic change*, 35, 397-414.
- SENAI, G. 2005. WUC drought management model: A Presentation to the National Workshop on Drought Planning *National Workshop on Drought Planning* Gaborone: Water Utilities Corporation, Botswana.
- SENTELHAS, P. C., DE FARIA, R. T., CHAVES, M. O. & HOOGENBOOM, G. 2001. Evaluation of the WGEN and SIMMETEO weather generators for the Brazilian tropics and subtropics, using crop simulation models. *Revista Brasileira de Agrometeorologia, Santa Maria*, 9, 357-376.
- SEWELL, R. D. & LANDMAN, W. A. 2001. Indo-Pacific relationships in terms of sea-surface temperature variations. *International Journal of Climatology*, 21, 1515-1528.

- SHAMSELDIN, A. Y. 1997. Application of neural network technique to rainfall-runoff modelling. *Journal of Hydrology*, 199 272-294.
- SHAW, E. M. 1994. Hydrology in practice. *Third Edition*. Chapman and Hall. London.
- SHRESTHA, S., BASTOLA, S., BABEL, M. S., DULAL, K. N., MAGOME, J., HAPUARACHCHI, H. A. P., KUZAMA, F., ISHIDAIRA, H. & TAKEUCHI, K. 2007. The assessment of spatial and temporal transferability of a physically based distributed hydrological model parameters in different physiographic regions of Nepal. *Journal of Hydrology*, 347, 153-172.
- SMEC 1991. Botswana National Water Master Plan Study: Final Report. *Department of Water Affairs, Gaborone, Botswana*.
- SMITH, M. B., KOREN, V. I., ZHANG, Z., REED, S. M., PAN, J. & MOREDA, F. 2004. Runoff response to spatial variability in precipitation: an analysis of observed data. *Journal of Hydrology*, 298, 267-286.
- SNOWY MOUNTAINS ENGINEERING CORPORATION & ENGINEERING HYDROLOGICAL ENVIRONMENTAL MANAGEMENT CONSULTANTS 2006. National Water Master Plan Review: Main Report. *Ministry of Minerals, Energy and Water Resources, Botswana Government*.
- SOROOSHIAN, S., GUPTA, V. K. & SINGH, V. P. 1995. Model calibration. In *Computer Models of Watershed Hydrology*. Water Resources Publications, USA.
- SRIKANTHAN, R. & MCMAHON, T. A. 1982. Stochastic generation of monthly streamflows *Journal of Hydraulic Division, American Society of Civil Engineers* 108 419-441.
- STEDINGER, J. R. & TAYLOR, M. R. 1982. Synthetic streamflow generation:2. Effect of parameter uncertainty. *Water Resources Research* 18 919-924.
- STERN, R. D. & COE, R. 1984. A model fitting analysis of daily rainfall data. *Jornal of the Roya Statistical Society. Series A (General)*, 147, 1-34.
- TADROSS, M. M. A. 2006. MM5 simulations of interannual change and the diurnal cycle of southern African regional climate. *Theoretical and applied climatology*, 86, 63-80.
- TOEWS, M. W. & ALLEN, D. M. 2009. Evaluating different GCMs for predicting spatial recharge in an irrigated arid region. *Journal of Hydrology*, 374, 265-281.

- TSHEKO, R. 2006. Comparison between the United States Soil Conservation Service (SCS) and the two models commonly used for estimating rainfall-runoff in south-eastern Botswana. *Water SA*, 32, 29-36.
- UPPALA, S.M. AND 45 CO-AUTHORS, 2005. The ERA-40 Reanalysis. *Quarterly Journal of the Royal Meteorological Society*, 131, 2961-3012.
- UVO, C. B., TOLLE, U. & BERNDTSSON, R. 2000. Forecasting discharge in amazon using artificial neural networks. *International Journal of Climatology* 20, 1495-1507.
- VON STORCH, H., ZORITA, E. & CUBASCH, U. 1993. Downscaling of Global Climate Change estimates to Regional Scales: An Application to Iberian Rainfall in Winter time. *Journal of Climate*, 6, 1161-1171.
- WAGENER, T., LEES, M. J. & WHEATER, H. S. 2002. A toolkit for the development and application of parsimonious hydrological models. In *Mathematical models of small watershed hydrology - Volume 2*. V.P. Singh & D. Frevert (eds). USA., 87-136.
- WAGENER, T. & WHEATER, H. S. 2006. Parameter estimation and regionalization for continuous rainfall-runoff models including uncertainty. *Journal of Hydrology*, 320, 132-154.
- WAGENER, T., WHEATER, H. S. & GUPTA, H. V. 2004. Rainfall-runoff modelling in gauged and ungauged catchments. *Imperial College Press, London pp 306*.
- WATTS, G. 1997. Hydrological modelling in practice. In *Contemporary Hydrology: Towards a holistic Environmental Science*, ed. By Wilby R, Wiley, Chichester.
- WHEATER, H. S. 2002. Hydrological Processes in arid and semi arid areas. In *Wheater H.S. and Al-Weshah (eds). Hydrology of Wadi Systems (IHP Regional Network on Wadi hydrology in the Arab region: . IHP-V, Technical Documents in Hydrology, UNESCO, 55, 5-22*.
- WHEATER, H. S. 2006. G-WADI – UNESCO's Global network for Water and Development Information for arid lands. . *International Scientific Conference "The Future of Drylands" (Tunis, 19–21 June 2006) Side event "Hydrological changes in arid and semi-arid areas under climatic and human influences: focus on the Mediterranean region", 21 June*.
- WHEATER, H. S., CHANDLER, R. E., ONOF, C. J., ISHAM, V. S., BELLONE, E., YANG, C., LEKKAS, D., LOURMAS, G. & SEGOND, M.-L. 2005. Spatial-temporal rainfall modelling for flood risk estimation. *Stochastic Environmental Research and Risk Assessment* 19, 403–416.

- WHEATER, H. S., ISHAM, V. S., CHANDLER, R. E., ONOF, C. J., STEWART, E. J., BELLONE, E., YANG, C., LEKKAS, D., LOURMAS, G., SEGOND, M.-L., FROST, A. J., PRUDHOMME, C. & CROOKS, S. 2006. Joint DEFRA/EA Flood and Coastal Erosion Risk Management R&D Programme: Improved methods for national spatial-temporal rainfall and evaporation modelling for BSM. *R&D Technical Report F2105/TR*. London.
- WHEATER, H. S., JAKEMAN, A. J. & BEVEN, K. J. 1993. Progress and directions in rainfallrunoff modelling. In: *Modelling Change in Environmental Systems*, Ed. A.J. Jakeman, M.B. Beck and M.J. McAleer, Wiley., 101-132.
- WHEATER, H. S., WOODS, B. B. & JOLLEY, T. J. 1997. An integrated model of arid zone water resources: evaluation of rainfall-runoff simulation performance. In: *Sustainability of Water Resources under Increasing Uncertainty*, IAHS Pubn., 240, 395-405.
- WILBY, R. L. 1997. Non-stationarity in daily precipitation series: Implications for GCM down-scaling using atmospheric circulation indices. *International Journal of Climatology*, 17, 439-454.
- WILBY, R. L., CHARLES, S. P., ZORITA, E., TIMBAL, B., WHETTON, P. & MEARNS, L. O. 2004. Guidelines for use of climate scenarios developed from statistical downscaling methods. 27 pp. Available for download from: <http://ipcc-ddc.cru.uea.ac.uk>.
- WILBY, R. L. & HARRIS, I. 2006. A framework for assessing uncertainties in climate change impacts: Low-flow scenarios for the River Thames, UK. *Water Resources Research*, 42, W02419, doi:10.1029/2005WR004065.
- WILK, J., KNIVETON, D., ANDERSSON, L., LAYBERRY, R., TODD, M. C., HUGHES, D., RINGROSE, S. & VANDERPOST, C. 2006. Estimating rainfall and water balance over the Okavango River Basin for hydrological applications. *Journal of Hydrology*, 331, 18-29.
- WILKS, D. S. & WILBY, R. L. 1999. The weather generation game: a review of stochastic weather models. *Progress in Physical Geography*, 23, 329-357.
- WORLD HEALTH ORGANIZATION & UNICEF 2005. WATER FOR LIFE, MAKING IT HAPPEN: DECADE FOR ACTION 2005–2015. *WHO/UNICEF Joint Monitoring Programme for Water Supply and Sanitation*, Switzerland.
- XIANG, L., SHENGLIAN, G., PAN, L. & GUIYA, C. 2010. Dynamic control of flood limited water level for reservoir operation by considering inflow uncertainty. *Journal of Hydrology*, doi:10.1016/j.jhydrol.2010.07.011.

- XU, C., WIDEN, E. & HALLDIN, S. 2005. Modelling Hydrological Consequences of Climate Change-Progress and Challenges. *Advances in Atmospheric Sciences*, 22, 789-797.
- YANG, C., CHANDLER, R. E., ISHAM, V. S. & WHEATER, H. S. 2005. Spatial-temporal rainfall simulation using generalized linear models. *Water Resources Research*, 41, 1-13.
- YANG, C., CHANDLER, R. E., ISHAM, V. S. & WHEATER, H. S. 2006. Quality control for daily observational rainfall series in the UK. *Journal of Water and Environment* 20, 185-193.
- YAPO, P. O., GUPTA, H. V. & SOROOSHIAN, S. 1996. Automatic calibration of conceptual rainfall-runoff models: Sensitivity to calibration data. *Journal of Hydrology*, 181, 23-48.
- YE, W., BATES, B. C., VINEY, N. R., SIVAPALAN, M. & JAKEMAN, A. J. 1997a. Performance of conceptual rainfall-runoff models in low-yielding catchments. *Water Resources Research* 33, 153-166.
- YE, W., BATES, B. C., VINEY, N. R., SIVAPALAN, M. & JAKEMAN, A. J. 1997b. Performance of conceptual rainfall-runoff models in Low-yielding catchments. *Water Resources Research*, 33, 153-166.
- YE, W., JAKEMAN, A. J. & BARNES, C. J. 1995. A parametrically efficient model for prediction of streamflow in an Australian benchmark catchment with complex storage dynamics. *Environment International*, 21, 475-758.
- YE, W., JAKEMAN, A. J. & YOUNG, P. C. 1998. Identification of improved rainfall-runoff models for an ephemeral low-yielding Australian catchment. *Environmental Modelling and Software*, 13, 59-74.
- YOUNG, P. C. & BEVEN, K. J. 1991. Computation of the instantaneous unit hydrograph and identifiable component flows with applications to two small upland catchments-comment. *Journal of Hydrology*, 129 389-396.
- YOUNG, P. C. & BEVEN, K. J. 1994. Data-based mechanistic modelling and the rainfall-flow non-linearity. *Environmetrics*, 5, 335-363.
- YOUNG, W., BRANDIS, K. & KINGSFORD, R. 2006. Modelling monthly streamflows in two Australian dryland rivers: Matching model complexity to spatial scale and data availability. *Journal of Hydrology*, 331, 242-256.
- ZEALAND, C. M., BURN, D. H. & SIMONOVIC, S. P. 1999. Short term streamflow forecasting using artificial neural networks *Journal of Hydrology* 214, 32-48.

- ZHANG, Z., KOREN, V., SMITH, M., REED, S. & WANG, D. 2004. Use of next Generation Weather Radar Data and Basin Disaggregation to improve continuous hydrograph simulations. *Journal of Hydrologic Engineering*, 9, 103-115.
- ZHI, L., WEN-ZHAO, L., XUN-CHANG, Z., FEN-LI, Z. 2009. Impacts of land use change and climate variability on hydrology in an agricultural catchment on the Loess plateau of China. *Journal of Hydrology*, 377, 35-42.
- ZHAO, Y., CAMBERLIN, P. & RICHARD, Y. 2005. Validation of a coupled GCM and projection of summer rainfall change over South Africa, using a statistical downscaling method. *Climate Research*, 28, 109-122.
- ZORITA, E. & VON STORCH, H. 1999. The Analog Method as a Simple Statistical Downscaling Technique: Comparison with More Complicated Methods. *Journal of Climate*, 12, 2474-2489.

Appendices

A. Rainfall simulations for individual rain gauges

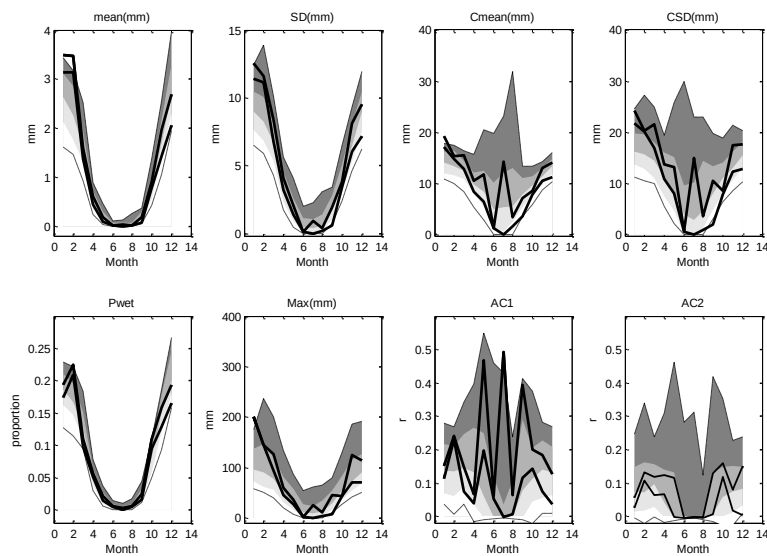


Figure A-1: Monthly statistics for gauge N1. The black lines indicate observed data (with uncertainty due to missing values). The grey scale indicates percentiles of the simulated data (10, 50 and 90 percentile) enveloped within the dashed minimum and maximum bounds. SD is standard deviation, Cmean and CSD is mean and standard deviation for wet days, Pwet is proportion of wet days, Max is daily absolute maximum values, AC1 and AC2 are autocorrelations lags 1 and 2

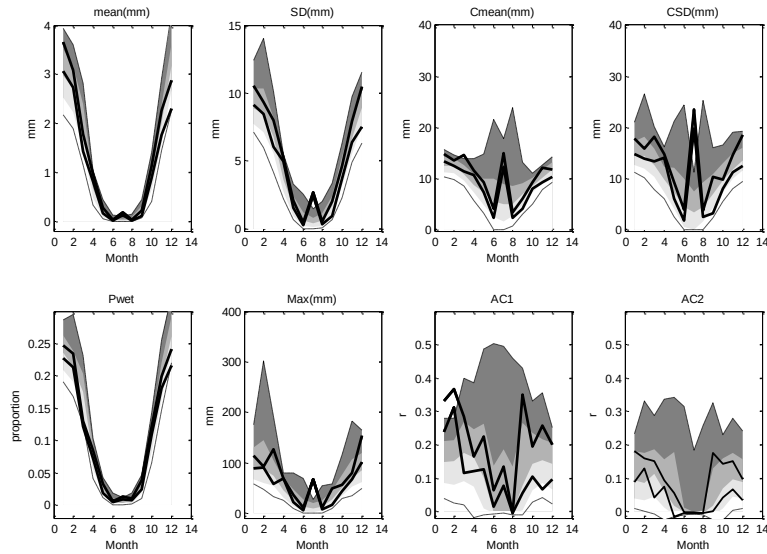


Figure A-2: Monthly statistics for gauge N2. The black lines indicate observed data (with uncertainty due to missing values). The grey scale indicates percentiles of the simulated data as shown in Figure A-1.

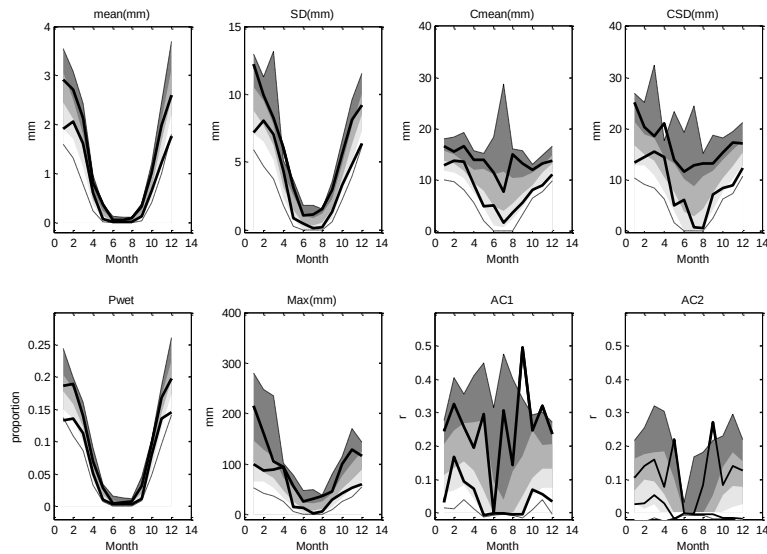


Figure A-3: Monthly statistics for gauge N3. The black lines indicate observed data (with uncertainty due to missing values). The grey scale indicates percentiles of the simulated data as shown in Figure A-1.

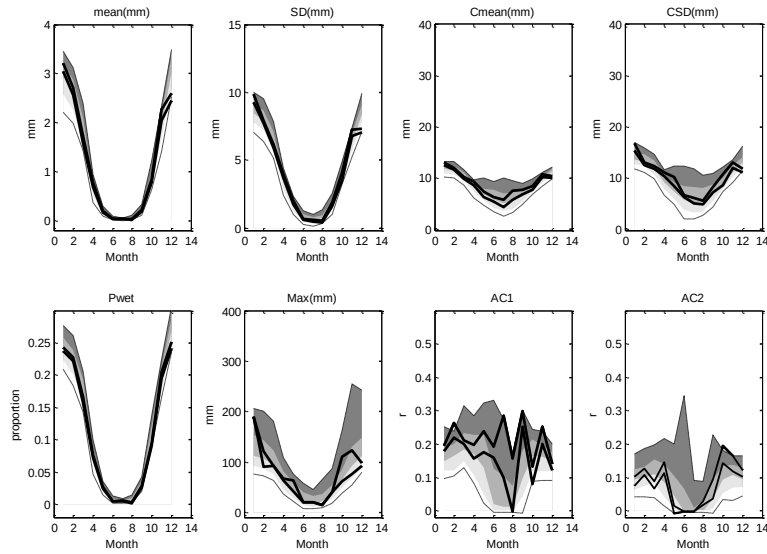


Figure A-4: Monthly statistics for gauge N5. The black lines indicate observed data (with uncertainty due to missing values). The grey scale indicates percentiles of the simulated data as shown in Figure A-1.

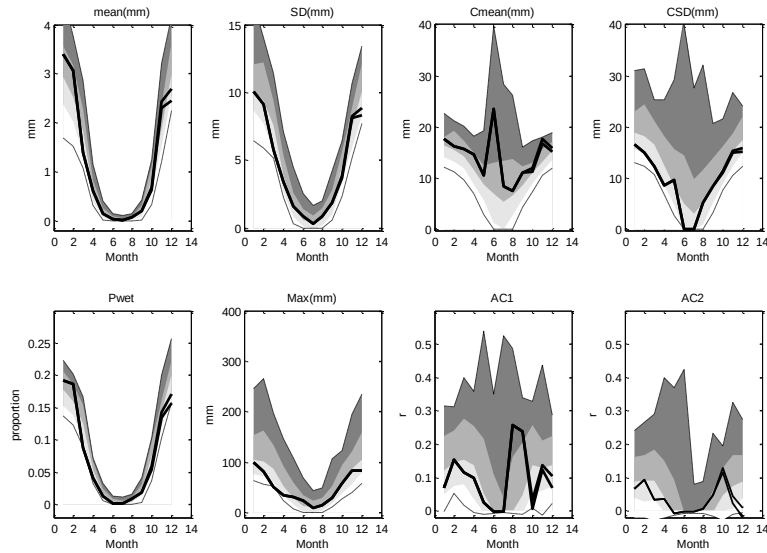


Figure A-5: Monthly statistics for gauge N7. The black lines indicate observed data (with uncertainty due to missing values). The grey scale indicates percentiles of the simulated data as shown in Figure A-1.

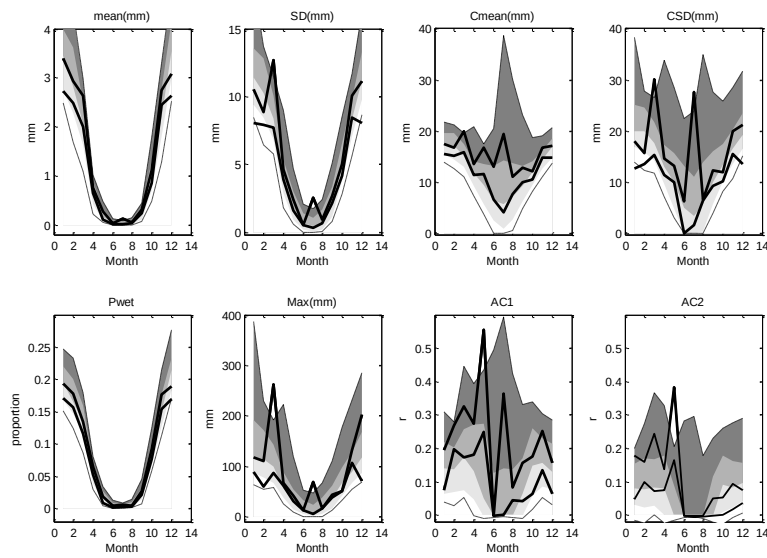


Figure A-6: Monthly statistics for gauge N8. The black lines indicate observed data (with uncertainty due to missing values). The grey scale indicates percentiles of the simulated data as shown in Figure A-1.

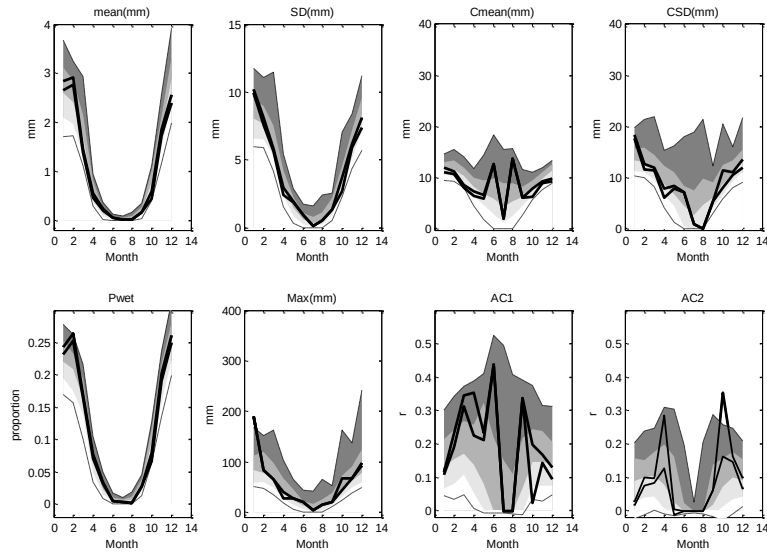


Figure A-7: Monthly statistics for gauge N9. The black lines indicate observed data (with uncertainty due to missing values). The grey scale indicates percentiles of the simulated data as shown in Figure A-1.

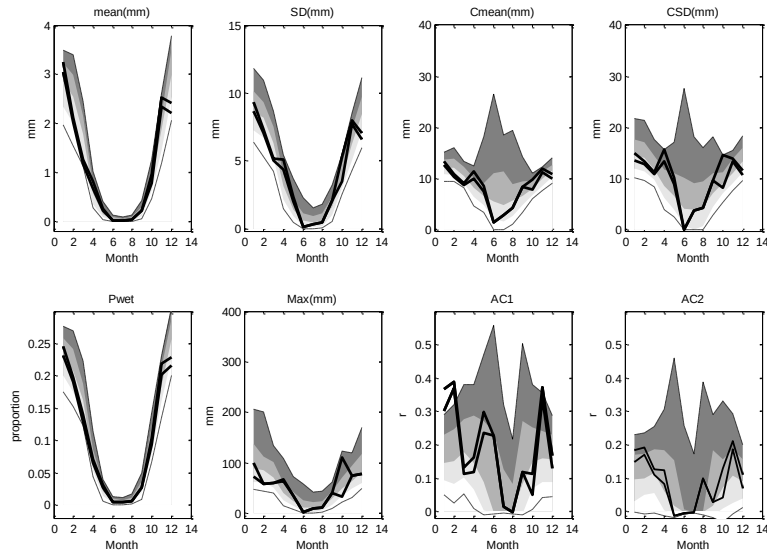


Figure A-8: Monthly statistics for gauge N10. The black lines indicate observed data (with uncertainty due to missing values). The grey scale indicates percentiles of the simulated data as shown in Figure A-1.

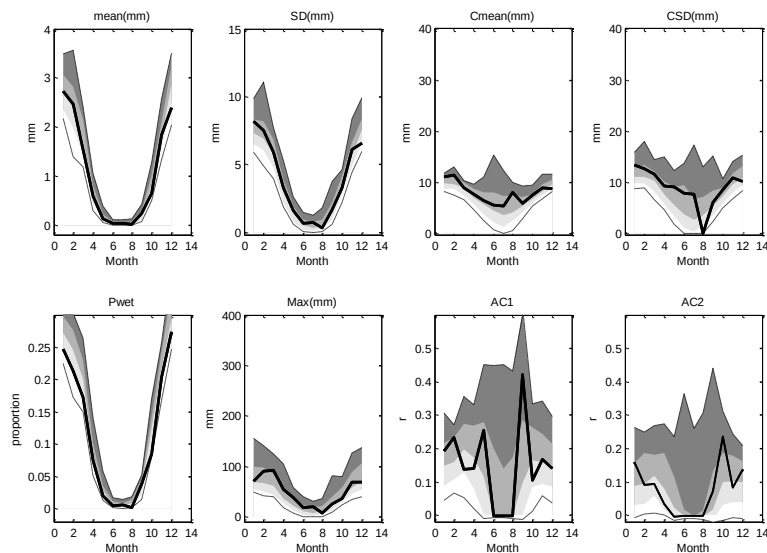


Figure A-9: Monthly statistics for gauge N11. The black lines indicate observed data (with uncertainty due to missing values). The grey scale indicates percentiles of the simulated data as shown in Figure A-1.

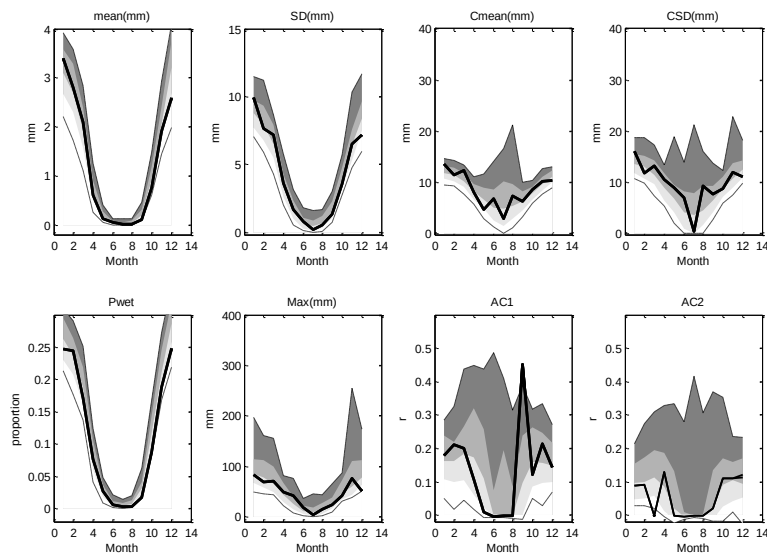


Figure A-10: Monthly statistics for gauge N12. The black lines indicate observed data (with uncertainty due to missing values). The grey scale indicates percentiles of the simulated data as shown in Figure A-1.

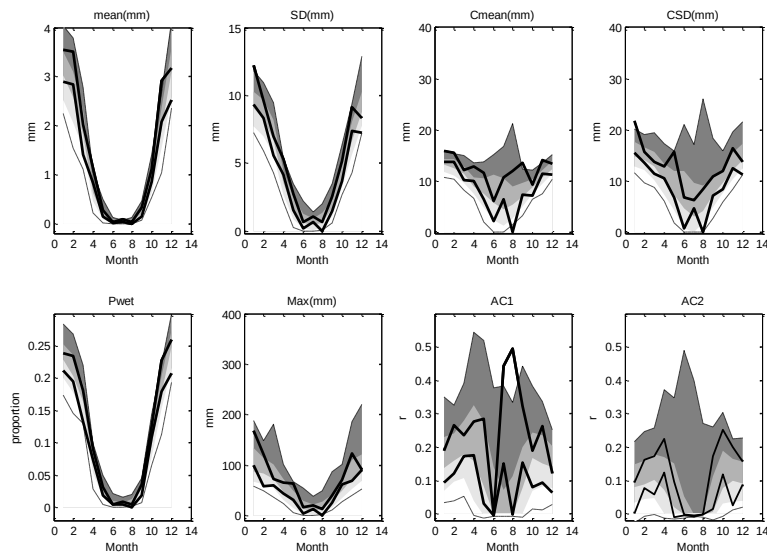


Figure A-11: Monthly statistics for gauge N13. The black lines indicate observed data (with uncertainty due to missing values). The grey scale indicates percentiles of the simulated data as shown in Figure A-1.

B. Calibration and validation using other objective functions

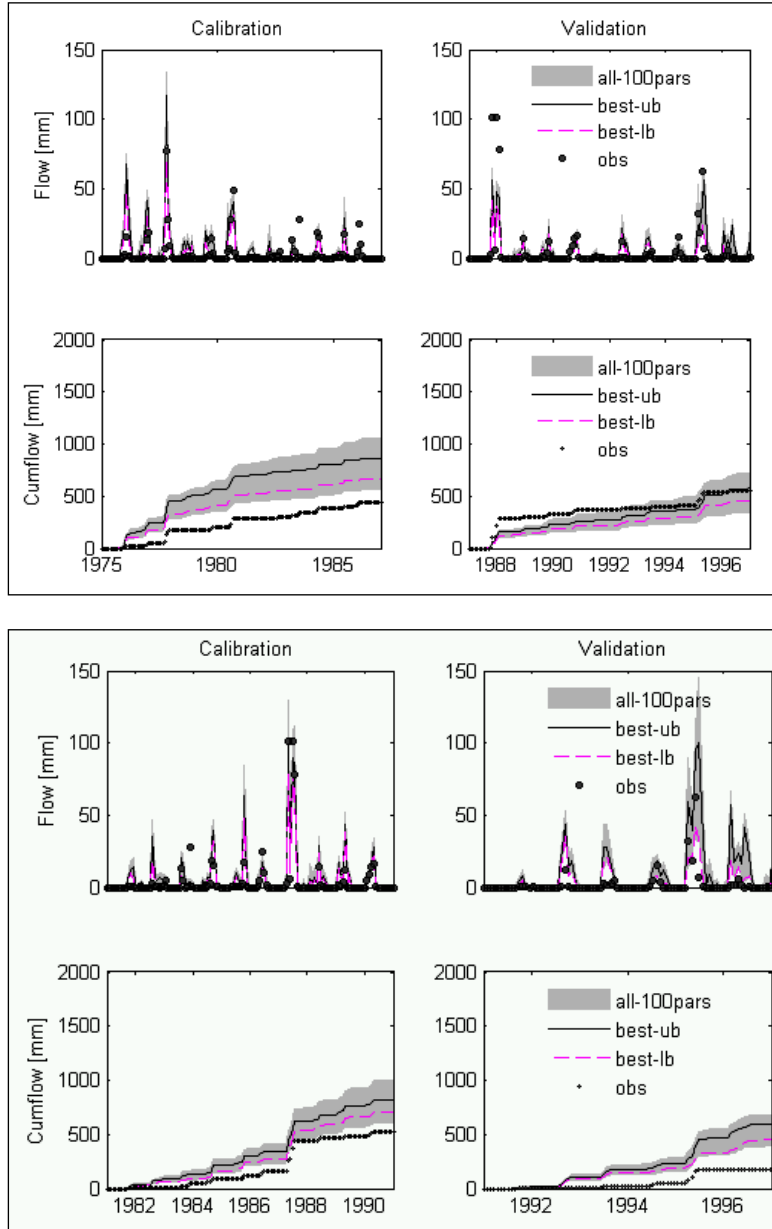


Figure B-1: Calibration and validation results for the outlet catchment based on the NSE* objective function. The black dots show observed flow data. The solid and dashed lines represent the upper and lower bounds of the best simulated flows from the 10 rainfall realizations. The grey area represents uncertainty arising from the top 100 parameter sets from all the rainfall realizations. The calibration period used are 1975-1987 (top plot) and 1981-1991 (bottom plot).

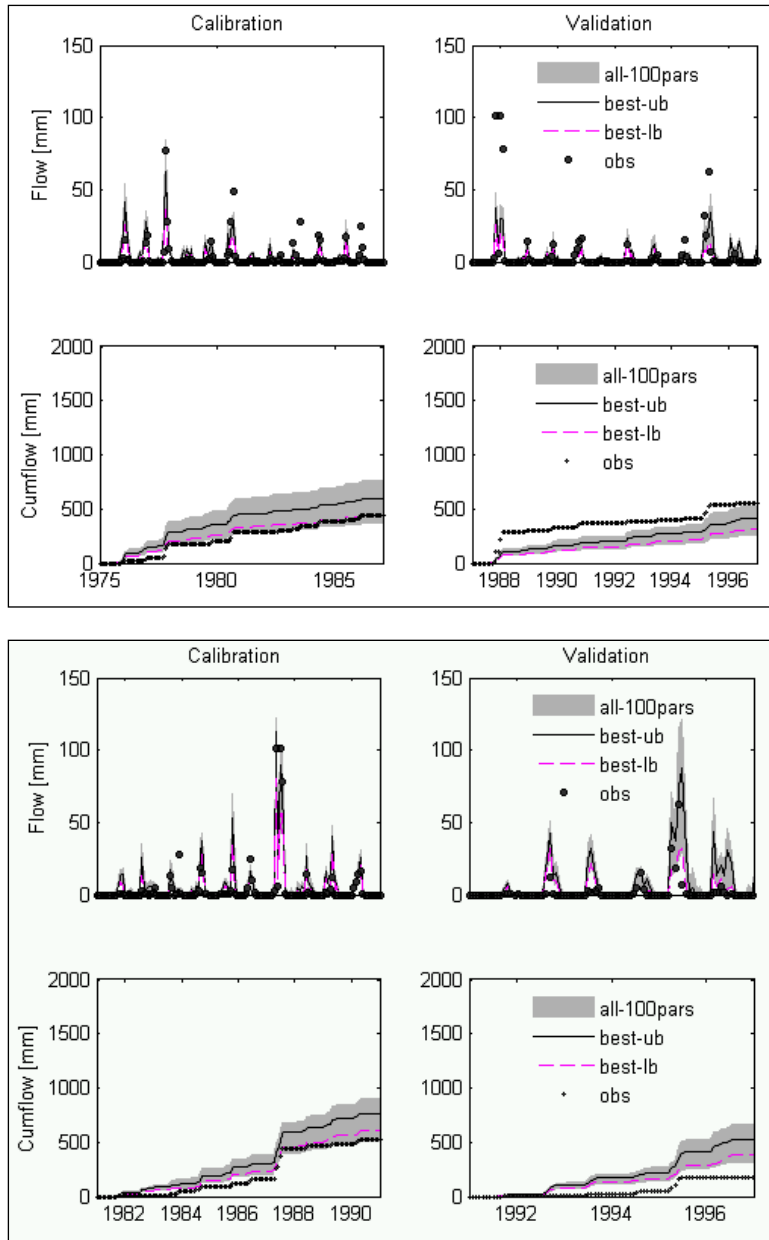


Figure B-2: Calibration and validation results for the outlet catchment based on the RMSE-LOW objective function. The legend is same as in Figure B-1. The calibration period used are 1975-1987 (top plot) and 1981-1991 (bottom plot).

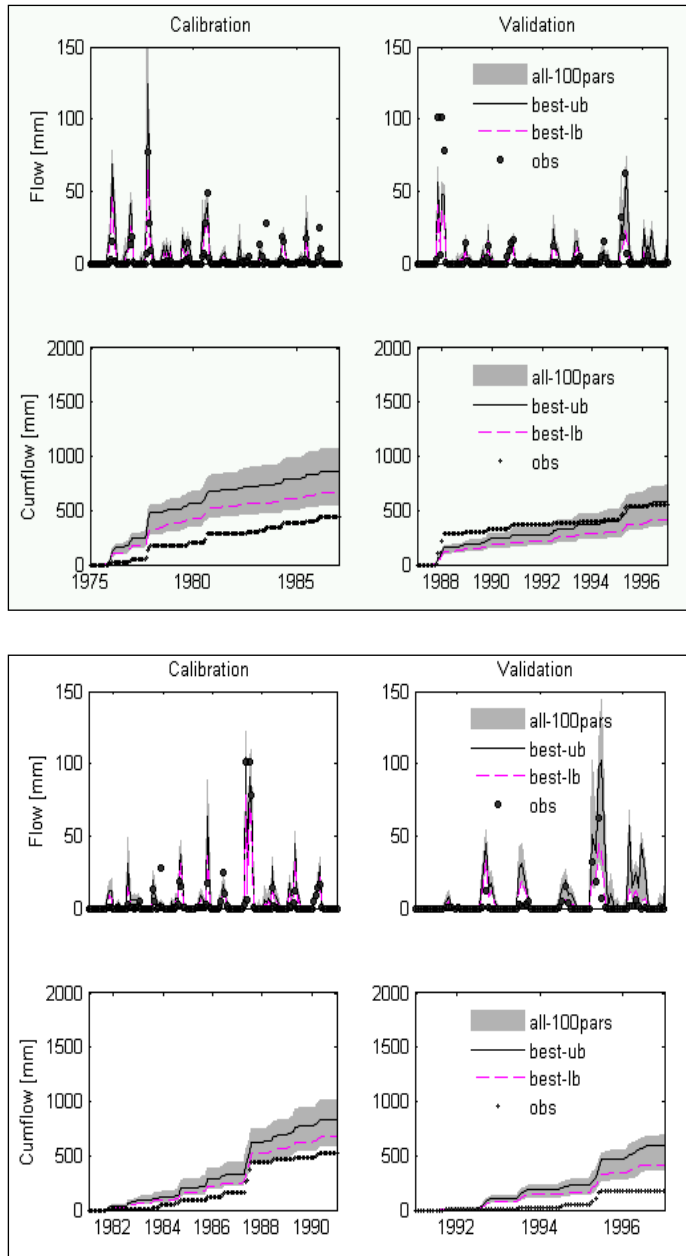


Figure B-3: Calibration and validation results for the outlet catchment based on the RMSE objective function. The legend is same as in Figure B-1. The calibration period used are 1975-1987 (left plot) and 1981-1991 (right plot).

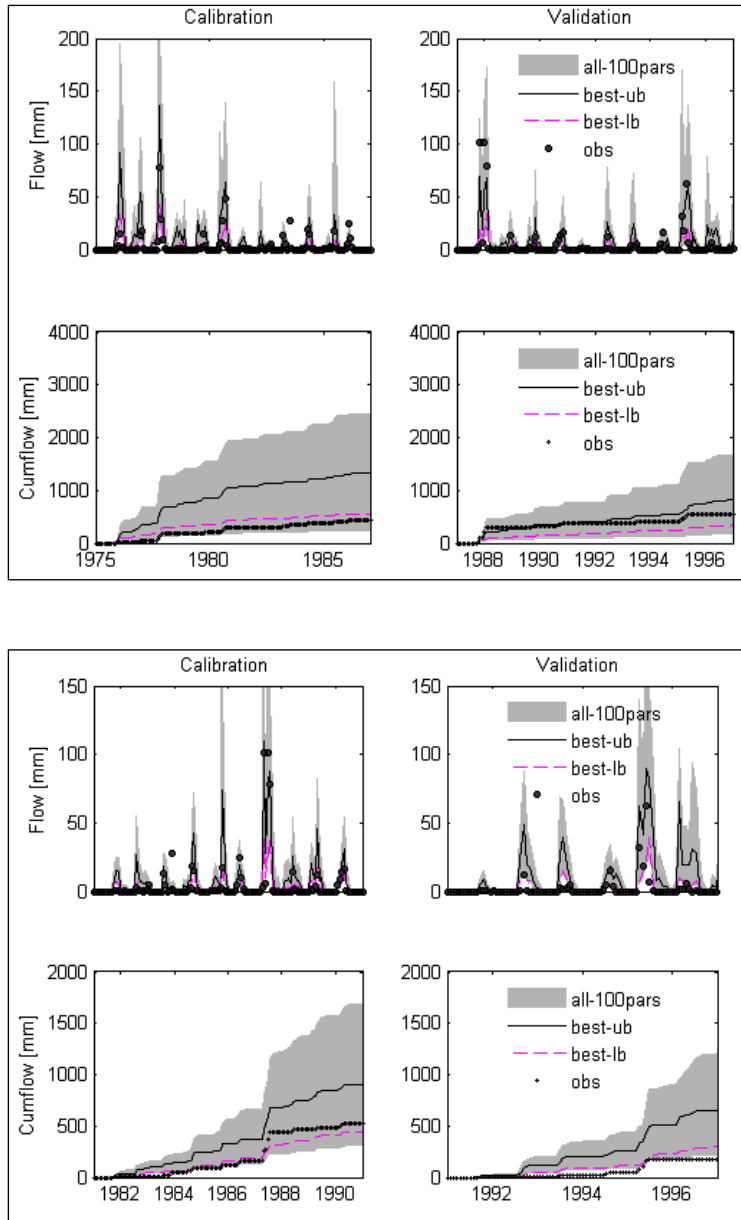


Figure B-4: Calibration and validation results for the outlet catchment based on the 10% tolerance objective function. The legend is same as in Figure B-1. The calibration period used are 1975-1987 (left plot) and 1981-1991 (right plot).

C. Parameter variability for the 1981-91 calibration period

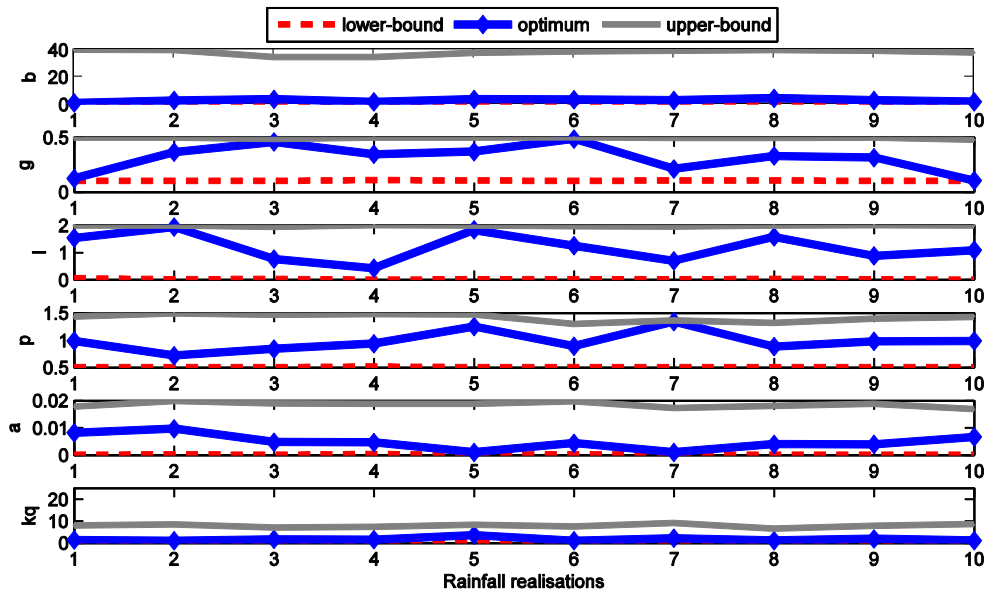


Figure C-1: Parameter variability for Mooke catchment plotted for each rainfall realization using the 1981-91 calibration period. The upper and lower bounds were computed from the best 100 parameters.

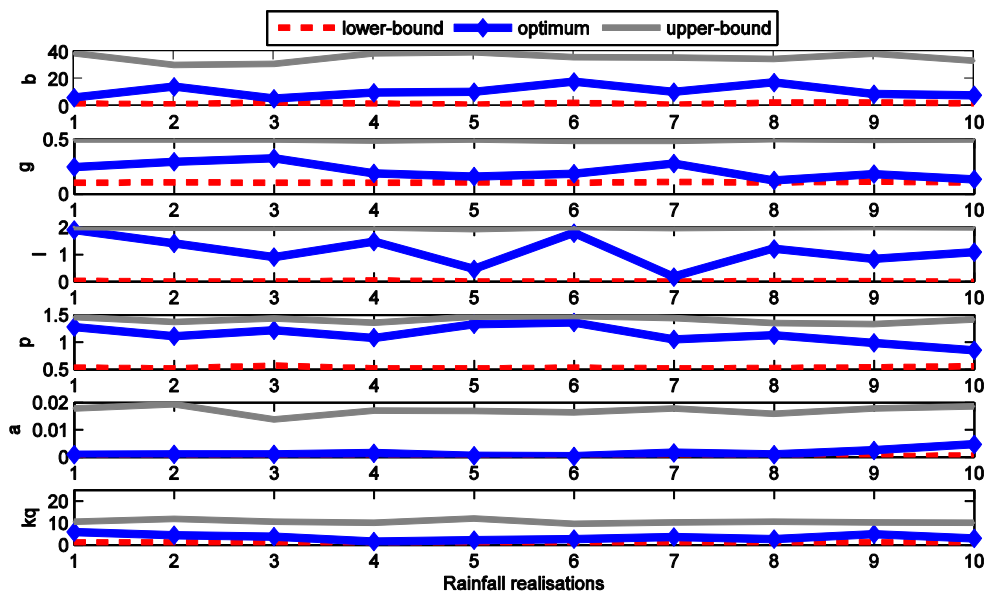


Figure C-2: Parameter variability for Ntshe catchment plotted for each rainfall realization using the 1981-91 calibration period. The upper and lower bounds were computed from the best 100 parameters.

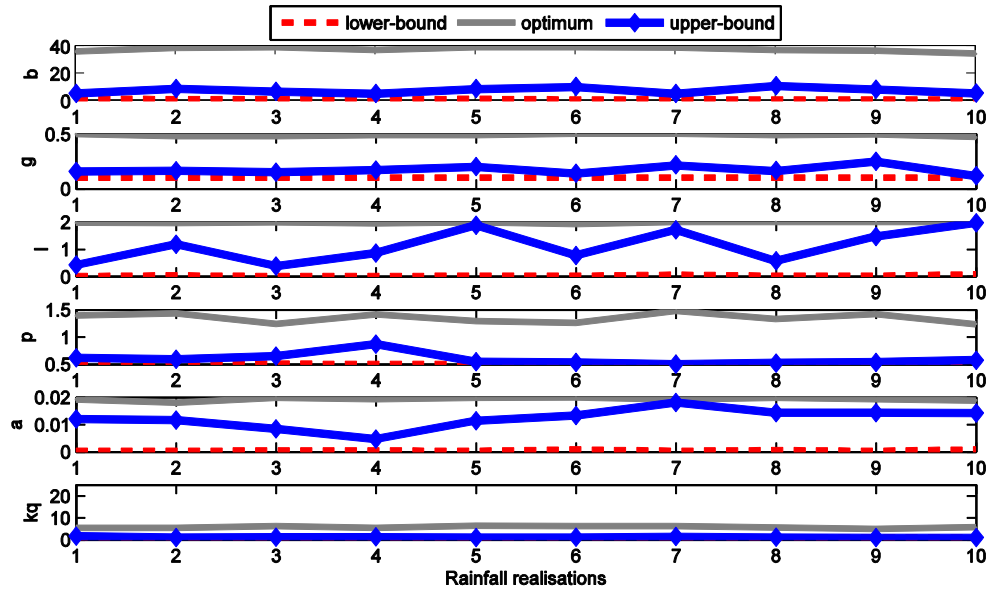


Figure C-3: Parameter variability for Tati catchment plotted for each rainfall realization using the 1981-91 calibration period. The upper and lower bounds were computed from the best 100 parameters.

D. Calibration and validation results for the 1981-91 period

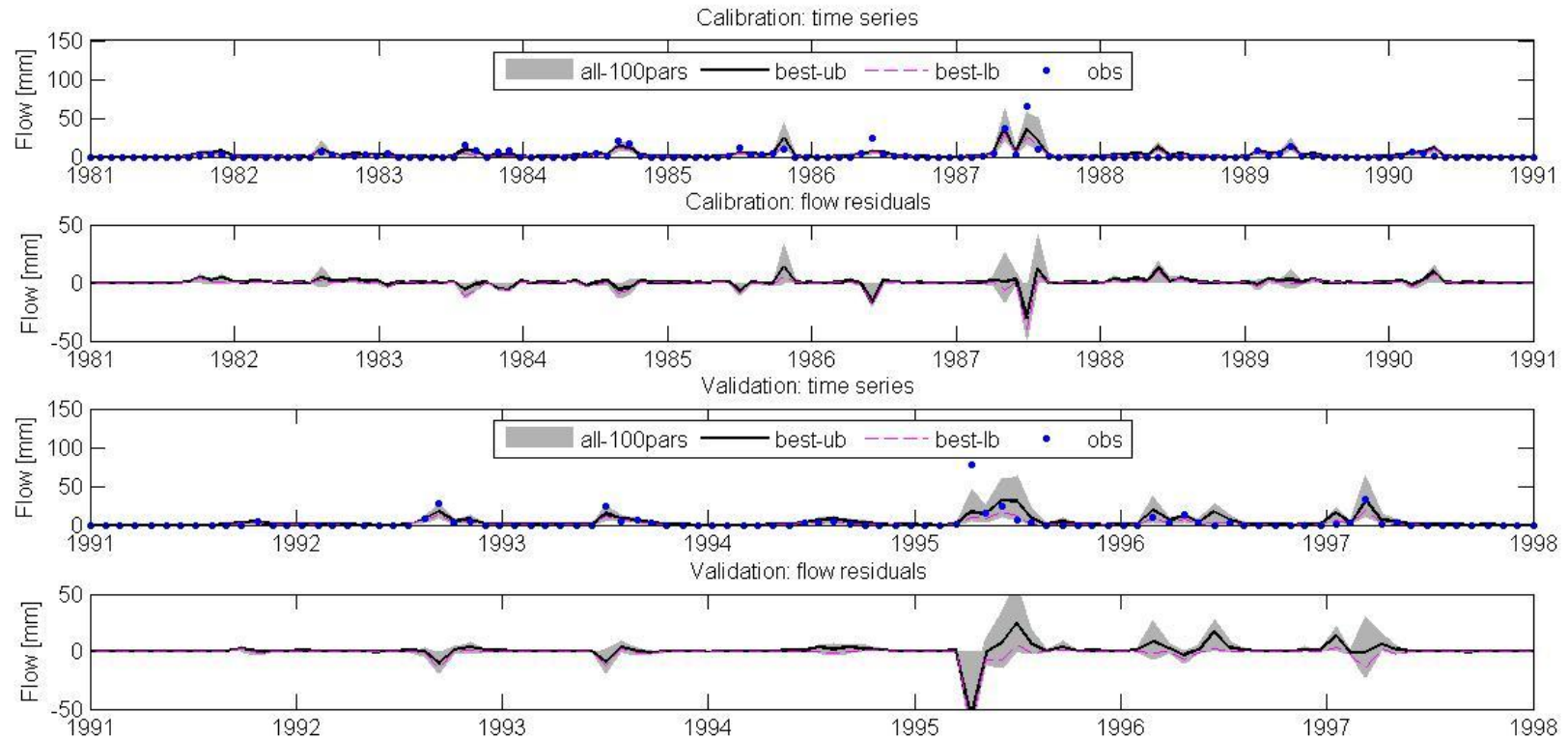


Figure D-1: Calibration (top two plots) and validation (bottom two plots) results for Tati subcatchment. The blue dots show observed flow data. The solid and dashed lines represent the upper and lower bounds of the best simulated flows from the 10 rainfall realizations. The grey area represents uncertainty arising from the top 100 parameter sets from all the rainfall realizations. The calibration period used is 1981-1991.

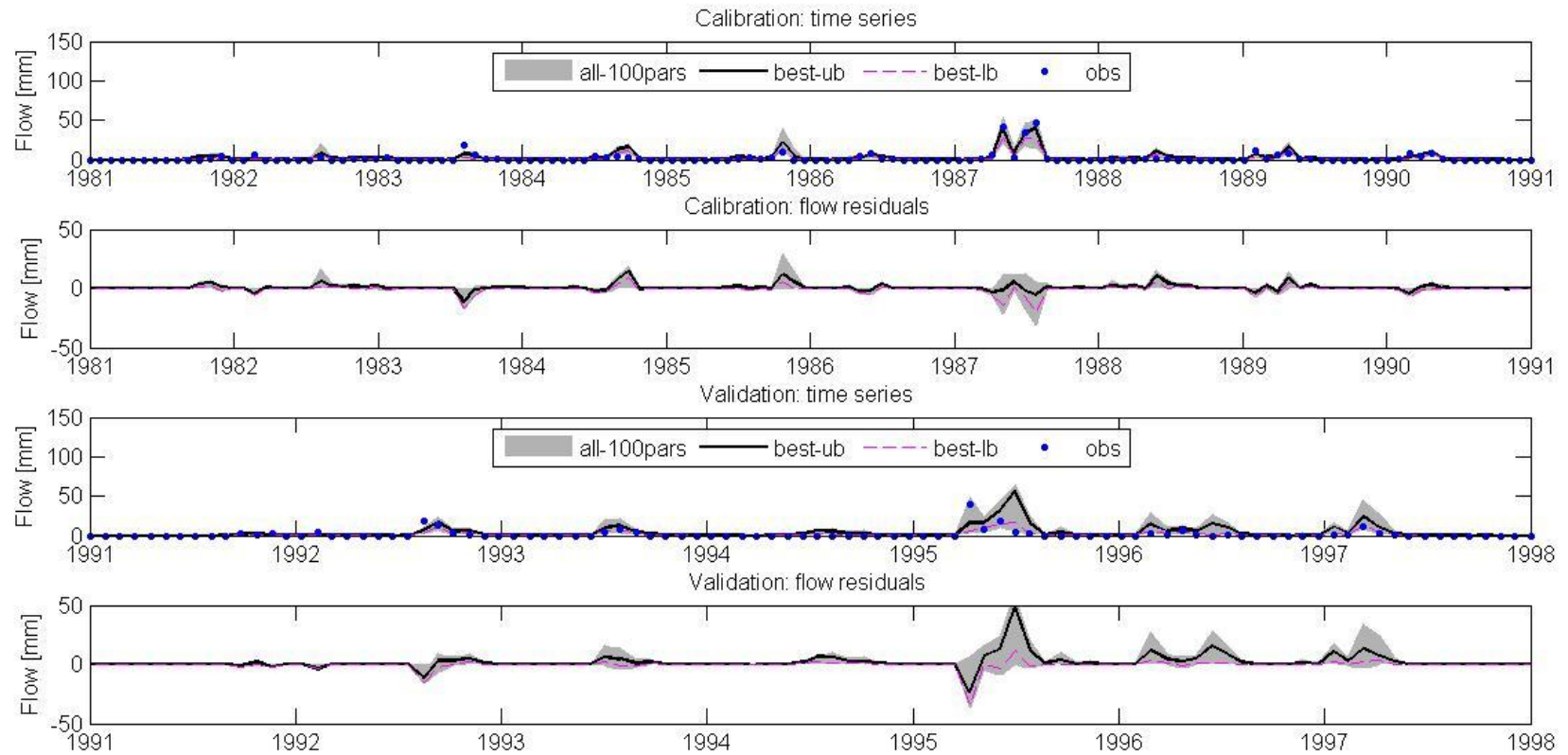


Figure D-2: Calibration (top two plots) and validation (bottom two plots) results for Ntshe subcatchment. The blue dots show observed flow data. The solid and dashed lines represent the upper and lower bounds of the best simulated flows from the 10 rainfall realizations. The grey area represents uncertainty arising from the top 100 parameter sets from all the rainfall realizations. The calibration period used is 1981-1991.

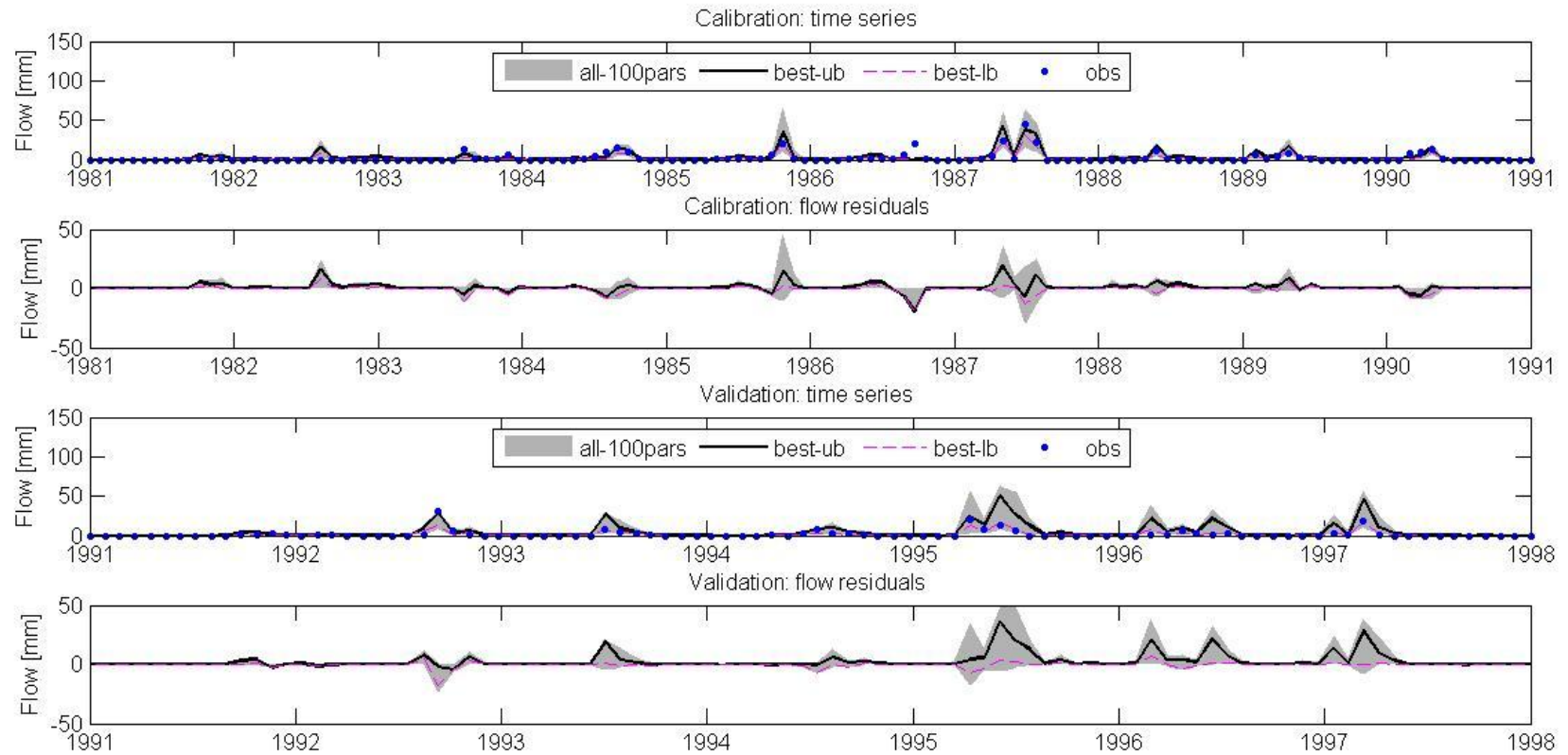


Figure D-3: Calibration (top two plots) and validation (bottom two plots) results for Mooke subcatchment. The blue dots show observed flow data. The solid and dashed lines represent the upper and lower bounds of the best simulated flows from the 10 rainfall realizations. The grey area represents uncertainty arising from the top 100 parameter sets from all the rainfall realizations. The calibration period used is 1981-1991.

E. Rainfall predictions using the CF method

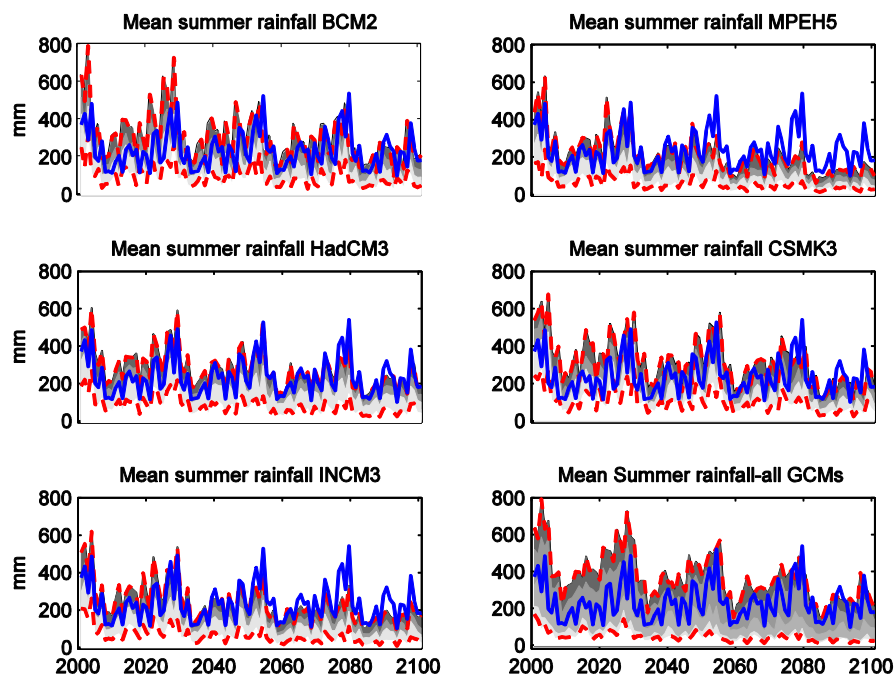


Figure E-1: Annual rainfall predictions from the 5 GCMs under the A1B scenario based on the change factor (CF) method. The dashed red lines represent the minimum and maximum uncertainty limits while the blue line represents the 50th percentile rainfall from the stationary climate.

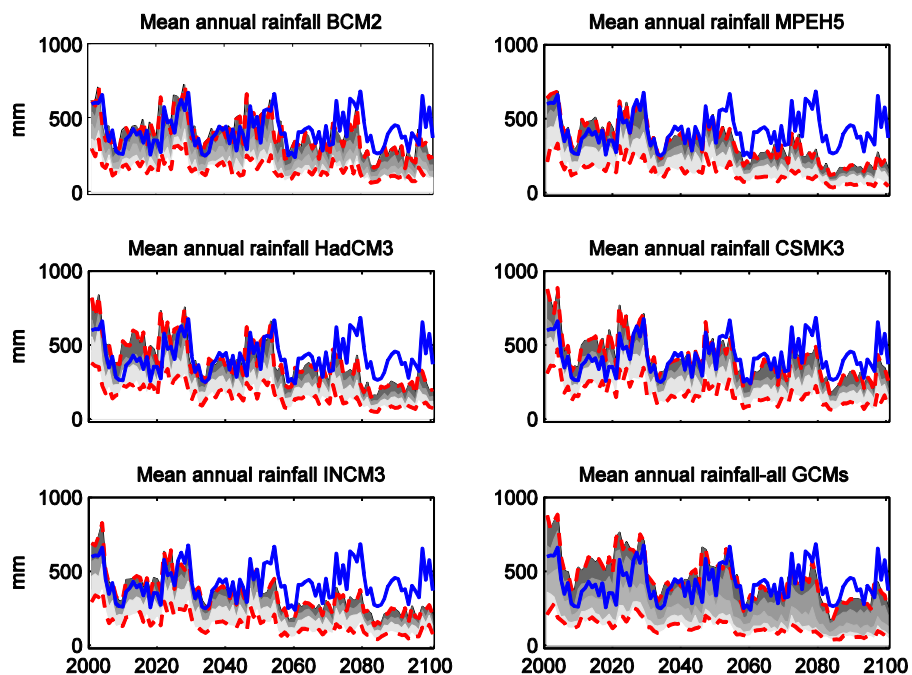


Figure E-2: Annual rainfall predictions from the 5 GCMs under the A2 scenario based on the change factor (CF) method. The dashed red lines represent the minimum and maximum uncertainty limits while the blue line represents the 50th percentile rainfall from the stationary climate.