EVALUATING UNCERTAINTY IN WATER RESOURCES ESTIMATION IN SOUTHERN AFRICA: A CASE STUDY OF SOUTH AFRICA

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ABSTRACT

Hydrological models are widely used tools in water resources estimation, but they are simple representations of reality and are frequently based on inadequate input data and uncertainties in parameter values. Data observation networks are expensive to establish and maintain and often beyond the resources of most developing countries. Consequently, measurements are difficult to obtain and observation networks in many countries are shrinking, hence obtaining representative observations in space and time remains a challenge. This study presents some guidelines on the identification, quantification and reduction of sources of uncertainty in water resources estimation in southern Africa, a data scarce region. The analyses are based on example sub-basins drawn from South Africa and the application of the Pitman hydrological model. While it has always been recognised that estimates of water resources availability for the region are subject to possible errors, the quantification of these uncertainties has never been explicitly incorporated into the methods used in the region. The motivation for this study was therefore to contribute to the future development of a revised framework for water resources estimation that does include uncertainty.

The focus was on uncertainties associated with climate input data, parameter estimation (and recognizing the uncertainty due model structure deficiencies) methods and water use data. In addition to variance based measures of uncertainty, this study also used a reservoir yield based statistic to evaluate model output uncertainty, which represents an integrated measure of flow regime variations and one that can be more easily understood by water resources managers. Through a sensitivity analysis approach, the results of the individual contribution of each source of uncertainty suggest regional differences and that clear statements about which source of uncertainty is likely to dominate are not generally possible. Parameter sensitivity analysis was used in identifying parameters which are important within

specific sub-basins and therefore those to focus on in uncertainty analysis. The study used a simple framework for evaluating the combined contribution of uncertainty sources to model outputs that is consistent with the model limitations and data available, and that allows direct quantitative comparison between model outputs obtained by using different sources of information and methods within Spatial and Time Series Information Modelling (SPATSIM) software.

The results from combining the sources of uncertainties showed that parameter uncertainty dominates the contribution to model output uncertainty. However, in some parts of the country especially those with complex topography, which tend to experience high rainfall spatial variability, rainfall uncertainty is equally dominant, while the contributions of evaporation and water use data uncertainty are relatively small. While the results of this study are encouraging, the weaknesses of the methods used to quantify uncertainty (especially subjectivity involved in evaluating parameter uncertainty) should not be neglected and require further evaluations. An effort to reduce data and parameter uncertainty shows that this can only be achieved if data access at appropriate scale and quality improves. Perhaps the focus should be on maintaining existing networks and concentrating research efforts on making the most out of the emerging data products derived from remote sensing platforms. While this study presents some initial guidelines for evaluating uncertainty in South Africa, there is need to overcome several constraints which are related to data availability and accuracy, the models used and the capacity or willingness to adopt new methods that incorporate uncertainty. The study has provided a starting point for the development of new approaches to modelling water resources in the region that include uncertain estimates.

DEDICATION

This study is dedicated to, my wife, Mercy, and our lovely daughter, Achel Tadiwanashe, for their patience and love all the time of this study.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

1.1 General background of the study

The scope of water resources planning and management has drastically changed in the last decade in most parts of the world (Heun and Koudstaal, 2001). This is partly because hydrometeorological data collection and analysis are not keeping pace with actual water development and management needs (Kundzewicz, 2007). Despite the increasing demands for water and the growing stress in the available water resources, calling for improved and scientifically-based management techniques, the largely inadequate funds available for data collection and maintenance of hydrometeorological services are reducing further especially in developing countries (Dube, 2006). The situation is worse in southern Africa (a data scarce region) where water in many areas has become a limited or even a scarce resource, either in quantity or quality. Rainfall-runoff models have long been invaluable tools in simulating information for use in making decisions for water resources planning and management (Rose and Peters, 2001), but these models are a simple representation of reality which makes their results uncertain (i.e. lack of sureness or complete knowledge about the outcome). Beven (1989, 2001a) has pointed out the limitations of the current generation of rainfall-runoff models and argued that the way forward must be based on realistic assessments of predictive uncertainty. Predictive uncertainty arises mainly from uncertainty associated with the model structure, input data and the parameter values. This study was motivated by one of the objectives of the International Association of Hydrological Sciences (IAHS) on Prediction in Ungauged Basins (PUB), which is a reduction of predictive uncertainty in modelling ungauged and poorly gauged basins (Sivapalan *et al*., 2003), which includes most parts of southern Africa.

The application of rainfall-runoff models for making predictions largely depends on the information relating to the spatial and temporal distribution of hydrologic processes (Jain *et al*., 2004). The reliability of this information might be questionable in the face of uncertainties associated with the collection and assessment of model input and output data. Furthermore, the problems of heterogeneity of process responses in a basin and unknown scale-dependences of parameters mean that the development of a single hydrological model based upon the fundamental "physics" of hydrology is not attainable

(Beven, 1989, 1993). As a consequence, hydrological models are simplified representations of the basin hydrological processes through aggregation into conceptual elements perceived to dominate the hydrological problem at hand, which means they exist to achieve specific tasks at specific spatial and temporal scales (Franks, 2007). If complex process-based models are used, they can only be over-parameterised and driven with significant uncertainty in input data and parameter values due to a lack of adequate model inputs at appropriate scales (Beven, 1989). Conceptual models with *a priori* specified structures based on the hydrologist's understanding of the relevant processes and with parameters calibrated against observed data, are therefore most commonly used in data scarce regions (Wheater *et al*., 1993).

The way hydrological models, whether conceptual or physically-based, represent natural hydrological processes at basin or sub-basin scales, leads to considerable uncertainty as a result of many issues. For instance, the neglect of important processes in hydrological modelling because of a lack of understanding of how a hydrological system works is an ultimate constraint on how the system can be predicted. However, there is not much that can be learned as long as the models that require calibration are adopted in making predictions rather than treating models simply as hypotheses about how the hydrological systems work and which might be rejected (Beven, 2002a, b). From this, it can be said that the very nature of hydrological modelling is inherently imperfect, which leads to uncertainties that cannot be easily quantified. The main sources of uncertainty in hydrological modelling have been discussed in many studies (Melching, 1995; Beven 2001a) and are related to errors in climate input data, use of inappropriate parameters or model structure and errors in the data used for model calibration and validation. All these uncertainties are often incorporated into what is referred to as hydrological uncertainty. The separation of these sources of uncertainty is a challenge because of complex compensation effects between them. It is therefore very difficult to represent the processes in nature, or to make predictions of future responses in basins of interest (often poorly or ungauged) without acknowledging the inherent uncertainty involved.

Uncertainty estimation (i.e. a process of identifying and quantifying uncertainty) has received increasing attention over the last two decades in water resources research. However, a significant part of the community is still reluctant to embrace uncertainty estimation in hydrological modelling, in spite of its importance (see e.g. Pappenberger and Beven, 2006). Most users of modelling results have been taking average values and ignoring any distribution or range of values around these averages. This long standing tradition has survived over the last decade and it is not surprising that modelling results are still very rarely presented with uncertainty bounds in research and practice. Instead, the quantification and reduction of uncertainty in the model input data, parameter values and the predictions in any hydrological modelling practice has largely been ignored in favour of model results verification (Higdon *et al*., 2004; Xia *et al*., 2005). Despite current modelling practice of placing more emphasis on verifying model results, uncertainty estimation must be part of any water resources estimation procedure. Beven (2006a) has recently proposed that not incorporating formal sensitivity and uncertainty analyses when applying a model ultimately results in undermining the science and value of hydrological models.

There exist several techniques for uncertainty estimation ranging from analytical, formal statistical, sensitivity or numerical through to non-probabilistic methods (Melching, 1995; Montanari, 2007). However, the selection and implementation of the appropriate uncertainty estimation method remains a challenge as they are better understood by developers of these methods rather than by practitioners. The appropriate method should depend on the purpose of the application and the availability of data. While the best method of uncertainty estimation is not yet known in ungauged or poorly gauged basins, non-probabilistic approaches are promising tools (Montanari, 2007). Besides, hydrologists do not require the best uncertainty estimation method, but theories and guidelines that are comprehensive and clear. In light of this, simpler and more understandable methods of quantifying uncertainty as well as guidelines to explicitly evaluate the different sources of uncertainty are urgently needed. This background raised important issues and motivates a need to further investigate the problems specific to the southern African region where uncertainty is expected to be high because of data scarcity and because large parts of the region are poorly gauged.

1.2 Modelling tools in southern Africa

There have been many discussions in southern African countries about appropriate modelling tools for water resources estimation in the face of the limitations of the relevant data. This is due to water resources management pressures as a result of gradual depletion of available water resources with increasing demand. Within this data scarce region, water resources planning and management decisions are frequently based on simulated information. One can classify most of the basins in southern Africa as poorly gauged basins due to the rather low and unevenly distributed observation stations of hydrometeorological variables of interest (i.e. rainfall, evaporation, runoff, etc).

It is common practice that all the available hydrometeorological data are used to establish a rainfall-runoff model to simulate representative time series of naturally available water resources. These estimates of natural streamflow are then used with the information on water use and other anthropogenic factors, such as land use change, within water resources systems models to estimate current levels of water availability. However, the reliability and accuracy of water use information, such as patterns of irrigation water use, changes in land use patterns and water utilisation practices is questionable. In South Africa, rainfall-runoff and water resources yield models are being developed in response to specific practical needs such as estimating available water resources or assessing impacts of development needs or climate change (Schulze, 2000; Hughes, 2004a). The emphasis is on the practical use of scientific research in the field of water resources planning and management. The hydrological models widely used in South Africa are the Pitman model (Pitman, 1973; Hughes, 2004b; Bailey and Pitman, 2005), a conceptual, semi-distributed monthly time-step model and ACRU (Agricultural Catchments Research Unit; Schulze, 1990; 1995), a conceptual, physically-based daily time-step agro-hydrological modelling system. These models have frequently provided valuable information for water managers. The Pitman model is traditionally calibrated against observed flow data (Pitman, 1973), but Kapangaziwiri and Hughes (2008) has recently developed an *a priori* approach for estimating some of the traditionally calibrated parameters directly from basin physical property data. The *ACRU* model is not a parameter fitting model and the parameters are designed to be estimated from the physical characteristics of the basin (Schulze, 2005).

One of the issues that has been neglected in water resources modelling in South Africa and many other southern African countries is the incorporation of the uncertainty that exists in the quantitative estimates of water resources availability in management decisions. If the treatment of uncertainty is to be advanced, an appropriate conceptual structure and practical methods are required for handling uncertainty. In addition, efforts to reduce predictive uncertainty such as establishment of ways to improve databases, and quantifying the spatial and temporal impacts of artificial influences in hydrological basins are needed. However, in practice there will always be uncertainty even if efforts are made to reduce the uncertainty and therefore there is a need for parallel approaches to incorporate uncertainty into estimates and reduce that uncertainty. It should therefore be clear that, for any water resources assessment procedure, uncertainty analysis is always relevant and there should be no reason for not incorporating it.

The selection of South Africa for the present study was based on data availability, that is, the existence of historical and quality-controlled datasets (rainfall, evaporation, geology, soils, regionalised parameter values, observed and naturalised flow data). While not without problems, these data have provided the baseline information for a wide range of water resources assessments in South Africa. Such information would be difficult to obtain from other countries in southern Africa. The availability of these datasets allows the methods and procedures that are relevant to the present study to be effectively tested and the findings would be applicable to the whole of southern Africa. This is because, in this thesis, it has been assumed that the characteristics of the test sub-basins from South Africa would be representative of the hydro-climatic and physical conditions mostly found in many parts of southern Africa region.

In spite of the number of models available for water resources assessments, the Pitman model was selected for use because it is the most widely used model for regional scale water resources planning in South Africa and many other countries in the region (Hughes, 1997; Hughes *et al*., 2006). The model is semi-distributed and has been previously applied at a wide range of sub-basin scales and climate conditions. While the general approach adopted for uncertainty assessment in this study is model independent (such as uncertainties associated with model input data or water use data), the analysis of uncertainties associated with parameter values is model dependent since any parameter estimation approach is not entirely independent of the model structure.

1.3 Rationale

It has been shown that the process descriptions used in current hydrological models may not be appropriate; that the data inputs are not representative, that the appropriate model parameter values may vary within sub-basin scales, that techniques for parameter estimation are often at inappropriate scales, and that there is uncertainty in the model structure (Beven, 2001a). Recognising these problems in hydrology, there will always be multiple acceptable models to represent a sub-basin of interest, all reproducing any observation of basin runoff to some acceptable level. There is therefore a need to work with existing hydrological models to make predictions within an uncertainty framework, which allows for such inherent equifinality (Beven, 1993) in models to match the current levels of observed data accuracy. In spite of this, and the fact that many ungauged basins exist, the current practice of water resources estimation using hydrological models in South Africa has not taken much account of uncertainty. The evaluation of the different sources of uncertainty will allow water managers to be able to identify the uncertainties that are important in influencing the final modelling results and focus resources efficiently. Given that the concept of uncertainty analyses is well understood by academics but is awkward for practitioners, the latter would welcome more guidance and increased awareness on this aspect. This would empower them to make appropriate decisions using cost-benefit analyses of various water resources management options (for example, risk analysis) that usually follow. Public discussions and policy decisions in South Africa are frequently based on deterministic model results since stakeholders believe that making decisions does not require total accuracy. However, this study contends that decisions are greatly enhanced if the confidence in the scientific results (uncertainty bounds) is known and incorporated into the decision-making process. It is therefore critical to encourage model users in South Africa to recognise the inherent uncertainty in their results and to start applying uncertainty principles in water resources estimation and consequently in the decision making process. There are, however, several constraints that must be addressed that are related to data availability and accuracy, as well as the capacity or willingness to adopt new methods that incorporate uncertainty estimates.

While many recent studies have focused on the effectiveness of uncertainty modelling approaches (Gupta *et al*., 2006; Beven, 2006b), this study contributes to the development of procedures and guidelines for uncertainty estimation for hydrological model users in South Africa. It presents some guidelines on the identification of sources of uncertainty and how these different sources of uncertainty can be quantified in the current hydrological modelling practice in South Africa. It also offers suggestions on alternative options to reduce some of these uncertainties and to improve the application of one of the recent versions of the Pitman model. While for complete uncertainty analyses, quantifying all sources of uncertainty and how they propagate within the model would be desirable, this was not feasible in this study as this would be a huge task beyond the resources and time available for a single research project. The main focus was on uncertainties associated with model input data, parameter estimation and water use data, although this is not intended to downplay the importance of uncertainty arising from suitability of the model structure. The expectation of the study is to raise awareness on the importance of incorporating uncertainty analyses in water resources modelling in South Africa. This is because it is widely accepted that conducting uncertainty analyses can provide guidance to improve the quality of decision making, to assess the robustness of decisions, and to understand whether the current knowledge is sufficient to make decisions.

1.4 Research questions

The study attempts to answer the following research questions:

1. What are the main sources of uncertainty in hydrological model applications in South Africa and/or the whole of southern Africa region?
2. How can the uncertainty be quantified given data and model constraints?
3. What are the alternative approaches of minimising uncertainty in model predictions?
4. If we introduce alternative approaches to reduce uncertainty, can they not introduce more uncertainty?

1.5 Study objectives

The study is aimed at contributing to the development of procedures and guidelines for the assessment of water resources estimation uncertainties in South Africa which are consistent with the constraints of the model structure, data and human resources. The emphasis is on the Pitman model, but some observations and analyses will also be relevant to other models that are commonly used to estimate water resources availability. It is also aimed at quantifying and suggesting the possible options of reducing the identified sources of uncertainty. Local and international trends and initiatives in water resources modelling are investigated and compared. The findings are used as a basis for developing guidelines for evaluating uncertainty in water resources estimations in South Africa. In this study three specific objectives have been identified:

1.5.1 Identify sources of uncertainty and quantify their individual impacts on model output uncertainties.

This should offer the hydrologist a valuable insight regarding the contribution of each individual source of uncertainty to the overall model output. Particularly:

- *Identification and classification of each source of uncertainty.*
- *Quantifying the propagation of each source of uncertainty (in particular input data and parameter uncertainty) to the model output uncertainty.*

1.5.2 Identify possible options for reducing uncertainty in model input data and parameter estimation.

The aim is to reduce sources of uncertainties identified and quantified in objective 1.5.1. In some instances, only the identification of sources of uncertainty would be achieved as the reduction component would require collection of more data and/or improved measurement techniques. The applicability of the options, are illustrated for selected hydrological problems in South Africa, particularly;

- *The potential use of satellite based rainfall data and correction procedures to improve spatially averaged rainfall estimates.*
- *The potential use of temperature time series data to estimate variations in potential evaporation demand.*
- *The application of a priori parameter estimation procedures including uncertainty for the Pitman model*.

1.5.3 Investigate the combined contribution of uncertainty sources to model output uncertainty.

This objective follows from objective 1.5.1 and is designed to assess the impacts of all the sources of uncertainty (including uncertainty in some water use data) collectively on model outputs and how these uncertainties interact within the same framework in order to achieve more complete information on overall model predictive uncertainty as an important requisite for an improved assessment of risk. This is because outputs from hydrological models are used as inputs to water resources yield models which simulate present day water availability which aid in decision making process for future management of risks. If the present day impacts are not adequately quantified, the availability of water resources for future development will not be accurately estimated even if the estimates of the natural water resources are.

1.6 Structure of thesis

Chapter 2 reviews the relevant literature and the theoretical background of the study. **Chapter 3** introduces the study area and general methodologies. **Chapter 4** introduces the potential sources of uncertainty and the procedures used to identify the main sources of modelling uncertainty in the application of the Pitman rainfall-runoff model. **Chapter 5** involves an assessment of uncertainty in the estimation of spatial rainfall and its propagation into streamflow predictions. Some alternative procedures and data sources (satellite data products) that can be used to reduce rainfall data uncertainty are reported in **Chapter 6**. **Chapter 7** provides a detailed analysis of uncertainties associated with the estimation of the potential evapotranspiration demand and how they impact on streamflow predictions. **Chapter 8** discusses procedures and results for parameter estimation, sensitivity and uncertainty analyses. **Chapter 9** describes a strategy that integrates evaluations of all the different sources of uncertainties including water use data within the same framework in a South African context. The overall conclusions and recommendations for the study are provided in **Chapter 10**.

2. LITERATURE REVIEW AND THEORETICAL BACKGROUND

This chapter has been structured such that the relevant literature drawn from mainly three databases, which are, the Science Direct, Scopus and Scirus as well as national reports, and the theoretical concepts in hydrological modelling including uncertainty estimation from both international and regional perspectives are presented. The general theory of rainfall-runoff modelling concepts and application of hydrological models in both gauged and ungauged basins are first introduced, followed by a review of the literature on identification and quantification of the sources of uncertainty in the application of hydrological models dating from the 1980s. An overview of existing uncertainty assessment techniques and potential options to reduce some of the sources of uncertainty are introduced and discussed. The final section then provides an overview of the current hydrological modelling practices in South Africa with special emphasis on model development and application, and the need to shift to a modelling practice that incorporates uncertainty in any water resources estimation process.

2.1 General rainfall-runoff modelling concepts

The increase in computing power has seen the development of rainfall-runoff models to simulate and extrapolate natural hydrology. The main objective of hydrological modelling is to provide reliable information for water resources planning and management through an understanding of the hydrological processes and their interaction. Any kind of modelling can be looked upon as a system that transforms the input into output, with a good example being the unit hydrograph model which is a linear transformation of effective rainfall to runoff (Duband *et al*., 1993). Rainfall-runoff models are mathematical representations of natural hydrological systems which can be very complex and highly variable in time and space (Pitman, 1973; Beven, 1989). Often, it is not possible or practical to represent the hydrological system in great detail, and simplifying assumptions are commonly made. This is done for a number of reasons, including a lack of basic data and that all the factors and processes affecting system behaviour are not fully understood (Beven, 2000a). Simplifications of the physics and lack of complete knowledge about the hydrological processes are problems always faced by hydrologists.

There are many different models in hydrology, which vary on lines of development or degrees of complexity (see e.g. Clarke, 1973; Wheater *et al*., 1993; Singh, 1995). They range from complex descriptions based on partial differential equations to simpler and less complex conceptual descriptions. Models are distinguished based on contrasting properties such as stochastic versus deterministic, conceptual versus physically-based, lumped versus distributed models, and others (Clarke, 1973; Abbott and Refsgaard, 1996). These divisions, as presented here, are more general than rigorous and may not encompass all concepts and views in the history of rainfall-runoff models. A fundamental distinction is between stochastic and deterministic models. Stochastic models are data based and assume some randomness or uncertainty in the simulated output as a result of randomness in input variables, while deterministic models are process based and assume single prediction of all its output variables being produced from a sequence of given inputs and that processes are defined in physical terms without a random component (Beven, 2001a, b).

2.1.1 Classification of hydrological models

Rainfall-runoff models have been classified on the basis of their structure as either black box (empirical), grey box (conceptual), or white box (physically-based) models (Clarke, 1973). Empirical models represent only the numerical relationship of observed output to observed input data without an understanding of processes and a very good example is a linear regression model that relates runoff volume to rainfall depth (Kokkonen and Jakeman, 2001). In contrast, physically-based models are based on the laws of thermodynamics, conservation of mass, momentum and energy such as St Venant equations (Beven, 2002a). These models treat a basin as a spatially variable system and processes involving a hill slope to the entire basin may be modelled (Beven, 2001b, 2002a). Between empirical and physically-based models exist conceptual models in which some understanding of hydrological processes is included in the model formulation. In conceptual modelling, the basin is perceived as consisting of several moisture storages through which rainfall inputs are routed by a process of moisture accounting, eventually to produce streamflow output, all of these elements are represented explicitly by mathematical relationships (Beven, 2001a).

Rainfall-runoff models are further classified on the basis of the scale at which they represent the basin hydrological system, that is, as either lumped or distributed in nature (Todini, 1988). With lumped models, a basin is treated as a single unit and rainfall inputs are related to streamflow outputs with no consideration of the spatial variations of processes and characteristics within the basin (Szymkiewicz, 2002). Alternatively, with distributed models an attempt is made to take account of the spatial variations of hydrological response within a basin, which is treated as a discrete unit (Abbott *et al*., 1986; Abbott and Refsgaard, 1996; Beven, 2001b). The discussion that follows attempts to give an overview of the way hydrological models evolved from simple lumped, through conceptual to more complex physically-based distributed models.

2.1.2 History of hydrological model development

Rainfall-runoff modelling effectively began in the 1880s with the development of the 'rational method' that relates streamflow directly to a measure of rainfall inputs, basin area, and a runoff coefficient (Dooge, 1957; Smith and Lee, 1984). The difficulty in applying this method was deciding on the value of the runoff coefficient because this parameter would not only vary from one basin to another, but also with the magnitude of an event and state of the basin before an event. In the 1960s, more complex lumped models were developed to explicitly reflect the perceptions of hydrologists about the processes of hydrological responses to rainfall inputs. This led to the unit hydrograph approach (Dooge, 1959; Newton and Vineyard, 1967) that attempts to predict the time distribution of discharge as well as its peak through a linear approximation process. Despite serving hydrologists quite well, the linear assumption of the unit hydrograph approach has been much criticized because hydrological responses to rainfall are non-linear (Dooge, 1979; Bates and Davies, 1988). This saw the introduction of conceptual-lumped models to account for non-linearity in rainfall-runoff responses, in particular when computers started to become widely available between the 1960s and 1980s. One of the earliest examples of such a model is the Stanford Watershed Model (Crawford and Linsley, 1966; Görgens, 1983), which is a lumped explicit soil moisture accounting model in that it represents different basin hydrological processes and storages (interception, upper soil moisture, lower soil moisture and groundwater) with several elements. The flows between these stores are controlled by different parameters, which require calibration for a particular application against observed data (Beven, 2001a). These models vary widely in terms of the number of parameters, from simple (Roberts, 1979; Diskin *et al*., 1973) to more complex structures (Crawford and Linsley, 1966). However simpler models are often preferred because they have few parameters that require calibration and their performances are often similar to those gained from using complex models (Young *et al*., 2006). Other examples of conceptual models are the Sacramento model (Burnash, 1995), the HBV (the Swedish name of Sweden's Meteorological and Hydrological Institute, where the model was developed) model (Bergström, 1995) and the Pitman model (Pitman, 1973). However, conceptual models can be made distributed by applying them to different sub-basins and routing the outputs to the point of interest using a river routing component, a strategy often called semi-distributed modelling. An example is a soil water balance (SWB) model (Schaake *et al*., 1996), which explicitly accounts for spatial variability in rainfall and model states. A semi-distributed modelling approach takes account of spatial heterogeneity of parameters over a basin but retains the more simple structure of the less data intensive lumped models. The limitation of such a strategy would be that each sub-basin would then require its own set of parameter values and rainfall inputs to be estimated.

In contrast to conceptual models, where parameters are frequently estimated through calibration against observed data, the parameters of fully physically-based distributed models are expected to be directly measurable from basin physical characteristics. Physically-based distributed models have the advantage of taking into account the variation of several basin processes and states at a number of locations distributed in the basin (Binley *et al*., 1991; Beven, 2001b; Moreda *et al*., 2006). It must be noted that, despite the distributed nature of these models, some degree of parameter 'lumping' occurs because the scale of the model is generally larger than the scale which characterises the operation of various hydrological processes (Beven *et al*., 1988). The important perceived difference between conceptual and physically-based distributed models is that the parameters of physically-based models may be validated with field measurements and are generally more suited for basins with no observed response data. Physically-based distributed models are often considered to be more appropriate in situations with no observed response data because of their basis in physical representation of the basin processes (Abbott *et al*., 1986). However, a major drawback of such models is their impracticality due to the amount of data inputs required and their complexity (Beven, 1989; Binley *et al*., 1991). Well-known examples of distributed models are TOPOMODEL (Beven *et al*., 1995), the MIKE SHE model (Rafsgaard and Storm, 1995) and the SWAT model (Arnold, 1992).

Given this wide variety of different rainfall-runoff models available, there is a real problem of model choice for any practical application. Model users often prefer simple models that are relatively easy to operate but represent important hydrological processes (Butts *et al*., 2004). Therefore, the semi-distributed modelling approach which attempts to bridge the gap between a simple lumped approach and the complex distributed modelling approach is most favoured. In this regard, Beven (2001a) summarises a number of criteria on which to base model choice including model availability, data input requirements, the ability of the model to make predictions and its assumptions. However, he further argued that some compromises have to be reached if these criteria are to be used for practical applications, otherwise all models would be rejected and hence model users must be able to evaluate the uncertainties associated with such compromises.

In practical water resources assessments, the scale of application of a hydrological model as well as the resolution of model input data, both spatially and temporally, has a major influence on its structure and detail (Klemeš, 1983; Schaake *et al*., 1996). With respect to spatial scale, aspects of natural processes that are important at one scale may not be relevant at another and therefore models can be scale dependent (Beven, 1995; Blöschl and Sivapalan, 1995). From a water management perspective, the spatial scale at which predictions are of practical importance ranges from property or cadastral scales, through catchment or basin scales to regional or national scales. Inevitably, more complex models would require more detailed data, measured at finer scales while the simpler models would require less detailed data, averaged over broader scales (Koren *et al*., 1999). Equally, there is little or no benefit in modelling at complex levels beyond what can be reasonably supported by the available data (Perrin *et al*., 2001). Conversely, simpler models that require simple inputs often do not adequately capture all the necessary hydrological processes operating in any given hydrological system (Wood *et al*., 1990). Temporal scale is reflected in the time-step of the model and rainfall-runoff models simulate the behaviour of hydrological systems over a period of time, which may range from fractions of an hour to decades or more. The time period over which a model is run also influences its complexity and it is rarely viable to apply highly complex models over long time periods, often due to a lack of climate data measured at shorter time steps (Finnerty *et al*., 1997). Therefore, a balance is needed between the available data, model complexity and the desired outputs from the model.

The history of rainfall-runoff models is such that it has evolved over the last few decades from simple empirical, through conceptual to complex physically-based models (Dooge, 1959; Binley *et al*., 1991), and back to simpler or parsimonious models (Perrin *et al*., 2003). This has largely been due to the search for appropriate modelling tools to achieve specific objectives. The concept of appropriate modelling means developing and selecting a model with a level of complexity that reflects the actual needs for modelling results (Jakeman and Hornberger, 1993). To understand hydrological processes, the model's ability to describe them is very important and a good fit of a model to observed data may be obtained by parameterisation of the different processes involved (Beven, 1989). The concept of parameter parsimony in describing hydrological processes is thus crucial and even more important when the models are used for predictive purposes (Perrin *et al*., 2003; Lazzarotto *et al*., 2006). Reliable predictions can only be achieved with models using a set of appropriate parameters that reflect the fundamental governing mechanisms involved in the basin (Beven, 1989). The main problems seem to be related to model complexity relative to data availability, choice of objective functions and the associated difficulties in identifying the chosen model structure and estimating its parameters (Yew Gan *et al*., 1997). These issues still constitute the largest obstacle to the successful application of water resources estimation models in both gauged and ungauged basins. This has seen the introduction of new modelling approaches and initiatives including fuzzy modelling techniques (Kundzewicz, 1995), top-down approaches to model development (Sivapalan and Young, 2006), calibration and uncertainty estimation in rainfall-runoff modelling (Beven, 2001a) and Prediction in Ungauged Basins (PUB) initiative (Sivapalan *et al*., 2003). These new approaches and initiatives are being introduced in recognition of the difficulties and limitations to the successful application of the current hydrological models to aid in decision making processes.

2.2 Calibration and validation of rainfall-runoff models

2.2.1 Model calibration

Rainfall-runoff models are a simple representation of the ‘real’ world, which means that their parameters necessarily aggregate the non-uniform basin hydrological processes using empirical relationships (Beven *et al*., 1998). Consequently, the parameters often lose their exact physical meaning and therefore, all models (whether simple, conceptual or complex physically-based) are normally calibrated against observed data to identify the model parameters appropriate for a given condition (Beven and Binley, 1992). This is because there are no measurement techniques that would allow the direct observation and independent estimation of the parameter values at a scale required by a model (Klemeš, 1983; Abbott *et al*., 1986). There are two classifications of model parameters that exist, namely; the calibration parameters that appear in empirical relationships and need to be calibrated from observed climate and runoff data, and the physically-based parameters that in principle are observed or estimated directly from measurements in the basin. The limitations of using physically-based parameters are related to their scale-dependences and the quality of information from which these parameters are derived (see e.g. Beven, 1989). A focus of the discussion in this section is on calibration parameters. The main reasons for calibrating models are threefold: to account for effects of the hydrological conditions in a particular sub-basin, to adjust for biases in climate inputs (such as rainfall measurement errors, spatial and temporal variability), and most importantly, to account for basin physical properties (soil and vegetation) which are highly non-uniform and essentially unknown or at least poorly known (Blöschl, 2006).

It has often been suggested or implied in the literature that the data used to calibrate hydrological models should be representative of the various phenomena experienced by the basin (Beven and Binley, 1992; Ao *et al*., 2006). Given the limitations of observed streamflow data, as well as the model structural constraints, it is frequently difficult to achieve unique model solutions when observed responses are available (Beven, 1993). In practice, the climate and streamflow data necessary to search for suitable parameters for an existing condition in gauged basins are often not reliable. Streamflow data may have missing and short records, in addition to variable effects of developments (e.g. small dam or irrigation abstractions) that need to be accounted for before use with a model designed to simulate natural conditions, while rainfall data may be sparse, or completely unreliable due to measurement errors or non-representativeness. There is therefore no general agreement on how best to calibrate hydrological models, as calibration is associated with uncertainties (see section 2.4 for more details) that cannot be easily separated (Gupta *et al*., 2006). In any calibration procedure, not all parameters are treated alike because some of the parameters are sensitive while others are not (Beven, 2001a). The most sensitive parameters are considered to have an important role in the physical processes and are explicitly involved in the parameter calibration process, while others are considered useful only for fine tuning the model results. The other parameters normally have their values fixed to their initial estimates throughout the calibration procedure as they are considered to have a negligible impact on model results (Beven, 2001a). The type of parameters in each case depends on the type of the rainfall-runoff model under consideration.

Two approaches are widely used to calibrate rainfall-runoff models, namely manual and automatic calibration approaches. Manual calibration requires an experienced user to adjust parameters interactively in successive model runs to improve results. In evaluating the quality of model fit to observed time series, human judgement and one or more objective functions are often used, for instance, the Nash-Sutcliffe Efficiency (Nash and Sutcliffe, 1970). The advantage with this procedure is that parameter values can be selected so that they are hydrologically meaningful. However, the weaknesses with this procedure are the inherent subjectivity involved, since it is a trial-and-error process and a time consuming and labour intensive process. Hence, the parameters derived are subject to bias and there is no clear point at which the calibration process is said to be complete.

Automatic procedures, on the other hand, use a computer algorithm to search the parameter space through performing multiple runs of the model such as the Shuffled Complex Evolution method (Duan *et al*., 1992; Vrugt *et al*., 2003). The advantage with this approach is that the computer does much of the work of exploring parameters rather than the user and the procedure is objective. The calibration process should ideally be able to define an optimum parameter set which cannot be normally achieved with manual calibration. However, the disadvantage of the approach is that this may essentially be a numerical exercise which produces parameters that may lack physical meaning (Hughes, 1997; Yapo *et al*., 1998). Despite this, automated calibration procedures can perform favourably when multiple objectives are used (Gupta *et al*., 1998; Bastidas *et al*., 1999; Madsen *et al*., 2002). A lot of literature on the automated calibration methods exist (e.g. Beven and Binley, 1992; Duan *et al*., 1992; Kuczera and Parent, 1998; Yapo *et al*., 1998; Madsen, 2000), but these methods suffer from 'equifinality' problems, where many parameter combinations give similar acceptable simulation results (Beven, 1993; Beven and Freer, 2001). However, Boyle *et al*. (2000) contemplated that a more robust calibration strategy would require the use of combined automated and manual approaches. This is particularly true for semi-arid regions where there is limited spatial information and highly non-linear rainfall-runoff relationships (Shah *et al*., 1996). Here the automated approach must be done after an initial manual calibration to fine tune parameters to physically acceptable ranges. Automatic techniques have been developed and tested for calibrating the Pitman model parameters in southern Africa, but did not give acceptable simulation results (Ndiritu and Daniel, 1999). This was attributed to model structure and data errors, because the optimisation process may generate parameter values that reflect the noise in data, rather than the real signal of the hydrological response (Hughes, 2004a). It is evident, therefore, that parameter values estimated through automatic procedures may be fraught with uncertainty, not limited to parameter sensitivity, parameter interdependences and the location of local or global optima (Beven, 2001a). While it may not be easy, the uncertainty associated with any parameter estimation or calibration process needs to be quantified (see section 2.4 for more details on this aspect)

2.2.2 Model validation

In testing if rainfall-runoff models can be generalised and assessing if the calibrated parameter values are suitable, the calibrated model should be run with an independent set of data or an independent period of the same data record, a process often referred to as model validation (Kapangaziwiri, 2008). When the comparison between the simulated and the observed streamflow is acceptable in relation to the result obtained during the calibration period, the model is said to be validated. A detailed scheme of validating models has been outlined by Klemeš (1986) which includes split-sample tests, differential split-sample tests, proxy-basin tests and differential proxy-basin tests. However, Hughes (1993) highlighted that the multi-criteria validation approaches assess model simulations with different variables to those used in calibrating the model, and have the potential to reduce the equifinality problems (Beven and Freer, 2001).

Despite the importance of validating models, in practice, independent datasets or long records for split-sample tests may not be available. This is a critical issue in southern Africa where even observed streamflow data to calibrate the models are already limited. In addition, the independent data useful to validate a model may not be representative and Klemeš (1986) postulated that the model should be validated for the intended purpose, beyond which model performance cannot be guaranteed. Typically validation statistics are often worse than for the calibration period and Rosbjerg and Madsen (2006) questioned whether a model can be validated at all.

2.3 Prediction in ungauged basins

A basin where no runoff data or where measurements do not relate to the condition being modelled is termed "ungauged". The application of hydrological models in ungauged basins has received much attention in the hydrological community in recent years through the International Association of Hydrological Sciences (IAHS) Decade on Prediction in Ungauged Basins (PUB) (Sivapalan *et al*., 2003) and this remains a difficult field in hydrological research (Wagener and Wheater, 2006; Wagener and Kollat, 2007). The application of rainfall-runoff models to ungauged basins requires that model parameters are estimated by other methods and a practical discussion of parameter estimation methods is given in Duan *et al.* (2001). The model parameters are either estimated by inferring from field measurements or remote sensing (*a priori* estimation) or by parameter regionalisation (transposing calibrated parameters from similar gauged basins or using the notion of hydrological similarity) approaches. In theory, estimating the parameters should be a straightforward task, but the extreme non-uniformity of basin physical conditions (e.g. soil properties) or the unresolved spatial and temporal variability of climate variables and model structure constraints may limit the estimation of the appropriate parameters in ungauged basins (Beven, 1989, 1993).

Modelling ungauged basins started a long time ago with the use of simple approaches such as the rational method. The increased availability of computers in the 1960s prompted the development of continuous watershed models (Nash and Sutcliffe, 1970) and since then one of the focus areas of research has been attempts to estimate parameters in ungauged basins. Different approaches have been used at different sub-basin scales which include the proxy-basin method (e.g. Klemeš, 1986), linear interpolation methods (e.g. Bergström, 1990), multiple regression approaches (e.g. Seibert, 1999; Fernandez *et al*., 2000; Mazvimavi, 2003), parameter mapping (Midgley *et al*., 1994) and *a priori* estimation methods (Duan *et al*., 2001). However, the problem is far from resolved given that regionalisation of parameters of rainfall-runoff models for prediction in ungauged basins is not an easy task and that the associated uncertainties are not always clear.

Data from gauged basins are frequently used to calibrate hydrological models and derive a set of parameters which are then used with a set of basin characteristics to derive regional relationships (Hughes, 1982), which form the basis for estimating parameters for ungauged basins. As an example, Hundecha and Bárdossy (2004) used a non-classical approach to develop regionalisation relations (transfer functions) between hydrological parameters and physical basin characteristics, while Merz and Blösch (2004) used the classical approach for regionalisation of parameters through regression methods for the HBV model. There are a number of problems associated with these regionalisation approaches. The approaches, for instance, require the parameters of the regionalisation relations to be calibrated in some way against observed data (Ao *et al*., 2006; Franks, 2007). There is uncertainty associated with the extent to which the rainfall-runoff relationships reflected in the observed data are sufficiently representative to allow a suitable parameter set to be quantified. However, the transfer of parameters is difficult as optimal parameter sets depend on model type and objective functions used (Gupta *et al*., 1998), parameters are themselves uncertain (Kuczera and Parent, 1998) and parameters are not unique (Beven and Freer, 2001). Consequently, there is high predictive uncertainty for ungauged basins even though regionalisation approaches based on parameter calibrations have been aimed at reducing parameter uncertainty (Franks, 2007). A good understanding of a particular model and a sound knowledge of hydrological processes within a natural system is necessary for developing reliable regionalisation approaches (Madsen *et al*., 2002).

Application of *a priori* parameter estimation approaches is also limited because they are fraught with the uncertainty associated with unknown scale-dependences of the parameters and problems of process responses being non-uniform (Beven, 1989; Binley *et al*., 1991). Despite this, investigations of physically-based parameter estimation approaches which do not require calibration to observed flow data are becoming popular for modelling ungauged basins (Gupta *et al*., 2006; Kundzewicz, 2007; Yadav *et al*., 2007). It is therefore appropriate to continue research on this aspect. Recent developments include improvements in the application of physically-based approaches to estimate model parameters directly from basin physical properties (Kapangaziwiri and Hughes, 2008) or use of alternative remote sensing data products to calibrate physically-based models (Baumgartner *et al*., 1997; Nandagiri, 2007). Additionally, Yadav *et al.* (2007) developed a model-independent approach to quantify basin hydrologic behaviour through the use of similar hydrological response indices within an uncertainty framework to constrain the parameter behaviour of ungauged basins.

The next section introduces the concept of uncertainty in water resources estimations given that it is an inherent element in the application of rainfall-runoff models due to compensation effects during the model calibration process. In situations where no observed response data (i.e. measured streamflow) are available, this uncertainty is likely to be severe, since these response data are normally used to reduce (at least) the uncertainty in the parameters (Blöschl, 2006). It is now generally accepted that all sources of uncertainty and their effect on model predictions should be quantified, since a reliable estimate of the prediction uncertainty is crucial for making efficient decisions on the basis of model simulations (Rosbjerg and Madsen, 2006).

2.4 Accounting for sources of uncertainty in hydrological modelling

The calibration of rainfall-runoff models for poorly gauged or ungauged basins and the simulation of basin development scenarios and water usage practices are problems faced by water resources managers (Ao *et al*., 2006). This is because they are frequently faced with short, patchy and unreliable climate and hydrological records with poor spatial coverages. Furthermore, the knowledge of geology, soil and land use is based on coarse scale maps that have not been generated using hydrologically relevant source data (Blöschl, 2006) and that appropriate databases of water use information are not always available. This makes the whole process of water resources modelling a challenge as the results could be highly unreliable due to the use of uncertain model inputs or inappropriate model parameter values (Beven, 2001a). Therefore, not accounting for sources of uncertainty could lead to false assumptions of modelling accuracy as well as consequent risks of potential outcomes and precludes the recognition of the need to reduce uncertainty and improve the reliability of the model results.

Incorporating uncertainty estimates in hydrological modelling is an emerging and crucial concept not only for scientists but for all water practitioners who use the model simulated results as it has significant impacts on the quality of the decisions. Despite its relevance, a significant part of the community is still reluctant to embrace uncertainty estimation in hydrological modelling. Pappenberger and Beven (2006) summarised seven common reasons why uncertainty analysis is not a normal and expected part of modelling practice, but argued that there should be no excuse for not incorporating uncertainty in water resources estimations. However, one of the main reasons that has so far prevented the full appreciation of the knowledge of uncertainty estimation is the impracticality of systematic testing and a lack of guidance in the use of many methods and applications that are available (Montanari, 2007). The problems of modelling hydrological processes have long been recognised and two issues need to be addressed in future modelling practice (Beven, 2006a). The first is how to estimate the uncertainty in hydrological modelling (in both gauged and ungauged basins) and reduce uncertainty using new datasets and improved estimation techniques. The second is how to present and use uncertainty in management decisions. This study will focus on the first issue.

It remains a challenge to those engaged in water resources planning and management to identify and quantify the main sources of uncertainty (Gourley and Vieux, 2006). It is also a challenge to develop methods and identify ways to reduce this uncertainty as well as how the uncertainty should be accounted for in decision making. Extensive literature on hydrological modelling has focused on various approaches to model parameter calibration and uncertainty analyses. Examples are the Generalized Likelihood Uncertainty Estimation (GLUE) by Beven and Binley (1992), the more recent Bayesian Recursive Estimation (BaRe) algorithm introduced by Thiemann *et al.* (2001), or the Shuffled Complex Evolution Metropolis (SCEM-UA) by Vrugt *et al*. (2003). Other studies have concentrated on the quantification of different sources of uncertainty (Kuczera *et al*., 2006; Kavetski *et al*., 2006; Rubarenzya *et al*., 2007; Wagener and Kollat, 2007), data assimilation (use of more information to constrain parameter values - Vrugt *et al*., 2005) and the general problem of estimating parameters in ungauged basins (Sivapalan *et al*., 2003; Yadav *et al*., 2007). To be able to interpret model results correctly, those engaged in model applications need to have information about possible uncertainties, their distribution and the consequences of using information containing uncertainties.

2.4.1 A topology of uncertainty in hydrological modelling

There are many definitions of uncertainty and perhaps the simplest is that "uncertainty is a general concept that reflects our lack of sureness or knowledge about outcomes which may be important in decision making" (Sayers *et al*., 2002). Beven (2000a) describes the risk of a possible outcome as uncertainty and that uncertainty differs from error in that an error represents a specific departure from "reality". Others postulate that uncertainties result from the natural complexity and variability of hydrological systems, and a lack of knowledge of the hydrological processes (e.g. Kundzewicz, 1995). There have been numerous attempts to distinguish between different types of uncertainty. Plate and Duckstein (1987) classified uncertainties into data uncertainties (e.g. measurement error), sampling uncertainties (e.g. sample size error), parameter uncertainties or model structural uncertainty (empirical equations and scaling laws), while Bernier (1987) distinguishes between natural uncertainty, that is related to the random nature of physical processes, technological uncertainty, sampling errors and model structure uncertainty. Melching (1995) distinguishes in detail between uncertainty related to (i) natural randomness (variability) of climate and hydrological data, (ii) errors in input data (precipitation, evapotranspiration, temperature, antecedent moisture conditions), (iii) errors in data used for model calibration and validation, (iv) use of inappropriate model parameters, and (v) use of incomplete or imperfect model structure. The source of uncertainties (i, ii and iii) depends on the quality of data and are independent of the model, whereas (iv) and (v) are more model dependent. The disagreement between observed and simulated outputs in rainfall-runoff modelling depends on all these sources of uncertainties. Table 2.1 shows a simple topology of uncertainty based on the major categories namely, real world environmental uncertainty (e.g. natural variability) and knowledge uncertainty (Environment Agency, 2000). A detailed description of each type of uncertainty in Table 2.1 and some background information are presented in the following sections.

Table 2.1 A simple topology of uncertainty (based on Environmental Agency, 2000).

Type		**Examples of sources**
a. Real world environmental uncertainty(e.g. Natural variability) (not reducible form of uncertainty)		-Randomness observed in nature (climate data) -Inherent variation in natural hydrological response systems
b. Knowledge Uncertainty *(This is a reducible form of uncertainty and is associated with ignorance or incomplete information)*	*i.* Model input data uncertainty	Climate data and hydrological data -missing/inaccurate records -non-representative data (spatial and temporal) -inappropriate temporal/spatial resolution -data processing
	ii. Model structural uncertainty	- Incomplete conceptual frameworks -Spatial and temporal averaging of a model -Ambiguous boundary conditions -Wrong process representation
	iii. Parameter uncertainty	-Lumping of parameters and scale issues -Parameter estimation process -Choice of objective functions -Use of inappropriate parameters -Parameter sensitivity and interactions

2.4.2 Real world environmental uncertainty versus knowledge uncertainty

Real world environmental uncertainty is related to variability, or a change in hydrological quantity (e.g. climate or streamflow) either in space or time. Variability occurs naturally or because of human activity (e.g. land use changes or management) and can be random (happening by chance) or systematic (trend or pattern) in nature (Environment Agency, 2000). Natural variability is related to the inherent unpredictable nature (occurrences and intensities cannot be predicted in advance) of hydro-climatic events. Variability is a form of uncertainty and the implications of understanding the differences between uncertainty and variability are relevant to decision making. The knowledge of variability can guide the identification of significant sampling uncertainty (e.g. number of raingauges) which might merit more focused study (Sawunyama and Hughes, 2007) or to ascertain whether the variability is due to "real" natural changing weather patterns. Climate variability is different from climate change in that the former is a natural variation in climate from one period to the next while the latter is a long-term alteration in the climate. The implication of real world environmental uncertainty is that natural variability may dominate and preclude the identification of trend signals in hydrological and climatic data either due to climate change or anthropogenic causes (Schulze, 2000, 2005). Climate variability may show trends when short records are used but these trends may disappear when more data are available. Because of climate variability, records of 30 years or shorter may not be useful for detecting climate change or other systematic trends (Schulze, 2005). While there is a need to quantify different sources of variability the decline in observation networks throughout the world represents a major constraint. The selection of time and space scales at which to resolve variability is often a challenging task to hydrologists since scale has a great effect on the perceived variability and a comprehensive review of scale related issues can be found in Blöschl and Sivapalan (1995).

Knowledge uncertainty is associated with the use of data with limited information or due to incomplete empirical knowledge or only a partial understanding of the processes, interactions and dependencies of different parts of the hydrological system (Beven, 1993, 2001a). The unrepresentativeness of input data, incomplete model structures and inappropriate parameter values form what is called "knowledge uncertainty'' (Table 2.1) and these are discussed below. However, knowledge uncertainty can be reduced through further research or measurements and through the use of improved approaches or models. The focus of recent studies on modelling uncertainty is on the quantification and reduction of knowledge uncertainty (e.g. Vrugt *et al*., 2005; Yadav *et al*., 2007).

2.4.3 Input hydro-climate data uncertainty

The uncertainties in input data (rainfall, evaporation demand and observed flow data) used in rainfall-runoff models are mainly associated with their spatial and temporal representation, errors in measurements, inconsistency and non-homogeneity of data, collection and processing of the data. The effects of errors in model input data related to measurement, inconsistencies and non-homogeneity in records have been studied

(Görgens, 1983; Seed and Austin, 1990; Schulze, 1995). One of the major causes for concern in model calibration is the fact that models can be fitted to input data that contain errors (Paturel *et al*., 1995; Oudin *et al*., 2006), which implies that the resulting parameter set cannot be considered representative of the real catchment response. Both climate and hydrological data are naturally continuous and variable in space and time and this presents a major challenge in obtaining representative observed time series (Smith *et al*., 2004; Habib *et al*., 2008).

The errors in estimation of rainfall may be due to inaccuracies of point rainfall measurements and these errors can be systematic or random. Systematic errors generally result in an under measurement of the true rainfall mainly due to wind effects as well as evaporative losses. Random errors can be caused by poor raingauge maintenance (e.g. leakage or damage), by the observer (inaccuracies in reading instrument) or can be introduced in the course of data processing and transmission (Görgens, 1983). Lack of representivity of spatial rainfall estimates may be related to limited gauging density or an inadequate distribution of point measurements (Sawunyama and Hughes, 2007) as well as inappropriate spatial interpolation approaches used to convert point data to spatial time series (Teegavarapu and Chandramouli, 2005). This has been confirmed by many other studies (Andréassian *et al*., 2001; Guo *et al*., 2004; Buytaert *et al*., 2006) which showed that the reliability of rainfall-runoff models is mainly associated with the ability to represent spatial and temporal rainfall characteristics.

Some of the initial studies of rainfall data uncertainties focused on how well networks of raingauges were capable of estimating total rainfall amounts using generated data (Troutman, 1983) and real gauged data (Krajewski *et al*., 1991; Shah *et al*., 1996; Andréassian *et al.*, 2001). Such studies commonly assume that the highest resolution data are approximately representative of the real pattern of rainfall behaviour (Obled *et al*., 1994). Goodrich *et al.* (1995) observed that rainfall could be considered spatially uniform for modelling small basins, and therefore does not contribute to parameter and output uncertainty. This assumption has been questioned since optimum parameter values are not independent of rainfall inputs (Görgens, 1983), while others recognised that bias in rainfall estimates may at least be partially compensated for by model parameter adjustment (Melching, 1995). It is clear that, no matter how physically-based or conceptual the hydrological models are, they will be sensitive to rainfall uncertainties (Faurés *et al*., 1995; Chaubey *et al*., 1999; Dong *et al*., 2005). The analyses from the various studies reported here were based mainly on adequately gauged small experimental sub-basins and extending such studies to large basins (with limited gauging networks) used for large scale water resources planning requires further research.

Other studies (Paturel *et al*., 1995; Nandakumar and Mien, 1997; Andréassian *et al*., 2004; Oudin *et al*., 2005) have assessed the sensitivity of rainfall-runoff simulations to uncertainties in potential evapotranspiration data. However, the quantitative effects on simulated runoff patterns of inadequate evaporation demand estimates have not been addressed fully in southern Africa (Sawunyama and Hughes, 2007). Fowler (2002) concluded that substituting mean potential evaporation estimates into a soil water balance model produces very similar results to using observed potential evaporation measurements under both dry and wet conditions. The problems with the data used to represent evaporation estimates in the models used in southern Africa are expected to be worse due to a lack of understanding of spatial and temporal variations of evaporation demand that vary within different hydro-climatic regions, in addition to the limited number of evaporation gauging stations.

Apart from rainfall and evaporation data uncertainties, further consideration is uncertainty in observed streamflow data used for model calibration. The main sources of errors are in the flow measurements and may be due to under-estimation and overflow of gauging structures since flow gauges will only measure certain flow ranges, in addition to rating curve inaccuracies especially at very high and very low flows (Peterson-Øverleir, 2006). Therefore, simulation of wet and dry years is often difficult when a model is calibrated using unrepresentative observed streamflow data. A further consideration is the length of the data period that is required to establish representative parameters (Anctil *et al*., 2004). Yapo *et al.* (1996) used a global optimisation method to calibrate a flood forecasting model and concluded that approximately 8 years of data are required to obtain stable calibrations. In contrast, Görgens (1983) found that more than 15 years of data are required to obtain acceptable calibrations in semi-arid situations. Moreover, it is often difficult to determine spatial variations from available streamflow data because many of the available time series have gaps due to missing data or are non-stationary due to time variant land use effects or water abstraction patterns which effectively shorten the record period (Smakhtin, 2001). The decline in quality of observed flow records and the increased number of ungauged basins makes it difficult to calibrate hydrological models with observed flow data. It is therefore difficult to regionalise model parameters for prediction in ungauged basins and alternative approaches are required.

2.4.4 Model structural uncertainty

Given that rainfall-runoff models are simplified representations of hydrological systems, the choice of model assumptions for process descriptions is often a key aspect in the model structure (Beven, 1989). The assumptions may exist in the conceptualisation and mathematical formulations of the model structure as well as the computer coding, contributing to model structure uncertainty. However, it is often difficult to separate uncertainty in model structure and uncertainty in the parameter values because the parameters are not independent of the model structure (Beven and Binley, 1992).

The degree of spatial and temporal averaging of hydrological processes that occurs in a model may introduce a degree of uncertainty to model outputs which may be difficult to quantify (Sieber and Uhlenbrook, 2005; Beven, 2006b). There is always a trade-off between computation time and the space and time resolutions used within a model (Beven, 1995). Very often, a coarse grid resolution introduces approximations and uncertainties into the model results. However, a finer resolution may not necessarily result in more accurate predictions despite a demand for more computer resources and input data. Besides, our limited understanding of hydrological processes even at small scales often results in inappropriate assumptions and, therefore, governing equations (Hughes, 1993; Beven, 2000a). Uncertainties may also arise when there are alternative sets of scientific assumptions for developing the same model. In such cases, if the results from competing models give similar conclusions (Beven, 1993), then one can be confident that the decision is robust in the face of the uncertainty. If, however, model formulations lead to different conclusions, further model evaluation might be required.

Model structural uncertainties are also associated with the understanding of hydrological storages and processes of water movement within the limitations of the time and space scales used in a model. Fully distributed models have been developed to represent surface, soil and subsurface flow processes in time and space (e.g. MIKE SHE, Rafsgaard and Storm, 1995). Despite the ability of a distributed model to account for spatial variability of the inputs and sub-basin characteristics and the use of measured parameters, only very approximate solutions could be achieved even with the best computers when the equations are applied at grid scales (Freeze and Halan, 1969). In spite of these models requiring high resolution observed data, local measurements to estimate parameters are generally at a coarser scale than the model scale. Some models have attempted to take account of the temporal and spatial heterogeneity of processes at sub-basin scales but in a parsimonious way (i.e. with a small number of parameters). Examples include the Probability Distributed Function (PDF) (Moore and Clarke, 1983; Moore, 1985), Arno model (Todini, 1996) and the Variable Time Interval (VTI) model (Hughes, 1993; Hughes and Sami, 1994). These models have been developed as semi-distributed, to account for the spatial variation of some variables within basins and include 'sub-grid' (i.e. variations at smaller scales than the sub-basins) effects as part of the model structure. Because of simplifications made, the non-linearities and thresholds of processes (Zehe *et al*., 2005) that exist in nature are not adequately represented by these models and hence, predictions though spatially variable, are more approximate than for fully distributed model. Therefore, a question still remains that if the model structure is inadequate can a satisfactory result be obtained with any set of parameters? Several authors have already concluded that the current model structures are not capable of reproducing the streamflow hydrograph or flow ranges with a single parameter set (Gupta *et al*., 1998; Uhlenbrook *et al*., 2004; Wagener and McIntyre, 2005).

2.4.5 Parameter uncertainty

Uncertainty in the choice of a parameter estimation method and the parameter values themselves remain very crucial aspects in the application of hydrological models in water resources estimations (Beven, 2001a). The problem is more acute in ungauged or poorly gauged basins as there are no observed flow data to reduce parameter uncertainty through calibration process (Wagener and Wheater, 2006; Goswami *et al*., 2007). It has already been noted in section 2.2 that one perceived problem with any calibration process are the effects of data errors (especially observed streamflow data) on the resulting parameter set and how these uncertainties may be propagated into other areas where the model is applied. One approach to reducing this problem could be to use *a priori* parameter estimation procedures based on basin physical properties (see also section 2.3). However, using *a priori* parameter values may be associated with uncertainties in physical property data and how the parameters are related to basin physical characteristics. Alternatively, when regionalisation approaches to parameter estimation are used, the uncertainties in parameter values may be related to uncertainty in the model structure and the hydro-climate data as well as the regionalisation methods themselves

The uncertainty associated with model calibration process is introduced from multiple sources (see e.g. Ao *et al*., 2006):

(i) *Model structure.* Given that model equations and its parameters are simple approximations of the description of the complex nature of processes (Beven, 1989), this will induce uncertainty in parameter values.

(ii) *The amount and quality of input data.* Inputs covering the same data period but with different temporal and spatial scales may lead to different parameter sets (Görgens, 1983; Bormann, 2005). The issue of appropriate data lengths for model parameter identification has been investigated (Yapo *et al*., 1996) with the conclusion that the required length mainly depends on data quality, model complexity and climate variability.

(iii) *The choice of initial parameter ranges.* This would affect parameter values, particularly when optimised, since the aim would be to find a parameter space wide enough such that acceptable fits of the model are not excluded, while at the same time, not so wide that parameter values have no sense or meaning or that they would result in unnecessary model runs (Beven, 2001a).

(iv) *The choice of objective function and optimisation algorithms used for model evaluation.* This could affect parameter sets, since the parameters are not independent of the objective functions and algorithms that are used (Gupta *et al*., 1998). Approaches to calibration based on a single objective function can lead to multiple parameter sets that are equally acceptable (Freer *et al*., 1996; Lidén and Harlin, 2000).

(v) *Equifinality.* This is a concept introduced by Beven (1993) that describes the situation where different parameter sets give similar simulation results because of parameter insensitivity and interactions. Beven (2001a) stated that this interaction can only be reduced when the number of parameters is small, one of the reasons for trying to identify parsimonious models.

It is beyond doubt that parameter uncertainty affects modelling results and their reliability (Melching, 1995; Uhlenbrook *et al*., 2004). Despite the many sources of parameter uncertainty stated above, most models appear to suffer most from (iv) and (v), which are related to parameter insensitivity and interactions as well as a lack of identfiability (Beven, 2001a).

With respect to point (v) above, equifinality is a result of trying to fit model parameters to available observed streamflow data and may arise from over-parameterization, data limitations and model structural errors (Uhlenbrook *et al*., 2004; Seiber and Uhlenbrook, 2005). The problem of equifinality has prompted a shift from identifying a single best parameter set towards finding a range of parameter sets that all result in model acceptability using the Generalised Likelihood Uncertainty Estimation (GLUE) methodology by Beven and Binley (1992), for example. The equifinality concept has been rejected by many (Yapo *et al*., 1998; Gupta *et al*., 1998; Boyle *et al*., 2000; Thiemann *et al*., 2001; Vrugt *et al*., 2003), in favour of finding an 'optimal' set of parameters in a Pareto or Bayesian sense using the global and multi-objective algorithm uncertainty estimation (MOCOM-UA). Beven (2006b), however, argues that the search for 'optimum' parameter sets has the risk of avoiding important issues of model acceptability and uncertainty, because a number of acceptably good fits can be found rather than just an 'optimum' parameter set. In his article, Beven further argued that the global optimum may change significantly with changes in streamflow data, errors in input data and changes in the objective functions that are used. Inevitably, through a parameter calibration process an objective function used to calibrate the model parameters implicitly assumes that all sources of uncertainties in the modelling process can be attributed to parameter errors (Ajami *et al*., 2007), which is not necessarily true in practice.

As model predictions are affected by other sources of uncertainty (see sections 2.4.1-2.4.4 above) and because of the highly non-linear nature of hydrological systems, it is not feasible to account for all the uncertainties from different sources through model parameter adjustment (Beven, 1993). Additionally, parameter insensitivity or interaction

(Beven, 2001a) is always present in the mathematical representations of natural systems and given the number of parameters used in physically-based models any parameter optimisation would be subject to far greater problems of interaction than simpler lumped conceptual type models (Beven, 1989; 2001b). As a consequence, parameters are not easily identifiable, making it difficult to regionalise the model parameters for use in ungauged basins. This is one of the reasons for a shift from the use of complex models with many parameters to simpler and less parameterised (parsimonious) conceptual models (Perrin *et al*., 2003). A number of studies have attempted to account for the different sources of uncertainty and the details of some of these approaches are discussed in section 2.5.

2.5 An overview of uncertainty estimation approaches

There is a rapidly growing body of literature on the estimation of predictive uncertainty in the application of hydrological models and the majority of the studies have concentrated on the development of algorithms for parameter estimation and uncertainty analyses (Beven and Binley, 1992; Thiemann *et al*., 2001; Vrugt *et al*., 2003) because parameter uncertainty is easier to quantify than other sources. There are a number of different approaches for addressing the problem of uncertainty in hydrology ranging from fractals, Bayesian, fuzzy-sets, random fields, time series, risk criteria and non-parametric methods (Kundzewicz, 1995). Uncertainty estimation aims at quantifying the overall uncertainty (i.e. spread or distribution) of model output (e.g. simulated streamflow) as a result of the propagation of different sources of uncertainty that arise in the model applications (such as input data, parameters or the model structure). Uncertainty analysis differs from sensitivity analysis which has been used for some time in rainfall-runoff modelling but has not been a standard procedure (Spear and Hornberger, 1980; Bastidas *et al*., 1999; Muleta and Nicklow; 2005). Sensitivity analysis only tries to understand how the variations in output are based on the variations in model input, the model parameters or structure without concentrating on the overall model output uncertainty (Saltelli, 2000). Many uncertainty analysis methods deal with parameter identifiability, ambiguity or uniqueness (Wagener *et al*., 2003), and thus include some elements of sensitivity analysis. Therefore, sensitivity analysis may be interpreted as a component of uncertainty analysis, but not the whole part. However, a separate discussion has been proposed for sensitivity analysis (section 2.5.1) because it is often confused with uncertainty analysis in practical applications. The uncertainty estimation methods that quantify amount of uncertainty in model output namely, first-order uncertainty analysis (i.e. mean-value first-order second-moment (MFOSM), advanced first-order second-moment (AFOSM)), Monte Carlo Simulation (MCS), Rosenblueth uncertainty analysis, Latin Hypercube simulation (LHS), Harr's point estimation method, (see the thorough review by Melching, 1995) and the Bayesian family of uncertainty analysis methods (e.g. GLUE by Beven and Binley, 1992; BaRe by Thiemann *et al*., 2001 and SCEM-UA by Vrugt *et al.*, 2003) are briefly discussed in section 2.5.2.

The formal application of sensitivity and uncertainty analyses in hydrological modelling serves several purposes: (i) to examine the behaviour of a model, (ii) to identify the important model input data or parameters, and the interactions between them, to guide the calibration of the model, (iii) to identify input data or parameters that should be measured or estimated more accurately to reduce uncertainty of model outputs and (iv) to quantify the uncertainty of the model results (Saltelli, 2000).

2.5.1 Sensitivity analysis

Sensitivity analyses attempt to ascertain how a model depends on its inputs, parameters, structure and framing assumptions (that is, reveal the relative contributions of different modelling elements to overall uncertainty). Therefore, sensitivity analysis can be part of uncertainty estimation methods to decide where effort in defining and reducing uncertainty should be concentrated. In rainfall-runoff modelling, sensitivity analysis is a widely used approach at successive steps of the modelling process such as data selection, model development, parameter estimation and uncertainty assessment (Refsgaard *et al*., 2006). The sensitivity analysis techniques are grouped into local and global techniques (Saltelli *et al*., 1999). The local techniques allow the response of outputs to variation of individual inputs or parameters while fixing the other parameters at their initial values. The global techniques allow for variation of all inputs or parameters and implicitly account for parameter interactions (Muleta and Nicklow; 2005). However, only a few studies explicitly discuss the effect of parameter interactions on the parameter identifiability and Bastidas *et al.* (1999) pointed out that most sensitivity analysis techniques are weak in dealing with issue of parameter dependency.

The existing sensitivity analysis studies, involving rainfall-runoff models mostly deal with the sensitivity to rainfall input data (Andréassian *et al.*, 2001; Fekete *et al.*, 2004; Xu *et al.*, 2006), the sensitivity to potential evapotranspiration input data (Andréassian *et al*., 2004; Oudin *et al*., 2005) and the sensitivity to model structure and parameter values (Butts *et al*., 2004; Vrugt *et al*., 2005). To date, sensitivity and uncertainty analyses of hydrological models have typically focussed on model inputs and parameter values as evidenced by the range of methods available for uncertainty propagation and for evaluating plausible parameter values (e.g. Beven and Binley, 1992; Thiemann *et al.*, 2001 ; Vrugt *et al*., 2003). The focus of these studies, and many others, partly reflect the assumption that uncertainties due to the input data and parameters are the most important. In practice, model structure uncertainty may be more important than parameter uncertainty in evaluating model performance, but such uncertainties are difficult to assess explicitly or to separate from other uncertainties during the calibration process (Beven and Binley, 1992). The effects of model structural uncertainty can be assessed, for example, by model validation and inter-comparison (e.g. Georgakakos *et al*., 2004). However, Beven (2006b) acknowledged that impacts of model structural uncertainty are difficult to quantify explicitly unless alternative model formulations are explored (use of flexible model structures) or, less ideally, if an appropriate error component is added. In practice, none of these is a straightforward task, and thus model structural uncertainty is usually neglected when a single model is used, and the model is assumed to be structurally “perfect”. There are few studies of sensitivity analysis for the southern African region (e.g Schulze, 1995) and hence there is a need for further research, in particular, using models developed in the region that are applicable to a wide range of climate conditions and sub-basin scales.

2.5.2 Approaches to estimate the amount of uncertainty present in model output

i. *Monte Carlo Simulation (MCS)* involves uniform random sampling of parameters and subsequently the determination of model output (Beven and Binley, 1992). MCS generates a large number of simulations of model parameters according to their corresponding probability distribution. The uniform distributions of lower and upper bounds are assumed to represent variations of calibrated parameters. The sampling number often determines the quality of the probability distribution of model output and the use of efficient sampling technique can restrict the number of simulations needed.

ii. *Latin hypercube simulation (LHS)* is a stratified approach that efficiently estimates the statistics of an output by dividing a probability distribution of each basic variable into N ranges with an equal probability of occurrence (1/N) (Helton and Davis, 2003). The order of ranges is randomized and the model is executed N times with the random combination of each basic variable values from each range for each variable. According to Melching (1995), this approach efficiently estimates the statistics of an output better than MCS.

iii. *Rosenblueth's point estimation method (RPEM)* uses a point-probability distribution to estimate the statistical moments (mean and covariance) of an output and was proposed to deal with symmetric, correlated, stochastic and asymmetric random variables in a Taylor series expansion (Rosenblueth, 1981; Binley *et al*., 1991). The samples of parameters are associated with the number of parameters (p) and 2^p parameter sets are needed.

iv. *Harr's point estimation method (HPEM)* involves the estimation of the statistical moments of the model output for a given number of parameters and model runs,(Harr Milton, 1989). The samples of parameters are associated with the number of parameters (p) and 2p parameter sets are needed; less than the number required for the Rosenblueth method.

v. *The first-order uncertainty analysis method* is a Taylor series expansion approximate linearization (MFORM) using the mean of a parameter range (Melching *et al*., 1990) and an improved approach (AFORM) that uses a 'likely' point and not the mean (Melching, 1992). The technique allows for the determination of a distribution of uncertainty of model output as a function of the parameters based on statistical moments.

The limitation of the MCS and LHS approaches is that they are computer intensive because they require many model simulations to establish acceptable parameter sets (Beven, 2001a). The point-estimation approaches (iii-v) are limited by the assumption of approximating linearity of a model, despite the use of approximate methods in practical situations where probability and statistical moments of model output cannot be derived analytically due to non-linearity and complexity in models (e.g. first-order uncertainty analysis, RPEM and HPEM). Therefore, having recognised the limitations of the above methods, the advanced numerical simulation approaches such as Bayesian and multi-objective methods were introduced.

vi. *Bayesian uncertainty analysis methods* are of the Monte Carlo family and these approaches estimate model uncertainty by combining prior information regarding the uncertainty of model inputs with the ability of different parameter sets to describe the available data on state variables. They commonly apply random sampling procedures to explore feasible parameter space in search of behavioural models or parameter sets (Gupta *et al*., 2006). An example is the MOSCEM approach (Vrugt *et al.,* 2003) which is a Bayesian strategy that estimates uncertainty related to model structural uncertainty.

vii. *Multi-objective approaches* normally evaluate uncertainty using predictions based on some Pareto "optimal" parameter sets (Gupta *et al*., 1998; Yapo *et al*., 1998). Here, behavioural models are defined as models that describe certain characteristics of the hydrograph response realistically.

viii. *The Generalised Likelihood Uncertainty Estimation (GLUE) method* (Beven and Binley, 1992; Freer *et al*., 1996) rejects the concept of an "optimal" parameter set in favour of the equifinality concept, allowing for multiple acceptable models or parameter sets based on some likelihood measures and performance thresholds.

The above (vi-viii) philosophies are currently the most widely accepted uncertainty estimation tools in hydrological applications. The practical limitations of applying the GLUE approach as an uncertainty estimation tool include subjective selection of likelihood functions and assessment of the threshold between behavioural and non-behavioural models, that is, how bad a performance measure has to be before it can be rejected as having no probability of representing the system (Moradkhani *et al*., 2005; Montanari, 2007). The multi-objective based approach has also been criticised for ignoring important issues of model acceptability (see e.g. Beven, 2006b).

The uncertainty methods summarised above may be broadly classified into approximate analytical methods, formal statistical methods, approximate numerical methods and non-probabilistic methods as in Montanari (2007). The *approximate analytical methods* propagate uncertainty using *a priori* assumptions about the different sources of uncertainties without the use of additional evaluation data (Hall and Anderson, 2002), but the inherent uncertainty in the modelling process results in questioning this approach. Typical examples are Monte Carlo error propagation and reliability methods. While *formal statistical approaches* use statistical models to account for sources of uncertainty (Smith and Krajewski, 1991), *approximate numerical approaches* quantify uncertainty by conditioning statistical inferences (e.g. GLUE) to available observed data, but these inferences are often questioned because of lack of statistical significance and statistical methods are not transparent to those unfamiliar with them (Mantovan and Todini, 2006). The *non-probabilistic approaches* are based on non-statistical measures and these include the use of fuzzy measures (Franks *et al*., 1998; Freer *et al*., 2004), frequency duration curves (Bonta and Cleland, 2003) or qualitative measures. The non-statistical approaches are useful in situations where observed data are scarce and where probability distributions or statistical measures might be difficult to evaluate.

Most of the uncertainty estimation methods described above do not explicitly separate out the different sources of uncertainty in rainfall-runoff modelling since their primary emphasis is on parameter estimation uncertainty. Appropriate procedures are, however, being developed to estimate and capture the propagation of different sources of uncertainty into model output uncertainty. These procedures include, simultaneous data assimilation (using more information) and parameter estimation (Moradkhani *et al*., 2005), simultaneous uncertainty estimation of input data and parameter estimation (Kavetski *et al*., 2003), Bayesian total error analysis to capture the combined impacts of input data, parameter and model structure uncertainty (Kavetski *et al*., 2006; Kuzcera *et al*., 2006) and the IBUNE approach to capture input, parameter and model structural uncertainties (Ajami *et al*., 2007). Most of these studies focus on handling uncertainty within a statistical framework in which assumptions about the nature of uncertainties are made. However, these assumptions may not always be justified in practical water resources modelling especially in data scarce regions where little information is available to describe probability distributions and allow valid statistical inferences (Montanari, 2007; Hughes, pers. comm.).

It should therefore be stressed that potential users are always faced with a difficult decision about which uncertainty analysis method to choose, since there are no universally applicable methods. Instead there are a range of different philosophies, assumptions and methodologies to choose from. It should be acknowledged therefore, that choosing a suitable uncertainty analysis method for a specific model application remains a challenge to water resources practitioners. However, if there is a choice between complex ways of quantifying uncertainty and conducting research focused on reducing important sources of uncertainty, spending money on reducing uncertainty would seem preferable to spending it on ways of describing it. In this regard, more simple and user-friendly approaches would be more useful for water resources practitioners. Therefore, in ungauged or poorly gauged basins, non-probabilistic techniques including sensitivity analysis may represent the most promising approaches for uncertainty estimation. In spite of significant progress made internationally on the development and application of uncertainty estimation methods in rainfall-runoff modelling, the most appropriate approaches are not always obvious and similar studies have not been carried out in the southern African region. Ultimately, any recommendations by this study for methods to be used should take into account the numerical complexity and difficulties of performing the analysis for practicing hydrological modellers in the region. This is expected to be quite a serious limitation, given the complexity (and computing software and hardware requirements) of some of the Bayesian approaches.

2.6 Reducing uncertainty in hydrological modelling

While investigations of ways of quantifying uncertainty, is one issue, recent research has also focused on attempts to reduce uncertainty and to increase the confidence and reliability of water resources estimations. The critical sources of uncertainties identified in hydrological modelling that often need attention are the model input data uncertainties (section 2.6.1) and parameter uncertainty (section 2.6.2). However, there have also been some discussions on issues of reducing model structural uncertainty and these are included in section 2.6.2.

2.6.1 Reducing input data uncertainty

The critical issues with the most important hydrological inputs (i.e. rainfall, temperature or evapotranspiration) are their spatial representation and the accuracy of the point measurements themselves. Within many developing countries and specifically many parts of southern Africa, observation networks have always been relatively sparse and are continuously decreasing (Hughes, 2004a). The uncertainty to be reduced is related to incomplete spatial coverage of in-situ measuring networks and accuracy of different methods of interpolating data from point observations to improve spatially averaged information.

With respect to rainfall input data, improvement in spatial estimation approaches are being suggested and remotely sensed products are becoming available to potentially reduce rainfall data uncertainty. The advantages of satellite data over raingauge networks are manifold; satellite-based data covers extended areas, allows rapid access for real-time hydrological applications and its spatial and temporal resolution can be high depending on the scale of the basin (Seed and Austin, 1990). While providing spatially and temporally continuous estimates of rainfall, remotely sensed products (both satellites and surface radar networks) have shortcomings which must be accounted for and corrected before they are used as model inputs (Pegram and Clothier, 2001; Hughes, 2006b; Andersson *et al*., 2006; Wilk *et al*., 2006). Spatial rainfall estimates derived from in-situ raingauges are therefore widely used as ‘ground truth’ for radar or satellite rainfall measurements (Seed and Austin, 1990). Remotely-sensed rainfall estimates (both radar and satellite) are becoming more readily available and are expected to offer an alternative to in-situ raingauge-based rainfall estimates in poor data areas in the future.

Several studies on the use of radar-based (Moore and Hall, 2000; Borga, 2002; Carpenter and Georgakakos, 2004) or satellite-based (Hsu *et al*., 1999; Koster *et al*., 1999; Sorooshian *et al*., 2000; Grimes and Diop, 2003) information to derive rainfall estimates have been reported. Radar estimates, although costly, when compared to raingauge data, were found to offer analytical improvement to rainfall analysis by providing a direct representation of the “true” spatial distribution of rainfall (e.g. Sun *et al*., 2003; Smith *et al*., 2004). However, because of cost implications, the impact of ground clutter, hail and bright band on rainfall estimates, radar networks remain unpopular in hydrological applications especially in developing regions (Terblanche *et al*., 2001). Satellite-based estimates are, on the other hand, often freely available and offer advantages of providing direct basin spatial averages in sparsely gauged areas thereby eliminating the problem of interpolation from point observations (Lee and Oh, 2006). The downscaling and ground-truthing of satellite-based data remain critical issues to be solved and satellite-derived rainfall estimates do not always compare well with raingauge data (Sawunyama and Hughes, 2008). The problem of scale manifests itself when measurements of rainfall rates provided by raingauge data are compared with the areal averaged rainfall remotely-sensed from satellite borne sensors (e.g. Sandham *et al*., 1998). Consequently, some models have been developed that combine satellite and raingauge data to account for local and regional variability in cloud and rainfall relations (Todd *et al*., 1999). The accuracy of the final operational satellite-based rainfall estimates are therefore dependent on these interpretative models that are also subject to calibration. In addition, there are frequently insufficient gauged data available to calibrate the satellite-based estimation methods. The impacts of uncertainty in remotely sensed rainfall estimates on runoff prediction uncertainty have been explored (Huffman *et al*., 1997; Sharif *et al*., 2002; Lee and Oh, 2006), but they are beyond the scope of the present study.

Although extensive literature on remotely sensed rainfall estimates exists, this has concentrated more on the development of methods to derive rainfall from satellite imagery (e.g. Kummerow *et al*., 1998; Todd *et al*., 1999; Xie *et al*., 2002) and comparison of satellite- or radar-derived rainfall estimates with those from gauges (e.g. Guo *et al*., 2004; Hughes, 2006a). However, few studies have investigated the comparative application of areal rainfall estimates from raingauges and satellite data for input into hydrological models (Grimes *et al*., 1999; Hughes, 2006a). Recent studies conducted to evaluate the impact of using operational satellite rainfall estimates in hydrological models in southern Africa (Thorne *et al*., 2001; Hughes, 2006a; Wilk *et al*., 2006; Sawunyama and Hughes, 2008) have emphasized the need to correct the satellite-based rainfall data to be consistent with the historical gauged data before using them as model inputs. However, such correction procedures have not been fully established and need to be investigated further.

With respect to evaporation demand, spatial variability is a major issue. Spatially interpolated pan-derived potential evaporation estimates are often used as inputs to hydrological models, despite the limited pan evaporation measurement networks (Sawunyama and Hughes, 2007). According to Schulze and Maharaj (2006) the extrapolation of evaporation pan data from measurements at a site to other locations could introduce substantial errors. The Penman type equations for estimating potential evaporation cannot be used in data scarce regions because all of the available meteorological data may not be available (Penman, 1956). In order to resolve this problem, temperature-derived estimates of potential evaporation (Hargreaves and Samani, 1985) offer an alternative, because they benefit from a higher density of temperature observation networks. Temperature information may be interpolated to ungauged locations more readily than evaporation pan data and may be extrapolated to altitudes beyond the range of observations because of the close association of temperature with physiographic factors (Schulze and Kunz, 1995). It is not surprising therefore that temperature estimates have been used as input variables in a wide range of climatological, hydrological and agricultural applications (Schulze and Maharaj, 2004). However, the complex relationships between temperature and evaporation demand can introduce uncertainty in estimates of the spatial variability of evaporation demand that cannot be easily quantified if estimation methods are not properly adjusted (Schulze and Maharaj, 2006). Schulze and Kunz (1995) showed that the Hargreaves and Samani (1985) method performed better than other temperature-based methods to calculate potential evaporation in South Africa. Recently, with the availability of remote sensing products, Immerzeel and Droogers (2008) calibrated a distributed hydrological model based on satellite-derived evapotranspiration. Therefore, there is a need to explore the possibility of using remotely sensing evapotranspiration to calibrate conceptual type models as well as to further investigate the use of temperature derived evapotranspiration estimates.

2.6.2 Reducing model structure and parameter uncertainty

A strong focus in current hydrological research (e.g. PUB) is the reduction of parameter and model structural uncertainty as part of any model evaluation (Refsgaard *et al*., 2006). Beven (2006b) argues that the dominant source of uncertainty does not lie in the predictions but rather in the mapping of the hydrological processes into the space of acceptable parameter sets. Furthermore, in evaluating a model, it is not only a matter of finding justifiable assumptions about the model structure but also of finding a set of parameters that satisfy some conditions of model acceptability. There is therefore, a need to develop improved model structures based on better understanding of physical processes and better mathematical representation (Sivalapan *et al*., 2003). However, while there are a number of studies that have quantified model structural uncertainty (Yapo *et al*., 1998; Vrugt *et al*., 2003), few have attempted to reduce it. A great deal more effort has been put focused on reducing parameter uncertainty (e.g. Beven and Binley, 1992; Thiemann *et al.*, 2001; Vrugt *et al*., 2003). Although this topic is covered quite extensively in the literature, the models in common use within South Africa have relatively fixed structures (from a natural hydrology point of view) and are not expected to change very much in the future. However, recent experience with the Pitman model (Hughes, 2004a) suggests that model improvements can often be considered, even for well established models if the improvements do not introduce additional problems of identifiability. In the example referred to (Hughes, 2004b), a more explicit ground water function was added that could be supported with available information from a national database of ground water characteristics (Conrad, 2005).

The approaches to reducing parameter uncertainty will depend on the methods of calibration or regionalisation (for ungauged basins) as well as the model structure and the objectives of a specific study. Physically-based parameter estimation approaches are being revised (e.g. Yadav *et al*., 2007; Kapangaziwiri and Hughes, 2008) and alternative information such as remote sensing data (Franks *et al.*,1998; Boegh *et al*., 2004) are being used in a bid to reduce parameter uncertainty and, hence predictive uncertainty, especially in ungauged basins. The approach of using more information (e.g. soil moisture, vegetation cover, etc.) to constrain parameters has been referred to as data assimilation (Moradkhani *et al*., 2005; Vrugt *et al*., 2005) and offers a promising solution. The value of using additional data to calibrate (or constrain) hydrological models in the absence of observed streamflow data has been studied (e.g. Uhlenbrook and Sieber, 2005). Multi-scale data (i.e. runoff from sub-basin) were compared to multi-response (i.e. concentrations of dissolved silica) in terms of the ability to reduce the uncertainty of discharge predictions (Uhlenbrook and Sieber, 2005). Franks *et al.* (1998) developed a simple methodology to estimate the extent of runoff-producing saturated areas based on single frequency microwave remote sensing to calibrate hydrological models in ungauged basins. Nandagiri (2007) investigated the feasibility of using areal potential evapotranspiration to calibrate a physically-based model in an ungauged basin in India. Boegh *et al.* (2004) incorporated remote sensing data (distribution of vegetation cover and land use) to derive correct predictions of potential evapotranspiration and the soil water balance using a physically-based hydrological model (MIKE SHE). Within southern Africa, Kapangaziwiri and Hughes (2008) developed a parameter estimation approach that directly uses physical basin properties to estimate the parameters for a semi-distributed Pitman conceptual model for use in both gauged and ungauged basins.

The revised approaches and new data products are meant to constrain the uncertainty associated with the usual reliance of rainfall-runoff data alone to calibrate hydrological models and the problems of existing parameter regionalisation techniques. The use of rainfall-runoff data alone, pre-assumes a perfect knowledge of the spatial patterns of inputs, initial and boundary conditions that are difficult to attain in practice, giving rise to uncertainty (Beven, 2001a; Franks, 2007). On the other hand, the sampling and measurement scale difficulties involved in using field measured parameter values and the errors involved in using *a priori* estimates would suggest that parameter values used in a model will always have some degree of uncertainty (Binley *et al*., 1991). Therefore, improving databases of high resolution data and revision of parameter estimation approaches are likely to be the most effective developments to reduce parameter uncertainty.

2.7 Hydrological modelling in southern Africa

2.7.1 Model development

Hydrological models have been developed and applied over a wide range of climatic regions for an extensive range of applications in southern Africa (Hughes, 1982). Despite the large number of mathematical models referred to in the literature (section 2.1), the models available in southern Africa, and specifically in South Africa, have been developed to serve specific practical purposes because resources are limited (Hughes, 2004a). Models that require more detailed data inputs such as fully distributed models have found little application in southern Africa given the resolution and accuracy of the available data. The tendency has been to develop and use less detailed models (in terms of data requirements) and work towards finding alternative sources of data (e.g. remote sensing) to ensure adequate information in the future. The models that have been developed are based on a conceptual understanding of hydrological processes and have a relatively large number of parameters (making them more complex in terms of the number of parameters to be quantified), even for monthly-time step models (Pitman, 1973). This stems from a tradition of attempting to represent processes of runoff generation through a conceptual approach rather than opting for simpler mathematical transformations with fewer parameters (Perrin *et al*., 2003). According to Hughes (2004a), one of the motivations for the conceptual approach used in South Africa is that the model parameters are more meaningful in terms of “real” hydrological processes and can be related to measurable basin characteristics (Kapangaziwiri, 2008). It appears that the purpose of applying a model as well as the type of information that is available should therefore dictate the type of model that is best to use for any hydrological problem.

The first rainfall-runoff models developed for South African conditions were the monthly and daily versions of the Pitman model (Pitman, 1973, 1978). The monthly Pitman model gained popularity as a practical water resources estimation tool and became the standard model recommended for the country (see section 2.7.3 for more details about available versions of the model). Another widely used model in South Africa is the ACRU model, a daily agrohydrological model named after the Agricultural Catchment Research Unit, which is frequently used in the assessment of hydrological responses to land use modifications and climate change (Schulze, 2000). The ACRU model has been designed around a multi-layer soil moisture accounting scheme and has a large number of parameters that require quantification. It is designed to be used in ungauged basins on the basis that its parameters are evaluated through default relationships with measurable catchment properties (soils, vegetation, geology etc). Hughes and Sami (1994) also developed a Variable Time Interval (VT1), semi-distributed, partly physics-based model with a facility to estimate some of the parameter values from physiographic data, but data limitations and a difficult calibration process limits the success in the application of this model in the region.

2.7.2 Model application

The Pitman and ACRU models are the most widely used in South Africa and the whole of southern African region for practical purposes. These models vary in terms of the time-step, data requirements, the number of parameters and sometimes the purposes they serve. However, choosing a hydrological model to use depends on the experience of the user with a particular model and the purpose of the modelling as well as the parameter estimation process. With the Pitman model, the parameter estimation is normally based on intuitive understanding of how the parameter values should change with changing basin properties and supported by calibration against the observed data. On the other hand, with the ACRU model, an *a priori* parameter estimation approach is used based on methods of directly estimating default parameter values from measurable properties. Schulze (2000) argued that the application of models in ungauged basins require that models are not calibrated and therefore, parameter values have to be quantified from measurable sub-basin characteristics. However, this approach suffers from the lack of availability of sub-basin data in a form and at a scale that is compatible with the model, inability to construct models where relationships between parameter values and sub-basin characteristics are understood and quantified, and the scale differences in model algorithms and the available data (Hughes, 2004a). In spite of the efforts by Hughes and Sami (1994) to incorporate concepts of representing parameters by probability distributions rather than single values (Moore, 1985), the problem has not yet been resolved.

While the application of calibration procedures in South Africa have been dominated by guidelines for manual calibration (Pitman, 1973), there have been several attempts to apply automatic optimization procedures to the Pitman and other models (Görgens, 1983; Ndiritu and Daniell, 1999, 2001). Mwelwa (2005), working with a semi-distributed version of the Pitman model on the Kafue basin in Zambia, found that it is difficult to obtain consistent calibrated parameter sets across several hydrologically similar sub-basins when using automatic calibration. Part of the problem is almost certainly related to errors in the input data and the fact that the model is being calibrated to the noise in the data, rather than the real signals. The perceived advantages and disadvantages of automatic calibration have already been referred to in section 2.2.1. The primary focus of most automated calibration approaches is now toward estimating parameter sets that include uncertainty bounds (see e.g. section 2.4 above).

There are few examples of parameter regionalisation in southern Africa and those that are available have focussed on the extrapolation of parameters from gauged basins by relating model parameters to catchment characteristics using regression relationships (Hughes, 1982; Mazvimavi, 2003). The other form of regionalisation has been parameter mapping applied by Pitman (1973) and Midgley *et al.* (1994) as part of the South African national database of simulated water resources availability. The latter used the knowledge of physiographic conditions in South Africa to produce regional maps of model parameters. Kapangaziwiri (2008) introduced an *a priori* approach to Pitman model parameter estimation based on a re-interpretation of the conceptual structure of the model and the conceptual meaning of the parameters (see also Kapangaziwiri and Hughes, 2008). The results were encouraging in that flows simulated were comparable at least (as well as to observed records) to those generated using the same model with existing regionalised parameter values. The parameter sets were, however, very different, an observation that is consistent with the recognized lack of parameter identifiability of the Pitman model parameters.

In spite of the above discussions, data availability used to drive models constitutes the most critical issue for successful model applications. Unfortunately, South Africa, like many developing countries in southern Africa, suffers from limited hydrological and climate data, with measuring networks being sparsely distributed or in many cases closed (Lynch, 2004). The degree to which the available hydro-climatic database of southern Africa is adequate to define large scale variations depends on the type of the variable and its temporal resolution (Schulze, 1997). The accuracy of areal rainfall estimated from point raingauges depends on the representativeness of the point measurements, the spatial variability of the rainfall, the size of the basin, duration of rainfall as well as the method used to estimate the areal distribution from the point measurements (Schulze, 2006). Schulze and Maharaj (2004) reviewed the problems associated with evaporation measured from pan measurements in South Africa and showed that all data obtained through existing networks are not necessarily accurate and great care should be taken in checking the reliability of these data. A number of reasons were therefore identified for using temperature information as a surrogate for estimating pan equivalent evaporation (Schulze and Maharaj, 2004; 2006). Spatial interpolation procedures have been developed to extend the spatial extent of estimates that are made from point measurements but their degree of accuracy remains questionable (Schäfer, 1991; Teegavarapu and Chandramouli, 2005).

The other challenge in hydrological model application is a lack of understanding of land cover/use changes as well as the variations (both spatial and temporal) of water utilisation or abstraction practices. While the impacts of small farm dams on streamflow dynamics are generally understood (Maaren and Moolman, 1986) and the spatial extent of their occurrence can be obtained from satellite imagery or aerial photography (Meigh, 1995), there is little quantitative information generally available about their storage capacities (Sawunyama *et al*., 2006). In addition, the information on groundwater resources may be available for large alluvial aquifer abstraction schemes (Görgens and Boroto, 2003), but not for smaller, more distributed abstractions. Without complete information of these anthropogenic changes in flow records, it is difficult to establish hydrological models that can generate reliable streamflow results given that naturalisation of flows will not be possible (Hughes *et al*., 2006). Unless the input information base is improved, neither the development of new models, nor improving the application methodology of existing models is likely to improve the situation. The choice seems to lie therefore between modifying techniques to make better use of existing data and collecting additional data to support the existing techniques (Hughes, 2004a).

Recent developments in remote sensing have seen improvement in the measurements of meteorological input data (e.g. rainfall and evaporation) and basin physical characteristics (e.g. soils and vegetation). Some studies in South Africa investigated the effects of using different levels of spatial detail in rainfall in hydrological models (Sawunyama and Hughes, 2007), while others have focused on improving the inputs to models by using radar coupled with stochastic space-time models of rainfall fields (Pegram and Clothier, 2001), or satellite-based rainfall estimates (Hughes, 2006a, b; Wilk *et al*., 2006; Hughes *et al*., 2006; Sawunyama and Hughes, 2008). While radar and satellite imagery for rainfall estimates (see also section 2.6.1) are able to provide real time spatial estimates of rainfall values, the primary source of rainfall data is still considered to be ground based gauge observations (Seed and Austin, 1990). However, if the existing trend of declining network density continues, this essential source of input data to hydrological models will be lost and it is unlikely that it can be adequately replaced with radar or satellite data.

In summary, it is worth noting that internationally, the focus on hydrological modelling has not been on practical model application and has commonly tended towards the more academic research issues (Hughes 2004a). There is therefore need to find ways to integrate international developments, which include the incorporation of uncertainty analyses approaches and tools, with tried and tested models that have been developed locally such as the Pitman model.

2.7.3 The Pitman Model

The Pitman model is a conceptual type, monthly time-step rainfall-runoff model that has a relatively large number of parameters associated with components that represent the main sub-basin scale hydrological processes (interception, surface runoff, soil moisture storage and runoff, groundwater recharge and discharge, evapotranspiration losses and routing). There are several versions of the Pitman model available, either the original form (Pitman, 1973), or several revisions and additions to its structure (Hughes, 2004b; Hughes and Parsons, 2005; Bailey and Pitman, 2005). The recent versions of the model also include several components to represent anthropogenic impacts (land use modifications, river abstractions and return flows, distributed small farm dams and large reservoirs). The Hughes (2004b) and Hughes and Parsons (2005) versions are spatially semi-distributed (based on sub-catchments with their own inputs and parameter sets) and the model is typically applied in small to medium catchments. The version of the model used in this study (GWPIT-Hughes, 2004b) includes more explicit interactions between surface and ground water than the original (Pitman, 1973) and is implemented as part of the Rhodes University's Spatial and Time Series Information Modelling software (SPATSIM) (Hughes and Forsyth, 2006). Detailed descriptions of the GWPIT version of the model components are well documented (see for example in Hughes *et al*., 2006 and Kapangaziwiri, 2008) and a less detailed conceptual structure is briefly described in Chapter 3, section 3.4 of this thesis.

The parameters of the model are 'conceptually-based' (within certain constraints associated with the time and space scales that the model typically operates over) in that they can be interpreted with respect to our conceptual understanding of the way in which sub-basin scale hydrological processes operate. This suggests that an opportunity exists to examine the conceptual interpretation of the model components and develop approaches to parameter estimation using well established principles of catchment hydrology and estimated physical basin properties. Kapangaziwiri and Hughes (2008) report on the development of such an approach and demonstrate that it has a great deal of potential compared with alternative regional parameter estimation approaches used in South Africa (Hughes, 1982; Midgley *et al*., 1994; Mazvimavi, 2003). The incorporation of uncertainty analyses as part of this approach as well as the whole modelling process, still needs to be investigated.

3. STUDY AREA, DATASETS AND GENERAL METHODS

3.1 Description of the hydro-climatic and physical characteristics of South Africa

Although the objectives of the present study refer to the southern Africa region, the test sub-basins were drawn from South Africa (see details in section 3.2) largely because these sub-basins are expected to be representative of the hydro-climatic and physical conditions found in most parts of southern Africa. In addition, South Africa has an extensive and relatively good quality database of information required for hydrological assessments compared to the other countries and hence is suitable for developing guidelines for incorporating uncertainty analysis into water resources estimation within the whole region. The general climate, hydrology, geology, soils, vegetation and land use characteristics of South Africa are summarised below. Factors such as rainfall, evaporation, soils, geology and land cover characteristics affect the total volumes of runoff generated from sub-basins but also affect the different components of flow regimes (high and low flows for example) in different ways.

3.1.1 Climate and hydrology of South Africa

While this section provides a general overview of climate and hydrology of South Africa, further details can be obtained from several sources including the national Surface Water Resources databases of South Africa, (WR90 - Midgley *et al*., 1994), the Integrated Water Resources of South Africa 2005 (WR2005-WRC, 2005), the South African Atlas of Climatology and Agrohydrology (Schulze, 1997, 2006) and the Agricultural Geo-Referenced Information System comprehensive database (AGIS, 2007).

3.1.1.1 Rainfall

Rainfall is one of the key driving variables of a hydrological model for any climate region. South Africa experiences highly variable rainfall, both spatially and temporally, which contributes to risks in the availability of sustainable water resources (Schulze, 1997). Mean annual precipitation (MAP) is generally below the world average of 860 mm/yr except in a few parts where it exceeds 1000 mm/yr and spatial variability is high across the country (Figure 3.1, based on information obtained from the national Surface Water Resources database of South Africa (WR90), Midgley *et al*., 1994) There are many organisations and private individuals that have recorded rainfall data in South Africa, including the South African Weather Service (SAWS), the Agricultural Research Council (ARC), the South African Sugar Association (SASA), the Department of Water Affairs and Forestry (DWAF) and municipalities. The majority of the national rainfall data are recorded at a daily time-step, but there are a number of sites that record data at finer intervals using continuously recording instruments.

In the past rainfall was measured at a relatively large number of daily total recording stations, many records extending back into the 19th century. However, more recently many of these stations have been closed and a gradual decline of stations reporting rainfall data in South Africa has been experienced (Lynch, 2004). This steady decline in number of rainfall stations is continuing due to the lack of maintenance of data observation networks. The situation is made worse by frequent missing data. The problems are most critical in high runoff mountainous areas where point rainfall displays considerable spatial variability. Dense raingauge networks are needed in such areas to obtain accurate estimates of areal rainfall as inputs into water resources estimation methods (Schulze, 2006). Figure 3.2 shows the spatial distribution of gauges with different record lengths and illustrates how few stations are available to quantify long-term patterns of variability.

Figure 3.3 illustrates the temporal variability of rainfall which is approximately inversely related to mean annual totals. The variability is least in the eastern high rainfall areas and greatest in the western semi-arid to arid parts of the country. The highest rainfall occurs in the mountain ranges of a small part of the Western Cape and the Drakensberg region of KwaZulu-Natal that are also characterized by low coefficients of variation. The low rainfall regions of Northern Cape have the highest coefficient of variation. Seasonal and monthly rainfall variability is considerably higher than annual variability (Schulze, 2006).

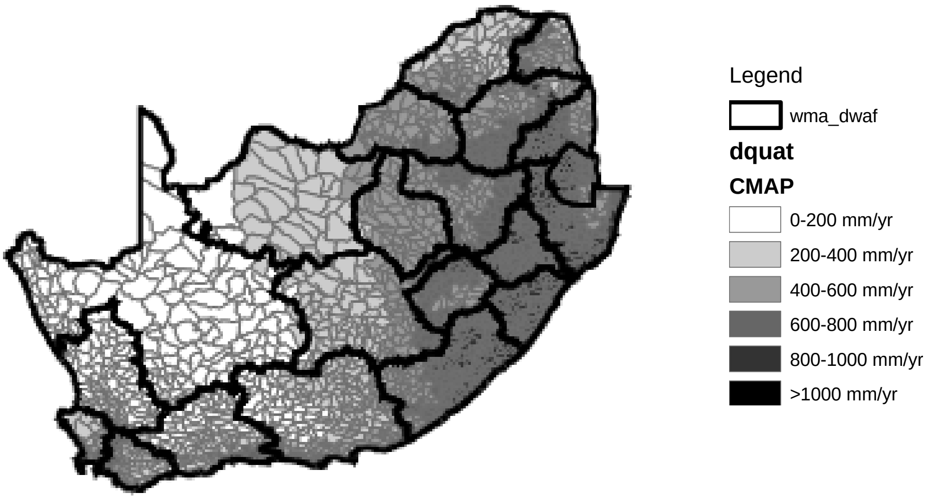


Figure 3.1 Distribution of Catchment Mean Annual Precipitation (CMAP) for different water management areas (WMA) in South Africa (after Midgley *et al*., 1994).

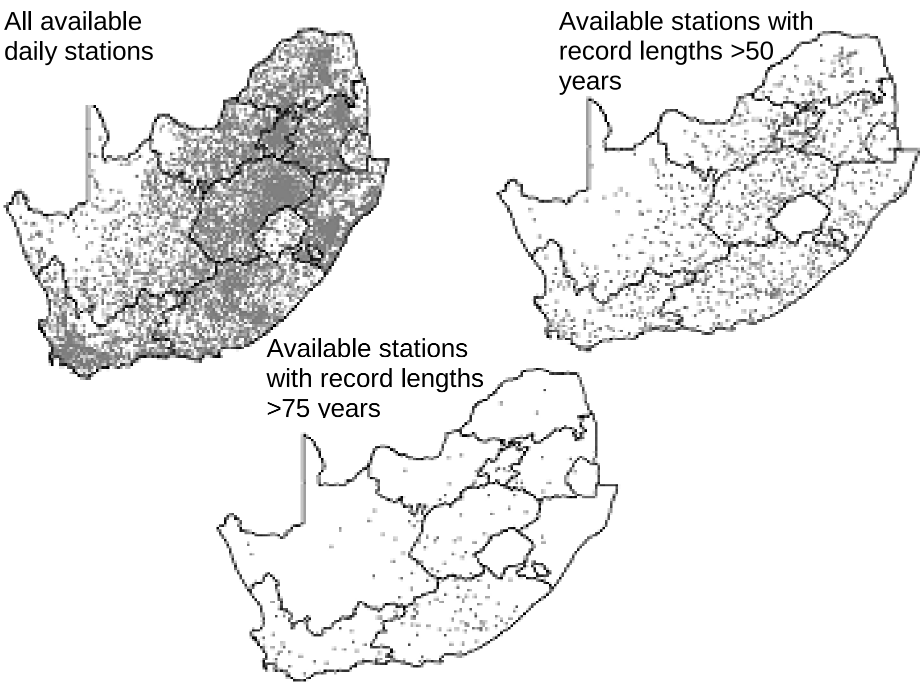


Figure 3.2 Distribution of number of rainfall stations in South Africa with different record lengths (Schulze, 2006).

There are three major seasonality zones in South Africa; the winter rainfall zone of the Western Cape, the bimodal rainfall zone of the Eastern Cape and the summer rainfall zone covering the majority of the rest of the country. Schulze (2006) further divided these seasonal zones (Table 3.1) into all year round, winter (June-August), early summer (December), mid-summer (January), late summer (February) and very late summer (March). In the Northern Cape, very late summer rainfall (associated with convergence systems) are experienced while the North West Province has mid-summer rainfalls (mainly convectional and convergence) which stretches into the Free State, Gauteng and Limpopo Provinces. The factors which influence rainfall types in different seasons vary from one province to another. In the eastern Drakensberg of the KwaZulu-Natal Province, the mid-summer rainfall is strongly influenced by the Inter-Tropical Convergence Zone (ITCZ) which moves southwards in summer (November-February), and is also influenced by orographic effects. Orographic rainfall dominates in the mountains of the eastern parts of the country, stretching from KwaZulu-Natal to Mpumalanga Province. The rainfall in the south western and southern coastal parts of the Western Cape Province is influenced by frontal systems developing in the southern Oceans and moving eastwards. These frontal systems bring cool, moist air during the winter season (June-August) and are far more extensive than isolated convectional systems. In the Northern Cape Province where air is dry and topography flat, the main rainfall-producing mechanism is the occasional convectional thunderstorm. The type of rainfall has strong influence on the areal distribution of rainfall in a river basin.

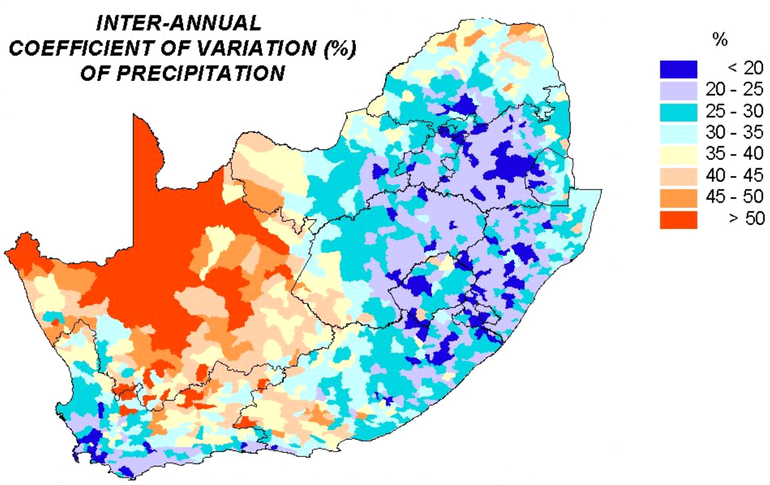


Figure 3.3 Coefficient of variation of rainfall over South Africa (Schulze, 2006).

Table 3.1 Distributions of rainfall seasonality in South Africa (excluding Swaziland and Lesotho) (Schulze, 2006)

Province	Dominant season	Sub-dominant season	
		I	ii
Limpopo	Mid-summer	Early summer	-
Mpumalanga	Early summer	Mid-summer	-
North West	Mid-summer	Late summer	-
Northern Cape	Very late summer	Late summer	Winter
Gauteng	Mid-summer	Early summer	-
Free State	Late summer	Mid-summer	Early summer
KwaZulu-Natal	Mid-summer	Early summer	Late summer
Eastern Cape	Late summer	Early summer	All year
Western Cape	Winter	All year	-

3.1.1.2 Potential evaporation

Potential evaporation is the second largest component of the water balance but the availability of potential evaporation data is far worse than for rainfall data. Evaporation from free water surfaces is likely to differ from that which occurs from land surfaces, which is further affected by variations in vegetation cover and land use patterns. This makes it very difficult to provide adequately representative measurements of potential evaporation demand for input to hydrological models. The amount of water consumed by soil and vegetated surfaces may take place at rates equal to the potential rate under wet soil conditions, but will be much lower when soils are dry or when plants are under stress (Schulze*,* 2006). There are few parts in South Africa where mean annual potential evaporation (MAE) is less than mean annual rainfall (Schulze, 1997). These are confined to the high rainfall areas where annual rainfall is greatly in excess of 1500mm/yr. Figure 3.4 shows that there are wide regional variations of mean annual potential evaporation in South Africa, which increases from east to west. Where potential evaporation is high, dry conditions will prevail unless if there is high rainfall to offset it. In semi-arid regions, for most of the rainfall events that occur, the generation of runoff is less dependent upon initial soil moisture conditions (which are dependent on evaporative losses) than on rainfall intensity characteristics and soil surface conditions.

Schulze and Maharaj (2006) showed that there are many methods of estimating potential evaporation, ranging from physically-based complex methods (that use more meteorological variables) to simple methods, with some based on single variables such as temperature. However, these methods give different results under different climatic conditions and a reference potential evaporation (such as evaporation losses from a free open water surface) is required against which other methods are compared and adjusted (Schulze and Maharaj, ,2006). In South Africa hydrologists have mostly favoured evaporation estimates using standard Symons pan and standard American A-type pan evaporimeters.

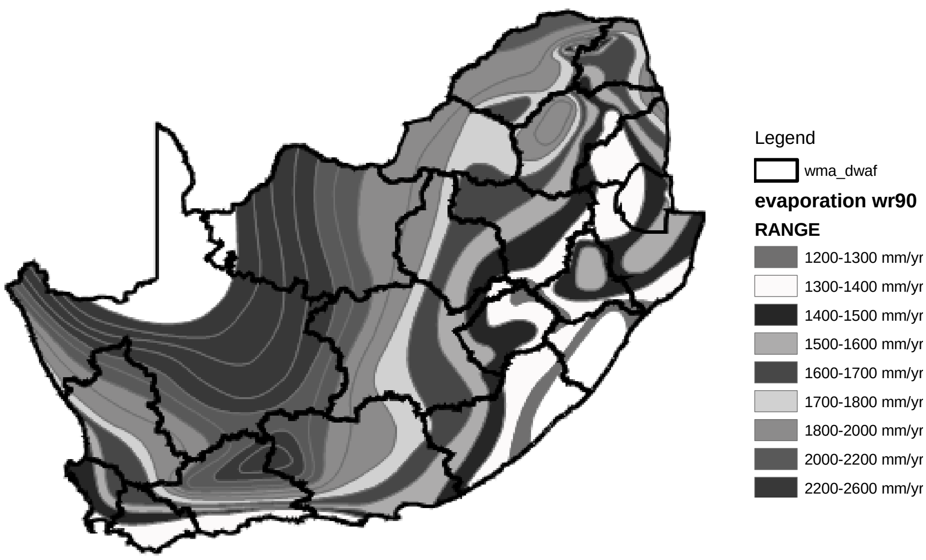


Figure 3.4 Distribution of Mean Annual Evaporation (MAE) in South Africa (after Midgley *et al*., 1994).

3.1.1.3 Temperature

Temperature variations over South Africa are strongly determined by altitude, latitude and proximity to large water bodies. Schulze (1997) showed that high altitude (1500-1700m) inland regions experience warm summer mean daily maximum temperatures (26-28°C) and cool winter mean daily minimum temperatures (0-2°C) with frost during the coolest months. The coolest months are generally June and July, while the warmest months are October and November. However, the northern parts of the coastal region experience warm winter and warm summer temperatures (ranging from 17-38°C), and the climate is strongly sub-tropical. The southern and south western coastal parts of the Western Cape experiences moderate winter temperatures (ranging from 4-20°C).

Temperatures generally decrease with increasing latitudes southwards in South Africa (Schulze, 1997). The general trend in the country shows that areas of high temperature experience high evaporation rates.

3.1.1.4 Groundwater recharge

Groundwater recharge can be an important component in runoff generation in some parts of South Africa through the replenishment of aquifers and subsequent discharge to rivers. Groundwater recharge occurs in a number of ways, as direct recharge (water added to ground water storage in excess of moisture deficits and evapotranspiration, by direct vertical percolation through the unsaturated zone), localised recharge (near surface concentration of water in the absence of well defined channels) or indirect recharge (percolation to the water table through the beds of water courses). Direct recharge is controlled by many factors such as the amount, type, duration and temporal distribution of rainfall and evaporation, surface slope, type of vegetation cover, interception and transpiration losses and soil infiltration capacity. In South Africa most ground water resources are contained within secondary aquifers, where the movement and storage of water is dominated by fracture zones. Many river channels follow fracture zones and thus provide favorable conditions for recharge through the stream beds. The heterogeneity in geological characteristics affects groundwater recharge and hence the available groundwater resources in the country. In arid areas, direct recharge from rainfall is less important and indirect recharge through river beds is often more important. According to Vegter (1995) the distribution of rainfall, particularly effective rainfall, over South Africa provides a rough indication of the variation in recharge. In addition, large variability of rainfall volumes is associated with an even larger variability in recharge volumes (Bredenkamp *et al*., 1995). The risk associated with the utilisation of groundwater resources is therefore expected to be greater in areas of high rainfall variability.

3.1.1.5 Runoff

The distribution of mean annual runoff (MAR) will clearly reflect the patterns of both rainfall and evaporation (Figure 3.5). Runoff is highest in the eastern parts of the country with isolated high values in the Western Cape, while the majority of the central and northern parts of the country have low mean annual runoff (Figure 3.5). MAP and MAR are not directly related, but runoff decreases rapidly with a decrease in rainfall because of high evaporation losses associated with low rainfall conditions. In low rainfall conditions, there are longer dry periods between rainfall events, soil temperatures are high and the air is often warm and dry. Therefore, evaporation of soil moisture is high and soil dries out to a much greater extent between successive rainfall events with the result that small rainfall amounts are quickly absorbed by the soil and then evaporate without generating any runoff. The relationship between rainfall, potential evaporation and runoff is such that the percentage of rainfall that becomes streamflow decreases with decreasing rainfall and increasing potential evaporation (Schulze, 1997). Moreover, the heterogeneity in rainfall patterns is often amplified in the spatial and temporal variability of streamflows (Schulze, 1997). Runoff is normally measured in South Africa using concrete weirs and flumes (rather than rated channel sections). The maintenance of streamflow gauges and the resulting databases is the responsibility of the Department of Water Affairs and Forestry (DWAF) and suffers from similar problems already referred to with respect to the network of rainfall observations.

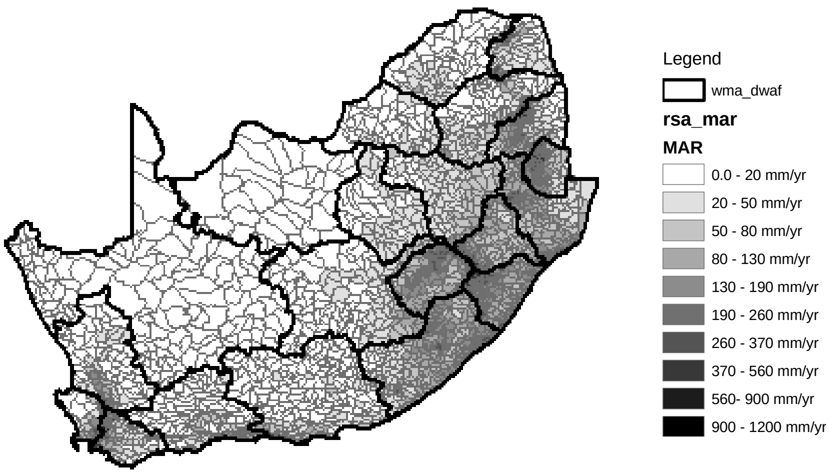


Figure 3.5 Distribution of Mean Annual Runoff (MAR) (in mm) in South Africa (after Midgley *et al*., 1994).

3.1.2 Topography, geology, soils, natural vegetation and existing developments

The main physical characteristics that are important for runoff generation processes and groundwater recharge are topography, soils, geology, natural vegetation and existing developments (land use, reservoirs and water transfers). This information is also essential for estimating hydrological model parameters in ungauged basins. The physical characteristics of South Africa and the sources of available data are briefly summarised below.

3.1.2.1 Topography

Topography is a feature of the physical landscape described in terms of slope, altitude and aspect (Schulze and Horan, 2006). Altitude and aspect have a major influence on climate as they clearly influence local rainfall gradients through orographic effects. Altitude (Figure 3.6) by itself does not present a complete description of terrain characteristics and slope (Figure 3.7) variations are expected to be more important in influencing local runoff responses to climate. There are five major characteristics that dominate the distribution of altitudes (Figure 3.6) over South Africa (Schulze and Horan, 2006):

- A generally narrow coastal strip of low altitudes, widening only along the north eastern coast of KwaZulu-Natal and flat terrain (gentle slopes) of the Western Cape.
- The steep sloping Great Escarpment, inland from the south and east coasts, the region where moderate to high rainfall occurs,
- The Drakensberg mountain range of KwaZulu-Natal and Lesotho Highlands.
- A vast interior plateau inland of the Great Escarpment dropping gently from the east to the west.
- High variation of altitudes in the Western, Eastern Cape, KwaZulu-Natal regions.

According to AGIS (2007), 83% of the country has slopes of 12% or lower and of this area 40% is level or very gentle (0-2%). These gently sloping areas often coincide with low rainfall zones (Figure 3.7). Only about 20% of the country has slopes greater than 20% and these areas commonly coincide with high rainfall zones (Figure 3.7). Topographic conditions exercise local controls on larger scale synoptic rainfall patterns. Altitude is a major determinant of temperature and evaporation demand variations and therefore topography has a large impact on runoff response. As an example, the Western Cape has complex topography with steep mountain slopes and large surrounding areas of flat, low-lying terrain (Midgley *et al*., 1994) giving rise to wide differences in climate and hydrological response over relatively short distances. Hilly topography with relatively high rainfalls are common in the south eastern coastal areas of South Africa, while generally flatter topography with drier conditions covers 65% of the most inland area of the country.

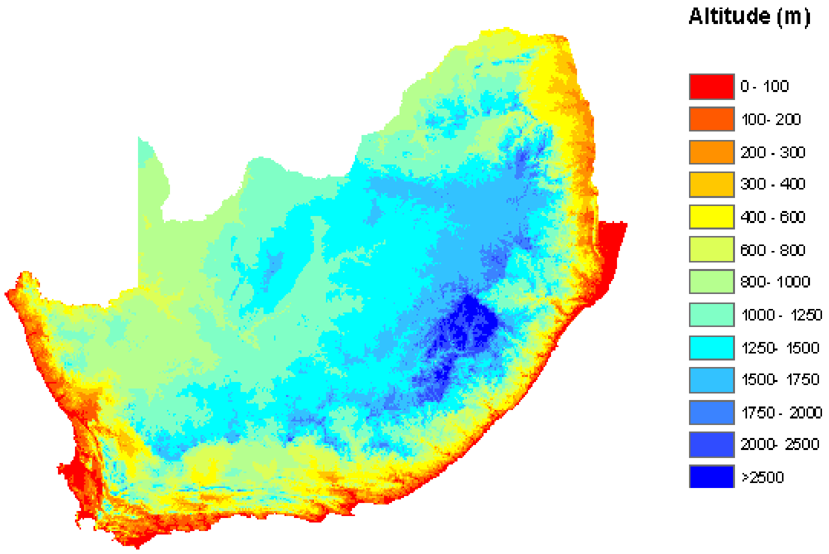


Figure 3.6 Variation in altitude in South Africa (Schulze and Horan, 2006).

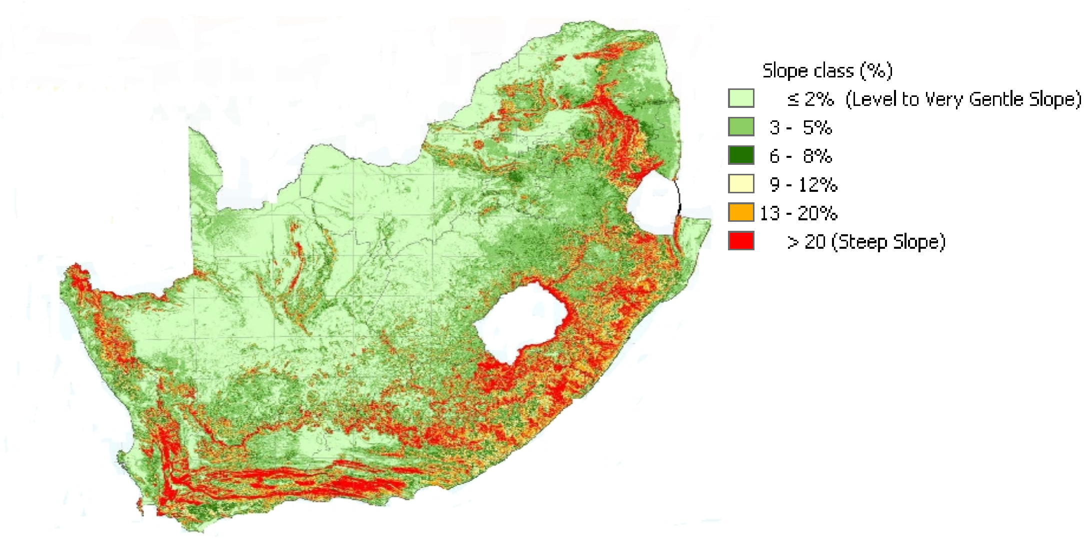


Figure 3.7 Slope map of South Africa (AGIS, 2007).

3.1.2.2 Geology

The majority of South Africa is underlain by fractured and weathered hard rock aquifers which do not exhibit primary porosity and groundwater flows are mainly controlled by structural features, such as faults and fractures (Bredenkamp *et al*., 1995). The fractured rock aquifers mainly comprise sandstones, siltstones, and layered shales and mudstones (AGIS, 2007). The Cape Fold Mountains of the Western Cape are associated with siliceous sandstone and shale rock formations. The sandstones of the Cape Fold Mountains contain both primary and secondary porosity leading to higher permeability. Siliceous sandstones are also found along parts of KwaZulu-Natal Province. The central regions of the country comprise predominantly mudstones and sandstones, which give rise to shallow soils, typically with a hardpan layer in the profile that inhibits infiltration (Schulze, 1997). Locally, in some of the larger river valleys, alluvial deposits represent important groundwater resources. The differential weathering of rocks results in the development of dolerite formations rising above sedimentary plains in the Karoo region of the Western Cape Province (AGIS, 2007). The Table Mountain Group which extends from the Western Cape to Eastern Cape comprises a thick sequence of hard sedimentary rocks dominated by fractured sandstones with a thickness ranging from 900 m to 5000 m (Rust, 1973). It is estimated that approximately 90% of South African groundwater occurs in secondary aquifers (Bredenkamp *et al*., 1995). More detailed geological descriptions of South Africa are provided by Council for Geosciences of South Africa (CGS, 1984).

3.1.2.3 Soils

Information relating to the hydrological characteristics of soils is critical to understanding the hydrological response of basins and therefore to *a priori* hydrological model parameter estimation approaches (e.g. Schulze, 1995; Kapangaziwiri and Hughes, 2008). The Soil Classification Working Group (SCWG, 1991) classified soils based on specific kinds of diagnostic horizons, with their properties and subdivisions and resulted in the concept of broadly defined soil forms, of which 73 have been identified in South Africa (Schulze, 1995; 1997). The Institute for Soil, Climate and Water (ISCW; formerly the Soil and Irrigation Research Institute, SIRI) of the Agricultural Research Council, in an effort to inventorise the factors that determine agricultural potential, initiated the Land Type surveys with the aim of delineating Land Types at 1:250 000 scale (with fieldwork at 1:50 000), defining each Land Type, and analysing soil profiles within Land Types (SIRI, 1987; Schulze, 1997). The Land Type information (SIRI, 1987) provides a valuable source of information from which existing databases of soil data were developed. The Midgley *et al.* (1994) database includes generalised information on soil depth classes (shallow, moderate, moderate to deep and deep) and texture (Loamy Sands (LmSa), Sand Loamy (SaLm), Sand (Sa), Sand Clay (SaCl), Sand Clay-Clay (SaCl-Cl), Sand Clay-Loamy (SaCl-Lm), Sand-Loamy Sands (Sa-LmSa), Sand Loam-Sand Clay Loamy (SaLm-SaClLm), Loamy Sands-Sand Loamy (LmSa-SaLm)) as shown in Figure 3.8 but provides no quantitative information. In the Schulze (1997) database, the soils were classified according to their hydrological responses to suit the requirements of the ACRU model with a focus on plant available water, texture classes and soil depths.

The most recent AGIS (2007) database (which includes GIS Land Type maps and tabulated Land Type information in computerised form) provides the most detailed spatial distribution data for the soils of South Africa. The information provided is based on relatively homogeneous land types, each one further divided into terrain units (hill tops, slopes, valley bottoms and channel zones). The data includes the percent area occupied by each terrain unit, the range of slope and the percent area and depth range of different soil series found within each terrain unit. Further information is provided about the clay content and texture class of each soil series.

It is therefore apparent that the basis for estimating hydrologically important soil parameters (porosity, water holding capacity and hydraulic conductivity) must be largely based on the descriptions of the texture characteristics contained within the various information sources. However, local factors, such as surface crusting and macropore development, can also strongly influence the hydrological response characteristics of soils. These factors are not documented in any of the information sources and have to be inferred from a combination of the soil type and surface cover conditions.

3.1.2.4 Natural vegetation and existing developments

The distribution of natural vegetation and existing developments (land use, reservoirs and water transfers) information is available in the WR90 (Midgley *et al*., 1994) and WR2005 (WRC, 2005) reports and can also be obtained from different agencies.

Distribution of natural vegetation: Natural vegetation represents an integrated reflection of diverse variables such as climate, geology and soils. In South Africa, the veld types of Acocks (1988) are often used to describe the distribution of natural vegetation. The density of vegetation is controlled by climate, soils and lithology. Regions of relatively dense vegetation cover are generally found in high rainfall areas. Vegetation can influence the amount of runoff as a result of interception of rainfall and extraction of water from the soil, both of which are subsequently evaporated. The central parts of the country contain many shallow-rooted grasses and woody shrubs. The shallow-rooted savanna vegetation types are mainly found in the Mpumalanga Province, while grasslands are common in the KwaZulu-Natal Province. The grasslands and savanna type vegetation are associated with lower transpiration rates. The Mediterranean type, the desert shrubs and the mid-latitude broadleaf vegetation types with deep-rooted roots cover the majority of the arid to semi-arid parts of country and these are associated with high transpiration losses. In addition, the amount of intercepted rainfall is greater with tall forest cover than short sparsely populated vegetation cover.

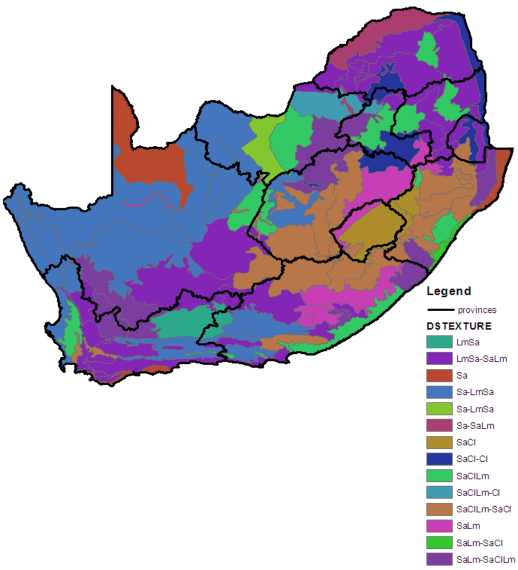


Figure 3.8 Generalised soil map of South Africa (Midgley *et al*., 1994).

Land use: Land use includes afforestation (eucalyptus and pine plantations), urban development and agriculture. Agriculture includes irrigated agriculture and dryland agriculture. The average annual evapotranspiration for irrigated lands varies greatly and, apart from the climatic controls, is dependent on the grass or crop type, quantity of water applied, and length of the growing season. Afforestation may greatly reduce base flows in the wetter parts of the country during dry seasons and irrigation abstractions may reduce downstream flows. During a drought, forests may experience moisture stress and wilting, whereas irrigated grasses and crops continue to grow and transpire at a normal rate (if water supplies are available for irrigation). Urban developments may contribute to more surface runoff due to impervious surfaces and may also affect water quality through the return of effluents to rivers.

Reservoirs and water transfers: The upstream development activities in a sub-basin include reservoirs (small and large), return flows (from wastewater treatment plants, for example) and water transfers, all which have major impact on available natural water resources. Small farm dams, as with large reservoirs, have a significant impact on downstream hydrology through the impoundment of streamflow, evaporation, abstractions and controlled or uncontrolled releases (Havenga *et al.,* 2007). In some parts of the country, especially in highly developed catchments, water transfers are implemented to ease the problem of water shortages

3.2 Characteristics of test sub-basins

Section 3.1 provided a summary of climate and physical characteristics of the study area at a national scale. Figure 3.9 shows the 1946 quaternary catchments that cover the whole country including Swaziland and Lesotho. The quaternary catchment scale is widely used for water resources planning and management in South Africa. However, in this study, a term 'sub-basin' which is more internationally accepted was used instead of 'quaternary catchment'. A total of 22 sub-basins (shaded in Figure 3.9) were selected to represent different climate regimes, largely based on mean annual rainfall and covering arid (<400mm/yr), semi-arid (400-600mm/yr), sub-humid (601-800mm/yr) to humid (> 800mm/yr). This number was found sufficient to ensure that different basin physical characteristics (i.e. topography, soils, vegetation and geology), and therefore different hydrological response characteristics within the climatic regions, are considered. The main characteristics of the selected sub-basins are given in Table 3.2 (from east to west, Figure 3.9).

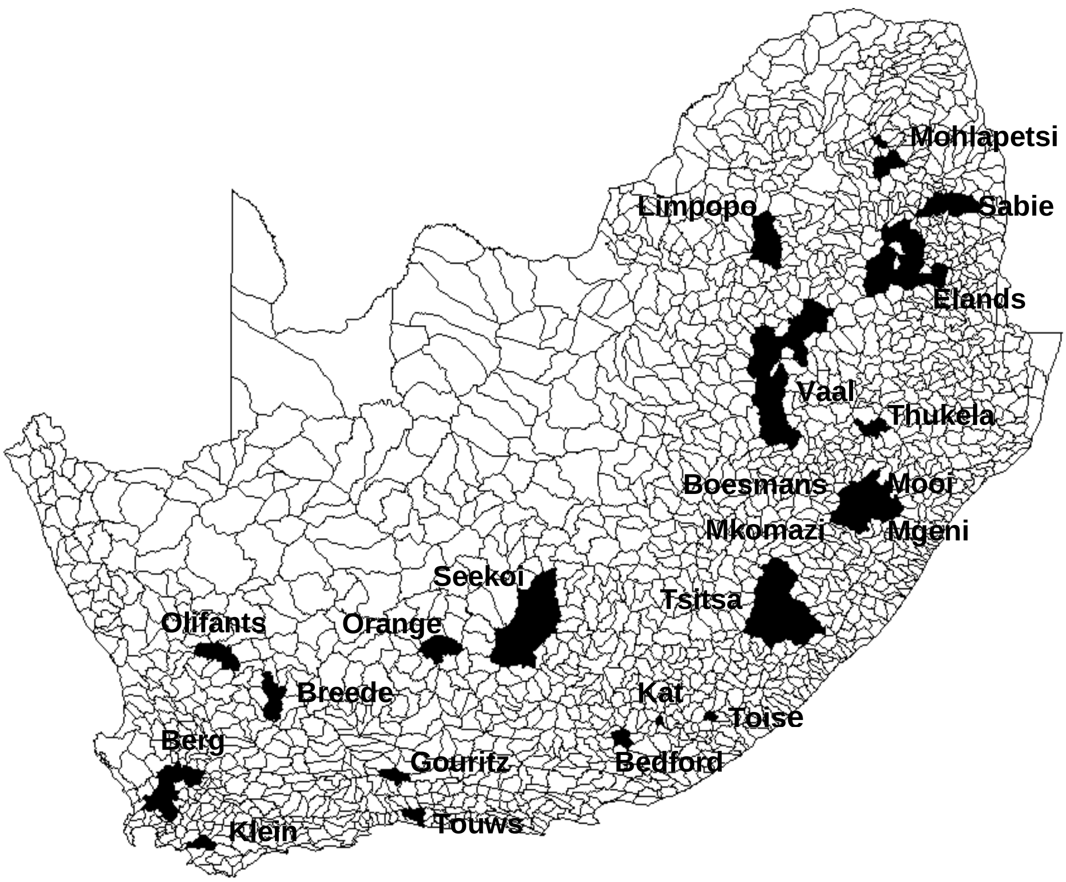


Figure 3.9 Map of South Africa showing location of test sub-basins used (shaded) from the 1946 quaternary catchment system.

Table 3.2 Characteristics of the selected river sub-basins (source: AGIS, 2007 & WR90 reports-Midgley *et al*., 1994).

Sub-basins & Area	**MAP (mm/yr)**	**MAE (mm/yr)**	**MAR (mm/yr)**	**Topography**	**Soils**	**Geology**
Sabie (X31A) 230km^2	1240	1400	452	Steep	Moderate to deep sandy clay loams	Mainly inter-bedded shale and quartzite underlain by dolomite and granite rocks.
Vaal (C12D) 898km^2	660	1580	59	Flat	Moderate to deep clayey	Fractured shales and sandstones
Elands (X21F) 397km^2	757	1400	106	Undulating	Shallow medium sandy clay loam	Comprises of shale and quartzite
Mkomazi (U10E) 327km^2	990	1300	312	Steep	Moderate to deep sandy clay loam	Mainly dolerite with small areas of fine-to medium grained sandstone
Mohlapetsi (B71C) 263km^2	746	1500	153	Steep upper slopes and gentle valley bottom	Shallow soils on upper slopes and deeper sandy loam	Mainly quartzite, shale and sandstone; and some parts of dolomite, chert and limestone
Limpopo (A23A) 357km^2	698	1750	42	Relatively flat	Moderately deeper sandy loam	Shale, quartzite and chert
Thukela (V60D) 308km^2	850	1500	125	Undulating to gentle	Soils are shallow sandy clay	Mainly sandstone with parts dolerite
Boesmans (V70B) 121km^2	1172	1300	360	Steep	Moderate to deep fine sandy clay loam	Sandstone formations
Mooi (V20A) 267km^2	1024	1300	314	Steep	Deep sandy clay loam	Mainly dolerite
Mgeni (U20B) 353km^2	988	1300	201	Undulating	Moderate to deep sandy clay	Mainly dark grey shale with dolerite, siltstone and sandstone
Tsitsa (T34H) 590km^2	905	1300	185	Steep	Deep sandy loam	Comprises of mudstone and sandstone
Toise (S60C) 216km^2	668	1500	80	Steep to undulating	Shallow fine sandy loam	Sandstone with some dolerite

Table 3.2 *continued.*

Sub-basins & Area	MAP (mm/yr)	MAE (mm/yr)	MAR (mm/yr)	Topography	Soils	Geology
Kat (Q94C) 135km^2	768	1600	91	Steep	Shallow sandy loam clay	Comprises of mudstone, shale and sandstone with parts of dolerite
Bedford (Q92F) 665km^2	415	1650	6	Flat	Moderate to deep fine sandy loam soils	Comprises of mudstone, shale and sandstone with dolerite
Seekoi (D32J) 1063km^2	324	800	4.6	Undulating to gentle	Shallow to moderately deep sandy clay loam	Shale, mudstone and sandstone and dolerite intrusions are common
Orange (D61B) 1196km^2	272	2100	2.8	Flat	moderate soil depths, mainly sandy clay loams	Mainly shales, mudstone and sandstone and dolerite intrusions are frequent
Gourtiz (J33D) 260km^2	380	2036	48	Steep	Shallow sandy loam	Mainly arenaceous shale, siltstone and quartzite sandstone
Touws (K40A) 87km^2	705	1400	214	Steep	Shallow loamy sand	Mainly quartzitic sandstone and subordinate shale of the Table Mountain Group; locally also schist as well as gneissic granite
Breede (H10C) 260 km^2	650	1650	266	Steep rocky outcrops and gentle valleys	Shallow to deep loamy sand	Mainly shale and sandstone
Klein (G40K) 429km^2	495	1430	45	Gentle sloping topography	Deep silt loamy	Mudstone, siltstone, shale and feldspathic sandstone
Olifants (E40B) 707km^2	235	1945	8.5	Undulating	Shallow sandy clay loam	Comprises of blue grey shale, but green when weathered
Berg (G10A-B) 126-172km^2	1580	1475	1015	Steep	Shallow to moderately deep loamy sands	Quartzitic sandstone of the Table Mountain Group. In the south, the lower mid slopes and foot slopes consist of quartzite

3.3 Summary of datasets

The datasets used in this study are rainfall, potential evapotranspiration, observed streamflow, basin physical property (geology, soils, vegetation, topography) and water use data (mainly irrigation abstractions and afforestation).

3.3.1 Raingauge rainfall data

Section 3.1.1.1 provided a general overview of the raingauge network and the different sources of rainfall data in South Africa. The daily point rainfall datasets used in the study were acquired from the former Computing Centre for Water Research (CCWR) while other data were acquired from the South African Weather Service (SAWS). The WR90 (Midgley *et al*., 1994) spatially averaged monthly rainfall time series, widely used for water resources assessments in South Africa, were also used in the analyses. While the WR90 rainfall estimates were based on the same original point raingauge information used in this study, the spatial rainfall generation of the WR90 data was based on Thiessen polygons (Dent *et al*., 1989; Midgley *et al*., 1994), while the Inverse Distance Weighting interpolation technique was used in this study. However, previous studies (Schäfer, 1991; Lynch, 2004) showed that the spatial interpolation of rainfall depends mainly on the information content of the original rainfall data rather than the interpolation approach used. This issue is discussed further in Chapter 5.

While comparisons can be made between the WR90 datasets and sub-basin rainfall data interpolated from the raingauge networks as part of the current study, explanations for the differences are not readily possible because the raingauges used in the WR90 study are not documented. The WR90 data were being updated during the course of this study (Bailey and Pitman, 2005) and the results were only made available towards the end of the project. It was therefore not possible to fully integrate these data into the rainfall uncertainty analysis.

With respect to the rainfall data used in this study, some of the raingauges selected for the interpolation process have records extending back to 1893 but others started after the 1950s. Similarly, there are large differences in the end dates of the records, some extending to the year 2000 and beyond, while other stations were closed much earlier.

Most of the raingauges have data available between 1920 and 1960 but there is a gradual decrease in the number of operational gauges from 1961 onwards. The selection of gauges to include in the analysis was based on initial simple checks on the quality of rainfall records and a record length of at least 14 years so as to include as many raingauges in the analysis as possible, while a length less than 14 will not be hydrological relevant as the period will be too short. All raingauges that did not meet these criteria were discarded from the analysis (see for example Appendix 1.1 for details of the gauges for selected sub-basins used in the study). Within different modelling periods it is likely that the number of gauges will therefore vary quite considerably causing problems in the generation of stationary sub-basin rainfall time series over extended periods of time (refer to Chapter 6, for further details). The following assumptions about the national rainfall data were used:

- The data have been previously quality controlled by the CCWR for any measurement errors and inconsistencies;
- The period with the maximum number of gauges represents the 'best' spatial coverage of rainfall variations. However, it is accepted that it is not possible to provide an absolute assessment of real spatial variations. This problem will be exacerbated in areas with steep rainfall gradients associated with orographic rainfall in mountain areas.

This study also used some detailed break point rainfall data for 28 raingauges within an area of 665 km^2 that are available for a period of 5 years (1988-1992). This network was established as part of an experimental basin (Bedford) to investigate hydrological processes and test hydrological models in a semi-arid region of South Africa (Hughes *et al*., 1993). While there are some gaps in the records for individual gauges, the performance of the raingauge network as a whole was found to operate with less than 10% gauge failure (Hughes and Sami, 1991).

3.3.2 Satellite rainfall data products

Given that the national network of ground based rainfall observations has been shrinking in recent years, the study decided to investigate the potential for using readily available satellite rainfall products. There are several satellite rainfall estimation methods reported in the literature that are used to derive final satellite rainfall datasets. The products range from global to regional datasets and include:

- National Oceanic and Atmospheric Administration's Climate Prediction Center Rainfall Estimation Algorithm RFE2.0 (NOAA's CPC RFE2.0; 1 day, 0.1 degree; Xie *et al*., 2002);
- NOAA CPC Morphing Technique (CMORPH; 30mins, 0.1 degree or 1 day, 0.25 degree, Joyce *et al*., 2004);
- TRIMM Real Time Multi-satellite Precipitation Analysis (TMPA-RT; 1 hr, 0.25 degree; Kummerow *et al*., 1998);
- Microwave InfraRed Algorithm (MIRA; 1 day, 0.1 degree; Todd *et al*., 2001; Layberry *et al*., 2005);
- Global Precipitation Climatology Project (GPCP; 1 day, 1 degree; Huffman *et al*., 1997);
- Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN; 6 hour, 0.25 degree; Hsu *et al*., 1999; Sooroshian *et al*., 2000).

The final rainfall estimates are based on merged information from several satellite imagery sources. A detailed evaluation of each of the sources and the methods used for all the datasets is beyond the scope of this study and reference can be made to the literature sources given above for more details. The focus in this study is on the use of the final operational rainfall estimates as inputs to regional hydrological models. Some of the global satellite products have already been used in hydrological modelling studies (Grimes et *al*., 1999; Todd *et al*., 1999; Thorne *et al*., 2001; Grimes and Diop, 2003). The GPCP and PERSIANN data sets were used as inputs to the Pitman hydrological model in southern African basins (Hughes, 2006b). In addition, Wilk *et al.* (2006) used rainfall estimates from Special sensor microwave (SGPROF) estimated using the Goddard Profiling Algorithm at 0.5° resolution, to estimate spatial rainfalls (1991-2002) in the Okavango River basin. Some of the practical considerations that need to be addressed before satellite datasets can be used successfully have been identified by Hughes (2006a, b). Existing hydrological models have typically been calibrated using historical gauged data, while the short periods of satellite data are insufficient to cover the various cycles of wet and dry periods found in hydrological records. At the same time, the relationships between gauged rainfall data and satellite derived rainfall data are not always clear and vary with satellite sources and across different regions.

While there are lot of studies on the application of global products (Todd *et al*., 1999; Thorne *et al*., 2001; Grimes and Diop, 2003; Hughes, 2006a, b) most of these are at quite coarse spatial scales compared to the required scales for water resources planning in South Africa. As part of developing spatially continuous and accurate rainfall datasets at more finer scales (spatially), NOAA's Climate Prediction Center derived gridded daily rainfall totals at 0.1°spatial resolution for the whole continent of Africa (NOAA's CPC RFE2.0 data) (Xie *et al*., 2002), which are available from 2001 and are continuously updated on daily basis. The NOAA CPC RFE2.0 data have been used in this study because they are available for the recent past when raingauge observations have declined even further in South Africa and because the temporal and spatial resolutions were considered suitable.

The NOAA CPC RFE2.0 rainfall datasets are satellite based rainfall outputs derived by merging several satellite estimates and station-based raingauge data (Love, 2004). The initial procedure did not incorporate an Advanced Microwave Sounding Unit (AMSU) satellite rainfall estimate assumed to potentially reduce bias in the final precipitation estimate (Xie *et al*., 2002). Therefore, with additional AMSU satellite estimates, the final African precipitation estimates (NOAA's CPC RFE2.0) were derived from four sources namely: Daily Global Telecommunications Systems (GTS) raingauges from up to 1000 stations, Special Sensor Microwave/Imager (SSM/I) satellite precipitation estimates at a frequency of up to 4 times a day, the Advanced Microwave Sounding Unit (AMSU) satellite rainfall estimate and Global Precipitation Index (GPI) cloud-top IR temperature precipitation estimates on a half-hour basis (Love, 2004). The final products are daily binary data and graphical output files produced at approximately 6Z-6Z, meaning that the rainfall daily totals are from 06h00 Universal Time one day to 06h00 Universal Time the next day with a spatial resolution of 0.1°. The Universal Time is based on the time at Greenwich Mean Time, England. The spatial extent of the data covers the whole of the Africa region from 40°S-40°N and 20°W-55°E. Despite the data used in this study being available from January 2001 to October 2006, the data are continuously being updated and are freely available from the internet, website (accessed in October 2006): ftp://ftp.cpc.ncep.noaa.gov/fews/newalgo_est.

3.3.3 Potential evapotranspiration data

Potential evapotranspiration data used in hydrological models in South Africa are often based on estimates from standard Symons or American A class pans (see also section 3.1.1.2). In South Africa evaporation is measured at about 300 DWAF stations, usually by means of Symons pan evaporimeters. The SAWS also equips their meteorological stations with A-type pan evaporimeters. The evaporation recorded by these two types of pans is significantly different because they are different installations but this difference may be reconciled by using existing relationships (Midgley *et al*., 1994). The data used in the present study were the fixed mean monthly evaporation estimates available in the WR90 reports (Midgley *et al*., 1994). The potential evaporation values were converted using appropriate pan factors (Midgley *et al*., 1994) to potential evapotranspiration that are used as inputs to the Pitman model. Some time series estimates were obtained from DWAF Symons pan measurements which are available at a limited number of sites (e.g. one gauge for a whole river basin covering approximately 10 000km^2).

Having recognised the limitation in the number of pan evaporation gauges to use in estimating representative time series variations in evaporation demand for each sub-basin (quaternary catchment) in South Africa, the study attempted to make use of temperature time series data that have more observation stations. Given that the Pitman model is typically used with pan evaporation data, variations in temperature time series covering a period 1950 to 1990 were used to estimate variations (from long-term means) in potential evaporation. The assumption was made that time series variations in evaporation demand could be estimated using equivalent temperature variations based on the following relationship:

$$\mathrm{E}_{ij} = \overline{\mathrm{E}}_j \times \frac{\mathrm{T}_{ij}}{\overline{\mathrm{T}}_j} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.1$$

where $\overline{\mathrm{E}}_j$ and $\overline{\mathrm{T}}_j$ are long-term monthly mean evaporation and temperature values for month j, while E_{ij} and T_{ij} are monthly evaporation and temperature values for year i. The spatial time series temperature data were obtained from a database prepared by Schulze and Maharaj (2006). These data are available as mean monthly temperature time series for 50 years for each of the 1946 quaternary catchments in South Africa and applicable for the purposes of the present study.

3.3.4 Observed streamflow data

The observed streamflow time series data were obtained from the DWAF database which is continuously updated (http:/www.dwaf.gov.za/hydrology, the data used in this study were downloaded in October 2006). These data are available as mean daily runoff values (m^3/s) which are aggregated to monthly flow volumes for use with the Pitman model. There are three main factors that affect the use of these data for assessing outputs from hydrological models; (i) poorly defined artificial upstream influences (upstream reservoir storage, dynamic patterns of abstractions, return flows and land use modifications notably commercial afforestation), (ii) gauge inaccuracies, particularly in the low flow part of hydrographs and (iii) the inability of some gauging structures to measure flows above certain thresholds.

The majority of the observed streamflow data in South Africa reflect anthropogenic changes within most river basins. While these changes can be identified, there are few reliable data sources from which to quantify their impacts and derive naturalised flows. In some cases the anthropogenic changes are relatively small and in some situations it is very clear that the observed streamflow data do not represent natural conditions, but rather some modified conditions. This may be because the upstream water resources developments are well understood or it may be because the 'signal' in the flow record is very clear. It is therefore frequently necessary to naturalise flows and examples of naturalised flow data can be found in the WR90 reports (Midgley *et al*., 1994). However, there are many situations where the extent of flow modification is not clear at all, or where there is clearly a present day influence but it is not straightforward to identify historical trends due to the unknown quantity of the impact.

DWAF uses various types of gauging structures (Figure 3.10) to monitor streamflows, including weirs (sharp crest, v-notch, vee crump, ogee spillway etc.) and flumes (slicing, parshall etc.). They all have different degrees of accuracy across the range of flows that they are designed to measure. Knowledge of the structure type can be very useful in assessments of the accuracy of the streamflow record. For example, many of older weirs are sharp crested weirs with relatively wide low flow sections. The rating curves are relatively insensitive to changes in weir pool depth during low flows, while the weir pools are also subject to problems of siltation.

Figure 3.10 Types of flow gauging structures used by DWAF (website: http://www.dwaf.gov.co.za/hydrology downloaded in June 2008).

DWAF attach quality codes to individual daily streamflow data values and some errors (such as gauge exceedance) are easily identified, while others related to such as weir pool siltation are not. Figure 3.11a (gauge X3H001, Sabie River, Mpumalanga Province) illustrates a potential problem in the observation of low flows prior to 1958. While this effect can be related to changes in upstream development impacts, there is no evidence to support such a conclusion and the non-stationarity is more likely to be due to gauging errors. An additional problem associated with many of the available streamflow records is that they have truncated peak flows due to the limited range of stage-discharge relationships. An extreme example is provided in Figure 3.11b using mean daily flow records for gauge X3H007 (White Water River, Mpumalanga Province). While the effects are relatively simple to identify using daily average data, the uncertainties can be obscured when these data are aggregated to monthly values.

The implications of using uncertain observed streamflow information to calibrate or to assess the output from rainfall-runoff models are clear. It is therefore essential that the streamflow data are carefully assessed (for errors, upstream development effects and possible non-stationarity) before they are used with a model. These checks should be performed on the higher resolution daily data, rather than the aggregated monthly streamflow volumes. In this study all the missing values were patched and the flows were checked for stationarity before they were used.

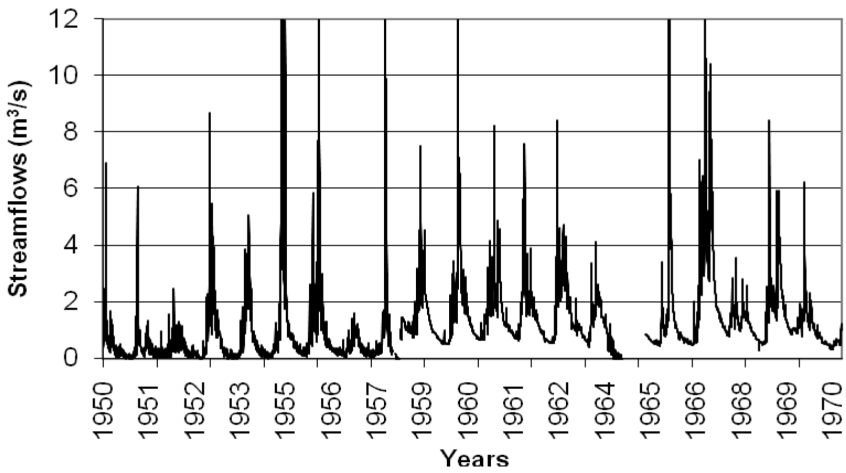


Figure 3.11a An illustration of non-stationarity in measured daily average streamflow time series record (gauge X3H001).

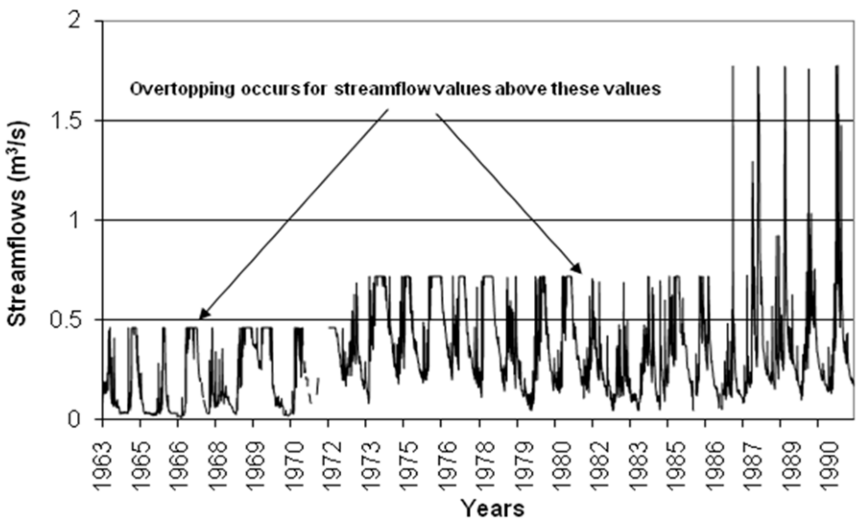


Figure 3.11b An illustration of the streamflow gauging exceedence errors in measured daily average streamflow time series record (gauge X3H007).

3.3.5 Basin physical property data

Information on soils, vegetation, topography and geology (see also section 3.1.2) is often critical in understanding the hydrological responses to climate inputs and is commonly required for hydrological parameter estimation or regionalisation (Kapangazawiri and Hughes, 2008). There are several possible sources of such information in a South

African context including topographic, geology, soil survey maps, Google Earth, the WR90 reports (Midgely *et al*., 1994), the South Africa Atlas of Climatology and Agrohydrology (Schulze, 1997) and the Agricultural Geo-Referenced Information System comprehensive database (AGIS, 2007). All these present the required information in different ways, with different spatial resolutions and with different degrees of direct relevance to hydrological modelling. The implication is that it is difficult to identify a single source of relevant information and most of these sources require at least some degree of interpretation or pre-processing before being used with a hydrological model (e.g. for parameter estimation). A common problem is that the spatial resolution of the data source does not correspond to that of the model. Uncertainties in misinterpretation of the physical property data will clearly affect the accuracy of parameter estimation methods, such as that proposed by Kapangaziwiri and Hughes (2008).

Experience gained throughout this study suggests that the information presented in AGIS (2007) database represents the most comprehensive source of basin physical property data, particularly with respect to topographic slope, geology and soils data relevant to hydrological modelling. The data are available online (www.agis.agric.za/agisweb/agis.html) in a GIS format, supported by more detailed 'Landtype' data (Table 3.3) which provides, soil depth, type and texture information based on terrain units. Despite the high level of detail contained within this database, the interpretation of the data for use with a hydrological model remains a challenge. Google Earth can be extremely useful to get an overall impression of topographic variations and land use.

3.3.6 Water resources development data

These data include upstream reservoirs (both large and small), abstractions, return flows and land use patterns (e.g. afforestastion, dryland and irrigated crops), all of which can have a significant impact on natural streamflows. Data are available from the WR90 reports (Midgley *et al*., 1994), WR2005 project (WRC, 2005) and DWAF Water Use Authorisation and Registration Management System (WARMS) database. Where a model is to be calibrated against observed flow data, or where these data are used to assess model output uncertainties, it is clearly important to understand what the observed data represent. As already noted in the section on streamflow data, the information available about existing water resources developments is frequently incomplete. For example, there is quite a lot of information available (volume and surface area) for registered dams, but there are many un-registered dams for which there is very little information. The amount of detail of water development data is therefore not usually adequate to accurately quantify their influences or uncertainties. Additional uncertainties are introduced through unknown variations in abstractions and return flows over the period of observations.

Table 3.3 An illustration of Landtype data format (soil depth ranges, slope, soil texture, and geology) obtained from AGIS (2007) for Gouritz sub-basin.

LAND TYPE / *LANDTIP* .... : **Fc147**
CLIMATE ZONE *KLIMAATSONE* ...... : 760S
Area / *Oppervlakte* .... : 27500 ha
Estimated area unavailable for agriculture
Beraamde oppervlakte onbeskikbaar vir landbou : 200 ha

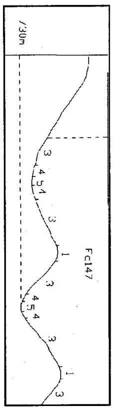
Occurrence (maps) and areas *Voorkoms (kaarte) en oppervlakte :*
3322 Oudtshoorn (27500 ha)

Inventory by *Inventaris deur :*
B H A Schloms
Modal Profiles *Modale profiele :*
None / Geen

Terrain uni *Terreineenhei*	1	3	4	5
% of land type *% van landtipe*	12	55	25	8
Area *Oppervlakte (ha)*	3300	15125	6875	2200
Slope / *Helling (%)*	1 - 4	15 - 40	2 - 4	1 - 3
Slope length *Hellingslengte (m)*	100 - 400	400 - 800	200 - 800	50 - 150
Slope shape *Hellingsvorm*	Y	Y	X	Z-X
MB0, MB1 (ha)	0	1512	4125	1540
MB2 - MB4 (ha)	3300	13612	2750	660

Soil series or land classes *Grondseries of landklasse*	**Depth** *Diepte* (mm)	MB	1 ha	1 %	3 ha	3 %	4 ha	4 %	5 ha	5 %	**Total** *Totaal* ha	%	**Clay content %** *Klei-inhoud %* A	E	B21	Hor	**Texture** *Tekstuur* Class / *Klas*	**Depth limiting material** *Diepte-beperkende materiaal*
Rock / Rots		4	2640	80	8319	55	138	2			11096	40.4						
Kanonkop Gs13, Platt Gs14, Williamson Gs16, Southfield Gs23	100-200	3	165	5	3781	25	1031	15			4978	18.1	8-15		10-25	A	Lmfi/meSa-SaLm	so
Zwartfontein Hu34, Shorrocks Hu36, Shigalo Hu46	200-500	1			908	6	2062	30			2970	10.8	8-15		10-30	B	LmmeSa-SaClLm	R
Mispah Ms10	50-100	3	495	15	1512	10	206	3			2214	8.1	3-15			A	meSa-LmfiSa	R
Skilderkrans Sw11, Broekspruit Sw21	200-300	1			454	3	1031	15			1485	5.4	8-15		35-55	B	SaCl-Cl	vr
Klipplaat Oa13, Leeufontein Oa16, Kirkton Oa23	600-1200+	0					688	10	660	30	1348	4.9	8-15		10-30	B	LmfiSa-SaClLm	R
Swartland Sw31	200-300	1			151	1	344	5			495	1.8	8-15		35-55	B	SaCl-Cl	vp
Dundee Du10	>1200	0							440	20	440	1.6	3-8			A	fi/meSa	
Vaalrivier Oa33, Levubu Oa34	600-1200+	0							440	20	440	1.6	6-10		8-15	B	Lmfi/meSa-SaLm	R
Coarse deposits/Growwe afsettings		2					1375	20	440	20	1815	6.6						
Stream beds/Stroombeddings		4							220	10	220	0.8						

LAND TYPE / *LANDTIP* .... : **Fc147** Continued *Vervolg*
Terrain type *Terreintipe :* C3
Terrain form sketch *Terreinvormskets*



For an explanation of this table consult LAND TYPE INVENTORY (table of contents)
Ter verduideliking van hierdie tabel kyk LANDTIPE - INVENTARIS (inhoudsopgawe)

Geology: Mainly arenaceous shale, siltstone and sandstone of the Witteberg Group with siltstone, shale and arenaceous shale of the Bokkeveld Group, both of the Cape Supergroup.

Geologie Hoofsaaklik sanderige skalie, sliksteen en sandsteen van die Groep Witteberg met sliksteen, skalie en sanderige skalie van die Groep Bokkeveld, beide van die Supergroep Kaap.

3.4 General modelling methodologies of the study

The overall objectives of this study were to identify sources of uncertainty in hydrological modelling (based on the literature and past experience), quantify the degree of uncertainty for individual sources, identify possible interventions to reduce uncertainty and combine individual sources to assess their combined impact on model outputs in a South African context. The details of the methods used in this study are briefly highlighted in section 3.4.3 but further details are presented in specific chapters that follow. For example, Chapter 4 presents a qualitative approach to identifying the hierarchy of uncertainty sources that eventually contribute to the uncertainty and associated risks in water resources decision making. The focus of this study has been on the uncertainty associated with simulations of natural hydrology, while the additional sources found in water resources management and operational planning are beyond the scope of this study.

Chapters 5 to 8 discuss the independent modelling experiments that were undertaken to address individual sources of uncertainty associated with rainfall-runoff modelling (specifically using the Pitman model). The input data (i.e. rainfall and potential evapotranspiration) and parameter uncertainties were quantified through a sensitivity analysis approach. These chapters also discuss possible approaches for reducing the uncertainty. Chapter 9 discusses the integration of the effects of different sources of uncertainty but also includes the evaluation of uncertainty in water use data (e.g. uncertainty in irrigation abstractions and afforestation) on modelling natural water resources availability. While observed streamflow data are used throughout these chapters to provide quantitative estimates of uncertainty, the focus is on providing estimates of uncertainty that will result from application of the model in ungauged or poorly gauged basins. The remainder of this chapter briefly describes the data processing and modelling tools that have been used to achieve the objectives of the study.

3.4.1 Data management and model application using the SPATSIM software

The major components of any hydrological modelling study are the efficient management of the required data, the effective integration of the data with the model and the availability of appropriate methods for assessing and analysing the model outputs. The Spatial and Time Series Information Modelling (SPATSIM) software (Hughes and Forsyth, 2006) was developed at the Institute for Water Research at Rhodes University for exactly these purposes. It incorporates a comprehensive data management system (using structured database tables) with a Geographical Information System (GIS) interface that allows data to be accessed and used in a spatial context. It has been designed to allow a wide range of generic data management and processing facilities to be combined with access to a number of hydrological and water resources management models.

Data access is managed through a spatial interface (using GIS shape files called features) linked to any number of data attributes (Figure 3.12). These attributes are user defined and cover a wide arrange of data types including text information, single values, tabular information (e.g. model parameter sets or seasonal evaporation values), time series data and graphic images (e.g. photographs of gauging structures).

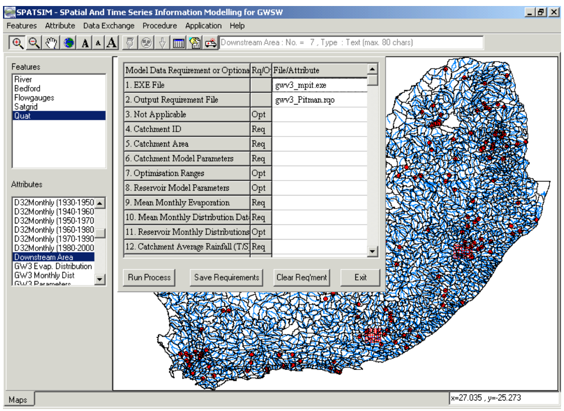


Figure 3.12 Screen image of SPATISM software also showing the model setup interface.

The SPATSIM software has internal facilities which include routines for importing different types of data, viewing, graphically displaying and editing data, sharing data with other users and further processing of data to create new information. Besides the internal facilities, SPATSIM has links with external models. The models linked to SPATSIM are developed as separate computer programs but using generic procedures to associate the data input and output requirements of the models with the data attributes of a specific SPATSIM application (Figure 3.12). Also linked to SPATSIM is an external time series analysis program referred to as TSOFT (Hughes *et al*., 2000). TSOFT (Figure 3.13a) can be used to graphically or statistically analyze and summarize all types of time series data and is designed *inter alia* for the assessment of observed data (e.g. error checking, identifying non-stationarity), comparison between observed and simulated data and the detailed investigation of model outputs. Available analysis methods include the generation of seasonal distributions, flow duration curves, threshold analyses and X-Y scatter plots used to compare two time series. The scatter plot option (Figure 3.13b) also generates comparative statistics that are typically used to compare observed and simulated flows during model calibration.

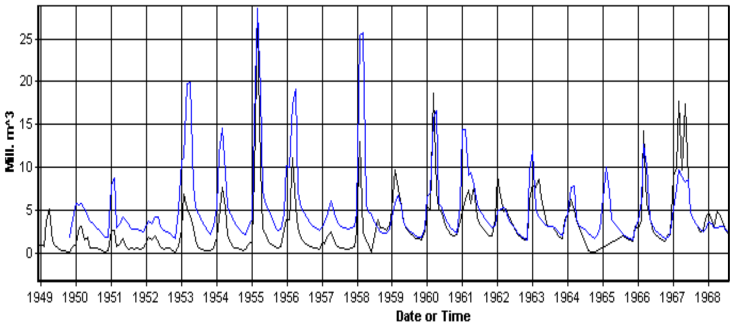


Figure 3.13a Graphical view of the observed (white) and simulated (blue) flow time series in the TSOFT analysis program.

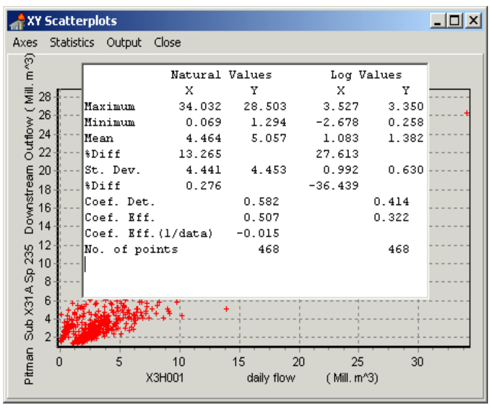


Figure 3.13b Output of comparative statistics as part of the X-Y scatterplot option in TSOFT.

The goodness-of-fit statistics generated as part of the X-Y scatter plot option (Figure and 3.13b) that were used in this study to evaluate model performance and assess accuracy of model outputs are summarised below:

a) Percentage differences in mean monthly flows {%Diff.Mn}:

$$\%Dff.Mn = \left[\frac{Mn_{sim} - Mn_{obs}}{Mn_{obs}}\right] x100 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots .. \ 3.2$$

where, Mn_{sim} is the mean of the simulated monthly flow time series and Mn_{obs} is the mean of the observed monthly flow time series. The acceptable percentage difference in mean flows was assumed to be within ± 5% in this study (based on the previous application of the model).

b) Coefficient of determination (R^2) – this describes the proportion of the total variance in the observed data that can be explained by the model or simulated data and is given by:

$$R^2 = \frac{\sum_{i=1}^{N} (O_{obs_i} - \Theta_{obs})(O_{sim_i} - \Theta_{sim})}{\left[\sum_{i=1}^{N} (O_{obs_i} - \Theta_{obs})^2\right]^{1/2} \left[\sum_{i=1}^{N} (O_{sim_i} - \Theta_{sim})^2\right]^{1/2}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.3$$

where, O_{obs} is the observed time series and Θ_{obs} is the mean of observed time series while O_{sim} is the simulated time series and Θ_{sim} is the mean of simulated time series and the comparisons are over a given period divided into N time increments which can be any duration (monthly or daily time-steps). The criterion can be over-sensitive to extreme values (outliers) and is insensitive to systematic differences between the simulated and observed flows.

c) Nash coefficient of efficiency (CE) by Nash and Sutcliffe (1970) is the most widely goodness-of fit criteria in hydrological modelling and is given by:

$$CE = 1 - \left[\frac{\sum_{i=1}^{N} (O_{obs_i} - O_{sim_i})^2}{\sum_{i=1} (O_{obs_i} - \Theta_{obs})^2}\right] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots ... 3.4$$

This criterion represents an improvement to R^2 because it is sensitive to differences between the observed and model simulated means and variances, but due to squared differences it is also sensitive to extreme values (outliers in data). If the square of the differences between model simulations and the observations is as large as the variability in the observed data, the CE=0, which means that simulated flows are not better estimators than the observed mean. A perfect fit between the two time series results in CE=1, while an acceptable minimum value can be assumed to be approximately 0.6 (based on previous experience).

d) Percentage differences of standard deviations of monthly flows {%Diff.Stdv}:

$$Stdv(\%) = \left[\frac{Stdv_{sim} - Stdv_{obs}}{Stdv_{obs}}\right] x100 \quad \text{......} 3.5$$

where, $Stdv_{sim}$ and $Stdv_{obs}$ represent the standard deviations of simulated and observed flows respectively. Acceptable percentage differences in standard deviations of monthly flows were assumed to be approximately ± 15% in this study.

The above objective functions (a-d) are calculated for both the un-transformed data (e.g. %Diff.Mn(Q); R^2(Q) CE(Q); %Diff.Stdv(Q)), which tend to be influenced by high flows, and log transformed data, to emphasis role of low flows (e.g. %Diff.Mn (InQ); R^2(InQ) CE (InQ); %Diff.Stdv(InQ)}. The coefficient of efficiency is also calculated for inverse transformed data (CE {1/data}).

3.4.2 SPATSIM version of the Pitman Model

The SPATSIM version of the model retains a large part of the structure of the original model (Pitman, 1973) but includes some recent developments designed to improve the general applicability of the model in the southern African region (Hughes, 1997). This version also includes the more explicit representation of surface and groundwater interactions as proposed by Hughes (2004b). A brief summary of the model structure is provided below, while a more detailed description can be found in Hughes *et al.*, 2006). Kapangaziwiri (2008) provides a full description (including all of the model algorithms and conceptual interpretation of the parameters.

3.4.2.1 Natural hydrology model components

The Pitman model is a semi-distributed conceptual model that consists of storages linked by functions designed to represent the main hydrological processes and can simulate the major natural water balance processes which prevail at basin scales (Kapangaziwiri, 2008). The semi-distributed nature of the model allows all sub-basins to be modelled with independent parameter sets and input time series within SPATSIM. The main inputs to the model are the parameter sets, monthly time series of rainfall totals and time series or fixed mean monthly distributions of potential evapotranspiration. Interception, soil moisture, and groundwater are the three main conceptual storages in the model. Figure 3.14 illustrates the main structure of the model while Table 3.4 provides a list of the parameters and their descriptions, including those for the optional development impact components (refer to section 3.4.2) of the model.

The Pitman model operates over four model iterations to reduce large changes in state variables and to avoid issues of order in which processes are accounted for on a long time-step model and the distribution of the total monthly rainfall over these iterations is controlled by a rainfall distribution (RDF) parameter. Low RDF values give more even distribution of rainfall with the effect being more pronounced for higher rainfall totals (Hughes *et al*., 2006). Rainfall is intercepted (based on the storage parameters PI1 and PI2 for two vegetation types) before reaching the surface and the interception function is based on a relationship between the relevant PI parameter and rainfall amount and is decreased by evaporation demand at the potential rate (Hughes *et al*., 2006). The balance of the rainfall is applied to the impervious area (parameter Fract.) and the surface runoff function (ZMIN, ZAVE and ZMAX). The latter is controlled by a symmetrical triangular distribution of catchment absorption (Box 1) as in the orginal version of the model (Pitman, 1973). However, the latter version (Hughes, 2004b) assumes a non-symmetrical distribution of catchment absorption (see Kapangaziwri, 2008 for details). The infiltration parameters describe the absorption capacity of the basin in response to different rates of rainfall input (Box 1). Rainfall that is not either intercepted or converted to surface runoff is added to the soil moisture storage (with a maximum value of ST) which is subject to evapotranspiration losses (parameter R). If this storage is exceeded, additional surface runoff is generated (Box 2), while soil moisture runoff from the storage is controlled by a non-linear power (POW) function with a maximum value of FT mm month^{-1} (at storage equal to ST). Both the surface and soil moisture runoff components are subject to lag and attenuation using parameter TL. A function similar to the soil moisture runoff function is used to determine recharge (RE) to the conceptual groundwater storage using parameters GPOW and GW (Box 2). The relationship is assumed to describe the rate at which water drains from subsurface storage to streams. Box 1 and 2 only shows the relationships of the parameters that were used in the sensitivity analysis in Chapter 8.

The details of the groundwater functions and the generation of groundwater contributions to streamflow are discussed by Hughes (2004b). Briefly, the model simulates groundwater gradients on the basis of the sub-surface water balance, which together with the transmissivity parameter (T) and the drainage density (D.Dens) are used to estimate outflows to the river channels. A further parameter is used to estimate evapotranspiration losses from groundwater in the channel riparian areas. Finally, a channel routing parameter is included but is only expected to be used when modelling very large sub-basins (greater than about 10 000km^2).

Box 1: Relationships between surface runoff generation parameters Zmin, Zave and Zmax.

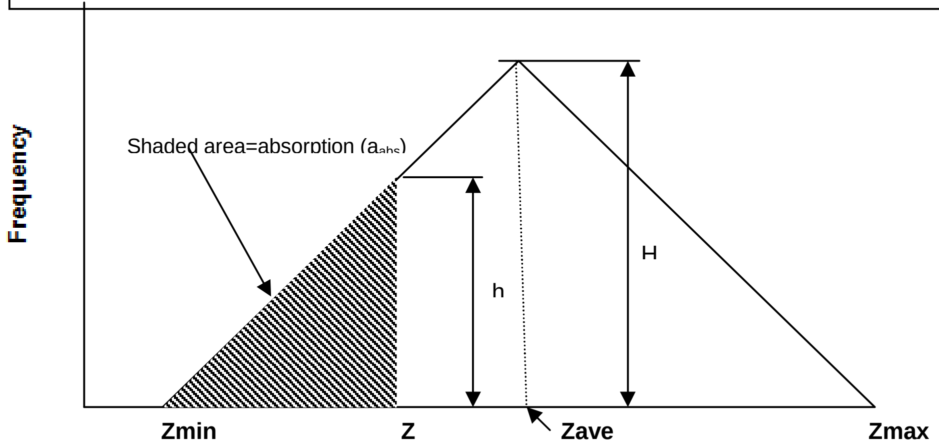


Illustration of the triangular frequency distribution of basin absorption rate, Z

For any given absorption rate, Z mm per month

$$a_{abs} = \left(\frac{(Z - Z\min)^2}{(Z\max - Z\min)(Zave - Z\min)} \right), \text{ for Zmin} \le Z \le \text{Zave}$$

$$a_{abs} = 1 - \left(\frac{(Z\max - Z)^2}{(Z\max - Z\min)(Z\max - Zave)} \right), \text{ for Zave} \le Z \le \text{Zmax,}$$

When Z=Z_{min}, a_{abs}=0 and with Z=Zmax, a_{abs}=1.

Where, Zmin is the minimum, Zave, is the average and Zmax is the maximum absorption rate.

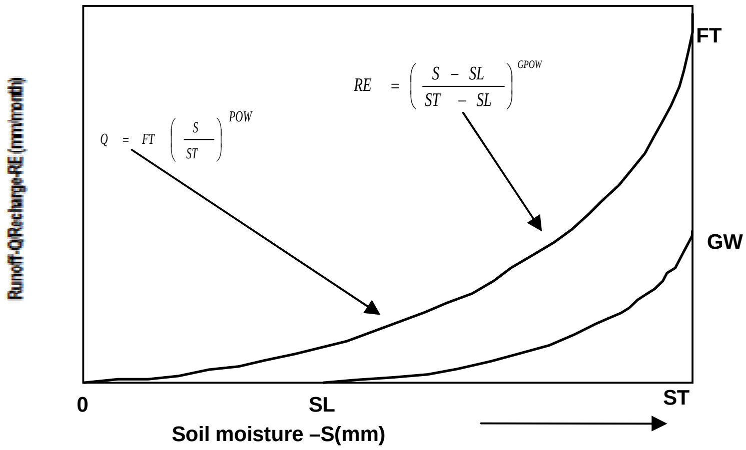
These equations are used to estimate monthly surface runoff, (Q mm per month). Given any rainfall input r,

$$Q = \frac{2}{3}\left(\frac{(r - Z\min)^3}{(Z\max - Z\min)^2} \right), \text{ for Zmin} \le r \le \text{Zave}$$

$$Q = r - Zave + \frac{2}{3}\left(\frac{(Z\max - r)^3}{(Z\max - Z\min)^2} \right), \text{ for Zave} \le r \le \text{Zmax}$$

$$Q = r - Zave \text{ , for r} \ge \text{Zmax}$$

Box 2: Relationships between the sub-surface runoff generation parameters (FT, ST, POW, SL, GW and GPOW)



S is the current soil moisture storage level in mm, ST is the maximum soil moisture storage capacity and SL is the lower limit of soil moisture state of the soil below which no groundwater recharge occurs. Q is the monthly discharge in mm/month, FT refers to runoff generated from the soil when soil moisture level is at its maximum (ST), POW represents the relationship between total basin moisture status and spatial distribution of this moisture. RE is the monthly recharge rate in mm; GW is the upper limit of the groundwater recharge rate (mm/month) at moisture state S, GPOW describes the shape of the relationship between moisture stored in the unsaturated zone and the volume of recharge

3.4.2.2 Model extension to developed sub-basins

The model includes several components to represent anthropogenic impacts on natural hydrology (land use modifications such as managed forest plantations, run-of-river abstractions and return flows, distributed small farm dams and large reservoirs). This version of the model has routines to account for abstractions from the river and the groundwater store for various purposes and there is an option to return a proportion of abstracted water to the river (Table 3.4). Small farm dam routines in the model account for surface storage (and abstraction) of runoff generated within a sub-basin, while for large reservoir storages a main reservoir water balance component (Hughes, 1992) is included. The latter receives inflows from all upstream sub-basins and can be setup with a number of abstraction and release operating rules based on the level of storage in the reservoir. Both reservoir components (small farm dam and main reservoir) estimate evaporative losses on the basis of power relationships between simulated volumes (Vol - obtained from the model water balance) and surface area (Area = $A*Vol^B$). While the model has been used quite frequently to simulate development effects, in complex situations (such as multiple water supply sources and complex operating rules) water resources systems models are more appropriate simulation tools.

3.4.3 Sensitivity and uncertainty analysis for the Pitman model in SPATISM

In a broad sense, all the sources of uncertainty that affect variability of model output are assessed through formal sensitivity and uncertainty analyses methods (Chapter 2, section 2.5). It is generally argued that uncertainty analysis coupled with sensitivity analysis can help to understand whether the current knowledge is sufficient to allow decision makers to make a reliable decision (Beven, 2001a). If not, such analyses can also help to identify which uncertainty sources require knowledge improvement in order to achieve the desired level of confidence in decision making. While sensitivity analysis determines the strength of the relation between a given uncertain model “input variable” (e.g. rainfall, evaporation or parameter) and model outputs, uncertainty analysis propagates input uncertainties into the model outputs (Saltelli, 2000).

Sensitivity analysis procedures consist of a strategy to vary the model inputs and a numerical measure to estimate how the model response has changed based on varying one or more inputs (Wagner and Kollat, 2007). The model then propagates model parameters and other uncertainties into model outputs. The SPATSIM facilities were used for these purposes through independent sensitivity assessments of each source of uncertainty; sensitivity to areal averaged rainfall uncertainty (Chapter 5 and 6); sensitivity to evapotranspiration data uncertainty (Chapter 7); and sensitivity to parameter estimation uncertainty (Chapter 8). With respect to climate data (i.e. rainfall and evaporation), the assessment technique required a ‘reference’ observed climate dataset against which other results could be compared. In this study the rainfall or evaporation realisations that are assumed to be most representative of sub-basin conditions were used as the ‘reference’. Additional rainfall or evaporation realisations were then assessed using a fixed parameter set for all model realisations. More details on the procedures are found later in the relevant chapters.

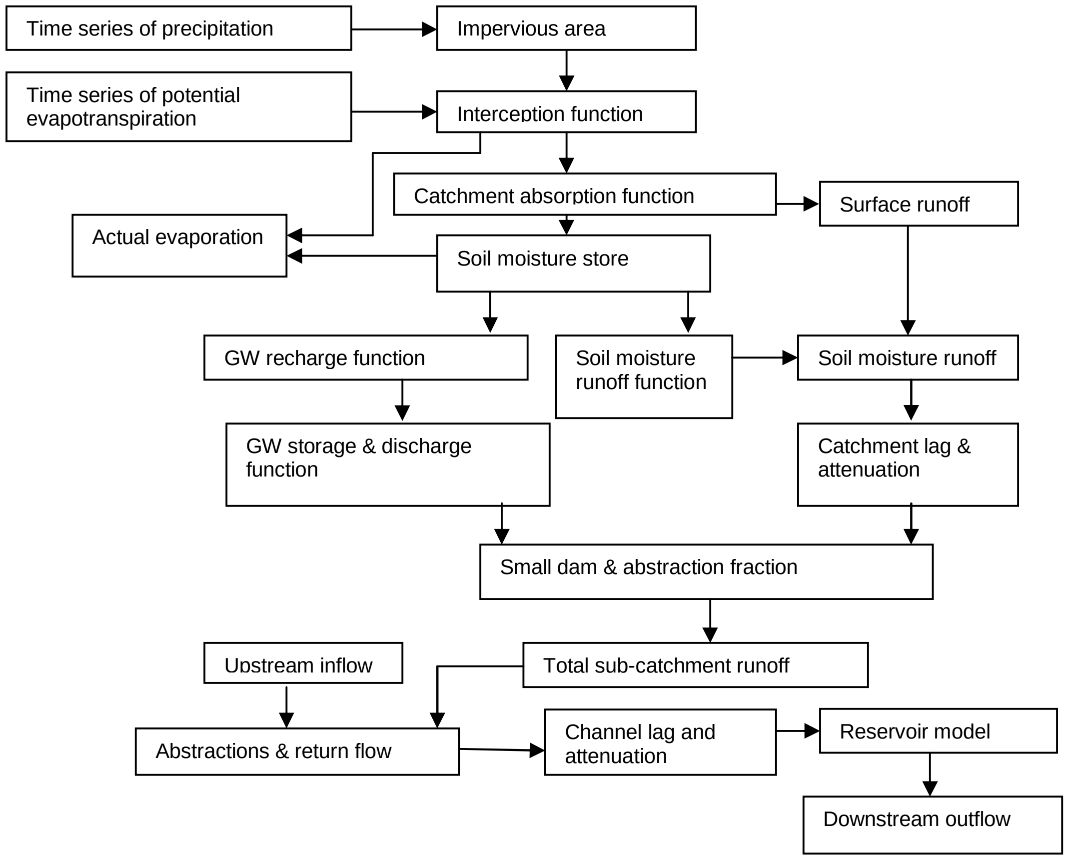


Figure 3.14 The main components of the Pitman model (after Hughes *et al*., 2006).

A separate software version of the model was used to investigate parameter sensitivity. It allows the 'best guess' parameter values to be modified over several steps with defined step sizes. The program then generates objective functions (based on comparisons with some input 'observed data' time series) for all possible combinations of the parameters that are varied. The 'observed data' used for comparison with the simulated data can be real observed data (in gauged basins), or could be the simulation based on the 'best guess' parameter set (for ungauged basins). This approach was adopted as it was simple to implement and provided a starting point for the development of more detailed sensitivity analysis and uncertainty assessment procedures. Despite the fact that it uses discrete parameter values as input rather than continuous parameter distributions, it is still possible to explore the extent of parameter non-uniqueness, which is a common problem with the Pitman model. A typical application of five parameters with seven steps (best guess and 3 steps either side) generates a total number of 16 807 ensembles. The parameter ranges are determined by subjectively (and therefore without probability statements) assessing the likely maximum and minimum values of estimated basin physical property data (Table 3.5), which are used as inputs in the parameter estimation method of Hughes and Kapangaziwiri (2008).

In the context of parameter uncertainty analysis, the same software version used in the sensitivity analysis was also used to generate ensemble simulations. The number of steps was reduced to 3, but with the inclusion of all the parameters expected to be estimated with uncertainty. The results of the multiple ensembles can be very useful in identifying which parameters are likely to influence uncertainty the most and therefore where the focus on accurate parameter estimation should be.

For the parameter sensitivity and uncertainty assessment (more details in Chapter 8), the parameter sets were varied, but with fixed inputs of rainfall and potential evapotranspiration data used for all the parameter combinations. Initially the parameters were estimated using the *a priori* parameter estimation technique of Kapangaziwiri and Hughes (2008), rather than the traditional manual calibration procedure. Figure 3.15 shows the paths followed in the developmental of the *a priori* approach. The assumption of the approach is that both the model structure and basin parameters are based on sound physical hydrology principles (Kapangaziwiri, 2008; Kapangaziwiri and Hughes, 2008). If a set of relevant basin physical properties are available then it is feasible using conceptual links between these properties and model parameters to develop physically-based parameter estimation procedures following the path depicted in Figure 3.15. The focus was on the main runoff generation parameters (ZMIN, ZAVE, ZMAX, ST, FT and POW, Table 3.4), while it is assumed that the approach could ultimately be extended to the full parameter set of the Pitman model (Kapangaziwri, 2008).

Table 3.4 Pitman model parameters including those of the reservoir water balance model (after Hughes *et al*., 2006).

Parameter	Units	Pitman model parameter description
RDF		Rainfall distribution factor. Controls the distribution of total monthly rainfall over four model iterations
AI	Fract.	Impervious fraction of sub-basin
PI1 and PI2	mm $month^{-1}$	Interception storage for two vegetation types
AFOR	%	% Area of sub-basin under vegetation type 2
FF		Ratio of potential evaporation rate for Veg2 relative to Veg1
PEVAP	mm $year^{-1}$	Annual sub-basin evaporation
ZMIN	mm $month^{-1}$	Minimum sub-basin absorption rate
ZAVE	mm $month^{-1}$	Mean sub-basin absorption rate
ZMAX	mm $month^{-1}$	Maximum sub-basin absorption rate
ST	mm	Maximum moisture storage capacity
SL	mm	Minimum moisture storage below which no GW recharges occurs
POW		Power of moisture storage–runoff equation
FT	mm $month^{-1}$	Runoff from moisture storage a full capacity (ST)
GPOW		Power of moisture storage-GW recharge equation
GW	mm $month^{-1}$	Maximum ground water recharge at full capacity (ST)
R		Evaporation-moisture storage relationship parameter
TL	months	Lag of surface and soil moisture runoff
CL	months	Channel routing coefficient
D.Dens		Drainage density
T	m^2 d^{-1}	Ground water transmissivity
S		Ground water storativity
Slope		Initial ground water gradient
AIRR	km^2	Irrigation area
IWR	Fract.	Irrigation water return flow fraction
EFFECT	Fract.	Effective rainfall fraction
RUSE	Mm^3 yr^{-1}	Non-irrigation demand from the river
MDAM	Mm^3	Small dam storage capacity
DAREA	%	Percentage of sub-basin above dams
A,B		Parameters in the non-linear dam area-volume relationship
IRRIG	km^2	Irrigation area from small dams

Table 3.4 *continued.*

Parameter	**Units**	**Reservoir model parameter description**
CAP	Mm^3	Reservoir capacity
DEAD	%	Dead storage
INIT	%	Initial storage
A,B		Parameters of non-linear dam area-volume relationship
RES1-5	%	Reserve supply levels (percentage of full capacity)
ABS	$Mm^3\ yr^{-1}$	Annual abstraction volume
COMP	$Mm^3\ yr^{-1}$	Annual compensation flow volume

Table 3.5 Input basin physical property data required for the estimation of parameters (ZMIN, ZAVE, ZMAX, ST, FT and POW) according to Kapangaziwiri and Hughes (2008).

Basin physical property	**Metric**
Soil texture (for ZMIN, ZAVE & ZMAX)	Range of infiltration rates for each texture class.
Soil Texture (for FT)	Range of permeability rates for each texture class.
Soil Texture (for ST)	Range of porosity values for each texture class.
Mean soil depth (for ST)	Mean soil depth and % basin area for upper, mid and lower slopes in the basin.
Drainage density (for FT)	Map estimation
Basin slope (for FT and ST)	Map or DTM estimation or measurement of mean basin slope.
Regional ground water gradient (for ST and FT)	Based on channel slope in lower part of basin by default.
Drainage vector slope (for ST and FT)	Based on classes of geological structure types in the unsaturated zone.
Storativity	
Depth to ground water (GW)	Based on mean basin slope and regional ground water gradient.

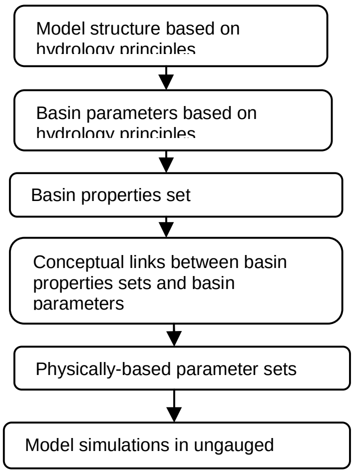


Figure 3.15 Flow diagram of *a priori* parameter estimation approach by Kapangaziwiri and Hughes (2008).

While useful, the statistical measures listed in section 3.4.1 can be limited in their applications in that they only consider part of the available uncertainty information in model outputs (i.e. mean flows, high flows or low flows etc). Decision makers sometimes are not only interested in the mean value and standard deviation of model outputs and this study includes a yield deficit statistic to evaluate model prediction uncertainty and their consequences on reservoir yield, which moves the research from a purely theoretical realm to one that is more relevant to water managers. The main reservoir function of the Pitman model structure has a facility to simulate the mean annual yield of a sub-basin at its outlet for a given draft (mean annual abstraction demand) and reservoir size. The method uses a yield deficit statistic to assess the impacts of different outputs realizations (based on different rainfall, evaporation or parameter scenarios) on decision making for future water resources planning. The approach integrates a variety of characteristics of the simulated flow time series into a single impact on the reservoir yield, is less sensitive to extremes and is expected to be more useful to a water resources manager. The mean monthly percentage yield deficit for each of the ensembles based on a user-defined reservoir capacity and required yield is expressed as:

$$YD(\%) = \left[\frac{Yield_{sim} - Yield_{\mathrm{Req}}}{Yield_{\mathrm{Req}}} \right] x100 \quad \text{...3.6}$$

where, $Yield_{sim}$ and $Yield_{req}$ represent the simulated and required yields, respectively.

4. IDENTIFICATION OF SOURCES OF UNCERTAINTY IN WATER RESOURCES AVAILABILITY ESTIMATION

4.1 Introduction

The main sources of uncertainty that are generally common to hydrological modelling are discussed extensively in Chapter 2. This chapter provides some guidelines for the identification and classification of the sources of uncertainty that need to be considered when making hydrological and water resources estimations in a South African context. However, there are additional models and tools (apart from those associated with hydrological modelling) that will be used in water resources decision making and how these decisions are converted into management options is critical (examples include socio-economic and climate change models). While these will also be subject to various sources of uncertainty, they are beyond the scope of this study. The focus of this study is on uncertainties associated with *simulating natural water resources availability* in poorly or ungauged basins using hydrological models (lower part of Figure 4.1), specifically, the Hughes (2004b) version of the Pitman model. This chapter discusses the hydrological uncertainties in the context of the uncertainty and risk in making decisions about future water resources development plans. The areas where future interventions have the potential to reduce or constrain uncertainties, and therefore future management risks, are referred to at the end of the chapter. Figure 4.1 proposes a hierarchy of sources of uncertainty associated with the type of modelling tools commonly used in southern African water resources assessment studies. The diagram identifies the different types of uncertainty at each level of a water resources decision making system, recognising that the propagation of these uncertainties increases the risk in decision making and of water management failures. This diagram has been based on the author's experience of the limitations of model applications combined with the sources of uncertainty and their interrelationships identified by previous studies (e.g. Beven, 2001a; Rubarenzya *et al*., 2007). The following sections discuss the uncertainty sources identified in Figure 4.1 starting at the top of the diagram.

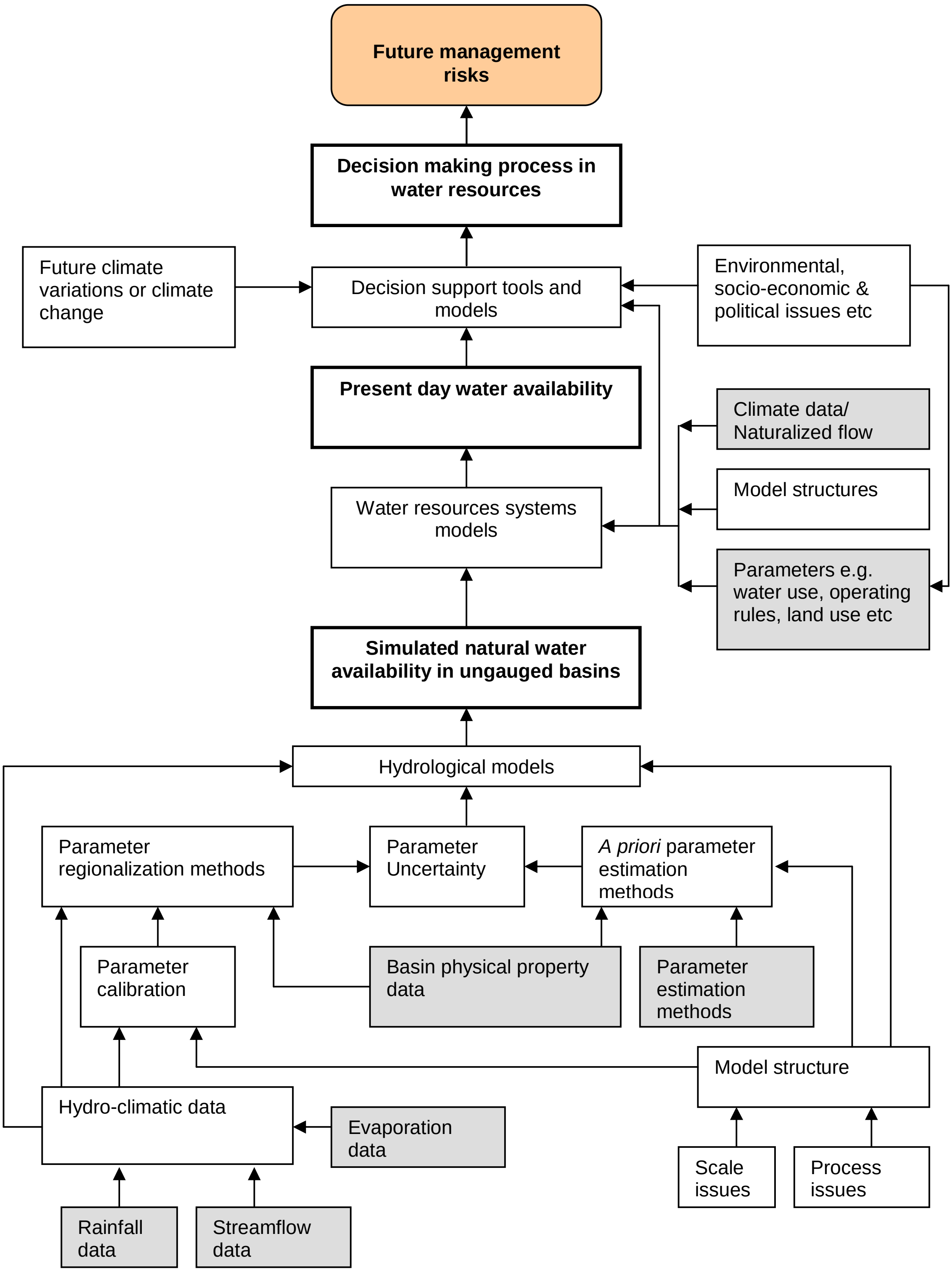


Figure 4.1 Hierarchal system showing the sources of uncertainty. The areas with the greatest potential for uncertainty reduction are shaded in grey.

4.2. Decision making support tools

Decision support tools are necessary to enable formal and more objective linkages to be made between climate, hydrology, institutional process and socio-economic models. The primary sources of uncertainty in decision making about future water resources management are mainly a function of the decision support tools that are used to aid in the decision making process. These tools include the same water resources systems models that are used to simulate present day water resources availability (see section 4.3). Additional tools may include climate prediction models, population and economic growth prediction models, as well as socio-economic models used to evaluate the benefits of different patterns of future water use. These tools suffer from uncertainty about the estimates of present day water availability (outputs from water resources system models), and future water resources availability related to future climate variability (Hudson and Jones, 2002; Andersson *et al.*, 2006) and change, financial, political, social, environmental factors, and land use changes that affect decisions that can be made (Figure 4.1). Uncertainties may also emanate from the evaluation of different management options using simple diagnostic or evaluation tools.

4.3. Water resources systems models

The uncertainty associated with estimation of present day water resources availability (Figure 4.1) is related to the uncertainties in the natural water resources availability (simulated by a rainfall-runoff model) and the extent to which existing developments (storage, abstractions, return flows, water transfers, land use modifications, etc.) have impacted on the natural water resources in a basin. These impacts are frequently simulated using water resources system models that can involve quite complex simulations of a wide variety of water storages, abstractions and return flows including operating rules that specify priorities under conditions of water shortage. As with any model, one of the sources of uncertainty is related to the way in which the model is formulated to represent the complexities of the real world, while the other sources of uncertainty relate to the input climate data (for example, evaporation losses from reservoirs) and the model parameters.

The existing information base for defining present day water use in South Africa is relatively weak, but is being improved through attempts by the Department of Water Affairs and Forestry to identify lawful water use as a necessary step towards implementing compulsory licensing as part of the National Water Act of 1998 (South Africa, 1998). While average or peak water demands may be known with relatively high levels of accuracy, actual water use in any one year may depend on the prevailing climate conditions and can be highly variable, particularly in terms of irrigation water use. While the necessary information (surface area – storage volume relationships, for example) available for large reservoirs is likely to be quite accurate (from bathymetric surveys), the same is unlikely to be true for the large number of small farm dams that exist in southern Africa. There are few studies that have attempted to derive the surface area-storage volume relationships for small dams in southern Africa (Maaren and Moolman, 1986; Meigh, 1995; Sawunyama *et al*., 2006) and the accuracy of these relationships remain questionable as they are derived from a limited sample of small dams in the region. Even if the impacts of small farm dams on downstream hydrology within sub-basins are well known and their surface areas can be derived from satellite imagery and aerial photography, there is little quantitative information generally available about their storage capacities (Havenga *et al.,* 2007), nor about the volumes of water abstracted.

4.4. Hydrological models: the case of the Pitman model

While some of the sources of uncertainty associated with the application of hydrological models are model independent (e.g. model input data), others are dependent on the specific model structure and the associated parameters. The uncertainties in the simulated natural water resources availability derived from rainfall-runoff models may be due to the uncertainty in the hydro-climatic data, model structure and parameter estimation methods as shown in Figure 4.1.

4.4.1 Hydro-climatic data uncertainty

The climate inputs most commonly used in hydrological models are rainfall and potential evapotranspiration and the necessity of accurate spatial estimates of these input data has been frequently investigated (Görgens, 1983; Schulze, 1995; Andréassian *et al*., 2004; Guo *et al*., 2004; Buytaert *et al*., 2006). Measured streamflow data, on the other hand, are used to calibrate or validate model performances. The limitations of observed streamflow data and the problems of naturalising streamflow data for use in simulation models in South Africa has been extensively discussed in Section 3.3.4 and will also be briefly revisited in section 4.4.3. The present section focuses on rainfall and potential evaporation uncertainty.

One of the biggest sources of uncertainty in the climate input data to hydrological models is related to the differences in spatial scale and extent between the climate observations and the models. While the lesser problem of gauge measurement accuracy should never be ignored, the issue of obtaining adequately representative observations to define climate spatial variations has long been recognised as one of the major factors limiting the success of any hydrological model application (Görgens, 1983; Krajewski *et al*., 1991; Andréassian *et al*., 2001, 2004; Dong *et al*., 2005). It is therefore clear that, while the characteristics of climate variables vary continuously in space and time, their measurements always occupy a limited number of space-time points. The accuracy of spatially averaged rainfall or evaporation estimated from point measurements depends on the representativeness of the point measurements, the spatial variability of these climate variables, the degree of spatial averaging (i.e. the size of the area) and the methods used to estimate areal distributions from point measurements.

The accuracy of most of the standard methods used in interpolating point data, such as Inverse Distance Weighting, Theissen polygons and Kriging (Schäfer, 1991) varies, depending on basin topographical characteristics and the density of the gauge network within the basin. With respect to rainfall, these methods usually fail to yield accurate estimates of spatially averaged (areal) rainfall in basins where there is marked variability in relief, experiencing strong orographic rainfall influences and they often leads to smoothing errors, which become source of error when threshold process are at play. Frequently inadequate raingauge distributions in elevated areas fail to capture systematic spatial variations of rainfall. Interpolation methods also generally fail to give accurate rainfall estimates in areas experiencing convective rainfall with typically high degrees of spatial variation within individual storms, and particularly when coupled with a sparse raingauge network (Schulze, 2006). As a result, random uncertainties occur as variations in the actual rainfall patterns during a storm may cause the representativeness of each gauge covering a specific area to fluctuate. While areal interpolation methods have been designed to make the best use of the available data, they are not able to substitute for inadequately representative observations. Shrinking observational networks are exacerbating this problem and attention is being focussed on alternative methods of obtaining areal rainfall estimates from radar (Pegram and Clothier, 2001) and satellites (Hughes 2006a, b). However, the importance of establishing the relationships between remotely sensed data and historical raingauge based measurements has already been noted (Hughes *et al*., 2006; Wilk *et al*., 2006).

With respect to evapotranspiration estimates, observations in South Africa have been mainly based on pan measurements, while the extent to which these measurements can be related to the potential evaporation demand used within many models is not very clear (Görgens, 1983). The immediate pan environment can substantially affect measurements and coupled with the very low density of observations suggests that available measurements are poor indicators of areal evaporation demand. The lack of representative time series of evaporation demand is almost certainly one of the reasons why it is common practice to use long-term monthly means within the Pitman model. However, the uncertainties resulting from ignoring inter-annual variations in evaporation demand are largely unknown. Some models have used evaporation estimates based on meteorological variables (Schulze, 1997) and specifically temperature based estimates given the fact that temperature data are more readily available and benefit from a higher density of observation stations (Schulze and Maharaj, 2004,2006). A further possibility is to make use of evaporation pan based monthly estimates, but perturbed on the basis of variations in temperature (applied by Hughes *et al*., 2006 in the application of the Pitman model in the Okavango River basin and see Section 3.3.3).

A further issue is associated with future water resources planning and allowing for potential non-stationarities in climate input data related to global warming and climate change (IPCC, 2007). While the outputs from regional climate models are improving (Schulze, 2005), there are still a number of uncertainties associated with the climate models, the downscaling methods and therefore the climate predictions (Hewiston and Crane, 2006). There are a number of examples in the literature where the uncertainties (demonstrated by variations in the application of different models or different carbon dioxide scenarios) are extremely large (Costa and Foley, 2000; Vörösmarty, 2002) and would clearly dominate any attempt at making decisions about future water resources management.

4.4.2 Model structure uncertainty

Model structure uncertainty is mainly a function of the way in which the hydrological processes are represented and the temporal and spatial scale approximations used in the model. The conceptual nature of the Pitman model and parameters suggests that they can be interpreted in terms of hydrological storages and processes of water movement, but within the limitations of the time and space scales used in the model. There is no guarantee that the scale at which model conceptual relationships have been established will match the scale at which the model is applied, using the same parameters, due to the high degree of heterogeneity of the real hydrological processes and to different sources of non-linearity. Beven (1995) demonstrated that even if conceptual relationships may be valid, ‘‘effective’’ parameters are simple approximations of the description of the complex nature of the processes and there is no general method available to derive these parameters from highly variable values of point measurements. In addition to the scale of application of a hydrological model, the resolution of the model input data, both in space and time, also has a major influence on the model structure and detail (Klemeš, 1983).

4.4.2.1 Time scale uncertainties

The Pitman model is a monthly time-step model and although there are internal iterations, the basic climate inputs are monthly totals. As an example, the model operates over four model iterations and the distribution of total monthly rainfall over these iterations is assumed to be controlled by a symmetric S-curve function that depends on the total rainfall and the rainfall distribution factor (RDF) parameter (Hughes, 1997). The model assumes low rainfall in the first and last iterations and higher rainfall in the middle pair (Kapangaziwiri, 2008) and these assumptions lead to greater uncertainties given that inter-month rainfall distributions can be highly variable in some climate zones. Other uncertainties are related to the assumptions about the interception storage, where total rainfall in one day is assumed to be concentrated in a single storm event and that the stored water evaporates completely in a single day (Pitman, 1973). In reality, with monthly-time step models, the validity of these assumptions depends on the rainfall distribution and patterns within a particular month. Potential uncertainties associated with time scale are also related to soil moisture storage thresholds, where models with different time-steps (daily compared to monthly, for example) exceed the storage thresholds under different model conditions.

4.4.2.2 Spatial scale uncertainties

Many basins have highly spatially heterogeneous hydrological processes with some parts of the basin generating far more runoff than others. Uncertainties therefore exist in how this heterogeneity is represented (if at all) in a coarse scale model. To a certain extent, these limitations in the model structure can be offset by the use of appropriate parameter quantification methods. Some of these problems may be overcome by applying the model at smaller spatial scales (the version used in this study is semi-distributed), but the impact of this approach on setting appropriate parameter values has not been adequately tested. Model scale may influence the way in which the parameter values are quantified and the relationship with the scale of measurable basin property data. The scale at which predictions are required, however, may not match the scale at which information is available to represent the important hydrological processes. Information might be at either finer or coarse scale in relation to the spatial scale of the model. The Pitman model is widely applied to a range of sub-basin scales from approximately $10km^2$ up to $10\ 000km^2$ and therefore spatial scale can play a major role.

4.4.2.3 Boundary conditions and process representation

Uncertainties in boundary conditions may be associated with assumptions made about the correspondence of surface and sub-surface basin boundaries and the destination of recharging water which may not be fully understood. Basin modelling is difficult because the system response is often controlled by its heterogeneity which is completely unknown and described, since the transformation of rainfall signals to discharge involve processes that are non-uniform and non-linear (Beven, 1989). The initial conditions ('warm up' period for the model during simulation) and the dynamics of rainfall events will activate a particular process (e.g. infiltration excess overland flow) involving threshold effects within a basin. The model routines should therefore be able to explicitly simulate the dynamics of different runoff generation mechanisms, mainly overland, sub-surface and base flows. If this is not the case, parameter interpretation may be difficult.

A simple example is the lack of snow accumulation and melting routines within the Pitman model. Although snow is not a major component of any South African basin, locally and in some years the effects may be relevant. To adequately simulate infrequent snowmelt effects, other model parameters would have to assume values that are inappropriate, given the model conceptualisation. Another example is related to the ability of a model to account for the effects on runoff of non-stationarity in vegetation cover, a characteristic that has been identified as important in some arid and semi-arid basins of southern Africa (Hughes, 1995; Hughes and Metzler, 1998).

4.4.3 Parameter uncertainty

A large amount of the international literature on hydrological model uncertainty discusses the issue of model parameter uncertainty (see the literature review in Chapter 2). The uncertainty is reflected in the degree to which a specific parameter set can generate model outputs that are representative (or 'behavioural' using the terminology of Beven, 2006b) of the hydrological response of a basin. The factors contributing to parameter uncertainty depend to a large degree on the methods that are used to determine an appropriate parameter set for ungauged basins. Figure 4.1 recognises two main generic approaches, while the actual methods will vary considerably in detail.

4.4.3.1 Uncertainty associated with parameter regionalisation or extrapolation

The bottom left hand side of Figure 4.1 illustrates the sources of uncertainty associated with a parameter estimation approach involving calibration on gauged basins followed by extrapolation or regionalisation to ungauged basins. In this case the uncertainties in the calibrated parameter set will be partly related to the input hydro-climatic data (see Section 4.4.1) and partly the calibration process, including interactions with the model structure. These uncertainties will be passed through to the regionalisation approach and added to by uncertainties in the methods (e.g. regression relationships) and data (e.g. basin physical properties) used for extrapolating the calibrated parameter sets to ungauged basins. Thus the uncertainties in the regionalised parameter sets are not independent of the uncertainties in the available hydro-climate data that were used to calibrate the parameters for the gauged basins. These dependencies could be quite complex and difficult to identify. The hydro-climatic data used to calibrate models often have short record lengths with many gaps and it is not always realistic to assume that the data are of good enough quality to achieve representative calibrations. The Pitman model has a large number of parameters that interact with each other such that single optimum solutions are rarely possible. The model is also usually calibrated manually and therefore different model users working on the same sub-basin may produce different calibration parameter sets giving equally good simulations. Because of too many parameters (the equifinality problem referred to by Beven and Freer, 2001), a model can be fitted to the 'noise' in the data rather than the signal (Hughes, 2004a). This makes the regionalisation process difficult and uncertain as there would be many acceptable parameter sets to choose from to use in determining regionalised relationships. In many applications the model structure remains fixed and therefore variations in the appropriateness of the model structure could be reflected in the variations in uncertainty in parameter values, which is based on the premise that parameter values can be adjusted to compensate for model structural problems.

Within the South African context, much of the observed flow data used for model calibration have poorly quantified development impacts, which are typically removed by naturalisation prior to use in model calibration. Without more detailed land use and water use data, this naturalisation process will always be uncertain and the calibrated parameter sets will reflect this uncertainty. Where observed flow data are scarce, the calibrated parameter sets may not provide sufficiently representative information upon which to base any regionalisation approach.

Part of the uncertainty emanates from the lack of precision of the statistical relationships or regionalisation indices between calibrated parameter values and the physical property data (Hughes, 1982; Mazvimavi, 2003). While methods are available, and have been presented in the literature, for quantifying these sources of uncertainty, their impacts on parameter sets for ungauged basins has been referred to less often (Yadav *et al*., 2007). Direct parameter mapping approaches, based on some measure of basin similarity (e.g. Midgley *et al*., 1994), using either physical property data and/or hydro-climatic data, often suffer from the qualitative (or subjective) nature of the mapping method. Some calibrated parameters may also be highly sub-basin specific, making it difficult to determine regional patterns.

4.4.3.2 Uncertainty associated with a priori parameter quantification

An alternative approach (see Figure 4.1) to parameter estimation (for both gauged and ungauged basins) is to use *a priori* parameter quantification (Kapangaziwiri and Hughes, 2008) based on basin physical property data and conceptual interpretations of the model parameters. The resulting parameter sets will reflect uncertainties associated with the physical property data and the methods used to relate the basin physical property data to parameter values. The assumption of this approach is that both the model structure and parameters are based on sound physical hydrological principles (Kapangaziwiri, 2008). One of the potential advantages of this type of approach, particularly in areas where hydro-climatic data are scarce, are that the uncertainties in parameter estimation should be independent of the hydro-climatic data uncertainties. This approach also overcomes many of the issues associated with non-uniqueness of calibrated parameter sets and equifinality (Beven, 2006b).

Uncertainties in the physical property data will be related to differences in the scale of the available data and the scale of modelling as well as the resolution and accuracy of the available information. In some cases the model scale may be finer than the available data and the differences between sub-basins may be difficult to quantify (refer also to Section 4.4.2 on model structure uncertainty). As an example, FAO (2003) provide an internationally accepted soil classification method (soil characteristics, soil horizons and soil properties) based on the Global Soil and Terrain (SORTER) database, but the spatial resolution of such data do not match the scale resolution of models used in South Africa (see Figure 4.2, top right). In other cases, the model scale may be coarser than the available data and uncertainties may be associated with the way in which the data are sampled to achieve a representative sub-basin value. In South Africa, the landtype database (AGIS, 2007), for example, has detailed soil information presented as depth ranges and texture classes but interpreting this information when estimating Pitman model parameters is often not a straightforward task as some up-scaling may be required (see Figure 4.2, bottom left). The main sources of uncertainty are associated with the spatial variation of depth and texture and the most appropriate method to specify basin averages. These disparities in the level and amount of detail of available soil information from different sources as illustrated in Figure 4.2 have implications for both *a priori* parameter estimation methods, such as that proposed by Kapangaziwiri (2008), as well as for regionalizing parameter values using regression type relationships.

The accuracy of the basin physical property data also includes the degree to which the available data are hydrologically appropriate. For example, soil characteristic information is frequently designed for agricultural use and values of hydrological relevance (porosity, water holding capacity, field capacity, hydraulic conductivity, etc) are often inferred from relationships with texture, structure or soil type (Schulze, 1997). The measurement techniques and scale (or number of point observations used) at which basin property data are originally measured are also important, but rarely specified as part of the final data products.

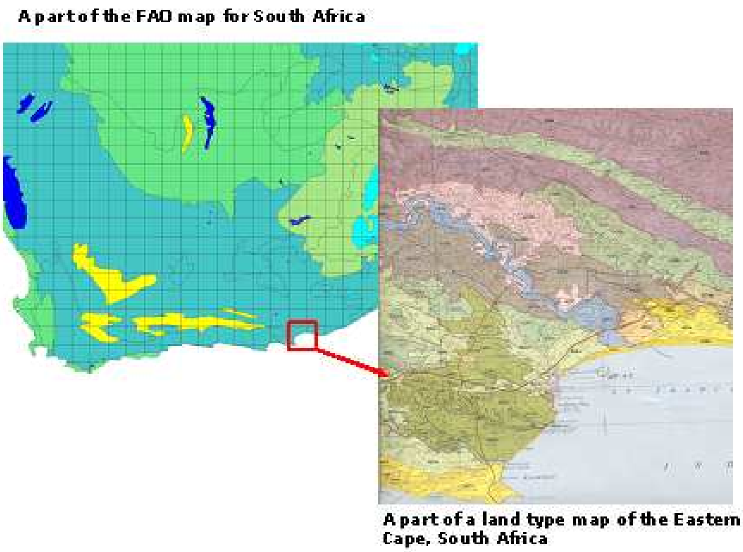


Figure 4.2 Illustration of the spatial scales and the level of detail of the soils information available from different sources (Kapangaziwiri, 2008).

The uncertainty issues related to the resolution and accuracy of the physical property data will combine with uncertainties in the *a priori* methods themselves and are expected to be associated with the extent to which the estimation equations reflect the conceptual structure of the model (Kapangaziwiri, 2008). These uncertainties are always difficult to quantify and isolate from uncertainties associated with physical property data.

Ultimately, there are many sources of uncertainty associated with parameter value estimation approaches and many of them will be inter-dependent. This presents a real challenge in terms of quantifying the overall uncertainty. While the literature review presented in Chapter 2 indicates that the issues of quantifying overall uncertainty have been widely covered in previous studies, the most appropriate approach to use in any specific modelling application will not always be obvious. While it is one thing to identify the primary sources of uncertainty, it is another thing to quantify this uncertainty in a specific situation.

4.5 Potential for reducing uncertainty

Several suggestions have been raised in the literature on the potential options of reducing the different sources of uncertainty in hydrological modelling (Section 2.6). However, the present section attempts to briefly identify potential areas of reducing uncertainty for specific modelling applications in South Africa and the most obvious areas are highlighted in Figure 4.1. Some of these are dealt with in further detail during later chapters, while others are beyond the scope of the present study.

Hydro-climatic (rainfall, evaporation and streamflow) data uncertainties may be reduced through more data collection (increasing network densities), improvements in the measurement techniques for some variables, as well as making better use of existing data through pre-processing methods. The use of spatially averaged information from satellites or radar also offers many possibilities, but may also introduce additional uncertainty when combined with more traditional ground based observations (Hughes, 2006a, b; Hughes *et al*., 2006; Wilk *et al*., 2006).

Improvements in the methods of measuring and interpreting basin physical property data is an area that offers a high potential for reducing uncertainty, especially given the increasing availability of alternative sources of information, such as remote sensing. However, improvements in the techniques used to integrate these data at appropriate modelling scales are also required for this potential to be realised. Another way of reducing parameter uncertainty is to increase the amount of information available to identify parameters, but the success of this depends on the ability of the model structure to handle more output variables (Beven, 2001a). An alternative way is to use different periods to identify model parameters and this leads to the multi-objective calibration approach for estimating model parameter values and model evaluation (Wagener *et al*., 2001). With respect to *a priori* estimation methods, improved parameter estimation methods (algorithms) that reflect the nature of the available data, but are also linked to the understanding of the model operation and parameter inter-dependencies are required. It stands to reason that improving databases of spatial data and revision of the parameter estimation approaches are the most critical areas to effectively reduce parameter predictive uncertainty. A method that potentially compliments the *a priori* parameter estimation approach is that proposed by Yadav et al. (2007) which is based on using regionalised runoff-response (basin behaviour) signatures to constrain behavioural model parameter sets.

Another target area is to reduce uncertainty in the accuracy of water use or basin development data. This is particularly important where observed flow data are used for model calibrations or evaluating other sources of uncertainty, but equally so when generating estimates of present day water availability using water resources systems models. Once again, remote sensing and satellite data sources have the potential to contribute.

One of the important issues to recognise from a practical point of view is that the focus areas for uncertainty reduction should be those that have the potential to produce relatively rapid, cost-effective and measurable results. In a southern African context, the focus is therefore unlikely to be on expanding the existing gauge (rainfall, evaporation and stream flow) networks. First of all these can be expensive to establish and maintain, while secondly it has proved difficult in the past to convince governments of the importance of such improvements. Perhaps the focus should be on maintaining existing networks and concentrating research efforts on making the most out of some of the emerging data products derived from remote sensing platforms.

5. UNCERTAINTY IN SPATIAL RAINFALL ESTIMATION AND IMPACTS ON SIMULATED RUNOFF

5.1 Introduction

This chapter explores the uncertainties associated with the estimation of spatially averaged rainfalls and the extent to which these uncertainties are propagated into streamflow predictions. Rainfall has been found to be the main driving force behind most hydrological processes and rainfall-runoff models are frequently more sensitive to rainfall inputs (Schulze*,* 1997, 2006) than other climate variables. It is therefore important that rainfall inputs should be as spatially and temporally representative as possible before they are used as model inputs. The accuracy of areal rainfall estimates depends on the representativiness of point raingauges, the degree of spatial and temporal averaging and the methods used to spatially interpolate raingauge measurements as referred to in section 4.4.1 in Chapter 4.

Studies of spatial and temporal resolutions of rainfall measurements have demonstrated the advantages of the improved accuracy of rainfall inputs in rainfall-runoff modelling (Krajewski *et al*., 1991; Andréassian *et al*., 2001; Dong *et al*., 2005). The pre-existing condition of deriving accurate areal rainfall estimates is that a representative sample of raingauges is available. Therefore, studies that analyse rainfall uncertainty should use relatively dense raingauge networks or alternatively raingauges should be located in the critical sites to capture any local scale physiographic effects. Data should also be pre-processed carefully to avoid systematic errors and reduce heterogeneity in the datasets (Schulze, 1997). While the implications for estimating sub-basin areal rainfall inputs to hydrological models are clear, there have been few attempts to quantify uncertainty and its impacts on simulated runoff through the application of the Pitman model in South Africa. In this chapter, an approach based on using real rainfall data from observation stations (not stochastic rainfall inputs) is used to thoroughly investigate the effects of various raingauge sampling methods and consequent areal rainfall estimation uncertainties on the uncertainty of generated runoff. With raingauge networks, uncertainties not only arise from limited spatial sampling but also from the location of the raingauges in a sub-basin with respect to real patterns of rainfall variation.

Most of the analyses are based on the national network of daily rainfall observations acquired from the former CCWR and/or SAWS, and using the various test sub-basins drawn from South Africa. However, one of the rainfall uncertainty assessments has been based on some short period, but higher spatial resolution rainfall data collected in the Bedford area as part of a semi-arid modelling research programme (Hughes and Sami, 1991). The Bedford (Q92F quaternary catchment) data cover approximately 665km^2 with a gauge density of 1 raingauge per 24km^2 and very little missing data over the 5 years of observation. In contrast the spatial resolution for the other sub-basins (using the national network of raingauges) is generally less than 1 raingauge per 100km^2 and varies over time as raingauges are added to, or removed from service. While the record lengths are typically much longer than the Bedford data, in many cases there are frequent periods of missing data.

Strictly, rainfall uncertainty cannot be easily quantified as there is no perfect rainfall observation and thus no means of obtaining the 'true' rainfall from which to estimate uncertainties (Schutlz, 1985). As a consequence, the reference datasets that use the highest number of raingauges were assumed to provide the 'best' estimate of the true rainfall against which other rainfall estimates (realizations) could be compared. There are, of course, situations where the highest density network will not provide a satisfactory representation of real rainfall variations. This is particularly the case in areas with strong orographic rainfall gradients, which have few raingauges in the elevated parts of the basin. However, the assumption that the highest density network provides the least biased estimate should still be valid in most cases.

5.2 Approaches to generate spatial rainfall data

While it is recognised that there are a number of alternative spatial interpolation approaches, the Inverse Distance Weighting procedure (IDW) has been used throughout this study. This technique was chosen because it is easy to use and not computer intensive, and when the density of the point data is sufficient and the variation in rainfall is not complex the method has been demonstrated to be adequate (Lynch, 2004). The IDW method typically uses 3 or 4 gauges lying within a maximum search radius to generate the sub-basin spatial averaged rainfalls. However, the inclusion of key raingauges with short records, or exclusion of those with long records, often relies on the intuition of the modeller. When there are missing data in the records, the interpolation approach uses the next closest raingauge and it is possible that the maximum number of raingauges may not be found within the maximum search radius. This approach prevents raingauges being used which are too far from the sub-basin even when optimally located raingauges have missing data periods.

There are numerous interpolation techniques that have been proposed in the literature which range from simple Thiessen polygons to more complex Kriging techniques (Syed *et al*., 2003). Some methods, such as weighted averages (Thiessen and Inverse Distance Weighting), are based directly on the original data points or mathematical formula that determine the interpolation surface, while Kriging techniques are based on statistical models to produce optimal interpolation of point data (Krajewski, 1987). Despite Kriging being the most powerful and effective tool, it does not address all the rainfall interpolation problems (Teegavarapu and Chandramouli, 2005) and is computationally intensive. As Lynch (2004) concluded, the IDW approaches, however, are not very reliable in areas of complex topography with sparse networks, especially where elevated parts of the basin are not represented by raingauges (see also Schäfer, 1991). For areas where the topography is complex, some correction procedures are frequently required to improve IDW based estimates, but such procedures must be simple and not the complex statistical approaches such as Co-Kriging (Krajewski, 1987). The spatial rainfall variations in such areas are often highly non-linear and not consistent, frequently varying with synoptic weather patterns. Previous approaches in South Africa have used additional weighting factors based on gridded mean annual or mean monthly rainfall data (Hughes, pers. comm.). The weighting factors are based on the ratios of the grid values averaged over the catchment to the grid values for individual raingauges. However, where mean annual rainfall spatial gradients are large there is a tendency for this approach to over-exaggerate extreme rainfalls. It is therefore reasonable to conclude that the most important consideration in the success of any spatial rainfall interpolation method is the information content of the raingauge network rather than the methods themselves.

5.3 Rainfall uncertainty assessment for the Bedford sub-basin

The Bedford experimental sub-basin (see Figure 3.9; Chapter 3) was established in 1987 (Hughes and Sami, 1991) to investigate hydrological processes and test hydrological models in a semi-arid region of South Africa. The total area covered by the sub-basin is approximately 665km^2 and it corresponds to quaternary catchment Q92F (Midgley *et al*., 1994). Break point rainfall data are available for 28 raingauges as shown in Figure 5.1 for a period of 5 years (1988-1992). This raingauge network represents one of the few South African examples of a relatively high spatial resolution of observations covering a complete sub-basin (quaternary catchment).

The objective of this part of the study was to assess the impacts of varying the spatial and temporal resolution of rainfall observations on estimates of spatially averaged sub-basin rainfalls and on the resulting streamflow volumes simulated by a monthly time-step rainfall-runoff model. The model was set up with a dense raingauge network (28 raingauges) which was then re-sampled to represent different reduced gauge densities. The following steps were used:

i. A grid of size 5 * 5 minutes of a degree was established, with a total of 12 grid squares (including grids not completely inside the sub-basin boundary) assumed to represent the 'total' sub-basin area. Table 5.1 and Figure 5.2 illustrate the assumed linkages between the grids.

ii. All 28 raingauge stations were used to establish both daily and monthly time series of spatially averaged rainfall for each of the 12 grids. The spatial averaging was based on the Inverse Distance Weighting procedure using a maximum of 3 gauges and a large enough search radius to ensure that no gauges will be excluded in a search to replace missing data. The spatially averaged monthly time series were generated in two different ways:
    a. Daily observed gauge rainfall data were used to create daily spatial averages and then aggregated to monthly averages.
    b. Observed monthly gauge rainfall data were used to generate monthly spatial averages. In this situation even one missing day in a gauge rainfall record means that the whole month for that gauge will be considered missing and an alternative gauge will have to be used.

iii. Sub-samples of the 28 raingauges were used to generate the spatially averaged rainfalls as in step ii. The sub-samples were selected semi-randomly on the basis of the station numbers using the following approach:

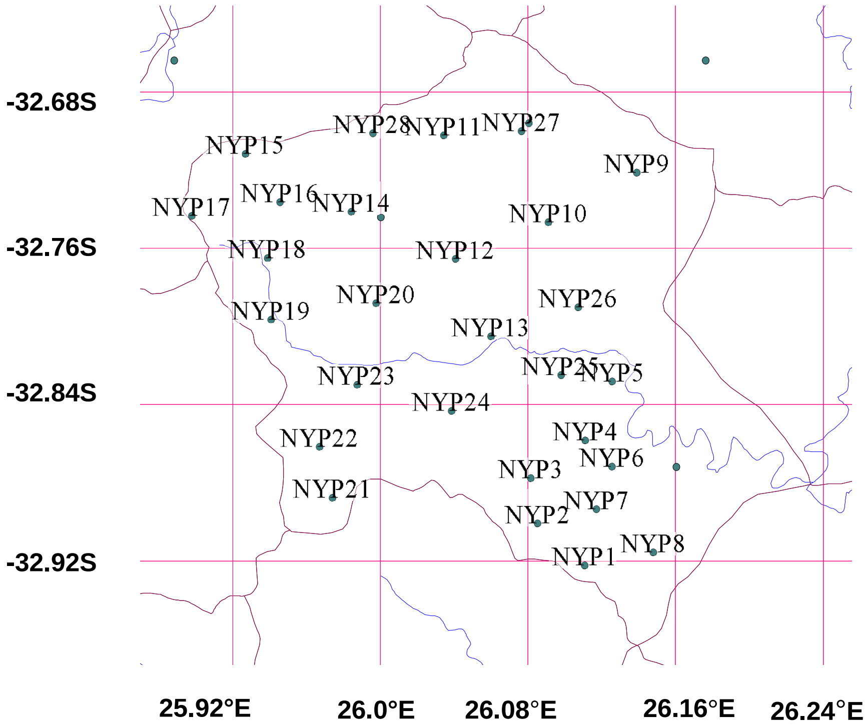
   a. 2 samples of 14 raingauges each (Figure 5.3), using the even and odd numbered stations (samples Even and Odd).
   b. 4 samples of 7 raingauges each (Appendix 2.1; i), using 50% of the even and odd numbered stations (samples Even50%1 and 2, Odd50%1 and 2).
   c. 8 samples of 4 raingauges each (Appendix 2.1; ii and iii), using 25% of the even and odd numbered stations (samples Even25%1 to 4, Odd25%1 to 4).

iv. The time series of spatial average rainfalls were compared for all the grids with the 'reference' time series generated using all the available rainfall data from 28 raingauges – step ii). A set of standard statistics from SPATSIM (see Chapter 3, section 3.4.1) were used to compare the time series.

v. All the spatial average rainfall time series were used as input to a monthly rainfall-runoff model. The model parameter values were set to be the same for all rainfall realizations and grids, and were based on a previous calibration of the revised version of the Pitman model (Hughes, 2004b) to simulate the pattern of monthly flows for Q92F quaternary catchment given in the WR90 database (Midgley *et al*., 1994). The calibration was based on the WR90 naturalised flows in the absence of any long time series of observed flows. The final analysis consisted of comparing the simulated flows for the different spatial rainfall inputs with the flows generated using the 'reference' rainfall data derived from 28 raingauges.

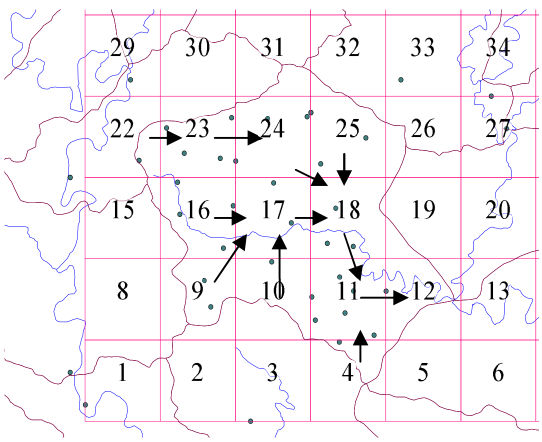
Table 5.1 Linkages between grids for Bedford sub-basin showing direction of flow.

Grid name	Flows into grid
22	23
23	24
24	18
25	18
16	17
17	18
18	11
9	17
10	17
4	11
11	12
12	Sub-basin outlet



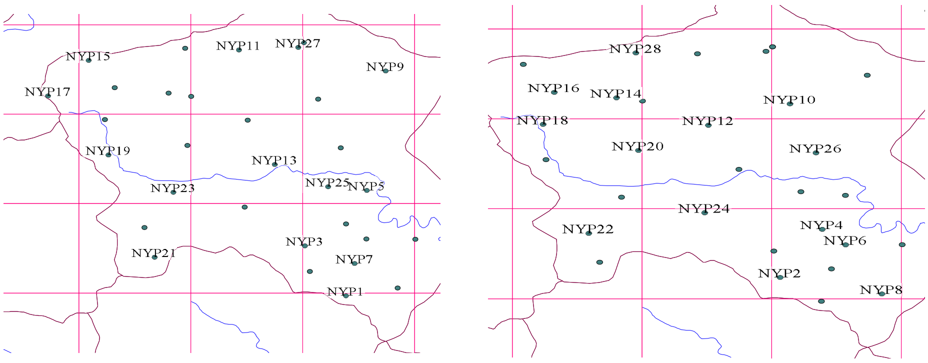
Scale: 1 min of a degree is equivalent to 1.85 km

Figure 5.1 Schematic for gridded Bedford sub-basin, showing the location of the 28 raingauges (NYP1 – NYP28).



Scale: 1 min of a degree is equivalent to 1.85 km

Figure 5.2 Schematic of 5' x 5' grids (total 12) representing the Bedford sub-basin area with arrows showing the direction of flow of water within the sub-basin.



Scale: 1 min of a degree is equivalent to 1.85 km

Figure 5.3 Distribution of 'Odd' (left-hand side) and 'Even' (right-hand side) samples (numbered) with 14 gauges each.

5.3.1 Results for Bedford example

Figures 5.4 and 5.5 illustrate the results for all 12 grid squares for the Bedford sub-basin for even and odd raingauge sub-samples respectively. The sub-samples were based on 14, 7 and 4 raingauges derived using a semi-random sampling procedure (step iii of the methodology above). The three sets of results on each graph refer to comparisons (against estimates generated based on all 28 raingauges and using the coefficient of efficiency statistics) of daily spatial data generated from daily gauge data, monthly spatial data generated from monthly gauge data and monthly spatial data aggregated from daily spatial data.

As might be expected, uncertainties in estimating daily spatial rainfall increase (low CE values) with a decrease in raingauge density (4 raingauges) more so than in estimating monthly spatial rainfall. The increased uncertainties are due to the higher variability in daily data than in monthly data (related to temporal averaging). The higher uncertainty for grid 4 may be related to extrapolation of rainfall data from nearby gauges as there are no raingauges which lie within this grid. The uncertainty in rainfall estimates for grid 11 (as in all other grids) as shown in Figures 5.4 and 5.5 derived using samples with reduced raingauge numbers (7 and 4 gauges) were expected. However, the uncertainty for the daily-daily estimate for grid 11 based on using a sample of 14 raingauges was not expected and may be due to the inability of raingauges to capture the actual rainfall variations within the grid. Moreover, the graphs (Figures 5.4 and 5.5) also show that the uncertainty in areal rainfall estimates can be reduced if daily data (higher temporal resolution) are used in spatial averaging and then aggregated to monthly values than using monthly spatial data generated directly from monthly gauge data (coarse temporal resolution).

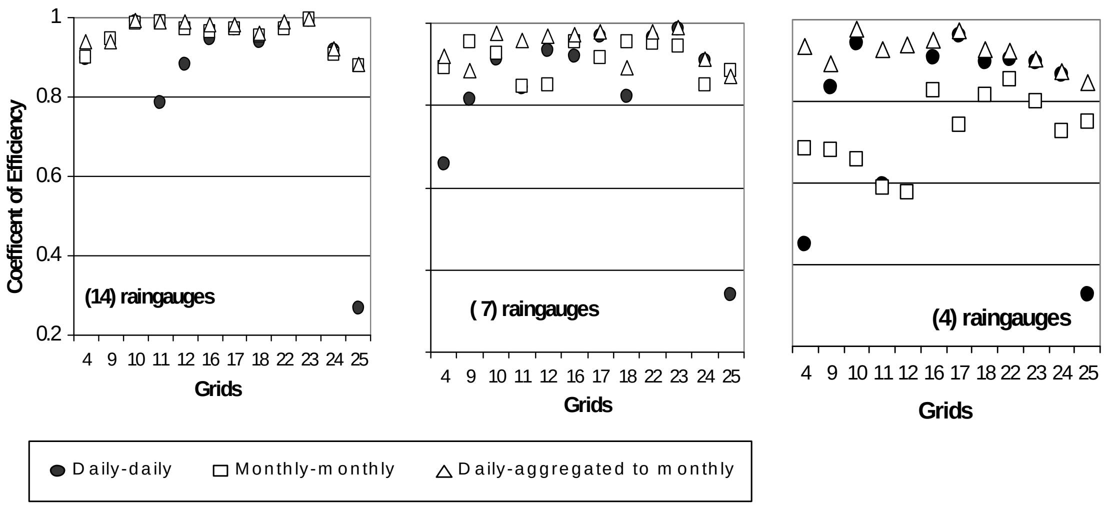


Figure 5.4 Comparisons (with estimates based on a sample of 28 gauges) of spatial average rainfall estimates using 14, 7 and 4 gauges based on even sub-samples.

It is interesting to note that the rainfall estimate based on a higher number of raingauges is not always better than one based on a lower number (see e.g. grid 25 comparison of the daily-daily rainfall estimate using 14 gauges in Figure 5.4 and that using 4 gauges in Figure 5.5). This serves to illustrate that the number of gauges is not the only factor that contributes to uncertainty in spatial rainfall estimates and that the spatial arrangement of those gauges is also important (Figure 5.6). In this specific case, the result is a consequence of the sampling procedure adopted and that the two 'best' gauges for grid 25 are both 'odd' (NYP9 and NYP27, see Figures 5.3 and 5.6). While the spatial arrangements of some of the raingauges are shown in Figures 5.3 and 5.6, the spatial arrangements of the other different samples of raingauges are in Appendix 2.1. From the analysis, one can deduce that the inclusion of gauges that are in the vicinity of the grid but not representative of rainfall variations may introduce uncertainty in the spatial rainfall estimates during the spatial interpolation process and that a larger sample does not necessarily give the 'best' rainfall estimate of real spatial variations in a sub-basin.

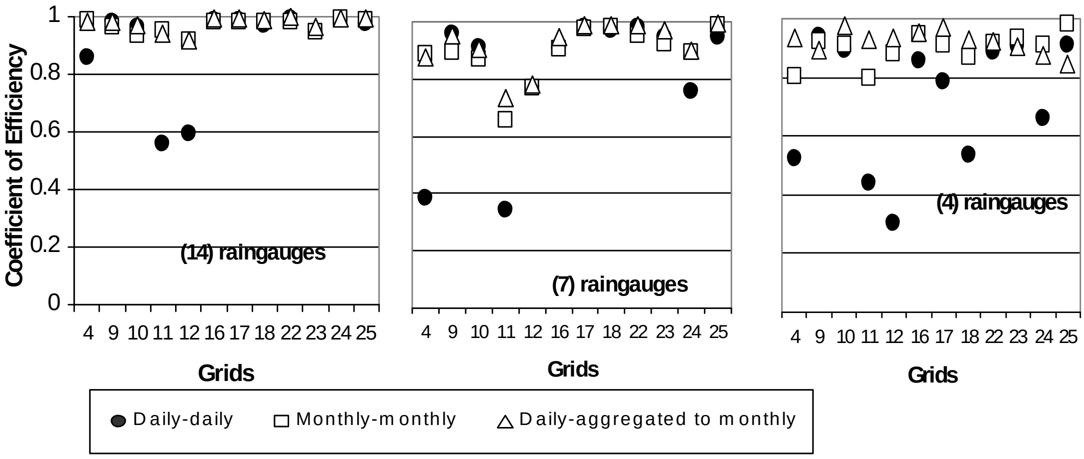


Figure 5.5 Comparisons (with estimates based on a sample of 28 gauges) of spatial average rainfall estimates using 14, 7 and 4 gauges based on odd sub-samples.

As an alternative to the use of objective statistics to assess rainfall uncertainties, differences in rainfall estimates can be illustrated using comparisons of rainfall frequency of exceedence curves. Figure 5.7 shows the results for three grids; one taken from upstream (i.e. grid 23), one from the middle (i.e. grid 17) and one from downstream (i.e. grid 11) and for four of the monthly rainfall realizations. There are clearly large differences for all the grid squares at high rainfalls. This is an important observation with respect to runoff estimation in a semi-arid sub-basin which will be dominated by high intensity rainfalls. The result may be due to systematic variations in rainfall depths that also depend on rainfall distribution and amount. A comparison of the rainfall frequency curves based on all 28 raingauges provides an indication that rainfall spatial gradients exist in the Bedford area, with some grids (grid 23 in the upstream part of the sub-basin) receiving higher maximum rainfalls (±190mm) than grid 17 in the middle part of the sub-basin (±160mm) and grid 11 downstream (±140mm). This result offers some explanation for the differences in spatial rainfall estimates derived from different gauge densities. The propagation of rainfall uncertainty within grids to simulated runoff uncertainty is dealt with later in this Chapter.

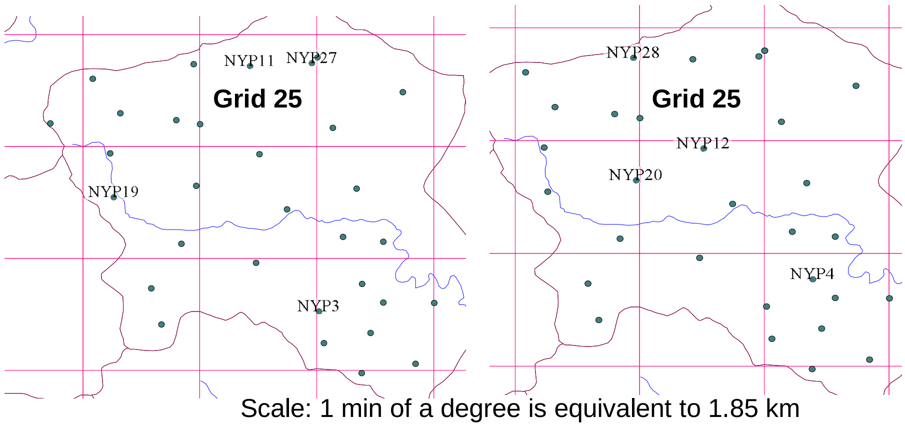


Figure 5.6 Distribution of 'Odd' (left-hand side) and 'Even' (right-hand side) samples with 4 raingauges each.

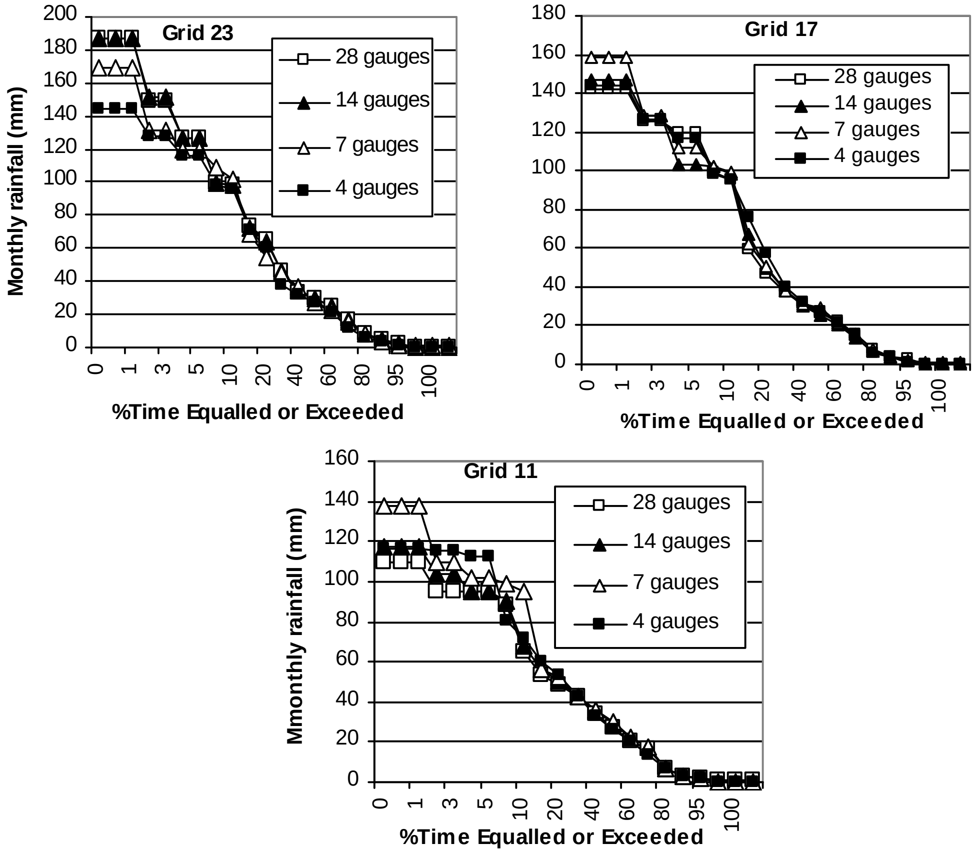


Figure 5.7 Monthly rainfall exceedence frequency curves for four realizations (based on even samples) over 3 grids.

5. 4 Assessment of rainfall uncertainty based on data from the national raingauge network

The previous section analysed the effects of reducing the spatial resolution of rainfall measurements on spatially averaged rainfall estimation using a short record raingauge from a dense network established for research purposes. The quality of raw data as well as the raingauge density is better than might be expected when using rainfall data from the national network, as would be case with water resources estimation in most of the sub-basins in South Africa. The sub-basins listed in Table 5.2 were selected partly because they all have relatively high raingauge densities at some time in the past, while others were selected based on their climate and topographical features (elevated or flat areas). This was necessary so that comparative analyses, similar to that carried out for the Bedford sub-basin, could be performed using a range of sub-basins. It is important to note however, that while the maximum number of raingauges in these sub-basins may have been quite high in the past, there are frequent gaps in the data and the number of gauges can vary quite substantially over time (see e.g. Appendix 1.1). For example, Figure 5.8 (left-hand side) and Table 5.3 both indicate that there are 46 raingauges which were operational over a common 20 year period (1930 to1950) (see Table 5.2) in the whole Seekoei River basin (a semi-arid and flat basin), while a maximum of 29 were still operational from 1950 to 1970. During 1980 to 2000, the number of operational raingauges reduced to 8. Figure 5.8 (right-hand side) and Table 5.4 illustrate another example, but from a humid and mountainous region (Berg River basin), where there were 16 operational raingauges during 1940 to 1960, which was an increase in the number of gauges compared to that from the period 1920 to 1940. However, from 1980 to 2000 the number of operational raingauges reduced to 5.

Historic raingauge data spanning the common period 1920-2000 were used to evaluate the effects of varying gauge density on sub-basin rainfall estimation and the propagation of this uncertainty into streamflow estimation uncertainty. The ‘Reference period’ in Table 5.2 refers to the period (20 or 30 years long) when data for the maximum number of raingauges were available for each basin. The final column of Table 5.2 refers to the number of raingauges that were active or operational during other periods, as well as during the reference period. Multiple realizations of areal averaged sub-basin rainfall were generated for all of the raingauge groups for the reference period. For example, six sub-basin rainfall time series were generated for the C83A to C sub-basins for the reference period 1930-1950 using the 15, 10, 9, 6, 4 and 3 raingauges also active during the listed periods (Table 5.2). In all cases the Inverse Distance Weighting procedure was used to generate spatially averaged sub-basin rainfalls using an un-restricted search radius and a maximum of 3 or 4 (depending on sub-basin size) gauges. Where some records have missing data, the interpolation procedure simply uses data from the next closest gauge (unless there are no more gauges available). As the sub-basin raingauge density decreases it is clear that more distant raingauges will be used.

Table 5.2 Number of raingauges available (in brackets) for the different rainfall realizations for 8 river basins (with a total of 31 sub-basins).

Basin region	Reference period	Time period & no of gauges
Vaal-C83A, B & C (250-830km^2), sub humid (3 sub-basins)	1930-1950 (15)	1940-1960(10) 1950-1970(9) 1960-1980(6) 1970-1990(4) 1980-2000(3)
Limpopo-A23A, sub-humid (682km^2) (1 sub-basin)	1930-1950(12)	1940-1960(8) 1950-1970(6) 1960-1980(5) 1970-1990(3) 1980-2000(1)
Orange-D32A to K (572 to 1443km^2), arid/semi-arid (10 sub-basins)	1930-1950(46)	1940-1960(31) 1950-1970(29) 1960-1980(24) 1970-1990(15) 1980-2000(8)
Sabie-X31A to G (7 sub-basins) (94 to 214km^2), humid	1950-1980(25)	1930-1960(12) 1970-2000(12)
Berg-G10A to D (126 to 687km^2),humid (4 sub-basins)	1940-1960(16)	1920-1940(7) 1960-1980(12) 1980-2000(5)
Lions-U20A-C (279-358km^2),humid(3 sub-basins)	1950-1980(11)	1930-1960 (5) 1970-2000(2)
Thukela-V70A-B (124 to 276km^2), humid (2 sub-basins)	1950-1980(5)	1930-1960(1) 1970-2000(4)
Vaal-C12D , (898km^2), sub-humid(1 sub-basin)	1930-1950 (7)	1950-1980(3) 1970-2000(1)

The various realizations of monthly spatial average rainfall time series were used as inputs to the hydrological model to assess the impacts on runoff generation. The model was not calibrated for each realization but a fixed set of regionalised model parameters based on Midgley *et al.* (1994) were used. The analyses were based on comparing the 'reference' rainfall estimate (the realization using the highest number of raingauges) with alternative estimates using a smaller number of gauges that were active during the other periods. Comparisons were made between the spatially averaged rainfalls (both daily and monthly) as well as between the patterns of runoff simulated when the model was driven by different rainfall realizations and several statistical measures of comparison referred to in section 3.4.1 were used.

Table 5.3 A list of raingauge stations for the Seekoei River basin (D32) example.

Sub-basin	Station name	Start year	End year	No. of years
D32A 715km^2	0118640W	1912	1998	76
	0118694W	1908	1953	45
	0118782W	1913	1941	28
D32B 581km^2	0119091W	1934	1982	48
	0119097W	1917	1983	66
	0119276A	1911	1989	78
	0119276W	1911	1989	78
	0119315W	1907	2000	93
D32C 849km^2	0144266W	1913	1956	43
	0144449W	1911	1978	67
	0144085W	1911	1976	65
	0144385W	1913	1954	41
	0144253W	1913	1950	37
	0144534W	1913	1953	40
	0144648W	1925	1952	27
D32D 850km^2	0118066W	1927	1947	20
	0118395W	1907	1989	82
	0143598AW	1893	1989	96
	1118460W	1925	1950	25
D32E 1155km^2	0143294W	1911	1946	35
	0143258W	1912	1978	66
	0143345W	1913	1990	77
	0143853W	1911	1962	51
	0143675W	1931	1944	13
D32F 1441km^2	0143579W	1911	2000	88
	0143784W	1878	1990	112
	0144250W	1931	1979	48
	0144182W	1923	1953	30
	0171177W	1914	1971	57
	0170885W	1922	1947	25
	0170889W	1906	1946	39
	0171117W	1914	1987	73

Table 5.3 *continued*.

D32G 1044km^2	0171446W	1913	2000	87
	0144602W	1941	1971	30
	0144580W	1920	1953	33
	0144697W	1932	1963	31
	0144791W	1884	1999	115
	0144795W	1911	1956	45
D32H 572km^2	0171652W	1941	1978	37
	0172027W	1945	1974	29
D32J 1063km^2	0171756W	1907	1989	82
	0171546W	1923	2000	77
	0172163W	1877	2000	123
D32K 823km^2	0200180W	1920	1946	26
	0199293W	1920	1952	32
	0199894W	1920	1961	41

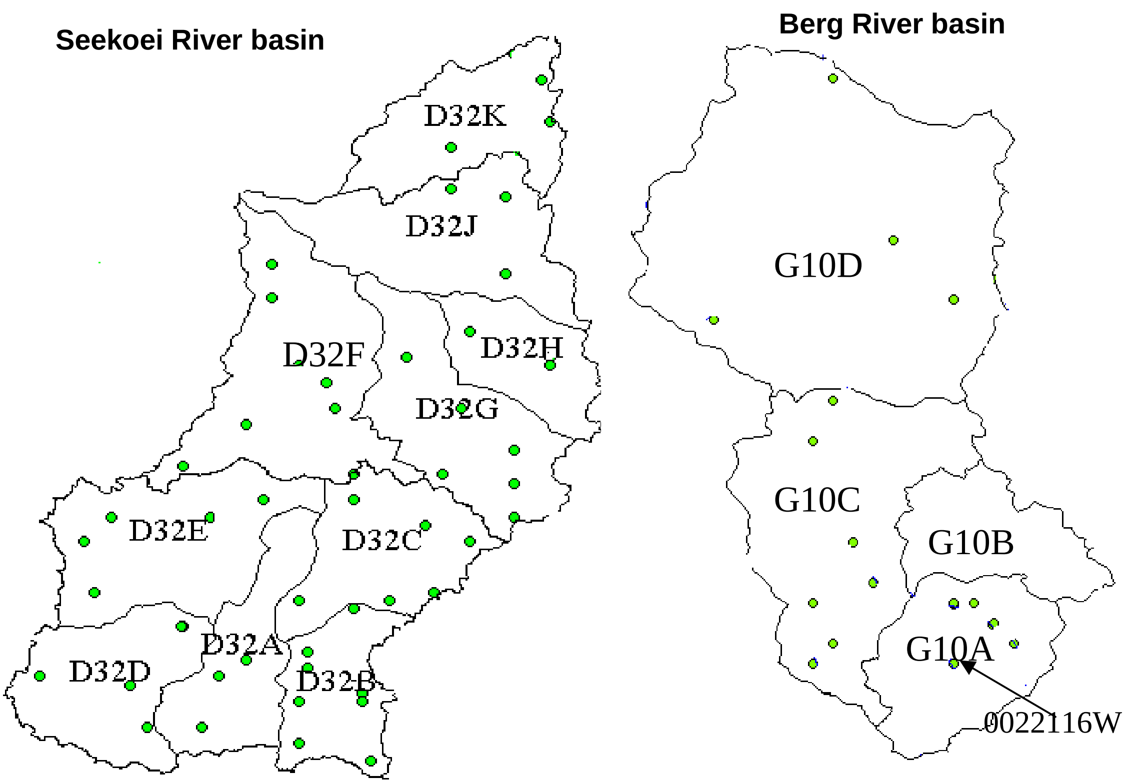


Figure 5.8 Schematic maps of two river basins in South Africa, the Seekoei River basin (D32A to D32K; left-hand-side) and the Berg River basin (G10A to D; right-hand side) with dots representing raingauge stations in each sub-basin.

Table 5.4 A list of raingauge stations for the Berg River basin (G10) example.

Sub-basin	Station name	Start year	End year	No. of years
G10A $172km^2$	0022116W	1920	1961	41
	0022204W	1942	1970	28
	0022205A	1942	1974	32
	0022174A	1942	1974	32
	0022113A	1919	1982	63
	0022113W	1919	2000	81
G10B $126km^2$	no gauges			
G10C $309km^2$	0021806W	1911	1991	80
	0021892W	1893	1975	82
	0021860A	1941	1991	50
	0021795A	1942	1989	47
	0021824W	1878	1986	108
	0021838W	1936	1991	55
G10D $688km^2$	0022009W	1930	1950	20
	0022038W	1904	2000	96
	0022004W	1931	1986	55
	0041836W	1941	1979	38

5.4.1 Rainfall uncertainty results and analysis

As might be expected, the results for most sub-basins show greater differences (compared to the reference estimate) as the number of gauges is reduced. The effects are typically much greater for daily rainfall estimates than for monthly. Figures 5.9 and 5.10 illustrate that there can be large differences in rainfall between sub-basins within the same area, particularly for daily rainfall estimations. Basin D32 (Figure 5.9A) illustrates that there is not always a simple relationship between gauge numbers and differences in rainfall estimates, particularly for daily rainfall. A reduction from 46 to fewer gauges has little impact in some sub-basins (D32E, F and K), but large impacts in others (D32B and C). In some other cases (e.g. D32B) the results deteriorated when the total number of gauges for the sub-basin was reduced to 15, while the results for D32F are still acceptable at that stage and only deteriorate when the number of gauges is reduced further. For D32H the impact is initially quite large but reduces despite a large reduction in the number of gauges. Similarly, basin G10 (Figure 5.9B) shows that there are larger differences in rainfall estimates in some sub-basins (G10A, C and D) than others (G10B). The analysis also showed that using the highest number of raingauges does not always result in better rainfall estimates than when a reduced number is used. For

G10A, when daily data are considered, a sample of 7 gauges gave better results than a sample of 12, but this effect is not repeated with the monthly estimations.

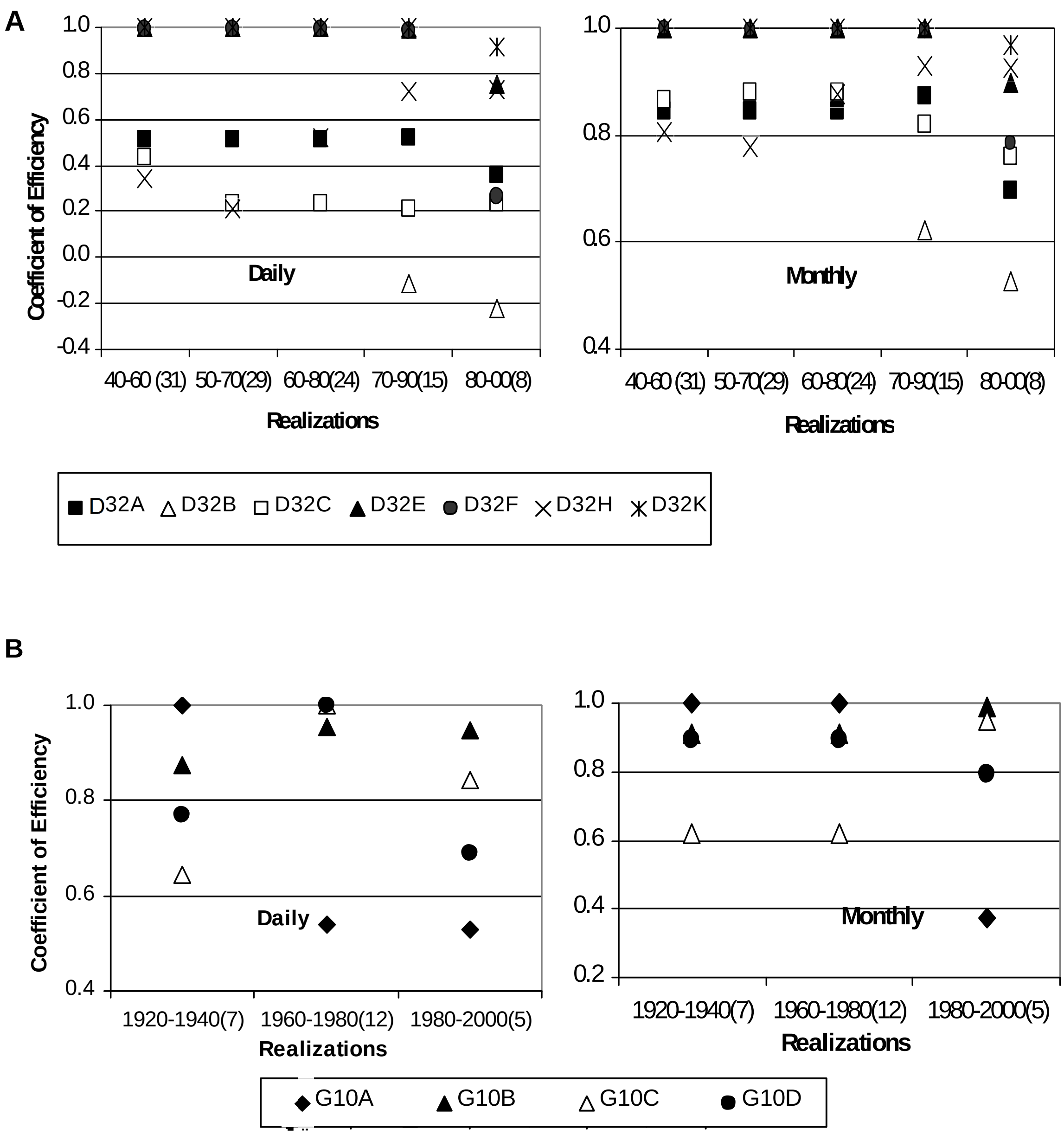


Figure 5.9 Comparisons of daily and monthly rainfall realizations with the reference period using coefficient of efficiency for Seekoei (**A**: D32, semi-arid climate) and Berg River (**B**: G10, humid climate) sub-basins.

Figure 5.10 illustrates the results for the Sabie (X31) basin, while Tables 5.5a and b show the results for the other examples with the addition of two further comparison statistics. The root mean square error (RMSE) measure used is given by:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\Theta - O_i)}^{2} \quad \text{......} 5.1$$

Where N is the number of observations, Θ is the estimated rainfall value and O_i is the actual value of the observation at gauge i.

The results in Table 5.5a show that a reduction in raingauge numbers can lead to substantial uncertainty in spatial rainfall estimation. When the R^2 and CE (which are dimensionless) are considered, a comparison between results in Table 5.5a and 5.5b demonstrate larger variability in daily rainfall estimates than monthly estimates as already demonstrated by Bedford sub-basin example in the section 5.3.

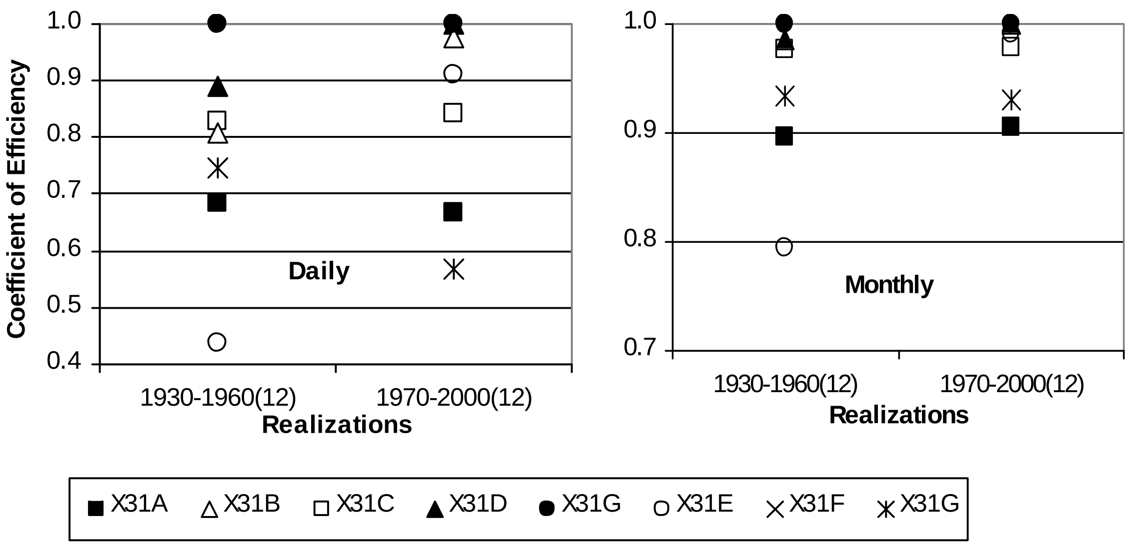


Figure 5.10 Comparisons of daily and monthly rainfall realizations with the reference period using coefficient of efficiency for Sabie (X31) sub-basins.

Table 5.5a Comparisons of daily spatial rainfall realizations with the 'reference' realization (in brackets are gauges available in the reference period).

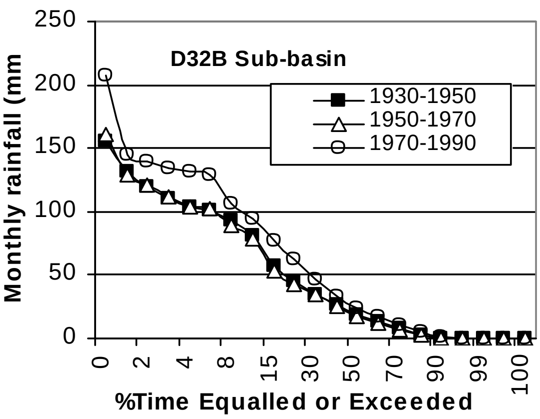
		Sub-basins			
Statistics	**Reference**	**C83A**		**C83C**	
No. gauges	C83A(15) & C83C(15)	10	3	10	3
RMSE R^2 CE		0.28 0.99 0.99	5.42 0.32 0.16	1.13 0.97 0.96	1.51 0.94 0.93
		U20B		**V70A**	
No. gauges	U2OB(8) & V70A(5)	5	2	4	1
RMSE R^2 CE		2.19 0.89 0.88	5.95 0.38 0.13	1.57 0.95 0.95	7.85 0.20 -0.20
		A23A		**C12D**	
No. gauges	A23A(12) & C12D(7)	3	1	3	1
RMSE R^2 CE		5.59 0.38 0.26	6.38 0.31 0.03	4.39 0.48 0.36	6.22 0.28 -0.29

Table 5.5b Comparisons of monthly spatial rainfall realizations with the 'reference' realization (in brackets are gauges available in the reference period).

		Sub-basins			
Statistics	**Reference**	**C83A**		**C83C**	
No. gauges	C83A(15) & C83C(15)	10	3	10	3
RMSE R^2 CE		1.56 0.99 0.99	35.41 0.68 0.68	4.18 0.99 0.99	6.51 0.99 0.99
		U20B		**V70A**	
No. gauges	U2OB(8) & V70A(5)	5	2	4	1
RMSE R^2 CE		7.85 0.99 0.99	34.87 0.78 0.75	7.86 0.99 0.99	43.48 0.74 0.71
		A23A		**C12D**	
No. gauges	A23A(12) & C12D(7)	3	1	3	1
RMSE R^2 CE		20.46 0.90 0.89	24.44 0.86 0.84	18.22 0.91 0.90	26.56 0.82 0.78

Figure 5.11 shows the variability of rainfall frequencies using different realizations for D32B and D32J sub-basins (Seekoei basin). The left-hand side of Figure 5.12 shows the individual raingauge curves which were used in estimating the monthly spatial averages for basin G10A (right-hand side). The effects of raingauge selection in the spatial

interpolation are clearly demonstrated. Figure 5.13 shows frequency curves for the other G10 sub-basins and the X31 sub-basins, while the frequency curves for the other basins (A23A, C12D, C83A, C83C, U20B and V70B) are provided in Appendix 2.2. The rainfall variability is high in areas of steep topography (G10 and X31 sub-basins) which impacts the real distribution of rainfall through orographic effects. If these orographic effects are not represented by the available gauge data, the interpolation approach will not be able to account for them. G10A sub-basin (Figure 5.12) illustrates a situation where not only the total number of raingauges available in a sub-basin contributes to rainfall uncertainty, but also the position of the gauges that are selected during sampling. The wider differences in rainfall estimates for 1940-1960 (the reference period) and other rainfall realizations may be due to the inclusion of a single raingauge (in this case, gauge 0022116W - see location in Figure 5.8) sampled during the spatial interpolation process, which records exceptionally higher daily rainfall amounts compared to the other raingauges available in the sub-basin (Figure 5.12, left-hand side). In this case, truly representative spatial rainfall for this basin may be difficult to quantify with the information available from the raingauge network alone. In such circumstances, additional analyses using assumptions of relationships between rainfall depth and topography may be necessary. However, this is beyond the scope of this study.



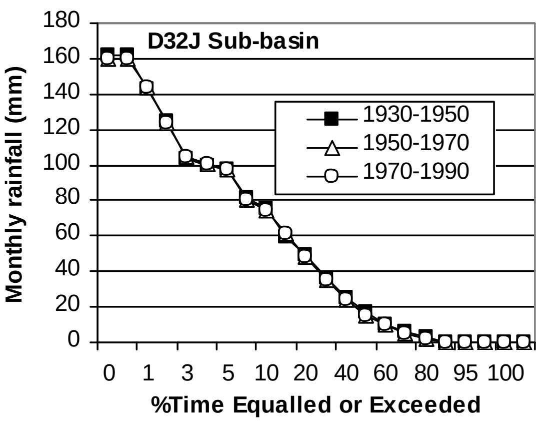


Figure 5.11 Monthly rainfall exceedence frequency curves for three realizations over two sub-basins (the solid square symbol represents the base period realization).

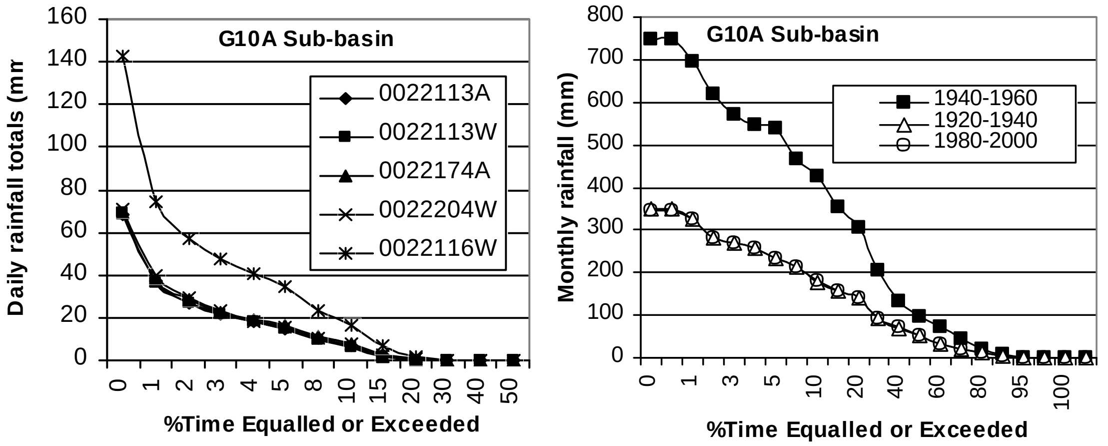


Figure 5.12 Effects of choice raingauges (left-hand side) used on estimating monthly spatial average rainfalls (right-hand side) for G10A sub-basin.

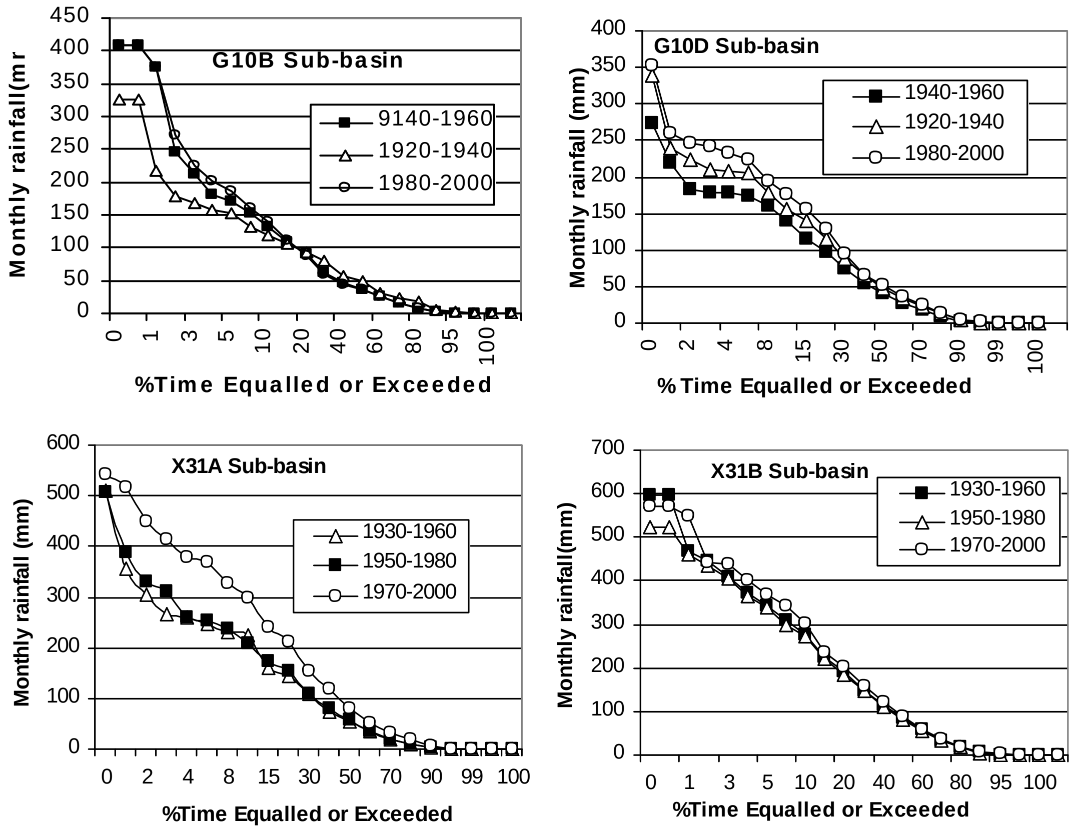


Figure 5.13 Monthly rainfall exceedence frequency curves for three realizations for G10 and X31 sub-basins (the solid square symbol represents the base period realization**).**

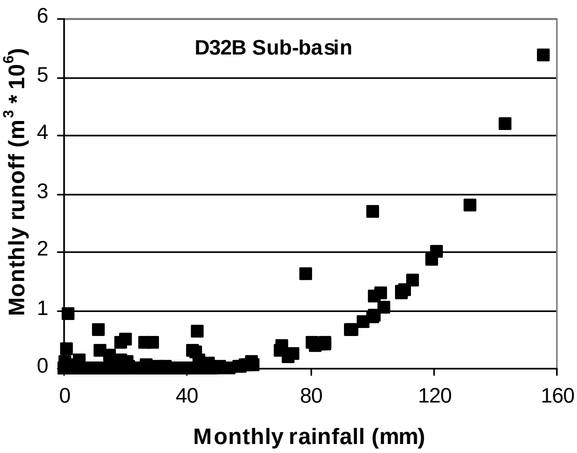
The rainfall uncertainties for the majority of the other sub-basins (see also Appendix 2.2) are less than for the G10 and X31 sub-basins, which suggests that the effects of raingauge density variations are site specific. However, the general conclusion is that the largest differences in monthly rainfall totals occur within high rainfall months which have a greater impact on uncertainties in simulated runoffs in both semi-arid and humid sub-basins. It is worth noting that there has been a further reduction in the number of active raingauges in most parts of South Africa since 2000, which means that future estimates of rainfall will be highly uncertain unless more complex methods are used in the spatial interpolation process. It must also be recognised that the real spatial variation in rainfall is often unknown and that the realization with the largest number of gauges will not necessarily generate the most realistic spatial rainfall estimate.

5.5 Model performance and runoff response to rainfall uncertainty

5.5.1 Analyses at sub-basin scale

An understanding of the relationship between rainfall and runoff is important in assessing model performance and investigating the effects of rainfall uncertainty on runoff estimation uncertainty. Figure 5.14 illustrates typical relationships between monthly rainfall and runoff for both semi-arid and humid sub-basins.

The scatter plots indicate that rainfall depths below a certain threshold in arid to semi-arid regions (left-hand side) hardly produce any runoff. This is expected from a consideration of the much higher initial soil moisture losses in arid to semi-arid regions compared with sub-basins in humid regions. High evaporation rates and infrequent rainfall contribute to the general lack of base flow in the semi-arid basins. High soil moisture deficits suggest that only high rainfall depths will generate any runoff. An exception to this is when relatively low monthly rainfall totals are made up of only a few high intensity events which could generate runoff through infiltration excess processes. Deep-rooted and sparse vegetation in the arid basins often result in high evapotranspiration rates and low interception and as such only high rainfall event depths can generate runoff. This contributes to non-linearities in the relationship between rainfall and runoff, but the overall result is a more consistent relationship than is found for humid regions. The implication is that uncertainties in spatial rainfall generation for rainfall below a certain threshold will not be important in terms of runoff generation. Figure 5.15 (D32 - a semi-arid basin), however, shows that even in semi-arid areas rainfall uncertainties are still propagated into simulated runoff responses. In some cases the differences are evident in the rainfall realizations (left-side of Figure 5.15) as well as the simulated runoff (right side of Figure 5.15). In others, despite similar RMSE values for all rainfall realizations, the realization based on a lower number of raingauges produce runoff RMSE values which are substantially higher (D32A and C).



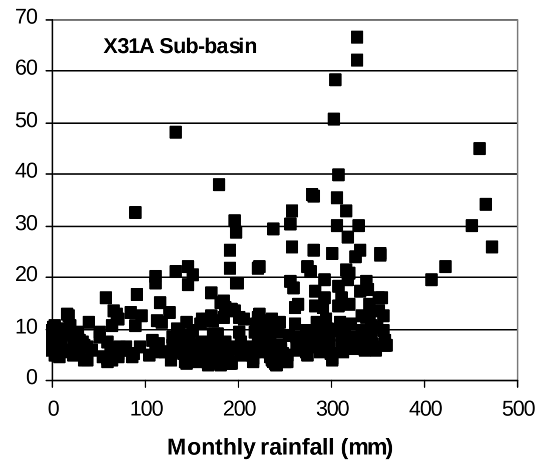
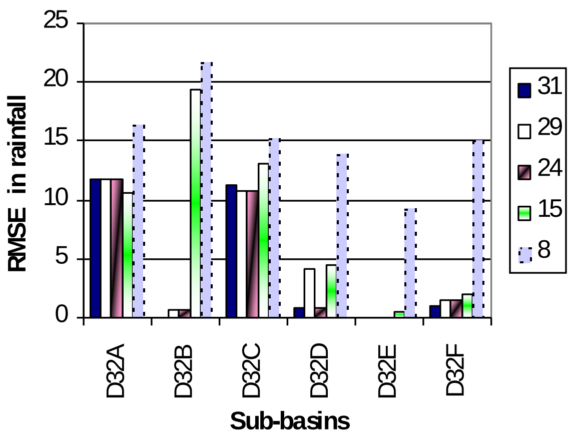


Figure 5.14 Relationships between rainfall and runoff for a semi-arid (left side) and a humid (right side) sub-basin.



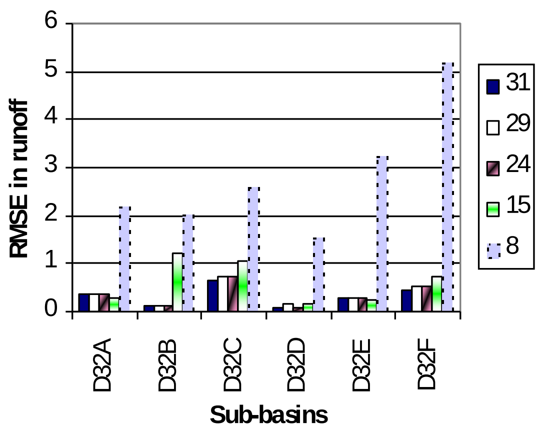


Figure 5.15 Root mean square error (RMSE) for individual sub-basin rainfall estimates in mm (left side) and sub-basin runoff response in $m^3 \times 10^6$ (right side) to different rainfall realizations (based on 31,29,24,15 & 8 gauges) for Seekoei basin.

In humid regions, more runoff generating processes are usually active, where both the rainfall characteristics (depth, duration and intensity) and the antecedent basin moisture characteristics will play major roles. Relationships between rainfall and runoff, therefore usually demonstrate far more scatter (Figure 5.14, right-hand side). This scatter can be further influenced by the presence of delayed runoff responses due to sub-surface drainage and groundwater discharge. It is therefore realistic to suggest that the importance of estimating spatial rainfall over the full range of values is greater in humid regions than in semi-arid regions. The consequences on runoff generation due to the use of uncertain rainfall estimates are illustrated in Table 5.6. The table provides statistics of comparison between time series of simulated monthly runoff generated for the reference period (highest gauge density) and the rainfall realizations using the gauges that are available during the other periods. Only the best case (relatively more gauges) and worst case (least number of gauges) scenarios are shown for each sub-basin.

Examples X31(A and B) in Table 5.6 show that even when different samples with equal gauge numbers are used, the model performance statistics can be substantially different. X31 also illustrates that the effects of rainfall uncertainty can be very different for closely adjacent sub-basins (X31A and X31B), which might reflect orographic effects on rainfall distribution. G10A and D illustrate how the flow simulations can be affected by even small changes in the number of available gauges. Most of the results for the other sub-basins in Table 5.6 show that the model performance deteriorates when the worst case scenario (least number of gauges) has been used. There are cases where this is not true and apart from the total number of raingauges required for adequate rainfall-runoff simulation, there are other important factors including orographic effects and the extent to which they are adequately represented by the gauges. The results do, however, demonstrate the high degree of uncertainty that can exist at the sub-basin scale related to the use of different combinations of raingauges as well as a consistent spatial interpolation method.

Based on the volume difference statistic (%Diff.Mn (Q)) in Table 5.6, the results indicate that the uncertainty related to spatial rainfall estimation can be extremely large. For the worst case rainfall estimation in sub-basin D32B (using 8 gauges still active during 1980 to 2000) the generated runoff is over 200% greater than the estimate based on the reference period gauges (using 46 raingauges). The results are similar for C83, G10, X31 and V70 sub-basins. In contrast, the uncertainty in U20B is very much less and the flow simulations based on 5 or 2 gauges are not very different. Similar patterns are observed for A23A, C12D and D32J sub-basins. The extent to which these findings, at the scale of single sub-basins, apply at wider basin scales is discussed in sub-section 5.5.2.

Table 5.6 Model performance simulation statistics based on different rainfall realizations when compared to reference simulations for each sub-basin (in brackets are gauges available in the reference period).

		Sub-basins			
Statistics	**Reference**	**D32B**		**D32J**	
No of gauges	(46)	32	8	32	8
%Diff.Mn(Q)		2.19	232.24	-0.97	7.4
R^2(Q)		0.96	0.23	1.00	0.99
CE(Q)		0.95	-10.85	1.00	0.99
%Diff.Mn(lnQ)		-1.70	79.60	3.32	0.01
R^2(lnQ)		0.94	0.48	0.99	0.97
CE(lnQ)		0.94	0.30	0.99	0.97
		X31A		**X31B**	
No of gauges	(25)	12	12	12	12
%Diff.Mn(Q)		78.67	6.58	-1.98	58.06
R^2(Q)		0.65	0.81	0.91	0.77
CE(Q)		-1.72	0.80	0.90	-0.36
%Diff.Mn(lnQ)		30.81	-4.62	-1.91	19.76
R^2(lnQ)		0.68	0.86	0.94	0.82
CE(lnQ)		-0.46	0.82	0.92	0.27
		U20B		**V70A**	
No of gauges	U20B(8) & V70A(5)	5	2	1	4
%Diff.Mn(Q)		-2.00	-2.00	-18.15	-0.79
R^2(Q)		0.97	0.88	0.64	0.99
CE(Q)		0.97	0.87	0.60	0.99
%Diff.Mn(lnQ)		-2.09	-2.99	-17.00	-0.91
R^2(lnQ)		0.98	0.95	0.78	1.00
CE(lnQ)		0.98	0.94	0.66	1.00
		A23A		**C12D**	
No of gauges	A23A(12) & C12D(7)	3	1	3	1
%Diff.Mn(Q)		5.91	0.78	19.20	21.98
R^2(Q)		0.62	0.34	0.80	0.46
CE(Q)		0.56	0.26	0.77	0.26
%Diff.Mn(lnQ)		25.71	40.00	30.61	29.93
R^2(lnQ)		0.89	0.82	0.81	0.65
CE(lnQ)		0.88	0.80	0.77	0.57

Table 5.6 *continued.*

Statistics	Reference	G10A		G10D	
No of gauges	(16)	7	5	7	5
%Diff.Mn(Q)		0.39	-65.35	38.16	65.35
R^2(Q)		1.00	0.82	0.94	0.94
CE(Q)		1.00	0.20	0.52	-0.10
%Diff.Mn(InQ)		0.11	-60.64	15.95	24.9
R^2(InQ)		1.00	0.92	0.97	0.97
CE(InQ)		1.00	0.55	0.93	0.84
		C83A		**C83C**	
No of gauges	(15)	10	3	10	3
%Diff.Mn(Q)		0.00	-27.51	-0.32	-11.86
R^2(Q)		1.00	0.11	1.00	0.45
CE(Q)		1.00	0.10	1.00	0.45
%Diff.Mn(InQ)		0.58	-5.13	-1.08	-1.27
R^2(InQ)		1.00	0.71	0.99	0.83
CE(InQ)		1.00	0.69	0.99	0.82

In general terms, the impact of rainfall uncertainty appears to be greater for semi-arid sub-basins, which are characterised by low runoff efficiencies (ratio of basin runoff to rainfall) and highly non-linear rainfall-runoff relationships (Shah *et al*., 1996), as well as areas where there are significant altitude related rainfall gradients that are poorly represented by the available gauges (G10 and X31). While these results tend to support the concept that lower runoff efficiencies will often lead to higher relative runoff errors for a given rainfall estimation error (Xu *et al*., 2006), there are other factors that clearly play a major role making simple generalisations less than completely valid.

5.5.2 Analyses at the basin scale

The previous section investigated the impacts of different spatial rainfall realizations on simulated runoff generated within single sub-basins (incremental flows). The extent to which variations in spatial rainfall estimates and simulated runoff balance each other out across sub-basins will clearly have an impact on simulated runoffs at basin outlets. The previous sub-section 5.5.1 has clearly demonstrated that the relatively large uncertainties can be associated with the preparation of rainfall data inputs to hydrological models at individual sub-basin scales (Faurés *et al*., 1995).

Returning to the Bedford example, Figure 5.16 illustrates the effects on runoff simulation at different points within the basin. Grid 23 is an upstream grid and the 'worst' simulation

(4 gauges) generates a peak monthly runoff which is 30% less than that of the ‘best’ simulation (28 gauges). In this quaternary catchment the situation is very similar when the individual grid runoff simulations are routed to the catchment outlet (grid 12). However, the propagation of rainfall differences to simulated runoff differences is not very conclusive in this example due to the short record length (very few months in which runoff is generated).

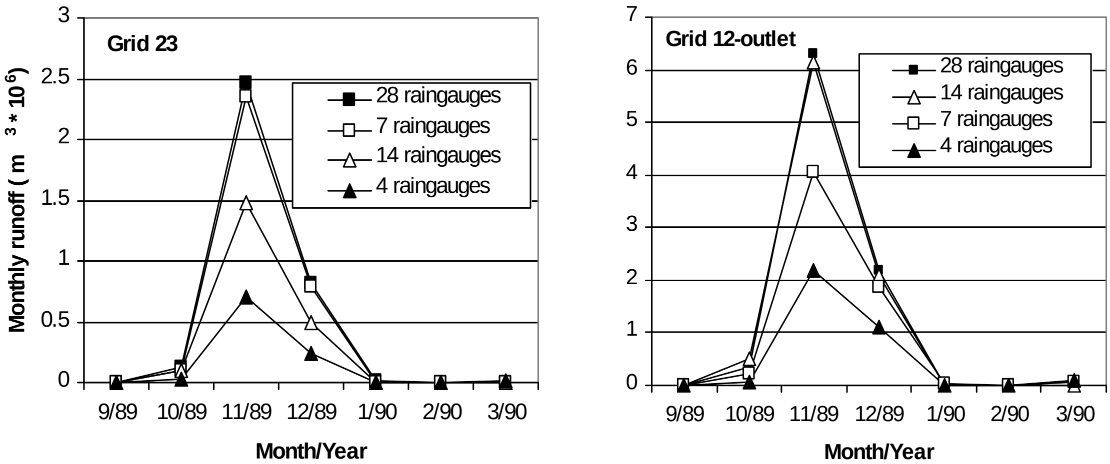


Figure 5.16 Illustration of the effects of reducing number of raingauges on simulated streamflow volumes in different grids (Bedford sub-basin example).

Figures 5.17 and 5.18 and Appendix 2.3 (in which the best rainfall realization is compared to the worst case rainfall realization) compare the rainfall input uncertainties and the extent to which they are propagated in the rainfall-runoff model to output uncertainties using the differences (expressed as percentages relative to the base period realization) in annual rainfall and simulated runoff totals. In the first humid example (X31A in Figure 5.17), differences in annual rainfall mostly fall within the range ±100%, while the corresponding runoff differences are mostly within 80% for the upstream sub-basin. For the downstream sub-basin (X31B) the rainfall errors are within ±30%, while the runoff differences frequently exceed 80% with a decreasing trend from 1970-1980 representing a dry period. The second humid example (G10A in Figure 5.17) is characterised by steep topography, where differences in rainfall and consequently simulated runoffs are all negative reflecting a systematic under-estimation of rainfall totals and simulated streamflow volumes. The simulated runoff differences are much less in the downstream sub-basin which could be partly attributed to the generally positive rainfall differences in the lower parts of the basin and the fact that G10D has a greater catchment area. The two examples (X31 and G10) further illustrate the effects of systematic rainfall uncertainty due to orographic effects.

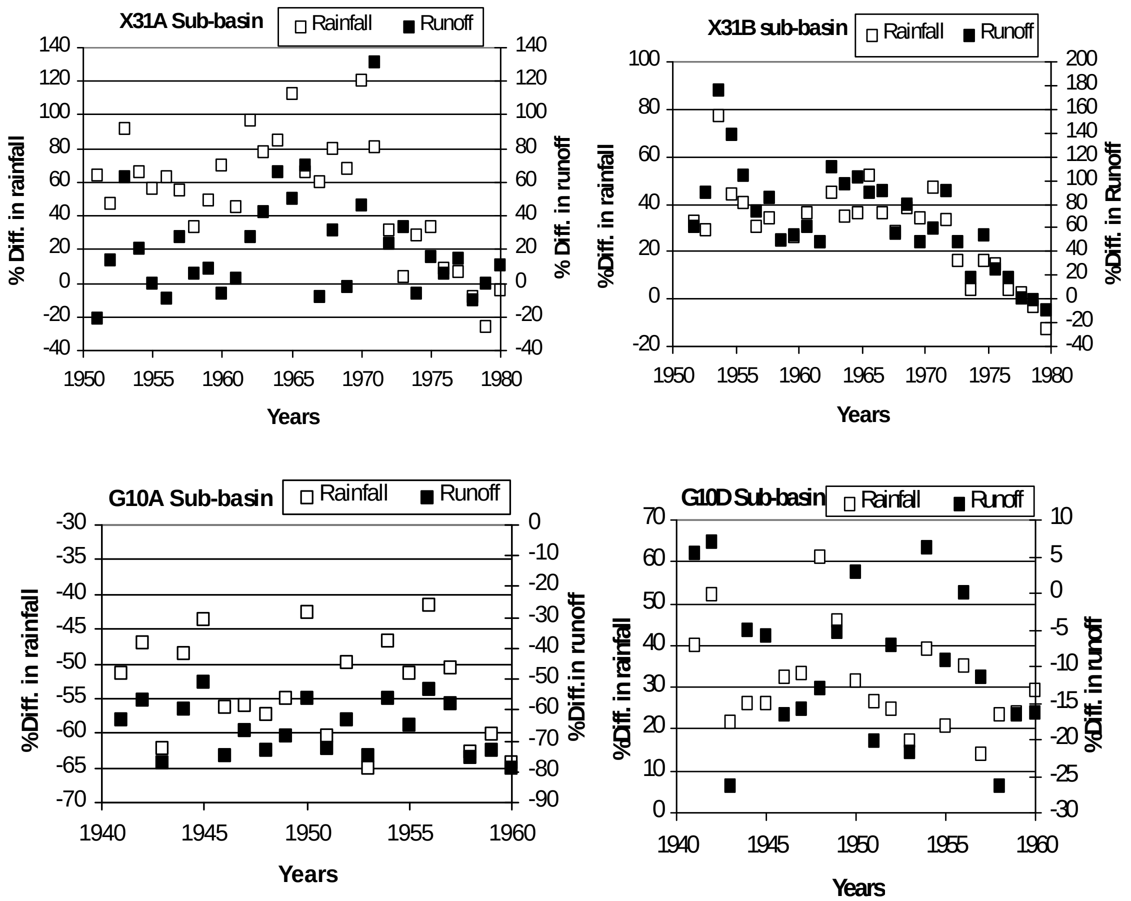


Figure 5.17 Percentage differences (relative to the base period realization) in estimated annual rainfalls and annual runoffs for one realization (few gauges) for humid Sabie (X31) and Berg (G10) sub-basins (upstream X31A,G10A & downstream- X31B, G10D).

Notes: % Diff. in rainfall and %Diff in runoff in Figures 5.17 and 5.18 represents percentage differences of using one realisation relative to the base period realization in annual rainfall and simulated runoff totals respectively

In a semi-arid example (for sub-basins in D32, Figure 5.18) the range of annual rainfall differences is within ±60%, while annual runoff differences are within 350% but the extremes can be as high as 750%. Generally, the results for D32A and D32B are similar, except for some extreme cases. For the downstream sub-basins (D32F and J), the runoff differences are relatively low and more evenly distributed between positive and negatives (i.e. ±100%), while there is an extreme case of 450% for D32F sub-basin. This is a result of upstream differences being relatively random and therefore being partly cancelled out as sub-basin runoffs are routed downstream.

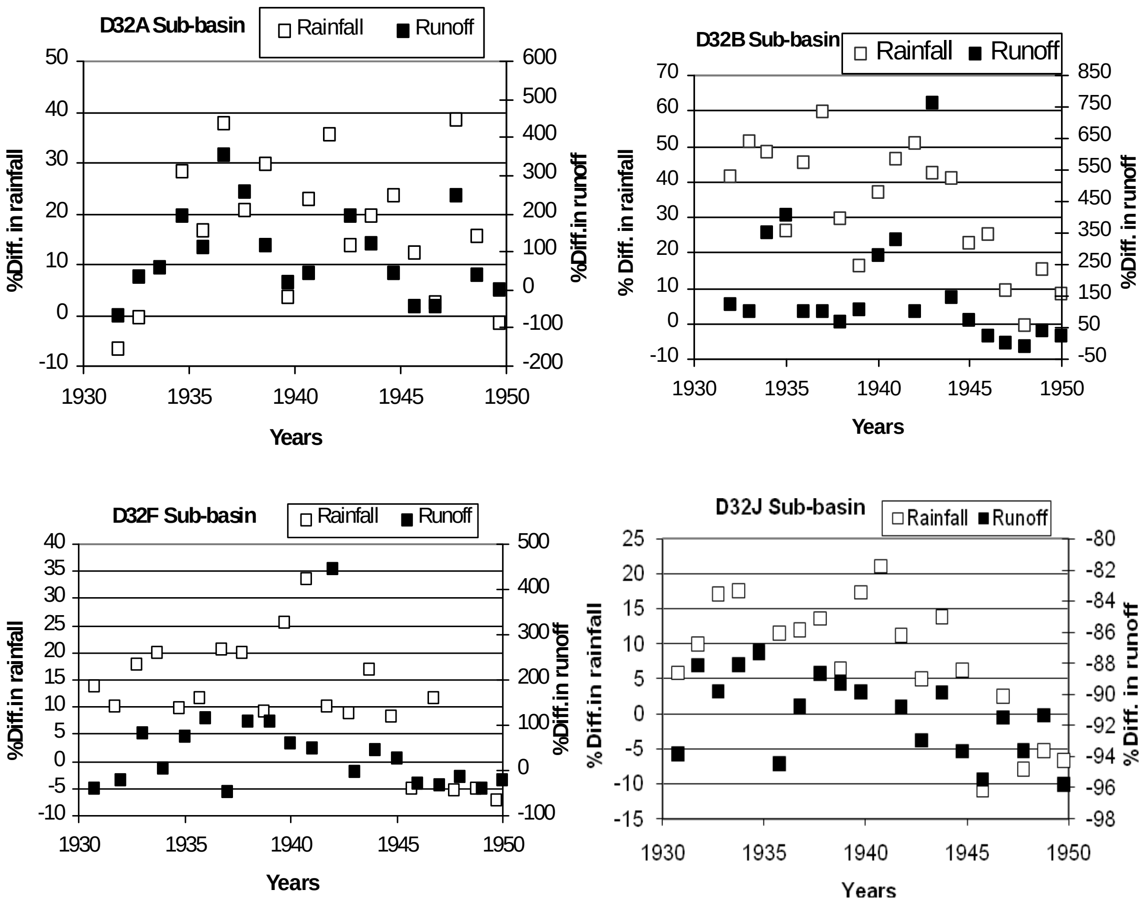


Figure 5.18 Percentage differences (relative to the base period realization) in estimated annual rainfalls and annual runoffs for one realization (few gauges) for semi-arid Seekoi sub-basins (upstream- D32A, B & downstream- D32F, J).

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5.6 Discussion and observations

5.6.1 Rainfall uncertainty analyses

It is apparent that in many parts of the world, networks of hydrometeorological observations are shrinking. South Africa is no exception and the sample of 8 basins used within this study illustrates the situation. In some cases the number of available raingauges has reduced by 50% or more and the situation after 2000 is even worse (Hughes and Mallory, 2008). It is therefore inevitable that the information content of the national rainfall monitoring network is declining and this part of the study has illustrated the potential impacts on estimations of spatial rainfall, which contributes to uncertainty in one of the key inputs to hydrological models.

The study has demonstrated that predicting levels of uncertainty consequent on a loss of observed rainfall information is not straightforward. The uncertainty is dependent on the temporal resolution of the raw gauge data and the model input as well as on the climatic characteristics of the basin. There are inevitably higher potential errors in the use of daily data given that individual gauge differences are expected to be greater at a daily time scale than at a monthly time scale. While only a monthly time-step model was used in this study, the implication of this observation for daily modelling, and particularly for real-time modelling based on daily data are clear. The Bedford example suggests that some advantages can be gained from using daily data in the spatial interpolation approach and then aggregating the daily spatial data to monthly totals. This is because the use of monthly data to estimate basin spatial average rainfalls tends to smooth the variations and noise in daily data. The present study has also demonstrated that significant uncertainties are introduced when a reduced number of raingauges is used to estimate the spatial rainfall and that these uncertainties vary both in space and time, which confirms studies carried out in other parts of the world (Andréassian *et al*., 2001).

Comparisons have been made between the relatively flat semi-arid D32 basin (where systematic rainfall variations are not expected) and the steeper, humid G10 and X31 basins. In the latter basins, orographic rainfall effects are expected to cause systematic variations in spatial rainfall and if these are not adequately represented by the gauge records no interpolation method can generate adequately representative spatial rainfalls.

However, Figure 5.9A (D32 basin) illustrates that even where systematic rainfall variations are not expected, large reductions in gauge numbers can lead to a high degree of uncertainty. Figure 5.10 (X31 basin) illustrates that even if two samples with equal gauge numbers are used in the spatial interpolation there can be relatively large differences in spatial rainfall estimations. The other examples in Table 5.5 illustrate that a small reduction in number of gauges can also lead to large differences in sub-basin rainfall estimations. The effects of spatial arrangement and sampling of raingauges on rainfall estimation were also demonstrated using data from both the Bedford example and national raingauge networks.

The analyses in this study have ignored the potential effects of errors in the data at individual raingauge stations. However, such errors are frequently difficult to identify given the large spatial variations in rainfall that are known to occur in most of the basins in South Africa (Schulze, 1995). Ideally, the same set of raingauges should be used over the entire record period to be simulated. However, with declining network densities this may not be possible and associated uncertainties must be quantified. Further difficulties arise in those areas (dominated by convective rainfall processes) where spatial variations in rainfall are essentially random and correlations between gauge totals even at the monthly scale are typically low. This issue could become even more important if conventional (gauges) and new sources (satellite data) of rainfall data are used together in hydrological models to make up for the lack of gauge data in the future (Hughes, 2006a, b). A general observation was that small increases in raingauge density for sparse networks can substantially reduce areal rainfall estimation uncertainty, while for already dense networks (highest number of representative raingauges) areal rainfall estimation uncertainty only decreases minimally with increased station density. A more general observation from the study is that the use of different combinations of raingauges can introduce substantial uncertainties on spatially averaged rainfall. Improved understanding of spatial rainfall patterns and the use of appropriate correction procedures are therefore needed to reduce uncertainties in spatial rainfall estimates.

5.6.2 Effects of rainfall uncertainty on runoff simulation uncertainty

The extent to which rainfall estimation uncertainties are propagated to uncertainties in runoff simulations depends on the nature of the runoff response to rainfall (as reflected in the parameter values of the model), spatial scale and the relationships between uncertainty and rainfall depth. For example, the majority of runoff in semi-arid basins is generated from moderate to high rainfalls (Figure 5.14), while for humid basins uncertainties for the full range of rainfall depths are important in runoff estimations. The extent to which uncertainties at sub-basin scales are smoothed or cancelled out at the basin scale depends to a certain extent on whether the uncertainties are systematic or random. In areas where topographic effects dominate (G10 and X31 basins, for example) spatial patterns of both rainfall (through orographic effects) and runoff uncertainties are likely to be systematic. In other cases, random uncertainties on individual sub-basins may cancel out at the basin scale. This has been demonstrated in this study (e.g. Bedford-grid elements and Seekoi sub-basins- D32A-D32J), where some of the errors in runoff estimation cancelled out when they are aggregated and routed through a number of sub-basins than when a single spatial element is used.

The effect of spatial variability of rainfall to response of sub-basins has similarly been reported in a large number of studies world wide (Obled *et al*., 1994; Smith *et al*., 2004). The sensitivity of runoff to rainfall uncertainties in the arid to semi-arid regions demonstrate the need to make significant improvements in rainfall monitoring possibly through the use of satellite or radar data (Hsu *et al*., 1999; Soorishian *et al*., 2000; Hughes, 2006a). Furthermore, runoff responses in semi-arid regions are such that there is a high proportion of zero flows which means that even for long observed flow records the information content can be very small (Ye *et al*., 1997) to successfully calibrate hydrological models, hence large uncertainties are induced into the model parameter estimation process. The situation is different in humid regions which have sustained baseflows through high groundwater recharge rates. Within South Africa these regions are also frequently mountainous and this means they have high rainfall gradients and hence the interpolation techniques must be improved to be able to account for rainfall variations caused by topographic influences. The implications of using rainfall inputs with such high variabilities would be an increase in the uncertainty in the modelled predictions. This is more apparent when a model is calibrated using observed hydro-climatic data, since rainfall uncertainties will be propagated into the parameter set. *A priori* parameter estimation approaches are not subject to the same problems and may offer some advantages over calibration based methods.

6. POTENTIAL REDUCTION IN SPATIAL RAINFALL ESTIMATION UNCERTAINTIES

6.1 Introduction

The previous chapter identified problems and uncertainties associated with using raingauge networks to generate spatially averaged rainfalls when the network densities are inconsistent over time. It showed that the current sparse raingauge networks frequently do not provide the resolution required to adequately describe the distribution of rainfall patterns. It also demonstrated that there are spatial and temporal inconsistencies in rainfall records when data from raingauges recording over different time periods and differing groupings are used to generate sub-basin spatially averaged rainfalls for a common period. The conclusions were that, different spatial time series of rainfall and simulated flow can result from the use of different raingauge groupings.

The present chapter focuses on the generation of long time series of spatial rainfall over periods that span very different raingauge network densities. The results from Chapter 5 suggest that such spatial time series will frequently be non-stationary due to changes in the quantity of available information (i.e. variation in number of gauges being used). A further issue is that 'real' non-stationarity could exist in the rainfall data due to changes in climate. Given the large reduction in the number of active raingauges in recent years, this introduces a high degree of uncertainty in the process of spatial rainfall generation. This chapter examines trends in the various spatially averaged rainfall datasets and proposes a non-linear correction approach based on inter-comparison of rainfall frequency characteristics to remove possible inconsistencies in the datasets. If climate change effects are considered to be present during any of the periods used, the methods presented here will not be directly appropriate and would require modification.

The objective of this chapter is therefore to isolate 'real' non-stationarities or trends (related to climate change or natural climate variability) from 'false' trends caused by the use of particular raingauges during interpolation or lack of representation of observations. Potential approaches that can be used to remove non-stationarities in spatial rainfall data are also investigated. The recent reduction in raingauge network density has been paralleled by the increasing availability of alternative rainfall data products, specifically near-global satellite based estimates. Many studies (e.g. Hughes, 2006a, b; Wilk *et al*., 2006) have investigated the integration of spatial rainfall estimates provided by satellite data with historical point estimates of rainfall from raingauge networks and noted that it is not a simple task. This chapter therefore includes satellite based rainfall estimates in the analysis to extend the available historical spatial raingauge data into the future when the existing number of raingauges is expected to decline. From a hydrological modelling perspective an appropriate comparison of the different types of generated spatial rainfall time series is to use them as model inputs and assess the model outputs (e.g. comparing simulated and observed flows).

To achieve the main objective of this chapter, the approach adopted is as follows:

- Trend analysis of individual raingauge data with long records to identify any ‘real’ (i.e. climate related) non-stationarities.
- Generation of long records of spatial rainfall time series using the IDW approach and trend analysis to identify problems with ‘false’ non-stationarity.
- An assessment of a non-linear correction procedure based on frequency of exceedence curves to correct ‘false’ non-stationarity.
- An assessment of the use of satellite rainfall data (uncorrected and raingauge-corrected) to extend raingauge based estimates into the future.
- An assessment of the effects on simulated runoff of using different spatial time series rainfall products.

6.2 Methods for assessing trends in rainfall records

South Africa has high inter-annual variability of rainfall under present climatic conditions (Schulze, 2000) and therefore examining a rainfall time series provides information about whether rainfall characteristics are consistent and stationary throughout the period of a record. Trends are assessed on a monthly (intra-annual) or an annual (inter-annual) basis. Annual rainfall totals are preferred for long-term water resource planning because inter-annual variations may be more important than intra-annual variations. The common causes of changes in rainfall data series are long-term climate variability, climate change and problems linked to data (Kundzewicz and Robson, 2004). The whole point of the trend analysis in this study is to see whether the spatially averaged rainfall time series generated using the IDW approach from a variable number of available point raingauge data can be considered ‘real’ (and if the process generates any trends). This is done by comparing trends in the spatial data with the trends in representative individual raingauge data with long records of at least 50 years. Trend analysis is also done on adjusted spatial rainfall time series to assess if the proposed non-linear correction method can remove any ‘false’ trends.

There are numerous methods for trend analysis ranging from simple statistics, moving averages, linear regression and to non-parametric tests (Kundzewicz and Robson, 2004). Simple statistics include the mean, median and standard deviation and while generally insufficient to determine trends, they form a starting point for more detailed analyses. The assessment of gradual trends in annual rainfall data series in this study involved visual interpretations of simple 5-year moving-averages and rainfall anomaly indices, and the application of a non-parametric Mann-Kendall statistical test, while the magnitude of a trend can be quantified using a regression method.

A 5-year moving-average is a simple process to smooth short-term variations in data and to eliminate sharp fluctuations in the annual rainfall values and illustrate trend directions. The rainfall anomaly index, which is a standardised annual rainfall departure from the long-term mean annual rainfall, was used as an index to indicate changing variability in different portions of the time series and to identify extremes but was also used in this study to assess stationarity in the rainfall records. Moving averages and the anomaly index graphs provide simple techniques for graphically identifying trends but do not determine the magnitude of a trend or whether the trend is statistically significant. A distribution-free Mann-Kendall test (Salmi *et al*., 2002; Ognuntunde *et al*., 2006) was used to test for the presence of significant trends in annual rainfall time series to complement the moving average and anomaly index approaches. The Mann-Kendall test approach determines the significance of a trend, which is considered more important than its magnitude in this study. The Mann-Kendall test is a simple rank-based test which is based on an alternative measure of correlation known as Kendall’s tau, and it is robust to the effect of extreme values and to non-linear trends (Hirsch *et al*., 1982). The test is used to determine upward or downward trends and to establish if a time series has remained relatively constant over time. In order to accomplish this, a statistic based on all possible data pairs is computed. The starting point is to arrange *n* data pairs in an increasing order and calculate all possible differences (x_i – x_j), where x_j precedes x_i in time. The difference is either positive (if $x_i > x_j$), negative (if $x_i < x_j$), or zero (if $x_i = x_j$) for each of the pairs. The number of positive differences minus the number of negative differences is then calculated. This becomes the Mann-Kendall test statistic S (Hirsch *et al.,* 1982) .Stated in statistical terms, the null hypothesis of randomness, H_0, states that the data, (x_1, x_2, … , x_n) are a sample of *n* independent and identically distributed random variables. The alternative hypothesis, H_1, states that the distribution of x_i and x_j are not identical for all $i, j \leq n$ with $i \neq j$). The test statistic is defined as:

$$S = \sum \sum Sgn\left(x_i - x_j\right) \quad \ldots\ldots 6.1$$

Where, x_i and x_j are values in years i and j respectively and, Sgn () is the function:

$$Sgn(\theta) = \begin{cases} 1, if\theta > 0 \\ 0, if\theta = 0 \\ -1, if\theta < 0 \end{cases} \quad \ldots\ldots 6.2$$

The standardised test statistic z is

$$z = \begin{cases} (s-1)\Big/(Var(S))^{0.5}, ifS > 0 \\ 0, ifS = 0 \\ (S+1)\Big/(Var(S))^{0.5}, ifS < 0 \end{cases} \quad \ldots\ldots 6.3$$

The mean (E(S)) and variance (Var(S)) of S are given by E(S) =0 and

$$Var(S) = \frac{n(n-1)(2n+5)}{18} \quad \ldots\ldots 6.4$$

respectively. The standardised z statistic is approximately normally distributed and is used to test the null hypothesis, H_0, that the data are randomly ordered in time, against the alternative hypothesis, H_1, that there is an increasing or decreasing trend. A positive or negative value of z indicates an upward or downward trend, respectively. H_0 is rejected at a particular level of significance if the absolute value of z is greater than the p-value i.e.:

$$|Z| > z_{1-\alpha/2} \quad \ldots\ldots 6.5$$

Where, $z_{1-\alpha/2}$ is the value of the standard normal distribution with probability of exceedance of α/2 (see Hirsch *et al.,* 1982 for further details about Mann Kendall test).

6.3 Non-linear rainfall correction procedure

The basis for developing a non-linear correction procedure is to correct rainfall frequency characteristics which may be very different between two data periods (Figure 6.1, left-hand side). While this may be real, differences in rainfall frequency characteristics may also be caused by different sources of data (Figure 6.1, right-hand side). The left-hand side graph illustrates that the rainfall frequency characteristics of spatially averaged rainfalls can be different if generated based on different groups of gauges. The right-hand side graph illustrates a similar effect but based on two different sources of data (i.e. raingauge and satellite based).

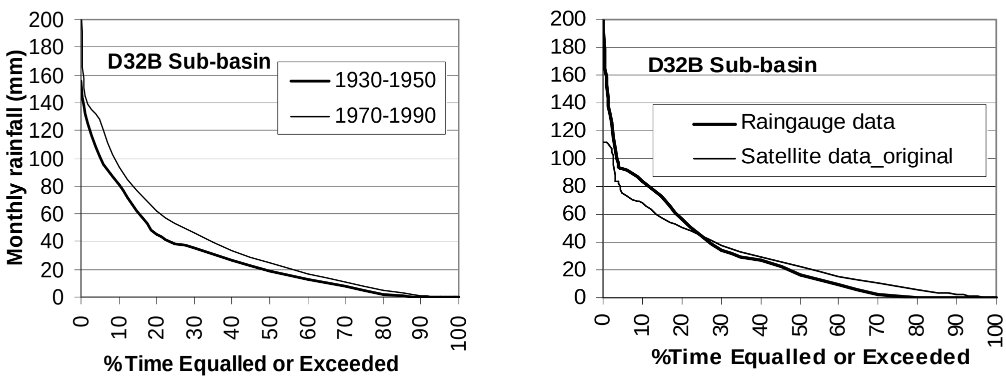


Figure 6.1 Monthly rainfall exceedence frequency curves for rainfall realizations for D32B sub-basin.

The correction procedure was developed to adjust the frequency characteristics of the original IDW spatially interpolated raingauge data using the frequency characteristics of a reference stationary time series dataset. The entire record period of 1920-2000 was used in the analysis. This was the longest period spanned by all the raingauge records that were available for this study. The development of the non-linear correction algorithm was based on an approach used by Hughes and Smakhtin (1996) to patch and extend streamflow time series and some minor adjustments to the algorithm were made in this study to correct the frequency characteristics of rainfall datasets. While the procedure is simple to apply when correcting rainfall characteristics of different spatial datasets covering the same period, the intention in this chapter is also to correct one dataset using another dataset when the two are not coincident in time. Under such circumstances, it is essential to recognise that the two datasets may have ‘real’ differences in rainfall characteristics as well as ‘false’ differences related to the information content of the raw data.

The non-linear correction procedure involves transferring source rainfall values to destination values (i.e. the corrected time series) through the use of similar percentage points (probabilities) from the respective rainfall frequency of exceedence curves (RFCs) which are a summary of the relationship between rainfall magnitude and frequency,and therefore the variability within a time series. The source rainfall record is the original IDW interpolated data, while the *destination RFCs* are based on WR90 rainfall data (Midgley *et al*., 1994). The assumption is that the *destination RFC* is representative of the frequency characteristics of ‘real’ rainfall. The procedure involves generating tables of monthly rainfall values for each spatial point and month for 17 fixed percentage points of the RFCs (i.e. 0.01, 01., 1, 5, 10, 20, 30, 40, 60, 70, 80, 90, 95, 99, 99.9 and 99.99%). These are used to identify the percentage points corresponding to each rainfall value in the time series, log-interpolation being used to define the position between fixed percentage points (see, Hughes and Smakhtin, 1996 for more details).

The algorithm is available in the SPATISM modelling software package and the procedure is illustrated in Figure 6.2. An estimate of the rainfall in any month at the destination point (corrected rainfall record) is made by identifying the percentage point position on the source RFC for the monthly rainfall in the source record and reading off the rainfall value for the same percentage point from the destination RFC.

6. 3.1 Selection of appropriate period to generate destination RFCs

It is a straightforward process to transform the data for the period 1920-1990, where the source (original IDW) and the reference (WR90) datasets are coincident in time. However, for the extended period 1991-2000, the transformation process was complicated by the fact that the WR90 reference data do not cover the last 10 years. The selection of the appropriate period to use for generating the *destination RFC* is therefore critical to the success of the transformation procedure. The total WR90 rainfall time series (1920-1990) is unlikely to be representative of the entire period of analysis up to the year 2000. An appropriate period was selected by visually identifying a period (testing several periods) within the 1920-1990 period that is climatically similar to the period 1991-2000 using appropriate (nearby) DWAF observed flow time series. The DWAF observed flows were used to establish periods with similar characteristics (e.g. sequencing of dry and wet years) because they were the only available and most reliable data that span the period 1991-2000. The selected period within 1920-1990 that has similar flow characteristics to the period 1991-2000 was used to derive the *destination* RFC from the WR90 data. The approach was complemented by the use of individual raingauges within the sub-basins, with long records that cover the entire period (1920-2000). The observed flows that are used should be first checked to ensure that they have not been heavily affected by major abstractions and impoundments. Where observed flows are heavily influenced by anthropogenic influences the approach will be difficult to implement especially if they are the only available data for a specific situation.

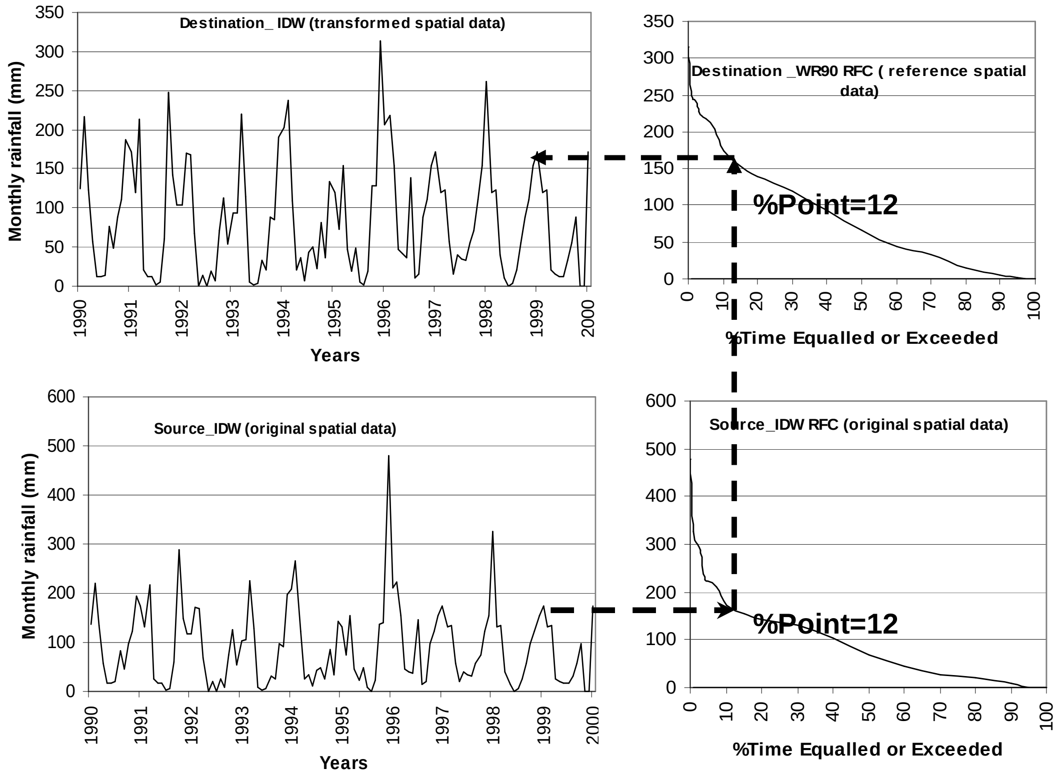


Figure 6.2 Graphical illustration of a non-linear correction process.

Using nine sub-basins as an example (Table 6.1), the WR90 rainfall time series for a 10-year period 1974-1984 was found to be suitable to derive *destination RFCs* (Table 6.1, last column) for most of the sub-basins in the central to eastern parts of South Africa, while the 10-year period 1966-1976 was considered suitable for sub-basins in the western parts of the country. However, there were a few exceptions where this general rule did not apply (Table 6.1).

Table 6.1 Sub-basins, DWAF gauges, areas, observed flow record and appropriate destination frequency curve periods for different regions.

Sub-basins	**Gauge**	**Area (km^2)**	**Observed flow data**	**WR90 destination RFC period**
A23A	A2H027	357	1978-2000	1974-1984
C12D	C1H004	898	1965-2000	1974-1984
D32A-J	D3H015	8330	1980-2000	1935-1945
G10A-C	G1H020	609	1966-2000	1966-1976
K40A	K4H003	87	1961-2000	1966-1976
U20B	U2H007	358	1960-2000	1974-1984
V20A	V2H005	267	1972-2000	1974-1984
V70A	V7H017	281	1973-2000	1974-1984
X31A	X3H001	174	1959-2000	1974-1984

6.4 Application examples and procedures based on raingauge data

The application examples were drawn from different regions of the country and include, Seekoei (D32A-J), Sabie (X31A-D), Berg (G10A-C), Boesmans (V70A-B), Mgeni (U20B), Mooi (V20A), Limpopo (A23A), Upper Vaal (C12D) and Touws (K40A) river sub-basins (Figure 3.9, Chapter 3). These basins represent a wide range of different climatic conditions and gauge density variations over time. The original IDW spatially averaged rainfall time series were compared with the longest individual raingauge records to asses if any trends that could be observed in the spatially averaged time series are ‘real’ and not a consequence of different raingauge inputs to the spatial interpolation process. The individual raingauge analysis was based on gauges drawn from each basin (Table 6.2) and their daily data patched for missing records using adjacent gauges before starting the trend analysis.

Table 6.2 Individual raingauge stations used in trend analysis.

Sub-basin	Station Name	SAWS No.	Start year	End year	Longitude	Latitude
Seekoei (D32A-J)	Colesberg	0172163W	1877	2000	25°6´ E	30°43´S
Berg (G10A-C)	Vrugbaar	0022038W	1903	2000	19°3´E	33 °38´S
Touws (K40A)	Bergplaats	0029294W	1924	2000	22°41´E	33°54´S
Limpopo (A23A)	Donkerhoek	0513827W	1903	2000	28°28 ´E	25°47´S
Vaal(C12D)	Leslie	0477772W	1912	2000	28°56´E	26°22´ S
Mgeni(U20B)	Impendle	0238636W	1926	1996	29°52´E	29° 36´S
Mooi(V20A)	East Meshlyn	0268441W	1925	1984	29°45´E	29°21´S
Thukela (V70A-B)	Heartsease	0299900W	1927	2000	29°2 9´E	29°01´S
Sabie (X31A-D)	Mac Mac	0594539W	1913	1992	30°49´E	2 4°59´S

***Note**: SAWS represent South African Weather Service.*

The raingauge based data analysis allowed three long spatial rainfall realizations to be established and comparatively assessed to identify their differences. The *first realization* consists of the WR90 (1920-1990) regional rainfall data (Midgley *et al*., 1994), which is one of the most widely available longest dataset used in water resources assessments in South Africa and known to be a stationary time series (WR90- Midgley *et al*., 1994). Given that in practice true spatial rainfall is not known, data are needed to compare others to when carrying out rainfall uncertainty assessment and thus since the WR90 data are widely used in South Africa, they were assumed to represent a de facto standard The updated WR2005 (1920-2005) data were recently made available through a Water Research Commission project (WRC, 2005), but were only completed towards the end of this study and could not be integrated into the present analysis. The uncertainty associated with both the WR90 and WR2005 datasets are largely unknown given that these were generated based on Thiessen polygons (Dent *et al*., 1989) using the same sample of gauges used in this study. The *second realization* is based on the IDW interpolated data (1920-2000) using the closet three or four raingauges to the sub-basin centroid. While there are often adequate gauges within the period 1920-1990, there is a further decline in raingauge numbers after 1990 which were used to generate the second realization. The *third realization* consists of the same rainfall data source as the second realization, but with the frequency characteristics corrected to be the same as the first realization (i.e. WR90 dataset).

6.5 Results of trend analyses in rainfall data series

6.5.1 Individual raingauge analysis

Examples of the results of the trend analyses for individual raingauge data are graphically presented in Figure 6.3 (G10A-C, V70B and K40A sub-basins) and Appendix 3.1, while statistical Mann-Kendall results for all the sub-basins are provided in Table 6.3. Except for K40A (gauge 0029294W), the rainfall anomaly index graphs show no presence of trends in the raingauge records. However, based on 5-year moving-averages (Figure 6.3) and statistical tests in Table 6.3, all the results, including K40A, show that there are no significant 'real' trends in annual rainfall time series for the sample of individual raingauge records. The raingauge analysis provides evidence that there are no 'real' non-stationarities due to natural variation of climate in the records and hence, provides a basis for investigating the existence of 'false' trends in the IDW spatially interpolated data.

Table 6.3 Mann-Kendall test summary statistics of individual raingauge analysis.

Sub-basins & SAWS No.	**N**	**Kendall tau**	**Test z**	**p-value**
G10A-C (0022038W)	96	0.061	0.880	0.379
K40A (0029294W)	76	-0.137	-1.749	0.128
D32A-J (0172163W)	123	-0.021	-0.350	0.726
A23A (0513827W)	96	0.046	0.671	0.502
C12D (0477772W)	88	-0.077	-1.060	0.298
U20B (0238636W)	70	0.034	0.411	0.681
V20A (0268441W)	60	-0.028	-0.313	0.755
V70A-B (0299900W)	73	0.057	0.714	0.475
X31A-D (0594539W)	79	-0.054	-0.707	0.480

Notes: *N is the length of time series in years, ** Trend is significant at α=0.05 level, *Trend is significant at α=0.1 level.*

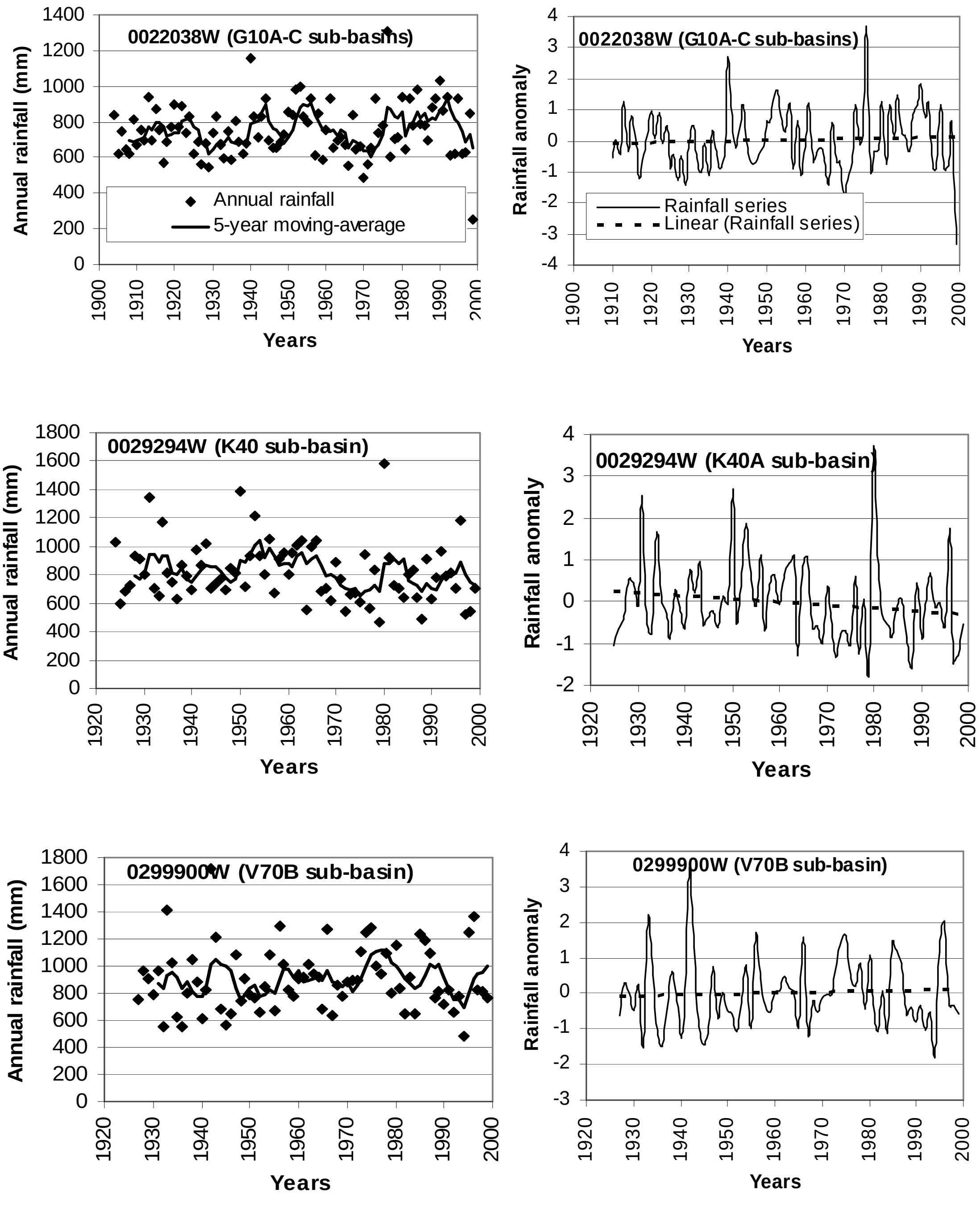


Figure 6.3 A 5-year moving-average (left side) and anomaly (right side) graphs for rainfall data raingauge based data for three sub-basins.

6.5.2 Analysis of spatially interpolated rainfall time series

The results of the trend analyses of IDW spatially interpolated data showed that there exist significant trends in rainfall records in some of the sub-basins (i.e. G10A and V70B), while no trends are observed in the records of the other sub-basins (Figure 6.4 and Table 6.4). Some of the results show that significant trends exist when based on a 0.05 level of significance, while others are only significant when a significance level of 0.1 is used. The trend observed in the G10A example is related to the inclusion of raingauge 0022116W (a problem already indentified in Chapter 5, Figure 5.12) during the first half of the period. The observed daily rainfall totals recorded at this gauge are exceptionally high in relation to other nearby raingauges in the sub-basin. The question remains as to whether the inclusion of this raingauge generates more or less representative spatial rainfalls (i.e. is the first and second half of the period representative of the 'real' spatial rainfall patterns). The trend for the V70B example is more gradual with a possible change occurring in early 1950s. Most of the gauge records start in the 1950s, with only a few extending back to the 1920s. For K40A, the non-significant trend identified using individual raingauge analysis (Figure 6.3), is not repeated in the interpolated data (Figure 6.4). The graphs of trend analyses for other sub-basins are presented in Appendix 3.1, with no signs of any trends, which support the results in Table 6.4. A conclusion that can be derived from this analysis is that the use of different raingauges available over different time periods, may give rise to significant 'false' trends in spatially interpolated rainfall records in some regions.

6.5.3 Analysis of corrected or adjusted spatial rainfall time series

The trend analysis results (Figure 6.5 and Table 6.5) show that any significant trends that exist in the original IDW data (e.g. A23A, G10A, D32J, V20A and V70B sub-basins) based on either 0.05 or 0.1 significance level were successfully removed. Graphical results for some of the example sub-basins are presented in Appendix 3.1. For the K40A example, the rainfall analysis (anomaly index) shows a minor trend that is not evident in the 5-year moving-average and statistical tests (Tables 6.3 and 6.5). It can be concluded that the non-linear correction procedure can remove 'false' non-stationarities that may be introduced during the spatial interpolation of rainfall data.

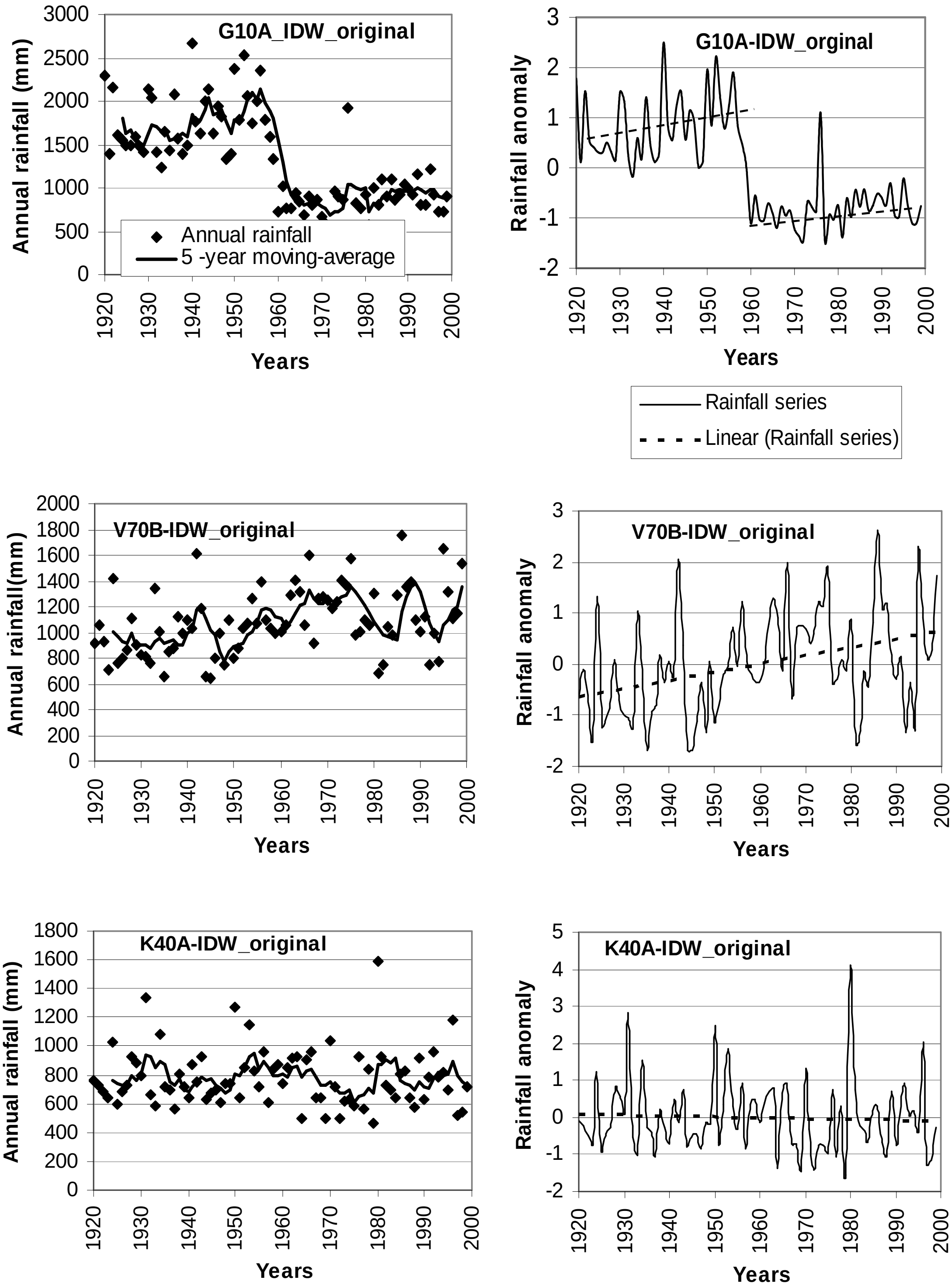


Figure 6.4 A 5-year moving-average (left side) and anomaly (right side) graphs for original spatially interpolated gauge data for three sub-basins.

Table 6.4 Mann-Kendall test summary statistics of IDW spatially interpolated data.

Sub-basin	**N**	**Kendall tau**	**Test z**	**p-Value**
A23A	80	0.142	1.861	0.063*
C12D	80	0.089	1.172	0.241
G10A	80	-0.419	-5.500	**0.001****
G10B	80	-0.037	-0.490	0.624
G10C	80	0.039	0.515	0.606
K40A	80	-0.043	-0.565	0.572
X31A	80	0.020	0.258	0.798
X31B	80	0.026	0.341	0.733
X31C	80	0.085	1.113	0.266
X31D	80	-0.075	-0.989	0.323
U20B	80	-0.069	-0.910	0.363
V20A	80	0.418	1.939	0.052*
V70B	80	0.261	3.423	**0.001****
D32B	80	-0.069	0.906	0.365
D32F	80	0.109	1.430	0.153
D32J	80	0.128	1.687	0.092*

Notes: *N is the length of time series in years, ** Trend is significant at α=0.05 level, *Trend is significant at α=0.1 level.*

6.6 Comparison of different raingauge based spatial rainfall realizations

The trend analyses results in section 6.5 were based on annual rainfall totals which tend to mask characteristics peculiar to each month. The information on monthly variations is important in water resources estimation especially for short term planning and intra-annual variations are expected to be higher than inter-annual variations. This section presents comparative statistics of both monthly and annual rainfall characteristics of three spatial rainfall realizations based on raingauge data (i.e. the WR90, original IDW, and the transformed data) to establish the differences in these datasets. A set of statistical measures (mean, standard deviation, coefficient of variance, root mean square error and coefficient of efficiency) and graphical presentations, which include frequency of exceedance, are used for this analysis.

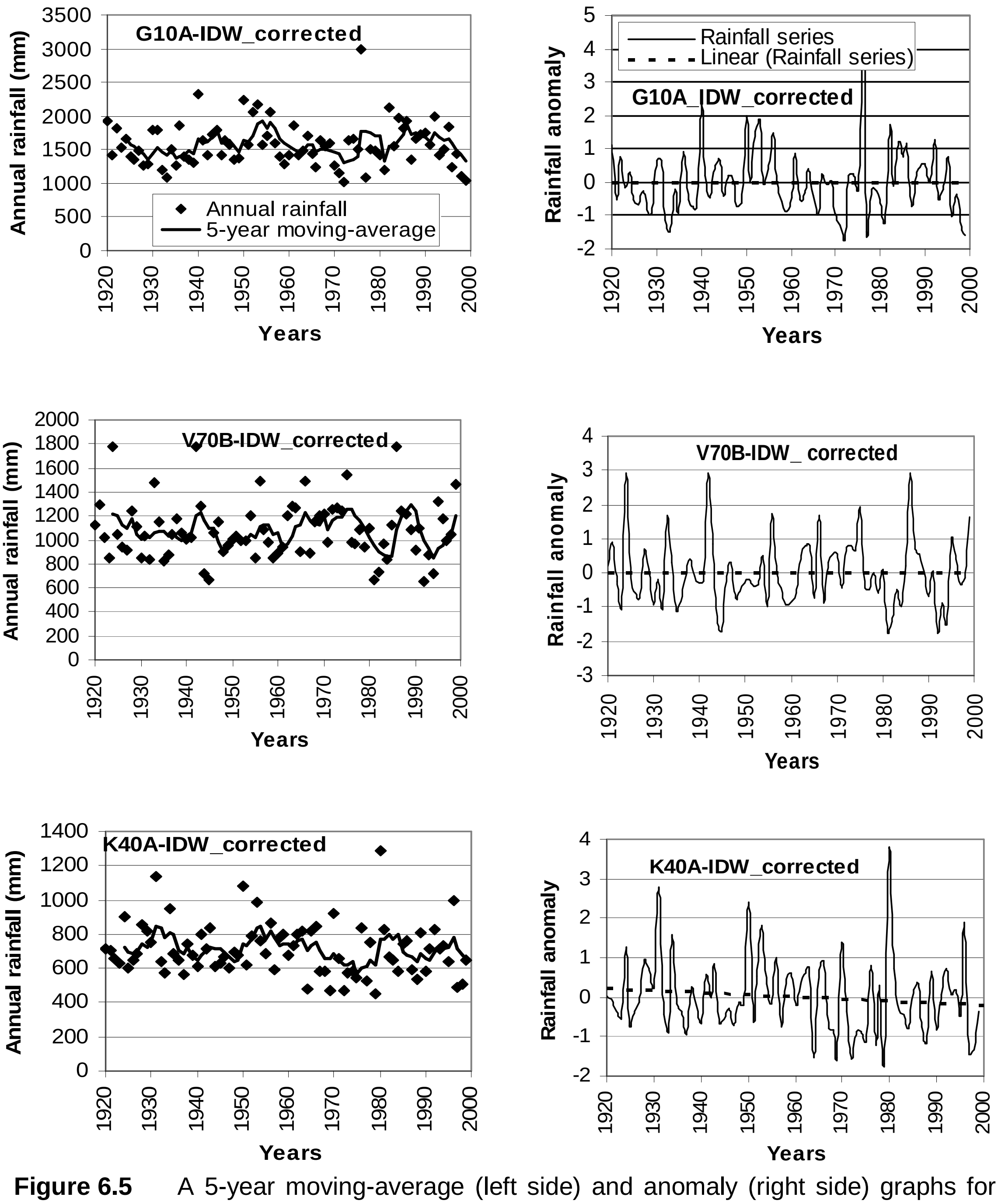


Figure 6.5 A 5-year moving-average (left side) and anomaly (right side) graphs for corrected spatial time series for three sub-basins.

Table 6.5 Mann-Kendall test summary statistics of transformed (corrected) data.

Sub-basin	N	Kendall tau	Test z	p-Value
A23A	80	0.017	0.224	0.822
C12D	80	0.070	0.922	0.365
G10A	80	-0.001	-0.017	0.987
G10B	80	0.040	0.523	0.600
G10C	80	0.073	0.956	0.339
K40A	80	-0.100	-1.313	0.189
X31A	80	-0.080	-1.055	0.291
X31B	80	0.004	0.050	0.960
X31C	80	0.018	0.233	0.817
X31D	80	0.014	0.183	0.855
U20B	80	0.012	0.167	0.867
V20A	80	0.055	0.724	0.469
V70B	80	0.013	0.174	0.861
D32B	80	0.036	0.474	0.636
D32F	80	0.035	0.465	0.642
D32J	80	0.049	0.640	0.522

Notes: *N is the length of time series in years, ** Trend is significant at α=0.05 level, *Trend is significant at α=0.1 level.*

The previous section showed that non-stationarities in datasets can be removed through employing a non-linear correction procedure which only corrects the frequency characteristics of rainfall. However, it is also essential to establish if the sequencing of the rainfall time series is adequate for all the datasets. The results (i.e. monthly characteristics) for two example sub-basins using three sets of statistics as presented in Figure 6.6 shows that there are major differences when the different spatial rainfall realizations are compared on a monthly basis. The WR90 data monthly characteristics are based on a 70 year period dataset (1920-1990), while the characteristics for the original IDW and the corrected IDW are based on an 80 year period dataset (1920-2000). Clearly, there are many inconsistencies in the original IDW rainfall monthly distribution characteristics when compared to WR90 (Figure 6.6) and this is supported by the annual statistics given in Table 6.6.

Table 6.6 Annual rainfall characteristics (i.e. monthly average, standard deviation and coefficient of variation).

i. Monthly average (AVE) in mm

Sub-basin	A23A	C12D	D32J	G10A	K40A	U20B	V20A	V70B	X31A
WR90	696.1	661.3	311.7	1598.3	708.9	983.6	1027.6	1092.6	1243.0
IDW_org	699.9	701.4	331.7	1325.4	775.7	1034.7	1016.5	1083.1	1127.6
IDW_corr	702.6	663.1	304.9	1573.6	710.1	981.7	1029.9	1080.2	1237.7

ii. Standard deviation (STDEV) in mm

Sub-basin	A23A	C12D	D32J	G10A	K40A	U20B	V20A	V70B	X31A
WR90	141.1	103.2	108.7	350.1	156.9	187.4	200.8	232.2	263.8
IDW_org	206.8	127.8	123.7	539.2	199.2	179.3	209.3	256.9	252.5
IDW_corr	146.6	108.2	107.1	328.3	153.8	176.4	200.9	240.2	260.2

iii. Coefficient of variance (CV)

Sub-basin	A23A	C12D	D32J	G10A	K40A	U20B	V20A	V70B	X31A
WR90	0.20	0.16	0.35	0.22	0.22	0.19	0.20	0.21	0.21
IDW_org	0.30	0.18	0.37	0.41	0.26	0.17	0.21	0.24	0.22
IDW_corr	0.21	0.16	0.35	0.21	0.22	0.18	0.20	0.22	0.21

Notes: *'orig' represents original & 'corr' represents corrected IDW rainfall data.*

The differences between the three datasets are mostly systematic over- and under-estimation of monthly rainfall totals, particularly in high rainfall months (Figure 6.7). Figure 6.7 illustrates results drawn from humid regions characterised by complex topography and steep slopes. The rainfall in these regions is topographically controlled (orographic type). G10A shows that for more than 50% of the time, the monthly rainfall totals (both high and low values) are systematically under-estimated by about 40% when based on the original IDW interpolated data which could have a major influence on model simulation results. This result is supported by differences in the statistics presented in Tables 6.6 and 6.7. However, for V70B, only high monthly rainfall totals are over-estimated which are often difficult to capture with point raingauges. The spatially averaged rainfall estimation uncertainties in areas of complex topography have been corrected by the transformation procedure to generate monthly rainfall characteristics that are consistent with the existing reference WR90 dataset (Tables 6.6 and 6.7).

The analysis has also demonstrated that mixed results occur when the spatial datasets (IDW original and corrected data) are compared relative to WR90 dataset (Table 6.7). The results show significant improvements after correcting the data in some cases (e.g. G10A, V70B) and no improvements in others (e.g. C12D, U20B) even after the correction of the original interpolated data. Figure 6.8 shows frequency curves for two examples drawn from a sub-humid region (Mgeni River basin; U20B) and from a semi-arid region (Seekoei River basin; D32J), characterised by undulating and relatively flat topography respectively. The rainfall experienced in U20B is largely caused by Inter-Tropical Convergence Zone (ITCZ), while D32J is dominated by convectional storms or convergence weather systems. As with some other basins (Table 6.7; A23A, D32J, C12D, U20B, V20A and X31A), corrections to the frequency characteristics of the original IDW data are not necessary. One of the reasons might be that there are enough raingauges distributed within the sub-basins to adequately characterise rainfall variability.

Table 6.7 Statistics of comparison for two rainfall realizations (relative to WR90 data) for a common period 1920-1990.

i. Root mean square error (RMSE) in mm

Sub-basin	**A23A**	**C12D**	**D32J**	**G10A**	**K40A**	**U20B**	**V20A**	**V70B**	**X31A**
IDW_org	26.3	18.0	12.7	65.2	19.3	27.9	26.0	32.6	35.4
IDW_corr	24.0	20.5	11.4	54.0	13.5	30.4	26.1	25.9	38.3

ii. Coefficient of efficiency (CE)

Sub-basin	**A23A**	**C12D**	**D32J**	**G10A**	**K40A**	**U20B**	**V20A**	**V70B**	**X31A**
IDW_org	0.80	0.87	0.81	0.72	0.73	0.84	0.89	0.85	0.88
IDW_corr	0.84	0.86	0.85	0.81	0.87	0.81	0.89	0.91	0.86

Notes: *'orig' represents original & 'corr' represents corrected IDW rainfall data.*

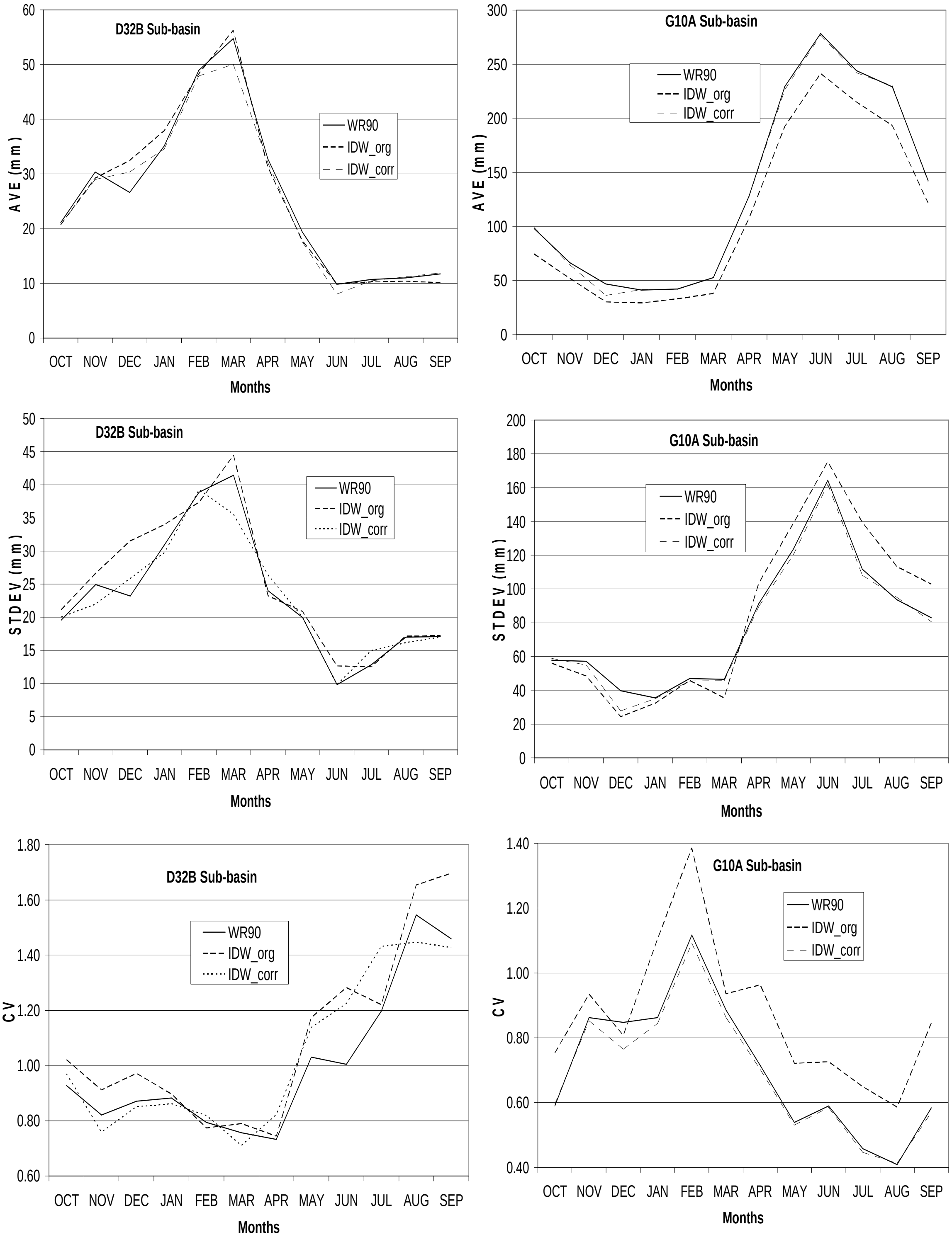


Figure 6.6 Monthly rainfall characteristics for two sample sub-basins (AVE is the long term average monthly rainfall; STDEV is the standard deviation and CV is the coefficient of variance).

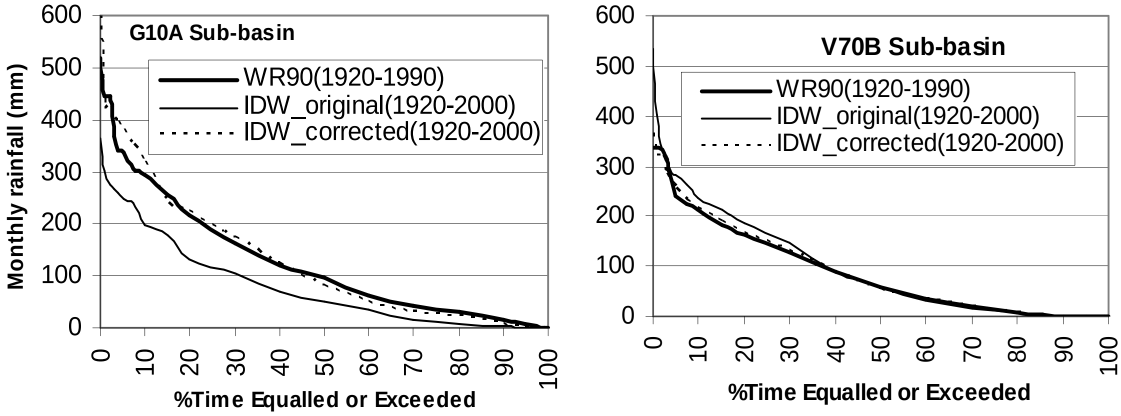


Figure 6.7 Comparison of rainfall frequency of exceedence curves for three raingauge based spatial rainfall realizations for G10A and V70B sub-basins.

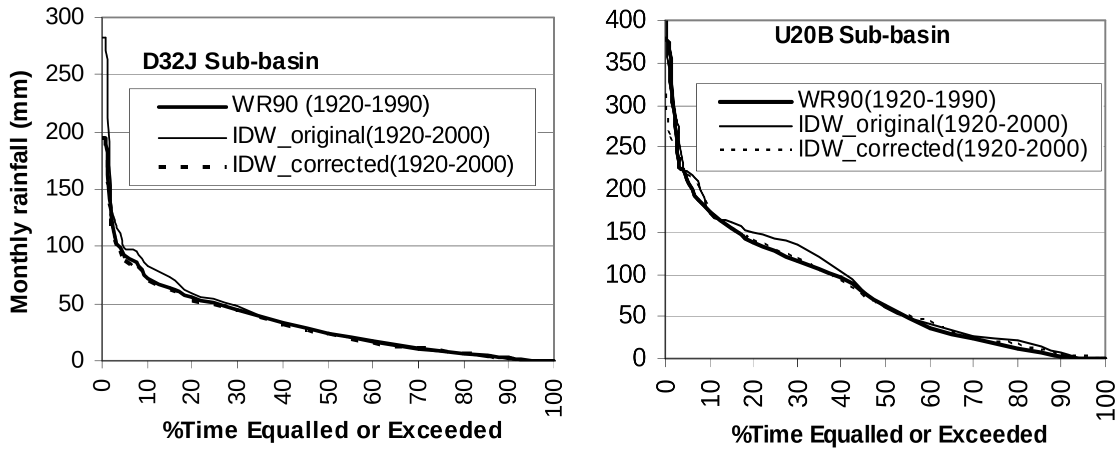


Figure 6.8 Comparison of rainfall frequency of exceedence curves for three raingauge based spatial rainfall realizations for D32J and U20B sub-basins.

6.7 Analysis of the potential use of satellite based rainfall data

The focus of the present section is on the integration of rainfall information from different sources (raingauge and satellite) into a single dataset. The fact that raingauge networks are continuously declining suggest that the introduction of satellite data products (e.g. Hughes, 2006a, b) can offer a potential alternative for defining basin rainfall data. Satellite based rainfall estimates provide spatial estimates over extended areas and are becoming more readily available. Section 2.6.1 reviewed the relevant literature on the potential application of satellite based rainfall estimates within hydrological models. However, there is need to combine raingauge and satellite data into a single stationary time series for use with a model and a single parameter set. The main challenge is that the records for the analysis are not coincident in time as the available periods of satellite data coincide with a large reduction in gauge numbers. The same correction procedure described in section 6.3 is applied to try and overcome this problem, since studies by Wilk *et al*. (2006) and Hughes (2006a) have already emphasized the need to correct the original satellite based estimates before they are used as model inputs. In spite of a recent decline in gauge numbers, raingauge networks are expected to remain an important source of rainfall data (Seed and Austin, 1990), but may require support from other sources to improve the quality of spatial rainfall information for use in hydrological assessments.

6.7.1 Data preparation

The satellite data product (available from 2001 to 2006) used is the NOAA CPC RFE2.0 data available in daily binary format (for more details refer to section 3.3.1) and the data were converted from binary to text format using a simple Delphi data extraction program (Figure 6.9, left-hand side). The derivation of rainfall spatial estimates for each sub-basin involved first selecting the appropriate grid squares covering each sub-basin (e.g. U10A in Figure 6.9, right-hand side). In Figure 6.9 (right side), the polygons represent sub-basin boundaries, the unlabelled points are raingauges, while V2H005 and U1H005 are DWAF streamflow gauges. The sub-basin spatial rainfall estimates were based on simple averages of the daily rainfall totals from appropriate grids lying within each sub-basin, which were then aggregated to monthly values.

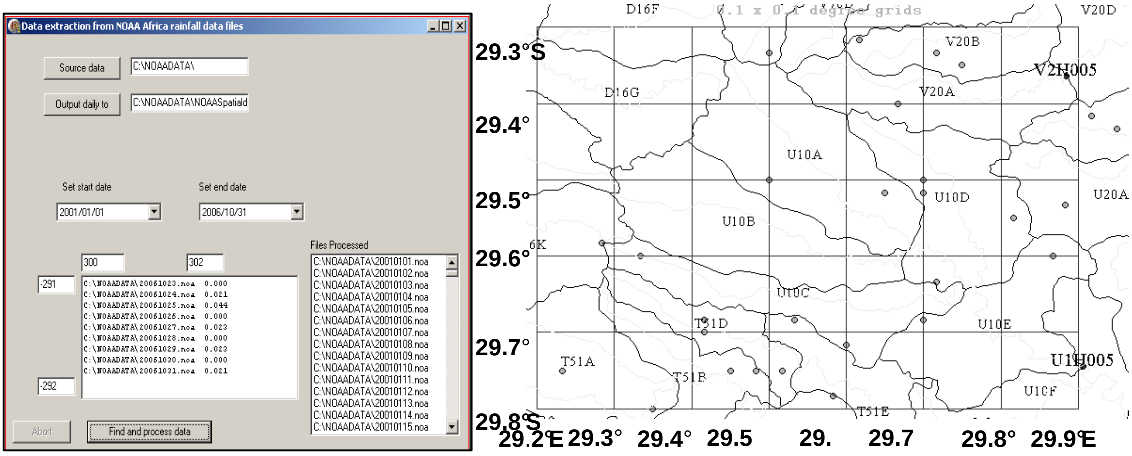


Figure 6.9 Data extraction window (left side) and gridded representation for deriving satellite-based rainfall estimates for individual sub-basins (right side).

6.7.2 Transformation of satellite based rainfall data

The first problem to be solved for combining raingauge and satellite data measurements is that point raingauge measurements cannot be directly compared with the spatial estimates produced by satellite imagery, since the former only provide information at a point, which might not be spatially representative. Therefore, existing WR90 historical spatial gauge based estimates are used in the analysis instead of individual point raingauge estimates. The alternative approach to spatially interpolate the gauge data over the same period with satellite data suffered two limitations. One of the problems is that the longest record period of the raingauges used is 1920-2000, while the satellite data covers the period 2001-2006. Secondly, the idea was to establish if a single model parameter set derived using one rainfall dataset can be applied to another dataset. It was therefore sensible to use the WR90 data which were used in establishing the existing regional parameter sets for the Pitman model (Midgley *et al*., 1994).

The *source RFC* in the transformation process (section 6.3) was calculated from the original satellite data time series, while a *destination RFC* was quantified from the WR90 rainfall time series. As presented in section 6.3, the selection of an appropriate period for establishing the *destination RFC* was based on visual identification of a period within 1920-1990 that is climatically similar to the satellite period (2001-2006) using DWAF observed flow records and a limited number of rainfall stations with data up to 2006. The WR90 rainfall time series for the period 1964-1974 was found to be suitable to derive *destination RFCs* (Table 6.8, last column) for most of the summer rainfall region (central to eastern parts), while the period 1970-1976 was considered suitable for the winter rainfall region (western part) of South Africa. However, they were exceptional cases (Table 6.8) where the generic reference periods identified did not appear to be appropriate.

Table 6.8 Sub-basins, DWAF gauges, areas and appropriate destination frequency curve period for different regions.

Sub-basins	**Gauge**	**Area (km^2)**	**Observed flow period**	**WR90 destination RFC period**
D32A-J	D3H015	8330	1980-2006	1925-1935
G10A-C	G1H020	609	1966-2006	1970-1976
G21C	G2H012	244	1973-2006	1970-1976
G40J-K	G4H006	600	1963-2006	1970-1976
Q94C	Q9H019	76	1972-2006	1964-1974
S60C	S6H003	215	1971-2006	1964-1974
T34A-H	T3H005	2597	1952-2006	1964-1974
T35A-K	T3H006	4268	1952-2006	1964-1974
U10A-E	U1H005	1744	1960-2006	1964-1974
U20B	U2H007	358	1960-2006	1964-1974
V20A	V2H005	267	1972-2006	1964-1974
V20A-D	V2H002	937	1950-2006	1964-1974
V20A-E	V2H004	1546	1960-2006	1964-1974
V60A-B	V6H004	658	1954-2006	1964-1974
V60D	V6H003	312	1954-2006	1964-1974
V70A	V7H017	276	1973-2006	1964-1974
V70B	V7H016	124	1973-2006	1964-1974
X12A-C	X1H016	581	1970-2006	1968-1980
X21F-K	X2H015	1554	1958-2006	1968-1980
X31A	X3H001	174	1959-2006	1968-1980

6.7.3 Inter-comparison of satellite based rainfall realizations

This section presents an inter-comparison of the original (refer to section 3.2.2, pp 69 for the details on how the product used in this study was derived) and corrected satellite rainfalls to establish the extent of their differences using time series and frequency curve graphs as well as root mean square error and coefficient of efficiency statistics. As an illustration, Figure 6.10 presents the results of the transformation approach using frequency of exceedence curves and time series plots for V70A. A comparison of the time series of the original satellite-based rainfall data with the DWAF station measured rainfall data indicates that the monthly rainfall distribution patterns and timing are generally consistent (Figure 6.10, left-hand side). The original satellite estimates under-estimate the WR90 monthly rainfall totals by up to 40%, mainly during wet years which would have major impacts on simulated streamflows if not corrected.

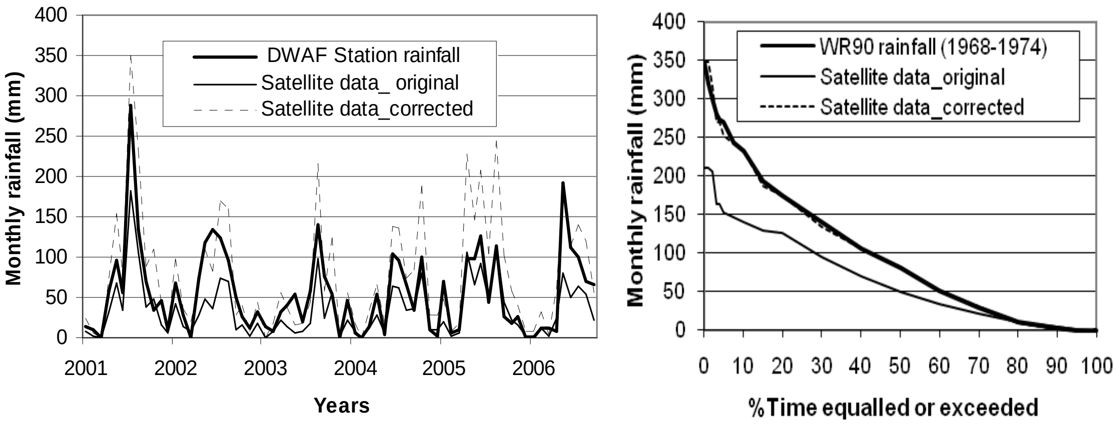
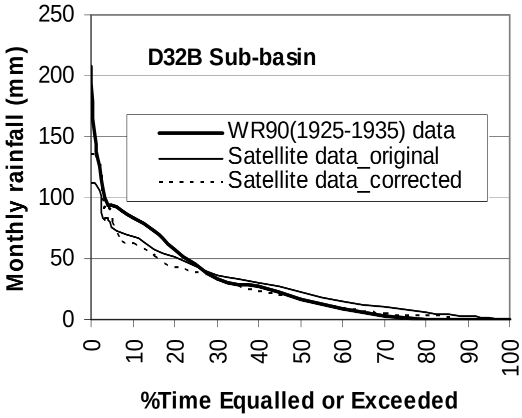


Figure 6.10 Comparison of the time series of satellite-based rainfall data (original and transformed) with DWAF station rainfall (left side) and frequency of exceedence curves of monthly rainfall totals of WR90 spatial data and satellite-based estimates (right side) for V70A sub-basin.

Figure 6.11 illustrates that there are cases where the original satellite based estimates matches closely with the frequency characteristics of the WR90 data (e.g. D32B and D32J sub-basin) before any transformation. This result was similar for all the D32 sub-basins (A-J) in the Seekeoi River basin. As the basin is flat it is possible that the satellite based data give a more representative estimate of spatial rainfall since there are no topographic effects which control rainfall distributions and are not reflected in the satellite estimates. However, the high spatial and temporal variability of rainfall and runoff in the semi-arid D32 sub-basins make the selection of the appropriate period for use in deriving destination RFCs difficult and, is the main limitation of the correction procedure. It must therefore be concluded that the period used to establish the destination RFC (Table 6.8) was inappropriate in this example.



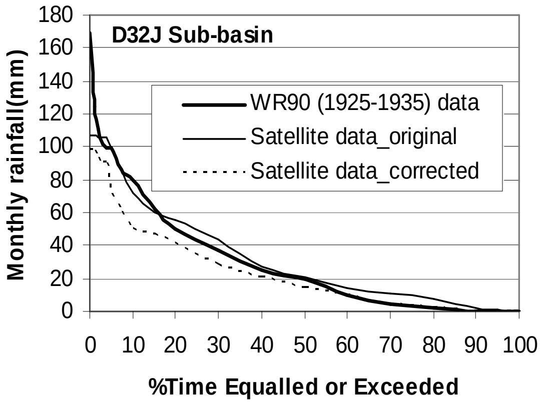


Figure 6.11 Comparison of frequency of exceedence curves of monthly rainfall totals of WR90 spatial data and satellite-based estimates for D32B and D32J sub-basins.

A summary of the statistics of inter-comparison between the original and corrected satellite data in Table 6.9 demonstrates that there are regions in the country where the original satellite data must be corrected and in others where it appears to be unnecessary. It is not surprising that most of the sub-basins with poor statistics are characterised by complex topography where satellite estimates tend to mask the orographic variations in rainfall data.

Table 6.9 Statistics of inter-comparison of original and corrected satellite data.

Sub-basin	Root mean square error (mm)	Coefficient of efficiency
C12D	12.26	0.92
D32A	6.22	0.94
D32B	6.91	0.93
D32C	9.13	0.88
D32D	6.22	0.93
D32E	8.13	0.88
D32F	9.90	0.85
D32G	11.20	0.85
D32H	12.27	0.83
D32J	11.30	0.85
G10A	**120.11**	**-8.52**
G10B	**80.95**	**-3.13**
G10C	**61.85**	**-2.26**
G40J	13.32	0.88
G40K	8.37	0.94
H10E	**117.5**	**-5.97**
K40A	12.64	0.85
Q94C	**33.04**	**-0.04**
S60C	13.06	0.90
T34A	25.78	0.61
T34B	22.93	0.69
T34C	18.17	0.80
T34D	19.60	0.80
T34E	25.96	0.61
T34F	14.70	0.91
T34G	24.68	0.84
T34H	9.34	0.96
T35A	16.29	0.86
T35B	14.25	0.90
T35C	12.57	0.93
T35D	27.26	0.82
T35E	14.31	0.94
T35F	10.62	0.95
T35G	6.89	0.98
T35H	12.88	0.94
T35J	15.68	0.92
T35K	14.43	0.93

Table 6.9 *continued.*

Sub-basin	Root mean square error (mm)	Coefficient of efficiency
U10A	35.98	0.53
U10B	25.87	0.77
U10C	25.37	0.78
U10D	18.57	0.88
U10E	20.50	0.86
U20B	21.75	0.83
V20A	22.27	0.82
V20B	16.92	0.90
V20C	12.41	0.95
V20D	7.55	0.98
V20E	6.41	0.99
V60A	19.39	0.88
V60B	15.62	0.92
V60D	12.31	0.95
V70A	**45.84**	**0.28**
V70B	**55.10**	**0.00**
X12A	22.80	0.80
X12B	26.36	0.72
X12C	30.05	0.64
X21F	21.47	0.81
X21G	27.28	0.66
X21H	**52.84**	**-0.37**
X21J	**53.47**	**-0.49**
X21K	**55.07**	**-0.63**
X31A	**89.73**	**-3.01**
X31B	**84.33**	**-1.86**
X31C	**88.94**	**-1.64**
X31D	**51.92**	**-0.18**

Note: *Bold values indicate worst or unacceptable statistics.*

6.8 Hydrological model response to different spatial rainfall realizations

The objective of this section of the study is to identify the extent to which the differences in rainfall spatial estimates (both raingauge and satellite based) are propagated into simulated runoffs. The simulated flows were assessed by comparing with observed flows using visual comparisons of time series and flow duration curves as well as the set of goodness-of-fit statistics presented in section 3.4.1. The model was run using fixed evaporation demand inputs and fixed parameter sets. The parameter sets were based on calibration against observed data using the WR90 rainfall data.

6.8.1 Model response to raingauge based rainfall inputs

This section evaluates the use of corrected spatially interpolated raingauge based rainfall data for both the calibration period (all observed data up to 1990) and the extended period (1991-2000) compared with the original spatial IDW interpolated data or the WR90 rainfall data. Table 6.1 in section 6.4 lists the sub-basins (quaternary catchment names), the associated DWAF streamflow gauges and the sub-basin areas. A total of five rainfall realizations are used and five model outputs were generated (Table 6.10).

Table 6.10 indicates that many of the simulations based on the IDW rainfall realizations are at least as good as the simulations based on calibration using the WR90 rainfall data. However, there are a number of cases where the original IDW rainfall data produced relatively poor results, which were improved by the use of the rainfall correction process. It is also evident that even some of the calibration results do not generate ‘acceptable’ results based on some of the statistics (note some of the large %Diff values when using log transformed flows). This is likely to be partly related to some un-accounted for upstream development effects in the observed data, as well as errors in the data. A further contributing factor is likely to be that none of the available rainfall inputs are ‘true’ sub-basin rainfall information. The similarity in results across all three simulations for the period up to 1990 for some basins could be related to the fact that all of the rainfall inputs are based on the same source sample of rainfall data and that these data are generally sufficient to provide inputs to the model.

For the extended period, 1991-2000 (Table 6.10) which is characterised by a reduction in raingauge numbers (relative to those of the period 1920-1990), some of the simulation statistics based on the original IDW data were poor (e.g. D32A-J, G10A, X31A) and some satisfactory (e.g. C12D, V20A, V70A), while for the corrected input rainfall data the statistics improved for most of the sub-basins. However, in some instances few gauges can give equally good results especially when the sub-basins are small. The correction procedure was very useful in removing large systematic uncertainties in spatial rainfall estimates. An example is provided in Figure 6.12 for the topographically complex group of sub-basins G10A-C, with the flows measured at downstream sub-basin G10C. The simulation statistics of the transformed (corrected) data are at least as good as the

WR90 flows for most of the sub-basins (e.g. A23A, D32J, V70A, V70B and K40A) as shown in Table 6.10. While the overall conclusion is that the correction procedure applied here has been demonstrated to be useful, there are examples where it has not worked (e.g. C12D). The main problem is almost certainly associated with the selection of the period to use in generating the destination RFC.

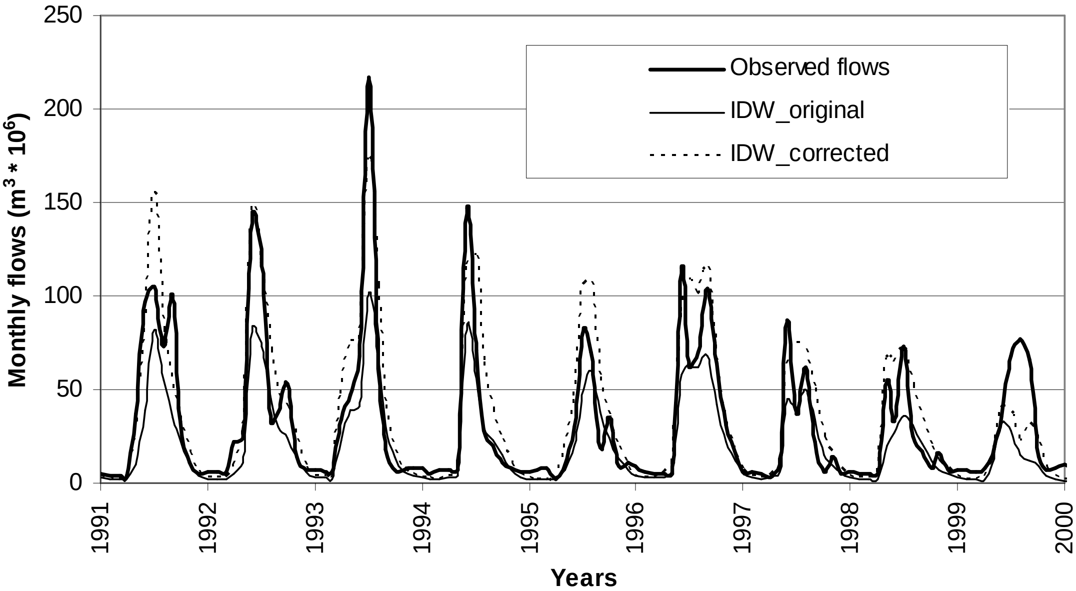


Figure 6.12 Comparison of monthly flows time series form October 1990 to September 2000 for Berg river sub-basins (G10C).

6.8.2 Model response to satellite-based rainfall estimates

Table 6.11 presents statistics of comparison of simulated flows (relative to observed flows) for two satellite based rainfall realizations. Figure 6.13 shows flow time series and flow duration curves respectively for the observed flows and the simulated flows based on the original and corrected satellite estimates for the V70A sub-basin. The simulation based on the original satellite based rainfall shows substantial under-estimation of both high and low flows, while flow hydrographs are well modelled by using the corrected satellite based data (Figure 6.13, left-hand side). Similarly, the flow duration curves illustrate (Figure 6.13, right-hand side) that the use of the original satellite data resulted in under-estimation of streamflow volumes by approximately 60% and that the corrected streamflow patterns are in close agreement with the observed flow patterns.

Table 6.10 Comparison of simulated statistics (with reference to observed flows) based on five rainfall realizations.

Sub-basins	**Data**	**Un –transformed flows (Q)**				**Log-transformed flows {ln(Q)}**			
		%Diff Mn	**%Diff Stdv**	**R^2**	**CE**	**%Diff Mn**	**%Diff Stdv**	**R^2**	**CE**
A23A	**1978-1990**								
	WR90	-5.5	-32.7	0.70	0.67	-18.1	-13.0	0.64	0.64
	IDW(org1)	10.7	13.0	0.69	0.67	-83.0	-7.8	0.64	0.57
	IDW(corr1)	**4.2**	-33.5	0.66	0.63	-81.9	-18.6	0.62	0.56
	1991-2000								
	IDW(org2)	6.9	65.9	0.80	0.23	-68.3	39.0	0.74	0.27
	IDW(corr2)	**-6.6**	**28.0**	**0.86**	**0.74**	**-63.0**	**24.9**	**0.79**	**0.50**
C12D	**1965-1990**								
	WR90	-29.3	-30.8	0.68	0.65	-25.9	-20.5	0.60	0.60
	IDW(org1)	10.2	-13.6	0.71	0.71	123.8	13.6	0.67	0.61
	IDW(corr1)	-23.2	-38.6	0.72	0.65	**30.1**	-20.9	0.64	**0.63**
	1991-2000								
	IDW(org2)	14.3	-15.9	0.58	0.57	58.5	24.1	0.68	0.23
	IDW(corr2)	-62.3	-49.8	**0.76**	0.56	-87.8	**-2.7**	0.68	0.02
D32A-J	**1980-1990**								
	WR90	14.6	6.8	0.91	0.89	-70.4	-33.3	0.57	0.48
	IDW(org1)	52.0	14.3	0.89	0.84	-90.5	-34.5	0.47	0.26
	IDW(corr1)	**-22.2**	-93.5	0.26	0.24	-64.7	-39.2	0.44	**0.38**
	1991-2000								
	IDW(org2)	439	207	0.51	-6.9	135	-48.9	0.22	-0.87
	IDW(corr2)	**19.0**	**-15.4**	**0.68**	**0.67**	**31.0**	**-25.7**	**0.42**	**0.35**
G10A-C	**1966-1990**								
	WR90	20.4	6.7	0.90	0.86	15.9	-15.6	0.84	0.77
	IDW(org1)	-36.4	-41.6	0.80	0.62	-9.8	-18.7	0.80	0.77
	IDW(corr1)	**17.3**	**4.7**	**0.83**	0.80	14.0	**-15.0**	**0.80**	0.74
	1991-2000								
	IDW(org2)	-33.9	-38.9	0.81	0.65	-18.4	12.8	0.79	0.50
	IDW(corr2)	**11.0**	**5.1**	**0.80**	**0.77**	**-2.1**	22.9	0.79	**0.68**
K40A	**1961-1990**								
	WR90	8.9	-21.2	0.65	0.65	-33.0	-12.8	0.65	0.60
	IDW(org1)	32.4	14.4	0.77	0.66	-35.1	8.6	0.66	0.47
	IDW(corr1)	**-4.4**	-30.1	0.76	**0.73**	**-12.8**	**4.3**	**0.67**	**0.62**
	1991-2000								
	IDW(org2)	47.2	50.6	0.71	0.13	-23.7	30.8	0.61	0.26
	IDW(corr2)	**6.6**	**-5.9**	**0.69**	**0.68**	**1.2**	**17.5**	**0.62**	**0.47**

Table 6.10 *continued*

Sub-basins	Data	Un –transformed flows (Q)				Log-transformed flows {ln(Q)}			
		%Diff Mn	**%Diff Stdv**	**R^2**	**CE**	**%Diff Mn**	**%Diff Stdv**	**R^2**	**CE**
	1960-1990								
U20B	WR90	15.9	21.7	0.68	0.65	-15.6	-7.2	0.67	0.64
	IDW(org1)	-8.0	-10.8	0.64	0.63	-6.9	-1.8	0.72	0.69
	IDW(corr1)	-13.2	-12.0	0.64	0.62	-9.8	5.7	**0.72**	**0.70**
	1991-2000								
	IDW(org2)	9.2	25.2	0.58	0.33	28.9	-21.0	0.52	0.48
	IDW(corr2)	-17.5	-25.7	**0.60**	**0.58**	**7.8**	-24.6	0.51	**0.50**
	1972-1990								
V20A	WR90	-15.4	-15.7	0.84	0.82	-17.2	22.1	0.81	0.64
	IDW(org1)	-13.6	-12.2	0.84	0.82	-17.6	21.9	0.85	0.69
	IDW(corr1)	-18.9	-19.3	0.83	0.79	-19.5	20.2	0.84	0.67
	1991-2000								
	IDW(org2)	-3.2	0.1	0.85	0.84	-19.9	31.4	0.85	0.64
	IDW(corr2)	-16.9	-25.1	0.85	**0.80**	**-12.6**	**9.5**	**0.86**	**0.80**
	1973-1990								
V70A	WR90	4.0	11.8	0.68	0.68	2.7	12.9	0.80	0.79
	IDW(org1)	-21.1	-24.0	0.87	0.81	-6.5	-14.1	0.86	0.84
	IDW(corr1)	**12.4**	-13.9	0.74	0.73	**0.3**	-15.9	0.82	0.82
	1991-2000								
	IDW(org2)	-2.0	0.8	0.70	0.66	3.0	-7.9	0.87	0.87
	IDW(corr2)	**0.6**	-5.5	0.68	**0.67**	4.9	-6.9	0.84	0.83
	1959-1990								
X31A	WR90	9.3	3.5	0.85	0.82	3.8	-1.1	0.85	0.82
	IDW(org1)	28.2	31.6	0.86	0.59	9.0	4.1	0.84	0.70
	IDW(corr1)	**8.4**	**-1.2**	0.84	**0.82**	**4.4**	-6.7	0.83	**0.80**
	1991-2000								
	IDW(org2)	39.7	23.8	0.81	0.52	17.1	-8.6	0.87	0.62
	IDW(corr2)	**10.7**	**-12.1**	0.75	0.74	**8.9**	15.7	0.83	**0.76**

Notes: *Bold values indicate improvement in statistics after transformation; IDW(org1)/(corr1) represents data period up to 1990; IDW(org2)/(corr2) represents data period from 1991-2000*

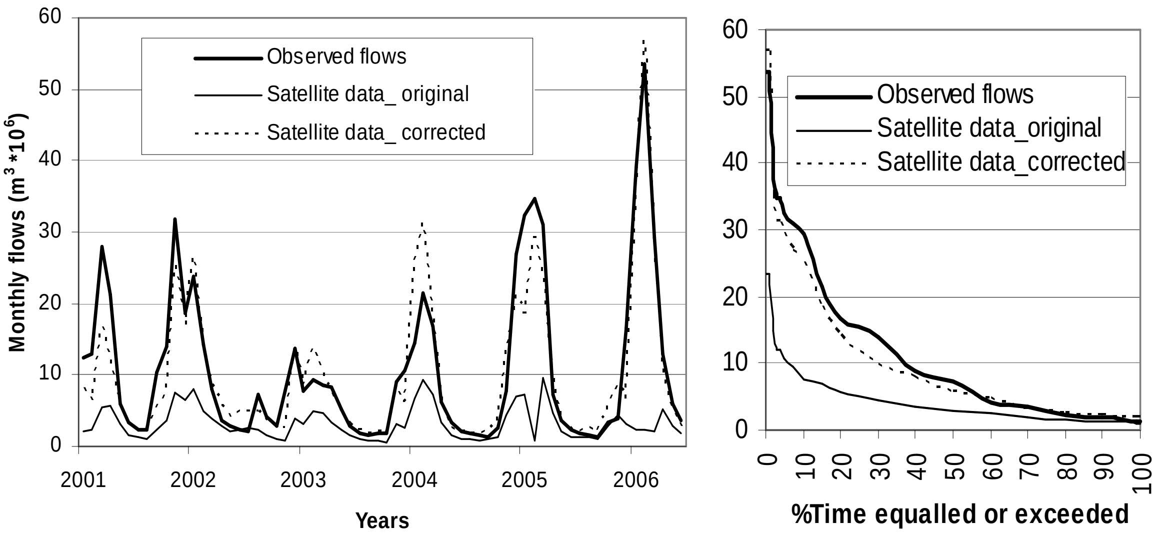


Figure 6.13 Comparison of monthly flow time series (left) and comparison of flow duration curves (right) for the October 2001- September 2006 period for V70A sub-basin.

Based on all the results of the sub-basins studied (Table 6.11), the original satellite-based estimates substantially under-estimated rainfall totals in 13 (65%) cases and generated poor simulation statistics for both un-transformed and transformed flows. This seems to be severe in sub-basins located in mountainous regions with steep topography (G10A-C, X31A, H10E, Q94C, V70B and U20B) where the effects of orographic rainfall are expected to be high leading to high rainfall spatial variabilities which could not be represented by satellite data. However, in most of these cases, when the corrected satellite data were used they generated substantially improved simulations based on the majority of the statistics presented in Table 6.11. There are other cases where improvements are marginal (e.g. G40J-K), while others are worse (e.g. D32A-J) as shown in Table 6.11.

Table 6.11 Comparison of simulated statistics (relative to observed flows) based on original and transformed satellite estimates.

Sub-basins	Data 2001-2006	Un –transformed flows (Q)				Log-transformed flows {ln(Q)}			
		%Diff Mn	%Diff Stdv	R^2	CE	%Diff Mn	%Diff Stdv	R^2	CE
D32A-J	Sat (org)	4.7	-7.7	0.41	0.34	9.9	7.3	0.14	-0.17
	Sat (corr)	72.7	1.1	0.39	0.18	70.2	-23.8	0.16	-0.17
G10A-C	Sat (orig.)	-79.4	-80.4	0.64	-0.11	-67.0	31.6	0.59	-2.87
	Sat (corr)	**12.6**	**8.5**	**0.77**	**0.71**	**-1.4**	**25.9**	**0.65**	**0.44**
G21C	Sat (orig.)	-67.6	-73.7	0.76	0.33	-2.4	-34.7	0.72	0.68
	Sat (corr)	**-20.0**	**-13.8**	0.54	**0.52**	22.6	**-25.6**	**0.72**	**0.68**
G40J-K	Sat (orig.)	-15.7	19.3	0.32	-0.08	40.3	-40.4	0.60	0.56
	Sat (corr)	-17.1	17.1	0.25	-0.22	82.3	-47.1	**0.61**	0.51
H10E	Sat (orig.)	-83.6	-82.2	0.78	-0.13	-188.5	40.4	0.78	-1.49
	Sat (corr)	**-18.1**	**-42.7**	**0.79**	**0.67**	**28.3**	**-23.5**	**0.71**	**0.66**
Q94C	Sat (orig.)	-77.9	-63.2	0.21	-0.35	-309.6	6.6	0.47	-2.73
	Sat (corr)	**-7.2**	**33.3**	**0.32**	**-0.28**	**-60.7**	**21.3**	**0.60**	**0.28**
S60C	Sat (orig.)	-41.0	-36.5	0.63	0.49	-452.7	-6.7	0.68	0.28
	Sat (corr)	**-23.8**	48.5	0.38	-0.40	-437.0	11.6	0.65	0.22
T34A-H	Sat (orig.)	**-24.5**	-25.8	0.61	0.54	-0.1	-34.7	0.61	0.59
	Sat (corr)	**14.1**	**7.3**	0.56	0.44	10.1	-19.4	0.62	0.57
T35A-K	Sat (orig.)	**0.1**	23.9	0.36	-0.05	4.8	-25.1	0.64	0.61
	Sat (corr)	6.7	**3.4**	**0.46**	0.34	8.4	**-24.9**	**0.70**	**0.64**
U10A-E	Sat (orig.)	-50.7	-62.4	0.78	0.32	-13.0	-27.5	0.88	0.67
	Sat (corr)	**13.5**	**-33.5**	0.69	**0.65**	**2.5**	-22.7	0.82	0.80
U20B	Sat (orig.)	-61.0	-63.4	0.79	0.18	-79.3	-8.3	0.78	0.07
	Sat (corr)	**-25.6**	**-15.0**	0.56	**0.49**	**-29.8**	**1.1**	**0.78**	**0.66**
V20A	Sat (orig.)	55.8	-55.9	0.79	0.29	-55.1	13.7	0.88	0.11
	Sat (corr)	**-25.6**	**-23.5**	0.72	**0.65**	-26.0	21.8	0.84	**0.58**
V20A-D	Sat (orig.)	11.7	3.4	0.58	0.49	7.7	-3.0	0.76	0.72
	Sat (corr)	-18.8	-24.5	**0.61**	**0.58**	-5.1	-7.6	**0.79**	**0.77**
V20A-E	Sat (orig.)	22.9	-4.3	0.59	0.52	27.0	-25.9	0.79	0.60
	Sat (corr)	**-13.0**	-28.4	0.55	**0.54**	**9.4**	-30.1	0.75	**0.70**
V60A-B	Sat (orig.)	-38.8	-49.3	0.50	0.42	-48.3	-28.0	0.74	0.71
	Sat (corr)	**9.6**	**-14.8**	**0.51**	**0.49**	199.4	-21.3	0.73	0.62
V60D	Sat (orig.)	-26.2	-34.9	0.54	0.51	-9.4	-17.2	0.63	0.63
	Sat (corr)	**4.3**	**-14.3**	**0.54**	**0.53**	-109.6	-18.9	0.63	0.55
V70A	Sat (orig.)	-62.0	-66.6	0.87	0.17	-43.0	-18.8	0.83	0.23
	Sat (corr)	**-3.2**	**-5.7**	**0.88**	**0.88**	**2.1**	**-9.4**	**0.87**	**0.87**

Table 6.11 *continued.*

Sub-basins	Data 2001-2006	Un –transformed flows (Q)				Log-transformed flows {ln(Q)}			
		%Diff Mn	**%Diff Stdv**	**R^2**	**CE**	**%Diff Mn**	**%Diff Stdv**	**R^2**	**CE**
V70B	Sat (orig.)	-51.7	-60.5	0.75	0.31	-72.3	-23.0	0.79	0.57
	Sat (corr)	**9.2**	**13.7**	0.65	**0.53**	**19.7**	**-5.4**	0.72	**0.70**
X12A-C	Sat (orig.)	62.7	70.7	0.30	-1.64	53.1	-16.8	0.52	-0.09
	Sat (corr)	**3.4**	**-30.0**	**0.72**	**0.69**	**15.2**	**-21.7**	**0.75**	**0.70**
X21F-K	Sat (orig.)	55.8	5.5	0.63	0.18	29.4	-27.1	0.66	0.05
	Sat (corr)	**-10.7**	-46.4	**0.70**	**0.60**	**2.8**	**-26.8**	**0.77**	**0.74**
X31A	Sat (orig.)	-80.0	87.0	0.43	-0.58	-99.0	-31.3	0.47	-3.48
	Sat (corr)	**-6.8**	**-23.5**	**0.53**	**0.53**	**1.1**	**-13.1**	**0.71**	**0.71**

Notes: *Sat (orig) represents original & Sat (corr) represents corrected satellite rainfall data; Bold values indicate improvement in statistics after transformation.*

V20A, X12A-C and X21F-K are examples where the original satellite data generated simulations in excess of observed streamflows, but improved after corrected satellite data are used. However, for D32A-J, the original satellite resulted in more acceptable model results than the corrected data, which indicates that satellite data can be used in their original form in some locations. In other sub-basins (T35A-K and V20A-D), the original satellite data generated acceptable results in terms of monthly volumes, while other statistics improved after correction which might be related to how the rainfall data is processed through the rainfall-runoff model. Comparison of the flow statistics between the WR90 data (calibration period) and the satellite data was not strictly possible as they covered different time periods and a few poorly simulated months in a six year period (satellite) data can affect the overall results far more so than within a much longer period (WR90).

6.9 Discussion

6.9.1 Rainfall analysis results

The first part of this chapter focussed on an analysis of trends and variations in rainfall records (both individual gauge and spatially interpolated data), since the objective of the overall chapter was to generate long and continuous spatially averaged rainfall datasets that are stationary, consistent and representative and which are useful for long-term water resources assessment projects. Long spatial rainfall databases are not readily available in many countries in southern Africa and this study offers approaches and alternative datasets that could be potentially used to achieve this goal. The analysis quantified some of the uncertainties associated with the generation of long spatial rainfall datasets using different sources of information (raingauge versus satellite data).

Trend analysis of the original IDW spatially interpolated raingauge data showed that in some situations (e.g. for G10A and V70B sub-basins, for example) different raingauge densities covering different time periods may introduce ‘false’ trends in the time series. However, based on individual raingauges with long records no ‘real’ trends were observed. When compared to WR90 data for a common period (1920-1990), there is evidence that information from the available raingauge data is more important than the spatial interpolation approach and this issue became critical when the extended period (1991-2000) was considered due to a further decline in number of active raingauges. Therefore, uncertainty in spatial rainfall generation appears to be mainly related to how representative the observation stations are for a particular sub-basin. A comparison of the spatial rainfall realizations showed that substantial uncertainties can exist when a non-stationary time series is compared to the WR90 dataset (Table 6.6) and that these results are climate dependent. An overall observation from the analysis is that there are situations where the use of reduced density networks with less information may result in poor estimates of spatial rainfalls. However, the use of a frequency based correction approach can improve the estimates.

With respect to satellite based data, the under-estimations of spatial rainfall in the sub-basins located in mountainous regions (e.g. G10A-C, H10E, V70A, V70B or X31A) may be attributed to satellite imagery (or the methods used to interpret the imagery) ignoring rainfall variations due to altitude, slope and aspect in those sub-basins where rainfall is mainly orographic in nature. Similar observations can be associated with the use of raingauge data over the extended period of 1991-2000 where there are fewer raingauges. Therefore in these regions, there is a need to carefully employ spatial rainfall correction procedures, or to ensure that raingauge networks are adequate for spatial rainfall estimation. This issue will remain a challenge in developing countries, where the allocation of financial resources to maintain raingauge networks is not always high on the agenda of most governments (Hughes, 2004a).

As rainfall information is always needed for hydrological assessments even in gauged basins, a method of correcting spatially interpolated data based on a period with few representative raingauges, using the frequency characteristics obtained from a period with a denser network, was therefore explored. Also explored was the potential use of satellite based rainfall estimates in situations where raingauge densities have declined further. The use of a correction procedure offers a solution to merging datasets that cover different time periods and ensures a higher degree of consistency in their statistical properties. The procedures involved in obtaining and processing the satellite data are relatively straightforward and require little training to put into practice. They are therefore consistent with the requirements of the region, where complex methods often fail due to a lack of training in their application.

The application of satellite based estimates for supplying rainfall inputs where gauge measurements are scarce appears to offer a potential future solution to a problem that is widespread in developing regions such as southern Africa. Similar studies that have been conducted (e.g. Barrera *et al.,* 2007) showed that remote sensing methods provide improved spatial coverage, and even when rainfall estimates at a single pixel are not precise, they provide relatively accurate areal-averaged rainfall estimations over sub-basins. However, in the present study the period to which satellite data were available is different to that of historical spatial raingauge based data (WR90), which makes the direct merging and comparison of spatial raingauge and satellite based data difficult. The need to correct satellite rainfall data products is dependent on the region and is specifically required in areas of complex topography where systematic rainfall variability is high.

6.9.2 Model simulation results

The effects of rainfall uncertainty on simulated runoff were assessed by using different rainfall realizations as inputs to a rainfall-runoff model and comparing model outputs to observed flows. The raingauge based spatial rainfall data analyses and subsequent flow simulation results showed that correction of the original IDW interpolated spatial rainfall estimates resulted in significant improvements in model results (Table 6.10) for the extended period (1991-2000) in some of the example sub-basins (e.g. G10A, V70B), while in others there were marginal improvements (e.g. V70A) and the results were worse in others (C12D). For the calibration period (all available data up to 1990), most of the model results (Table 6.10) based on all rainfall realizations (including the corrected data) are not very different from each other, except for the sub-basins characterised by steep topography (G10A-C, K40A and X31A). The results suggest that simple correction procedures based on adjusting rainfall frequency characteristics can be used when information is lost through a reduction in gauge network density. The effects on model results of different raingauge based rainfall inputs varied from region to region, and some of the variations are dependent on the climate and basin physical properties such as slope. The humid areas with complex topography often receive orographically controlled rainfalls and therefore variations in rainfall inputs will have a greater impact on modelled flows, while for the Seekoei River basin, which is flat and semi-arid, the impacts of differences in rainfall inputs on modelled flows are far less. The general observation from the analysis indicates that with the existing networks of raingauges and limited access to information about the individual raingauges, the choice of interpolation method in some parts of South Africa is less important than the inclusion of key raingauges. The results support the conclusions reached in other studies by Schäfer (1991) and Wilk *et al.* (2006) in South African catchments and the Okavango River basin respectively.

With respect to satellite based rainfall data, the application of the non-linear spatial correction procedure generally improved the simulation results in most of the sub-basins used (Table 6.11). However, in some of the sub-basins (e.g. G40J-K, T34A-H, S60C and Q94C), no improvements are evident. This might be partly related to inadequacies in the RFE 2.0 algorithm used to derive satellite based rainfall data. According to Love *et al.* (2004) the algorithm does not capture warm cloud rainfall especially along coastal regions, where warm cloud effects dominate. This is consistent with the analysis by Todd *et al.* (1999) who showed that successful application of remotely sensed information suffers from the problems of the inadequate validation of the techniques used in deriving satellite rainfall data. However, there are cases (e.g. D32A-J) where the original satellite data resulted in good simulations and corrections were unnecessary and offered no advantages. With the limited number of sub-basins used in this study it is very difficult to reach firm conclusions, but in the absence of dense monitoring networks in the future, these alternative data sources together with simple correction procedures appear to offer a solution to providing rainfall input data to hydrological models.

It is also important to note that fixed parameter sets were used for all rainfall realizations, but Beven and Binely (1992) concluded that different parameter sets should be used with different rainfall inputs. Görgens (1983) and Oudin *et al.* (2006) pointed out that, the sensitivity of a rainfall-runoff model to uncertainty in rainfall input data also depends upon its interaction with parameters and the model structure and therefore further research is needed to understand these interactions. The focus of the present study was to discover if an alternative raingauge based spatial rainfall dataset and satellite data could be adjusted or corrected to make them consistent with historical spatial rainfall data used during model calibration. It should be emphasized that the alternative of calibrating the model using satellite data is not practical due to the current short period of data available. According to Görgens (1983) six years of data would be too short to be used to establish alternative parameter sets in most parts of South Africa. Even, if this were possible for gauged sub-basins, extrapolation to ungauged basins would contribute to a high degree of uncertainty. Part of this uncertainty would be related to the differing degrees to which the satellite data are representative of real rainfall variations.

For all the model simulation results presented here, it should be recognised that while the observed streamflows were used as a basis for comparison they are far from perfect for the purpose. The streamflows contain inaccuracies in gauging both low and high flows and none of them can be said to be completely natural, such that differential developmental effects may occur between data periods. While every attempt was made to select sub-basins that are ‘relatively’ natural and not affected by developments, this is almost impossible in South Africa. The alternative of naturalising the streamflows relies upon accurate information about the nature of water resources development projects and their impacts. This information is often not available or unreliable and has the potential to introduce additional uncertainty into the modelling process.

7. UNCERTAINTY IN POTENTIAL EVAPOTRANSPIRATION ESTIMATION AND IMPACTS ON SIMULATED RUNOFF

7.1 Introduction

Potential evapotranspiration (PE) constitutes one of the primary components of the water balance of a basin and is a key input to rainfall-runoff models (Andréassian *et al*., 2004). There are many techniques available for estimating potential evaporation (that is converted to potential evapotranspiration using appropriate factors) comprising both direct and indirect methods. The direct methods measure evaporation from the land surface and include the American class A pan and the Symons pan. The indirect methods, which vary in complexity and data requirements estimate potential evaporation from climatic variables. They include temperature-based equations (e.g. Blaney-Criddle), equations that combine temperature and radiation (e.g. Priestley-Taylor), equations which include an allowance for humidity and wind (e.g. Penman or Penman-Monteith), or energy balance equations (e.g. SEBAL; Mckenzie and Craig, 2001). Hydrological model calibrations are necessarily tuned to the particular form of PE estimate chosen (Andréassian *et al*., 2004). A comparison of 27 potential evapotranspiration estimation models by Oudin et *al*. (2005) showed that rainfall-runoff model efficiency can be improved by using simple temperature-based PE models, which only require mean daily temperature data.

Methods that use temperature for estimating potential evapotranspiration have been successfully applied in South Africa (Hargreaves and Samani, 1995; Schulze and Kunz, 1995; Schulze and Maharaj, 2004, 2006). This is because temperature data are available for a relatively long time period and benefit from a dense network of observation stations compared to pan measurements (Schulze and Maharaj, 2004). Given that South African hydrologists favour pan evaporation measurements (Schulze and Maharaj, 2004), a further possibility that is explored in the present study is the use of pan based mean monthly evapotranspiration estimates, but perturbed on the basis of time series variations in monthly temperature data (see section 3.3.3 and Hughes *et al.*, 2006). This is a very different approach compared to methods followed by most studies which assessed evapotranspiration uncertainties based on using different PE formulae

(Andréassian *et al*., 2004; Oudin *et al*., 2005). In South Africa, pan evaporation measurements, even with short records, are used for the determination of mean evapotranspiration rates (Midgley *et al*., 1994). This is because potential evapotranspiration has relatively small variations from year to year at a given location and therefore relatively short records can be used to obtain reasonably accurate estimates of mean monthly values (Schulze and Maharaj, 2006).

Although it is intuitively clear that a more suitable evaporative demand input should have a positive impact on hydrological simulations, it is striking that few studies have focused on the validity of using long-term mean PE instead of time-varying PE (Folwer, 2002; Andréassian *et al*., 2004) and the sensitivity of hydrological models to uncertainty in potential evapotranspiration estimates (Görgens, 1983; Paturel *et al*., 1995; Oudin *et al*., 2005). It has been common practice in South Africa model applications to make use of long-term mean values of PE data, largely due to a lack of appropriate meteorological data needed to compute time series of PE and an apparent lack of sensitivity of rainfall-runoff models to PE even under extreme dry and wet conditions (Folwer, 2002). This lack of sensitivity is mainly related to the availability of water to satisfy potential evapotranspiration demand and the fact that actual evapotranspiration is often controlled by available moisture rather than the demand over monthly time steps. Despite model insensitivity to potential evapotranspiration inputs (Burnash, 1995), it remains unclear whether rainfall-runoff models are able to benefit from the use of time series PE estimates. The quantitative effects of including the time series variations in potential evapotranspiration demand on simulated streamflows within a southern African context have not been addressed.

While some of the studies in the literature (e.g. Folwer, 2002) investigated the possibility of using actual potential evapotranspiration compared to using long-term means, the focus of the present study is on using time series deviations from the mean rather than the actual values of potential evapotranspiration. This chapter therefore, presents an assessment of the uncertainties associated with potential evapotranspiration estimates used with the Pitman model and examining the extent to which these uncertainties are propagated into streamflow predictions for a range of sub-basin scales and climate regimes.

7.2 Application examples and procedure

20 of the sub-basins and the pan based evaporation data referred to in section 3.2 and section 3.3.3 respectively were used to assess the effects of including time series variations in PE demand within Pitman model. The spatial distribution of pan evaporation measurements is such that they are found at sites which are not always representative of higher altitudes where runoff is generated (Schulze and Maharaj, 2006).

The first part of the analysis involved deriving possible potential evapotranspiration realisations. The Pitman model uses either long-term mean monthly Symons pan potential evapotranspiration estimates, expressed as a percentage of mean annual evapotranspiration (MAE) as shown in Table 7.1 or monthly time series of evapotranspiration estimates, expressed as fractions of the long-term mean monthly values and referred to as T/S (Pan). The approach of using deviations rather than actual values of potential evapotranspiration allows the model to be flexible in its requirements. The time series deviations can be based on either pan measurements or on other data, such as temperature. Pan observations (either monthly means or time series) are typically converted to sub-basin potential evapotranspiration data using pan factors (Midgley *et al*., 1994). Potential evapotranspiration rates for sub-basins without pan evaporation measurements were estimated by extrapolating from nearby pan gauged sub-basins. While the focus of this study is not on the uncertainty in absolute values of PE, Görgens (1983) already demonstrated that the errors which could be incurred when extrapolating pan evaporation data in South Africa can contribute to uncertainty in model results.

Table 7.1 Mean monthly distribution of potential evapotranspiration (PE) (expressed as a percentage of MAE) (Midgley *et al.,* 1994) for G10A sub-basin

OCT	NOV	DEC	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP
8.77	12.4	15.47	16.12	13.44	12.29	6.12	3.24	2.4	2.21	3.24	5.3

As an alternative to using the limited time series pan-based potential evapotranspiration estimates, the use of time series deviations perturbed on the basis of temperature data was also explored. The procedure involved expressing the monthly temperature values as fractions (deviations) of their long-term mean monthly values for each calendar year (based on equation 3.1) and referred to as T/S (Temp). A third option is the use of A pan equivalent potential evapotranspiration values estimated using existing regional relationships (which combine temperature and radiation) given in Schulze and Maharaj (1991). The equations, for a given region and a specified month (Schulze and Maharaj, 1991, 2006), take the general form:

$$E_{apan}(i)=b_0 T_{max}(i) R_a(i)+b_1 z-b_2 P_{md}(i)+b_3 \quad \text{7.1}$$

Where, E_{apan} = A-pan equivalent potential evapotranspiration estimate (mm.month^{-1}); Tmax = monthly mean of daily maximum air temperatures (℃); R_a = mean extra-terrestrial solar radiation for the month; z = altitude (m); P_{md} = median monthly precipitation (mm); i = month of the year, and b_0-b_3 = regression constants. Figure 7.1 shows the three time series of potential evaporation demand data expressed as deviations from their monthly mean values for G10A. The A pan equivalent potential evapotranspiration values were generated only for illustration purposes to investigate if there are any differences between deviations derived from these estimates and single monthly mean temperature values.

Figure 7.1 illustrates that there are no real differences between using simple temperature data and the A pan equivalent estimates. However, both are very different (much lower range variations) compared to deviations based on data from a single pan. The differences may be attributed to local variations in pan evapotranspiration data or errors in measured pan data as it is always difficult to account for rainfall effects. The differences may also be attributed to the fact that temperature ignores the other variations due to additional ‘weather’ related factors, an indication that temperature is a relatively poor predictor of potential evapotranspiration demand, despite being the ‘best’ from a data availability point of view. Based on the illustration in Figure 7.1 it was therefore sufficient to derive potential evapotranspiration time series deviations based on temperature data.

The final part of the analysis involved assessing the effects of uncertainty in potential evapotranspiration inputs on simulated runoff. While the potential evapotranspiration inputs into the rainfall-runoff model were varied, the same model parameter sets and rainfall inputs (Midgley *et al.*, 1994) were used for all model runs. One part of the analysis involved a comparison of simulated streamflows based on using three potential evapotranspiration realizations (Mean (Pan), T/S (Pan), T/S (Temp)) for a few sub-basins. The Mean (Pan) realization was used as reference as this represents common practice in South Africa. For basins where there are no suitable pan time series data, only two realizations were used.

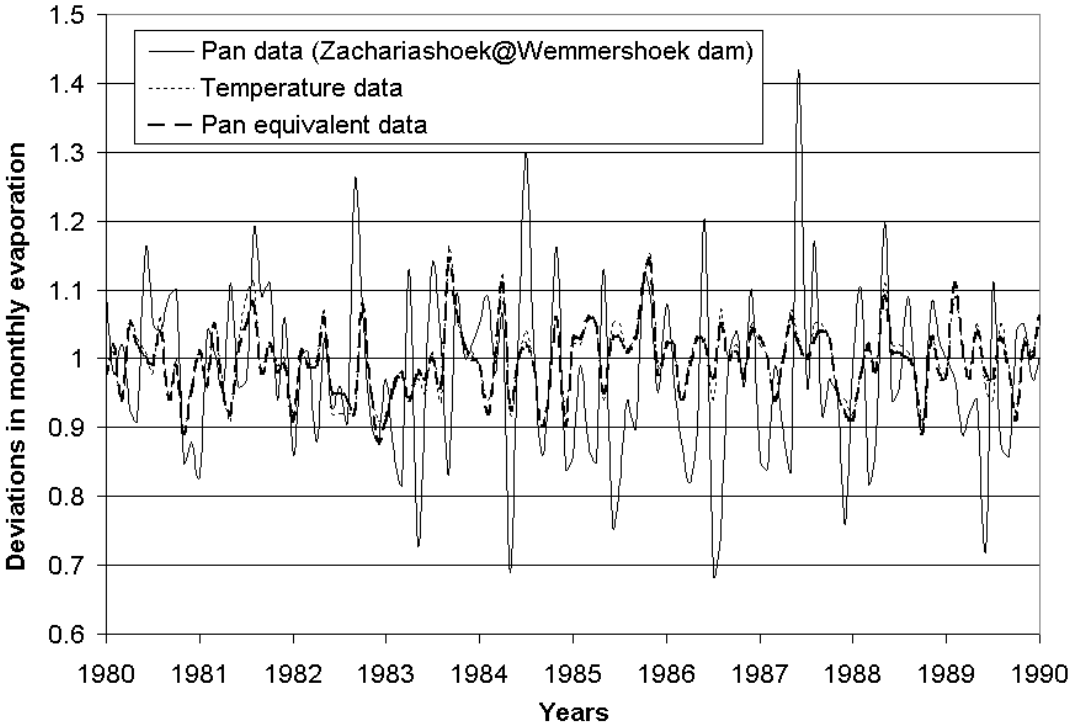
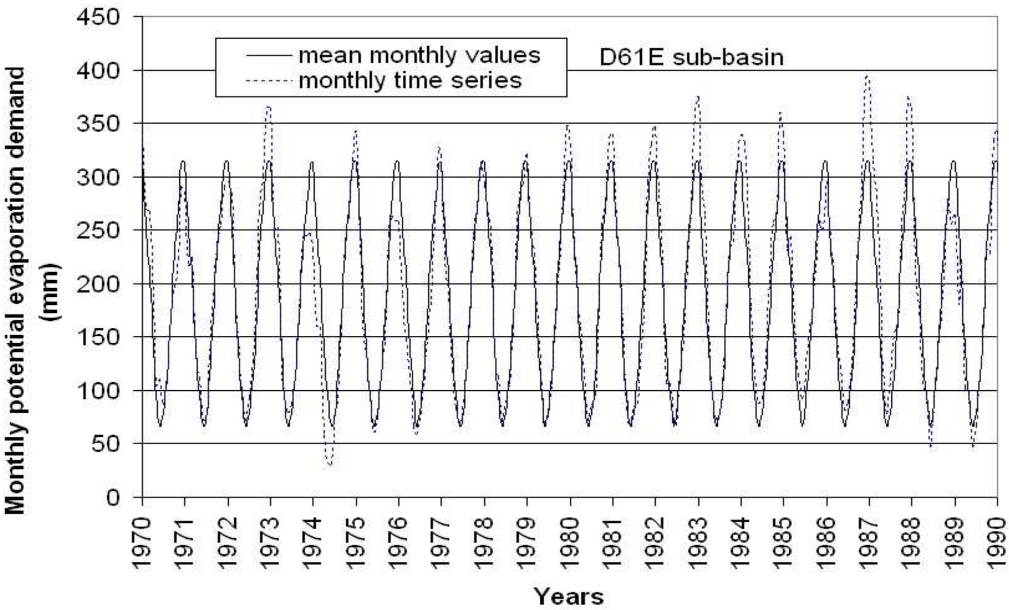


Figure 7.1 Comparison of monthly evapotranspiration time series deviations (expressed as fraction of long term means) based on three realizations for G10A sub-basin.

7.3 Results and discussion

The model inputs consisted of long-term mean PE estimates only and time series perturbed using deviations in temperature data as shown graphically in Figures 7.2 and 7.3 for four selected sub-basins. The comparisons demonstrate that some of the extreme values are pronounced in some sub-basins and that there are possible regional differences, with higher values found in D61E and G10A than in A22B and C81G.



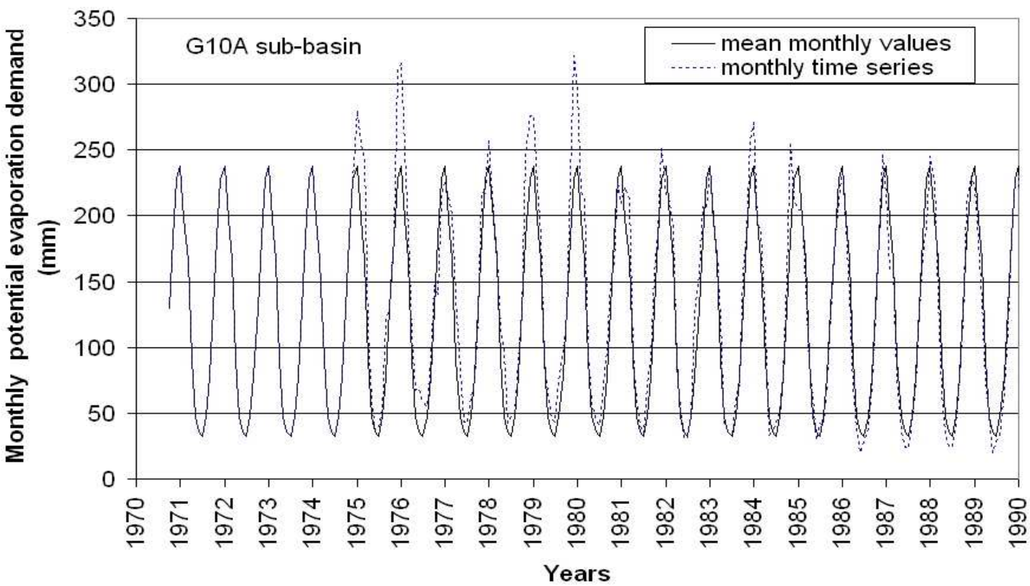
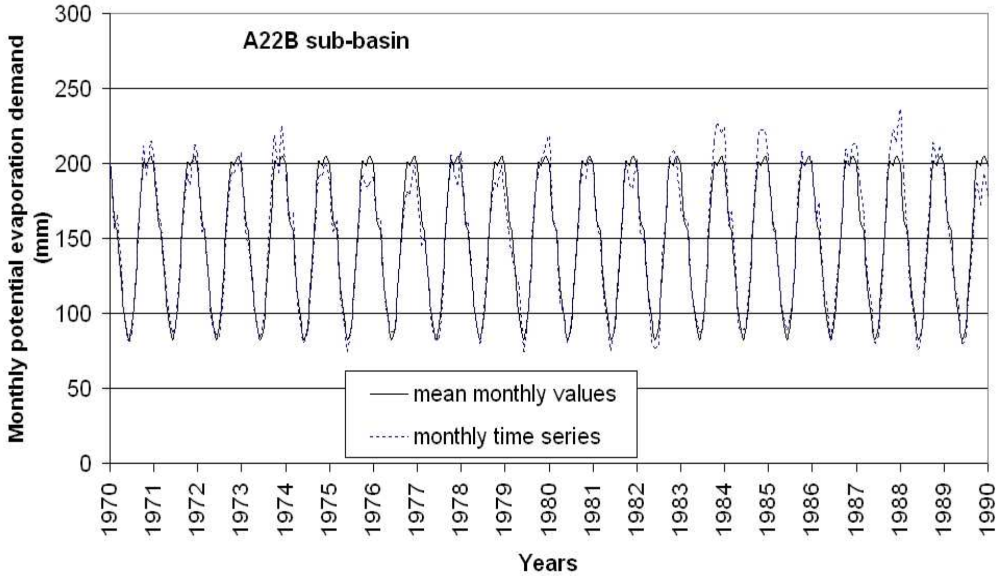


Figure 7.2 Comparison of monthly potential evapotranspiration demands derived from using fixed mean monthly and time series estimates perturbed on the basis of variations in temperature data for D61E and G10A sub-basins.



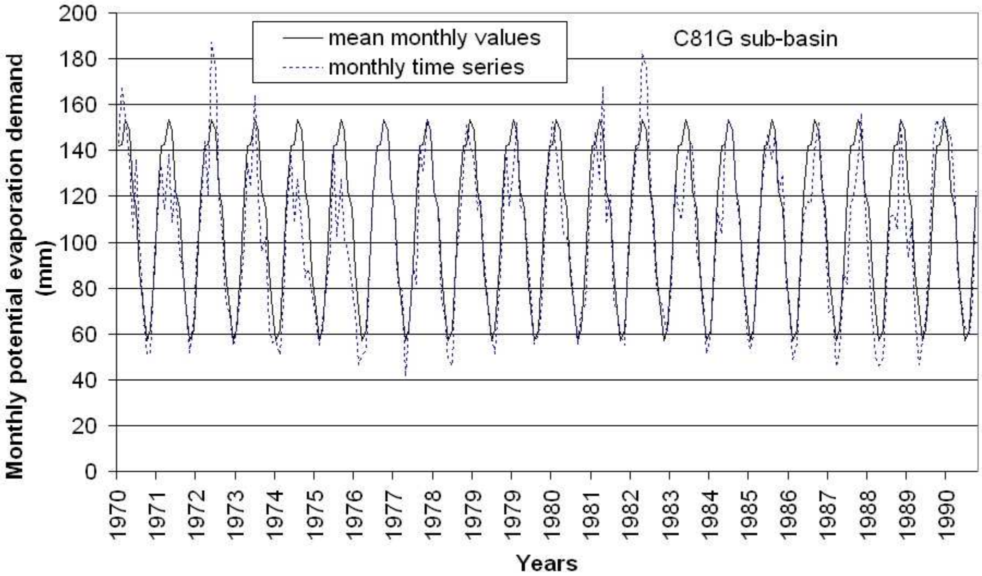


Figure 7.3 Comparison of monthly potential evapotranspiration demands derived from using fixed mean monthly and time series estimates perturbed on the basis of variations in temperature data for A22B and C81G sub-basins.

7.3.1 Effects of including time series variations in potential evaporation demand

Table 7.2 lists the simulation results of using the two PE time series variations compared to the reference simulation results using long-term monthly mean PE data. There are substantial differences in the simulation statistics for some sub-basins, despite their long-term means being the same. The differences are greater when using time series of pan evapotranspiration data than when using time series perturbed from temperature data. This may be due to differential local effects such as the quality of pan data as well as the pan factors used in estimating pan based time series variations.

Table 7.2 also illustrates that there are regional differences in the results, for example D61E and G10A sub-basins in the winter rainfall region have relatively lower percentage differences of mean flows than sub-basins A22B, C81G and X31A located in the summer rainfall region. Table 7.2 indicates that most of the differences in mean monthly flows are positive and that the effects are greater on un-transformed flows (i.e. high flows) than on transformed flows (medium to low flows), for most of the sub-basins. This result is partly a consequence of the model structure which references all monthly evaporation demands to the maximum potential evaporation value in the time series. Within the model structure, the evaporation function depends on the current month's potential evaporation relative to the month with the highest potential evaporation. If a single month (rather than the peak calendar month value in a fixed seasonal distribution) has a lot higher potential evaporation value than most other months in the time series (1987 for D61 in Figure 7.2), the effect is to reduce the effective evaporation demand in other months. The result is generally lower actual evapotranspiration rates, lower soil moisture losses and thus higher simulated runoffs compared to using fixed monthly distributions. This effect is less evident in the winter rainfall region when moisture availability is more important in determining actual evaporation during the season of high potential evaporation demand (summer). While the results in Table 7.2 are based on sub-basins where both pan and temperature data are available within a sub-basin, Table 7.3 present the results for the other sub-basins where there are only temperature data to assess the regional differences.

Table 7.2 Mean (Mn), standard deviation (Stdv), their percentage differences respectively and coefficient of efficiency (CE) (relative to mean monthly pan data) of monthly flows for simulations using different potential evapotranspiration inputs.

Sub-basins, Area & Simulation periods	Data	Un–transformed flows (Q)					Log-transformed flows {ln(Q)}				
		Mn	Stdv	%Diff Mn	%Diff Stdv	CE	Mn	Stdv	%Diff Mn	%Diff Stdv	CE
A22B	Mean PE	0.74	2.27				-1.99	2.11			
284km^2	T/S (Pan)	1.18	3.40	60.7	49.7	0.55	-1.42	1.92	-28.8	-9.0	0.84
1966-1990	T/S (Temp)	0.81	2.32	10.6	2.4	0.99	-1.50	1.67	-24.8	-20.7	0.84
C81G	Mean PE	2.63	4.52				0.37	0.92			
434km^2	T/S (Pan)	3.54	6.33	34.4	40.4	0.74	0.61	0.95	64.5	3.8	0.90
1970-1990	T/S (Temp)	2.74	4.70	7.8	4.0	0.99	0.47	0.89	26.6	-2.2	0.98
D61E	Mean PE	0.30	1.86				-4.49	8.20			
1090km^2	T/S (Pan)	0.34	2.23	13.2	19.4	0.94	-4.47	8.21	-0.5	-0.1	1.0
1960-1990	T/S (Temp)	0.30	1.86	0.0	0.0	1.0	-4.40	8.20	0.0	0.0	1.0
E40A & 40B	Mean PE	1.10	3.54				-3.57	9.37			
1648km^2	T/S (Pan)	1.23	4.01	11.8	13.4	0.86	-3.53	9.39	-1.1	-0.2	1.0
1951-1990	T/S (Temp)	1.20	3.53	-0.1	-0.2	1.0	-3.58	9.37	0.1	0.0	1.0
G10A-G10C	Mean PE	31.76	37.27				2.62	1.48			
609km^2	T/S (Pan)	31.99	37.78	0.72	1.3	1.0	2.62	1.48	0.1	0.4	1.0
1966-1990	T/S (Temp)	31.81	37.26	0.2	-0.02	1.0	2.62	1.48	0.00	0.00	1.0
U20B	Mean PE	5.85	8.10				1.26	0.95			
358km^2	T/S(Pan)	6.28	8.88	7.2	9.5	0.94	1.36	0.91	7.4	-4.8	0.94
1960-1990	T/S (Temp)	6.10	8.33	4.2	2.8	1.0	1.32	0.93	4.7	-2.8	0.99
X31A	Mean PE	4.73	3.38				1.37	0.57			
174km^2	T/S (Pan)	5.65	3.66	19.2	8.3	0.91	1.58	0.53	14.8	-7.0	0.85
1959-1973	T/S(Temp)	4.97	3.43	4.8	1.7	0.99	1.43	0.55	4.2	-2.9	0.98

***Notes**: **Mean PE-** represents simulation based on using fixed mean monthly potential evapotranspiration (PE) from pan data ,* **T/S (Pan)** *– represents simulation based on additional use of monthly time series potential evapotranspiration based on pan data, **T/S (Temp)-** represents simulation based on additional use of monthly time series potential evapotranspiration based on temperature data. Mn and Stdv values are in $m^3 * 10^6$/month.*

In contrast to the results in Table 7.2, Table 7.3 suggests that the effects on low to moderate flows (transformed statistics) are the largest. In many respects, this is more logical result as changes in the potential evaporation demand would be expected to change the low flow regime more than high flows. As far as high flows are concerned, it might be expected that arid to semi-arid sub-basins (A22B, D61E, E40A-B, Q94C, S60C) would be most affected by the changes in PE model inputs, as such basins lose a higher proportion of their rainfall through potential evapotranspiration than humid sub-basins (G10A-C, G21C, U10A-E, U20B,V60D, X12A-C, X31A). The differences in the arid basins (e.g. E40A-B and D51A-B in the Northern Cape), are largely confined to those months when high rainfalls generate runoff due to exceedence of the main moisture storage component in the model, which is typically small in arid regions with shallow soils. The overall results (Tables 7.2 and 7.3) demonstrate that the effects of including time series variations of potential evapotranspiration demand are dependent on the climate of the region. Sub-basins located in the Western Cape region (e.g.G10A-C, G21C, K40A) receiving high rainfall in winter months (June and July which correspond to low temperatures) are less sensitive to changes in potential evapotranspiration inputs. Sub-basins from the central to eastern parts of the country (e.g. A22B, B71C, C12D, C81G,S60C, U20B V60D, X31A) that receive high rainfall in summer months (October and November which correspond to higher temperatures and hence higher potential evapotranspiration rates) are more sensitive to uncertainties to potential evapotranspiration inputs.

The preceding analysis compared simulation results to illustrate the uncertainties associated with using different PE inputs to the model without any reference to observed flows. Table 7.4 repeats the analysis for the fixed monthly means and the temperature based time series variations but using statistics of comparison with the available observed flows. In some situations there appear to be substantial benefits of using time series variations of potential evapotranspiration estimates, but also suggests that a parameter set established using mean monthly evaporation demand would not be appropriate if time series variations are included. Table 7.5 illustrates the results of a limited re-calibration exercise that attempted to determine parameter sets that are more appropriate to use in combination with time series variations of potential evaporation demand.

Table 7.3 Comparison of mean (Mn) and standard deviation (Stdv) and their percentage differences (relative to mean monthly pan data) respectively and coefficient of efficiency (CE) of monthly flows for simulations using two potential evapotranspiration inputs.

Sub-basins, Area	Data (1950-1990)	Un–transformed flows (Q)					Log-transformed flows {ln(Q)}				
		Mn	**Stdv**	**%Diff Mn**	**%Diff Stdv**	**CE**	**Mn**	**Stdv**	**%Diff Mn**	**%Diff Stdv**	**CE**
B71C	Mean PE	2.98	2.78				0.87	0.6			
263km^2	T/S (Temp)	3.24	2.96	8.7	6.5	0.98	0.97	0.57	11.5	-5.0	0.96
C12D	Mean PE	4.06	8.75				0.50	1.11			
898km^2	T/S (Temp)	4.35	8.97	7.1	2.4	0.99	0.60	1.10	20.8	-0.8	0.97
D51A-B	Mean PE	1.06	4.26				-4.38	8.54			
1645km^2	T/S (Temp)	1.06	4.24	0.0	-0.5	1.0	-4.35	8.59	-0.7	0.6	1.0
G21C	Mean PE	1.16	2.75				-1.64	2.69			
244km^2	T/S (Temp)	1.17	2.78	0.9	1.1	1.0	-1.64	2.68	0.0	-0.4	0.99
K40A	Mean PE	0.89	1.08				-0.54	0.88			
72km^2	T/S (Temp)	0.89	1.08	0.0	0.0	1.0	-0.55	0.88	1.9	0.0	1.0
Q94C	Mean PE	0.64	1.00				-0.98	0.90			
76km^2	T/S (Temp)	0.66	1.01	3.1	1.0	1.0	-0.91	0.87	-7.1	-3.3	0.99
S60C	Mean PE	1.11	1.97				-0.51	0.99			
215km^2	T/S (Temp)	1.19	2.00	7.2	1.5	0.99	-0.40	0.95	-21.6	-4.0	0.98
T34A-H	Mean PE	39.72	51.37				3.14	0.99			
2597km^2	T/S (Temp)	41.05	52.54	3.4	2.3	1.0	3.19	0.97	1.6	-2.0	0.99
U10A-E	Mean PE	51.81	54.70				3.52	0.91			
1744km^2	T/S (Temp)	52.94	55.22	2.2	1.0	1.0	3.54	0.89	0.6	-2.2	1.0
V20A	Mean PE	7.17	8.17				1.28	1.31			
267km2	T/S (Temp)	7.36	8.24	2.7	0.9	1.0	1.35	1.24	5.5	-5.3	1.0
V60D	Mean PE	2.81	4.66				0.14	1.30			
312km^2	T/S (Temp)	3.01	4.89	7.1	4.9	0.99	0.25	1.25	77.8	-3.4	0.98
V70B	Mean PE	3.78	4.23				0.82	1.02			
124km^2	T/S (Temp)	3.88	4.25	2.7	0.5	1.0	0.87	1.00	6.1	-2.0	1.0
X12A-C	Mean PE	6.34	4.40				1.69	0.53			
581 km^2	T/S (Temp)	6.76	4.56	6.6	3.6	0.98	1.76	0.51	4.1	-3.8	0.97

Table 7.4 Comparison of percentage differences of mean and standard deviations (relative to observed data) and coefficient of efficiency (CE) of monthly flows for simulations using two potential evapotranspiration inputs.

Sub-basins, Area	**Data & Simulation period**	**Un–transformed flows (Q)**			**Log-transformed flows {ln(Q)}**		
		%Diff Mn	**%Diff Stdv**	**CE**	**%Diff Mn**	**%Diff Stdv**	**CE**
B71C	**1970-1990**						
B7H003	Mean PE	2.6	-35.2	0.56	28.6	-31.0	0.51
263km^2	T/S(Temp)	5.0	-32.9	0.56	43.4	-34.4	0.45
C12D	**1960-1990**						
C1H004	Mean PE	-17.7	-28.8	0.61	127.5	-30.0	0.50
898 km^2	T/S(Temp)	-10.6	-26.5	0.63	183.2	-30.2	0.49
G21C	**1973-1990**						
G2H012	Mean PE	-0.1	1.0	0.70	-69.0	-29.6	0.42
244km^2	T/S(Temp)	6.3	-0.5	0.69	-68.7	-32.2	0.35
K40A	**1961-1990**						
K4H003	Mean PE	8.9	-21.2	0.65	-33.0	-12.8	0.60
87km^2	T/S(Temp)	8.3	-21.9	0.65	-31.9	-12.2	0.60
Q94C	**1972-1990**						
Q9H019	Mean PE	-20.3	-28.1	0.76	-17.1	-36.8	0.58
76km^2	T/S(Temp)	-16.9	-27.1	0.77	-24.0	-38.8	0.56
S60C	**1971-1990**						
S6H003	Mean PE	9.7	-14.0	0.52	-25.4	-21.9	0.72
215km^2	T/S(Temp)	-3.0	-11.9	0.57	-44.8	-24.8	0.68
T34A-T34H	**1952-1990**						
T3H005	Mean PE	9.2	9.3	0.67	11.4	-23.7	0.65
2597km^2	T/S(Temp)	16.4	12.2	0.66	13.1	-24.8	0.63
U10A-U10E	**1960-1990**						
U1H005	Mean PE	-8.4	-31.3	0.70	6.4	-25.7	0.80
1744km^2	T/S(Temp)	-7.0	-31.2	0.70	7.2	-26.9	0.78
V20A	**1972-1990**						
V2H005	Mean PE	-15.4	-15.7	0.82	-17.2	22.1	0.64
267km^2	T/S(Temp)	-14.0	-15.3	0.82	-13.4	15.7	0.73
V60D	**1954-1990**						
V6H003	Mean PE	-8.3	-7.3	0.48	-24.0	-6.4	0.58
312km^2	T/S(Temp)	-2.7	-5.1	0.48	62.0	-13.5	0.61
V70B	**1973-1990**						
V7H016	Mean(Pan)	4.0	-9.9	0.69	25.7	-9.8	0.79
124km^2	T/S(Temp)	6.5	-9.5	0.69	31.7	-12.0	0.77
X12A-X12C	**1970-1990**						
X1H016	Mean PE	0.17	-16.8	0.48	7.7	-26.9	0.62
1554km^2	T/S(Temp)	15.6	7.9	0.62	10.4	-25.8	0.51

Table 7.5 Mean (Mn), standard deviation (Stdv), their percentage differences respectively and coefficient of efficiency (CE) (relative to observed flows) of monthly flows for simulations using three evapotranspiration inputs.

Sub-basins, Area & Simulation periods	**Data**	**Un–transformed flows (Q)**					**Log-transformed flows {ln(Q)}**				
		Mn	**Stdv**	**%Diff Mn**	**%Diff Stdv**	**CE**	**Mn**	**Stdv**	**%Diff Mn**	**%Diff Stdv**	**CE**
G10A-C	Observed	26.40	33.72				2.41	1.48			
609km^2	Mean PE	31.76	37.27	20.3	10.5	0.88	2.62	1.48	8.6	-0.1	0.82
1966-1990	T/S (Pan)	31.99	37.78	21.2	12.0	0.87	2.62	1.48	8.7	-0.6	0.82
	T/S (Temp)	31.81	37.26	20.5	10.5	0.87	2.62	1.22	8.8	-0.1	0.81
	Re-calibrate T/S(Pan)	27.77	30.79	**4.2**	**-8.7**	**0.89**	2.64	1.32	**8.8**	-10.6	**0.82**
U20B	Observed	5.05	6.66				1.10	1.02			
358km^2	Mean PE	5.21	7.42	3.2	12.5	0.63	1.16	0.93	5.3	-8.6	0.66
1954-1990	T/S (Pan)	5.66	8.30	12.1	25.8	0.53	1.25	0.90	13.8	-11.8	0.65
	T/S (Temp)	5.45	7.62	7.9	15.4	0.61	1.22	0.91	11.2	-11.1	0.66
	Re-calibrate T/S(Pan)	5.12	7.75	**1.5**	17.4	0.60	1.16	0.89	**5.3**	-13.1	**0.66**
X31A	Observed	4.21	3.35				1.17	0.77			
174km^2	Mean PE	4.67	3.33	10.8	-0.5	0.63	1.36	0.57	15.6	-26.7	0.59
1959-1973	T/S (Pan)	5.58	3.58	32.5	7.0	0.47	1.57	0.53	33.2	-32.1	0.38
	T/S (Temp)	4.90	3.39	16.2	1.1	0.60	1.42	0.55	20.5	-28.8	0.53
	Re-calibrate T/S(Pan)	4.12	2.92	**-2.3**	-12.8	**0.64**	1.25	0.54	**6.0**	**-30.5**	**0.60**

Note*: Bold values show improvements after re-calibration using time series variations of pan potential evapotranspiration.*

The parameters that were adjusted during the re-calibration process were mainly the maximum soil moisture storage capacity (ST – generally increased) and the groundwater recharge (GW – generally decreased) parameters. The results indicate that only limited improvements in the simulations could be achieved in terms of CE values, but some improvements are seen in streamflow volumes.

7.4 Observations

This part of the study demonstrated that including time series variations of potential evapotranspiration can have substantial impacts on simulated flows. This result is partly a consequence of the model structure, which was designed to operate with fixed mean monthly values of potential evapotranspiration. Most of the effects can be attributed to isolated high potential evapotranspiration values in the time series, which has the effect of reducing the PE demands in the other months. This conclusion is consistent with the much greater impact of using pan data based variations which are much greater than temperature based variations (Figure 7.1). Anticipating this result would require a quite detailed knowledge of the model structure (see Kapangaziwiri, 2008). The effects related to the structure of the specific model used within this study might explain why the results are different to previous studies (Andréassian *et al*., 2004; Oudin et *al*., 2005) that suggest that models can be relatively insensitive to changing PE demand inputs. This study suggests that regional differences do occur within South Africa. This result is not surprising, given the large differences in seasonal rainfall and PE demand patterns that occur between the winter and summer rainfall regions of the country. Substantial variation in the ratio of rainfall to PE demand (an index of aridity) will also inevitably contribute to the effects of using different PE demand inputs to the model.

The overall conclusion is that, while it may appear to be an attractive option to include time series variations of PE demand, these may be incompatible with the model structure and create further additional uncertainty. Certainly, a parameter set that has to be established using a fixed seasonal distribution should not be used with time series variations of PE. The alternative would be to adjust the structure of the model to be compatible with both types of potential evaporation demand input.

8. UNCERTAINTY IN PARAMETER ESTIMATION AND RESULTS OF THE PITMAN MODEL

8.1 Introduction

The previous chapters (i.e. Chapter 5-7) focussed on assessing the individual contributions of rainfall and evapotranspiration input data uncertainties on streamflow prediction uncertainty. The analyses used existing regional model parameters (Midgley *et al*., 1994) derived through manual calibration of the model and identified some of the problems associated with using a single parameter set with different model input realisations. Manual calibrations can rarely be achieved without some degree of non-uniqueness in the estimated parameters and this leads to uncertainties in the model predictions. This chapter focuses on assessing the uncertainties associated with the parameters of the Pitman monthly model estimated through an *a priori* estimation approach. Chapter 4 identified the main sources of uncertainty associated with the parameter estimation methods (i.e. regionalization and *a priori* methods) for ungauged basins. One conclusion was that the factors contributing to parameter uncertainty depend to a large degree on the methods used to determine an appropriate parameter set. The uncertainty associated with the use of parameter regionalization methods have been extensively studied (Gupta *et al*., 2006). The primary focus of this study is on uncertainty estimates associated with the application of the physically based parameter estimation method of Kapangaziwiri and Hughes (2008) referred to in section 3.4.3. The advantage of this approach is that the parameter uncertainties are independent of the input data uncertainties, overcoming the issue of non-uniqueness of calibrated parameter sets and equifinality (Beven, 2006b). In addition, the parameters estimated by directly relating them to basin physical property data are interpretable in physical rather than statistical terms. According to Ao *et al.* (2006), the reliability of direct parameter estimation using basin physical characteristics depends on (i) model parameters that have exact meanings, (ii) extensive databases of spatial physical property data, (iii) establishment of relationships between basin physical property data and parameter values, (iv) establishment of parameter basin characteristic transfer functions and (v) the use of GIS techniques. Yadav *et al.* (2007) have already referred to the impacts of uncertainty in basin physical property data and catchment response characteristics on the parameter sets for ungauged basins.

One of the most critical aspects in modelling both gauged and ungauged basins is to identify parameters that are representative of the system under study. Even when the input data and model parameters are well known, model predictions are often different from the observed data, because models are simplified approximations of complex natural processes. This means that parameters aggregate the complex and heterogeneous real-world characteristics in a mathematical relationship (Beven, 1989). These parameters are often 'conceptual' rather than directly measurable entities (Wagener and Kollat, 2007).

While recent developments in parameter estimation and uncertainty analyses (Beven, 2001a; Gourley and Vieux, 2006) could be applied in the southern Africa context, their application would be limited to a relatively small number of catchments where observed data exist. Additional constraints are related to the willingness of model practitioners to adopt new methods. This chapter attempts to create a platform for developing strategies to assess the effects of parameter uncertainty on model outputs, which also take into account the constraints that exist in southern Africa. The main objectives of this chapter are:

- To estimate feasible (behavioural) parameters using the parameter estimation approach of Kapangaziwiri and Hughes (2008).
- To explore the sensitivity of model outputs to parameter value differences.
- To assess the impact of parameter uncertainty on model output uncertainty in a very simple way.

8.2 Parameter uncertainty estimation approaches

A summary of the approaches for parameter and uncertainty estimation (e.g. first order analysis, GLUE, Monte Carlo, fuzzy approaches etc) is presented in section 2.5. One of the critical issues is that using a strictly statistical framework for uncertainty analysis is not always possible, largely because the statistical properties and distributions of the input information are frequently unknown. The focus therefore shifts to identifying the feasible range of parameter values and generating model outputs that can all be considered possible or 'behavioural'. However, it is still necessary to have some method of identifying those parameter sets that can be considered to generate 'behavioural' outputs (Yadav *et al*., 2007).

Kapangaziwiri (2008) and Kapangaziwiri and Hughes (2008) demonstrated the potential of using an *a priori* parameter estimation approach based on conceptual interpretations of some of the Pitman model parameters linked to measurable physical basin properties. However, this previous study did not consider uncertainty. The approach proposed to quantify parameter uncertainty in this study involves using different assumptions about the basin physical property data to derive 'best' guess parameters as well as lower and upper bounds for a given sub-basin. This is considered to be a first attempt at incorporating uncertainty into the parameter estimation approach and that there will be a high degree of subjectivity involved. It is therefore recognised that further work will be required in the future to remove some of the subjectivity. While uncertainties associated with the model structure are largely ignored in this approach, model scale (space and time) issues affect the interpretation of the available basin physical property data. Therefore, some aspects of model structural uncertainty are incorporated into the parameter estimation process.

8.3 Approach to the analysis of the Pitman model parameters

The conceptual nature of the Pitman model offers opportunities for revised physically based parameter estimation approaches (Kapangaziwiri and Hughes, 2008) to be used in obtaining appropriate parameter sets, but the large number of parameters (see e.g. section 3.4.2, Table 3.4) suggests that the use of the model is associated with issues of parameter identifiability, non-uniqueness and equifinality (Beven, 1993). Previous experience of the Pitman model suggests that different groups of model users frequently apply different approaches to calibration and parameter estimation, making it very difficult to integrate parameter sets in regional studies (Hughes, 1997). The parameter estimation approach of Kapangaziwiri and Hughes (2008) represents an attempt to find a solution to this problem whilst retaining the widely accepted structure of the model. However, the integration of parameters based on using different physical property data is not a straightforward task and there remain unresolved scale issues. These are related to the integration of basin-wide variations of such properties as soil depth, slope, hydraulic conductivity, transmissivity and many more variables. Without established integration methodologies, it is not possible to avoid an element of subjectivity in the basin average values that are used and this introduces uncertainties in the parameter estimation process. In this study the following steps were followed to estimate three sets of parameters (best 'guess' as well as lower and upper bounds) for use in a parameter sensitivity and uncertainty analysis:

- Initial identification of parameter conceptual interpretations (section 8.3.1).
- The quantitative estimation of parameters based on basin physical properties (section 8.3.2).
- Parameter exploration or sensitivity analysis (section 8.3.3).
- Parameter and output uncertainty analysis (section 8.3.4).

8.3.1 Initial identification of parameter conceptual interpretations

A full description of the revised version of the Pitman model and its parameters is provided in Kapangaziwiri (2008) together with detailed explanations of the conceptual interpretations of all the parameters. A brief description of the model and its parameters has been provided in section 3.4.2, while Table 8.1 provides a summary of the parameters which are expected to be important in any sensitivity and uncertainty analysis. The focus in Table 8.1 is on differences in parameter importance for different climate regions, while other factors such as topography, geological setting and soil-vegetation relationships are equally important. These interpretations can be used to constrain parameter values in the process of developing a 'behavioural' model and also form a basis for a more quantitative approach to parameter estimation. The important component of this step is the development of a conceptual understanding of the hydrological processes that are dominant in the basin being modelled in the context of the model structure and its parameters.

Table 8.1 Conceptual interpretations and assumptions about importance parameters as an initial guide for parameter sensitivity analysis.

Parameter	Model effects	Relevance to different flow regimes	
		Semi-arid	Humid
RDF Non-dimen.	Affects the time distribution of rainfall within a month	Can have large effect in high rainfall months and is linked to whether ST is likely to be exceeded.	Will not have a large effect, except in tropical areas where high monthly rainfalls occur.
AI % area	Impervious area directly connected to channel - rarely used under natural conditions and not part of uncertainty analysis (AI=0).		
PI mm month^{-1}	Interception capacity	Expected to be greater for humid zones with higher surface cover.	
ZMIN ZAVE ZMAX mm month^{-1}	Control surface runoff generation. ZAVE is typically set half way between ZMIN and ZMAX.	Main source of runoff generation. ZMIN will strongly affect small events, while ZMAX will affect the size of all events.	Generally less important, but can be locally important in some basins, especially if heavy rainfall is experienced, or if parts of the basin have thin soils or soils with low infiltration rates.
ST mm	Interacts with many other parameters and its effects are very dependent on other parameter values. Determines the maximum limit of soil moisture storage.	Size of ST determines how frequently storage is exceeded during high rainfall months.	ST determines (together with other parameters) the amount of baseflow runoff and recharge. Large values mean that changes are gradual for the same rain inputs.
FT mm month^{-1}	Maximum runoff from moisture storage at ST. Determines the balance between evaporation and runoff.	Expected to be 0 in most cases but may represent unsaturated zone fracture flow in steep basins.	Very important parameter having a strong influence on all aspects of the simulated flow regime.
POW Non dimen.	Power of the relationship between moisture storage and runoff. Controls the rate of runoff from the soil for any moisture state.	If FT > 0, POW is expected to be high, suggesting very variable runoff generation (ephemeral rivers). In catchments with very short-lived baseflow.	Together with FT, has a large impact on simulated runoff generation.
R Non-dimen.	Controls the rate at which evaporation reduces as soil moisture is depleted.	Not very important as high rates of evap. dry soil storage quickly at any R.	Can have important impacts on the amount and time distribution of runoff.
TL Months	Runoff routing parameter.	Rarely used in calibration but could be important if sub-catchment size is very variable.	
GW mm month^{-1}	Maximum groundwater (GW) recharge depth at ST.	Frequently unimportant as groundwater rarely contributes to streamflow. However, for some semi-arid model applications it is important to simulate recharge and flow into static channel pools.	Important parameters in determining total volume of groundwater contribution to streamflow.
GPOW Non-dimen.	Power of the relationship between S and recharge. Controls the rate of recharge from the soil for any moisture state.		
SL mm	Limiting soil moisture level for recharge.		Typically set to 0 as GPOW usually adequate to control recharge distribution.
DDENS km km^{-2}	Effective drainage density for GW inputs to streamflow.	Frequently unimportant as groundwater rarely contributes to streamflow.	Important parameters in determining the rate and temporal variability of groundwater inputs to streamflow.
T m^2 d^{-1}	Groundwater transmissivity		
S Non-dimen.	Groundwater storativity		
RSF %	Parameter that determines riparian evaporation losses from GW storage.	Important in ensuring that GW recharge does not accumulate to generate baseflow.	Can be important in the overall water balance between recharge and GW inputs to streamflow.
TLGMax mm month^{-1}	Channel loss parameter for both incremental runoff (within one sub-catchment) and runoff from upstream sub-catchments.	Can be very important where upstream areas experience perennial flow which is partly lost to seepage.	Not important as flow is assumed to be out of GW and channel transmission losses not present.

8.3.2 Quantitative parameter estimation based on basin physical properties

The initial focus of the physically based parameter estimation approach has been on some of the parameters listed in Table 8.1 (ZMIN, ZAVE, ZMAX, ST, FT and POW) and is based on the physical interpretation of the parameters and the search for estimation equations using measurable basin physical properties (Kapangaziwiri, 2008). If parameter values can be constrained using physical basin properties earlier on in the parameter quantification process, the parameter regionalization is expected to be less uncertain. This implies that the use of physical basin properties in determining the parameter sets reduces the subjectivity in manual calibration and, therefore, equifinality, making it possible to obtain a basin specific, physically-based optimum parameter set. Figure 3.15 in section 3.4.3, already presents the paths followed in the developmental of such *a priori* parameter estimation approach. It is an inherently uncertain approach partly because precise relationships are not possible and partly because the spatial resolution and accuracy of the available physical basin information are typically less than suitable. Although the approach is known to be uncertain it is a different matter to realistically quantify that uncertainty. The best that can be achieved at present is to make use of the likely ranges (e.g. Table 3.5, in Chapter 3) of the basin physical property estimates based on the quality of the available information (e.g. AGIS, 2007). AGIS (2007) provides relatively detailed information about topography and soil types. The soil type data is in the form of depth ranges and texture classes for different topographic units within the sub-basins. There is therefore uncertainty associated with the interpretation of the AGIS information required by the parameter estimation procedure.

For each parameter, three values were obtained, the ‘best’ guess or initial value, a lower value and an upper value. The bounds (lower and upper value of each parameter) are determined based on an interpretation of how the parameters interactively generate either lower or upper runoff. Given that in some instances there is more than one runoff generation mechanism (e.g. soil moisture and groundwater functions) such as in humid conditions, a direct approach of establishing the parameter bounds will not be possible and some sampling approaches are needed. In an attempt to address this problem, a simple manual sampling process was used. The lower and upper runoffs were used to represent the likely simulation uncertainty bounds due to parameter uncertainty. The limited observed streamflow data available in some of the sub-basins were used to evaluate the simulation bounds, but in the absence of this information the simulated flow bounds are compared with the simulations based on the ‘best guess’ parameter set.

8.3.3 Parameter sensitivity analysis

Despite a wide spectrum of studies of parameter estimation, interdependences and sensitivity analysis available in the literature (Sorooshian and Gupta, 1983; Beven, 1989, 1993; Beven and Freer, 2001; Gupta *et al*., 1998, Boyle *et al*., 2000), there have been few attempts to apply similar approaches to the models in common use in southern Africa. Irrespective of the method used for parameter estimation, one often has little sense of which of the model parameters most influence model output and hence the need for sensitivity analysis. Sensitivity analysis is based on multiple runs of the model using appropriate parameter value combinations. The parameter exploration version of the Pitman model (which allows for parameter interactions) as described in section 3.4.3 was used for this purpose. The output from this program is a list of parameter values and a range of objective function statistics (section 3.4.1) comparing each model result with an ‘observed’ time series. In the absence of observed data simulated flows based on using the ‘best guess’ parameter set are used to compare with other simulations.

The sensitivity analysis results can be used to constrain the uncertainty analysis together with the expected relevant information (framing assumptions) in Table 8.1. In this sense, sensitivity and identifiability are similar issues. If the results are not sensitive to parameter changes, the parameter is not identifiable, but at the same time, the importance of getting the value correct is not important either. The parameters that are not sensitive should therefore not affect model output uncertainty. The sensitivity analysis should focus on groups of parameters that affect similar hydrograph components. This would be strongly linked to the basin physical property data and climate region. Parameter sensitivity analysis is a necessary, but not a sufficient requirement for identifiability, since values of a sensitive parameter that produce good model performance (relative to observed data) can still be distributed over a relatively wide range of feasible parameter space (Wagner *et al*., 2001, 2003).

8.3.4 Parameter uncertainty analysis

The same version of the model used in section 8.3.3 can be used to generate ensembles within defined uncertainty bounds. In section 8.3.3 it was appropriate to limit the number of parameters involved in each run of the model, but to have several steps either side of the initial parameter value. Sensitivity analysis can assist in identifying those parameters that should be included in the uncertainty analysis. In the uncertainty analysis all parameters that are expected to be uncertain must be varied. The number of parameter steps is restricted to three (minimum, initial and maximum parameter value), while the number of parameters included will be large. A maximum of 10 parameters could be included in the uncertainty analysis to generate 59 049 simulations with a model run time of approximately 20 minutes. The resulting flow ensembles determine the simulation uncertainty bounds due to parameter uncertainty. Constraining parameter uncertainties in the absence of measured flow data (i.e. in ungauged basins) remains a challenge (see Yadav *et al*., 2007). In the absence of an alternative approach the ensembles are compared to the simulated flows based on the 'best guess' parameter set, assumed to be the most likely result. The effects of parameter uncertainty on simulated runoff are assessed using goodness-of-fit measures, together with visual comparisons of time series plots and flow duration curves. The yield deficit (based on a hypothetical reservoir and abstraction volume) outputs for each ensemble can also be used to assess the differences in the ensemble flow regime characteristics. The yield deficit statistic integrates many characteristics of a simulated flow regime (including intra- and inter-annual variations) and can be more useful than single objective functions as noted already in Chapter 3.

8.4 Application examples and results

The application of the procedures presented above is illustrated using 10 examples from South Africa (Chapter 3, Figure 3.9); sub-basins of the upper Vaal River (C12D), the Towus River (K40A), the Sabie River (X31A), the Gouritz River (J33D), the Breede River (H10C), the Boesmans, a Thukela tributary (V70B), the Mgeni River (U20B), the Berg River (G10B), the Elands River (X21F) and the Mooi River (V20A). The physical properties for these sub-basins have already been presented in section 3.2. The selection of the sub-basins for this analysis was mainly influenced by the availability and quality of observed streamflows, despite the focus being on ungauged basins. The use of observed flows was to validate the methods used for parameter estimation, sensitivity and uncertainty analysis so that confidence in the approaches can be assessed before application to ungauged basins. The sub-basins were also chosen to reflect the diversity of typical basin physical properties (i.e. soil properties, geological and topographical conditions; climate and runoff regions). The size of the sub-basins ranged from as small as 87km^2 (K40A sub-basin) to 901km^2 (C12D sub-basin).

The model input requirements (i.e. rainfall and potential evapotranspiration), have been taken from Midgley *et al.* (1994) and were fixed throughout the analysis. The parameters considered for sensitivity and uncertainty analysis were restricted to FF (in some sub-basins), ZMIN, ZMAX, ST, FT, POW, GW, GPOW, DDENS and RSF, while the remaining parameters were assumed to be estimated without uncertainty for the purposes of this study. The parameter estimation process for ZMIN, ZMAX, ST, FT and POW has been based on the procedure described in Kapangaziwiri and Hughes (2008) using information on soils and topography largely derived from the Agricultural Geo-referenced Information System (AGIS, 2007) of the South African Agricultural Research Council. The AGIS (2007) soils and topography data are supported by information from a database of groundwater characteristics for South Africa (Conrad, 2005). This database provides values for the storativity and transmissivity parameters of the model as well as estimates of mean annual recharge which can be used to establish appropriate values for the parameters GW and GPOW.

8.4.1 Parameter estimates, sensitivity and uncertainty results

Three sets of parameters (initial value, lower and upper bounds) were estimated using the methods of Kapangaziwiri and Hughes (2008). The table also includes the sensitivity comments for each parameter and the three objective functions (coefficient of efficiency (CE), percentage mean flows (Mn) for both un-transformed and transformed values, and the yield deficit (%YD)) as well as the recharge rates associated with each parameter set. The results for C12D (Table 8.2), H10C (Table 8.3), J33D (Table 8.4) and X21F (Table 8.5) sub-basins are discussed in detail while additional results are provided in Appendix 4.1.

C12D is a sub-humid sub-basin and the uncertainty in parameter values is mostly related to the estimation of soil properties (texture classes and soil depth). The sub-basin is flat, characterized by moderate to deep clayey soils which are assumed to have restricted drainage, particularly in the lower soil horizons and are underlain by fractured shales and sandstones. The variations in maximum soil moisture absorption rates will result in a substantial difference in simulated runoffs and yield deficits (i.e. yield deficits ranging from 5.6 to 70.9%) as shown in Table 8.2. The yield deficits were based on a 65 * $10^6 m^3$ reservoir (approximately equal to the observed mean annual runoff) and an annual abstraction demand of 80 * $10^6 m^3$/yr (distributed appropriately for irrigation requirements). Given the poorly drained soils and low gradient (slope of 2-4%), it is assumed that there will be no rapid soil moisture distributions during a rainfall event in this sub-basin (Kapangaziwiri, 2008) and therefore very little sub-surface flow. The sensitivity analysis results (Table 8.2) showed that the model is sensitive to ZMIN and ZMAX, where the parameter ZMAX is more identifiable at a value of between 400 and 420 (Figure 8.1, left-hand side). Figure 8.1 (right-hand side) shows the flow duration curves for the three simulations and the observed flows. Clearly the model output uncertainty bounds are wide. It was not considered necessary to generate ensemble simulations in this situation as the relationships between simulated flow characteristics for the lower and upper bound parameter sets (Table 8.2) are very clear.

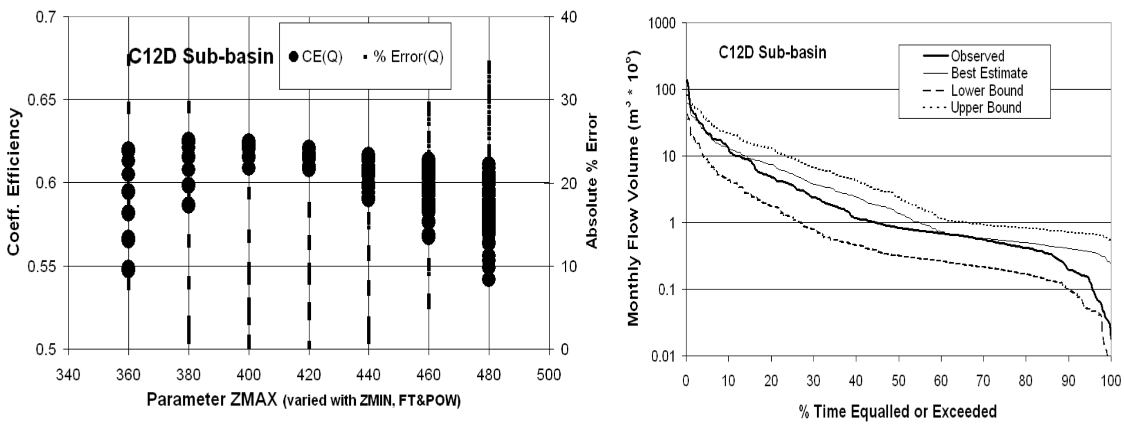


Figure 8.1 Sensitivity plot (left-hand side) based on 2401 simulations and flow duration curves (right-hand side) for C12 sub-basin (simulation period is 1960-1990).

Table 8.2 Basin property data, parameter estimates and objection function values for C12 Sub-basin.

Sub-basin; gauge area	**C12D; (C1H004-901km^2)**			
i. Basin physical property data	**Initial value**	**Uncertainty bounds**		
		Lower runoff	**Upper runoff**	
Soil texture	SaClLm=60%; SaCl=25%; Cl=15%	SaClLm=50%; SaCl=30%; Cl=20%	SaClLm=70%; SaCl=20%; Cl=10%	
Drainage Density (km/km^2)	1.70	1.70	1.70	
Mean basin slope (BS) (%)	3.0	2.0	4.0	
Regional GW slope (GS) (%)	1.0	1.0	1.0	
Drain. Vector slope (VS) (%)	100	100	100	
Mean soil depth (m)	1.30	1.50	0.75	
FT soil depth (m)	1.43	1.73	0.78	
Soil porosity	0.33	0.32	0.34	
Vertical variation (%)	40	40	40	
Soil Permeability(m/day)	0.36	0.27	0.37	
Depth to GW (m)	25	25	25	
GW storativity (*1000)	2.0	2.0	2.0	
Unsat transmissivity (m^2/day)	0.0	0.0	0.0	
ii. Physically based parameters & Obj. function. values				**Sensitivity comments**
ST (mm month^{-1})	172.0	220.0	100.0	Not sensitive in the range of 120 to 250.
FT (mm month^{-1})	0.8	0.4	1.0	Although low flows are sensitive to changes in FT, the estimates are constrained by the low basin slopes.
POW	4.0	6.5	3.5	Not sensitive given low FT values.
ZMIN (mm month^{-1})	20.0	80.0	20.0	The overall volume of runoff is very sensitive to both of these parameters.
ZMAX (mm month^{-1})	420.0	500.0	320.0	
GW (mm month^{-1})	14.0	8.0	20.0	Dry season low flows are very sensitive to changes in recharge.
GPOW	4.0	4.0	4.0	
DDENS (km km^{-2})	0.2	0.2	0.2	Groundwater response is sensitive to DDENS estimates.
RSF (%)	0.2	0.3	0.1	Dry season low flows are moderately sensitive to riparian losses.
Mean recharge (% of rainfall)	1.4	1.0	1.9	The results and statistics given in the the 3rd and 4th two columns are based on model runs using the parameter values in the rows above for the equivalent column.
CE(Q) / CE (lnQ)	0.62/0.57	0.45/0.15	0.46/0.28	
%Mn(Q)/ %Mn(lnQ)	-2.1/190.6	-63.3/-488.2	65.5/459.8	
Yield deficit (%)	26.7	70.9	5.6	

H10C is also a sub-humid sub-basin and most of the boundary consists of steep rocky outcrops with moderate to gentle slopes in the central part of the sub-basin. The soils are loamy sands and vary in depth across the sub-basin, from very shallow on the upper slopes to moderately deep in the valley bottom. The geology is mainly shale and sandstone of the Bokkeveld group (although a Table Mountain Sandstone ridge occurs in the southern part of the basin). Sensitivity analysis of different groups of parameters suggests that most of them are sensitive (Table 8.3), with parameter ST being the most identifiable (Figure 8.2, left-hand side). The complex nature of the topography and the variation in soil depths across the whole sub-basin suggest that ST is an important parameter in the uncertainty analysis. The output uncertainty (Figure 8.2, right-hand side) is wide and there are many occasions when the observed flows are close to the lower bound flow simulations. This is a consequence of not accounting for water use for irrigation from a large number of small farm dams within the sub-basin, which represents an unaccounted for uncertainty in this part of the study. All of the output ensembles were run with a 113 * $10^6 m^3$ reservoir capacity (approximately equal to the observed mean annual runoff) and an annual abstraction demand of 141 * $10^6 m^3/yr$ to give the yield deficits range (2- 50%) in Table 8.3.

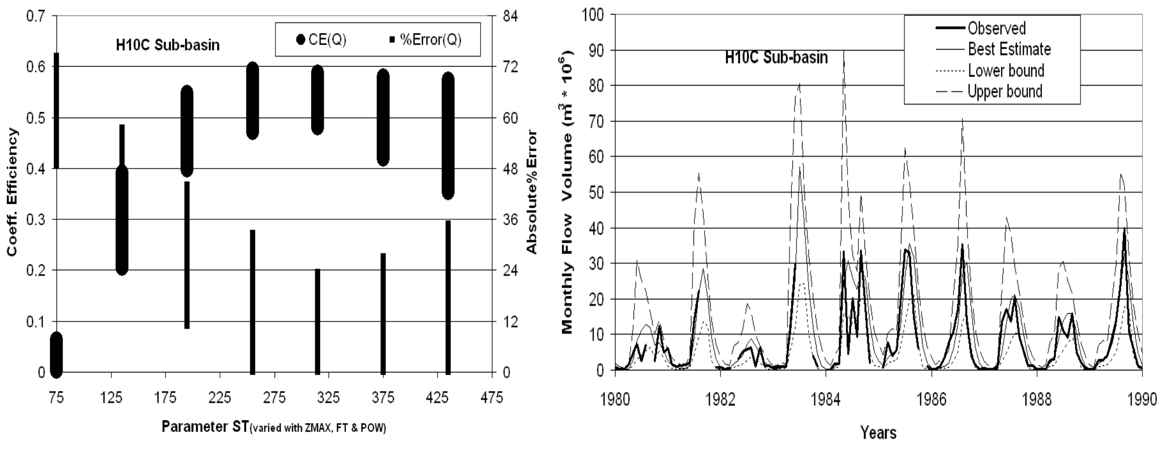


Figure 8.2 Parameter sensitivity plot (left-hand side) based on 2401 simulations and flow time series (right-hand side) for H10C sub-basin.

Table 8.3 Basin property data, parameter estimates and objection function values for H10C Sub-basin.

Sub-basin; gauge area	**H10C; (H1H003-656km^2)**			
i. Basin physical property data		**Uncertainty bounds**		
	Initial value	**Lower runoff**	**Upper runoff**	
Soil texture	Sa=25%; LmSa=60%; SaClLm=10% SCl=5%	Sa=30%; LmSa=60%; SaClLm=5% SCl=5%	Sa=40%; LmSa=50%; SaClLm=10% SCl=0%	
Drainage Density (km/km^2)	1.90	1.90	1.90	
Mean basin slope (BS) (%)	18.0	18.0	14.0	
Regional GW slope (GS) (%)	1.0	1.0	1.0	
Drain. Vector slope (VS) (%)	2.0	3.1	2.0	
Mean soil depth (m)	0.65	0.29	1.15	
FT soil depth (m)	0.76	0.34	1.35	
Soil porosity	0.40	0.40	0.39	
Vertical variation (%)	80	80	80	
Soil Permeability(m/day)	2.44	3.21	2.44	
Depth to GW (m)	25	25	25	
GW storativity (*1000)	2.0	2.0	2.0	
Unsat transmissivity (m^2/day)	2.5	2.5	2.5	
ii. Physically based parameters & Obj. function. Values				**Sensitivity comments**
ST (mm month^{-1})	255.0	137.0	405.0	Sensitive in the range of 130 to 410.
FT (mm month^{-1})	43.9	31.1	57.1	Seasonal hydrograph shape and overall water balance sensitive to changes in FT.
POW	1.8	2.0	2.1	A change in POW affects overall water balance.
ZMIN (mm month^{-1})	0.0	0.0	0.0	The overall volume of runoff is sensitive to ZMIN and ZMAX.
ZMAX (mm month^{-1})	1200.0	1100.0	1400.0	
GW (mm month^{-1})	40.0	30.0	50	Low flows are sensitive over the range 10 to 70.
GPOW	3.0	2.9	3.1	Low flows not sensitive to GPOW change.
DDENS (km km^{-2})	0.4	0.3	0.5	Overall flow sensitive to values within the range 0.1 to 0.7
RSF (%)	0.2	0.1	0.3	Low flows sensitive over the range 0.1 to 0.3
Mean recharge (% of rainfall)	8.7	6.3	11.9	The results and statistics given in the 3rd and 4th columns are the extremes of all 6561 ensembles using the parameter bounds given in the 3rd and 4th columns above
CE(Q) / CE (lnQ)	0.58/0.67	-0.08/0.24	0.61/0.75	
%Mn(Q)/ %Mn(lnQ)	-1.8/13.3	-38.9/-54.6	67.7/39.7	
Yield deficit (%)	27.0	50.0	2.0	

For J33D, a semi-arid sub-basin, one of the main sources of uncertainty is the definition of spatial variations in rainfall, which is dominated by highly variable convective storms in summer. The sub-basin has steep topography with shallow sandy loam soils, while the geology of the area is mainly arenaceous shale, siltstone and quartzite sandstones. Minor irrigation activities are practiced along the channel margins in alluvial soils and supplied from in-channel weirs or off-channel storage dams. As with C12D the parameters for J33D that generate the least and most runoff are relatively simple to derive from the expected range of basin physical properties. The main runoff generation mechanism is through surface runoff, controlled by infiltration parameters ZMIN and ZMAX, which are dependent on soil texture properties. As illustrated by the sensitivity plot (Figure 8.3, left-hand side), the sensitivity analysis of this sub-basin is difficult to interpret and is dependent on the objective function selected. While groundwater recharge rates and interflow are expected to be small (low FT and GW values) the observed flow duration curve (see Figure 8.3-right side) suggests that zero flows are only expected for some 5% of the time and that low flows are a significant component of the flow regime despite the aridity of the sub-basin. The yield deficit analysis, with a 13.5 * $10^6 m^3$ reservoir capacity (approximately equal to the observed mean annual runoff) and an annual abstraction demand of 10 * $10^6 m^3$/yr (distributed appropriately for irrigation requirements), resulted in a range of deficits of 2-34% (Table 8.4). The results demonstrate that the output uncertainty due to parameter uncertainty is not wide, as shown by the relatively narrow range between the upper and lower bounds in Figure 8.3 (right-hand side). However, compared to observed flows, the simulations are not very good and low flows area always over-simulated.

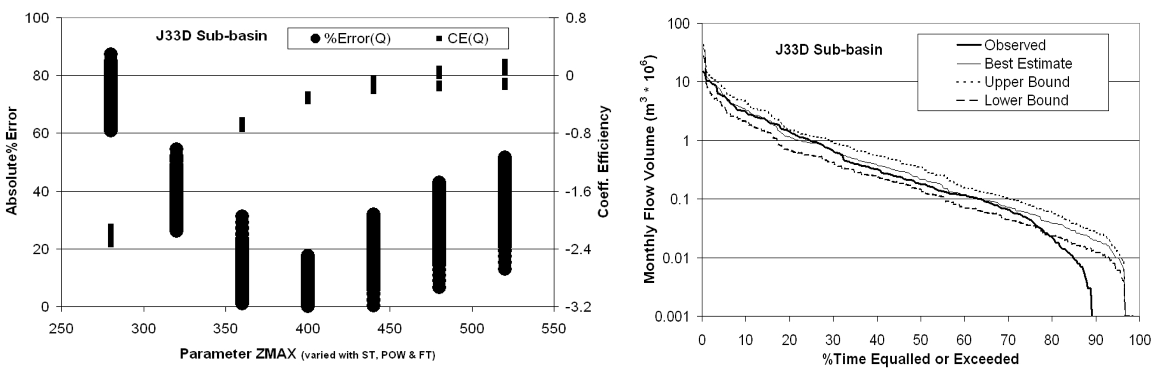


Figure 8.3 Parameter sensitivity plots (left-hand side) based on 2401 simulations and flow duration curves (right-hand side) for J33D sub-basin.

Table 8.4 Basin property data, parameter estimates and objection function values for J33D Sub-basin.

Sub-basin; gauge area	**J33D; (J3H012-688km^2)**			
i. Basin physical property data		**Uncertainty bounds**		
	Initial value	**Lower runoff**	**Upper runoff**	
Soil texture distribution	Sa=10%; LmSa=60%; SaClLm=20% SCl=10%	Sa=5%; LmSa=50%; SaClLm=30% SCl=15%	Sa=15%; LmSa=70%; SaClLm=10% SCl=5%	
Drainage Density (km/km^2)	1.30	1.30	1.30	
Mean basin slope (BS) (%)	15.0	10.0	20.0	
Regional GW slope (GS) (%)	1.0	1.0	1.0	
Drain. Vector slope (VS) (%)	4.2	4.2	4.2	
Mean soil depth (m)	0.30	0.50	0.19	
FT soil depth (m)	0.39	0.63	0.24	
Soil porosity	0.38	0.37	0.39	
Vertical variation (%)	80	80	80	
Soil Permeability(m/day)	0.47	0.36	0.62	
Depth to GW (m)	25	25	25	
GW storativity (*1000)	1.0	1.0	1.0	
Unsat transmissivity (m^2/day)	0.5	0.4	0.6	
ii. Physically based parameters & Obj. function. values				**Sensitivity comments**
ST (mm month^{-1})	110.0	164.0	80.0	Flows sensitive in the range of 20 to 200.
FT (mm month^{-1})	3.8	3.0	4.2	Flows are sensitive to changes in FT.
POW	2.2	2.4	2.0	Changes in FT affect overall volume of runoff.
ZMIN (mm month^{-1})	0.0	0.0	0.0	The overall volume of runoff is very sensitive to both of these parameters.
ZMAX (mm month^{-1})	310.0	400	280.0	
GW (mm month^{-1})	5.0	4.0	6.0	Dry season low flows are very sensitive to recharge values less than 5 and not sensitive for higher values.
GPOW	2.5	3.0	2.0	Dry season low flows are very sensitive to changes in recharge.
DDENS (km km^{-2})	0.2	0.1	0.3	Groundwater response is sensitive to DDENS estimates.
RSF (%)	0.3	0.4	0.2	Dry season low flows are sensitive to riparian losses.
Mean recharge (% of rainfall)	1.1	0.7	1.6	The results and statistics given in the 3rd and 4th two columns are based on model runs using the parameter values in the rows above for the equivalent column.
CE(Q) / CE (lnQ)	-0.32/0.22	0.07/0.22	-0.66/0.22	
%Mn(Q)/ %Mn(lnQ)	-2.0/-19.7	-39.9/-51.4	20.1/-89.0	
Yield deficit (%)	9.0	34.0	2.0	

X21F is a sub-humid sub-basin characterized by undulating topography with shallow sand clay loams. The geology comprises mainly shale and quartzite. The main source of uncertainty is in the estimation of soil texture and depth. Given that the soils are shallow, the main runoff generation mechanism is through surface runoff, controlled by infiltration parameters ZMIN and ZMAX. However, sensitivity analysis (Table 8.5) showed that the most sensitive parameters are ZMAX and FT. Figure 8.4 (left-hand side) shows that ZMAX is identifiable over the range of values that were tested. The yield deficit analysis, with a 57 * $10^6 m^3$ reservoir capacity (approximately equal to the observed mean annual runoff) and an annual abstraction demand of 57 * $10^6 m^3$/yr (distributed appropriately for irrigation requirements), resulted in a range of deficits of 0.7%-30.6% (Table 8.4). While the 'best' estimate parameter set generated results that are close to the observed moderate to high flows, the upper bound set generate better results for most of the low flows. It is possible that the extreme low flows of the observed records are impacted by some abstractions.

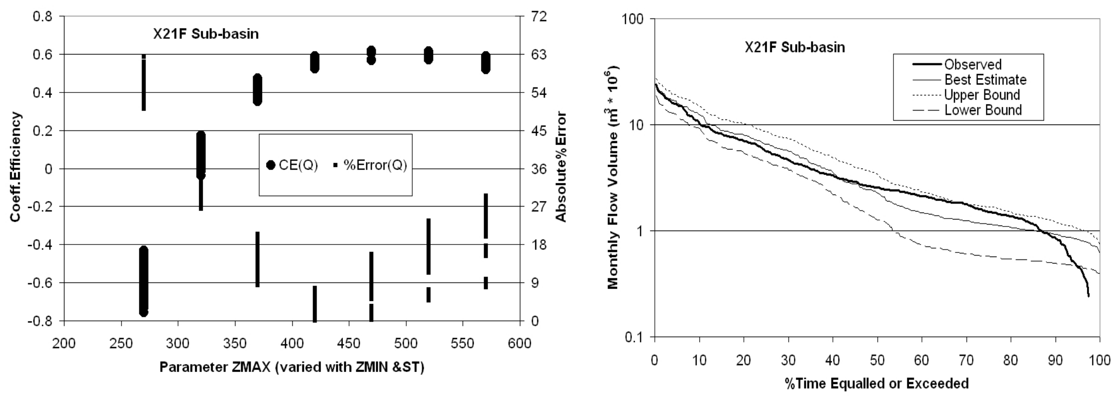


Figure 8.4 Parameter sensitivity plot (left-hand side) based on 343 simulations and flow duration curves (right-hand side) for X21F sub-basin.

Table 8.5 Basin property data, parameter estimates and objection function values for X21F Sub-basin.

Sub-basin; gauge area	X21F; (X2H011-397km^2)			
i. Basin physical property data	**Initial value**	**Uncertainty bounds** **Lower runoff**	**Upper runoff**	
Soil texture	SaClLm=60%; SaCl=30%; Cl=10%	SaClLm =50%; SaCl =35%; Cl=15%	SaClLm =70%; SaCl =25%; Cl=5%	
Drainage Density (km/km^2)	1.9	1.9	1.9	
Mean basin slope (BS) (%)	7.0	4.0	10.0	
Regional GW slope (GS) (%)	1.0	1.0	1.0	
Drain. Vector slope (VS) (%)	5.3	5.3	5.3	
Mean soil depth (m)	0.67	0.80	0.42	
FT soil depth (m)	0.74	0.94	0.47	
Soil porosity	0.33	0.34	0.33	
Vertical variation (%)	60	60	60	
Soil Permeability(m/day)	0.27	0.27	0.47	
Depth to GW (m)	25	25	25	
GW storativity (*1000)	1.0	1.0	1.0	
Unsat transmissivity (m^2/day)	0.5	0.0	1.0	
ii. Physically based parameters & Obj. function. values				**Sensitivity comments**
ST (mm month^{-1})	140.0	163.0	96.0	Mean flows sensitive to ST over the range 80 to 200.
FT (mm month^{-1})	4.6	1.2	8.5	Overall flow volumes sensitive to FT.
POW	2.1	2.1	2.1	Slightly affects flow volumes.
ZMIN (mm month^{-1})	10.0	0	10.0	ZMIN is not sensitive over the range 0 to 20 and ZMAX is sensitive for a given range.
ZMAX (mm month^{-1})	420.0	500	400	
GW (mm month^{-1})	18.0	10	25	Overall flows sensitive to GW for values less than 25.
GPOW	3.0	3.5	2.5	Not sensitive over a given range.
DDENS (km km^{-2})	0.2	0.1	0.4	Overall flow volume sensitive to changes in DDENS.
RSF (%)	0.1	0.2	0.1	Affects low flow parts of the flow hydrograph.
Mean recharge (% of rainfall)	4.7	2.3	7.1	The results and statistics given in the 3rd and 4th two columns are based on model runs using the parameter values in the rows above for the equivalent column.
CE(Q) / CE (lnQ)	0.54/0.63	0.52/0.08	0.33/0.60	
%Mn(Q)/ %Mn(lnQ)	3.3/-5.0	-29.4/-53.1	32.2/23.6	
Yield deficit (%)	6.5	30.6	0.7	

While the physical property data, model parameters and objective function values for the other six sub-basins (G10B, K40A, U20B, V20A, V70B and X31A) are given in Appendix 4.1, the sensitivity plots and flow duration curves are provided in Figures 8.5 and 8.6 respectively. The results suggest that some of the parameters are very sensitive while others are not at all (refer to previous examples and Appendix 4.1). The overall results for the 6 sub-basins show that parameters ZMAX, ST and GW are relatively well defined over the range of values tested (Figure 8.5), while ZMIN, FT, POW, GPOW and DDENS are not identifiable in some sub-basins but are sensitive. An exceptional case is U20B where parameter DDENS is sensitive and identifiable. The sensitivity tests presented here are dependent on the objective functions used and some parameters appear to be sensitive to either high or low flows depending on the runoff generation mechanism. The differences in sensitivity tests also reflect the importance of parameter interactions and the fact that FT and GW may not be identifiable because both can be used to generate the low flow signal. Fixing one of these parameters then makes the other more identifiable. The regional differences (Figure 8.5) in sensitivity tests are a consequence of the differences in sub-basin physical properties (mainly soil texture and depth, geology characteristics) and climatic differences.

The analysis of model output uncertainty results (Figure 8.6) suggest that simulated flows in different sub-basins respond differently to parameter uncertainty. The uncertainty bounds for G10B, K40A, U20B, V20A and V70B sub-basins are relatively wide while X31A has relatively narrow uncertainty bounds. In sub-basins G10B, K40A and V70B, the observed flows are closer to the lower bound than the upper bound, which suggest less optimistic water development solutions. However, for sub-basins, U20B and V20A, the observed and the ‘best’ estimate are closer to the upper bound than to the lower bound, which suggest a more optimistic water development solution. These findings are important in decision making processes when planning for further development of the sub-basins. All of the above observations about the uncertainty results need to be viewed with caution because of the subjective nature of the process used to establish parameter bounds. While every effort was made to be consistent, it is recognized that a more objective is required.

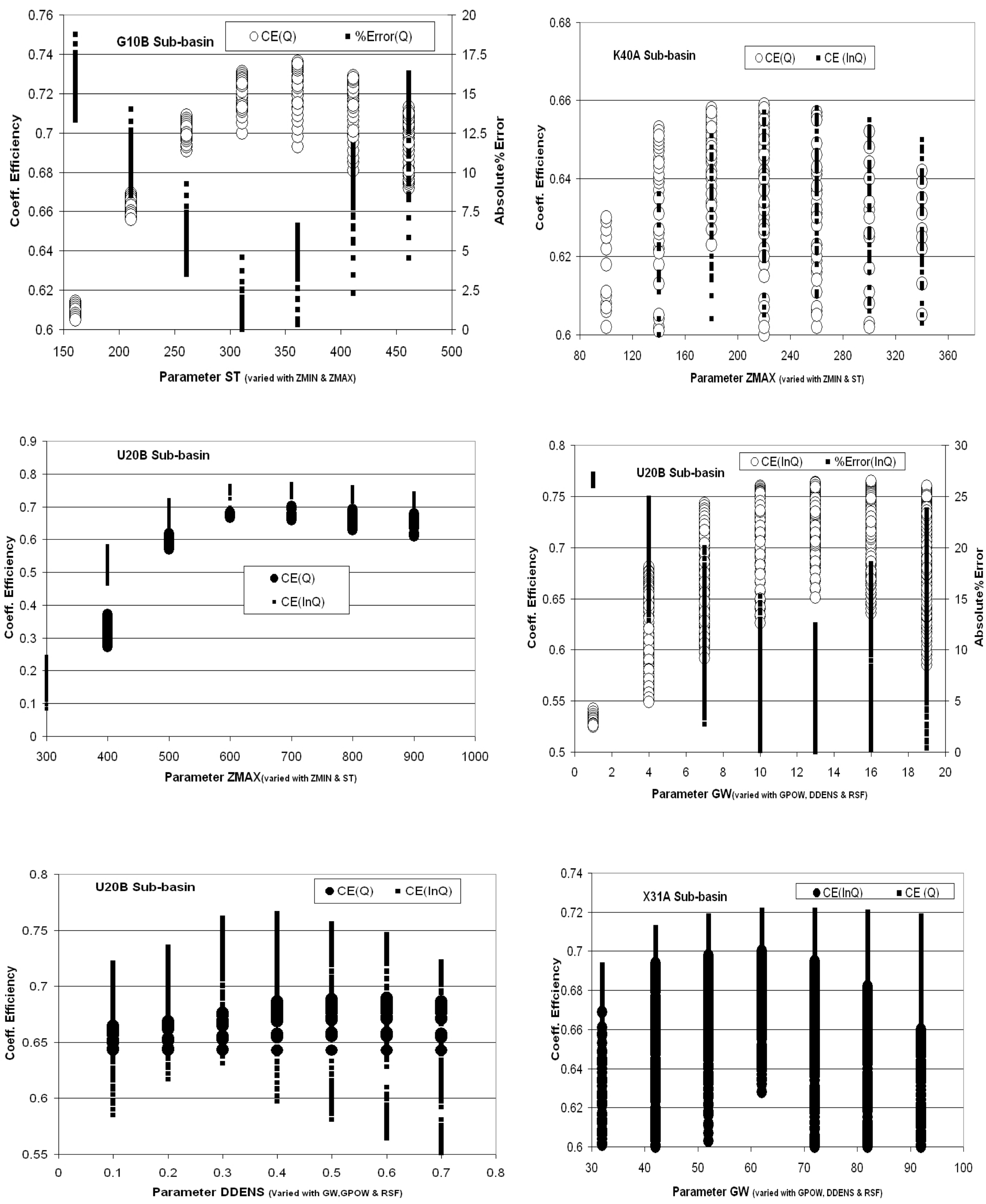


Figure 8.5 Illustrations of parameter sensitivity analysis plots for different sub-basins.

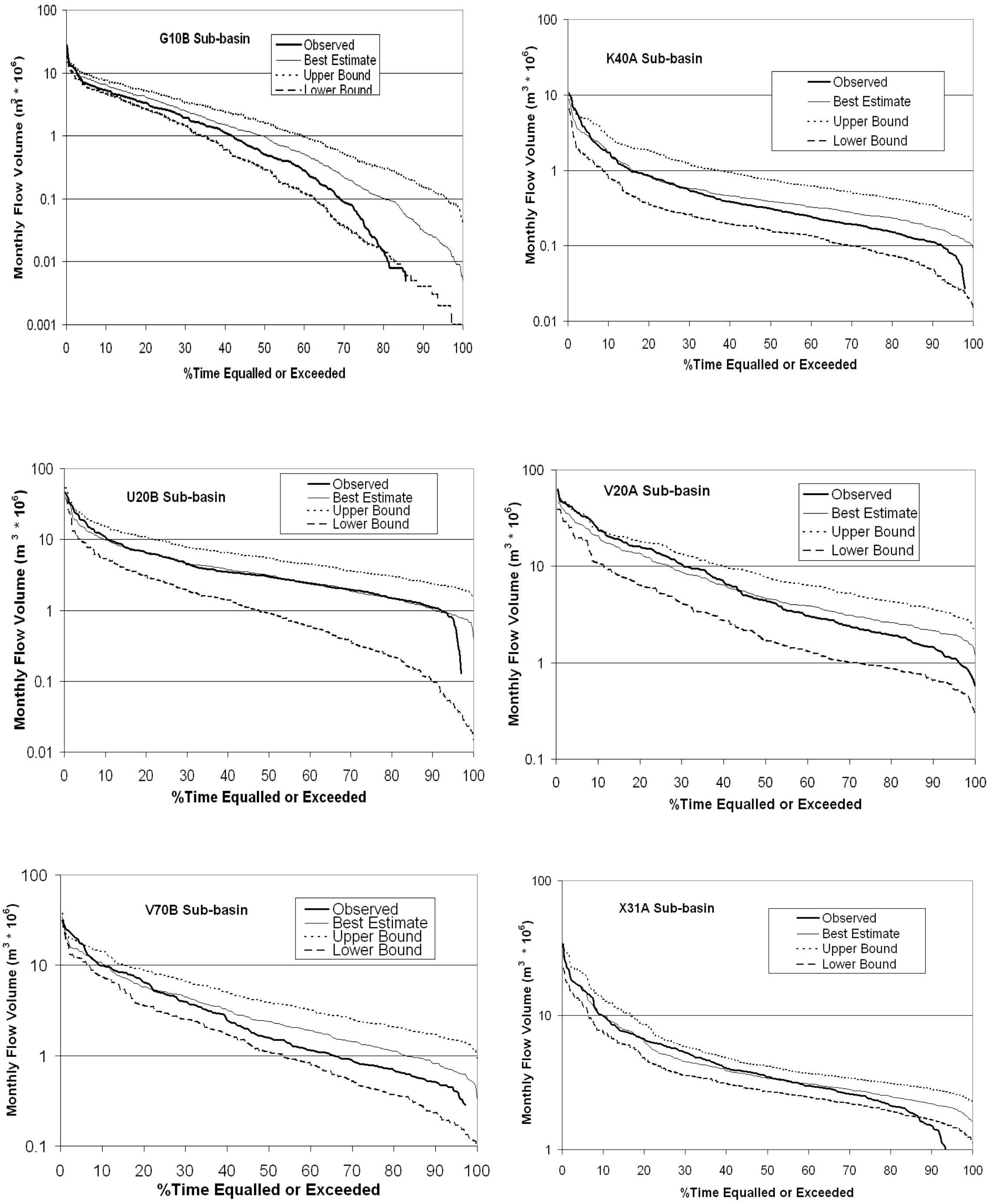


Figure 8.6 Uncertainty analysis based on flow duration curves (observed, best estimate & simulation uncertainty bounds) for different sub-basins.

8.5 Discussion

Decision makers who use results of hydrological modelling studies to assess the effects of various development impacts need guidance from modellers on the propagation of uncertainty in model simulations and what the implications are for policy making. Parameter uncertainty is but one of the sources of modelling uncertainty to consider. This part of the study presented a starting point for the evaluation of the impact of parameter uncertainty on water resources estimation using the revised version of the Pitman model (Hughes, 2004b). While it is known that climate input data (rainfall and potential evapotranspiration) influence the estimation of some of the parameters of the Pitman model, these were fixed in this analysis and the parameter estimation approach used is independent of the climate input data. While model structure uncertainty associated with spatial and temporal averaging is always present in any modelling process, this was ignored and effectively considered to be part of the parameter estimation process. One of the major causes of uncertainty is the scale issues associated with understanding the relationships between parameter values and measured physical properties.

Many of the existing approaches to deriving acceptable parameter sets with uncertainty rely upon information from observed flow data (Gupta *et al*., 1998; Beven, 2006b). In the past, the knowledge gained from gauged basins has been extrapolated to ungauged basins through direct regionalization of model parameters. The success of this approach has been limited, partially due to unknown impacts of model structural errors and the lack of calibration strategies that preserve the physical meaning of parameters (Wagener and Wheater, 2006). However, the approach adopted in the study made use of *a priori* parameter estimation methods (Kapangaziwiri and Hughes, 2008) that are applied independently of any observed flows. The main problem with this approach is how to identify parameter ranges or bounds that are realistic from an uncertainty point of view. In this study, the bounds have been set using a rather subjective interpretation of the uncertainties in physical property data (with no sampling involved) which are used as inputs into the parameter estimation equations. While this is clearly not a satisfactory long-term solution, it represents a first step towards the development of relevant approaches to analyse uncertainty in the Pitman model parameters. The results presented in this chapter have to be seen in the light of this subjectivity and the fact that no probability statements can be made about the upper and lower bounds of the simulations. Further research work is already in progress to address this deficiency in the methods (Kapangaziwiri and Hughes, pers.comm.).

As might be expected, the most important parameters vary depending on sub-basin climate and physical property conditions and the relatively simple (and easy to apply) approach to sensitivity analysis served to identify important parameter interactions. The parameters ZMAX (e.g. in sub-basins C12D, K40A, J33D, U20B, V20A, X21F) and ST (e.g. in sub-basins G10B, H10C and V70B) were the most sensitive and identifiable parameters (depending on the objective function used) for most examples used but FT was found to be more identifiable for X21F. These parameters are controlled by soil properties such as texture and depth. A high level of parameter identifiability indicates that a parameter is important during either high or low flow periods depending on the objective function used. In some cases parameters GW (e.g. U20B, X31A sub-basins) and DDENS (e.g. U20B sub-basin) were also sensitive and these are controlled by the geological settings. There are also distinct differences between the rainfall-runoff response characteristics of the sub-basins studied and these are largely attributed to differences in the geology and soil characteristics. The sensitivity of surface runoff generation parameters reflects the dominance of surface and soil moisture runoff contribution to total streamflow, while sensitivity of recharge and groundwater discharge parameters reflects the dominance of base flow contribution to total streamflow in some areas.

There is generally low sensitivity in some of the parameters which suggests a degree of parameter interdependence. The sensitivity analysis will help to indentify insignificant and redundant parameters and provides support for further evaluation of the model in an effort to simplify it. As a decision aid, isolation of those parameters with the most effect on model outputs would support the design of further data collection to improve the accuracy of the physical property data. One of the important issues is the differences in scale between many physical data sources and the scale of the model.

The information available at regional scales (e.g. the WR90 database-Midgley *et al*., 1994 or FAO soils map) is difficult to interpret and translate into parameter estimates using the methods of Kapangaziwiri and Hughes (2008). For example, soil depth data are given as qualitative descriptions (moderate to deep, shallow etc). The more spatially detailed AGIS (2007) data are more suited for the purpose, but there are still limitations with respect to their interpretation. Soil depths, for example, are provided as ranges for each soil type, while soil texture distributions are provided for each topographic unit within land type zones. The depth ranges have to be interpreted into the most appropriate value for model parameter estimation equations. While it is obvious that these interpretations are subject to uncertainty it is less than obvious how the uncertainty should be quantified. A further problem is the relevance of the original data sources with respect to the model structure and the physical meaning of the parameter values. For example, much of the hydrogeological data available (Bredenkamp *et al*., 1995) have been derived from borehole records and pumping tests. The extent to which this information is relevant at a sub-basin scale model is largely unknown and uncertain at present and therefore, further evaluations of hydrogeological data are necessary.

9. EVALUATION OF THE COMBINED CONTRIBUTION OF UNCERTAINTY SOURCES TO MODEL OUTPUT UNCERTAINTY

9.1 Introduction

Previous chapters have demonstrated that the performance and outputs of a hydrological model are profoundly affected by many sources of uncertainty related to hydro-climatic data and parameter values as well the model structure itself. The results from these chapters suggest that individual sources of uncertainty contribute in different ways under different climate and sub-basin physiographic conditions and that clear statements about which source of uncertainty is likely to dominate are not generally possible. In this part of the study an attempt is made to integrate the combined effects of different sources of uncertainty on total output uncertainty for a limited number of sub-basins. However, the previous chapters focused on the simulation of natural flows and ignored uncertainty in estimating water use data that would be required to accurately estimate present day water resource availability. The main objectives of this chapter are therefore:

- To include an assessment of the contribution of water use data uncertainty to simulated runoff uncertainty.
- To assess in a simple way the combined effects of different sources of uncertainty on overall model output uncertainty.

9.2 Assessment of impacts of uncertainty in water use data

The extended version of the Pitman model (section 3.4.2) which includes several components to represent anthropogenic or water use impacts (land use modifications such as managed forest plantations, run-of-river abstractions and return flows, distributed small farm dams and large dams) on natural hydrology is used to assess the impacts of uncertainty in water use data on estimating present day water availability. Water use data are among the most unreliable information in many developing countries because observations of actual (rather than licensed) water use are relatively uncommon. The water uses considered in this part of the study are streamflow reductions due to managed forest plantations and direct runoff-of-river irrigation abstractions. However, in some instances irrigation water may be abstracted from small farm dams rather than directly from streamflows, but a lack of capacity-area relationships often hinders a comprehensive assessment of the impacts of small farm dams on streamflow reductions, despite their relevance in providing water for supplementary irrigation. Forest plantations, run-of-river irrigation abstractions and distributed small farm dams represent important components of the present day water balance of a number of South African basins. The impacts of large dams and the associated operating rules are equally important, but the Pitman model is not really appropriate for simulating these effects. In such situations, water resources system models are far more appropriate estimation tools. As such the sub-basins used in this part of the study do not have large dams.

9.2.1 Sources of uncertainty

Information on forest plantations and irrigated areas as well as on storage volumes and surface areas of small farm dams is provided in the national water resources assessment studies (i.e. WR90 and WR2005). However, additional information is available from the Water Use Authorisations and Registration Management System (WARMS) database which is being developed by DWAF as part of the process of registering existing lawful water uses within South Africa. There exist disparities between water entitlements, or registered use, and actual use and these have been noted in many unpublished South African studies of present day water availability (e.g. Hallowes and Lecler, 2005).

A source of uncertainty in small farm dams is a lack of information on the exact number of small dams, their capacity-area relationships and the sub-basin area above these dams. The source of uncertainties in irrigation water demand arises from the lack of information on the exact area under irrigation in a particular sub-basin. The uncertainty may also be related to the type of crop being irrigated, and the irrigation method and the source of water (run-of-river or small farm dams). Due to a lack of data on crops, the crop-dependent water demand and the seasonal distribution of this demand, an average annual irrigation demand per hectare for each sub-basin is often adopted. With respect to forest plantation effects on streamflow reduction, the uncertainties are associated with the estimation of the total planted area, as well as tree type, density, stage of growth and growing conditions. Despite the large amount of work that has focussed on estimating water use by managed plantations in South Africa (e.g. Schulze, 2000; Gush *et al*., 2002) it remains difficult to incorporate accurate estimates into hydrological models. There has been substantial debate over the most appropriate approach to be used to estimate the changes in natural hydrology resulting from changes in land use with a strong focus on water use by managed forest plantations (Gush *et al*., 2002).

Given that the water use information is given as annual aggregated values, rather than time series values, it is difficult to quantify time series variations of water use for any simulation period. This can cause substantial uncertainty in quantifying accurate estimates of present day and future water resources. The uncertainties in water use may also be caused by the differences on the information obtained by different agencies in different times. As an illustration, for U20B, the annual irrigation demand given in the WR90 database (Midgley *et al*., 1994) is 9.92 * $10^6 m^3$ while the WARMS database (i.e. 2006 estimates) reports a value of 11.7 * $10^6 m^3$. Similarly, for K40A, the estimated annual irrigation demand varies from 7.31 * $10^6 m^3$ (Midgley *et al*., 1994) to 0.11 * $10^6 m^3$ (WARMS). Additional uncertainties are related to the monthly variations in irrigation demand associated with actual rainfall amounts. While the model can account for this effect through part of the irrigation demand being met by a defined fraction of rainfall (a model parameter representing effective rainfall), there is no information available about how individual irrigation farmers actually manage irrigation applications. Apart from abstractions from large dams (not dealt with in this study) irrigation water may be obtained from run-of-river abstractions or from small farm dams. Both can be simulated by the model, but the information on the volume-surface area relationships of small farm dams is generally not available which introduces uncertainty in evaporation loss estimates.

In this study, the effects of water use uncertainties are mainly confined to uncertainties in the areal extent of irrigation and afforestation (Table 9.1). The irrigation demand is based on a fixed seasonal distribution of demand for the most likely crop in each sub-basin. The main source of irrigation water for all sub-basins used in this study is through run-of-river abstractions but there are a few exceptions (X31A & U20B), where water is also obtained from small farm dams. An assessment of the impacts of small farm dams is based on full supply volumes and assumed capacity-area relationships. The total full supply volume (cumulative) of small farm dams in X31A sub-basin, for example is 0.05 * $10^6 m^3$, while for U20B sub-basin is 11.08 * $10^6 m^3$, based on information from the WR90 database. The other sub-basins have no significant storage in small farm dams. The afforestation effects on streamflow reductions are based on fixed changes to interception (PI) and evaporation demand (FF) parameters of the Pitman model as recommended in Hughes (1997). Table 9.1 presents the information on water use data that is readily available to a water resource manager without detailed site investigations. Two or three realizations (depending on the availability of information) of present day conditions based on irrigation and afforestation areas given in the WR90, WR2005 and WARMS databases are used in the analysis. The existing WR90 regional model parameter sets (Midgley *et al*., 1994), rainfall and evapotranspiration inputs were fixed for all model runs for this analysis.

Table 9.1 Areas under irrigation and afforestation for different sub-basins from different sources.

Sub-basin & Area		**G10B** ($126km^2$)	**K40A** ($87km^2$)	**U20B** ($353km^2$)	**X31A** ($230km^2$)
Source	Data	Area covered (in km^2)			
WR90	Irrigation	3.1	8.8	16.3	0
	Afforestation	15.0	58	49.0	188
WR2005	Irrigation	3.18	-	7.79	0
	Afforestation	0.02	-	42.7	153.7
WARMS2006	Irrigation	-	1.5	30.4	0
	Afforestation	-	42.7	36.0	181.7

***Note**: There is no information for G10B from the WARMS2006 database and for K40A from the WR2005 database.*

The effects of uncertainty in estimating water use on water resources availability are quantified in terms of the impacts on mean annual runoff (MAR) and the results are presented in Table 9.2. The table shows the effects of irrigation abstraction, afforestation and the combined effects of the two, on sub-basin MAR. It has already been noted that there are a number of sources of uncertainty in water use data, as well as the way in which water use information is used in the model. However, with one exception, most of these will have smaller effects than differences in areal extent of irrigation and afforestation. The one exception is the water use by different trees and plantation management approaches (e.g. planting in riparian areas or excluding such areas). However, an assessment of these uncertainties is a very specialised topic and beyond the scope of this study.

As mentioned earlier, irrigation abstractions can be either through run-of-river abstractions or from small farm dams. These two scenarios were assessed for U20B for which reasonably reliable information on small farm dams was available from the WR90 database. The results from this analysis (Table 9.2, bold values) showed that small farm dams decrease the MAR by a greater amount (14.8%) than equivalent run-of-river abstractions (5.3%). The reasons for this are attributed to the additional losses from reservoir evaporation and the fact that the irrigation requirements can be more completely sustained during low flow periods. The flow duration curves for K40A and U20B in Figure 9.1 illustrate the differences in flow realizations (derived from different combinations of water uses) from the natural flow simulations and the observed flows. While the observed flow duration curve for K40A is outside the ensemble range for most of the time, the observed flows lie within the range of all the flow realizations for U20B. The differences in flow realizations from the observed flow for K40A are an indication of unaccounted for uncertainty in parameter values and in the water use data.

Table 9.2 Realizations of simulated mean annual runoff (MAR) for different water uses in four sub-basins.

Sub-basin		G10B	K40A	U20B	X31A
		Mean annual runoff (m^3 * 10^6)/yr			
Source of data	No. abs.	91.6	18.0	67.6	115.7
WR90	Irr. only.	90.1	15.5	64.0;**57.6**	-
	Aff. only.	88.9	12.1	59.8	80.8
	Aff & Irr.	87.4	10.0	56.2;**49.8**	-
WR2005	Irr. only.	90.1	-	65.8	-
	Aff. only.	91.6	-	60.8	86.7
	Aff & Irr.	90.1	-	59.0	-
WARMS2006	Irr. only.	-	17.4	61.6	-
	Aff. only.	-	13.4	61.8	81.9
	Aff & Irr.	-	12.9	56.1	-

***Note**: No. abs- represents no abstraction realization where a natural flow is simulated; Aff- represents afforestation and Irr- represents irrigation water use abstractions, Bold values in the column 4 represent impacts of farm dams (for irrigation use) on streamflow.*

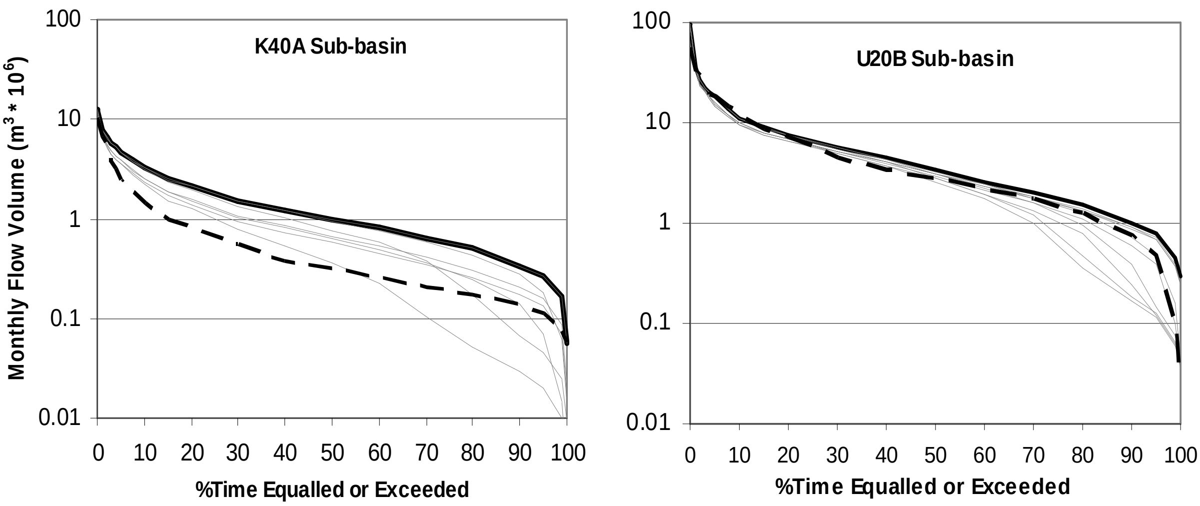


Figure 9.1 Flow duration curves (based on 10 realizations) showing effects of uncertainty in water use data (Bold line represents simulated natural flow and dotted bold line represents observed flow).

9.3 Combined propagation of uncertainty sources through the Pitman model

Despite the clear importance of separating all the sources of uncertainty in hydrological practice (Beven, 2000b), there are very few studies (e.g. Ajami *et al*., 2007) which have made attempts to explicitly account for all the different sources of uncertainty in rainfall-runoff modelling within the same framework. The few methods that have attempted this, such as the Bayesian Total Error Analysis (Kavetski *et al*., 2006) and the Integrated Bayesian Uncertainty Estimator (Ajami *et al*., 2007), have used statistical or data-driven approaches. Given the limited availability of data and resources in southern Africa, these methods are often inappropriate for use in the region. In this study, through a sensitivity analysis approach on a limited number of sub-basins, combined or collective contributions of climate input data, model parameter (assumed to include model structure uncertainty in this study) and water use uncertainties on simulated runoff are quantified within the SPATSIM framework. The analysis was performed by creating different scenarios or realizations of different sources of uncertainty, combine their contribution and propagate them through the model to generate simulation ensembles that include the expected range of model output uncertainty. The scenarios (based on assessments from the previous chapters), include different formulations of rainfall input, potential evapotranspiration estimates, water use data and parameter sets (Table 9.3). In this study, uncertainty propagation was evaluated based on both the simulated mean annual runoff (MAR) and the simulated yield of hypothetical reservoirs at each sub-basin outlet. The simulated yields are based on a mean annual achieved abstraction demand (at 90% level of assurance of supply). The reservoir sizes were set equal to about 1 x MAR of observed flows and the annual abstraction demand was assumed to be distributed by irrigation demands based on sub-basin information. Table 9.4 presents information on reservoir volumes (full supply volume) and mean annual required demands for three sub-basins.

9.3.1 Results of uncertainty propagation

Table 9.5 presents the results of the combined effects of propagating the different sources of uncertainty through the Pitman model to simulated mean annual runoff and how this would affect simulated yields. The results are based on ensemble streamflow simulations covering a wide spectrum of all the possible combinations of different uncertainty sources (i.e. rainfall, evapotranspiration, parameters and water use uncertainties in Table 9.3), all which will conjunctively have an influence on simulated reservoir yields. As expected, any change in simulated runoff resulted in a change in yield as presented in Table 9.5. The model output uncertainty assessment is based on comparisons of flow duration curves (see e.g. Figures 9.2, 9.3 and 9.4) and achieved yields (Table 9.6 and Figure 9.5).

Table 9.3 Description of scenarios used in the uncertainty analysis

Scenario	Description
R1	WR90 zonal rainfall (Midgley *et al*., 1994) (1920-1990).
R2	IDW spatially interpolated data (1920-2000).
R3	Same as 'R2' but with frequency characteristics corrected based on 'R1' (1920-2000).
E1	Fixed monthly pan based evaporation demand (Midgley *et al*., 1994).
E2	Monthly time series evaporation demand based on pan data (start dates are different in different sub-basins).
E3	Monthly time series evaporation demand perturbed from temperature data (1950-2000)
PW	Existing WR90 regional parameters values based on calibration against observed flows (Midgley *et al*., 1994).
PB	The 'best' estimate parameter values estimated by parameter estimation approach of Kapangaziwiri and Hughes (2008).
PL	The lower bound parameter values also estimated by parameter estimation approach of Kapangaziwiri and Hughes (2008).
PU	The upper bound parameter values also estimated by parameter estimation approach of Kapangaziwiri and Hughes (2008).
W1	This represents irrigation and afforestation data based on WR90 database.
W2	This represents irrigation and afforestation data based on either WR2005 or WARMS data.

Table 9.4 Hypothetical reservoir sizes and mean annual required abstraction demand

Sub-basin	G10B	K40A	U20B
Reservoir volume ($10^6 * m^3$)	93.1	8.5	63.6
Mean annual required demand ($10^6 * m^3$)/yr	80.1	7.7	52.1

The flow duration curves in Figures 9.2, 9.3 and 9.4 illustrate that the uncertainty bounds of simulated flows are increased when all the sources of uncertainty are considered than when rainfall, evaporation and water use uncertainties are included individually. In gauged sub-basins (K40A and U20B), the available observed flows are included into the flow duration curves but in ungauged sub-basins (G10B) the 'best estimate' flows are used to assess for comparison with the ensembles. The best estimate flow was generated based on using the combination, WR90 rainfall input (R1), mean monthly evapotranspiration (E1), 'best guess' parameter values estimated using Kapangaziwiri and Hughes (2008) approach (PB) together with water use data from the WR90 database(W1) (Table 9.3). For G10B, the flow duration curves (Figure 9.2, left-hand side) show two distinct groups of ensembles which clearly reflect uncertainty in rainfall input data due to the high spatial rainfall gradients in this mountainous region. The inclusion of parameter uncertainties (upper and lower bounds) (Figure 9.2, right-hand side) contribute a large amount of uncertainty. For K40A (Figure 9.3) most ensembles under-estimate observed flows, mainly in the low flow regime. This may be a reflection of unaccounted for sources of uncertainty or because the 'best-guess' parameter set is not very behavioural. For U20B, Figure 9.4 (left-hand side) shows that the uncertainties due to rainfall, evaporation and water use alone are relatively small and that parameter uncertainty dominates (Figure 9.4, right-hand side). The parameter uncertainty is mainly caused by uncertainty associated with the inability to accurately relate physical property data to the parameter values and how the Pitman model responds to these effects given that the scale of physical property data does not match the model scale. With respect to water use data, the uncertainties vary from sub-basin to sub-basin and this is a reflection of the differences in the information on areas covered by irrigation and afforestation in relation to the total sub-basin size.

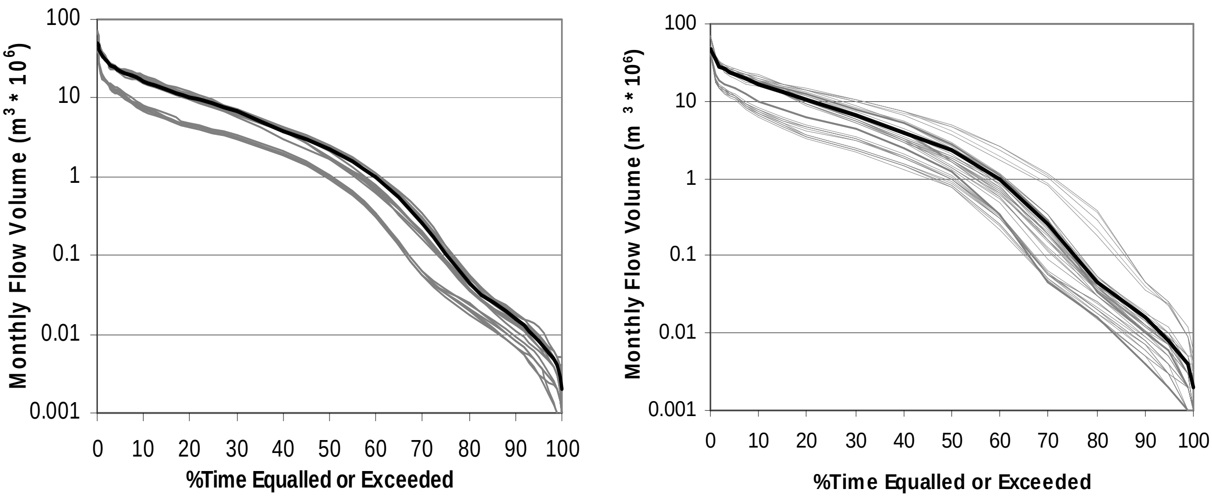


Figure 9.2 Flow duration curves of uncertainty ensembles (left-hand side - no parameter uncertainty included; right-hand side - all sources of uncertainty included) for G10B sub-basin. (Bold lines represent best estimate flows).

Table 9.5 Ensemble simulations of MAR and yield for three sub-basins.

Sub-basin	**G10B**		**K40A**		**U20B**	
Realization	***MAR (m^3*10^6)/yr***	***Yield (m^3*10^6)/yr***	***MAR (m^3*10^6)/yr***	***Yield (m^3*10^6)/yr***	***MAR (m^3*10^6)/yr***	***Yield (m^3*10^6)/yr***
R1, **E1**, PW, W1.	87.4	77.2	10.0	7.3	56.2	47.4
R1, **E2**, PW, W1.	86.7	78.6	11.4	7.5	63.1	48.7
R1, **E3**, PW, W1.	91.6	79.1	10.7	7.3	60.7	49.5
R2, E1, PW, W1.	50.7	50.7	14.1	7.5	62.6	50.4
R2, E2, PW, W1.	48.9	48.3	14.9	7.6	68.4	49.8
R2, E3, PW, W1.	50.7	50.8	14.2	7.4	66.2	50.0
R3, E1, PW, W1.	88.2	76.2	10.0	7.4	55.4	48.1
R3, E2, PW, W1.	87.1	75.9	10.5	7.3	61.9	49.1
R3, E3, PW, W1.	90.1	76.6	10.1	7.2	59.5	49.2
R1, E1, PW, W2.	90.1	77.9	12.9	7.7	59.0	48.9
R1, E2, PW, W2.	89.4	79.1	14.1	7.7	65.9	49.7
R1, E3, PW, W2.	94.4	79.4	13.6	7.7	63.5	50.6
R2, E1, PW, W2.	52.8	52.8	17.3	7.7	65.5	51.0
R2, E2, PW, W2.	50.9	50.2	18.3	7.7	71.3	50.6
R2, E3, PW, W2.	50.3	49.6	17.5	7.7	69.1	50.8
R3, E1, PW, W1.	90.8	77.4	13.0	7.6	58.2	49.5
R3, E2, PW, W2.	89.6	77.2	13.5	7.7	64.6	50.0
R3, E3, PW, W2.	92.7	77.8	13.0	7.6	62.4	50.1
R1, E1, PB, W1.	67.4	64.7	5.9	5.1	57.8	48.4
R1, E2, PB, W1.	66.7	64.8	7.0	5.4	63.5	49.6
R1, E3, PB, W1.	71.4	67.0	6.9	5.6	61.1	49.7
R2, E1, PB, W1.	33.3	33.6	9.1	6.6	64.1	50.8
R1, E2, PB, W1.	32.0	32.2	10.0	6.2	69.1	50.3
R1, E3, PB, W1.	31.3	31.5	10.0	6.4	66.7	50.4
R3, E1, PB, W1.	68.6	64.8	6.4	5.3	56.9	49.0
R3, E2, PB, W1.	67.9	63.1	6.4	5.0	62.6	49.5
R3, E3, PB, W1	70.6	65.8	6.4	5.3	60.3	49.6
R1, E1, PB, W2.	69.9	66.6	7.9	6.7	60.4	49.8
R1, E2, PB, W2.	69.1	66.9	8.9	6.6	66.1	50.3
R1, E3, PB, W2.	73.9	68.7	9.6	6.9	63.8	50.8
R2, E1, PB, W2.	35.0	35.3	11.4	7.4	66.7	51.4
R2, E2, PB, W2.	33.6	33.6	12.0	7.3	71.7	51.1
R2, E3, PB, W2.	33.0	32.9	12.7	7.5	69.4	51.0
R3, E1, PB, W2.	72.8	67.1	7.8	6.6	59.5	50.2
R3, E2, PB, W2.	70.2	64.6	8.4	6.3	65.2	50.3
R3, E3, PB, W2.	73.0	67.2	8.5	6.6	62.9	50.4

Table 9.5 *continued.*

Sub-basin	G10B		K40A		U20B	
Realization	***MAR (m^3*10^6)/yr***	***Yield (m^3*10^6)/yr***	***MAR (m^3*10^6)/yr***	***Yield (m^3*10^6)/yr***	***MAR (m^3*10^6)/yr***	***Yield (m^3*10^6)/yr***
R1, E1, PL, W1.	62.1	60.5	2.5	2.3	45.0	41.3
R1, E2, PL, W1.	61.4	60.2	2.9	2.9	50.5	43.9
R1, E3, PL, W1.	66.0	63.2	2.8	2.7	47.6	43.1
R2, E1, PL, W1.	28.1	28.5	4.3	3.5	49.8	45.8
R2, E2, PL, W1.	27.0	27.3	4.8	3.5	55.1	47.0
R2, E3, PL, W1.	28.3	29.1	4.8	3.7	52.5	46.9
R3, E1, PL, W1.	63.3	60.6	2.2	2.2	43.9	42.1
R3, E2, PL, W1.	62.6	58.8	2.4	2.6	49.1	45.1
R3, E3, PL, W1	65.3	62.1	2.4	2.8	46.8	44.9
R1, E1, PL, W2.	64.7	62.5	3.4	3.3	47.6	43.3
R1, E2, PL, W2.	63.9	62.4	3.8	3.6	52.7	45.2
R1, E3, PL, W2.	68.7	65.0	4.3	4.0	50.5	45.2
R2, E1, PL, W2.	29.8	30.2	5.6	4.6	52.4	47.5
R2, E2, PL, W2.	28.6	28.8	6.3	4.4	57.2	47.7
R2, E3, PL, W2.	30.1	30.8	6.1	4.8	55.1	48.0
R3, E1, PL, W2.	65.8	62.5	3.2	3.2	46.5	44.2
R3, E2, PL, W2.	65.0	60.7	3.5	3.4	51.7	46.8
R3, E3, PL, W2.	67.8	63.8	3.4	3.4	49.5	46.7
R1, E1, PU, W1.	77.2	71.9	7.9	6.5	68.8	52.1
R1, E2, PU, W1.	76.3	72.5	9.1	6.7	76.1	52.2
R1, E3, PU, W1.	81.1	73.6	8.9	6.9	72.7	52.2
R2, E1, PU, W1.	42.2	42.3	11.5	7.4	75.9	51.9
R2, E2, PU, W1.	40.7	40.3	12.2	7.2	81.8	52.1
R2, E3, PU, W1.	42.3	42.5	12.8	7.5	79.2	51.8
R3, E1, PU, W1.	78.3	71.1	7.8	6.5	67.9	51.6
R3, E2, PU, W1.	77.5	69.3	8.4	6.3	74.9	51.9
R3, E3, PU, W1.	80.3	71.1	8.3	6.6	71.8	51.6
R1, E1, PU, W2.	79.7	73.2	10.5	7.5	68.5	51.9
R1, E2, PU, W2.	78.9	74.0	11.6	7.6	75.4	53.5
R1, E3, PU, W2.	83.7	74.9	12.3	7.7	72.2	52.0
R2, E1, PU, W2.	44.0	44.1	14.5	7.6	75.6	51.8
R2, E2, PU, W2.	44.2	44.3	15.5	7.7	81.2	51.9
R2, E3, PU, W2.	44.2	44.2	15.2	7.6	78.6	51.7
R3, E1, PU, W2.	80.7	72.4	10.5	7.5	67.6	51.5
R3, E2, PU, W2.	79.9	70.8	11.1	7.4	74.1	51.8
R3, E3, PU, W2.	82.7	72.3	10.9	7.4	71.6	51.5

Notes*: The yield estimate is a simulated value based on a mean annual achieved abstraction demand and a hypothetical reservoir design size. Shaded rows are grouped to form set 1 (see Table 9.6) where evaporation is varied (E1, E2, E3) while other sources are fixed.*

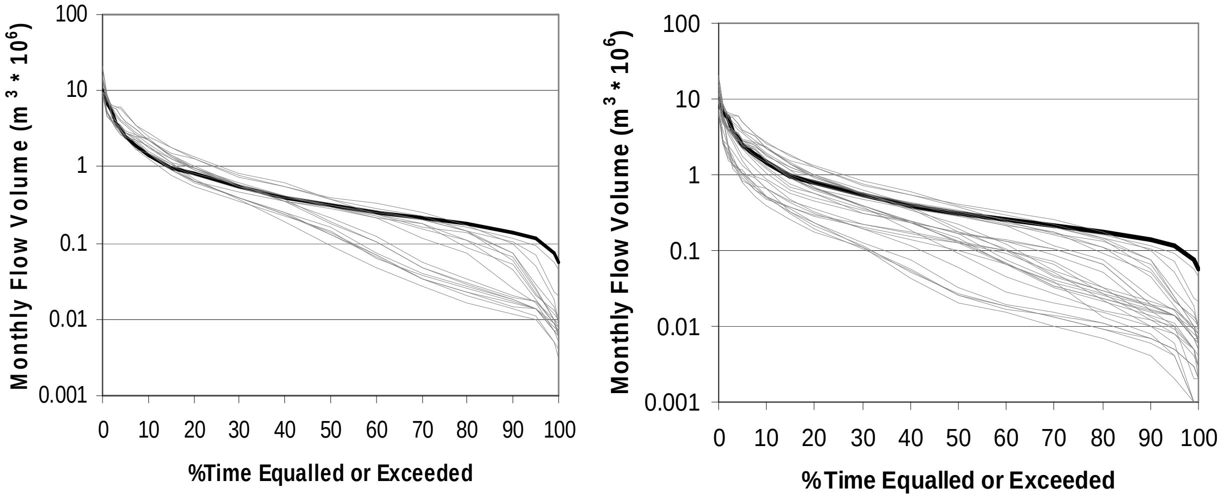


Figure 9.3 Flow duration curves of uncertainty ensembles (left-hand side - no parameter uncertainty included; right-hand side - all sources of uncertainty included) for K40A sub-basin (Bold lines represent observed flows from 1965-2000).

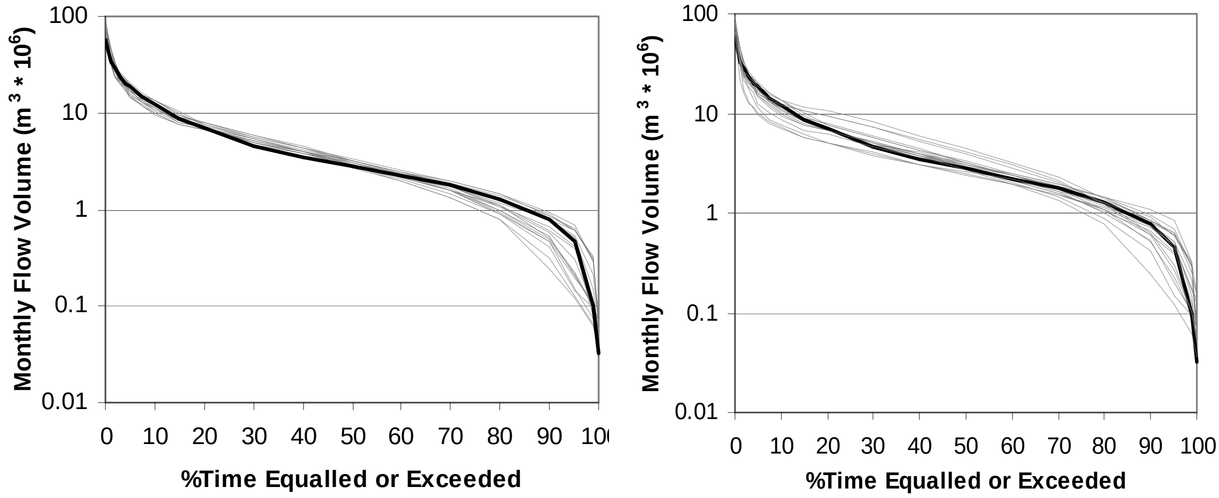


Figure 9.4 Flow duration curves of uncertainty ensembles (left-hand side - no parameter uncertainty included; right-hand side - all sources of uncertainty included) for U20B sub-basin (Bold lines represent observed flows from 1954-2000).

Table 9.6 summaries the results of the uncertainty analysis using the minimum and maximum yield estimates selected for ‘sets’ of ensembles. A ‘set’ is defined by those ensembles which have one source of uncertainty varying, while fixing the other three sources (the ‘shaded rows’ in Table 9.5 form ‘set 1’ in Table 9.6 for evaporation uncertainty). There are therefore 24 evaporation uncertainty sets, 24 rainfall uncertainty sets, 18 parameter uncertainty sets and 36 water use uncertainty sets (but only 18 are shown in

Table 9.6). The last two rows of Table 9.6 give the average of the maximum and minimum values for all the sets and the percentage differences between these averages.

Table 9.6 Summarised results of combined contribution different uncertainty sources on simulated mean annual yields ($m^3 * 10^6$) for three sub-basins

G10B sub-basin

Set	Evaporation		Rainfall		Parameter		Water use	
	Min Yield	Max Yield	Min Yield	Max Yield	Min Yield	Max Yield	Min Yield	Max Yield
1	77.2	79.1	50.7	77.2	60.5	77.2	60.5	62.5
2	48.3	50.8	48.3	78.6	60.2	78.6	60.2	62.4
3	75.9	76.6	50.8	79.1	63.2	79.1	63.2	65.0
4	77.9	79.4	52.8	77.9	28.5	50.7	28.5	30.2
5	49.6	52.8	50.2	79.1	27.3	48.3	27.3	28.8
6	77.2	77.8	49.6	79.4	29.1	50.8	29.1	30.8
7	64.7	67.0	33.6	64.8	60.6	76.2	60.6	62.5
8	31.5	33.6	32.2	64.8	58.8	75.9	58.8	60.7
9	63.1	65.8	31.5	67.0	62.1	76.6	62.1	63.8
10	66.6	68.7	35.3	67.1	62.5	77.9	71.9	73.2
11	32.9	35.3	33.6	66.9	62.4	79.1	72.5	74.0
12	64.6	67.2	32.9	68.7	65.0	79.4	73.6	74.9
13	60.2	63.2	28.5	60.6	30.2	52.8	42.3	44.1
14	27.3	29.1	27.3	60.2	28.8	49.6	40.3	44.3
15	58.8	62.1	29.1	63.2	30.8	49.6	42.5	44.2
16	62.4	65	30.2	62.5	62.5	77.4	71.1	72.4
17	28.8	30.8	28.8	62.4	60.7	77.2	69.3	70.8
18	60.7	63.8	30.8	65.0	63.8	77.8	71.1	72.3
19	71.9	73.6	42.3	71.9	-	-	64.7	66.6
20	40.3	42.5	40.3	72.5	-	-	64.8	66.9
21	69.3	71.1	42.5	73.6	-	-	67.0	68.7
22	73.2	74.9	44.1	73.2	-	-	33.6	35.3
23	44.1	44.3	44.3	74.0	-	-	32.2	33.6
24	70.8	72.4	44.2	74.9	-	-	31.5	32.9
Average	**58.2**	**60.3**	**38.9**	**70.2**	**50.9**	**68.6**	**54.1**	**55.9**
%Diff.		**3.4**		**44.6**		**25.7**		**3.1**

Table 9.6 *continued*

K40A sub-basin								
Set	**Evaporation**		**Rainfall**		**Parameter**		**Water use**	
	Min Yield	**Max Yield**	**Min Yield**	**Max Yield**	**Min Yield**	**Max Yield**	**Min Yield**	**Max Yield**
1	7.3	7.5	7.3	7.5	2.3	7.3	2.3	3.3
2	7.4	7.6	7.3	7.6	2.9	7.5	2.9	3.6
3	7.2	7.4	7.2	7.4	2.7	7.3	2.7	4.0
4	7.7	7.7	7.6	7.7	3.5	7.5	3.5	4.6
5	7.7	7.7	7.7	7.7	3.5	7.6	3.5	4.4
6	7.6	7.7	7.6	7.7	3.7	7.4	3.7	4.8
7	5.1	5.6	5.1	6.6	2.2	7.4	2.2	3.2
8	6.6	6.6	5.0	6.2	2.6	7.3	2.6	3.4
9	5.0	5.3	5.3	6.4	2.8	7.2	2.8	3.4
10	6.6	6.9	6.6	7.4	3.3	7.7	6.5	7.5
11	7.3	7.5	6.3	7.3	3.6	7.7	6.7	7.6
12	6.3	6.6	6.6	7.5	4.0	7.7	6.9	7.7
13	2.3	2.9	2.2	3.5	4.6	7.7	7.4	7.6
14	3.5	3.7	2.6	3.5	4.4	7.7	7.2	7.7
15	2.2	2.8	2.7	3.7	4.8	7.7	7.5	7.6
16	3.3	4.0	3.2	4.6	3.2	7.6	6.5	7.5
17	4.4	4.8	3.4	4.4	3.4	7.7	6.3	7.4
18	3.2	3.4	3.4	4.8	3.4	7.6	6.6	7.4
19	6.5	6.9	6.5	7.4	-	-	5.1	6.7
20	7.2	7.5	6.3	7.2	-	-	5.4	6.6
21	6.3	6.6	6.6	7.5	-	-	5.6	6.9
22	7.5	7.7	7.5	7.6	-	-	6.6	7.4
23	7.6	7.7	7.4	7.7	-	-	6.2	7.3
24	7.4	7.5	7.4	7.7	-	-	6.4	7.5
Average	**6.0**	**6.2**	**5.8**	**6.5**	**3.4**	**7.5**	**5.1**	**6.0**
%Diff.		**4.3**		**11.4**		**55.1**		**15.2**

Table 9.6 *continued*

K40A sub-basin								
Set	**Evaporation**		**Rainfall**		**Parameter**		**Water use**	
	Min Yield	**Max Yield**	**Min Yield**	**Max Yield**	**Min Yield**	**Max Yield**	**Min Yield**	**Max Yield**
1	47.4	49.5	47.4	50.4	41.3	52.1	41.3	43.3
2	49.8	50.4	48.7	49.8	43.1	52.2	43.9	45.2
3	48.1	49.2	49.2	50.0	43.1	52.2	43.1	45.2
4	48.9	49.7	48.9	51.0	45.8	51.9	45.8	47.5
5	50.6	51.0	49.7	50.6	47.0	52.1	47.0	47.7
6	49.5	50.1	50.1	50.8	46.9	51.8	46.9	48.0
7	48.4	49.7	48.4	50.8	42.1	51.6	42.1	44.2
8	50.3	50.8	49.6	50.3	45.1	51.9	45.1	46.8
9	49.0	49.6	49.6	50.4	44.9	51.6	44.9	46.7
10	49.8	50.8	49.8	51.4	43.3	51.9	51.9	52.1
11	51.0	51.4	50.3	51.1	45.2	53.5	52.2	53.5
12	50.2	50.4	50.4	51.0	45.2	52	52.0	52.2
13	41.3	43.9	41.3	45.8	47.5	51.8	51.8	51.9
14	45.8	47.0	43.9	47.0	47.7	51.9	51.9	52.1
15	42.1	45.1	43.1	46.9	48.0	51.7	51.7	51.8
16	43.3	45.2	43.3	47.5	44.2	51.5	51.5	51.6
17	47.5	48.0	45.2	47.7	46.8	51.8	51.8	51.9
18	44.2	46.7	45.2	48.0	46.7	51.5	51.5	51.6
19	52.1	52.2	51.6	52.1	-	-	48.4	49.8
20	51.8	52.1	51.9	52.2	-	-	49.6	50.3
21	51.6	51.9	51.6	52.2	-	-	49.7	50.8
22	51.9	53.5	51.5	51.9	-	-	50.8	51.4
23	51.7	51.9	51.8	53.5	-	-	50.3	51.1
24	51.5	51.8	51.5	52.0	-	-	50.4	51.0
Average	**48.7**	**49.7**	**48.5**	**50.2**	**45.2**	**51.9**	**48.6**	**49.5**
%Diff.		**2.0**		**3.4**		**13.0**		**1.9**

Notes: *%Diff represents percentage differences between minimum (min) and maximum (maxi) average yields and is given by: {100 x (maximum average-minimum average value)/maximum average value}. Minimum and maximum values represent a range of yield VALUES when one source of uncertainty is varied, while others are fixed. A 'set' represents a number of combinations which are grouped (the shaded rows in Table 9.5 represents set 1) where one source of uncertainty is varied while others in the combinations are fixed.*

The average values of minimum and maximum yield estimates for all sets (Table 9.6) were used to compare the ranges of individual sources of uncertainty when propagated with other sources through the model. As an example, for G10B (Table 9.6), the range of achieved yields (based on averages) due to evaporation uncertainty is 58.2 * $10^6 m^3$ to 60.3 * $10^6 m^3$, with a difference of 3.4%, while the range due to rainfall uncertainty is 38.9 * $10^6 m^3$ to 70.2 * $10^6 m^3$, with a difference of 44.6%. The range due parameter uncertainty is 50.9 * $10^6 m^3$ to

68.6 * 10^6m^3, with a difference of 25.7%, while the range due to water use data uncertainty is 54.1 * 10^6m^3 to 55.9 * 10^6m^3, and a difference of 3.1%. To illustrate the differences between sources of uncertainty and sub-basins Figure 9.5 uses pie charts based on the percentage differences of the average minimum and maximum yield estimates given in Table 9.6. It has been assumed that the sum of these percentage differences represents a measure of the total uncertainty and that the individual differences represent the relative contribution of each source.

The results indicate that the major source of uncertainty is either rainfall (i.e. 59% for G10B) or parameter value estimation (i.e. 64% for K40A and 64% for U20B; Figure 9.5) depending on the sub-basin. In the three examples, evaporation and water use uncertainties are relatively small. This information is useful to both hydrologists and water resources managers and it allows concrete decisions in water resources planning to be made about future risks of using uncertain information and where efforts to reduce uncertainty should be focussed.

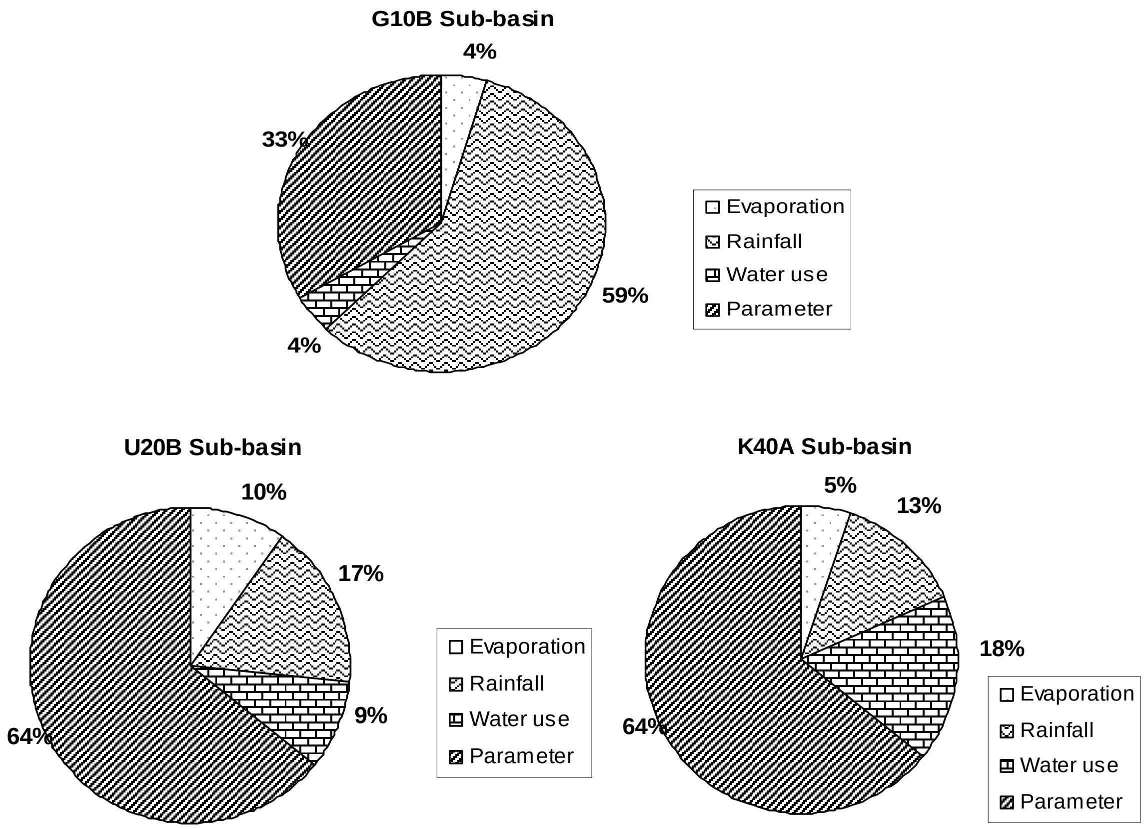


Figure 9.5 Pie charts showing combined contribution of different uncertainty sources to total output uncertainty based on the achieved yield from a hypothetical reservoir.

9.4 Discussion and observations

With respect to the assessment of the impacts of water use uncertainties on streamflows, this study presents some limited findings. The impacts vary from sub-basin to sub-basin (i.e. G10B, K40A and U20B), with impacts greater for K40A, since a relatively greater portion of this sub-basin is afforested (over 60% of the total sub-basin size). The impacts also vary when different sources of information are used in the model, given that the databases of water use in South Africa will not necessarily give the same information (e.g. WR90 versus WR2005 or WARMS). The model is designed to account for three types of water use; streamflow reduction activities (afforestation), the effects of distributed farm dams and associated abstractions and run-of-river abstractions. The uncertainty in forestry is related to a number of factors which are frequently either unknown or their effects poorly understood. While there are parameters of the model that can have their values modified to simulate forestry impacts, establishing appropriate values is far from straightforward. Apart from simply the afforested area, the age and tree density, the location of the forestry within the sub-basin (slopes, hilltops or riparian areas), the tree type and the effective rooting depth are all factors that could affect water consumption. In addition, given that forestry areas may be mapped from satellite images, often narrow unforested areas within blocks of plantations will be included, which tends to overestimate afforested areas. The streamflow reductions due to afforestation are important components of water use licencing in South Africa but detailed analyses are beyond the scope of the present study.

There are also inherent modelling uncertainties associated with the simple reservoir water balance approach used to assess the impacts of farm dams within the model structure. While spatial coverages of small farm dams information are available and additional information on abstraction from farm dams is available from WARMS, neither of these provide the required information in a suitable format for the model. Additional information includes catchment areas, volumes and surface areas, which is available from the WR90 and WR2005 databases, but the information on capacity-area relationships is usually not available and some assumptions have to be made. It was therefore relatively difficult to quantify the farm dam parameters of the model from existing information, in spite of attempts made for U20B sub-basin. A further source of uncertainty is associated with the use of a monthly time step and the fact that run-of-river irrigation abstractions are assumed to be evenly distributed throughout the month. Moreover, the effects of abstracting water for irrigation from either small farm dams or directly from streamflows may be ill-defined. In general, it can be concluded that the uncertainty in water use is associated with the inability to accurately define the present day water uses within sub-basins and representing these in an integrated way using model parameters. The information on 'real' water use in many parts of the country is lacking and inaccurate, and constrains the successful implementation of water availability estimation tools. While the WARMS database represents a serious attempt to address this issue, it is apparent that limitations exist in terms of the willingness and ability of existing water users to supply accurate information.

With respect to the assessment of a collective contribution of different uncertainty sources, the results of this part of the study suggest that while input climate data (mainly rainfall) always contributes substantially to total uncertainty, there may be many situations where parameter uncertainty dominates. G10B and K40A represent examples where high spatial rainfall variability occurs and the lack of adequate observations contributes to the uncertainty in climate input data. In G10B, an area with steep topography, rainfall uncertainty dominates, because orographic effects play a dominant role in the spatial rainfall variability. In some instances (e.g. K40A and U20B), the dominant source of uncertainty is in the quantification of model parameters. The uncertainty in the parameter estimates is made up of uncertainty in the physical property data, as well as in the estimation equations themselves. Part of this problem lies in the scale differences between the physical property data and the model. However, it must be accepted that the methods used in this study to quantify the uncertainty ranges require further development. Some of the differences in the contributions of parameter uncertainty can be attributed to the lack of a consistent approach to interpreting the physical property data. While Kapangaziwiri and Hughes (2008) suggest that the methods used to generate the 'best' estimates of parameters appear to be successful, methods to generate uncertainty bounds have yet to be properly developed.

Overall, the results show no evidence that the contribution of different uncertainty sources is additive but that there are variations on how they contribute to total output uncertainty in different sub-basins. This is partly because the methodology used to estimate model parameters is independent of the model input data. However, an important observation is that a collective assessment of uncertainty is more informative than individual assessments of the contribution of uncertainty sources to total modelling uncertainty. This kind of analysis gives a clear picture of the effects of uncertainty sources on total model uncertainty, which was not possible in the initial experiments when individual sources of uncertainties were considered separately.

Ultimately, this is a limited illustration of how uncertainty sources can be combined in a water resource estimation process and a more consistent strategy must be developed. Moreover, simulating ensembles with ranges of uncertainty for each source illustrates that care is needed to generate useful results and that MAR as well as yields can be very different. These differences could be very confusing to a practical water resources manager and the information should be translated into a format that can be readily interpreted by decision makers. One possibility would be to develop expressions of confidence in the various yield estimates resulting from the ensembles. This has not been possible in this study because the methods of uncertainty analysis used here still require further development. Specifically, additional components are required that can be used to evaluate the degree to which any ensemble can be considered behavioural. One approach would be to further develop the methods of estimating the inputs (climate data and parameters) such that some measure of the probability of each possible input is quantified. An alternative approach has already been suggested by Yadav *et al.* (2007) and essentially involves quantifying regional measures of hydrological response that can be used to evaluate the likelihood of any of the simulated ensembles.

10. CONCLUSIONS AND RECOMMENDATIONS

10.1 Introduction

The purpose of this chapter is to summarise the main findings of the study and relate them to the study objectives. In addition, it also highlights some important recommendations for further research work. The context of the study is the relatively long history of the practical application of hydrological models in southern Africa (specifically, South Africa), but virtually no formal recognition of the uncertainties involved. In recent years there has been an increasing recognition of the need to account and incorporating estimation of uncertainty into water resources decision making. The international literature provides many examples of different possible approaches to achieving this objective. However, it is not clear how these can be applied in a South Africa context, given the type of model in common use, the data constraints and the willingness of practising hydrologists to adopt new methods.

While formal uncertainty analysis has not formed part of hydrological modelling practice in South Africa, the limitations of the model results have been recognised. Model applications are often hampered by:

- A high degree of spatial and temporal variation in hydro-meteorological data.
- A lack of adequately long or continuous time series records of rainfall, evaporation and streamflow data.
- Uncertainty in parameter estimation methods, mainly for ungauged basins.
- Limitations of the model structure.
- A lack of quantitative understanding of land cover/use changes, and both spatial and temporal variations in water utilisation data.

It is therefore surprising that, while many of the impacts are understood, there have been no attempts to incorporate some form of uncertainty assessments into standard modelling practice. This study therefore represents a first step towards employing uncertainty principles in water resources assessment studies. The study evaluated the main sources of uncertainty that are common in water resources estimation within a South African context and presents some generic guidelines on the identification of (Chapter 4), quantification of, and potential options for reducing (Chapters 5-9) the different sources of uncertainty in water resources estimation within a data scarce region using a hydrological model developed and widely used in the region.

10.2 Conclusions and recommendations

The main findings of this study are that uncertainty in water resources estimation depend upon the quality and availability of data, the human and technical resources available, the models being developed and used and the management decisions being made. The level of uncertainty and how it propagates through rainfall-runoff models therefore tends to vary from one region to another. One of the critical components of this study was to identify the potential sources of uncertainty within a southern African context, given that this would allow an evaluation of the deficiencies in climate data, parameter estimation methods as well as the model structure. This study proposed a hierarchy of sources of uncertainty associated with the type of modelling tools (including the Pitman hydrological model) commonly used in the region. This hierarchy was used as a guideline to identify the different types of uncertainty in each level of a water resources decision making system, the propagation of these uncertainties and how they will affect the risks involved in water resources decision making. Previous water resources planning decisions in South Africa have been taken without considering the uncertainty in quantifying both natural and present day water resources, despite the fact that model estimates have always been known to be imprecise. The risk associated with using such information can be substantial.

While it has long been recognised that hydrological models should not be more complicated than specific applications require, recent research has consistently reiterated the need to balance model complexity with the quality and resolution of the information available to quantify the model inputs (Perrin *et al*., 2001). High resolution input data are of little use when the models themselves are inherently uncertain, as is always the case with hydrological models (Beven 2000b). The present study and many other researchers (e.g. Blöschl and Sivalapan, 1995) have argued for improvements in field observations at scales that match that of the models being used and the improvements in collecting hydro-climatic data as a key source of information for reducing uncertainties in hydrological modelling. Indeed, estimates of model output uncertainties will be unreliable if the assumptions upon which they are based are not appropriate. In principal, this implies detailed analyses of the climate and basin physical properties and the careful inspection of the assumptions that are introduced in the modelling process. In practice, however, this assumes an in-depth analysis and expertise, including a detailed knowledge of the model structure, that is, rarely, if ever available to water resources managers (Blöschl, 2001).

The following broad conclusions and recommendations have been drawn from the study:

i. While water resources managers typically rely on scattered networks of rain, evaporation and stream gauges to assess how much water is available in a sub-basin, this study showed that substantial uncertainties exist in using such information. The study demonstrated that the dominant source of uncertainty in simulating natural hydrology is highly variable, depending on the degree of spatial variation of rainfall and evaporation from different climatic regions in South Africa. While the effects of rainfall variability are greater for daily than monthly estimates, aggregating daily to monthly values resulted in improved spatial rainfall estimates than directly using monthly values within the model. The resulting uncertainties in simulated streamflows varied greatly between semi-arid and humid regions due to their differences in rainfall-runoff response relationships. Most importantly, substantial uncertainties in rainfall estimates were observed mainly in mountainous areas (especially in elevated parts) where observation networks are too scarce to capture high spatial rainfall variability. A rainfall frequency curve based correction procedure was developed and used in this study to generate long stationary spatial rainfall estimates using both gauge and satellite based datasets. The approach ensures that data from two different sources are consistent in their frequency characteristics, but there remain some unresolved issues with respect to the successful application of satellite based rainfall estimates in some parts of the country. The differential effects of using different evaporation inputs varied between the two main climatic regions in South Africa (smaller effects in the winter rainfall region and greater effects in the summer rainfall region). However, the important conclusion is that, while it may appear to be an attractive option to include time series variations of potential evapotranspiration demand, these may be incompatible with the model structure and create further modelling uncertainty. Another important aspect is that the observed streamflows used to validate model results often contain inaccuracies in gauging both low and high flows and few of the available records can be assumed to be completely natural. Differential developmental effects may also occur between data periods and thus the current observed flow data in South Africa should not be entirely relied upon without some form of adjustment or correction (naturalisation).

ii. It is recommended therefore that hydro-climatic (rainfall, evaporation and streamflow) data uncertainties be reduced by more data collection through improvements in the measurement techniques (such as maintaining the existing network densities), further use of new satellite data products and making better use of the existing data through pre-processing methods. However, it is important to recognise that from a practical point of view, uncertainty reduction should focus on those interventions that have the potential to produce relatively rapid, cost-effective and measurable results. In a southern African context, the focus is therefore unlikely to be on introducing new gauge (rainfall, evaporation and stream flow) networks. These networks can be expensive to establish and maintain and it has proved difficult in the past to convince governments in southern African countries of the importance of such improvements. There is a perception that readily available satellite data products (which capture the spatial distribution of rainfall) can offer better estimates of rainfall. However, this study concludes that historical raingauge stations are not replaceable and the two sources should be used conjunctively, together with appropriate correction procedures to adjust the frequency characteristics of satellite data to be consistent with historical gauge data (Hughes, 2006 a, b; Wilk *et al*., 2006).

iii. There has been a general shift in recent research efforts away from using calibration methods to estimate model parameters to approaches that are calibration-free in order to reduce predictive uncertainty in ungauged basins. This is a result of the challenges in finding optimal model parameters in gauged basins and subsequently transferring them through regionalisation methods (such as regression approaches) to ungauged basins. The major problems are that many of the existing streamflow data are of poor quality and that information on water abstractions is often not available. Uncertainty also exists in the regionalisation methods themselves. This precludes the proper validation of hydrological models for application in ungauged basins. The uncertainty of model output is of concern in sub-basins with limited historical data and when rainfall-runoff models are applied to conditions outside the range for which they were calibrated and verified (Yu *et al*., 2001). Despite this, many of the existing approaches for deriving acceptable parameter sets with uncertainty rely upon information from observed flow data (Gupta *et al*., 1998; Beven, 2006b).

In light of the above, the present study made use of *a priori* parameter estimation methods (Kapangaziwiri and Hughes, 2008) that are applied independently of observed flows and climate data, to estimate the Pitman model parameters. In spite of being seen as an improvement to parameter regionalisation and mapping methods (Midgley *et al*., 1994; Mazvimavi, 2003), the approach is not without shortcomings. One of the problems is related to the identification of parameter ranges or bounds that are realistic from an uncertainty point of view. The parameter uncertainty bounds used in this study have been set using rather subjective interpretations of the uncertainty in physical property data, such as soil depth, texture, slope ranges and geological characteristics from AGIS (2007) information. The parameter uncertainty assessments presented in this study have to be seen in the light of this subjectivity and the fact that no probability statements can be made about the upper and lower bounds of the simulation (i.e. only bands are presented with no confidence intervals). While this is clearly not a satisfactory long-term solution, it represents a first step towards incorporating parameter uncertainty in South Africa.

A parameter sensitivity analysis demonstrated that the most important model parameters vary from one region to another depending on climate and physical characteristics. The contribution of uncertainty in individual parameter values to the output uncertainty is therefore, similarly variable within the region. Parameter sensitivity analysis is useful for identifying parameter interdependencies in specific sub-basins, and therefore which parameters should be focussed on in an effort to reduce prediction uncertainty. These observations about regional variations could contribute to the future development of modelling procedures for use in ungauged basins. The main challenge of using physically-based parameter estimation methods is the relevance of the original data sources with respect to the model structure and the physical meaning of the parameter values. Even if alternative data sources (such as remote sensing data) for estimating basin physical property data are used in the future, similar problems will be experienced. The alternative approach is to combine the *a priori* parameter estimates and the regionalised key signatures of basin behaviour to constrain model parameters in ungauged basins (Yadav *et al.*, 2007).

iv. This study recommends that there is a need to further establish generalized regional parameter ranges and establish the more identifiable and uncertain parameters. Definitive and non-subjective procedures for establishing parameter bounds for uncertainty estimation within the southern Africa region are yet to be established and will depend upon the amount and type of information that is available. If a high level of confidence can be expressed in the information available on topography, soil types and depths, vegetation cover and hydrogeological conditions, the parameter bounds are expected to be narrow, while poor quality information will clearly lead to a wide range of possible parameter values. If observed data are available in a nearby sub-basin which is hydrologically similar (based on similar basin properties and climate), model calibration can be used to reduce the parameter bounds, otherwise regional constraints are used. It stands to reason that improving databases of spatial data and revision of the parameter estimation approaches are the most critical areas to effectively reduce parameter prediction uncertainty in data scarce areas.

v. This study used a framework for assessing the combined contribution of uncertainty sources to total modelling uncertainty. The approach is consistent with the model limitations and data available and allows direct quantitative comparison between model predictions obtained using different sources of information. The initial results from independent assessments of uncertainty sources suggest that individual sources of uncertainty contribute in different ways under different climate and sub-basin physiographic conditions and that clear statements about which source of uncertainty is likely to dominate are not generally possible. The approach to integrate uncertainties was achieved through a simple ensemble approach of model simulations using a set of realizations of rainfall, evapotranspiration input, parameters and water use data. The rainfall estimates used for the ensemble simulations were derived from raingauges (i.e. original and corrected records). The potential evapotranspiration estimates (mean and time series values) were derived from pan measurements, while additional time series were perturbed on the basis of temperature data. The uncertainty in water use data was also incorporated but mainly considering uncertainty in irrigation and afforestation demands. The model parameters were perturbed within their physical bounds using the parameter estimation approach of Kapangaziwiri and Hughes (2008) to create combined input-parameter-water use ensembles. Evaluating the contribution of different sources of uncertainty to total model prediction uncertainty is important for understanding which is the greatest source of uncertainty and therefore where to direct future efforts to reduce uncertainty. The results from integrating all the sources of uncertainties showed that parameter uncertainty is likely to dominate in most situations. However, in some parts of the country, especially those with complex topography, rainfall uncertainty can be equally dominant, while the contribution of potential evaporation and water use data uncertainty was relatively small. Regional differences were apparent in the results of the uncertainty analysis and an improved understanding of the classification of basin physical properties and climate is a prerequisite to evaluate uncertainty using the methods presented here.

vi. Many efforts in developing tools to evaluate the total contribution of uncertainty sources in recent studies (e.g. Ajami *et al*., 2007) have been statistical or data-driven approaches, which might be difficult to employ in data scarce areas. While the approaches used in this study to quantify uncertainty are able to define ranges or envelopes of uncertainty, defining uncertainty in more probabilistic terms is currently very difficult to achieve (Montanari, 2007). The study only provides a basis for further investigations into the use of more widely used probability (Yadav *et al*., 2007) and fuzzy (Yu and Yang, 2000; Freer *et al*., 2004) uncertainty analysis methods. However, Hall and Anderson (2002) postulated that much human reasoning about hydrological systems is *possibilistic* rather than strictly probabilistic. In such instances, it is reasoned whether a given scenario will happen, without necessarily attaching probabilities to the likelihood of it happening, particularly in situations of very scarce information. Water resources managers do not necessarily require the best uncertainty estimation method, but guidelines that are clear and appropriately related to the risks involved in the decision making process. This study therefore recommends that the uncertainties in water resources estimation must be acknowledged, quantified and minimised in both research and practice and properly communicated to water managers and the public using simple but informative approaches.

vii. While in a broader sense the focus of the study was on southern Africa, the analyses were based only on South African examples. It is therefore important to extend similar studies to other countries within the region. These would contribute to a better understanding of how uncertainties vary from region to region, from country to country or even from data provider to data provider. However, sources of data are not always easy to access and therefore improvements in the effective management and sharing of data are necessity for regional modelling studies.

viii. This study recommends further work to assess model structure uncertainty, possibly through development of flexible conceptual models or to consider top-down approaches to modelling. The modelling approach presented in this study was based on a fixed model structure and a subsequent estimation of parameters through an *a priori* approach using physical basin properties. The approach is called a bottom-up, or reductionist approach, since there is a spatially explicit representation of the model structure based on knowledge of the underlying physics (Ebel and Logue, 2006), basin physical properties and climate inputs. Such an approach results in a very complex model structure (Pitman 1973, Hughes, 2004b), making it difficult to understand the meaning of model output and evaluate the uncertainty associated with using such a complex model structure due to many interactions of uncertainty sources (Beven, 1993). An alternative to the bottom-up approach has been suggested (Young, 1998) based on ideas for a top-down analysis framework by

Klemeš (1986). The idea is that the parameters of the model structure should relate to the dominant basin characteristics controlling its responses, rather than based on an *a priori* estimation approach or model calibration process. Such an approach has been tested by Yadav *et al.* (2007), and the success of its application in southern Africa region will also depend on the availability of basin response information which is sadly lacking.

If the treatment of uncertainty is to be advanced within the southern Africa region, an appropriate conceptual structure and practical methods are required for handling uncertainty. These issues must be addressed if an important aim of developing uncertainty analyses tools is to encourage more widespread criticism of data and hydrological models in the region, which will create avenues for further research. In addition, efforts to reduce predictive uncertainty such as improvements in spatial databases, and quantifying the spatial and temporal impacts of artificial influences in basins are needed. However, in practice there will always be uncertainty even if efforts are made to reduce the uncertainty and therefore there is a need for parallel approaches to incorporate uncertainty analyses into estimates and reduce the uncertainty. Unless the input information base is improved, neither the development of new models, nor improving the application methodology of existing models is likely to improve the situation. The choice seems to lie therefore between modifying existing techniques to make better use of existing data and collecting data to support the existing techniques.

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APPENDICES

Appendix 1.1 A list of raingauges covering different time periods for each sub-basin.

(i)

Sub-basins	Station name	Start year	End year	No. of years
A23A	0513 894W	1979	2000	21
	0514 023W	1933	1953	20
	0513 862W	1979	1998	19
	0513 827A	1984	1999	15
	0513 827W	1904	2000	96
	0513 795W	1981	2000	19
	0513 643W	9106	1986	80
	0513 611W	1966	2000	34
	0513 550W	1949	2000	51
	0513 521W	1979	1992	13
	0513 584W	1977	1991	14
	0513 524W	1909	1978	69
	0513 556W	1978	2000	22
	0513 676W	1909	1924	15
	0513 677W	1913	1978	65
	0513 738W	1906	1943	37
	0513 558W	1982	2000	18
	0513 742W	1979	2000	21
	0513 743W	1920	1959	39
	0513 529W	1915	1948	33
	0513 349W	1921	1948	27
	0513 528W	1974	2000	26
	0513 496W	1914	1968	54
	0513 466A	1979	2000	21
	0513 465A	1924	1973	49
	0513 465W	1960	2000	40
	0513 464W	1906	1962	56
	0513 494A	1905	1982	77
	0513 494W	1905	1959	54
C12D	0440637W	1934	1977	43
	0477629W	1925	1953	28
	0477772W	1906	2000	94
	0478029W	1923	1952	29
	0441215W	1913	1955	42
	0478330W	1984	2000	16
	0478360W	1912	1975	63
	0478510W	1976	1990	14
	0478175W	1934	1951	17

(ii)

Sub-basins	Station name	Start year	End year	No. of years
C83A	0331 704W	1977	1996	19
	0331 616W	1927	1943	16
	0332 017W	1925	1940	15
	0331 828W	1940	2000	60
	0331 740W	1913	1982	69
	0331 893W	1917	1956	39
	0332 206W	1924	1966	42
	0332 201W	1919	1957	38
	0331 658W	1913	1949	36
C83B	0331 467W	1974	2000	26
	0331 470W	1977	1994	17
	0331 474W	1927	2000	73
	0331 590W	1980	2000	20
C83C	0367 506W	1977	1996	19
	0367 417W	1981	1995	14
	0367 597W	1925	1949	24
	0367 600W	1925	1949	24
	0331 423W	1977	1993	16
	0331 455W	1933	1996	63
	0331 607W	1977	2000	23
	0331 520A	1948	1991	43
	0331 520W	1948	1983	35
	0331 521W	1955	1990	35
	0331 672W	1977	1994	17
	0331 432W	1921	1945	24
	0331 402W	1977	2000	23
	0331 375W	1919	1964	45
	0331 436W	1905	1938	33
	0331 524W	1904	1931	27
	0331 554W	1922	2000	78
	0331 585AW	1980	2000	20
	0331 794W	1925	1977	52
	0331 883W	1905	1949	44
U20B	0268806A	1969	1989	20
	0268891W	1967	1987	20
	0269111A	1947	1989	42
	0269114A	1929	1981	52
	0269147A	1953	1989	36
	0269295A	1932	1985	53
	0238543A	1936	1980	44
	0238662A	1972	1989	17
	0239002W	1953	2000	47
	0239184A	1903	1989	86
	0238636W	1927	1996	70

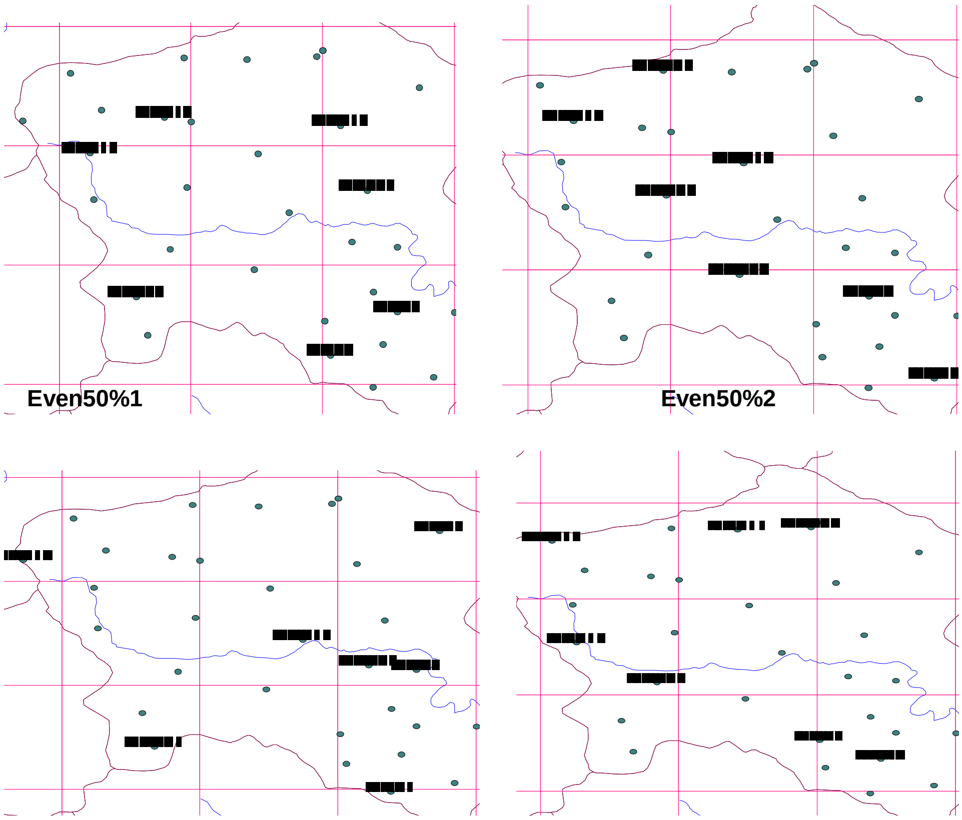
(iii)

Sub-basins	Station name	Start year	End year	No. of years
V70 A & B	0267887W	1947	1993	46
	0267862W	1959	1977	18
	0267693W	1962	2000	38
	0299900W	1927	2000	73
	0268548W	1926	1953	27
	0268614W	1919	1950	31
	0268199W	1955	2000	45
V20A	0268352A	1953	2000	47
	0268441W	1925	1985	60
	0268614W	1919	1950	31
	0268380W	1968	1989	21
K40A	0029291W	1933	1977	44
	0029294W	1924	2000	76
	0029297W	1920	1980	60
	0594539W	1914	1992	78
	0595030W	1965	2000	35
	0594596W	1910	1989	79

(iv)

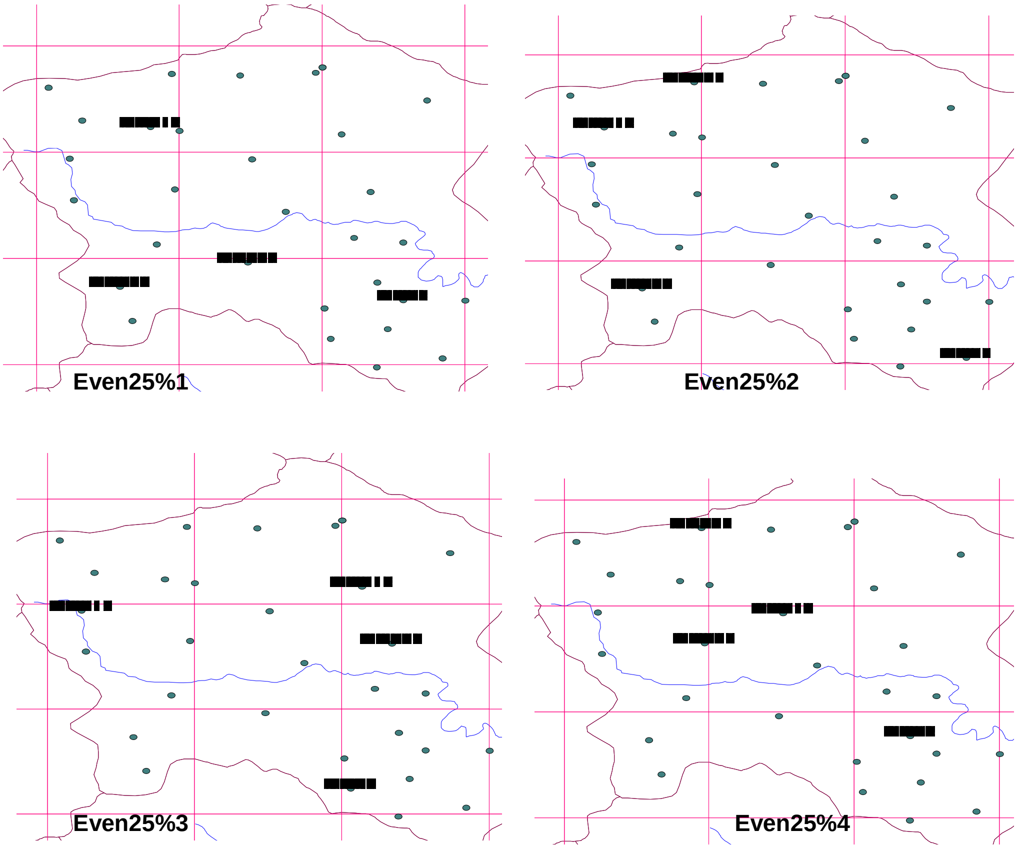
Sub-basins	Station name	Start year	End year	No. of years
X31A	0555280A	1928	1982	54
	0555280W	1961	1994	32
	0555487W	1903	1954	23
	0555483W	1957	2000	43
X31B	0555486W	1973	2000	27
	0555579W	1933	2000	67
	0555639W	1927	1960	33
	0555664W	1960	2000	40
	0555573W	1932	1995	63
	0555662W	1952	2000	48
X31C	0555631W	1942	2000	58
	0594779W	1943	2000	57
	0594539W	1914	1992	78
	0595030W	1965	2000	35
	0594596W	1910	1989	79
X31D	0555698W	1923	1941	18
	0555878W	1929	1993	64
	0556183W	1958	1999	41
	0556127A	1977	1991	14
X31E	0595025W	1972	2000	28
	0594802W	1950	2000	50
	0594828W	1963	2000	37
	0594623W	1933	1958	25
	0595110W	1905	1996	91
	0595202W	1935	1972	37
X31F	0594806W	1935	2000	65
	0594715W	1949	1994	45
	0594626A	1949	2000	51
	0594626W	1906	1977	71
X31G	0594896W	1914	1952	38
	0595210W	1931	1978	46
	0556212A	1969	1991	22

Appendix 2.1 Graphs of sub-samples of raingauges (showing spatial arrangement) used in the Bedford sub-basin analysis.

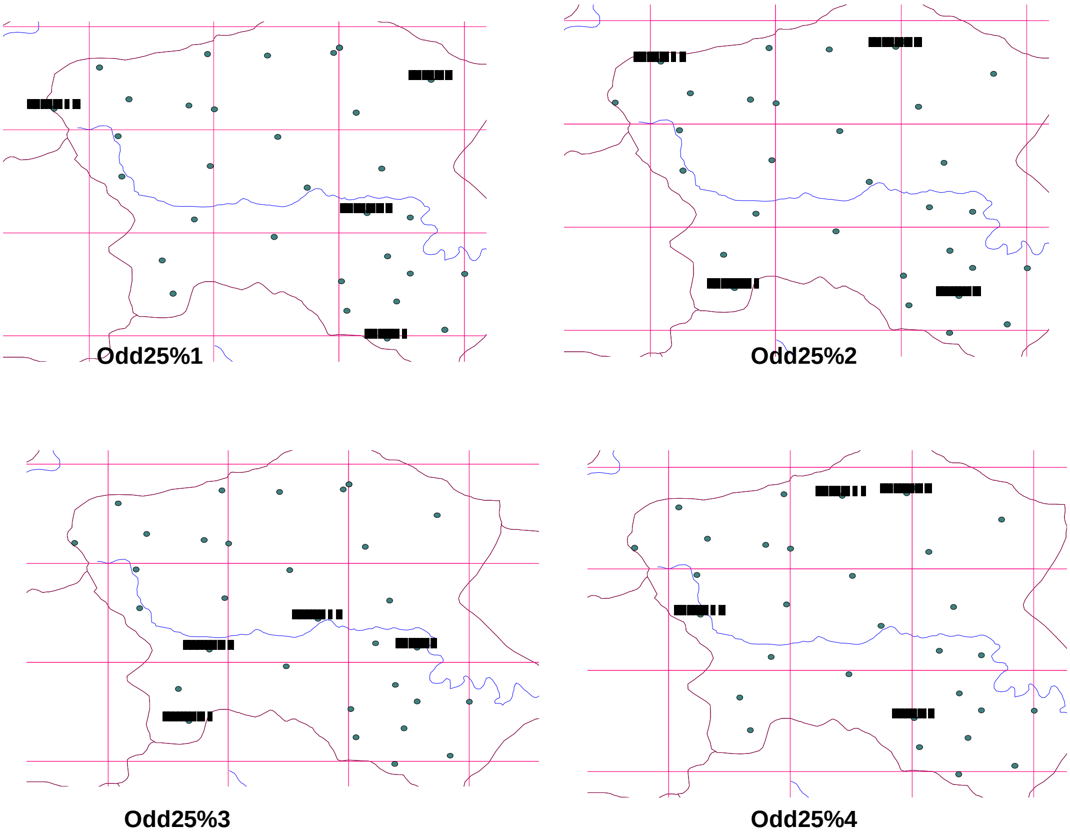


Odd50%1 **Odd50%2**

i. Distribution of 'Even50%1' and 2; and 'Odd50%1' and 2 samples with 7 gauges each.

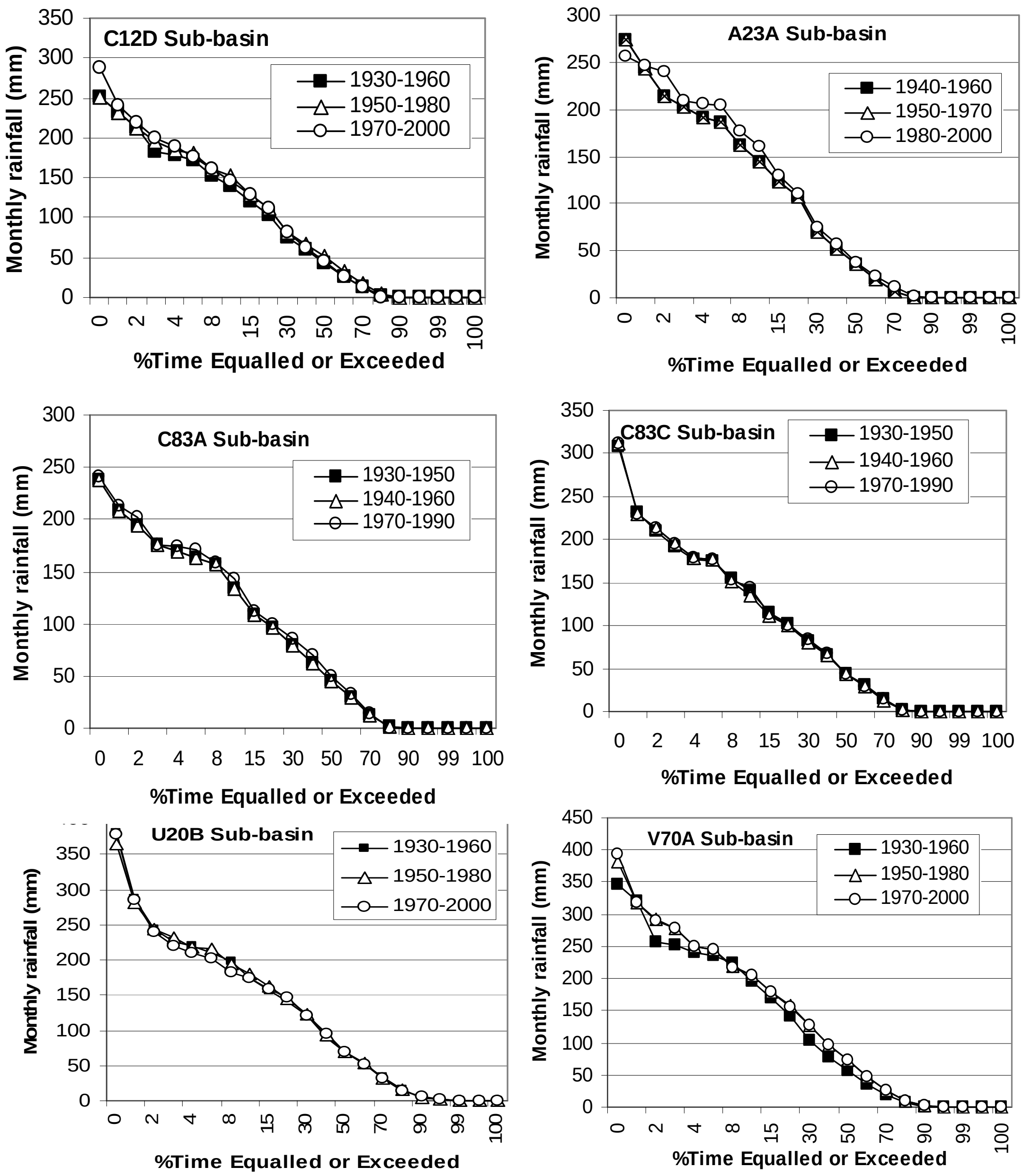


ii. Distribution of Even25% samples (1 to 4) with gauges each.

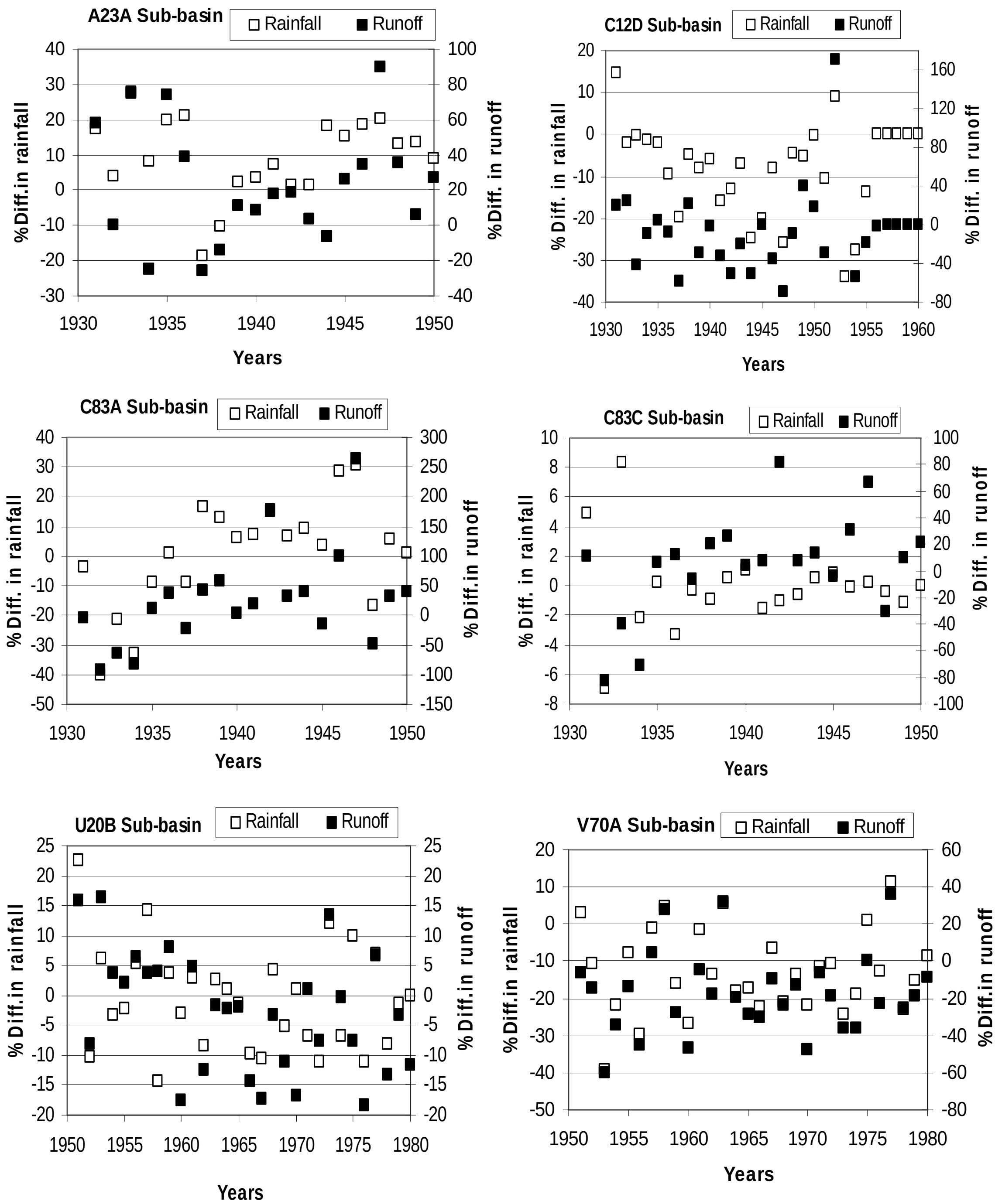


iii. Distribution of Odd25% samples (1 to 4) with gauges each.

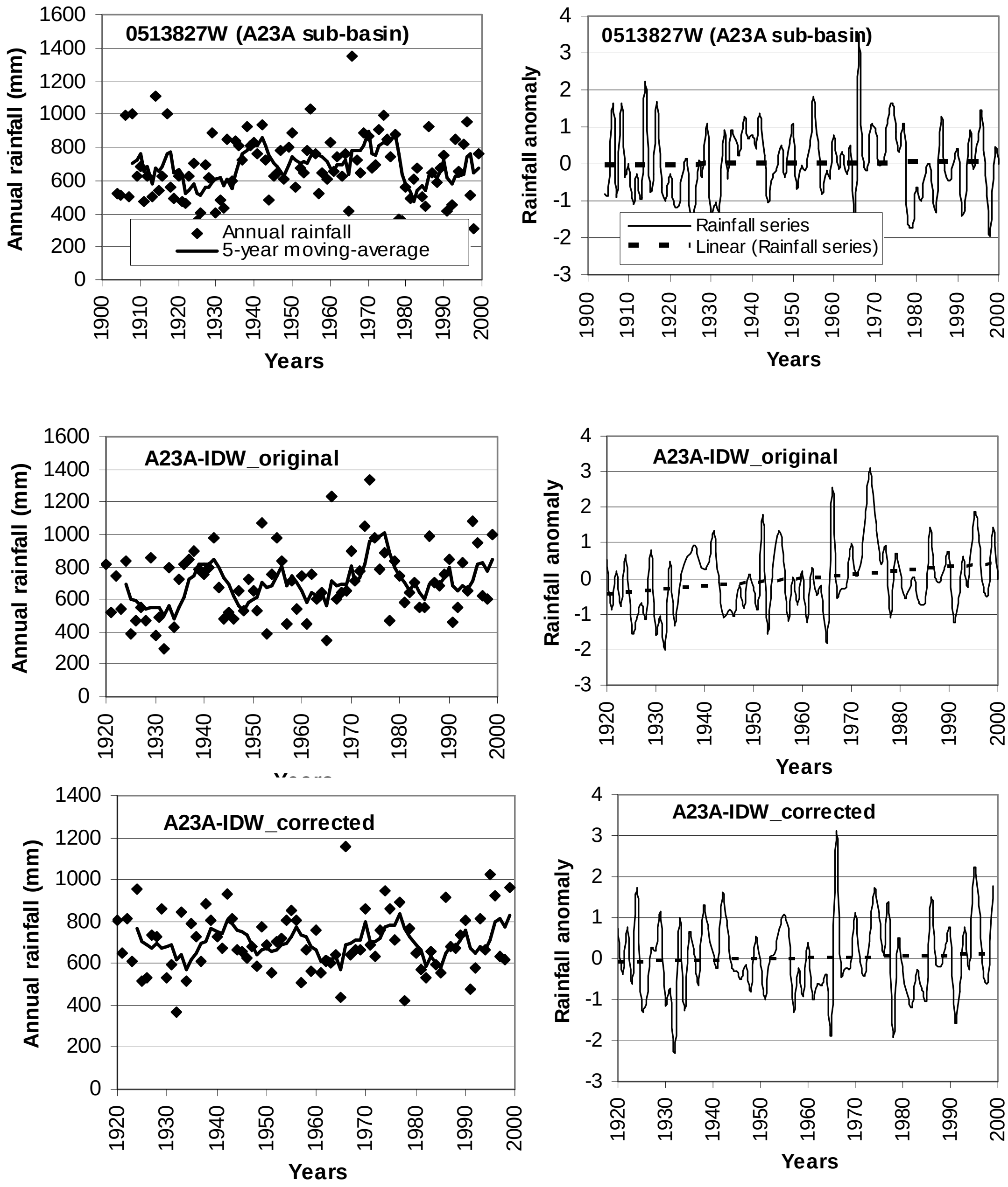
Appendix 2.2 A set of monthly rainfall exceedence frequency curves for three realizations over selected sub-basins.



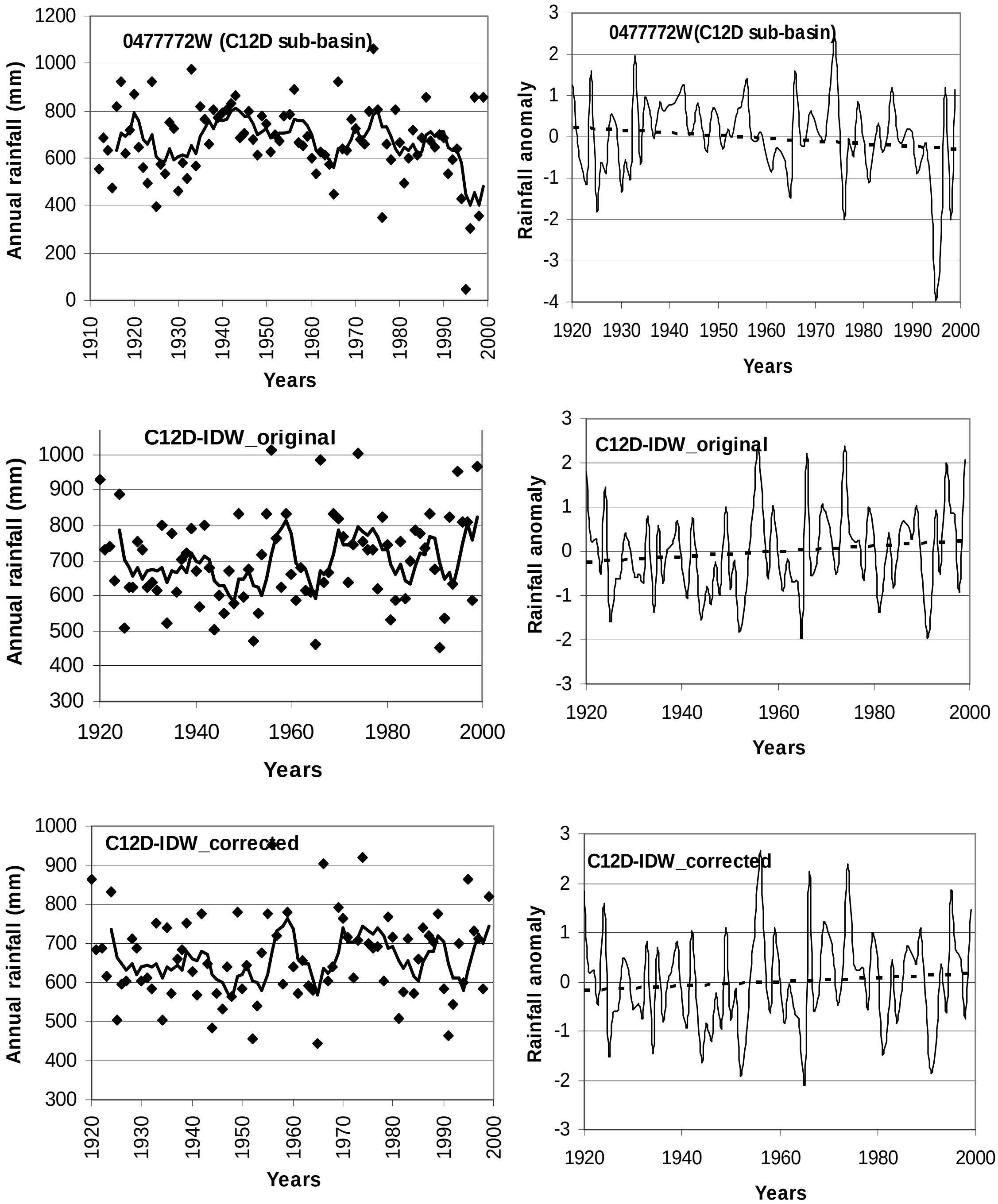
Appendix 2.3 Percentage differences (relative to the base period realization) in estimated annual rainfalls and annual runoffs for one realization.



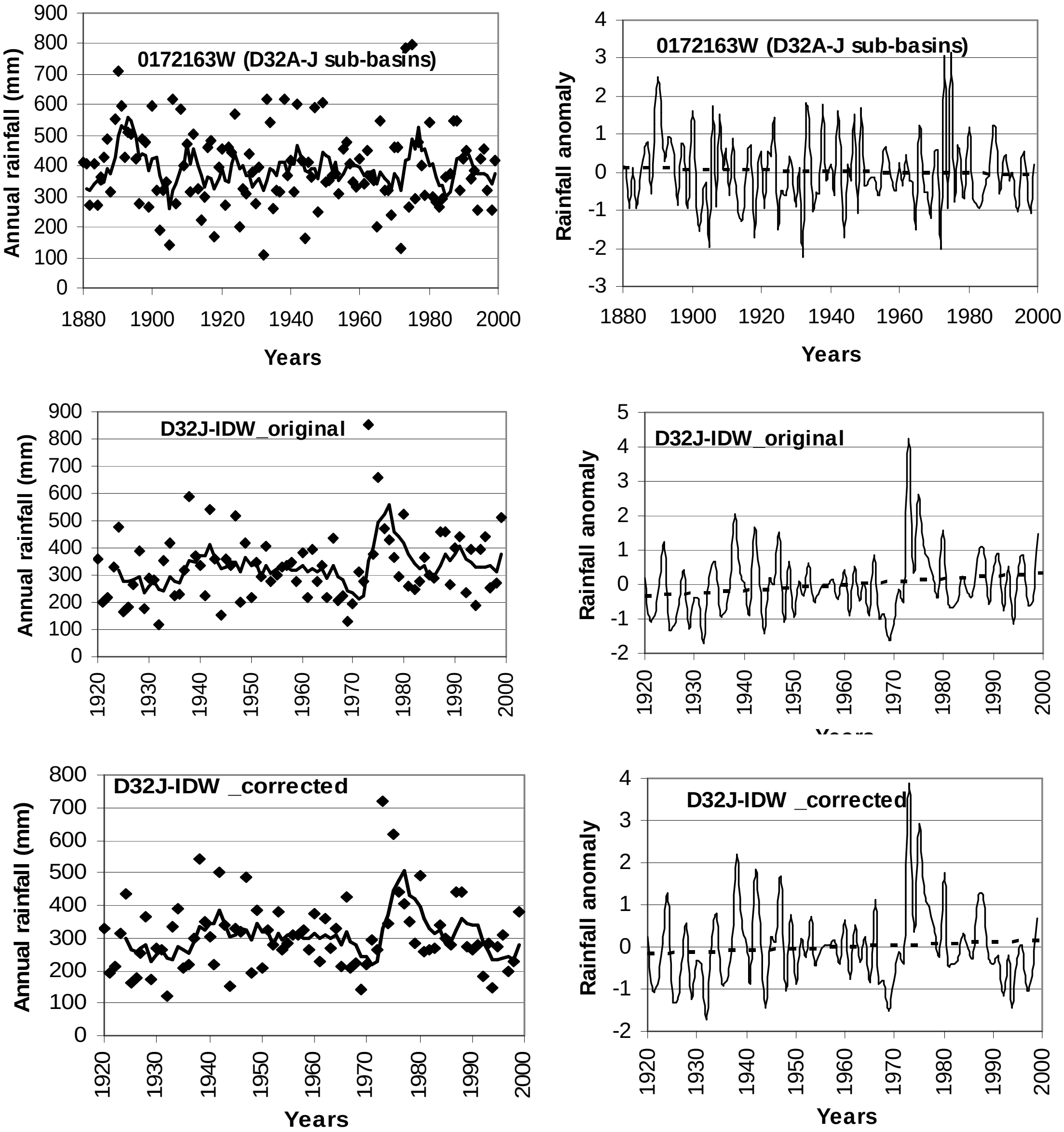
Appendix 3.1 Graphs of 5-year moving-averages and rainfall anomalies for individual raingauge, IDW original and IDW corrected spatial data analyses for different sub-basins.



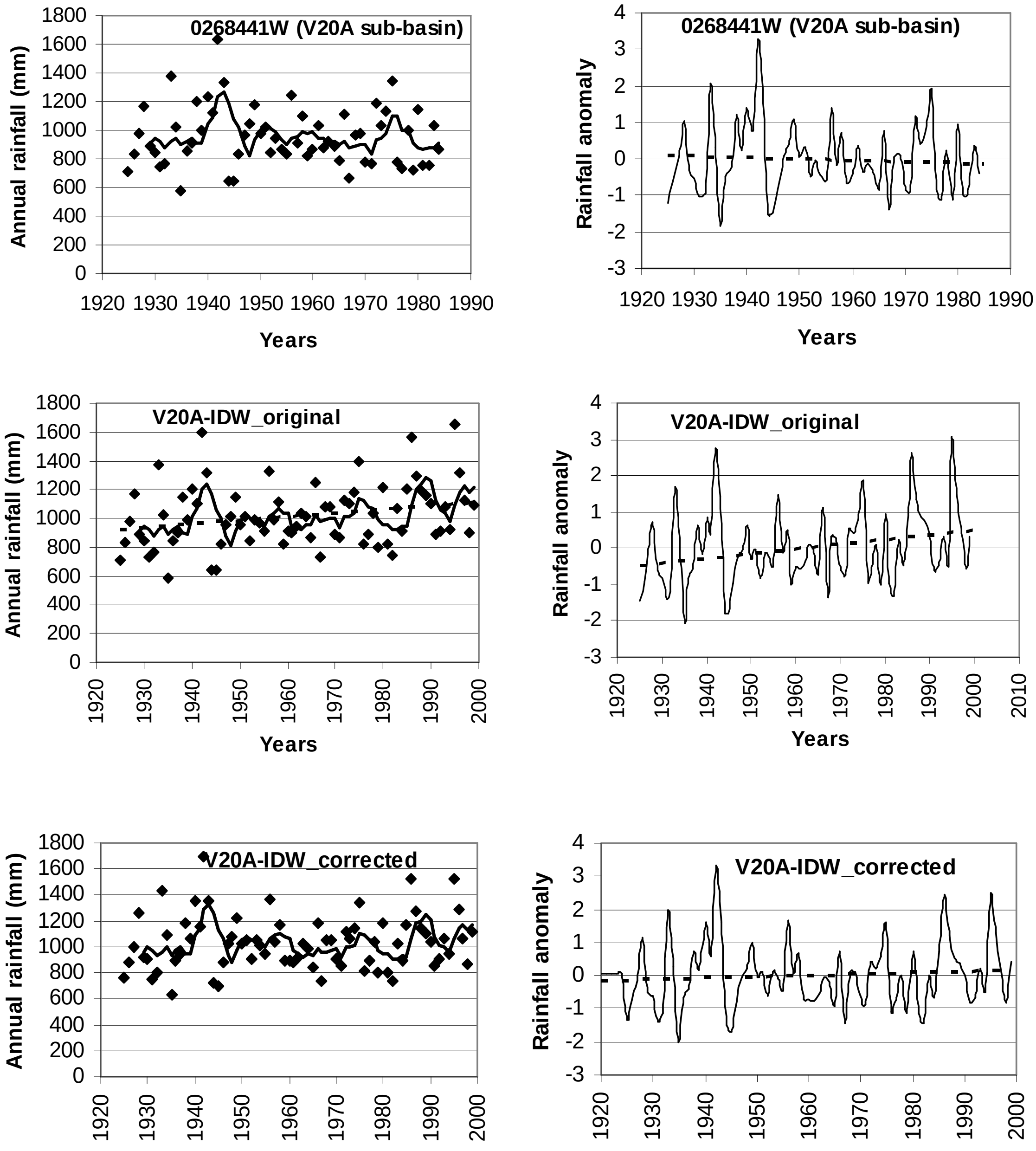
i. Summary of results for A23 sub-basin.



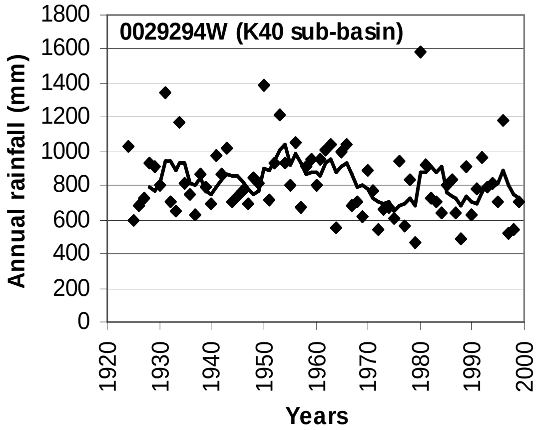
ii. Summary of results for C12D sub-basin.

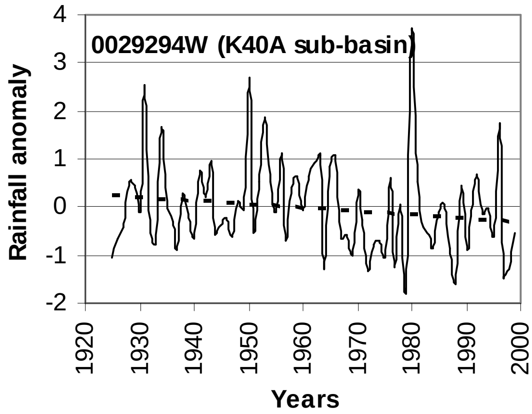


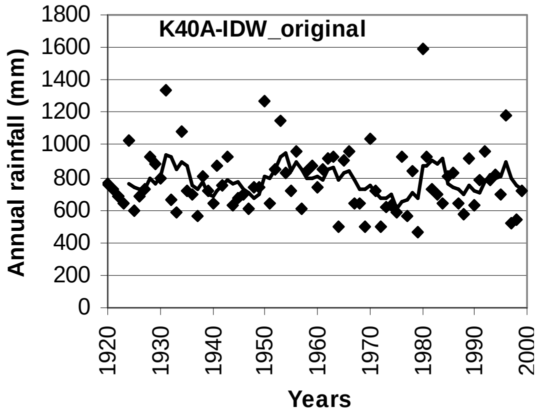
iii. Summary of results for D32J sub-basin.

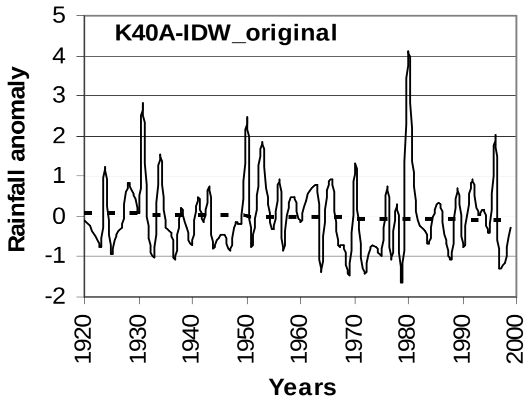


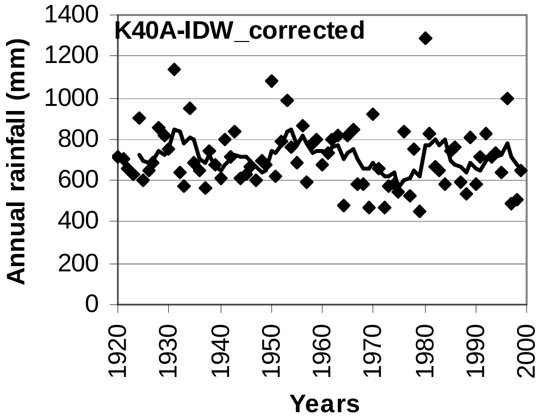
iv. Summary of results for V20A sub-basin.

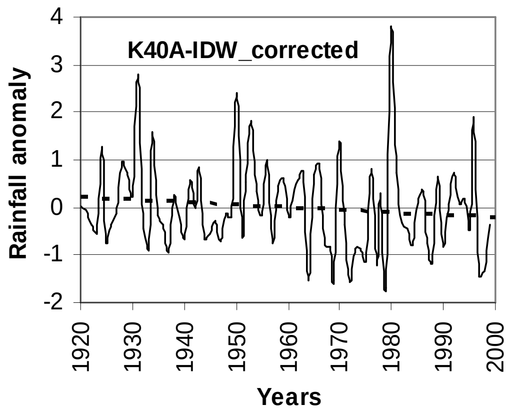




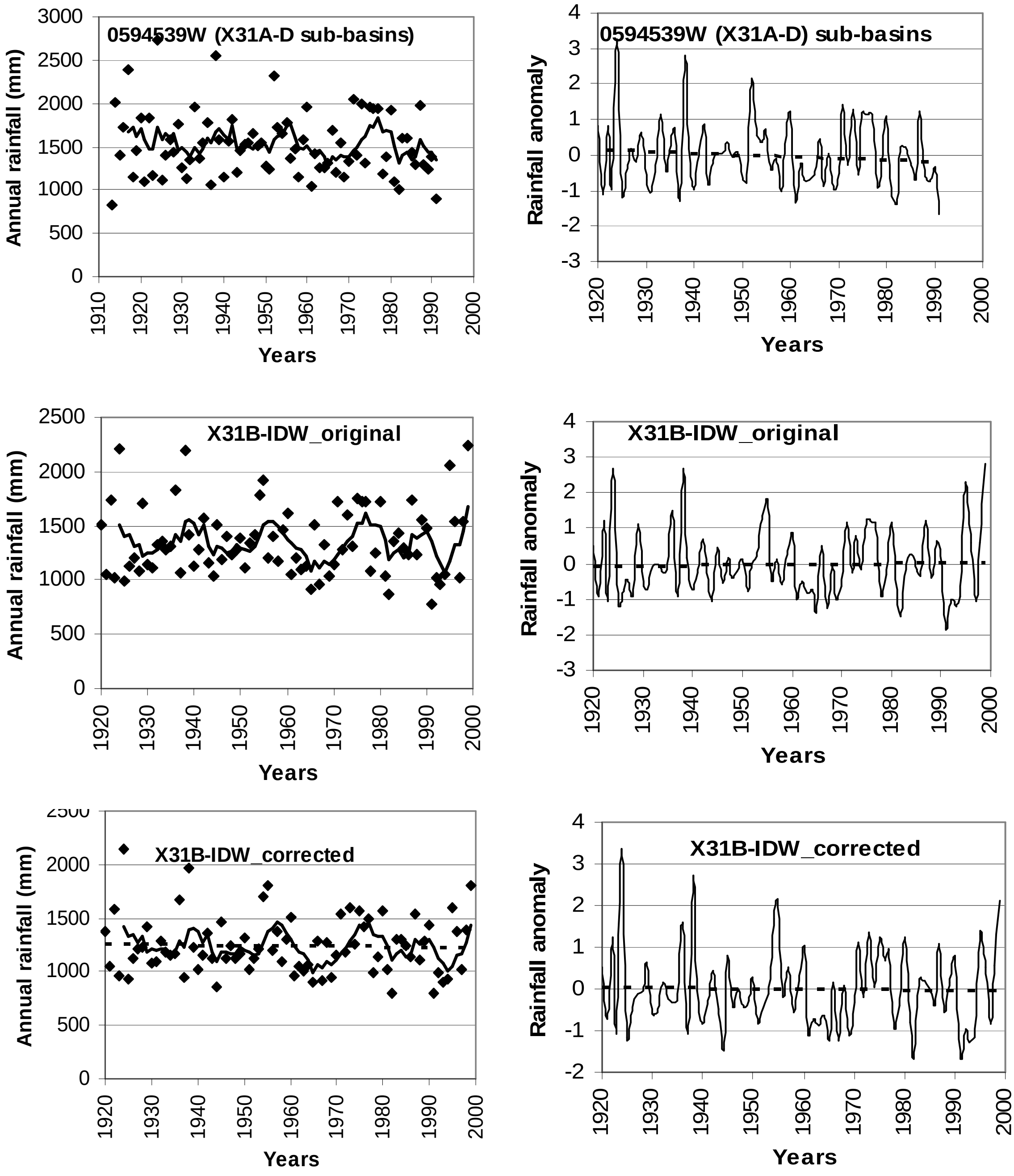






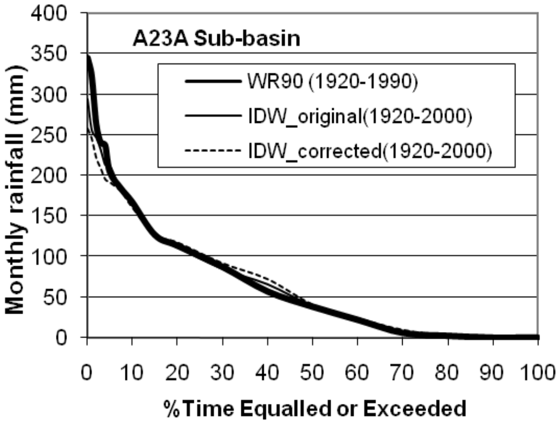


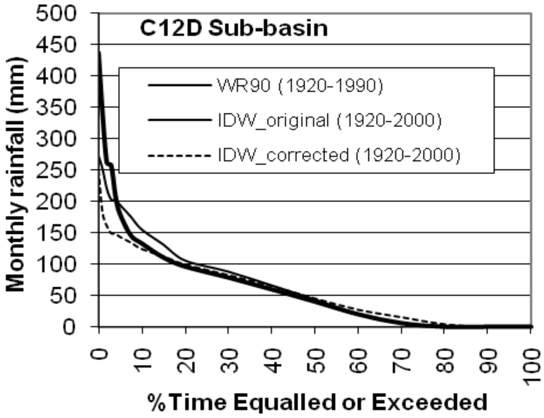
v. Summary of results for K40A sub-basin.

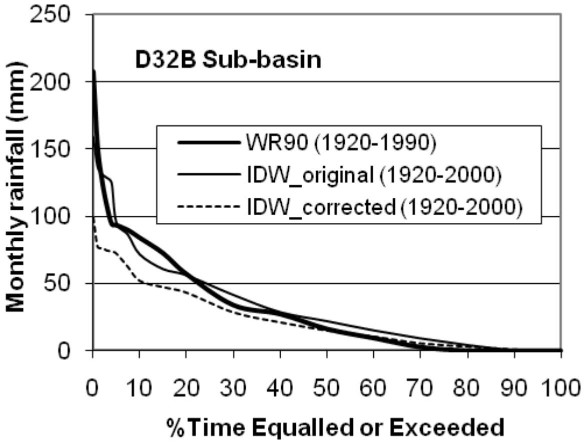


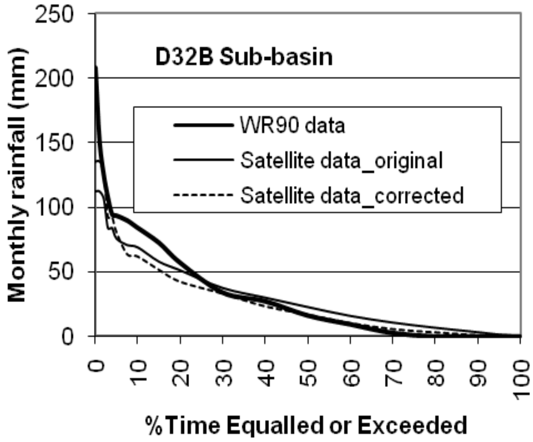
vi. Summary of results for X31B sub-basin.

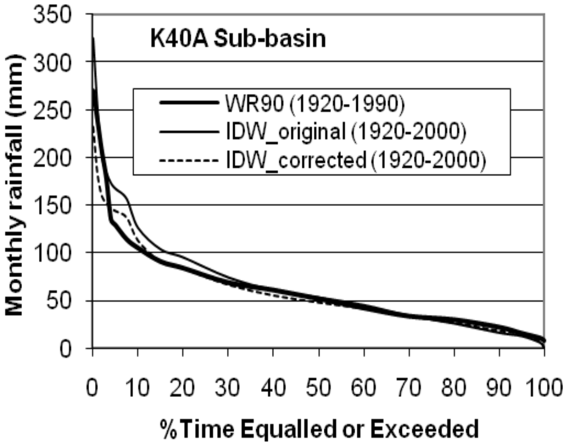
Appendix 3.2 Frequency of exceedance curves showing comparisons of spatially-averaged (both raingauge-based and satellite-based) rainfall estimates.

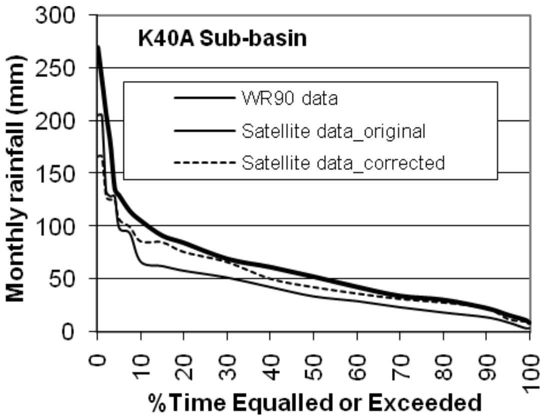


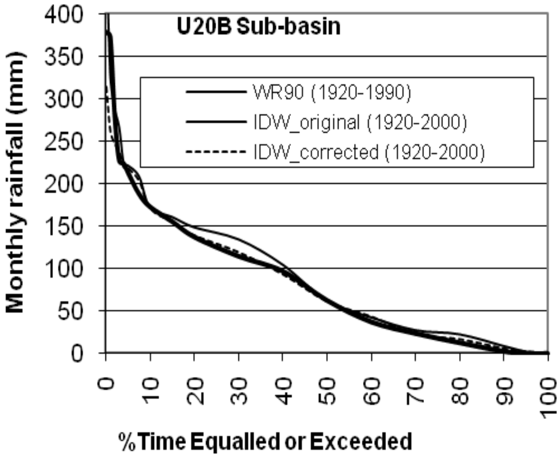


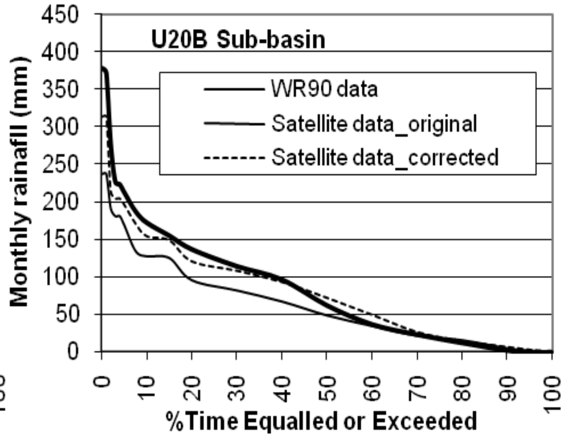


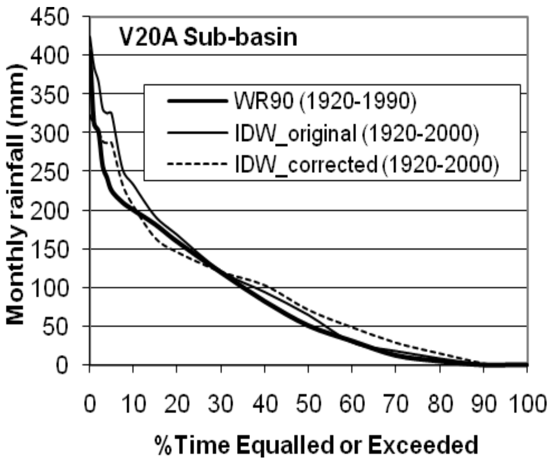


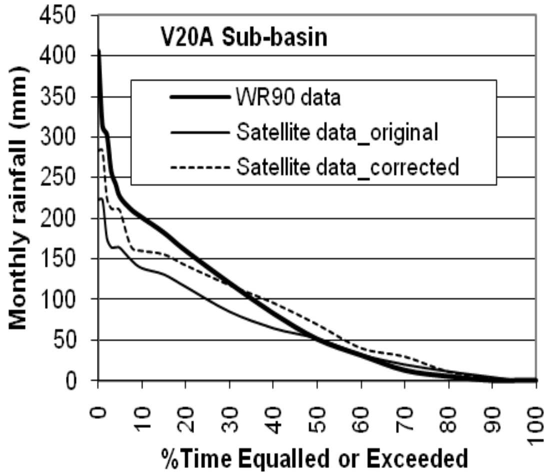


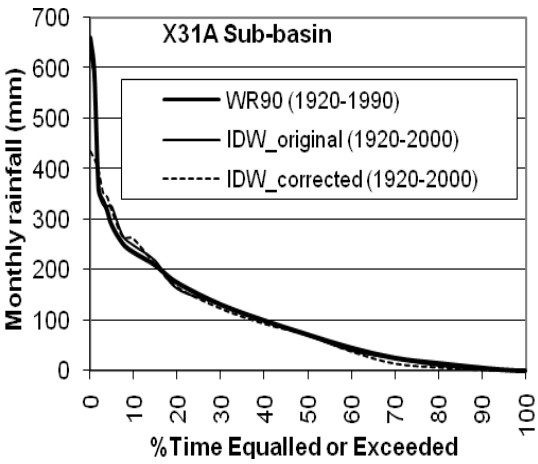


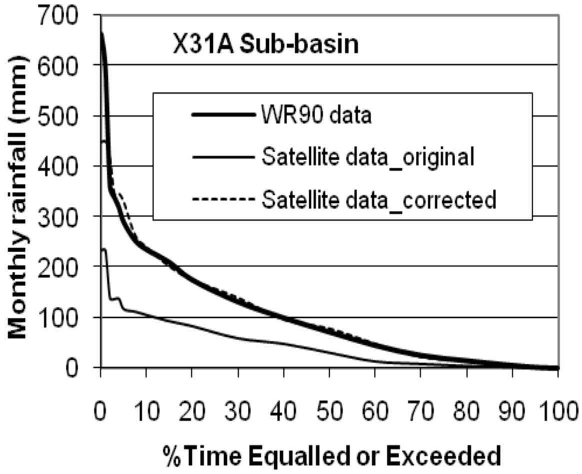

U20B Sub-basin
WR90 (1920-1990)
IDW_original (1920-2000)
IDW_corrected (1920-2000)
Monthly rainfall (mm)
%Time Equalled or Exceeded


U20B Sub-basin
WR90 data
Satellite data_original
Satellite data_corrected
Monthly rainfall (mm)
%Time Equalled or Exceeded


V20A Sub-basin
WR90 (1920-1990)
IDW_original (1920-2000)
IDW_corrected (1920-2000)
Monthly rainfall (mm)
%Time Equalled or Exceeded


V20A Sub-basin
WR90 data
Satellite data_original
Satellite data_corrected
Monthly rainfall (mm)
%Time Equalled or Exceeded


X31A Sub-basin
WR90 (1920-1990)
IDW_original (1920-2000)
IDW_corrected (1920-2000)
Monthly rainfall (mm)
%Time Equalled or Exceeded


X31A Sub-basin
WR90 data
Satellite data_original
Satellite data_corrected
Monthly rainfall (mm)
%Time Equalled or Exceeded

Appendix 4.1 Basin property data, parameter estimates and objection function values.

Sub-basin; gauge area	**G10B; (G1H003-46 km^2)**			
i. Basin physical property data	**Initial value**	**Uncertainty bounds** Lower runoff	**Upper runoff**	
Soil texture	LmSa=20% SaClLm =40%; SaCl=20%; Cl=20%	LmSa=15% SaClLm =35%; SaCl=25%; Cl=25%	LmSa=25% SaClLm =45%; SaCl=15%; Cl=15%	
Drainage Density (km/km^2)	1.5	1.5	1.5	
Mean basin slope (BS) (%)	30	20	35	
Regional GW slope (GS) (%)	1.0	1.0	1.0	
Drain. Vector slope (VS) (%)	4.2	4.2	4.2	
Mean soil depth (m)	0.90	1.0	0.60	
FT soil depth (m)	1.07	1.21	0.69	
Soil porosity	0.37	0.37	0.38	
Vertical variation (%)	80	80	80	
Soil Permeability(m/day)	1.07	0.81	1.85	
Depth to GW (m)	25	25	25	
GW storativity (*1000)	2.0	2.0	2.0	
Unsat transmissivity (m^2/day)	2.0	1.5	4.0	
ii. Physically based parameters & Obj. function. values				**Sensitivity comments**
ST(mm month^{-1})	311.0	338.0	227.0	ST sensitive to overall flows.
FT (mm month^{-1})	38.5	23.4	55.1	Overall volume sensitive to FT.
POW	2.2	2.3	2.3	Affects flow volumes.
ZMIN(mm month^{-1})	50.0	20.0	60.0	ZMIN is not sensitive and ZMAX is sensitive for a given range.
ZMAX (mm month^{-1})	500.0	610.0	400.0	
GW (mm month^{-1})	10	10	10	Overall flows slightly sensitive to changes in GW over a given range.
GPOW	3	3.5	2.5	Affects both recharge and total flow.
DDENS (km km^{-2})	0.6	0.4	0.6	Low flow volume sensitive to changes in DDENS.
RSF (%)	0.1	0.2	0.1	Low flow volume slightly sensitive to changes in RSF.
Mean recharge (% of rainfall)	3.1	3.0	3.2	The results and statistics in the 3rd and 4th columns are two extremes of all 6561 ensembles using the parameter bounds given in the 3rd and 4th columns above.
CE(Q) / CE (lnQ)	0.73/0.87	0.73/0.83	0.68/0.86	
%Mn(Q)/ %Mn(lnQ)	0.54/-8.8	-6.9/-20.5	13.5/-13.9	
Yield deficit (%)	11.1	16.4	4.8	

Sub-basin; gauge area	U20B; (U2H007-353 km^2)			
i. Basin physical property data		**Uncertainty bounds**		
	Initial value	**Lower runoff**	**Upper runoff**	
Soil texture	LmSa=10%; SaClLm=30%; SaCl=40% Cl=20%	LmSa=15%; SaClLm=20%; SaCl=40% Cl=25%	LmSa=20%; SaClLm=25%; SaCl=40% Cl=15%	
Drainage Density (km/km^2)	2.5	2.5	2.5	
Mean basin slope (BS) (%)	16.0	13.0	20.0	
Regional GW slope (GS) (%)	1.0	1.0	1.0	
Drain. Vector slope (VS) (%)	3.1	3.1	3.1	
Mean soil depth (m)	0.80	1.0	0.5	
FT soil depth (m)	0.93	1.13	0.59	
Soil porosity	0.46	0.45	0.47	
Vertical variation (%)	80	80	80	
Soil Permeability(m/day)	0.27	0.27	0.47	
Depth to GW (m)	15	15	15	
GW storativity (*1000)	2.0	2.0	2.0	
Unsat transmissivity (m^2/day)	1.0	1.0	2.0	
ii. Physically based parameters & Obj. function. values				**Sensitivity comments**
ST(mm month^{-1})	307.0	386.0	215.0	Slightly affects the total flow.
FT (mm month^{-1})	11.0	11.6	25.5	Flow hydrograph and volume sensitive to changes in FT.
POW	2.2	2.1	2.4	POW is slightly sensitive over a given range.
ZMIN(mm month^{-1})	10.0	20.0	40.0	ZMIN is less sensitive but ZMAX is sensitive within a range 400 to 800.
ZMAX (mm month^{-1})	600.0	800.0	700.0	
GW (mm month^{-1})	10.0	8.0	20	GW affects recharge and hence total flow.
GPOW	3.0	3.0	2.8	Similar effect to GW but is less sensitive.
DDENS (km km^{-2})	0.4	0.2	0.5	Affects overall flow volume.
RSF (%)	0.2	0.2	0.1	Moderately sensitive to low flows.
Mean recharge (% of rainfall)	3.2	2.8	6.0	The results and statistics in the 3rd and 4th columns are two extremes of all 19863 ensembles using the parameter bounds given in the 3rd and 4th columns above.
CE(Q) / CE (lnQ)	0.63/0.67	0.46/-2.4	0.71/0.78	
%Mn(Q)/ %Mn(lnQ)	2.8/7.5	-51.6/-107.6	39.3/38.9	
Yield deficit (%)	4.0	43.5	0.01	

Sub-basin; gauge area	K40A; (K4H003-87 km^2)			
i. Basin physical property data	**Initial value**	**Uncertainty bounds**		
		Lower runoff	**Upper runoff**	
Soil texture	LmSa=30%; SaClLm=60%; SCl=10%	LmSa=20%; SaClLm=65%; SCl=15%	LmSa=40%; SaClLm=55%; SCl=5%	
Drainage Density (km/km^2)	1.70	1.70	1.70	
Mean basin slope (BS) (%)	20.0	15.0	25.0	
Regional GW slope (GS) (%)	1.0	1.0	1.0	
Drain. Vector slope (VS) (%)	4.2	4.2	4.2	
Mean soil depth (m)	0.35	0.60	0.27	
FT soil depth (m)	0.41	0.71	0.32	
Soil porosity	0.35	0.34	0.36	
Vertical variation (%)	80	80	80	
Soil Permeability(m/day)	1.85	0.81	2.44	
Depth to GW (m)	25.0	25.0	25.0	
GW storativity (*1000)	2.0	2.0	2.0	
Unsat transmissivity (m^2/day)	2.5	1.0	4.0	
ii. Physically based parameters & Obj. function. values				**Sensitivity comments**
ST(mm $month^{-1}$)	140.0	221.0	100	ST not sensitive over the range 50 and 250.
FT (mm $month^{-1}$)	26.4	13.1	39.3	FT slightly sensitive for a range of values between 5 and 45.
POW	2.0	2.5	2.0	A change of POW has no effect on flows.
ZMIN(mm $month^{-1}$)	50.0	75.0	60.0	Overall flows sensitive to change in ZMAX and not sensitive to ZMIN for given range of values.
ZMAX (mm $month^{-1}$)	220.0	340.0	180.0	
GW (mm $month^{-1}$)	15.8	14.0	20.0	Flows sensitive for values between 5 and 25.
GPOW	2.0	2.3	1.8	No effect on flows.
DDENS (km km^{-2})	0.4	0.3	0.2	Sensitive to dry season flows for values greater than 0.4
RSF (%)	0.2	0.3	0.1	Flows less sensitive over the range 0.1 and 0.3
Mean recharge (% of rainfall)	3.50	2.96	4.85	The results and statistics in the 3rd and 4th columns are two extremes of all 19863 ensembles using the parameter bounds given in the 3rd and 4th columns above.
CE(Q) / CE (lnQ)	0.66/0.69	0.43/0.17	0.66/0.69	
%Mn(Q)/ %Mn(lnQ)	-4.8/-16.2	-49.8/-74.5	57.3/59.8	
Yield deficit (%)	6.0	44.2	0.01	

Sub-basin; gauge area	**V20A; (V2H005-267 km²)**			
		Uncertainty bounds		
i. Basin physical property data	**Initial value**	**Lower runoff**	**Upper runoff**	
Soil texture	LmSa=25% SaClLm=40%; SaCl=20%; Cl=15%	LmSa=20% SaClLm=50%; SaCl=20%; Cl=10%	LmSa=30% SaClLm=45%; SaCl=20%; Cl=5%	
Drainage Density (km/km^2)	2.1	2.1	2.1	
Mean basin slope (BS) (%)	25	20	30	
Regional GW slope (GS) (%)	1.0	1.0	1.0	
Drain. Vector slope (VS) (%)	4.2	4.2	4.2	
Mean soil depth (m)	7.20	1.0	0.5	
FT soil depth (m)	0.90	1.20	0.59	
Soil porosity	0.36	0.33	0.35	
Vertical variation (%)	80	80	80	
Soil Permeability(m/day)	0.617	0.270	1.1	
Depth to GW (m)	25	25	25	
GW storativity (*1000)	3.0	3.0	3.0	
Unsat transmissivity (m^2/day)	2.5	2.0	5.0	
ii. Physically based parameters & Obj. function. values				**Sensitivity comments**
ST(mm month^{-1})	276.0	327	207	Overall flows sensitive to ST.
FT (mm month^{-1})	27.3	18.9	50.2	Overall volume sensitive to FT.
POW	2.0	2.0	2.0	Not sensitive.
ZMIN(mm month^{-1})	20.0	40	10	Flows not sensitive to ZMIN, but sensitive to ZMAX for a given range.
ZMAX (mm month^{-1})	450.0	500	360	
GW (mm month^{-1})	20.0	15	25	Overall flows sensitive to changes in GW over a given range.
GPOW	3.0	3.5	2.5	Affects both recharge and total flow.
DDENS (km km^{-2})	0.4	0.3	0.5	Overall flow sensitive to changes in DDENS.
RSF (%)	0.2	0.3	0.1	Slightly sensitive to flow volume.
Mean recharge (% of rainfall)	4.9	4.0	5.0	The results and statistics in the 3rd and 4th columns are two extremes of all 19863 ensembles using the parameter bounds given in the 3rd and 4th columns above.
CE(Q) / CE (lnQ)	0.79/0.83	0.69/0.80	0.82/0.76	
%Mn(Q)/ %Mn(lnQ)	-14.4/4.1	-30.6/-9.1	14.4/20.4	
Yield deficit (%)	3.2	16.8	0.01	

Sub-basin; gauge area	V70B; (V7H016-121 km^2)			
i. Basin physical property data	**Initial value**	**Uncertainty bounds** Lower runoff	**Upper runoff**	
Soil texture	SaClLm=60%; SaCl=20%; Cl=20%	SaClLm=55%; SaCl=25%; Cl=20%	SaClLm=65%; SaCl=20%; Cl=15%	
Drainage Density (km/km^2)	1.70	1.70	1.70	
Mean basin slope (BS) (%)	25.0	20.0	30.0	
Regional GW slope (GS) (%)	1.0	1.0	1.0	
Drain. Vector slope (VS) (%)	4.2	4.2	4.2	
Mean soil depth (m)	0.60	1.0	0.40	
FT soil depth (m)	0.69	1.13	0.44	
Soil porosity	0.34	0.34	0.33	
Vertical variation (%)	80	80	80	
Soil Permeability(m/day)	0.81	0.47	1.10	
Depth to GW (m)	25	25	25	
GW storativity (*1000)	2.0	2.0	2.0	
Unsat transmissivity (m^2/day)	2.5	2.0	5.0	
ii. Physically based parameters & Obj. function. values				**Sensitivity comments**
ST(mm month^{-1})	206.0	298.0	151.0	Sensitive to both low and high flows.
FT (mm month^{-1})	24.9	19.3	35.7	Overall volume sensitive to FT.
POW	2.0	2.0	2.0	Not sensitive.
ZMIN(mm month^{-1})	60.0	10.0	20.0	ZMIN is not sensitive over the given range and ZMAX sensitive for values less than 400.
ZMAX (mm month^{-1})	450.0	600.0	400.0	
GW (mm month^{-1})	15.0	10.0	30.0	Both low and high flows slightly sensitive over a given range.
GPOW	2.0	2.3	1.5	Affects both recharge and total flow.
DDENS (km km^{-2})	0.4	0.3	0.5	Overall flow sensitive within the range 0.1 and 0.7
RSF (%)	0.2	0.3	0.1	Moderately sensitive to flow volume.
Mean recharge (% of rainfall)	6.1	4.2	11.5	The results and statistics in the 3rd and 4th columns are two extremes of all 19863 ensembles using the parameter bounds given in the 3rd and 4th columns above.
CE(Q) / CE (lnQ)	0.70/0.77	0.59/0.47	0.73/0.82	
%Mn(Q)/ %Mn(lnQ)	0.56/29.9	-27.2/-53.0	35.7/84.8	
Yield deficit (%)	9.3	23.8	0.01	

Sub-basin; gauge area	X31A; (X3H001-174 km^2)			
i. Basin physical property data		**Uncertainty bounds**		
	Initial value	**Lower runoff**	**Upper runoff**	
Soil texture	SaClLm=70%; SaCl=15%; Cl=15%	SaClLm=60%; SaCl=20%; Cl=20%	SaClLm=70%; SaCl=20%; Cl=10%	
Drainage Density (km/km^2)	1.50	1.50	1.50	
Mean basin slope (BS) (%)	25.0	20.0	30.0	
Regional GW slope (GS) (%)	1.0	1.0	1.0	
Drain. Vector slope (VS) (%)	2.0	2.0	2.0	
Mean soil depth (m)	0.74	1.0	0.5	
FT soil depth (m)	0.89	1.21	0.59	
Soil porosity	0.34	0.34	0.33	
Vertical variation (%)	80	80	80	
Soil Permeability(m/day)	0.36	0.27	0.47	
Depth to GW (m)	25	25	25	
GW storativity (*1000)	4.0	4.0	4.0	
Unsat transmissivity (m^2/day)	4.5	3.5	5.0	
ii. Physically based parameters & Obj. function. values				**Sensitivity comments**
ST(mm $month^{-1}$)	297.0	367.0	230.0	Sensitive in the range of 150 to 450.
FT (mm $month^{-1}$)	15.2	12.2	16.4	Seasonal hydrograph shape and overall water balance sensitive to changes in FT.
POW	1.9	1.9	1.9	Change in POW affects overall water balance.
ZMIN(mm $month^{-1}$)	0.0	0.0	0.0	The overall volume of runoff is sensitive to changes in ZMIN and ZMAX.
ZMAX (mm $month^{-1}$)	700.0	750.0	560.0	
PI(Forest) (mm $month^{-1}$)	4.0	5.0	3.0	Forest interception, affecting all runoff components.
FF	1.4	1.5	1.3	Increased evapotranspiration from forest affecting recharge and runoff from soil moisture
GW (mm $month^{-1}$)	60.0	58.0	68.0	Low flow sensitive over the range 30 to 90.
GPOW	2.0	2.1	1.9	Low flows moderately sensitive to GPOW change.
DDENS (km km^{-2})	0.4	0.3	0.5	Overall flow sensitive within range 0.2 to 0.6
RSF (%)	0.2	0.3	0.1	Slightly sensitive within the range 0.1 to 0.3
Mean recharge (% of rainfall)	14.1	12.3	16.1	The results and statistics in the 3rd and 4th columns are two extremes of all 19863 ensembles using the parameter bounds given in the 3rd and 4th columns above.
CE(Q) / CE (lnQ)	0.71/0.69	0.50/0.61	0.73/0.70	
%Mn(Q)/ %Mn(lnQ)	-4.3/0.56	-17.3/-9.3	15.3/10.5	
Yield deficit (%)	13.0	23.8	4.3	