ESTABLISHING A WATER RESOURCES ASSESSMENT SYSTEM FOR ESWATINI (SWAZILAND) INCORPORATING DATA AND MODELLING UNCERTAINTY

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COLI NDZABANDZABA

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Supervisors: Prof. D A Hughes and Dr J Tanner

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ABSTRACT

The uneven distribution of water resources availability globally puts pressure on environmental and human or socio-economic systems and has complex implications for the interactions within these systems. The natural environment and water resources are increasingly threatened by development, and water management crises are still occurring. This is exacerbated by the lack of accurate and adequate information on these systems. In Eswatini, for example, the pressure on the available water resources is mounting due to increasing water demand for irrigation while information about natural hydrological conditions and levels of water resources developments are uncertain. In addition, the practical application of hydrological models for water resources assessments that incorporate uncertainty in Eswatini has yet to be realised. The aim of the study, therefore, was to develop a water resource assessment system that is based on both observed and simulated information and that includes uncertainty. This study focusses on a regional water resource assessment using an uncertainty version of the Pitman monthly rainfall-runoff model whose outputs are constrained by six indices of natural hydrological response (i.e., mean monthly runoff, mean monthly groundwater recharge, Q10, Q50 and Q90 percentage points of the flow duration curve and % time of zero flows) for each of the 122 sub-basins of the transboundary catchments of Eswatini. A 2-step uncertainty modelling approach was tested, validated and then applied to all the sub-basins of Eswatini. The first step of the model run establishes behavioural, but uncertain model parameter ranges for natural incremental sub-basin hydrological responses and the model is typically run 100 000 times for each sub-basin. The parameter space that defines the uncertainty in parameter estimation is sampled based on simple Monte Carlo approach. The second step links all the sub-basin outputs and allows for water use parameters to be incorporated, where necessary, in order to generate cumulative sub-basin outflows. The results from the constraint index analysis have proved to be useful in constraining the model outputs. Generally, the behavioural model outputs produced realistic uncertainty estimates as well as acceptable simulations based on the assessment of the flow duration curves. The modelling results indicated that there is some degree of uncertainty that cannot be easily accounted for due to some identified data issues. The results also showed that there is still a possibility to improve the simulations provided such issues are resolved. The issues about the simulation of stream flow that were detected are mainly related to availability of data to estimate water use parameters. Another challenge in setting up the model was associated with establishing constraints that match the parameters for natural hydrological conditions for specific sub-basins and maintaining consistency in the adjustment of the model output constraints for other sub-basins. In an attempt to overcome this problem, the study recommends additional hydrological response constraints to be used with the Pitman model. Another main recommendation relates to the strong cooperation of relevant catchment management authorities and stakeholders including scientists in order to make information more available to users. The new hydrological insight is derived from the analysis of hydrological indices which highlighted the regional variations in hydrological processes and sub-basin response across the transboundary basins of Eswatini. The adopted modelling approach provides further insight into all the uncertainties associated with quantifying the available water resources of the country. The study has provided further understanding of the spatial variability of the hydrological response and existing development impacts than was previously available. It is envisaged that these new insights will provide an improved basis for future water management in Eswatini.

Keywords: Hydrological response indices, Pitman model, uncertainty, hydrological modelling, Eswatini, regionalisation, model output constraints

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CHAPTER ONE: INTRODUCTION

This chapter presents an overview of the entire thesis for the research study. Firstly, it briefly sets a background for the study and a description of the identified research problem. The research aim and objectives that this study intended to achieve are presented. The significance of the study, especially to Eswatini, in the context of uncertainty and water resources decision making is given. Lastly, the structure of the thesis is outlined.

1.1 General background information

1.1.1 Water availability, management and challenges

Water, as a key element in natural resources systems, is increasingly realised as an important and main economic driver as well as a cornerstone of most human endeavours. However, the uneven distribution of water resources availability across the globe continually puts pressure on environmental and human/socio-economic systems and has complex implications for the interactions within these systems. A catchment is not only where humans live but it is also where they derive their livelihood from. Socio-hydrological systems exhibiting adverse natural variability or human-induced changes (or both) (Hirsch & Archfield, 2015; Koutsoyiannis, 2013; Marani & Zanetti, 2014) necessitates development of new approaches to decision-making (Fuller, 2011; Korteling et al., 2013; Singh et al., 2014; Lauro et al., 2019). Global water crises are increasingly discussed by the scientific community (IAHS, 2015; Sivakumar, 2011; Srinivasan et al., 2012) and are of great concern to water resources researchers, practitioners and affected stakeholders.

Globally, the natural environment and water resources are increasingly threatened by development (Sivapalan et al., 2003). While it is recognised worldwide that the management of water resources should be environmentally sustainable and that adequate protection of aquatic ecosystems is extremely important (Bullock et al., 2009), water management crises are still developing in most parts of the world. Consequently, sustainable management policies and practices are required to respond to these trends (Sivapalan et al., 2003; Wagener & Gupta, 2005), but these can only be developed on the basis of adequate information about the natural resource availability, its variability in time and space, as well as information about existing and future uses. A global perspective on hydrology, with the increasingly interrelated nature of environmental change and human impacts on climate, including resource use, is necessary (Bierkens, 2015; Vörösmarty et al., 2015).

1.1.2 Environmental systems, change and the future

The pressure on the environmental and human systems and the consequent implications will frequently change the environmental-human systems interactions. Although models have been used to predict the future climate, it should be noted that these are not perfect representations of the real world (Fenicia et al., 2008) and the climate system is complex and not possible to control and constrain, making it highly uncertain. While future changes are still largely unknown, Beven (2011) argues that since the projections of the current regional climate models (RCMs) do not represent an adequate basis for hydrologic models and impact studies, our current and future adaptation response should be dependent on the *willingness to pay* principle. Although climate change model outputs have been considered to be an inappropriate basis for impact studies and adaptation purposes, this however does not imply that model outputs should no longer be relied upon for the prediction of future climate change-induced impacts, but rather be cautiously used and considered as a mere 'stochastic reference frame' (Beven, 2012). The question about modelling impacts still remains: on what assumptions should impact studies be conducted? Another important issue is that there remains a gap in effective communication of the output of climate change impact studies to users.

Robust tools and approaches still need to be developed and applied in the context of environmental change to respond appropriately to the complexities related to, and posed by, continuous change in the systems. Environmental systems models (including hydrological and GCMs) often rely on complex systems understanding and data used for forcing them. They also rely on assumptions such as the model structure adequately represents the real world and the forcing data are representative of reality.

Since GCMs are the only available tool for comprehensive future climate evolution prediction (Flato et al., 2013; Wibig et al., 2015; Lembo et al., 2020), while modelling studies are currently the most feasible approach to investigate climate change impacts on water resources (Bronstert, 2004), our abilities to predict the future will continue to be limited even if we develop 'perfect' hydrological models (Beven, 2012). There are many problems associated with using models for process understanding. A properly evaluated model with good performance, may not necessarily be credible enough (Kryasanova et al., 2018). How can a model be effectively tested (Beven, 2019)? This is a question that needs careful consideration. The way modelling is carried out is increasingly dependent on data availability. Data-based models do not really represent the physics of the modelled process (Solomatine et al., 2008) and there is a need for pragmatic (or hybrid) approaches. For example, the integration of a hybrid of data-driven models with physically-based models to improve process understanding and management of socio-hydrologic systems (Mount et al., 2016) may be appropriate.

Models are useful for scientific purposes including comparative studies (Harmel et al., 2014; Beven, 2019; Triana et al., 2019). Models play an important role in decision-making (Harmel et al., 2014; Beven, 2019) which usually occurs in a complex, rapidly-evolving and uncertain context (Borgomeo et al., 2018). It is very important that the uncertainty of the model predictions (current and future) of the hydrological system do not deviate much from reality (Beven, 2019) because this may have negative implications on decision-making (Justin et al., 2012; Triana et al., 2019). Improvement in process understanding needs to help water resources managers to make better decisions, and deal with uncertainty appropriately to eventually reduce risk in water resources management (Beven, 2019).

1.2 Statement of the problem

The pressure on the available water resources of Eswatini is mounting mainly due to ever-increasing agricultural water demands. About 96% of the water resources are currently used for irrigation (Swaziland Government, 2009; Matondo & Msibi, 2010), while there is also an increasing demand for domestic water supplies. Most of Eswatini's rivers are trans-boundary, are frequently impounded by large dams, and cover a wide range of climate and topographic conditions. However, there is a limited amount of accurate information on the available water resources. Information about natural hydrological regimes and current levels of water use and abstractions are uncertain, yet decisions still have to be made. The problem of data availability is exacerbated by some issues associated with access to the information that does exist. The gap between availability and access continues to hinder effective and efficient data sharing in the region of the trans-boundary basins of southern Africa. On the other hand, the potential for the practical application of hydrological models for water resources assessments in Eswatini has yet to be realised.

It follows that there is a need for a detailed assessment of the available water resources as well as current and future uncertainties. More comprehensive, up-to-date and accurate water resources data and information are necessary for sustainable management. The key issue is the beneficial use of all available data, coupled with simulation modelling to generate the information required for sustainable decision making.

1.3 Research aim and objectives

The aim of this research was **to develop a water resources information system that is based on both observed and simulated information and that includes uncertainty**. Previously, water resources estimates for ungauged areas within the region have been largely based on single simulations that ignore all of the inherent uncertainties in the available data and the modelling approaches used. One of the key objectives was therefore to quantify realistic uncertainty bounds for estimates of available water resources based on modelling. The system comprises of both 'hard' (i.e., based on measured and provable facts from reliable sources) as well as 'soft' (qualitative and difficult to measure) information. The basis of the system is the Pitman rainfall-runoff model that has been widely applied in southern Africa. While there are many hydrological models available, the Pitman model has been applied most frequently in this region. This study is therefore designed to add to the growing experience base of this model. It was anticipated that the system would provide valuable information for decision-making purposes in future water resources assessment and management in Eswatini and contribute to the objectives of *Panta Rhei* (an international hydrological research initiative which is aimed at improving our understanding of change in a hydrological system and putting science into practice while promoting sustainable societal development: Montanari et al., 2013). The aim was achieved through the following specific objectives:

- **To obtain and collate all available local water resources data sets, both observed and simulated for the five major river basins of Eswatini**.. These uncertain data are used in the pre-modelling analyses as well as to force the rainfall-runoff model and form part of the information system.

- **To quantify regional characteristics of natural hydrological response and the associated uncertainty bounds**. This analysis was based on previous model results from the WR2012 study (http://waterresourceswr2012.co.za/). It was assumed that the uncertainty will vary from being relatively low in areas where reliable information is available, to high in largely ungauged parts of the country. Catchment classification was based on hydrological responses quantified from previous modelling studies combined with topographic regions.

- **To set up an uncertainty version of the Pitman rainfall-runoff model using the regional characteristics of natural hydrological response to constrain the model output and to establish behavioural, but uncertain parameter sets**. The uncertainty version of the Pitman monthly rainfall-runoff model was set up for all gauged and ungauged sub-basins of the country based on the regionalised response constraints.

- **To incorporate existing water use and other modifications to the natural hydrological response in the model set-up.** It was assumed that in many parts of the country these modifications are also subject to available information uncertainty. The water use component of the model accounts for most possible modifications that exist in the country.

- **To identify key regions and data sources where existing uncertainties might impact adversely on water allocation management decision-making and to recommend possible interventions which might be used to realistically reduce the uncertainties (and therefore decision-making risk)**. While it is impractical to eliminate all uncertainty, it remains imperative to reduce it, wherever possible, to improve sustainable decision making in water resources management. The ultimate rationale for this study was to reduce decision-making risk, where possible. While identifying uncertainties is useful in its own right, reducing them is of greater value to water resources management.

1.4 Rationale and significance of the study

The focus of this study was not on achieving the best (model) performance but on quantifying and constraining uncertainty in water resources assessment to support and improve decision-making and minimise decision making risks. The basis for the study is linked to 'putting science into practice' in the sub-Saharan region while providing valuable data which will be easily accessible to intended users. The information system established through this research will form a basis for future small- and large-scale national water resources-related studies. This will in turn promote the practical application of hydrological science not only in Eswatini but in the region as a whole.

The findings from this study are expected to provide valuable information for decision-making purposes in water resource assessment and management in Eswatini. Since the demand for hydrologic modeling has increased due to the recent focus on uncertainties, the application of the Pitman model is expected to promote the endeavors of the international initiatives from various hydrological research communities, such as the Prediction in Ungauged Basins (PUB: Sivapalan et al., 2003; Hrachowitz et al., 2013) and *Panta Rhei*. It is anticipated that this study may identify certain key issues that need to be addressed in the model itself. The findings may also make some contributions towards certain objectives that resulted in the development of the model. Hughes (2013) identified three specific areas of research that were directed to the Pitman model: improving model realism through adjustments to the structure, improving model parameter estimation approaches that could be applied to both gauged and ungauged basins and also incorporating uncertainty assessments in to the application of the model.

Although substantial improvements have been made to the Pitman model over recent years (Hughes, 2013a), the model has seen limited application in Eswatini. Notably, the most frequently used model has been the WatBall model which has been mainly applied for climate change studies (see Matondo & Msibi, 2009; Matondo et al., 2004a; Matondo et al., 2004b; Matondo et al., 2005; Swaziland Government, 2002; Swaziland Government, 2010). Considering these improvements in the Pitman model, its approach may be suitable for large-scale challenges, such as climate change, in order to allow for the comparison between areas and enable the identification of regions which will be most vulnerable in the country (e.g., Lane et al., 2019). For large-scale challenges, such as climate change, this approach (used in the Pitman model) will allow for the comparison between areas and may enable the identification of regions which will be most vulnerable (Lane et al., 2019).

1.5 Study context and main contributions

Following international trends in hydrological science and research such as PUB and *Panta Rhei*, this research study builds upon a growing body of literature that addresses the issues of hydrological model uncertainty and obtaining behavioral parameters sets. It was focussed on uncertainty estimation in predictions as well as identifying and addressing the existing gaps in uncertainty analysis. Its main focus was to set up an information system that will provide a reference point for future water resources assessments and modelling in the country. The study was undertaken in the context of constrained hydrological regionalisation and uncertainty in a data-scarce area (Figure 1.1). The disciplinary context is the link between the science of hydrological modelling and the practical need of water resources management for robust estimates of water availability in largely ungauged areas.

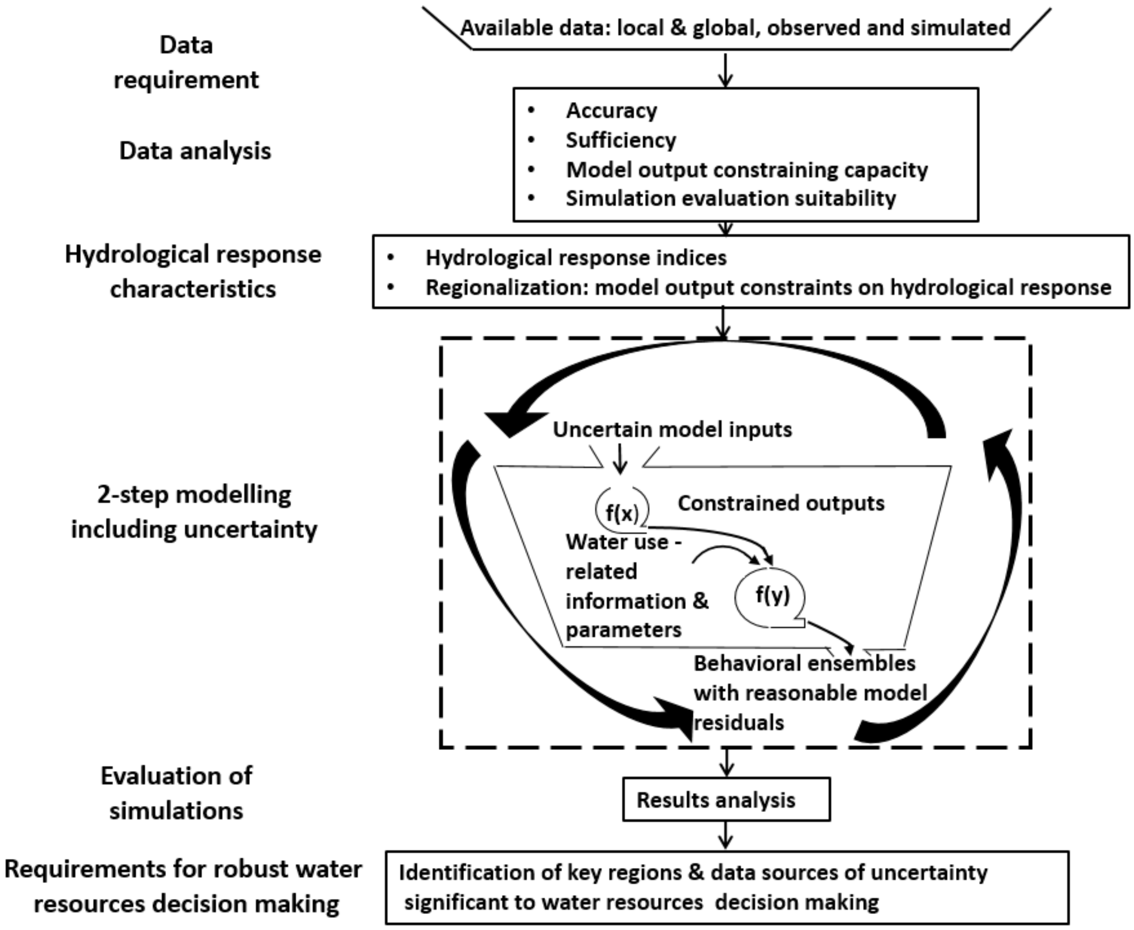

Figure 1.1: Research flowchart

The main contributions of the thesis are: understanding of the regional variation in hydrological processes and sub-basin hydrological response as well as more insights into the existing development impacts in the country; possible estimation of inherent uncertainties in data and modelling approaches required to reduce risk in water resources decision making; a system that can be used as a basis for assessing available water resources of the country that takes into consideration data scarcity; application of a more objective hydrological modelling approach whose outputs are constrained using observed data to generate behavioural parameter sets. All these contributions are expected to provide an improved basis for water management in Eswatini in the future.

1.6 Thesis structure

Subsequent to this thesis introduction is a review of relevant literature and the theoretical background on which this research is embedded. The research study area as well as datasets used in the entire study and that form the assessment system are described in Chapter three. Chapter four presents the procedure followed to establish regional model output constraints on hydrological response and the outline of the hydrological modelling approach applied. The findings and their discussion are presented in Chapter five. Conclusions and recommendations are made in Chapter six.

CHAPTER TWO: LITERATURE REVIEW AND THEORETICAL BACKGROUND

This review focuses, firstly, on uncertainty and water resources decision making. Secondly, progress in water resources estimation methods is reviewed, specifically highlighting issues of estimating realistic uncertainty in order to analyse risk in different situations. Thirdly, the review provides an in-depth focus on hydro-climatic observations and associated data, as well as how these impact on model outputs and uncertainty in the results. Finally, the review focusses on the regional application of water resources estimation models with emphasis on uncertainty estimation.

2.1 Uncertainty and decision making in water resources assessments (WRA)

2.1.1 Information requirements for WRA to support robust decision-making

What kind of information is needed for making decisions about water resources assessments in conditions of uncertainty? We record and gather data to meet specific requirements for different purposes (Stewart, 2015), and those data must be fit-for-purpose, that is, the data must be appropriate for the intended application. Information relating to natural conditions and developed conditions, as well as future possible situations relating to both development and climate change impacts is required. However, for various reasons (limited human and financial resources, for example) there are many areas where recorded data are lacking and therefore decisions have to be made on the basis of simulated data, which are inevitably uncertain. Uncertainty in information is related to measurement errors and how representative the available data are. This includes the uncertainty in the data used to force models (climate data and water use data). When models are used as alternatives or substitutes for real data, then the outputs of these are subject to a wide range of additional uncertainties that are related to how the model is structured and how it is used. In recent years it has been increasingly recognised that these uncertainties need to be explicitly quantified and that robust decision making needs to account for them in risk-based assessments. The following sub-sections explore some of these issues in more detail.

2.1.2 Quantifying realistic uncertainty

The first issue that needs to be addressed is, therefore, how to quantify realistic uncertainty in the absence of accurate data. Estimating uncertainty realistically depends on the availability of reliable information that is well-understood and accurate, and on limitations that are based on correct assumptions (Beven, 2005; Beven, 2016). Realistic uncertainty estimation requires improved analysis of the observation process (Mcmillan and Westerberg, 2015) and an understanding of impacts of this improvement on hydrological metrics (Westerberg and Mcmillan, 2015). The use of methods of comparison between data and models may also enhance the understanding of uncertainty (Beven and Smith, 2015; Nearing and Gupta, 2015).

First, evaluating the appropriateness of the information by hydrologists (Dottori et al., 2013; Serinaldi, 2015) forms a critical part of uncertainty estimation. Secondly, valid assumptions must be made about the nature of the uncertainty sources (Beven, 2005). Categorising uncertainty into different sources (uncertainty decomposition) is therefore necessary, but it can be complex, especially where there are no sufficient data in order to understand the influence of each source of uncertainty on the overall model output. While there are many examples of detailed mathematical analysis of error sources in data (Renard et al., 2010; Montanari & Baldassarre, 2013; Moges et al., 2020), these are not always either appropriate or possible in data scarce areas, where 'errors' are difficult to quantify even if they are suspected of being present. The third issue relates to applying model benchmarking (e.g., Siebert, 2001; McMillan et al., 2012; Nicolle et al., 2014; Newman et al., 2017; Seibert et al., 2018; Lane et al., 2019), and the use of scientific methods to develop a standard of comparison between model outputs (Best et al., 2015, Nearing and Gupta, 2016). Finally, the use of the concept of ‘limits of acceptability’ (Bevin, 2006a), an approach to identify behavioural models on the basis of their simulation of observed data (e.g., Liu et al., 2009; Vrugt and Beven, 2018), must be considered.

Modelling must account for uncertainty in outputs. In order to achieve this, models must be based on valid hypotheses and should account for different settings of environmental change and non-stationarity in hydrological response (Wagener, 2007; Hughes, 2015). Model outputs should no longer be based on a single output using a single set of estimated (or guessed) parameters, but should rather simulate ensembles of outputs that are identified as being behavioural in some way (e.g., Beven, 2006a; Hrachowitz et al., 2014; Kapangaziwiri et al., 2012; Nijzink et al., 2016; Tumbo and Hughes, 2015; Westerberg et al., 2011; Westerberg et al., 2014; Yadav et al., 2007; Zhang et al., 2008). A number of previous studies have used regionalised basin response characteristics (hydrological indices) to achieve this objective and to constrain the ensembles of model outputs (Yadav, 2007; Hrachowitz et al., 2014; Tumbo & Hughes, 2015; Ndzabandzaba & Hughes, 2017; Nijzink et al., 2018). McMillan et al. (2017) recommend that models should enable direct generation of multiple possible uncertainty estimates of flow ensembles that are consistent with measured stage series, and they should take into account uncertainty in stage-flow relationships. Lastly, to allow for detailed analysis of risk, signature uncertainties in regionalisation must be estimated to account for regionalisation uncertainty in estimation models (e.g., Westerberg et al., 2016).

2.1.3 Risk analysis and water resources decision making

While risk analysis is complex (Gui et al., 2013), its main requirements are related to information and uncertainty. Vucetic and Simonovic (2011) demonstrated the importance of information and how it can be improved by applying tools that incorporate risk and uncertainty. Reliable approaches to uncertainty estimation in WRA are the basis for risk analysis under different situations in order to select, for example, an option associated with low risk, even if the costs exceed the expected benefits (Bugman, 2005; Power and McCarthy, 2006, Kirker et al., 2005; Uusitalo, 2015).

Gui et al. (2013) conclude that risk analysis must be appropriately sophisticated to match the complexity of the water resources systems. Borgomeo at al. (2019) combine a traditional risk-based decision analysis with uncertainty-based decision making in order to enhance the robustness in water resources systems under different risk circumstances. The main concern regarding uncertainty and risk in decision making is providing decision makers with a clear understanding of the problem critique, and so enabling them to analyse the problem with confidence (Zio, 2009; Aven and Ezio, 2011). Analysing risk under different situations will require predictions that are very close to the assumed boundary conditions and are based on detailed approximation, especially if decisions are to be made at a large scale (Beven, 2019).

Communication of uncertainty is still a problem in water resources management. In order to improve communication, decision makers need a clearer understanding of how uncertainty is interpreted (Kundzewicz et al., 2017). This is also needed to avoid and reduce risk in decision making. Communicating the assumptions on which the models are based (Beven, 2016), the meaning of the model outputs and their estimated uncertainties (Faulkner et al., 2007), as well as possible implications to decision making is crucial. However, given the complex nature of uncertainty, Beven (2016) argues that communicating the meaning of the various uncertainty estimates to decision makers may be difficult, and can be even more difficult when these uncertainties have to be communicated to stakeholders and those parties affected by decisions (Rangecroft et al., 2018).

The solution would be to involve decision makers, stakeholders and affected parties in the development of assumptions behind the model outputs (Beven, 2019; Garcia-Diaz et al., 2019). This kind of involvement will help to achieve mutual understanding between modellers and managers of the role of models in management (Garcia-Diaz et al., 2019), and therefore models can help support water resources decision making.

2.2 Trends in hydrological modelling

2.2.1 Advances

Many developments have taken place since the conception of models in hydrology. Hydrological models, based on parameters (measured and estimated indirectly) together with equations that describe water flow by linking the inputs and outputs, are absolutely necessary in the field of hydrology. In the early stages of the computer revolution around the 1960s, simple models were developed to carry out computations that had not existed previously, resulting in numerical and stochastic hydrology (Singh, 2018). A number of advances in hydrology followed, including modelling (Singh, 2018). Wider access to computers led to the development of conceptual models (e.g., Dawdy and O'Donnel, 1965) aimed at modelling the complex connectedness of soil-surface runoff generation processes (Todini, 2011). The advances resulted in the development of variable contributing area models and distributed models (Todini, 2011), and later, data-driven as well as complex physics-based models.

Simulation of the entire hydrological cycle and the development of techniques for reservoir management and river basin simulation, for example, were then possible because of greater computer power (Singh, 2018) Some of these techniques were used to calibrate hydrological models (Duan et al., 2003; Beven, 2012). Later, progress in numerical mathematics (perhaps due to the development of computational and analysis tools) made 2- and 3-D modelling possible, (Remson et al., 1971; Bear, 1979; Pinder and Celia, 2006; Singh, 2018), an advance that was followed by simulation of water quantity and quality simultaneously and modelling at large spatial scales, coupled with high temporal resolution (Sorooshian et al., 2008; Molle and Wester, 2009). Modelling that integrated hydrology with other disciplines such as ecology (Singh, 2018), geology (Fetter, 1980; Delleur, 1999; Singh, 2017) and geomorphology (Baker et al., 1988; Bates and Lane, 2002; Beven and Kirkby, 1993) was achieved. Climate change and global warming then became an important part of hydrological modelling (Arnell, 1997). Continually increasing computer power enhanced the early development of tools such as remote sensors for data acquisition, storage, and retrieval (Croley, 1980; Hoggan, 1989) and as computing power has increased, improving understanding of hydrological process, models have become more sophisticated.

As models reflected the increasing complexity of hydrological modelling, the concept of equifinality gained traction, based on the recognition that, in an open system, different parameter sets may lead to the same result. Complex systems often require complex models. Son and Sivapalan (2007) argue that model complexity must be commensurate with data availability as well as parameters that can be derived from the field measurement data or from unambiguous inferences. Currently, the trend in hydrological modelling is towards simpler models, that is, parsimonious models designed to achieve a simpler representation of the dominant component processes with fewer parameters. These models have low equifinality so that they can be automatically calibrated. However, some developments have not followed these trends. The question about how complex a model should be remains open to debate. A key trend is towards uncertainty analysis, as we need to understand how much we do not know in order to determine the degree of uncertainty in assessments.

Many challenges in hydrological modelling have been noted in the midst of the advances. In processed-based modelling (modelling aimed at achieving a detailed representation of hydrological processes), challenges such as the issue of scaling (how best to represent the effects of small-scale heterogeneities on large-scale fluxes and interactions among processes) was addressed, for example, by Wood et al. (1988), Bloschl and Sivapalan (1995), Reggiani et al. (2001) and Beven (2006). The challenge of effectively resolving dominant processes has been addressed through disaggregating the domain into the highest resolution grid possible. It has also been solved by isolating and examining alternative modelling approaches to represent scaling and heterogeneity. The challenge of spatial integration is overcome by using the concept of hydrological similarity (e.g., Clark et al., 2017).

2.2.2. Challenges

Several hindrances still exist in modelling. Specific barriers to progress in distributed modelling include inadequate datasets for rigorous experimentation with models in a wide range of hydrological settings (Semenova and Beven, 2015; Fatichi et al., 2016). Secondly, there is the lack of a framework for identifying model and data deficiencies, as opposed to compensating by calibration and uncertainty estimation (Semenova and Beven, 2015). The third problem relates to the failure to learn how to improve model structures from hydrological process investigations of stream flow and travel times in catchment systems (Semenova and Beven, 2015; Fatichi et al., 2016). Lastly, is the lack of adequate theory to establish parameters for processes that are influenced by scale in heterogenous domains (Semenova and Beven, 2015; Fatichi et al., 2016). Specific challenges in process-based modelling, where the aim is to represent explicitly the dominant processes, include the trend towards 'hyper' resolution models over large geographical domains, which may result in parameter generalisation of hydrological processes at that scale (Clark et al., 2017). Challenges with respect to process-based models include difficulty in their use, scalability of physical laws, and prohibitive computational times (Fatichi et al., 2016).

2.2.3 Significance of models

2.2.3.1 Modelling as a science vs. modelling in practice

Models are essential for both science and practice. The purpose of modelling as science must contribute to the purpose of modelling in practice (Beven, 2019). Models can be scientifically interesting in that they advance our understanding of hydrology, but they are also useful tools for water resources management. Models are used to test science and learn in order to apply it correctly in practice (Beven, 2019), because it is impossible to measure all things in all places and thus to plan for the future (Semenova and Beven, 2015). Modelling in practice often requires a compromise type of model that accounts for the data availability in practice.

Research in modelling has shown that there is a gap between science and practice (Blöschl et al., 2013; Hrachowitz et al., 2013). While several models have closed this gap (Boughton, 2004; Young, 2006; Arheimer et al., 2011), Hughes (2013a) noted that the application of science practice at an acceptable level would be a major challenge in the IAHS *Panta Rhei* (Montanari et al., 2013) decade. In southern Africa, for example, the challenge of applying science to practice is mainly directed at the implementation of uncertainty analysis in models used for decision making (Hughes, 2013a). Some of the constraints in applying science to practice have been the lack of guidance on both the uncertainty methods and their application (Beven and Pappenberger, 2006).

2.2.3.2 Models as assessment and prediction tools

Models are used in science and in practice for assessment and prediction purposes. Water resources assessments rely increasingly on the application of hydrological models as a technique for assessing the availability of water resources in the absence of sufficient observed data (Viola et al., 2012; Eduardo et al., 2016). Hydrological models use mathematical and statistical techniques for modelling and forecasting natural and physical systems. While their structure ought to be parsimonious to ensure parameter *identifiability* and *equifinality* reduction (Son and Sivapalan, 2007), they should not be considered as accurate and complete representations of reality, but simply perceptual modelling tools.

In the context of improving model prediction and uncertainty estimation, it is important to first recognise and distinguish the different types of uncertainty and then select a suitable type of model (Refsgaard et al., 2013). Conceptual-type models are often preferred over physically-based models because of their better computational efficiency, simplicity and applicability (Kan et al., 2017). They (conceptual models) have a clearer physical meaning than data-based models (Li et al., 2014) and are often associated with better simulations than complex models (Refsgaard and Knudsen, 1996; Fowler et al., 2016). Conceptual models can be used in data-scarce conditions (Dakhlaoui et al., 2017). However, findings on the ability of conceptual models to simulate and predict stream flow under non-stationary conditions are contradictory (e.g., Vaze et al., 2010; Kling et al., 2015; Dakhlaoui et al., 2017).

2.2.4 'Packaging' models for use in practice

Significant progress has been made in the development of software to implement hydrological models since their conception. In the last 50 years, development of new tools and techniques for analysis of hydrological and water resources data has been rapid (Singh, 2018) while a wide variety of software packages has been made available (Douglas-Smith et al., 2020) that implement multiple methods of uncertainty/sensitivity analysis (USA) with open-source code and documentation with little restriction to the end-user (Douglas-Smith et al., 2020).

Many problems are associated with model packaging tools. The tools (USA) are difficult to use because they are new, the programming language is complex, intended users are not familiar with the methods used, yet there has been so much published about these tools (Douglas-Smith et al., 2020). This situation is exacerbated because sufficient guidance is unavailable (Douglas-Smith et al., 2020). Many of these tools were established outside hydrology (e.g., mathematics), yet they were tailored for applications relevant to hydrology, such as water resources planning (Singh, 2018). While substantial advances in computing and modelling have been made (Clark et al., 2017), computing in hydrology is a present-day challenge as we usually use available computing resources to their limit (Kollet et al., 2010; Wood et al., 2011). Running highly complex models for a large number of model configurations is problematic, especially if the modelling includes experimenting with different model parameter sets and different process parameterisations (Clark et al., 2017). Only a single deterministic simulation for a short time may be permitted as we try to run models to their computational limits (Maxwell et al., 2015; Fatichi et al., 2016). These limitations hinder opportunities for model analysis, improvement and uncertainty analysis (Clark et al., 2017), and it is necessary to find practical solutions in order to advance understanding.

Solutions to the highlighted problems include exploiting advances in parallel (e.g. exa-scale) computing (Falgout et al., 2006; Falgout, 2008; Kollet et al., 2010; Wood et al., 2011; Paliconi and Putti, 2015; Ogden et al., 2015; Fatichi et al., 2016), that is, by running a complex model at the finest grid resolution possible over the domain of interest (e.g. Maxwell et al., 2015; Maxwell and Condon, 2016) in order to understand clear spatial controls on hydrological processes (Clark et al., 2017). Improving numerical solvers is another solution as numerical errors in simple models often contaminate model analysis and complicate model calibration (Kavetski et al., 2006; Kavetski and Clark, 2010; 2011; Clark et al., 2017). As numerical solvers are important in identifying computational errors, improving them (solvers) will reduce the contamination of model analysis caused by numerical errors. This will result in simpler model analysis and calibration. Third, the use of model configurations that avoid redundant calculations while still capturing dominant catchment processes is necessary (Clark et al., 2017), for example, through the use of hydrological similarity or a regionalisation concept which will eliminate the need for repeating calculations for areas of similar forcing properties and other catchment characteristics. This can reduce run times by a half to a third (Newman et al., 2014; Chaney et al., 2016). Lastly, the use of quasi-scale invariant parameterisations (e.g., multiscale parameter regionalisation) enables the estimation of transfer function parameters at coarser resolutions instead of using a high-resolution model setting (e.g., Kumar et al., 2013), resulting in large-scale predictions that are computationally efficient (Clark et al., 2017).

Blair et al. (2019) suggest that facilitating software should support the development of models or ensembles of models ready to be tailored for the uniqueness of places, and automating the learning process associated with it. Black-box models, for example, need to be improved in terms of internal software architecture or used in practice to support decision making (Blair et al., 2019). The requirements for this include the existence of multiple sources of data, understanding the information about a particular place, and integration of different models. Douglas-Smith et al. (2020) and Blair et al. (2019) discuss the need for appropriate software architectures that consist of user-friendly interfaces and is service-oriented (e.g., Salas et al., 2020). Salas et al. (2020) established an Open Data and Open Modelling framework to allow different models to be easily integrated, enabling direct heterogeneous model coupling. Douglas-Smith et al. (2020) highlight the need for maintained model packages that will support uncertainty and sensitivity analysis methods and approaches that will be more accessible. They argue that even when visualisations are provided, users may require an alternative way of viewing the outputs, hence the complexity (real or perceived) may hinder the uptake of these tools. The authors suggest that user-led efforts, coupled with sufficient documentation are required for widespread adoption of model packages which will support informed decision making.

2.3. Hydro-climatic observations, water resources developments and associated data

2.3.1 Data requirements

Selecting appropriate data for hydrological modelling remains a problem (Nijzink et al., 2018), yet making the right kind of data available and developing effective ways of obtaining new data for different purposes should be given serious attention (Beven, 2019). Hydrological research initiatives and advances in technology have made hydroclimatic data accessible (Rabiei et al., 2016; Stewart et al., 2012; Hut et al., 2010; Tauro et al., 2018). For example, the Measurements and Observations in the XXI century (MOXXI) project is a good, recent attempt to address data issues, such as how to close the gap between observation and the advanced data analysis capabilities aimed at understanding hydrological processes (Tauro et al., 2018). Identified ways of filling in these gaps include the use of remote sensing and satellite-based retrieval algorithms (Joyce et al., 2004) which have improved hydrological modelling over the past 50 years (Triana et al., 2019).

Many kinds of data are necessary for various hydrological purposes. For example, input data for modelling includes forcing climate (precipitation, evapotranspiration) and stream flow to calibrate and validate water resources models. Other data include physical characteristics (such as soil, geology, land cover and use, topography, river bathymetry and groundwater characteristics) for parameterisation, regionalisation and model transfer from gauged to ungauged areas.

Many aspects must be considered when addressing data requirements for a typical WRA: temporal and spatial resolution (Cecinati et al., 2017; Hegerl et al., 2019; Michelon et al., 2020); correct assumptions on data accuracy (Beven, 2008b; Beven 2018; Beven, 2019b); the temporal span (Tan et al., 2020); assumptions on types and true non-stationarity (long-term non-stationarity as opposed to seasonal variability) (Koutsoyiannis, 2011; Koutsoyiannis and Montanari, 2015; Ajami et al., 2017; Beven, 2016; Lu et al., 2019); the availability of metadata (Ceola et al., 2015), and physical bounds (Pappenberger et al., 2006; Beven, 2016; Beven, 2019). Other important aspects include the usefulness of the data for understanding current change and the variability of natural and impacted conditions, and in forming a basis for understanding future changes (Harrigan et al., 2014). Another aspect relates to the usefulness of data in regionalisation approaches (Beven and Westerberg 2011; Westerberg et al., 2016), and in developing frameworks to understand similarity in hydrology (e.g., Wagener et al., 2007; Jin et al., 2018). Next, is the usefulness of data for model output constraining (Michelon et al., 2020), that is, filtering model outputs using observed or measured data. The last aspect is the importance of data for understanding the connection between patterns of landscape features and catchment hydrological response (Troch et al., 2015; Yoshida and Troch, 2016).

A discussion of the requirements of data with respect to the highlighted aspects of each of these types of data follows. This discussion of data required for a typical WRA is limited only to the main aspects. These are: temporal resolution, spatial resolution, accuracy, metadata, non-stationarity, periodicity, temporal span and consistency.

Temporal resolution: Temporal resolution is the frequency at which a measurement is made and high-resolution data are necessary for hydrological modelling (Wang et al., 2009; Sikorska and Seibert, 2018a). Temporal resolution (e.g., of rainfall data) that is required for a typical WRA depends on the scale (Tauro et al., 2018) and purpose of analysis. Data must have sufficient temporal resolution in order to capture changes in short-term climate extremes (Prakash et al., 2018; Hegerl et al., 2019) and highly variable hydrological processes. Tarnavsky et al. (2013) argue that daily temporal resolution of rainfall may not be sufficient for accurate modelling of infiltration and runoff (Tarnavsky et al., 2013). Decision making, especially in areas of complex terrain, requires data of high temporal resolution; data that are able to enhance both risk evaluation and the efficiency of the model (Chiaravalloti et al., 2018). Schilling (1991), for example, proposed one-minute temporal resolution for urban hydrology, while Berne et al. (2004) identified five-minute temporal resolution of rainfall measurements for catchments of the order of 1000 ha. Results from a study by Lyu et al. (2018) suggest that urban catchments smaller than 100 ha require a temporal resolution of five minutes and those which are greater than 100 ha require a 15-minute temporal resolution in order to constrain relative biases of flood peak within 10% (i.e., effectively reduce uncertainty in flood peak modelling). A study by Tarnavsky et al. (2013) highlighted the need for finer temporal resolution (i.e., hourly) of rainfall data to make realistic simulations in dry catchments, however, such data are rarely available in data scarce regions.

Spatial resolution: Spatial resolution relates to the size of a geographical area that can be discerned by a measuring device. The higher the spatial resolution, the more accurate the hydrological response simulation (Lobligeois et al., 2013). Many factors influence the level of spatial resolution of data (Cecinati et al., 2017), such as the scale (Tauro et al., 2018) and purpose of the analyses. For instance, a sufficiently fine resolution is required to capture the variability of urban hydrological processes (Cecinati et al., 2017) as urban areas are sensitive to small-scale spatial variability (Cristiano et al., 2017). Tarnavsky et al. (2013) argue that a spatial resolution (rainfall) of less than 2 km is appropriate for most hydrological modelling studies at dryland catchments, taking into consideration the scale at which rainfall patterns and spatial variability occur. Schilling (1991) argues the need for a 1 km spatial resolution for urban hydrology, while Berne et al. (2004) identify the necessary spatial resolution of about 3 km of rainfall measurements for catchments of the order of 1000 ha. Ochoa-Rodriguez et al. (2015) proposed that catchments of less than 1 ha require rainfall inputs of approximately 100 m resolution, while those between 1 ha and approximately 100 ha require a spatial resolution of 500 m. For those greater than 100 ha, a spatial resolution of 1 km appears to be adequate. Jiang and Wang (2019) concluded that a spatial resolution of 1 to 30 m is required for interpretation of land use/cover information in order to simulate human impacts on the hydrological cycle. Fu et al. (2011) concluded that high spatial resolution of precipitation input (i.e., about 500 m) may improve simulations in catchment sizes between 250 km^2 and 1000 km^2 but it cannot improve simulations for large-scale models (greater than 1000 km^2).

Hyper-resolution data (Wood et al. 2011), in the order of 1 km (Bierkens et al., 2015), may be useful in understanding catchment characteristics and processes in greater detail and are important for developing 'hydrological models of everywhere' (Beven, 2003), at locally-relevant resolution (Bierkens et al., 2015), but must be used with caution.

Data accuracy: Data accuracy is a key element in water resources assessments; the accuracy level of data required depends on their intended application (e.g., planning, designing, operation, etc.) (Stewart, 2015) and is directly related to the precision in stream flow simulation. Accurate data are critical for understanding the hydrological cycle at small and global scales as well as for science applications (Ma et al., 2018; Prakash et al., 2018; Sikorska and Siebert, 2018b; Lu et al., 2019). Accuracy is very important in areas characterised by complex terrain (Chiaravalloti et al., 2018) or in situations where there is highly dynamic temporal and spatial distribution of a hydroclimatic variable, such as rainfall (Tauro et al., 2018). Moreover, Michelon et al. (2020) argue that there is still a challenge in understanding rainfall patterns in mountainous areas. The required accuracy for variables such as water depth estimates depends on the characteristics of the study area (Tauro et al., 2018). As a result, Stewart (2015) concluded that high accuracy is a requirement in studies focusing on environmental risk, including flood and drought, for example. Similarly, Yassin et al. (2019) showed that the effects of gridded precipitation data accuracy on stream flow simulation are significant on the headwaters, but diminish downstream.

Metadata: All aspects of metadata (i.e., information about data) are important and need to be included in different kinds of data to serve different purposes. Typically, both raw and modified data for specific purposes should be accompanied by detailed metadata (Ceola et al., 2015; Horne, 2015). Data required for WRA must be accompanied by characteristics such as details on data origin, spatial and temporal resolution, description of the observing instrument, information on data collection, measures of data quality, coherence of measured method and instrument (Ceola et al., 2015). This is important as they are used as quality control (Schellekens et al., 2017) in deciding whether the datasets are relevant for a hydrological study and this may promote transparency and data sharing (Ceola et al., 2015).

Non-stationarity and assumptions on periodicity: Data with the potential to be used to understand the types of temporal changes (and their drivers) are needed in order to predict realistic uncertainty in WRAs. Gridded global datasets (e.g., precipitation) have large differences in spatio-temporal patterns, even among those using the same data sources (Beck et al., 2017). These differences can make generalisations of findings of regional studies difficult, and result in poor understanding of climate non-stationarities and in wrong uncertainty estimates (Beck et al., 2017). Data need to have a strong ability to capture the non-stationarity in variables such as precipitation (e.g., Lu et al., 2019; Tan et al., 2020). A time series that would allow the detection of non-stationarity in seasonal as well as annual intervals is essential (Lu et al., 2019). Data are required that are usable to easily identify changes in the time series in order to conduct, for example, realistic impact analyses (Hegerl et al., 2019). A study of comparison of models by Šraj et al. (2016) concluded that non-stationary models tend to estimate flood quantiles better than stationary models.

Temporal span and consistency: Sufficiently long and consistent data are necessary for many purposes and the record length of the time series required depends on the intended use of the data. Global long-term daily data based on gauge-only records (Contractor et al., 2020) will be significant in various hydrological applications, such as planning (Tan et al., 2020) and in predicting the future conditions in a changing world (Bayazit, 2015). The temporal span of any record is important in deciding which dataset to use for a specific need and area under consideration (Tan, et al., 2020). In yield analysis studies, for example, a data record of 10 to 20 times the critical period (e.g., resulting in drought) is required to achieve reasonable stability (Stewart, 2015). In cases of little variability in stream flow, and where the focus is on seasonal storage (less than one year), a temporal span of 10 to 20 years may be satisfactory, while in semi-arid to arid areas, a record of 50 to 100 years may be used (Stewart, 2015). A record of 25 years may be sufficient for extreme precipitation frequency analysis in humid areas, while more than 50 years is required for regions with a distinct periodic fluctuation of precipitation, and 40 to 50 years is adequate for extreme precipitation frequency analysis (Sevruk and Geiger, 1981).

2.3.2 Declining networks

As much as adequate observation and widespread availability of large-sample datasets is a key requirement for progress (Gupta et al., 2014), most river basins of the world are ungauged (Blöschl et al.,2013) owing to the decline of stream flow gauging networks (see Hannah et al. 2011); a situation that requires serious attention. Traditional monitoring systems have many limitations such as insufficient spatial coverage, and limited ability to measure complex hydrological processes. Observations based on these systems are still too inadequate to fully understand system processes (Tauro et al., 2018). The observations have consistently decreased since the 1980s (Tauro et al., 2018) and this is not likely to improve to a satisfactory level, partly because the advances in technology have overtaken the long-established system. Declining observations, including scarcity of data in catchments worldwide, increase the value of alternative sources of data in modelling (Hulsman et al., 2020). The MOXXI initiative and the Surface Water and Ocean Topography (SWOT) satellite (2021 launch) are typical examples of addressing the need for new monitoring approaches in order to increase accuracy, and spatial and temporal resolution of hydrological observations (Tauro et al., 2018). Freely available, global, remotely-sensed data on stream water levels, for example, can fill the existing flow observation gaps related to spatial coverage in poorly or ungauged basins (Hulsman et al., 2020).

2.3.3 Future data needs: global vs. local data

In the future, data requirements are expected to change because of developments in new hydrological modelling approaches and unknown future environmental changes. There is no doubt that the significance of data in the development of models will escalate in the future (Mount et al., 2016). The recent inclination towards the application of regionalisation approaches in modelling (Sood and Smakhtin 2015) will increase the need for data quantity that is sufficient for catchment similarity studies, regionalisation methods and model output constraining. In addition to data quantity and physical bounds considerations, continuous data will also be essential for defining and incorporating likely future non-stationarities and periodicity in water resources assessment. New automated *in situ* sensing technologies (Wolf et al., 2012), which will provide high-quality time series of data to validate space-borne measurements such as vegetation, are necessary (Tauro et al., 2018) to improve stream flow simulation and model performance. Alternative monitoring methods and observations are also necessary for consistent model evaluation to overcome the existing information limitations related to, for example, accuracy and resolution (Mount et al. 2016). Such sources of data should be tested and validated through comparison with other sources in different settings, using different models with unlike structures that account for input and parameter uncertainty.

Can satellite data replace ground-based observations? Satellite recording is vital for global coverage (Hegerl et al., 2019) and can offer a promising alternative source on a larger scale with acceptable resolution (Jiang and Wang, 2019). *In situ* data are important for validating and calibrating satellite datasets, as well as for long-term monitoring (Hegerl et al., 2019) and can provide accurate precipitation data (Jiang and Wang, 2019). The results from a study by Yi et al. (2018) showed that ground-based precipitation data proved to be the most accurate source of all others, for example, multi-satellite, data assimilation and numerical weather predictions. In more data scarce areas, however, satellite data may be all that is available (van der Wel, 2000).

Both satellite and *in situ* observations are important for water resources assessment. Satellite data have many benefits. The application of satellite-based data as an alternative to *in situ* measurements has improved stream flow simulation (Jiang and Wang, 2019), by allowing modelling in data-scarce areas. Some satellite-based precipitation products have high spatial and temporal resolutions, but their accuracy varies widely over different regions (e.g., Lu et al., 2019; Tan et al., 2020). This necessitates the use of multi-satellite data estimates for various hydrological applications since they combine the advantages of several satellite-based sensors in order to estimate more accurately gridded rainfall, for example (Prakash et al., 2018). The tendency is shifting towards the merging of the more frequent infra-red (IR) observations and higher accuracy of microwave (MW) observations (Tan et al., 2020) in order to reduce estimation errors (Tauro et al., 2018).

2.3.4 Access to data

The importance of access to data is being recognised and several attempts have been made to make data available with few restrictions in order to promote modelling of the hydrological cycle of the entire globe. Efforts to make datasets available to the global community have long been compromised by economics and ownership-related problems (Gupta et al., 2014) which hinder environmental research and progress in modelling in most parts of the world (Beniston et al., 2012), especially in developing countries (Sood and Smathkin, 2015).

Access to data is essential to improve model predictions under changing conditions (Thirel et al., 2015b). Although access to local information is still a problem in some countries (Arheimer et al., 2020), in other countries access to national data has improved greatly (e.g., Horne 2015). Efforts have been made to simplify access to both global and local data and interpretation for decision makers from online-based platforms through protocols and tailor-made user interfaces with few restrictions on their use (Snow et al., 2016; Schellekens et al., 2016). The regular use of the 'Creative Commons' data licensing approach (i.e., free distribution of copyrighted 'work') is the main feature of the information series produced by national authorities (Horne, 2015). Arheimer et al. (2020) demonstrated the usefulness of open data when they used more than 30 open global datasets for forcing and parameter estimation, and more than 20 000 time series of river flow from 5338 gauges from across the globe to model hydrological processes in more than 130 000 catchments.

Better access to national data archives will require coordinated efforts from countries (Sood and Smathkin, 2015). It is important to provide global hydrological data that are relevant locally (Arheimer et al., 2020) in order to appreciate the value of data and the importance of data sharing. The exchange of global input and local data and knowledge is necessary to improve global hydrological models (Arheimer et al., 2020). Improved access to more global and local data will expand the *calibrated area* of the globe and will improve the overall accuracy of modelling (Sood and Smathkin, 2015; Contractor et al., 2020). It will make possible the understanding of existing uncertainties in water resources assessments (McMillan et al., 2017).

2.3.5 Impacts of data scarcity on model outputs and uncertainty in the results

Data scarcity is a pivotal problem and a source of considerable uncertainty in hydrology (Tauro et al., 2018). While observed stream flow data are rarely completely accurate, we often do not fully understand what they imply or represent, especially because of non-stationarity and the impacts of upstream development (Thirel et al., 2015a), which are often poorly (or not) quantified (Beven, 2019). Scarcity of data makes it difficult to understand the input-output processes of hydrological systems which may result in wrong assumptions of parameter values and predicted outcomes (Beven, 2019). Data scarcity can limit or restrict parameter estimation procedures and hinder rigorous model testing (see for example in Hulsman et al., 2020). While data scarcity presents an opportunity for hydrological modelling, especially in developing countries, it compromises model outputs and can worsen uncertainty in the results.

2.3.6 Non-stationarities in water resources assessments

True non-stationarity relates to temporal changes that are beyond natural variability, and ostensible non-stationarity refers to changes that are part of stochastic variability within stationary time series. Hydroclimatic observations are not always stationary (based on data analysis), but many models generate stationary outputs, given non-stationary inputs. For example, in some models, parameters are established without the consideration of non-stationarity in hydrological processes. In the past, water resources management systems have been based on stationarity assumptions (Milly et al., 2008) as in many developing countries, data on water resources developments are non-existent, or do not account for non-stationarities. Schilling and Stakhiv (1998) concluded that hydroclimate is still within the range of natural variability and/or the effective range of optimally operated infrastructure. Milly et al. (2008) argue that stationarity assumptions are no longer valid because of the significant anthropogenic change of climate. Therefore, the current procedures for designing water-related infrastructure must be revised (Kundzewicz et al., 2008) and newly established water resources systems and developments should also be based on non-stationarity assumptions. Water resources infrastructure designed under stationarity assumptions may be negatively affected by the recently observed non-stationarities.

The key question is how to ensure that non-stationarity is appropriately incorporated into the quantification of water resources. In addressing this, water resources assessment studies should first consider non-stationarity, not only in model inputs and outputs, but also in some catchments' physical characteristics, such as, land use or cover and water resources use and development, to constrain modelling uncertainty. Secondly, the distinction between the types of non-stationarity is crucial (Koutsoyiannis, 2011). Thirdly, the key issue that must be considered and made clear in measuring and understanding non-stationarity is the temporal scale. Fourthly, it is also important to identify the main drivers of non-stationarity, which include catchment scale (Blöschl and Sivapalan, 1995), complexity (non-linearity) of different hydrological processes influencing catchment response (Mcdonnell et al., 2007; McGlynn et al., 2004), variability in the input (Schymanski, 2008; Sivapalan, 2005), as well as climate (e.g. Lauro et al. 2019) and anthropogenic forcing. Lastly, climate-driven variabilities can be easily simulated with a single parameter set (Hughes, 2015), and these parameters must be established by calibration that accounts for different seasons to ensure enough signals in the observed data. This approach will allow for the identification of appropriate parameter values that can adequately simulate current and future catchment response in different seasons (Hughes, 2015). However, Kling et al. (2015) noted that it can be a challenge to simulate discharge with reasonable model performance in semi-arid areas where there is a strong non-stationarity in rainfall. This is perhaps due to poorly-understood soil-surface runoff generation processes in these areas.

Non-stationarity in climate does not necessarily imply (or result in) direct non-stationarity in hydrological response. It may imply, to a certain extent, non-stationarity in model parameters and/or assumptions (that are directly related to climate). This has been observed in many regions where, for example, rainfall increases but runoff decreases (Ajami et al., 2017).

Four main challenges associated with non-stationarity are:

- the quantitative predictions of stream flow changes at basin scale remain largely uncertain, and the current generation of climate models does not clearly represent precipitation changes in certain areas (Intergovernmental Panel on Climate Change, 2007a, 2007b; Milly et al., 2005; Nohara et al., 2006);
- anthropogenic changes, such as land-use change can be more difficult to account for in estimation models, due to their non-linearity, than abstractions and infrastructural developments (Liu et al., 2009), and this is further exacerbated by insufficient anthropogenic water-use information;
- stochastic models based on random variability often exhibit apparent non-stationarity;
- differentiation between long-term variability characteristics and shorter periods of model residuals that might contain stationary statistical characteristics is difficult (Beven, 2016).

2.4 Regional application of models

2.4.1 Catchment classification and hydrological regionalisation

Catchment classification is an open-ended search for similarity in catchments. Classification is performed using different approaches mainly controlled by data availability issues. Wagener et al. (2007) proposed a framework for catchment classification that considers both the physical characteristics and hydrological response dimensions. As a result, the authors provide a list of requirements for such a classification framework that takes into account the data requirements for catchment classification.

Different studies have used different approaches to classify catchments. Some studies have developed approaches based on topography to classify catchments hydrologically, especially in ungauged catchments, for example, Gao et al. (2019). Numerous studies have relied upon basin characteristics (see Latron et al., 2003; Manus et al., 2009) where a selection of characteristics is used as similarity metrics for catchment classification (e.g., Wolock et al., 2004; Reichl et al., 2009; Szolgayova et al., 2014). Some have used mean discharge, runoff indices, flow (duration) characteristics (e.g., Troth, 2013; Merheb et al., 2016; Tumbo and Hughes, 2016; Kelleher et al., 2017; Ndzabandzaba and Hughes, 2018) while others applied isotopes (e.g., Tarafdar et al., 2019) to understand the hydrological responses of catchments. Jin et al. (2018) tested a combination of some of these approaches to determine the physical attributes that can be used as similarity factors for a specific hydrologic function.

Many advantages and disadvantages of these various approaches have been identified. Oudin et al. (2010) and Ali et al. (2012) contend that physical characteristics have the potential to describe watersheds generally in relation to hydrological response. In addition to this view, Jin et al. (2018) argue that hydrologic similarity based on physical catchment characteristics needs to be examined. Singh et al. (2014) and Loritz, et al. (2018) explored the question of which characteristics exert primary control on hydrological dynamics, and discovered that only a portion of topographic characteristics is relevant for simulating observed stream flow and storage dynamics. Therefore, Jin et al. (2018) argue that the question of whether hydrological response can be determined entirely by physical characteristics still exists. Some studies have shown the lack of strong evidence of the positive relationship between some physical attributes and hydrological response (see Mertz and Blöschl 2009; Leyet al., 2011; Ali et al., 2012). This may be due to insufficient catchment descriptors (Sawicz et al., 2014) and may have a direct effect on the choice of hydrological regionalisation approach and the way it is carried out.

Depending on data availability, both catchment physical characteristics and hydrological response can be used for catchment classification and hydrological regionalisation according to homogeneity. Many hydrological regionalisation approaches have been based on physical basin properties (e.g., topography, geology, soil, vegetation, etc.). Unfortunately, their success is often limited, not only by the uniqueness of place concept, but also by deficiencies in the data available to quantify the physical properties, as well as the relatively large spatial scales used in practical hydrological modelling (Kapangaziwiri et al., 2012) and the inherent complexities of these scales (McDonnell et al., 2007).

The dominant climatic and landscape controls on hydrologic behaviour are time-scale dependent (Atkinson at al., 2003; Farmer et al., 2003; Son and Sivapalan, 2007) as is the concept of hydrological similarity time variant (Loritz etal., 2018), that is, similarity of catchments varies with time. Consequently, Loritz et al. (2018) propose a framework for understanding and examining process organisation and functional similarity of hydrological systems. They hypothesise that similar hydrological systems are complementary, and not mutually exclusive. Parameter estimation should therefore be based on catchment hydrological response that accounts for spatially and temporally unique catchment characteristics and complex processes. Hydrologic similarity based on hydrological response is, therefore, the basis for transferability of information and for generalisation of hydrologic understanding and catchment classification (Sawicz et al., 2011). Grayson et al. (2002) argue that observed spatial patterns of hydrological response can be an effective discriminator of "behavioural" and "non-behavioural" models and used to constrain model outputs.

2.4.2 Model output constraining

Ways of resolving uncertainty in hydrological modelling have improved. Quantifying behavioural parameter sets has been recognised as an effective modelling approach in reducing uncertainty in the outputs of a hydrological model. Earlier methods of regionalising parameters of hydrological models focussed on directly estimating parameter values from physical basin data (Kapangaziwiri and Hughes, 2008) in a single model run (Hrachowitz et al., 2014; Kapangaziwiri et al., 2012; Nijzink et al., 2016; Tumbo and Hughes, 2015; Westerberg et al., 2011; Westerberget al., 2014; Yadav et al., 2007; Zhang et al., 2008) or identifying relationships between pre-calibrated model parameters and basin properties (Mazvimavi, 2003; Pokhrel and Gupta, 2009). More recently there has been a focus on using measured or estimated catchment response characteristics (indices or signatures) to constrain the ensemble outputs of an uncertain hydrological model. Model output constraints (indices or signatures) can be estimated from different catchment physical characteristics and observations, such as precipitation, evapotranspiration, groundwater, and stream flow descriptors. The latter is the widely used signature for constraints.

The use of constraints in modelling has several advantages, chief of which is that it is model independent. For instance, subjectivity is reduced as the constraints are based on observations from the catchment. Secondly, the indices of hydrological response condition the parameter space in a model run and are an alternative to stream flow calibration (Nijzink et al., 2018) and parameter regionalisation. Thirdly, constraints are valuable to limit the feasible model parameter space, that is, it has the capacity to reduce parameter search space in a model (Hrachowitz et al., 2014; Nijzink et al., 2018) in order to reduce the time the model runs. Lastly, model output constraints are important to improve hydrological process representation in the absence of stream flow data (Nijzink et al., 2018).

Several issues must be considered when implementing constraints in hydrological modelling. Model output constraining can be implemented as *a priori* defined inequality limits on parameters or on hydrological processes (Nizjink et al., 2018). Depending on the model structure that is used, some models may require a few constraints while others may require many in order to effectively constrain a model output. Different types of constraints (e.g., aridity, soil moisture, groundwater characteristics) may be used to constrain different hydrological processes (evapotranspiration, soil moisture storage, groundwater recharge and discharge) in a model. The availability of data mainly determines the choice of hydrological signatures to be used as constraints. The constraints may be applied directly to a specific catchment on a model to address other issues in hydrology such as equifinality, assessing model structures (Euser et al. 2013), and understanding watershed response with limited data (Blume et al. 2007). The above examples of applications of these indices in modelling have prompted research interest in hydrological signatures (e.g., Westerberg et al., 2016; Zhang et al., 2018). For example, developed constraints can be regionalised (e.g. Yadav et al. 2007) and these types (regionalised constraints) are often based on catchment physical characteristics in data-scare areas. In semi-gauged areas, basin physical characteristics are linked to watershed dynamic response characteristics in order to regionalise constraints. Where stream flow data are available, hydrological response characteristics are used to develop and regionalise constraints.

2.4.3 Model identification

Model identification relates to the process of estimating or establishing appropriate model parameters. Improvement in hydrological modelling has greatly influenced the process of model identification in various ways. Parameter estimation has been based on two major approaches; *a priori* estimation (without reference to stream flow) and *a posteriori* estimation (e.g., parameter transfer to an ungauged basin after successful calibration in a donor watershed). Earlier modelling approaches used the conventional way of establishing suitable model parameters, referred to calibration (estimation of realistic parameter values or ranges of the chosen model structure) and validation (applying the model to a different setting thus justifying that the model is an acceptable representation of the system). Triana et al. (2019) demonstrate that relying on model performance metrics when using a traditional approach of estimating parameters (of a conceptual model, for example) from a single domain cannot guarantee appropriate representation of a hydrological system. As a result, the trend is not to use observed stream flow data to calibrate or fit a model in the traditional sense, but to use them together with other characteristics such as rainfall, ET and groundwater flow in the process of quantifying some of the sub-basin constraint indices (Tumbo and Hughes, 2015). Model constraining ensures that a model structure is capable of mimicking the observed hydrological response of a catchment. Triana et al. (2019) argue that model identification should take into account issues such as equifinality, model inadequacy, and constraint inadequacy.

As all parameters are crucial for simulation outcome (Guo and Su, 2019), it is essential to perform an analysis of the sensitivity of parameters. The sensitivity of model parameters is usually analysed at the final level of modelling, where a detailed examination of parameter interaction and performance trade-offs is conducted. Sensitivity analysis may be performed using various approaches which have usually been confined to univariate or bivariate (first-order or simple interactions) effects on model response (Pechlivanidis et al., 2011); this might be due to high computational requirements. Wagener et al. (2004) extended this procedure to include the evaluation of the dynamic sensitivity of model parameters to identify, for example, periods in which specific parameters are sensitive, as well as the time in which parameters converge to optimal values. Sreedevi and Eldho (2019) apply a classical two-stage sensitivity analysis for parameter identification in a physically-based distributed model in order to simplify the calibration procedure.

2.4.4 Model evaluation and uncertainty assessment

Model evaluation is an assessment of how well a model simulation compares with observed system response and is usually performed through the use of *goodness of fit*. Many approaches have been developed to assess model simulations against observed system response. Matott et al. (2009) provide a functionality matrix for some of the tools which employ quantitative methods of model evaluation (including their sub-classifications) with their impact as well as capabilities, and group them based on the identified six assessment approaches. These methods are: data analysis, identifiability analysis, parameter estimation, uncertainty analysis, multi-model analysis, and Bayesian networks. Approaches to testing both a single model and multiple models (Lidén and Harlin 2000; Unduche et al. 2018) should have the following dimensions as pointed out by Wagener (2003) and Wagener et al. (2003): (i) model performance, (ii) parameter uncertainty and (iii) 'realism' or conservation of hypotheses.

Many contrasting methods of calibrating models and estimating uncertainty (e.g., analytical, computer algebra and sampling-based) have been developed. These include Markov Chain Monte Carlo sampling, sequential data assimilation using the Ensemble Kalman Filter (EnKF), the Random Walk Metropolis (RWM), Shuffled Complex Evolution (SCE-UA: Duan, Sorroshian and Gupta, 1992), Shuffled Complex Evolution Metropolis (SCEM-UA: Vrugt et al 2003b), Differential Evolution Adaptive Metropolis (DREAM: Vrugt et al., 2009) and Simultaneous Optimisation and Data Assimilation (SODA) sampling algorithms. Some of these methods aim at one optimal parameter set. In other approaches, a parameter involves one set of random variables that follow a certain joint probability distribution (Jiang et al., 2017).

While significant progress has been achieved in uncertainty estimation, there are still challenges. A recent focus in uncertainty estimation is the use of multi-model predictions. In such methods of multi-model predictions, simulation sets are combined and the uncertainty is averaged using the Bayesian Model Averaging (BMA: Barnard, 1963; Roberts, 1965, Leamer, 1978). Examples of the application of this specific approach are given by Neuman (2003), Vrugt et al. (2006), Vrugt and Robinson (2007), Duan et al. (2007), Rojas et al. (2008), Zhang et al. (2009), Dong et al. (2011), Dong et al. (2013), Yan et al. (2017), Jiang et al. (2017), Liu and Merwade (2018) and Muhammad et al. (2018). However, uncertainty estimation can be very complex, especially in cases involving ontological uncertainty, where belief plays a crucial role in the uncertainty estimates (Beven 2016). The difficulty of estimating uncertainty is more pronounced in stream flow predictions under climate change due to the large compounded uncertainties from Global Circulation Models (GCMs), which are often transferred to rainfall-runoff models and not separated from hydrologic uncertainty. The problem of estimating model structural uncertainty and its contribution to overall uncertainty, as well as the use of different uncertainty analysis approaches in applying different hydrological models has still not yet been tackled. Many uncertainty analysis algorithms and frameworks have been developed. These include the Shuffled Complex Evolution Metropolis algorithm: SCEM (Vrugt et al., 2003b); the multi-objective extension of SCEM (Vrugt et al., 2003a); the Generalised Likelihood Uncertainty Estimation: GLUE (Beven and Binley, 1992); the Bayesian recursive estimation technique: BaRE (Thiemann et al., 2001); the dynamic identifiability analysis framework: DYNIA (Wagener et al., 2003); the maximum likelihood Bayesian averaging method: MLBMA (Neuman, 2003); the dual state-parameter estimation methods (Moradkhani et al., 2005a; Moradkhani et al., 2005b); and the simultaneous optimisation and data assimilation algorithm: SODA (Vrugt et al., 2005). Some of these methods include uncertainty analysis explicitly (e.g., SCEUM-UA, BaRe, GLUE) while others don't. Beven and Smith (2015) argue that since statistical measures assume that all errors can be treated as if they were random (which is not always the case), it follows that an improved analysis of uncertainty is necessary.

Valid assumptions about the nature of the uncertainty sources should be made in order to separate effects of different uncertainties on model output (Beven, 2005). Mount et al. (2016) argue that *a priori* assumptions about the data to be modelled using statistically-based empirical models are often less reliable in developing complex predictive models. Separating uncertainty and their effects rely on good assumptions about data. Separating uncertainty can be very complex and is often compromised by lack of data (Sellami et al., 2016). The problem of separating uncertainty resulting from inputs (e.g. rainfall) can be aggravated by epistemic uncertainty emanating from a lack of knowledge of hydrological response representation, model forcing data and observed responses (Beven, 2016). It is therefore necessary to understand these uncertainties by improved analysis of the observation process (Mcmillan and Westerberg, 2015), and to understand the impacts of these uncertainties on hydrological metrics and/or simulation (Westerberg and Mcmillan, 2015). An alternative to this solution would be to apply methods of comparison between data and models (Beven and Smith, 2015; Nearing and Gupta, 2015) and evaluate the appropriateness of the information that hydrologists provide to decision makers (Dottori, et al., 2013; Serinaldi, 2015).

Efficiency criteria (i.e., statistics-based assessments of model performance) are commonly used to provide an objective evaluation of models. Krause et al. (2005) compared different efficiency criteria (e.g., Nash-Sutcliffe Efficiency, i.e., NSE and its log-transformed version, Coefficient of determination, index of agreement, relevant efficiency criteria) for model assessment. They found that none of the criteria performed ideally, and so recommended that the selection of a criterion should be guided by the intended use of the model. Legates and McCabe (1999) evaluated the widely-used *goodness of fit* measures (such as NSE, index of agreement and their modifications) in hydrological models. They concluded that correlation and correlation-based measures should not be used to assess *goodness of fit* because they may be misleading in deciding whether or not a model is a good predictor. On account of these limitations, Xiong et al. (2009) investigated some of the widely used measures, such as the containing ratio by Beven and Binley (1992); Freer et al. (1996); Montanari (2005); Beven et al. (2008); Xiong and O'Connor (2008).

Following their investigation, Xiong et al. (2009) introduced new indices (e.g., the average deviation amplitude and its dimensionless variant, the average relative deviation amplitude) for characterising the prediction bounds in models and their relationships, as well as their application in an uncertainty framework. Rather than having the estimated result as a point value, these indices express it as a prediction interval, in the form of a band defined by bounds of a specified level of confidence, thus assessing and analysing the quality of the uncertainty bounds in models. These indices can also be used as a basis for comparing bounds generated from different uncertainty estimation methods/systems (Xiong et al., 2009) and contrasting model hypotheses. Since these individual measures only consider a particular property of the bound, Shi et al. (2019) developed a composite measure for assessing the complex behaviour of uncertainty bounds in hydrological models that can efficiently generate an aggregated uncertainty index which may guide reasonable uncertainty assessments in many environmental modelling applications.

In addition to the above solution to the problem associated with correlation and correlation-based measures, Gupta et al. (2009) decomposed the NSE and mean squared error in order to facilitate analysis of relative importance of their different components, and showed the problems caused by these interactions. Subsequently, they introduced an improved version of the NSE, that is, the Kling-Gupta efficiency, in order to take into account different types of model errors, such as errors in mean, variability and dynamics. The Kling-Gupta efficiency was then later modified by Kling et al. (2012). Pool et al. (2018) proposed an improvement of the modified Kling-Gupta efficiency to include non-parametric components. They demonstrated that the modified Kling-Gupta efficiency generally results in better model performance. Some modifications on statistical methods were also proposed by Harmel et al. (2010) and Ritter and Munoz-Carpena (2013) in order to improve *goodness of fit* conclusions. However, Triana et al. (2019) pointed out that a set of metrics in a single domain modelling approach might not be sufficient to judge the performance of a model, especially with respect to uncertainty.

The main question is how do we know we have a good model with realistic uncertainty bounds? This relates to understanding how to assess models under epistemic uncertainties (Beven, 2019). A possible answer to this question is through the use of rigorous testing for model invalidation in gauged and ungauged basins, based on both objective and subjective judgements (Beven and Lane, 2019). This invalidation approach may require the involvement of decision makers (and/or stakeholders implicated in a decision) in order to assess the outputs as well as the assumptions on which the model is based for the purpose of model invalidation (Beven, 2019). This kind of evaluation depends on the availability of forcing data, as well as data for calibration and validation (Beven, 2019). The blind validation approach of Ewen and Parkind (1996) applied by Parkin et al. (1996) and Bathurst et al. (2004) requires that the modeller defines some criteria for acceptability before making any model runs. This approach is related to the 'limits of acceptability' approach applied in the GLUE methodology (e.g., Beven, 2006; Beven, 2009; Beven, 2016a). Beven (2006) introduced model evaluation for the purpose of identifying behavioural models in the context of 'limits of acceptability' (an approach used in order to either accept or reject models) reflecting different sources of uncertainty. This approach is a form of a framework for testing models with reference to hypotheses about perceived realistic catchment behaviour (Liu et al., 2009). Liu et al. (2009) contended for the definition of these limits prior to a model run, though it is practically difficult to define them in a completely *a priori* way, hence the tradition is to define with the data that are available. This approach has since been successfully applied in many studies (e.g., in hydrological modelling: Liu et al. 2009; Schaefli, 2016; Teweldebrhan et al., 2018; Teweldebrhan et al., 2019 and in flood modelling: Blazkova and Beven, 2009; as well as in water quality modelling: Hollaway et al., 2018). A study by Coxon et al. (2014) evaluated multiple competing hypotheses of hydrological behaviour in different catchments within the 'limits of acceptability' framework, and demonstrated the significance of the influence of model structure on performance and on simulating hydrological response in different catchments. Later, a framework for rejecting or accepting models in the context of 'limits of acceptability' was recommended by Beven (2018) and methods for developing them (limits of acceptability) for use in hydrological models are proposed by Beven (2019). This approach has shown how differences in model performance varied between catchments and the model constraints used (e.g., Coxon et al. 2014), as well as how inadequate sampling in model space can result in unjustified rejection of a model (e.g., Vrugt and Beven, 2018) whose uncertainty estimate may be realistic.

Another aspect of a good model is the conservation of known evidence of a system. Beven (2019) proposes an assessment based on whether or not a model violates some established proof on the nature of hydrological system response: a model that must give the right results for the right reasons (Kirchner, 2006). Model rejection based on rigorous invalidation requires that we either improve modelling, or improve data, or improve decision making and will enable learning in order to enhance our understanding of hydrological processes and systems (Beven, 2019).

Yilmaz et al. (2008) and Thirel et al. (2015a) address a similar question of what a good model is, in the context of identifiability and transferability. In their paper, they refer to Coron et al. (2011) who argued that model identifiability and precision in relation to parameters are crucial. Coron et al. (2011) point out that model identifiability and precision are compromised by dependency on statistical characteristics of hydroclimatic data used for calibration, and by dependency on the input data quality and availability. Beven (2019) argues that care must be exercised when considering the quality and value of available data in model evaluation. Transferability will ensure that models do not overfit the specific condition of a calibration period (Andréassian et al., 2012), otherwise, overfitting result in capturing only a portion of possible variation in hydrological processes (Beven, 2016). Transferability often improves the performance of a model (e.g., Beck et al., 2016). Similarly, Yilmaz et al. (2008) demonstrated that a process-based diagnostic approach to model evaluation, whereby the cause of poor model performance and inadequacy is detected and analysed, can provide a useful basis for establishing consistent estimates of model parameters to guide model improvements.

2.5 Summary and conclusion

Data are significant in hydrology because all hydrological knowledge is ultimately derived from observations/measurements and experiments (Kirchner, 2006). Numerous data have been made available to improve modelling (Arheimer et al., 2020) and to simplify uncertainty analysis (Fatichi et al., 2016). However, some datasets, such as global gridded precipitation, differ widely in accuracy, even among those using the same sources (e.g., Eum et al., 2014; Beck et al., 2017). It is clear from the reviewed literature that the problems in hydrology are yet far from being solved. Major factors that affect the overall uncertainty in model prediction are complex, first and foremost because of shortcomings in the accuracy and resolution of data for hydrological modelling. The key data issues in hydrological modelling are related to accuracy and resolution. While improving accuracy and resolution together with long-term time series is critical for uncertainty analysis, resolution that is too high may not necessarily improve uncertainty estimation and model performance (Sikorska and Seibert, 2018a). Understanding how to use these high-resolution data to extract the right information for modelling purposes is important (Dottori et al., 2013). True advances will involve applying the appropriate approaches in solving relevant problems to achieve solutions to hydrological problems. "A realistic assessment of uncertainty in predicting how places respond will mean that a modeller is much less likely to be obviously wrong in those predictions" (Beven, 2019). This kind of uncertainty estimation will result in a learning process that may help reduce uncertainty in order to make robust water resources planning and management decisions in spite of inadequate data.

CHAPTER THREE: STUDY BASINS AND DATASETS

This study focussed on the five transboundary basins of Eswatini, namely; Komati, Mbuluzi, Usuthu, Ngwavuma and Phongola (Phongolo/Pongola). The physical characteristics such as climate, soil, geology, topography, and hydrogeology, as well as observation networks and major water resources development are discussed. Both observed and previously simulated data were collated to establish the information system. Some of these data were only used to describe the physical characteristics of the basins that form the study area and to estimate the natural hydrology parameters of the model. This chapter only presents and discusses the datasets that were used to set up the Pitman rainfall-runoff model (a justification of using the Pitman model is provided in sub-section 4.1). The main datasets include rainfall, potential evaporation, stream flow and groundwater recharge.

3.1 The general physiography of Eswatini

The physiographic zones of Eswatini are shown in Figure 3.1 and a brief overview of the physiography (i.e., topography, climate, geology, soils, landcover, etc.) is given in Table 3.1. The climate of the physiographic zones has been classified according to the Köppen climate classification system (Köppen, 1918). The climate was classified as follows: Cwb (subtropical highland) influencing the Highveld, Cwa (humid subtropical) influencing the Middleveld and Lubombo, and BSh (hot semi-arid) influencing the Lowveld.

The Highveld receives the highest rainfall amount with mean annual rainfall (MAP) decreasing easterly. MAP ranges from slightly above 500 mm in the Lowveld to approximately 1 400 mm in the Highveld and slightly over 1 000 mm in some escarpment sub-basins, while mean annual potential evaporation (MAPE) varies from 1 300 mm to 1 500 mm.

Most of Eswatini is underlain by ancient granites and gneisses of the Kaapvaal Craton of Archean age which occupy the highland area in the western and central parts of the country. In the east are sedimentary and volcanic rocks of the Karoo Supergroup.

The soil types can be subdivided into nine broad categories ranging from raw mineral soils to holomorphic soils. Soil depth increases easterly. The relationship between topography (and indirectly climate) is very obvious, with all the hydromorphic soils located in the Lowveld.

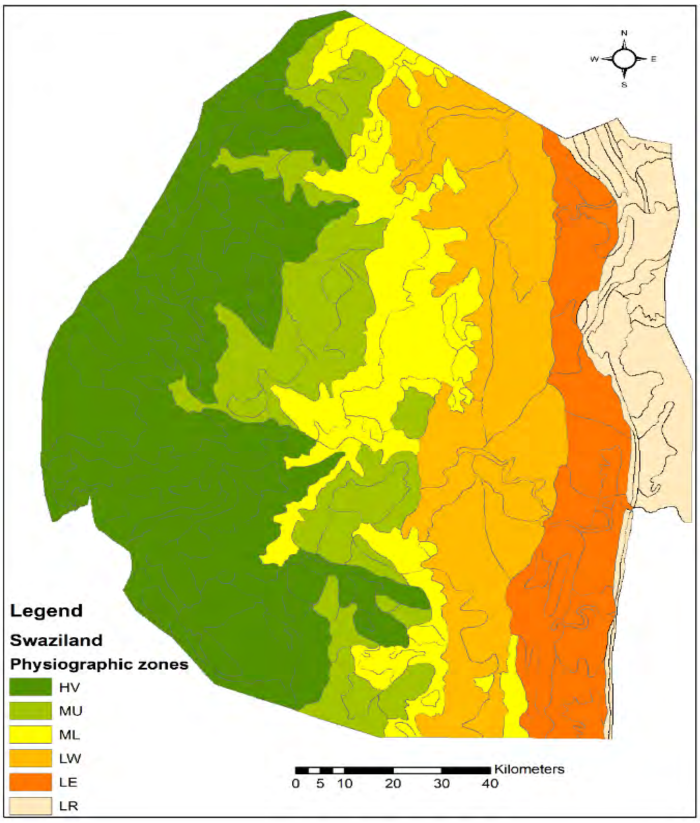

Figure 3.1: Physiographic zones (HV: Highveld, MU: Upper Middleveld, ML: Lower Middleveld, LW: Western Lowveld, LE: Eastern Lowveld, LR: Lubombo) of Eswatini based on climate and topography (Remmelzwaal and Waveren, 1994).

Table 3.1: Brief description of the physiographic regions of Eswatini

Zone	*Category*	*Altitude (m)*	*Topography*	*Geology & soils*	*Landcover*	*Climate*		
						MAP (mm)	*MAPE (mm)*	*Mean temperature (°C)*
Highveld (HV)		950-1605	Hilly and steep	Granite, Shallow soils with outcrop	Predominantly grassland with minor forests	890-1250	1400	17
Middleveld	Upper (MU)	550-800	Hilly	Gneiss, granite, rock outcrops & stony ground	Savannah & bushes	730-1165	1430	19.3
	Lower (ML)	400-650	Gently sloping with isolated hills			600-1020	1460	20.5
Lowveld	Western (LW)	200-400	Undulating plains	Mainly gneiss and some basalt, granites & sandstone. Deep soils, mainly clayey.	Savannah	550-820	1460	21.3
	Eastern (LE)	150-300	Relatively flat terrain			590-820	1500	22.4
Lubombo (LR)		250-650	Slightly hilly plateau	Loamy on Ignimbrite	Savannah, Shrubs & bushes	710	1450	19.2

Figures 3.2 and 3.3 show that there is a significant change in land cover between the years 1990 and 2015. In 1990, the country was mainly covered by natural vegetation (e.g., bushland, woodland, and grassland). The increase of cropland and commercial forests resulted in a decrease in natural vegetation (Government of Swaziland, 2016). Within the same period, urban areas increased and some grasslands changed to bushlands.

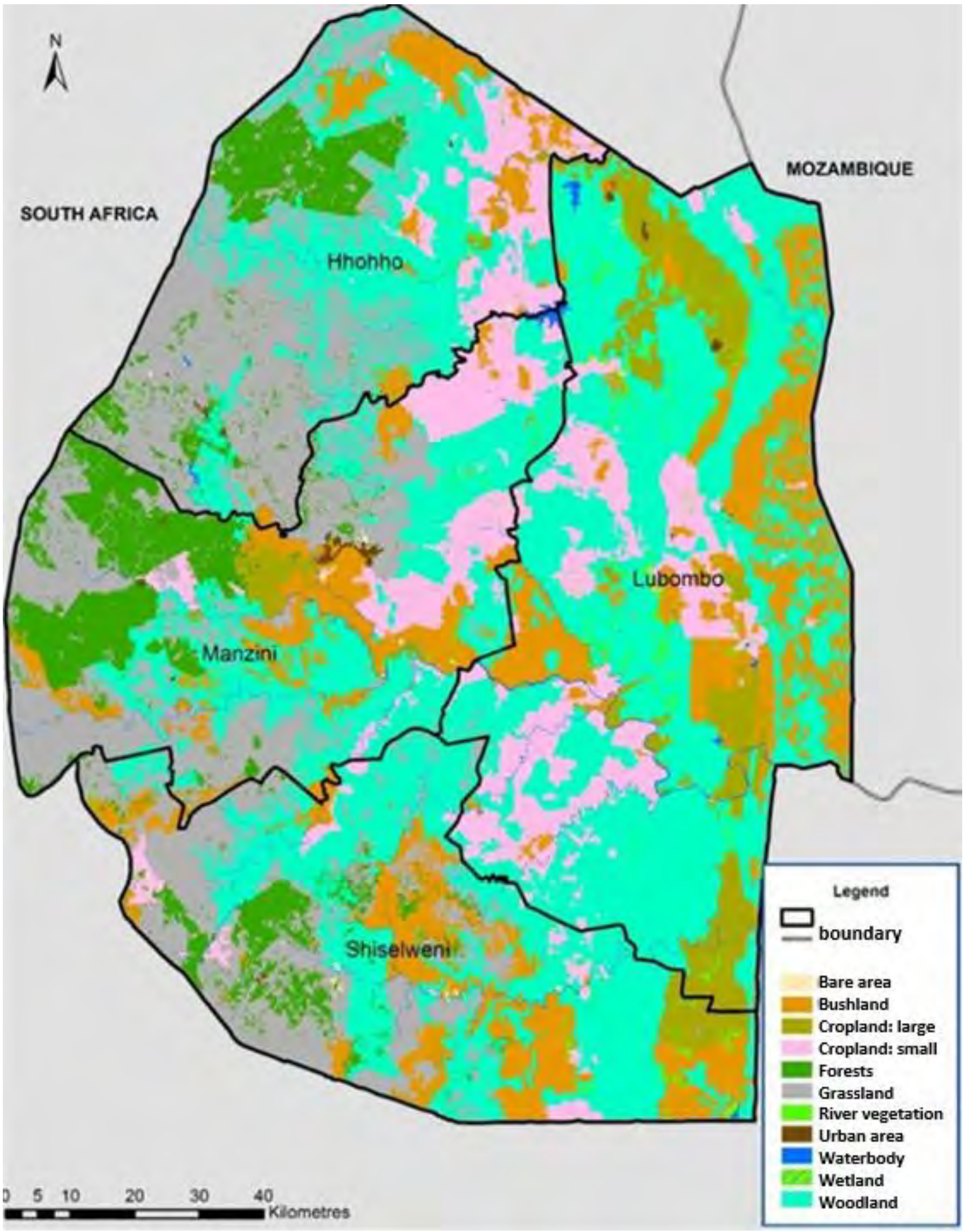

Figure 3.2: Landcover of Eswatini in 1990 (Government of Swaziland, 2016)

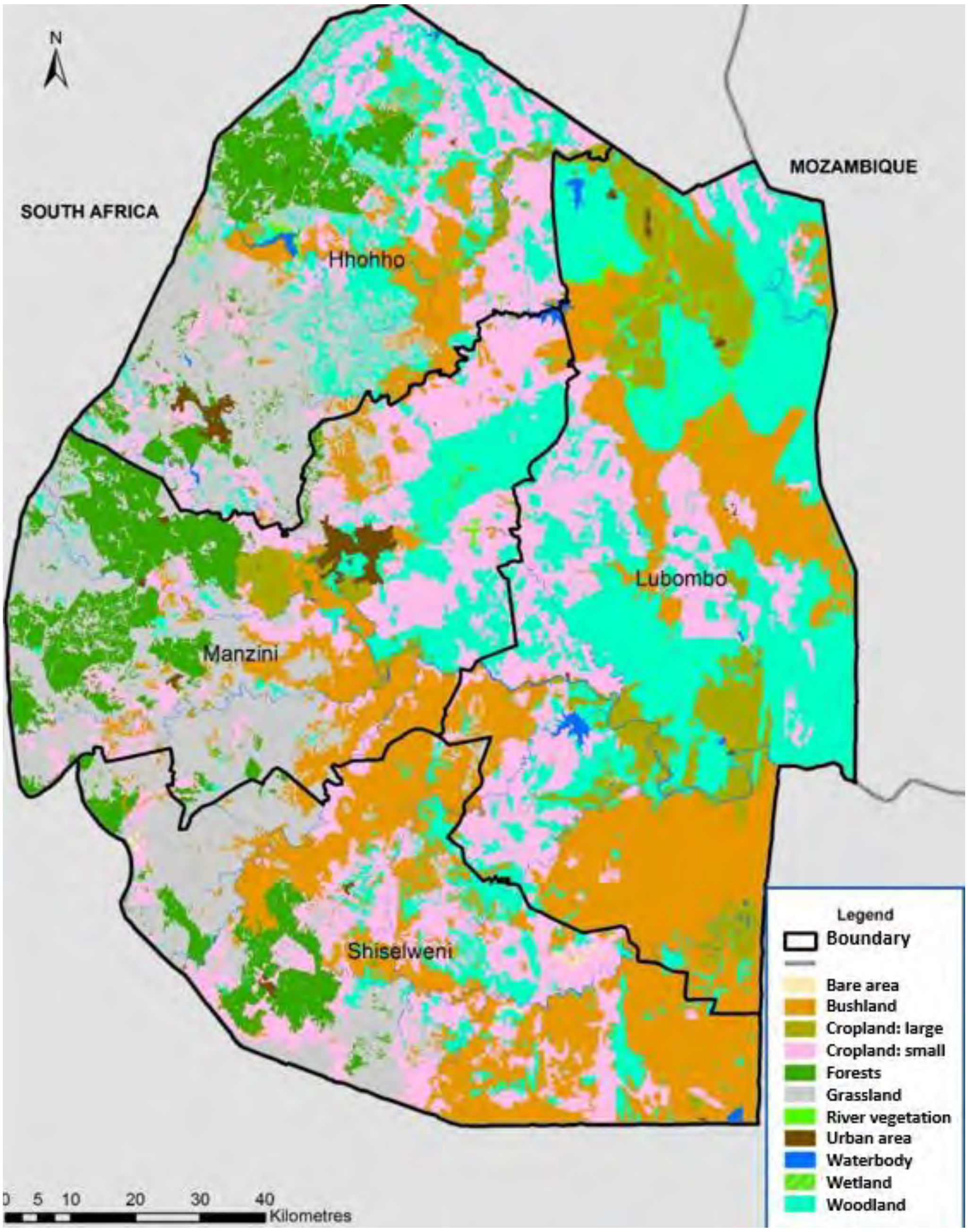

Figure 3.3: Landcover of Eswatini in 2015 (Government of Swaziland, 2016)

3.2 Detailed description of the transboundary basins of the study area

The study area includes Eswatini and some upstream catchments in South Africa represented by 122 sub-basins (Midgley et al., 1994) whose areas vary from 95 km^2 to 790 km^2. These 122 sub-basins (commonly referred to as quaternary catchments: Midgley et al., 1994) fall within a total of five secondary catchments including three trans-boundary basins (the Komati, Usuthu and Phongola rivers), as well as two basins internal to Eswatini (the Mbuluzi and Ngwavuma rivers) and have a total area of 38 950 km^2.

The area is topographically highly diverse and also covers parts of the Highveld of South Africa (western areas of the Komati River basin at an elevation of 1 600 to 1 700 mamsl), the highly dissected steep escarpment areas and lower foothills (Middleveld) within both countries and the Lowveld region of Eswatini in the east at an elevation of 250 to 300 mamsl. The spatial variation in elevation is shown in Figure 3.4. The narrow strip of the Lubombo Mountains (elevation up to about 650 mamsl) represents the eastern border between Eswatini and Mozambique.

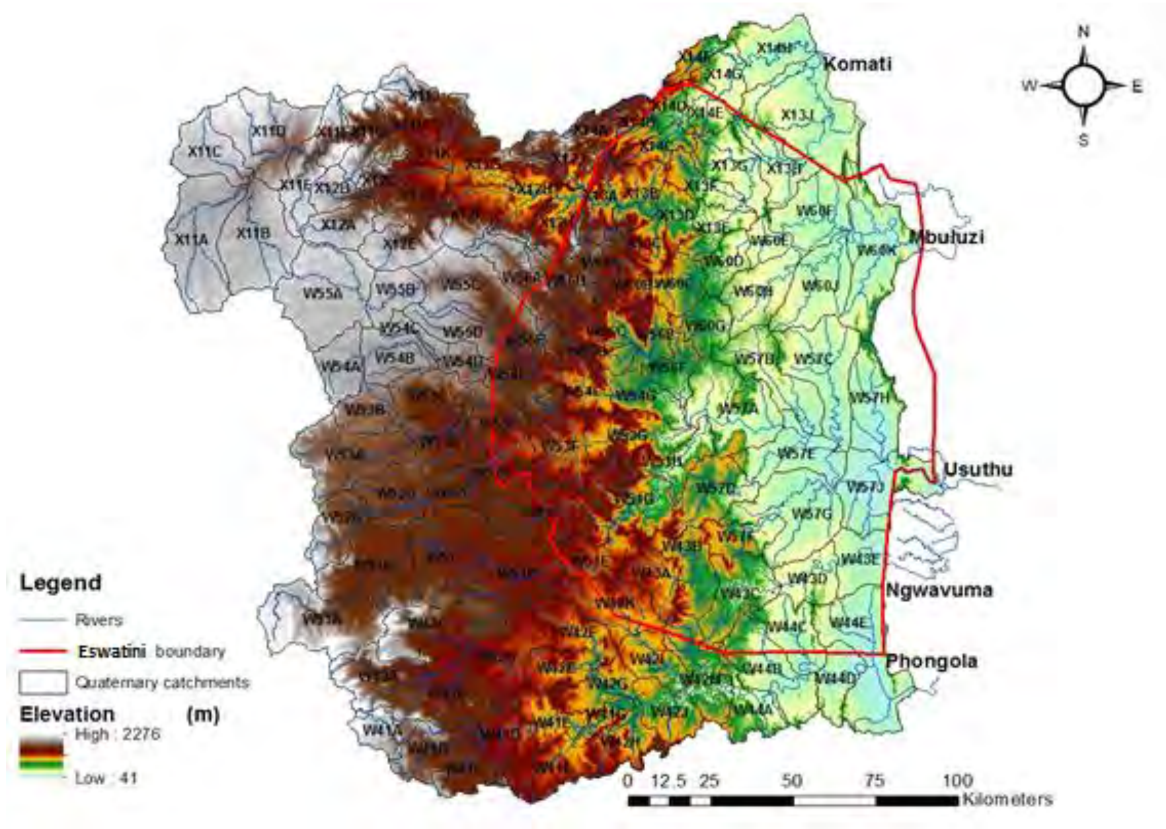

Figure 3.4: Elevation of the sub-basins, with topography data based on Farr (2007)

The climate of the study basins (including the South African catchments) is mainly subtropical with hot and wet summers and cold and dry winters. The Komati is the wettest of all the basins, while Ngwavuma has the highest runoff ratio (Table 3.2). The variations in rainfall and potential evaporation are largely a reflection of the topography (Midgley et al., 1994).

Table 3.2: Area and estimated inflows and outflows for all basins within Eswatini (Manyatsi & Brown, 2009)

Catchment	Area (km^2)	Rainfall (mm)	Inflow (naturalised) {x 10^6 m^3 /a}	Outflow (naturalised) {x 10^6 m^3 /a}
Phongola	1010	400-600	Nil	59
Ngwavuma	1305	600-900	Nil	156
Usuthu	12903	600-1000	896 (386)	2357 (1358)
Mbuluzi	3065	700-1200	Nil	460 (208)
Komati	8354	800-1400	762 (555)	1488 (638)
TOTAL	25626	Mean: 850	1809	4551 (2448)

Figure 3.5 shows the distribution of stream flow gauging stations and location of major dams (Table 3.3). More detailed information on the gauges is given in later sub-sections.

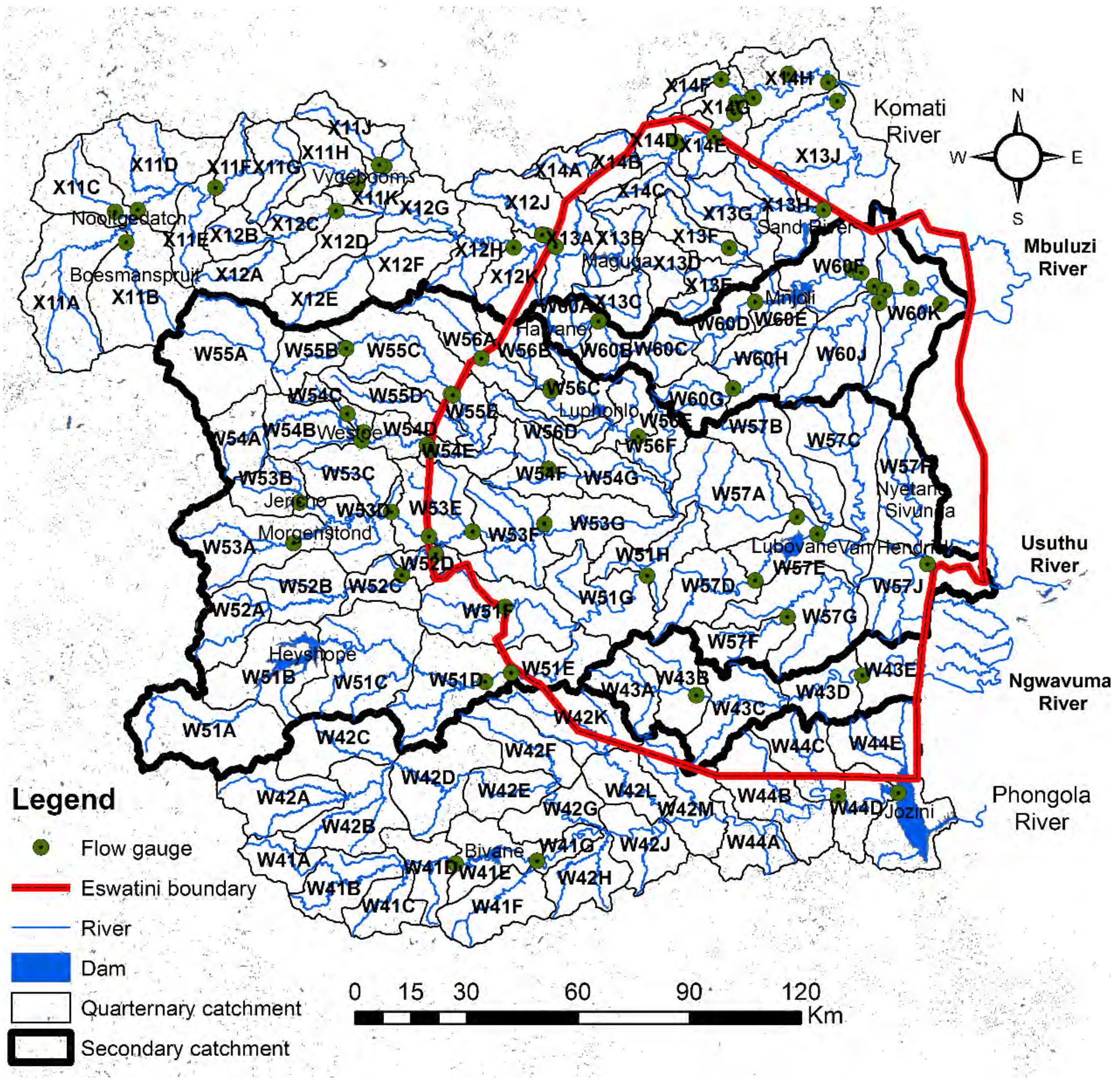

Figure 3.5: Study area showing catchments, rivers and flow gauge stations and major dams

The basins include headwater areas in South Africa that are highly developed to provide water supplies for agriculture, industry and cooling water for coal-fired power stations. Some of the data on the levels of water use of these catchments are not very reliable. Within Eswatini, much of the water use is based on distributed direct abstractions. Water use-related information including some known dams in all the basins is provided in Table 3.3. The physical characteristics, land use, water uses and water resources-related developments are briefly presented for each basin in the following sub-sections.

Table 3.3: Information on water resources developments

Catchment	*Name of dam*	*Quaternary catchment*	*Area (km^2)*	*Height (m)*	*Capacity (Mm^3)*	*Use**	*Date of construction*
Komati	Driekoppies	X14G	18.7	50	251	1	1998
	Shiyalongubo	X14B	-	-	2.3	1	-
	Maguga	X13B	10.4	115	332	2,1	2001
	Sand river	X13H	7	25	50.3	1	1965
	Vygeboom	X11H	3.6	48	78.1	2,3	1971
	Nooitgedacht	X11C	4.6	42	78.4	2,3	1962
	Boesmanspruit	X11B	0.4	9	1	2,3	1976
	Lomati	X14A	0.6	38	5.1	3	1987
Mbuluzi	Hawane	W60A	0.7	12	2.8	3	1984
	Mnjoli	W60E	14.8	41	153	1	1980
Usuthu	Hendrick van Eck	W57J	1.5	22	9.9	1	1969
	Sivunga	W57H	1.2	11	5.9	1	1972
	Nyetane	W57H	1.4	21	6.8	1	1970 (raised 1992)
	Lubovane	W57E	13.9	224	154.8	1	2007
	Kelvinside	W55A	0.3	5	0.3	1	1987
	Westoe	W54B	7.3	25	61.1	3	1968
	Morgenstond	W53A	9.8	43	100.8	3	1978
	Jericho	W53B	10	20	59.9	3	1966
	Heyshope	W51B	50.4	29	453.4	3	-
	Mkimkomo	W56F	-	-	3.2	2	1963
	Luphohlo	W56A	1.2	-	23.6	2	1984
Pongola	Lavumisa	W44E	0.3	16	0.4	3	1996
	Pongolapoort	W44E	100	89	2450	1	1973
	Bivane	W41E	-	-	113	1	-

**Major water uses– 1: Irrigation, 2: Hydro-power generation, 3: Potable water supply, 4: Power plant cooling*

3.2.1 Komati basin

The total catchment area of Komati that was considered for this study is 8 810 km^2. MAP ranges from 600 mm to 1260 mm and MAPE varies from 1 400 mm to 1 500 mm. The Komati basin, originating from the flat Highveld of South Africa at an elevation of 2 000 mamsl, flows through the escarpment (in both South Africa and Eswatini) and reaches an elevation of 270 mamsl in the Lowveld region of Eswatini before exiting back into South Africa. The geology is characterised by Granitoid and rock outcrops. The basin is characterised by raw mineral, deep red loam and very acidic (Ferrisolic and Ferralitic-Fersialitic set) soil, especially in the middle and lower catchments, while the upper catchment is dominated by loamy-sandy to sandy-loam soil. Land cover in the uppermost catchments is dominated by cultivation and some minor afforestation, while the middle and lower are characterised by natural vegetation with the lower catchments (within Eswatini) also including cultivation.

Water resources developments in the upper part of the Komati include abstractions for both irrigation and non-irrigation purposes (urban domestic use and cooling thermal power plants) through the Boesmanspruit, Nooigedacht and the Vygeboom Dam. The lower parts of the basin are also highly developed (e.g., including Maguga, Sand River and Driekoppies Dam) for irrigation of sugar cane and domestic purposes. There are three interbasin transfer (IBT) schemes that transfer water out of the basin (Table 3.4). The main crops cultivated in the Komati basin are sugar cane and mixed vegetables.

Table 3.4: Information on IBTs involving the Komati and Mbuluzi basins

Transfer from	To	Use	Volume (million m^3/a)	Description
X11D	B11G	To support thermal power generation	40	Water is impounded through Nooitgedacht Dam to Duvha power station
X11D	B12B	To support thermal power generation	45	Water is impounded through Nooitgedacht Dam to Hendrina and Arnot power stations (Olifants basin)
X11H	B12B	To support thermal power generation		Water is impounded through Vygeboom Dam to Hendrina and Arnot power stations (Olifants basin)
X13G	W60K	Irrigation	136 (variable)	Water is abstracted through canal to Mbuluzi

3.2.2 Mbuluzi basin

Mbuluzi (called Mbeluzi in Mozambique) is a secondary catchment of the Maputo basin. Based on the aims of this research, only the Eswatini part of the catchment is considered for this study. It consists of 10 quaternary catchments, covering an area of 2 987 km^2. MAP varies from 800mm and 1 200mm while MAPE is approximately 1 400 mm to 1 500 mm. The river originates from the Ngwenya Mountains at an elevation of 1 400 mamsl in the Highveld of Eswatini and it flows easterly before entering Mozambique at an elevation of 150 mamsl. The

Mbuluzi catchment has a diverse climate. The surface is covered by rock outcrops, Lithosolic, Psedopodzolic, and Vertisolic soils. The land cover is characterised by natural grasslands, shrub in the upper to middle parts of the catchment and cultivated lands in the Lowveld.

Major water uses in the Mbuluzi include irrigation of sugar cane and urban water supply in the lower parts of the catchment. There is a general lack of readily available information related to existing water resource developments, such as the level of water use and documentation of reservoir operating rules (for example Mjoli Dam, established to impound water for irrigation).

3.2.3 Usuthu basin

Usuthu basin, the largest of all the five basins, covers an area of 12 502 km^2. MAP ranges from 600 mm to 1 150 mm and MAPE ranges between 1 400 mm and 1 500 mm. The upper catchment is relatively flat and the terrain varies widely in the rest of the catchment. The sub-basin elevation range varies from 35 m to 235 m. Its geology and hydrogeology are complex. The catchment, more especially in Eswatini, is dominated by rock outcrops, Ferrisolic, Ferralitic-Fersialitic and Lithosolic soils. The upper catchment is covered by loamy sands to sandy loam soils.

Water use developments include municipal and industrial supply from Jericho, Morgestond and Westoe dams, and irrigation supply from Heyshope Dam in the upper catchment and Lubovane, van Hendrick, Sivunga and Nyetane dams for irrigation in the lower catchment. There are some run-of-river abstractions for irrigation as well as industrial and urban domestic demand in the lower catchments. The basin is characterised by four complex IBT schemes that transfer water out of the basin to the Olifants and the Vaal catchments mainly for power stations with some for domestic supply to the Gauteng area (Table 3.5). The main irrigated crops grown in the Usuthu basin include seasonal vegetable crops, maize, soya beans, potatoes, rye grass, wheat, lucerne and pecan nuts.

Table 3.5: Information on IBTs involving the Usuthu basin

Transfer from	To	Use	Volume (million m^3/a)	Description
W53B	B20F	To support thermal power generation	4 (occasional)	From Jericho Dam to Kendall power station via Boesmanspruit and Nooigedacht Dam. This transfer does not occur all the time
W53B	B11E	To support thermal power generation	15 (occasional)	From Jericho Dam to Matla power station via Boesmanspruit and Nooigedacht Dam. This transfer does not occur all the time.
W53B	B11D	To support thermal power generation	32 (occasional)	From Jericho Dam to Kriel power station via Boesmanspruit and Nooigedacht Dam. This transfer does not occur all the time.
W51B	C11L	Domestic	63	From Heyshope Dam to meet urban water demands in the Vaal catchment.

3.2.4 Ngwavuma basin

The Ngwavuma basin has a total area of 1 501 km^2. MAP ranges from 600 mm in the Lowveld to 800 mm in the steep Highveld region of the country, meanwhile annual potential evaporation varies from 1 500 mm (in the Lowveld) to 1 400 mm (in the Highveld). The basin rises from an elevation of 1 170 mamsl and exits Eswatini at an elevation of 170 mamsl. The headwaters are characterised by relatively steep slopes while most quaternary catchments are relatively flat with elevation ranges of 75m to 220m mamsl. Both the geology and hydrogeology of Ngwavuma basin are complex. The upper catchment consists of a mixture of sandy, loamy and clay soils, while the lower catchment is dominated by rock outcrops, Ferrisolic, Ferralitic-Fersialitic, Pseudopodzolic and Intertropical brown soils. Land cover is characterised by shrubs and commercial forests in the headwaters and natural forests in the lower parts of the catchment.

The main water use is afforestation in the headwater catchments and sugar cane irrigation in the lower catchment. There are no large-scale storage facilities. There is some dry land cropping in the downstream part of the catchment and domestic water uses as well as some small-scale industrial water uses.

3.2.5 Phongola (Phongolo) basin

The Phongola basin considered for this study covers an area of 7 780 km^2 and falls mainly within South Africa. The quaternary catchments within Eswatini cover an area of about 1 000 km^2. MAP ranges from 550 mm to 1 050 mm, and MAPE range is estimated at 1 400 mm to 1 500 mm. The basin originates in South Africa at an elevation of 1 900 mamsl (at W42A) and flows through forested (natural and man-made) landscapes and mountainous terrain, through the heavily developed valley of Phongola to 100 mamsl (at W44E) before entering Mozambique. The soil cover for the Eswatini portion is mainly rock outcrops, Ferralitic, Regosolic soils. The rest of the catchment is characterised by loams, sands and clays.

Water demand is not very high, more especially in the most downstream catchments. There are some storage facilities reflecting major water resources developments such as the Bivane Dam (previously known as Paris Dam) mainly established to meet the increasing irrigation demand in the surrounding catchments and the Jozini Dam which was established mainly for irrigation purposes. Most of the anticipated irrigation which formed the basis for its construction (Jozini) never took place due to unclear reasons, resulting in large unutilised water in the dam (Department of Water Affairs and Forestry, 2002; van Vuuren, 2009). Maize, wheat, sugar cane and mixed vegetables are predominantly cultivated crops in the Phongola catchment.

3.3 Datasets

3.3.1 Observed data

3.3.1.1 Stream flow

All available daily and monthly flow data recorded by the Eswatini Department of Water Affairs and South African Department of Water and Sanitation were obtained for the 73 gauging stations shown in Figure 3.5 (all concrete weirs). These include those with short records, from less than five years of data. The information on the gauge stations including those which are not usable and were excluded in the evaluation of the model simulations as well as the characteristics of available data for each basin are presented in Tables 3.6 to 3.10.

Table 3.6: Gauge stations, period of observation and data availability in the Komati basin

Quate-rnary	Head-water	Gauge	Period of record (years)	% missing data	Status of flow condition	Reason for exclusion
X14D	NO	GS11	58	46.6	Impacted	
X14E	NO	GS34	32	57	Impacted	
X14F	YES	**X1H012**	24	5.6	Near-natural	Flow pattern inconsistent with other related data.
X14G	NO	X1H049	15	16.7	Impacted	
X14G	NO	X1H048	16	4.2	Impacted	
X14G	NO	X1H047	16	2.1	Impacted	
X14G	NO	X1H005	3	5.6	Impacted	
X14G	NO	X1H014	46	6	Impacted	
X14H	NO	X1H004	1	41.7	Impacted	
X14H	NO	X1H052	10	4.2	Impacted	
X11B	YES	**X1H009**	6	0	Near-natural	Record too short for analysis use.
X11C	NO	**X1H033**	55	0	Impacted	
X11E	NO	X1H017	42	1.6	Impacted	
X11F	NO	X1H018	42	8.2	Impacted	
X11H	NO	X1H036	43	0.2	Impacted	
X11J	YES	**X1H019**	42	5.2	Near-natural	
X11K	NO	X1H020	41	0.4	Impacted	
X12C	NO	X1H016	44	0.2	Impacted	
X12H	NO	X1H001	105	3.5	Impacted	
X12J	YES	**XH1021**	38	1.1	Near-natural	
X13A	NO	GS29	12	19.4	Impacted	
X13D	NO	GS45	15	36.7	Impacted	Record not representative of cumulative flows.
X13F	YES	**GS42**	34	53.4	Near-natural	
X13H	NO	GS30	35	48.6	Impacted	
X13J	NO	X1H003	74	2.2	Impacted	

**Bolded stations reflect observed flows that are representative of the whole headwater quaternary catchment. Grey shading represents an excluded gauging station.*

In the Komati, there is a fair distribution of hydrological stations across the catchment. However, the active observation network has worsened since the 1980s. Within the territory of Eswatini one station is known to be no longer operational (GS18), some have significant missing data (e.g., GS30, GS34, GS42) with only one station (GS11) being reliable with continuous data of 27 years (Table 3.6 and Figure 3.5). The stations in South Africa also only have data for a limited period of time (e.g., X1H004: 1932 – 1938, X1H005: 1949 – 1952, X1H006: 1955 – 1964, X1H007: 1958 – 1965 and X1H008: 1965 – 1971).

The distribution of hydrological stations across the Mbuluzi catchment is poor. The record for stream flow data are long (often more than 40 years). The data are poor with many stations having missing data of more than 60% and the record is often unusable.

There is a reasonable distribution of hydrological stations across the Usuthu catchment. The percentage of missing data is low (more than half of the stations have less than 10% of missing data) and most of the data are usable. Several stations (i.e., 26%) have a data record of more than 50 years.

Table 3.7: Gauge stations, period of observation and data availability in the Mbuluzi basin

Quate-rnary	Head-water	Gauge	Period of record (years)	% missing data	Status of flow condition	Reason for exclusion
W60A	YES	**GS4**	53	32.8	Near-natural	
W60D	NO	GS3	54	32.9	Impacted	
W60F	NO	GS35	39	80.6	Impacted	Record is poor and unusable due to missing data. Record not representative of cumulative flows.
W60F	NO	GS36	37	74.6	Impacted	Record not representative of cumulative flows.
W60F	NO	GS37	37	64.2	Impacted	Data are not available.
W60G	YES	**GS10**	8	0	Natural	
W60K	NO	GS38	36	72.5	Impacted	Record is neither representative of incremental nor cumulative flows. Record is poor and unusable due to missing data.
W60K	NO	GS39	29	61	Impacted	Data are not available.
W60K	NO	GS20	40	77.3	Natural & impacted	
W60K	NO	GS41	38	62.7	Impacted	Record is neither representative of incremental nor cumulative flows. Record is poor and unusable due to missing data.
W60K	NO	GS40	38	65.4	Impacted	Record is neither representative of incremental nor cumulative flows. Record is poor and unusable due to missing data.
W60K	NO	GS32	34	34.8	Impacted	

**Bolded stations reflect observed flows that are representative of the whole headwater quaternary catchment and are those that were first used to guide the constraint analysis and to validate the estimated (ranges) natural headwater catchment hydrological response. Grey shading represents an excluded gauging station.*

The stream flow observation network of the Ngwavuma consists of two gauging stations with limited data. The stations are not adequately located to enable the estimation of the impact of the water resources developments (sugar cane irrigation) downstream.

Table 3.8: Gauge stations, period of observation and data availability in the Usuthu basin

Quaternary	Headwater	Gauge	Period of record (years)	% missing data	Status of flow condition	Reason for exclusion
W56A	YES	GS33	34	53.7	Impacted	Record is not representative of incremental flows.
W56B	NO	GS15	46	28.1	Impacted	
W56B	NO	GS43	18	8.3	Impacted	
W56E	NO	GS24	37	51.6	Impacted	
W56E	NO	GS2	55	26.8	Impacted	
W57A	NO	GS6	55	21.5	Impacted	
W57D	YES	**GS12**	35	32.4	Near-natural & impacted	
W57E	NO	GS19	41	52.2	Impacted	
W57F	YES	***GS13***	24	0	Natural	
W57J	NO	GS16	18	72.2	Impacted	Record is poor and unusable due to missing data.
W55B	NO	W5H011	51	0.3	Impacted	
W55C	NO	W5H024	38	2.9	Impacted	
W54B	NO	*W5H007**	17	2.5	Near-natural	
W54B	NO	W5H036	50	1.2	Impacted	
W54C	YES	*W5H008*	68	2.8	Near-natural & impacted	
W54D	NO	GS31	34	53.9	Impacted	
W54D	NO	W5H025	45	1.3	Impacted	
W54F	NO	*GS9*	61	17.8	Impacted	Record is not representative of cumulative flows.
W53A	YES	*W5H004*	40	6.3	Near-natural	
W53A	YES	**W5H038**	37	0	Impacted	
W53B	YES	*W5H003+*	16	13.5	Near-natural	
W53B	YES	W5H034+	53	0.02	Impacted	
W53D	NO	W5H026	39	0.2	Impacted	
W53E	NO	GS21	38	36.2	Impacted	
W53F	NO	GS5	49	24.7	Impacted	
W52C	NO	W5H005	64	0.5	Impacted	
W52D	NO	GS22	38	41.7	Impacted	
W51B	NO	W5H039	36	0	Impacted	
W51D	NO	W5H022	46	5.6	Impacted	
W51F	YES	GS39	29	78.5	Impacted	Record is not representative of incremental flows.
W51G	NO	GS7	52	26.8	Impacted	

**Bolded stations reflect observed flows that are representative of the whole headwater quaternary catchment and are those that were first used to guide the constraint analysis and to validate the estimated (ranges) natural headwater catchment hydrological response. Asterisks (*) indicate other headwater catchments whose flow data reflect natural conditions and can also be used to validate constraints. A plus (+) indicates that the latter is a continuation of the former record. Grey shading represents an excluded gauging station.*

Table 3.9: Gauge stations, period of observation and data availability in the Ngwavuma basin

Quaternary	Head-water	Gauge	Period of record (years)	% missing data	Status of flow condition
W43B	NO	GS27	23	46.7	Impacted
W43D	NO	GS8	53	34.3	Near-natural & impacted

The hydrological observation network coverage of the Phongola basin is fair. The length of hydrological data is long for most stations (39 to 65 years). The percentage for missing data is low for all the stations (less than 10%).

Table 3.10: Gauge stations, period of observation and data availability in the Phongola basin

Quaternary	Headwater	Gauge	Period of record (years)	% missing data	Status of flow condition
W41D	NO	W4H004	64	7.6	Impacted
W41E	NO	W4H016	15	0	Impacted
W44C	NO	W4H006	45	2.4	Impacted
W44D	NO	W4H002	39	10.9	Impacted

Most stations in the whole basin are located at the outlets of sub-basins, and they represent total catchment cumulative runoff. The flows are impacted by highly non-stationary upstream impacts during in the entire period of the record. Some of the stations have records as early as the 1950s yet the data are frequently unreliable and have large periods of missing data. Some are sufficiently gauged with continuous data spanning over a period of 20 years. Some gauges are known to poorly represent high flows due to rating table limitations and many were heavily impacted by tropical cyclone Domonia that occurred in 1984. There is typically a long period of missing data (several years) following this cyclone and many of the later records that exist appear to be suspect. They are very inconsistent with patterns of flow that occur prior to the cyclone even in areas that are relatively un-impacted by water resources developments.

3.3.1.2 Groundwater recharge

The Groundwater Resources Assessment (GRA) II data: (Conrad, 2005; DWAF, 2006; Maitre & Colvin, 2008), initiated by the South African Department of Water Affairs and Forestry (DWAF), was aimed at quantifying the groundwater resources for South Africa, including Eswatini and Lesotho and provides estimates such as recharge, storage, baseflow, and groundwater use. Estimates of mean annual recharge (minimum, median and maximum) were obtained from the South African national GRA II project database. The estimates are based on different methods and previous experience (Hughes, 2013) suggest that the maximum estimates are unrealistically high and do not really represent recharge to the aquifer (i.e., they may include interflow in fracture zones above the groundwater table (Hughes, 2010)). The minimum and median GRA II values are therefore used as the uncertainty range in this study.

3.3.2 Simulated data

3.3.2.1 Rainfall

WR90/2005: The study basins are not well gauged in terms of rainfall and evapotranspiration records. Midgley et al. (1994) used 51 rain gauges for the WR90 study to generate the regional rainfall data for 70 years (1920 to 1990), while a further 79 were identified but not used due to short records or excessive missing data. The WR2005 datasets (Middleton & Bailey, 2008) are 85-year (1920 – 2005) rainfall estimates for quaternaries based on observed data from a similar number of rainfall stations. In the WR2005 study the catchments are divided into rainfall zones (Figure 3.6), each zone representing groups of quaternaries having similar rainfall characteristics. Rainfall stations of more than 15 years of data within 10 km of the rainfall zone and those within the rainfall zone boundary were considered (WR2005 User guide, 2008). While it might be considered possible to update the WR90/2005 rainfall data, this is unlikely to be worthwhile, given that the observed network of rainfall stations throughout the southern African region has deteriorated in recent years.

The WR90/2005 studies included pre-screening to identify gross outliers and non-linearity (using single mass plots), classifying the rainfall stations into groups of similar records (identifying and flagging outliers using the ClassR program (Middleton and Bailey, 2011)), and patching of gross outliers and missing monthly data using the PatchR program (Middleton and Bailey, 2011) were done to process the raw data. Those records exhibiting excessive non-linearity were excluded from the evaluation (Middleton and Bailey, 2011).

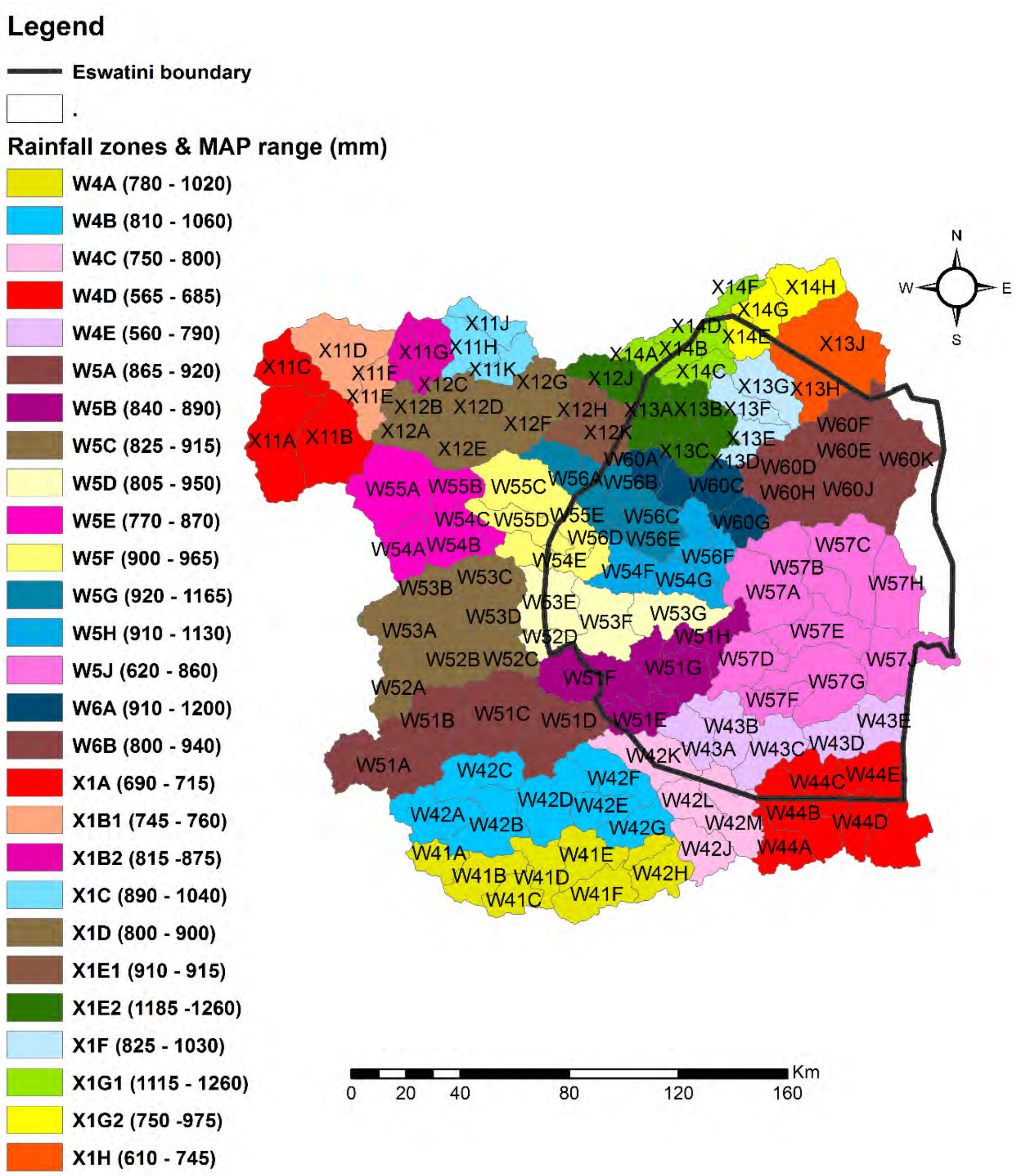

Figure 3.6: WR2005 rainfall zones and MAP range (Middleton & Bailey, 2008)

3.3.2.2 Evapotranspiration

WR90: A total of 13 evaporation measuring stations located mostly at the sites of major reservoirs were considered for potential evaporation estimation (Midgley et al., 1994). These limited sites were used to estimate potential evapotranspiration values using pan factors for both A-pan (South African Weather Services (SAWS)) and S-pan (Department of Water Affairs (DWA)).

3.3.2.3 Naturalised flows

WR90, WR2005, and WR2012: These are streamflow simulations available from the WR90 database (Midgley et al., 1994), the WR2005 database (Middleton & Bailey, 2008) and the more recent update WR2012 database (http://waterresourceswr2012.co.za/) of the regional water resources assessments that cover all of the quaternary sub-basins of South Africa, Eswatini and Lesotho. These were generated using similar (but not exactly the same) versions of the Pitman (1973) monthly rainfall-runoff model that is being used in this study (see next chapter for more details about the different versions of the Pitman model). However, the basic model structure is the same for all versions of the model. While the details of the model calibration approach are not fully documented, it is known that they were based on manual calibration against naturalised (i.e., all assumed water uses removed) observed stream flow data, followed by a relatively subjective parameter regionalisation process.

3.4 Summary

This chapter highlights that the highly developed transboundary basins are data-scarce and the observation networks are inadequate. Most of the hydrological stations which were excluded are located in the territory of Eswatini and 50% of these are in the Mbuluzi basin. There is a lack of information related to water resources development, such as volume of water use, their non-stationarities and the lack of documentation on the operating rules of reservoirs. This can make it very difficult to establish a representative model and reproduce patterns of observed stream flows. Addressing the many broad scale hydrologic issues such as planning and management of these transboundary water resources should therefore be a priority.

CHAPTER FOUR: HYDROLOGICAL MODELLING METHODS

This chapter presents a description of an uncertainty modelling approach that was used for the study. Prior to the modelling phase, the sub-basin hydrological response is quantified to facilitate hydrological regionalisation and to constrain the model output. A two-step uncertainty hydrological modelling approach is applied based on regionalised constraint indices (which are subject to revision) in order to generate uncertain, but behavioural model outputs. Initial ranges of model output constraints on sub-basin hydrological response are estimated based on previous model simulations. The first model run aims to identify realistic parameter sets that match the assigned constraints on natural hydrological response and allows for the refinement of parameters and constraints, where necessary, before any water uses are incorporated in the model. The second model run uses the outputs from step one to simulate stream flow that reflect either natural or impacted conditions. The simulations are then evaluated using suitable performance statistics.

4.1 Justification for using the Pitman model

The Pitman model contributes significantly to advances in hydrological modelling including uncertainty assessment particularly in southern Africa and is the most widely used hydrological model in the region (Hughes, 2013a). It has extensive and successful applications in both South African basins and elsewhere in southern Africa (e.g. Mazvimavi, 2003; Mwelwa, 2004; Hughes et al., 2006a; Hughes et al., 2006b; Wilk et al., 2006; Kapangaziwiri, 2007; Sawunyama, 2008; Ndiritu, 2009; Hughes et al., 2010a; Hughes et al., 2010b; Kapangaziwiri, 2011; Hughes et al., 2011; Sawunyama et al., 2011; Ayeni and Kapangaziwiri, 2012; Tshimanga, 2012; Tirivarombo, 2012; Tshimanga and Hughes, 2012; Linhoss et al., 2012; Tanner, 2013; Tshimanga and Hughes, 2014; Tumbo, 2014; Hughes, 2015; Mohobane, 2015; Tumbo and Hughes, 2015; Tanner and Hughes, 2015; Hughes, 2016; Hughes and Gray, 2017; Ndzabandzaba and Hughes, 2017; Oosthuizen et al., 2018; Mvandaba et al., 2018). The Pitman model has been applied in large-scale international hydrological projects. For example, it was identified as a potentially useful tool for regional water resources assessment and was used to develop procedures and guidelines for application of models in the region during the SA FRIEND Phase I (Hughes, 1997) and Phase II project (Hughes et al., 2002; Meigh and Fry, 2004). The model has also been applied with success to other parts of the world (e.g. Hughes 2015; Bharati and Gamage, 2010; Wilk and Hughes, 2002).

The Pitman model has been through a number of improvements tailored for research, science and practice since its inception (Figure 4.2 and Section 4.4.2). First, is the development of software to facilitate the application of the Pitman model (Hughes et al., 2000; Hughes, 2002; Hughes and Forsyth, 2006), as well as other water resources assessment models. Second, is the inclusion of the groundwater component in the model structure to improve sub-surface water flow generation (Hughes, 2004). Third is the development of a framework to establish parameter values, explore parameter inter-dependencies and set parameter uncertainty bounds for the model (Kapangaziwiri and Hughes, 2008; Hughes et al., 2012). Fourth, is the incorporation of an uncertainty framework into the model for stream flow predictions in both gauged and ungauged basins of southern Africa (Kapangaziwiri et al., 2009; Hughes, 2016). Fifth, is the incorporation of a wetland sub-model (Hughes et al., 2014). Sixth, is the incorporation of a stochastic model that attempts to predict the impacts of climate change on future water resources availability (Hughes, 2015). Lastly, is the inclusion of a saturation-excess function of the model to improve stream flow simulation in areas characterised with dambo-type geomorphological features (Hughes and Mazibuko, 2018) found in some parts of southern Africa.

Another advantage of using the Pitman model is that it is less data intensive than some other models. Its conceptual nature is suitable for application to data-scarce areas like Southern Africa. Major input data for the model are precipitation and potential evapotranspiration. Others include water resources developments and stream flow data which are used to evaluate the model simulations.

The parameters of the Pitman model account for all hydrological processes prevalent in the region of southern Africa. These processes include interception, evapotranspiration, soil and groundwater storage, groundwater recharge, surface runoff, interflow and groundwater runoff contributions to stream flow including routing.

Other advantages associated with the Pitman model are that it is semi-distributed. Catchments can be divided into smaller units (sub-basins), as small as 50 km^2. The spatial scale at which the model is run is highly flexible and is able to capture the main heterogeneity in the domain of large river basins. This is critical in modelling that incorporates uncertainty.

4.1.1 The Pitman model uncertainty framework

The modelling methodology followed in this research is illustrated in Figure 4.1. This includes the analysis of all available data, both observed and previous simulations. These data are used to establish uncertain initial constraints and parameter ranges for natural hydrology. First, the model allows for the simulations of natural flow conditions, where applicable, which can be evaluated against observed flow data representing such flow conditions. Incorporation of any water uses in the model set-up can be done (where necessary) in order to simulate impacted flow conditions. The model parameters and constraints can be modified where necessary, after comparison of simulations against observed stream flow (i.e., either reflecting ‘natural’ or impacted conditions) has been made (Figure 4.1).

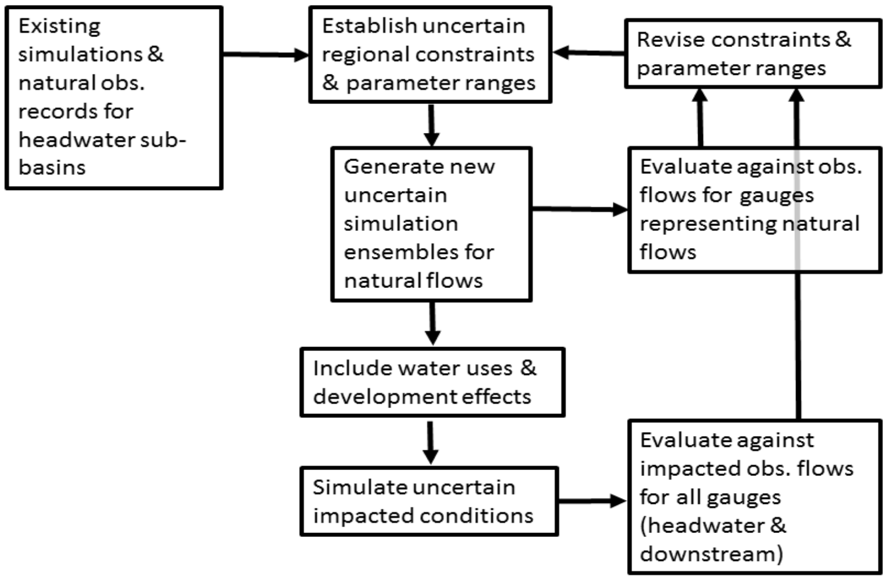

Figure 4.1: Flow diagram for reducing uncertainty in regional hydrological modelling, illustrates the iterative process of quantifying the initial constraints, testing and validating the ensemble outputs and refining the constraints

Previously, the uncertainty framework proposed by Kapangaziwiri, et al. (2008) used catchment scale signatures of hydro-climate response (Budyko relationships) and the slope of flow duration curve to constrain simulated catchment behaviour. In this study, Kapangaziwiri et al. (2008) found that these Budyko relationships were generally good (narrow confidence bands) and characterised by high R^2 values. However, the FDC curve constraints required further refinement. The uncertainty framework was later modified by Kapangaziwiri (2011) and Kapangaziwiri et al (2012) where runoff ratio, slope of the flow duration curve and mean annual groundwater recharge were used as model output constraints. Kapangaziwiri (2011) and Kapangaziwiri et al (2012) tested the runoff ratio constraint, and concluded based on the analysis of this constraint, that the results were generally acceptable and the model output ensembles were within the expected ranges of constraint uncertainty. From the analysis of the slope of the FDC constraint, Kapangaziwiri (2011) and Kapangaziwiri et al (2012) found that many sub-basins exhibited FDC ensembles that lie within the constraint limits, implying low uncertainty and that the outputs were behavioural. From the groundwater recharge constraint analysis, it was concluded that only a few sub-basins were characterised by output ensembles that were considered behavioural (Kapangaziwiri, 2011; Kapangaziwiri et al., 2012). Kapangaziwiri et al (2012) concluded that these constraints are insufficient to cover all the components of basin response under diverse hydro-climatic conditions, such as South Africa. Subsequent to these modifications and conclusions, Hughes (2015) and Hughes (2016) further modified the uncertainty framework and applied additional model output constraints in order to incorporate general uncertainty principles and improve the model structure so that it is appropriate for most southern African conditions. The current constraints used in the most recent version of the Pitman model are discussed later in section 4.3.

4.2 Characteristics of natural hydrological response

Table 4.1 indicates that there are very few observed data that represent natural incremental sub-basin hydrological response in the basins of Eswatini. Due to the scarcity of observed data, previous simulations available from the WR90 study (Midgley et al., 1994) and WR2005 study (Middleton and Bailey, 2009), or more recent updates (http://waterresourceswr2012.co.za/) of the regional water resources assessments that cover all of the quaternary sub-basins of South Africa, Eswatini and Lesotho were therefore used to establish the hydrological response/model output constraints. The pre-existing regional Water Resources simulations were generated using similar versions of the Pitman (1973) model used in this study. The model calibration approach is not fully documented but it was based on manual calibration against naturalised observed stream flow data, followed by a relatively subjective parameter regionalisation process. It is assumed that the main uncertainties in these previous simulations would be related to the naturalisation of the observed stream flow data and the parameter regionalisation process used to establish parameter sets for ungauged sub-basins. It is also assumed that these simulations represent the best existing knowledge of the regional patterns of hydrological response and therefore were considered appropriate for setting the initial constraint index ranges.

There are some advantages and disadvantages of using the pre-existing simulations. The first advantage is that all the sub-basins can be included in the constraint analysis. The second advantage is that this study builds upon previous understanding of developing a calibrated and regionalised model for the area. The disadvantage is that the initial constraints could be based on false assumptions made in the previous studies about regional patterns of hydrological response variations and about the impacts of upstream developments on the existing observed stream flow data. As this study uses an uncertainty approach as well as a testing and validation process, it is expected that these disadvantages may be overcome and either eliminated or included as part of the overall uncertainty quantification.

The left, top middle and the middle parts of Figure 4.1 summarise the steps that were followed to establish the natural hydrological response in this study. The first level of hydrological response determination was based on the estimation of runoff ratio (as mean annual flow/mean annual rainfall to avoid sub-basin scale effects) from the simulated data plotted against aridity index (Aridity index=mean annual potential evapotranspiration/mean annual rainfall: AI = PE/P) in trying to identify regional groupings. To validate these simulated values, the few available observed incremental flow data for the nine sub-catchments were used. This validation was limited to the gauged headwater quaternary catchments reflecting 'natural' or near-natural hydrological response and that are representative of the whole quaternary catchment (Table 4.1). The second level involved the estimation of all the other constraints (subsection 4.3).

Table 4. 1: Summary of the available observed stream flow data and their ability to represent either natural or developed conditions

Gauge location and upstream impacts	Usefulness	Number
Headwater areas with low impacts.	Useful for establishing constraints and checking incremental natural flow simulation results.	9
Headwater areas with large impacts.	Useful for checking incremental simulation results after addition of water uses. However, issues of non-stationarity in water use patterns can affect the value of the observed data.	11
Downstream gauges with low impacts.	Useful for checking cumulative natural flow simulation results and for refining incremental sub-basin constraints.	2
Downstream gauges with large impacts.	Useful for checking cumulative flow simulation results after addition of water uses. Non-stationarity in water use patterns have to be considered.	50
Total		72

4.3 Initial model output constraint ranges and regionalisation

Observed stream flow data are not used to calibrate or fit the model in the traditional sense. They are used in the process of quantifying some of the sub-basin constraint indices (Tumbo and Hughes, 2015). An iterative process of quantifying the initial constraint ranges, testing and validating the ensemble outputs and refining the constraint ranges where possible to reduce uncertainty is illustrated in Figure 4.1. The specific modelling for generating the ensemble simulations is discussed in more detail later in this chapter.

Constraint ranges are initially identified based on available information (Naturalised flow data or suitable observed flows in this case). During the modelling process, there are opportunities to adjust these initial ranges should it become clear that some of the constraints are incompatible with others (e.g., groundwater recharge being too low or high relative to the flow response or zero flow constraints). More explanation is given later, in Section 4.5.3. A simple procedure was followed to establish the initial ranges of the constraints. The constraints are mean monthly runoff volume (MMQ in m^3X10^6), mean monthly groundwater recharge depth (MMR in mm), the 10th, 50th and 90th percentiles of the flow duration curve expressed as a fraction of MMQ (i.e., Q10/MMQ, Q50/MMQ, Q90/MMQ) and the percentage of time that zero flows are expected (% Zero flows). The MMQ and FDC constraints were plotted against aridity index to identify regional groupings and to check for any inconsistencies. Only Q10/MMQ, Q50/MMQ, Q90/MMQ and MMQ constraints were regionalised, as they were standardised. An analysis of topography (e.g., slope, altitude range) and climate regions was used as an additional guide in the regionalisation process. A total of six hydrologically-similar groups of sub-basins were therefore identified. For some of the constraints simple regression models were used based on relationships with the aridity index (long-term mean annual potential evaporation divided by rainfall). However, for others the ranges were simply based on the spread of values within the physiographic zones, in the absence of any clear relationships with aridity.

A more formal and quantitative regionalisation process based on physical catchment data (soil, geology, etc.) was not followed in this study for two reasons. Firstly, past experience of attempting such approaches in the southern Africa region has not been very successful, partly because of the lack of appropriate or sufficient physical sub-basin property data (Mazvimavi, 2003). Secondly, the whole modelling approach to be used allows for a high degree of initial uncertainty in the constraint ranges and therefore a more complex classification approach was considered to be unnecessary.

4.4 The conceptual semi-distributed monthly Pitman model

4.4.1 The structure of the Pitman model

The structure of the groundwater version of the modified Pitman model (Hughes, 2004; Hughes, 2013) accounts for all the key processes in the southern African region (Figure 4.2). A description of all the model components and associated parameters are provided in Section 4.4.2. Parameter uncertainties are described in section 4.4.3.

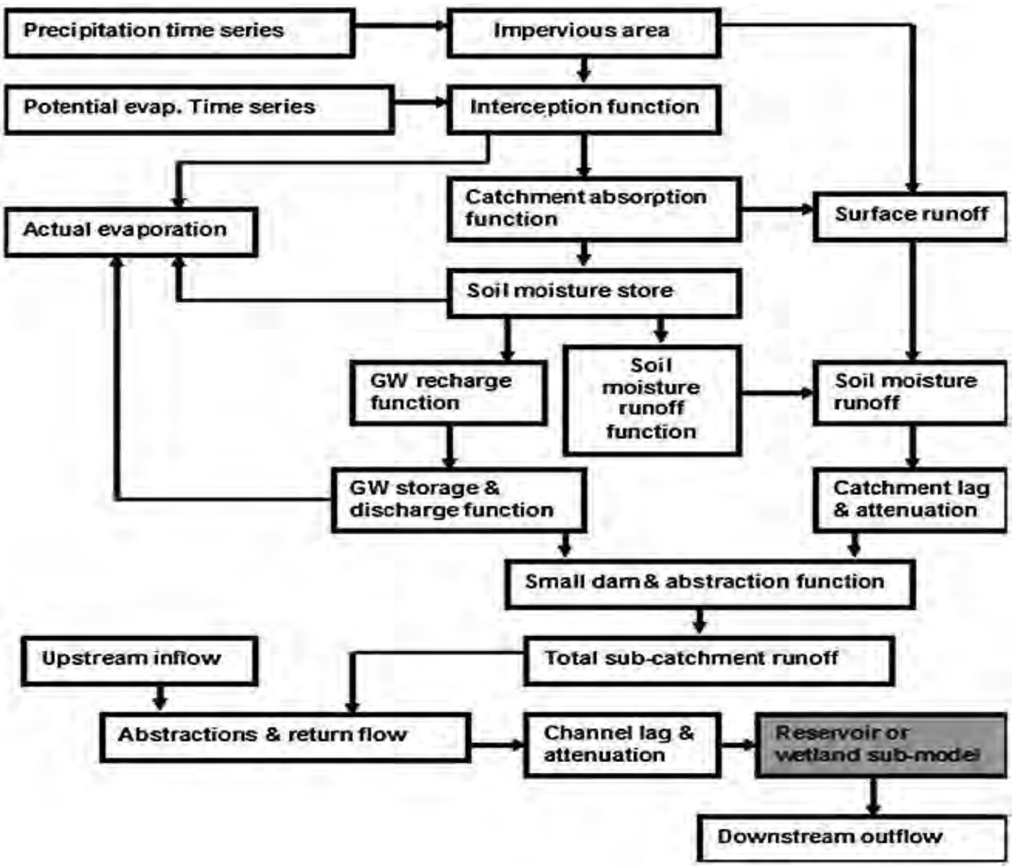

Figure 4.2: The structure of the Hughes' groundwater version of the Pitman model (Hughes, 2004; Hughes et al. 2014). Changes to the structure of the original version of the model include the introduction of groundwater functions. The reservoir and wetland sub-models (in grey) are other recent major inclusions to the model. The inclusion of a saturation excess runoff function is the most recent improvement of the model structure.

4.4.2 Model components and parameters

The model components are classified into two groups: those affecting natural hydrology, and those related to the water use component of the model. The model uses *a priori*-estimated parameters to represent all the natural catchment scale processes that exist in southern African basins (interception, evapotranspiration, soil and groundwater storage, groundwater recharge, surface runoff, interflow and groundwater runoff contributions to stream flow, routing, etc.). Where relevant data are available, detailed physically-based parameter estimation routines by Kapangaziwiri and Hughes (2008) can be employed to establish model parameter values. The routines are an attempt to translate data and information uncertainty into uncertainty in parameter estimation (Kapangaziwiri and Hughes, 2008). The water use component of the model consists of parameters to represent modifications of the natural hydrology in a catchment via direct abstraction from rivers and through small- and large-scale reservoir storages. Impacts of non-stationarities on water use can be simulated in cases where there is a clear distinction between two flow regimes (i.e., 'natural' and impacted conditions), by simulating the non-impacted and impacted periods separately. An explanation of parameters is summarised below. A more detailed description is given in Hughes (2004); Hughes and Parsons (2005); Hughes et al. (2007); Kapangaziwiri (2007); Kapangaziwiri and Hughes (2008); Kapangaziwiri (2011) and Hughes (2013a).

4.4.2.1 Natural hydrology component and associated parameters

Figures 4.3 – 4.6 illustrate the algorithms for the major processes (evapotranspiration, interflow and runoff) in the Pitman model and Table 4.2 is a list of the model natural hydrology parameters, while Appendices 1 – 6 are uncertain parameter values used in the model for example sub-basins as well as the values for each region. The functions associated with the natural hydrology component can be grouped into interception, evapotranspiration and runoff.

Interception: This function accounts for the proportion of rainfall that does not reach the ground due to interception by various kinds of vegetation cover, also allowing for seasonal variations. The interception parameter PI is allowed to vary between summer and winter, and it can be set for two different vegetation types which are grassland and forestry (Kapangaziwiri, 2010) (Table 4.2).

Evapotranspiration: The parameter R defines the rate at which actual evapotranspiration declines as the relative moisture content (S) decreases due to reduction in potential evaporation rate. More effective evapotranspiration at low moisture storage levels would imply lower values of R. An R value equivalent to 1 would imply less effective ET as both the soil moisture storage and potential demand decrease (Figure 4.3) (Hughes, 2013a). The parameter FF is an evaporation scaling factor for the second type of vegetation relative to the first, while AFOR is the proportion of the basin covered by vegetation type two.

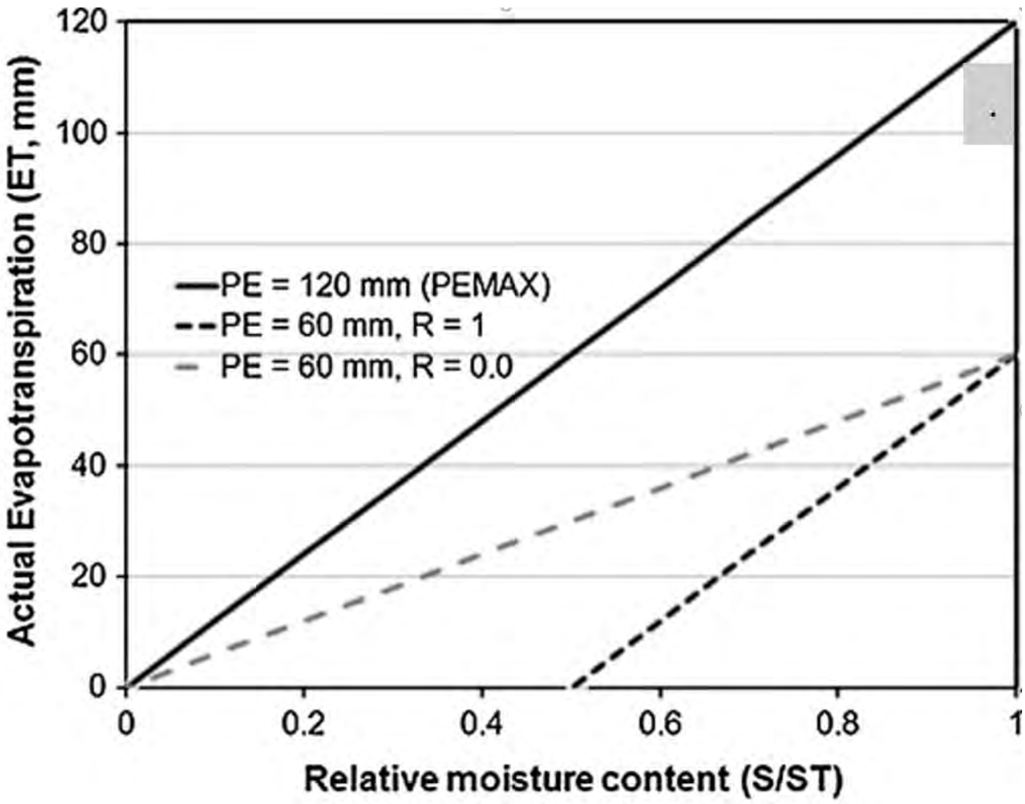

Figure 4.3: Algorithm for the evapotranspiration process (Hughes, 2013a). PE is potential evaporation, PEMAX is maximum potential evaporation and ST is the maximum soil moisture storage parameter. Lower values of R imply more effective evapotranspiration at low soil moisture levels.

Runoff: The parameter AI (for highly-impervious areas) can be used in very rocky catchments or highly urbanised catchment areas prohibiting infiltration to generate quick runoff. Apart from using the AI parameter, there are four other main processes responsible for the generation of stream flow in the Hughes' (2013) version of the model. All runoff (except GW) is routed through parameters TL (runoff time lag in months for soil and surface components) and CL (responsible for channel routing in large catchments). The four main processes are discussed below:

The *saturation excess runoff* function: this is a new function of the Pitman model which is based on the variable source area concept (Hughes and Mazibuko, 2018).

This function is governed by the following equation:

Saturation excess runoff (SER as a fraction) = $[(S – ST \times SSR)/(ST – ST \times SSR)]^{SPOW}$, (Eq. 4.1)

hence

Saturation excess runoff (volume, in mm month^{-1}) = SER x Rainfall (mm month^{-1}), (Eq. 4.2) where S represents the current depth of moisture storage (mm), ST represents the maximum storage parameter (mm), SSR represents the maximum storage depth (mm) for runoff to occur, and SPOW represents the power of the relationship (Hughes and Mazibuko, 2018). When S is less than ST x SSR, SER is set to be zero. The variable SER increases non-linearly with increasing catchment average wetness and is conceptually equal to the percentage of the catchment that is saturated from which saturated excess runoff can occur during rainfall periods. The effects of changing SSR while maintaining a fixed value of SPOW and changing SPOW while maintaining a fixed value of SSR are demonstrated in Figure 4.4.

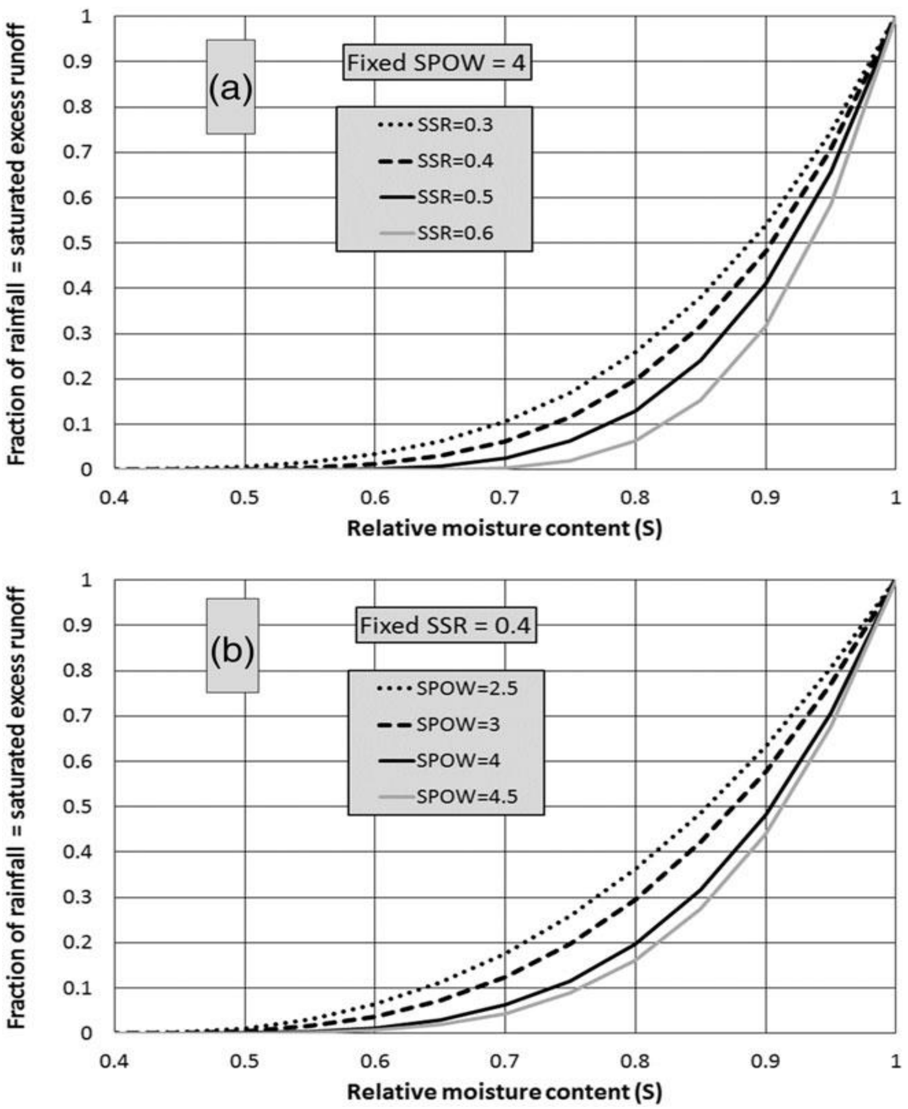

Figure 4.4: Saturated area surface runoff function (Hughes and Mazibuko, 2018). The shape of the relationships between relative moisture content and saturated excess runoff for fixed values of SPOW and SSR is illustrated.

The *surface runoff* function: this employs a triangular distribution of catchment absorption rates (Figure 4.5: Pitman, 1973) that is governed by parameters ZMIN and ZMAX in mm month^{-1} as well as ZAVE if the triangle is considered to be asymmetrical (Hughes 2013a; Hughes and Mazibuko, 2018). The depth of surface runoff for any given monthly rainfall (mm month^{-1}) is represented by the shaded area of the cumulative distribution function as depicted in Figure 4.6a (Hughes 2013a; Hughes and Mazibuko, 2018).

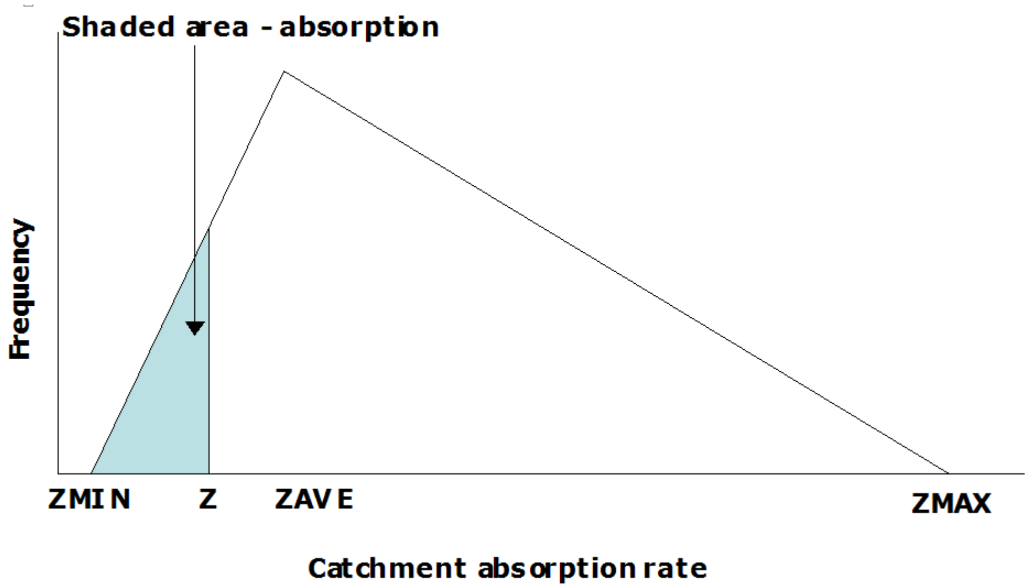

Figure 4.5: Triangular distribution of basin absorption rate, Z (ZMIN, ZAV E, ZMAX). The distribution determines the frequency of the amount of rainfall that can be absorbed at different rates.

Interflow function: Figure 4.6b illustrates the interflow function. The algorithm is a non-linear relationship between the relative moisture storage and interflow runoff with two parameters: (i) a scale parameter (FT), representing the maximum interflow runoff in mm month^{-1} and (ii) a power parameter (POW). Relative moisture storage is defined as the ratio of storage in any month (S mm) and the maximum moisture storage (ST mm) (Hughes and Mazibuko, 2018).

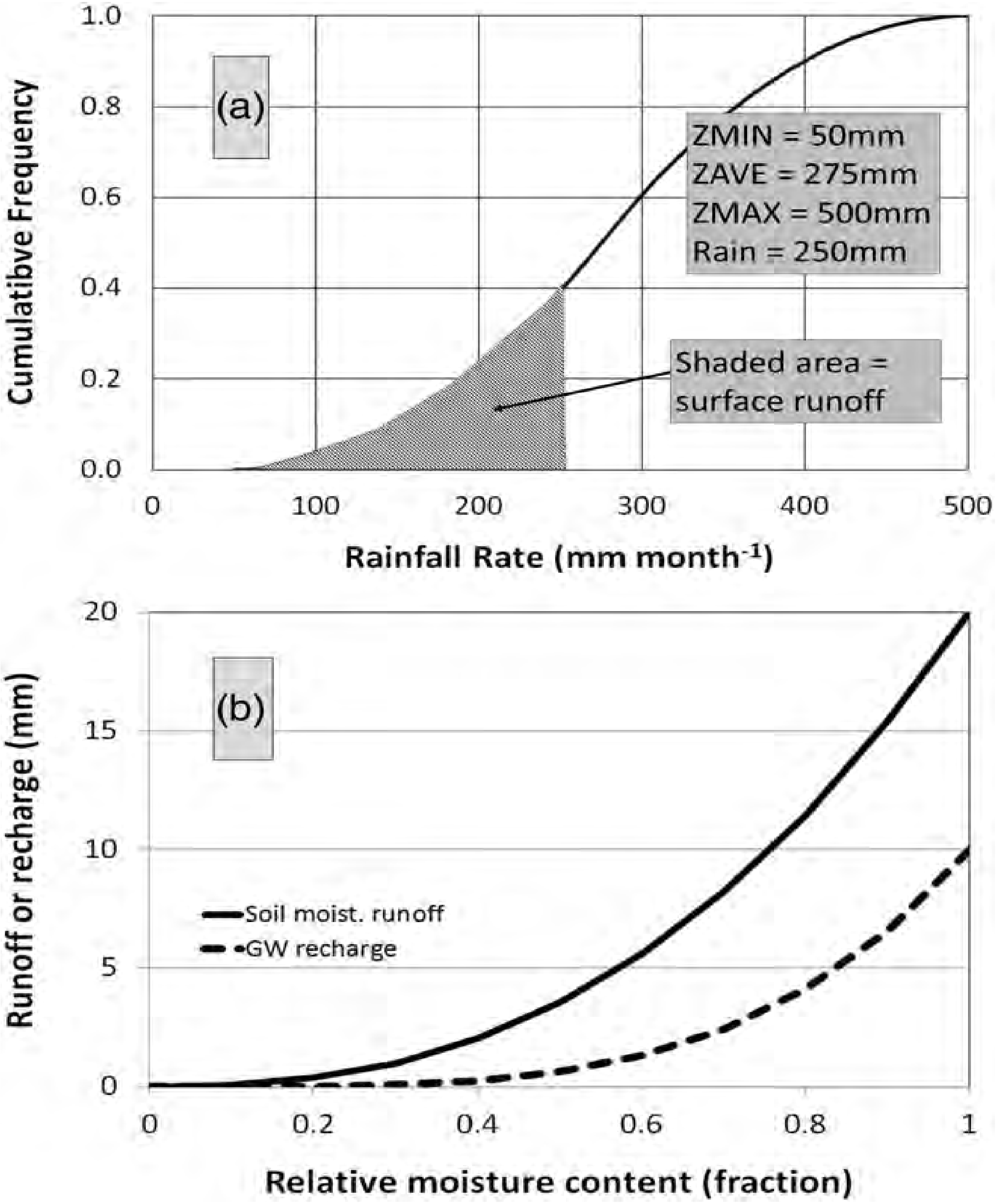

Figure 4.6: Surface runoff, interflow and groundwater recharge functions (Hughes and Mazibuko, 2018)

Groundwater recharge: This runoff generation function is similar to the interflow function with comparable parameters GW (mm month^{-1}) and GPOW (Hughes, 2013a; Hughes and Mazibuko, 2018). Groundwater recharge is assumed to decrease with the decline in soil moisture. Recharge depth is routed through the groundwater zone to finally contribute to river flow (Hughes, 2004; Hughes, 2013a; Hughes and Mazibuko, 2018). Figure 4.7 illustrates the simple sub-surface processes represented in the model. The catchment is divided into a number of slope elements based on the catchment area and a drainage density parameter (DDENS) in which the water balance components and simple geometry are used to fix the two gradient lines (one near to the channel and one distant from the channel) within each slope element (Hughes, 2004).

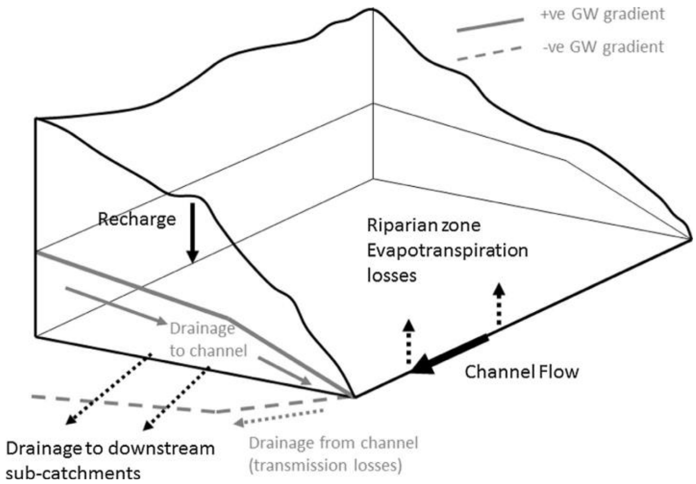

Figure 4.7: Geometry of the groundwater sub-component of the Pitman model (Hughes, 2004a)

The estimate of groundwater discharge into streams is a function of transmissivity (T), storativity (S), drainage density, rest water level and the riparian strip factor (RSF). Channel transmission losses (TLG) are considered to be a function of the characteristics of the channel, groundwater, as well as the underlying channel material (Tanner, 2013).

Table 4.2: Natural hydrology parameters for the Pitman model

Parameters	Units/expression	Description
Surface water parameters		
RDF		Rainfall distribution factor
AI	Fraction	Proportion of impervious surface of sub-basin
PI1s, PI1w	mm	Summer and winter interception storage for vegetation type 1
PI2s, PI2w	mm	Summer and winter interception storage for vegetation type 2
PEVAP	mm	Annual basin potential evaporation
ZMINs, ZMINw	mm month^{-1}	Summer and winter minimum basin absorption rate, respectively
ZAVE	mm month^{-1}	Mean basin abstraction rate
ZMAX	mm month^{-1}	Maximum basin abstraction rate
ST	mm	Maximum moisture storage capacity
SSR	mm	Minimum storage depth for runoff to occur
SPOW		Power of the relationship in the SER equation
SL	Mm	Soil moisture below which there is no recharge
POW		Power of the moisture storage runoff equation
FT	mm month^{-1}	Runoff from moisture storage at full capacity
R		Evaporation-moisture storage relationship parameter
TL	months	Lag of surface runoff
Groundwater parameters		
GW	mm month^{-1}	Maximum recharge depth at maximum moisture capacity
TLGMax	mm	Maximum channel loss
GPOW		Power of the moisture storage recharge equation
DDENS	km km^{-2}	Effective drainage density
T*	m^2 day^{-1}	Transmissivity
S*		Storativity
RG		Regional groundwater drainage slope
Rest water level	m	Aquifer depth below surface
RSF	%	Riparian strip factor

**Free parameters are those that were considered uncertain in the model set-up, and are italicised.*

4.4.2.2 Water use component and associated parameters

The Pitman model consists of a water use component with parameters for both large and small reservoirs including weirs for direct river abstractions. This component is used to represent most water resources developments and to simulate various water uses/abstractions in the southern African region.

Farm dam and run-of-river abstraction parameters with associated distributions

Table 4.3 provides a list of all the parameters for the water use components while their seasonal distributions are presented in Table 4.4. The model allows for water use through farm dam storages for irrigation, run-of-river abstractions for both irrigation and non-irrigation demands, as well as groundwater abstractions to satisfy various demands. Evaporation from farm dams (and large reservoirs) is estimated based on the relationship between surface area and simulated dam volume defined by the exponential equation in Table 4.3 where A and B are empirical constants.

Table 4.3: Pitman model water use parameters

Parameters	Units	Description
Main parameter attribute: Farm dam and run-of-river		
AIRR	Km^2	Total run-of-river irrigated area
IWR		Irrigation return flow fraction to the channel
Effective rainfall fraction (EFFECT)		Proportion of rainfall that meet irrigation demand
Non-irrig. Direct demand	Ml/a	Annual Run-of-river direct demand for non-irrigation purposes
Maximum dam storage	Ml	Maximum storage capacity of farm dam
% Catchment area above dam	%	Percentage area commanded by the farm dam
A in area volume relationship		Parameter in non-linear dam area-volume relationship
B in area volume relationship		Parameter in non-linear dam area-volume relationship
Irr. Area from dam		Total area irrigated by from farm dam
GW Abstraction (upper slopes)	Ml/a	
GW Abstraction (lower slopes)	Ml/a	
Main parameter attribute: afforestation		
AFOR	%	Percentage area of sub-basin under vegetation type 2
FF		Ratio of potential evaporation rate for Veg2 relative to Veg1
PI2s	Mm	Summer interception storage for vegetation type 2 (forest)
PI2w	Mm	Winter interception storage for vegetation type 2 (forest)
Reservoir sub-model parameters		
Reservoir capacity	MCM	Reservoir storage capacity
Dead storage	% capacity	Dead storage of the reservoir
Initial storage	% capacity	Reservoir storage at the beginning of simulation
A in Area (m2) = A*volume $(m^3)^B$		A parameter in area-volume relationship defined by the equation Area = $A*Vol^B$
B in Area (m2) = A*volume $(m^3)^B$		B parameter in area-volume relationship defined by the equation Area = $A*Vol^B$
Reserve level 1-5	% capacity	5 levels of operating rules used to reduce abstraction of reduced storage
Annual abstraction	MCM	Annual demand from reservoir
Annual compensation flow	MCM	Downstream compensation releases in to river
AR in Reserve (%)=AR*volume $(\%cap)^{BR}$		To define the % reduction in default release requirements for low reservoir storages
BR in Reserve (%)=AR*volume $(\%cap)^{BR}$		

Reservoir parameters and associated distributions

The water use component consists of a reservoir sub-model with parameters (Table 4.3) and associated seasonal distributions (Table 4.4) of the total demand. The reservoir in any sub-basin is supplied by the cumulative flow at the outlet of that sub-basin which contains a reservoir, as opposed to the 'farm dams' that are supplied by incremental flows. The initial reservoir storage capacity (as a percentage) prior to the start of any simulation needs to be specified. The reservoir sub-model allows for all possible abstractions for multiple purposes and the parameters ensure that the storage is depleted accordingly through distributed abstractions, downstream compensation as well as evaporation. Depletion continues until the dead storage of the reservoir is reached.

Table 4.4: Monthly distributions for farm dams and run-of-river- abstractions, and large reservoirs

Distribution	Units/expression	Description
Farm dam		
Monthly distribution weights		Used to distribute parameter values for all the months
Monthly irrigation demand	mm	Depth of monthly irrigation requirement for the appropriate crop(s) grown in the sub-basin.
Monthly water use	Fraction	Annual non-irrigation demand
Groundwater use	Fraction	Total demand from groundwater
Reservoir sub-model		
Normal drafts	fraction	Controls reservoir abstraction
Monthly reserve drafts (5 levels)	fraction	To distribute the 5 operating rule levels
Normal compensation flow	fraction	To distribute annual compensation flows
Compensation flow reserve (5 levels)	fraction	Control the flow reserves

4.4.3 Model forcing and calibration data

Forcing data are made up of time series of monthly rainfall depths, annual potential evapotranspiration depth and fixed seasonal distributions of potential evaporation. The evaporative demands are by default specified as fixed long-term seasonal distributions (e.g. those estimated by Midgley et al., 1994 applicable to the catchments of South Africa, Lesotho and Eswatini) due to shortage of sufficiently accurate data that adequately cover the region of southern Africa (Hughes, 2013a). Where necessary, the distributions can be varied for the simulation record to account for non-stationarities in climate. A time series of observed monthly flows is used as an appropriate hydrological response signature to evaluate the model simulations.

4.5 The modelling interface: SPATSIM

The model is applied within the Spatial and Time Series Information Modelling (SPATSIM: Hughes et al., 2000; Hughes, 2002; Hughes and Forsyth, 2006) interface which consists of a GIS functionality. SPATSIM software (http://iwr.ru.ac.za/iwr/software/spatsimupdate.php) is a modelling framework that is used as a database storage and for the analysis and management of all kinds of spatial information (i.e., time series and non-time series). It is also used to facilitate the running of the Pitman model and other water resources models. The modelling interface has improved the efficiency of the application of the Pitman model, by incorporating uncertainty analysis procedures.

'Features' are spatial coverages for the sub-basins in the form of GIS shapefiles. These may include sub-basin boundaries, rivers, dams, flow gauges and rainfall gauges. All spatial data, such as monthly rainfall, stream flow, evapotranspiration, are loaded into the software through these 'Features'. Associated with each shapefile are the 'Attributes' which are populated with spatial data. The spatial data stored in 'Attributes' are accessed through database tables. Detailed information on SPATIM can be found in Hughes and Forsyth (2006).

4.5.1 Options used to run the Pitman model

Three options were used to run the model. The Single run model is an option that does not incorporate uncertainty. It runs the model using one parameter set and generates a single model simulation. With this option, the model parameters are manually calibrated. The model can simulate more than 400 sub-basins in the spatial distribution system. The cumulative stream flow simulations are stored in an attribute and can be viewed and analysed visually as well as through the use of objective functions (section 4.5.3.2). Other outputs from the model include simulated groundwater recharge and discharge, reservoir volumes and spills, evapotranspiration and channel losses, etc. The incremental and cumulative uncertainty run options (two-step modelling) form the uncertain modelling approach used in this research and are discussed in sub-section 4.5.3. The single run can be applied prior to the incremental run option as a guide in estimating likely model parameter ranges in cases where there are many sub-basins to be simulated with uncertainty. This can help reduce the time spent on establishing the parameter ranges during the incremental modelling phase. The incremental run option uses *a priori* parameter distributions to generate ensembles for incremental natural flows for each sub-basin, and these ensembles are constrained by suitable hydrological signatures. The cumulative option is applied to simulate present-day stream flow conditions using parameter sets saved during the incremental run as well as water use parameters, where applicable. The incremental and cumulative uncertainty options are considered ideal to realistically estimate and reduce uncertainty since the simulation of stream flow conditions is based on uncertain *behavioural* model outputs (i.e., all those model outputs that fall within or match the established constraints). This uncertainty approach is therefore appropriate in areas that are data-scarce, such as the transboundary basins of Eswatini.

4.5.2 Parameter sampling

The parameter input consists of the: (i) mean (used to represent the average parameter value), (ii) standard deviation (i.e., a measure of how the parameter values deviate from the mean parameter value), (iii) dependency index (used to assume whether or not the uncertainty is the same throughout the sub-basins), (iv) distribution type (used to specify the type of distribution used in the uncertainty analysis, with a value of 0 indicating that the parameter is not treated as uncertain), (v) minimum and (vi) maximum (represent the sampling limits: define the parameter space). In this study, uniform distribution sampling was used based on the minimum and maximum parameter values. If sufficient information is available to estimate the parameter values, the sampling limits can be reduced by narrowing the parameter ranges. If the uncertainty is assumed to be similar in some sub-basins, such sub-basins are grouped by assigning an index (dependency index) to this group prior to the running of the model. Where a dependency index is used, the sampling procedure is designed to generate similarly relative wet or dry simulations from all the sub-basins in the same group (i.e., the samples are drawn from the same part of each sub-basins parameter range, even though the parameters can be very different in each sub-basin).

Typically, a range (minimum and maximum) that defines the uncertainty in parameter estimation is sampled using a simple random sampling approach that assumes uniform distribution. A Monte Carlo method (i.e., a broad class of computational algorithm) is applied to perform a random sampling from the defined distribution of a parameter, which can be Normal, Log-Normal or Uniform, depending on the distribution type specified. Parameter space sampling is therefore carried out to generate multiple parameter sets and simulate either observed near-natural or present-day flow conditions of all available gauges.

4.5.3 The two-step uncertainty modelling approach of the Pitman model

Figures 4.8 and 4.9 illustrate the uncertainty framework that is used with the SPATSIM version of the Pitman model that works towards obtaining sub-basin behavioural ensembles based on constraints on the sub-basin response, using a two-step uncertainty approach. Figure 4.8 illustrates how uncertainty from individual sub-basin outputs can influence the degree of uncertainty on the downstream flow. The first step (i.e., Stage one) ensures that the natural conditions, including uncertainty, are represented well in the model set-up before any modifications to the natural stream flow conditions can be incorporated and simulated during the second step (i.e., Stage two). In doing so, uncertainty can be estimated realistically.

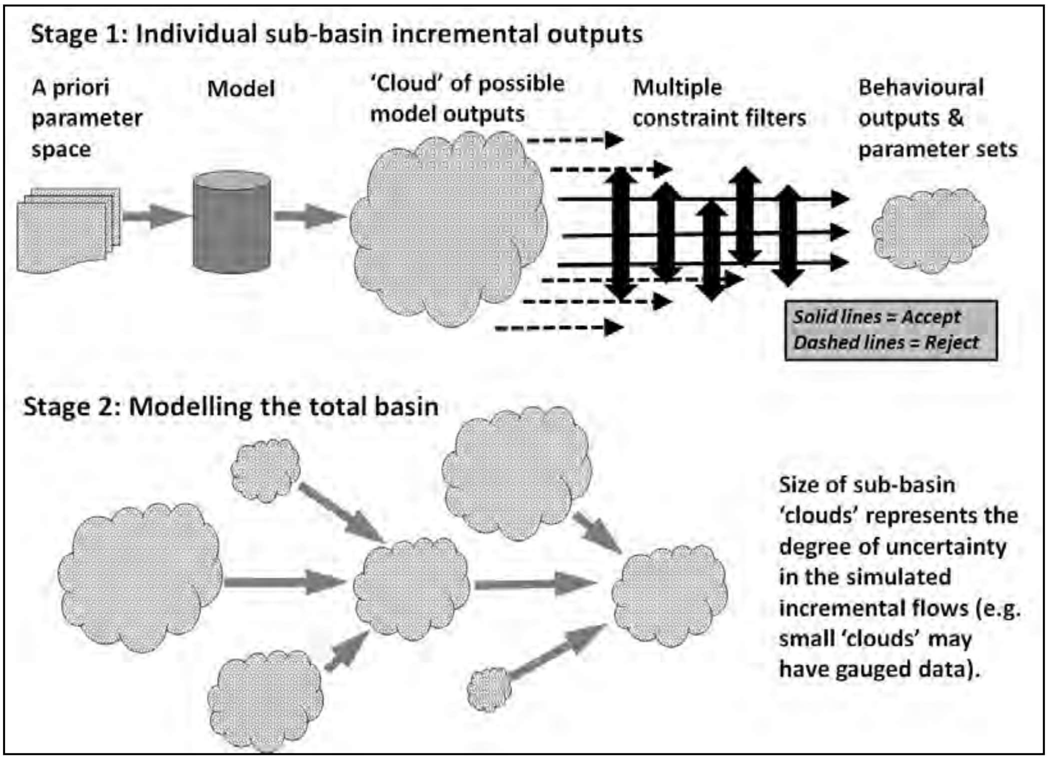

Figure 4.8: Generalised uncertainty framework for the Pitman model (Hughes, 2016). Step one (i.e., Stage one) of the framework is designed to identify 5 000 behavioural parameter sets using regional constraint ranges before Step two (i.e., Stage two) can be run.

In this approach, two model runs are implemented: incremental uncertainty run (with unlimited number of sub-basins simulated independently) and cumulative uncertainty run. The two-step approach (Figure 4.8) is explained by Figures 4.1 and 4.9.

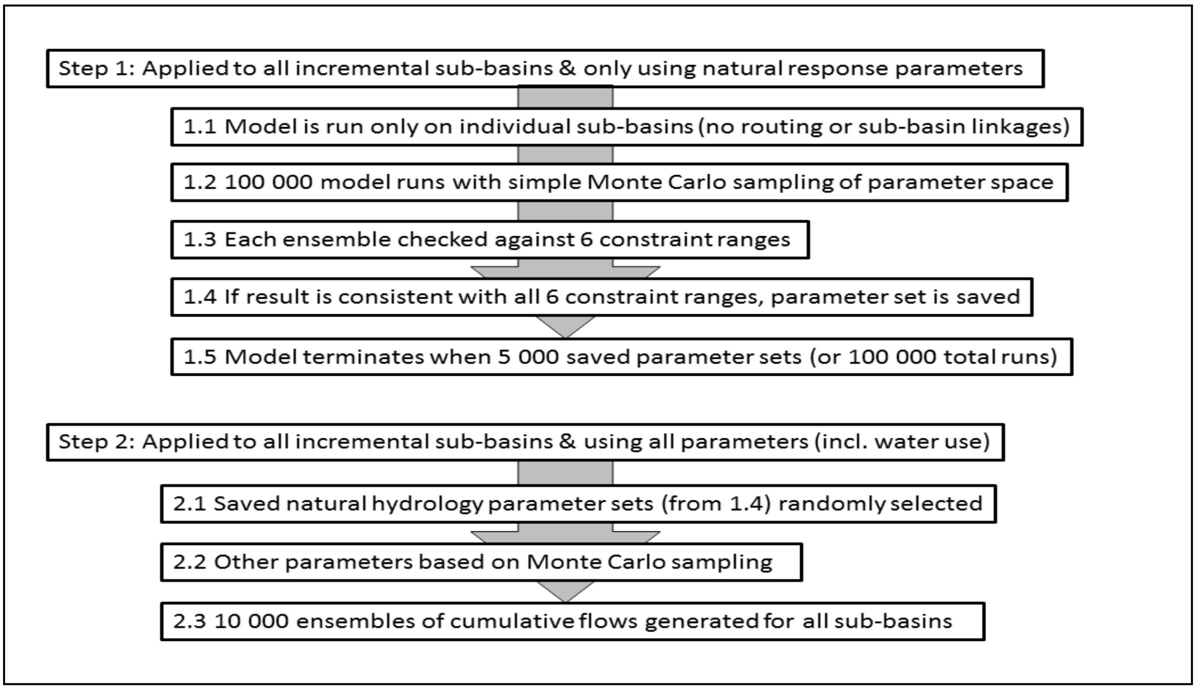

Figure 4.9: Two-step process for generating behavioural ensembles using the uncertainty version of the Pitman model

4.5.3.1 Step one: Incremental uncertainty run

The first step simulates the incremental natural flows for all of the sub-basins and links between sub-basins are ignored (i.e., cumulative flows are not generated). The inputs to the first step are the climate forcing data, a set of ranges (minimum and maximum) defining the feasible parameter space for all of the model parameters that affect the incremental sub-basin natural hydrology (i.e., downstream routing and water use parameters are not included) and a set of ranges defining the constraints on the behavioural response of the sub-basins.

The model interface allows the user to specify the total number of model runs (typically 100 000), as well as the maximum number of behavioural solutions that are desired (typically 5 000). Each model run is based on independent random sampling of the parameter ranges assuming that the minimum and maximum values define a uniform distribution.

The outputs from this step are then assessed based on the constraints using a utility for checking the consistency of constraints and parameters. If the model results for each sub-basin run fall within the ranges of all the constraints for that sub-basin, the result is considered behavioural and the parameter set values are saved to a database for use in step two. The model continues to run until either the maximum number of saved parameter sets has been achieved or the maximum number of model runs is reached. The outputs cannot be statistically analysed until step two is run (i.e., comparisons with observed data cannot be made). However, a model utility (see Figures 4.10 – 4.11) is available to view the distributions of the individual parameter and constraint indices within all of the saved behavioural ensembles and adjust where applicable and appropriate and rerun. This utility is used to examine the distributions of constraint and (selected) parameter values within the behavioural simulations generated for a single sub-basin. The frequency distributions of the constraint values across five divisions (between the minimum and maximum values of the constraint) are shown in the top left graph, while the distributions of the selected parameter values using 10 sub-divisions of the total parameter range are shown in the other graphs. Figure 4.10 shows the outputs that occur if no behavioural ensembles are found. This utility can be used to better align the parameter ranges to the constraints or vice versa (i.e., shift, reduce or increase the range of some parameters and/or constraints) or to check that the constraints are consistent with each other. In this study where a regional approach was applied, consistency in making changes to the constraints was maintained by shifting the constraint ranges where applicable. In situations where no (or very few) behavioural simulations are generated (e.g., Figure 4.10), often due to incompatibilities between the constraints and parameters, progressive adjustment is required (Figure 4.11, top diagram) by setting more appropriate ranges in order to achieve better simulation and increase the number of behavioural solutions (Figure 4.11, bottom diagram).

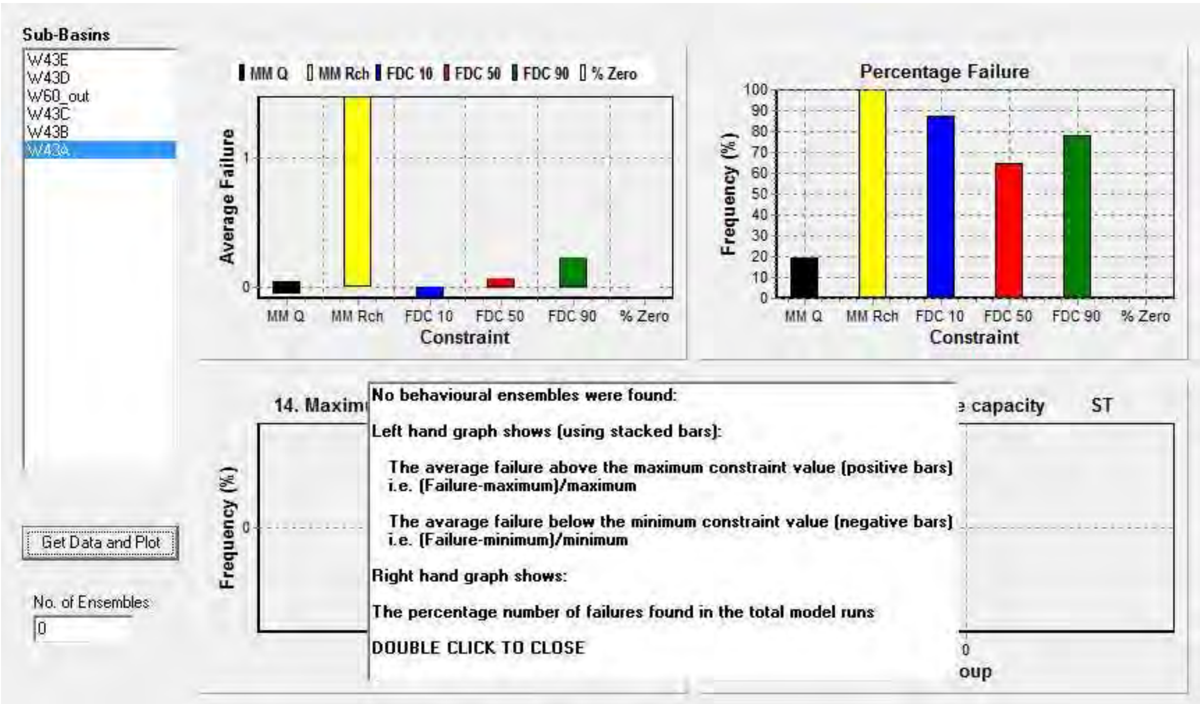

Figure 4.10: An example of model failure where no behavioural ensembles are generated. In this example, the ranges of the parameter sets used during Step one do not match the established constraints. This utility can therefore be useful in providing a guideline in terms of which parameters and constraints need to be adjusted, and how to adjust them. After this result, the constraints were shifted to better align them with the parameters.

In other situations a combination of an even or good distribution of the established constraints across the groups (i.e. lower or minimum to upper or maximum group) may be achieved. These well-distributed constraints as well as main discharge-generating parameters may be characterised by false ranges resulting in, for example, over-simulation of low flows and under-simulation of high flows (and vice versa). This can also be resolved through a procedure similar to the one outlined in Figures 4.10 – 4.11.

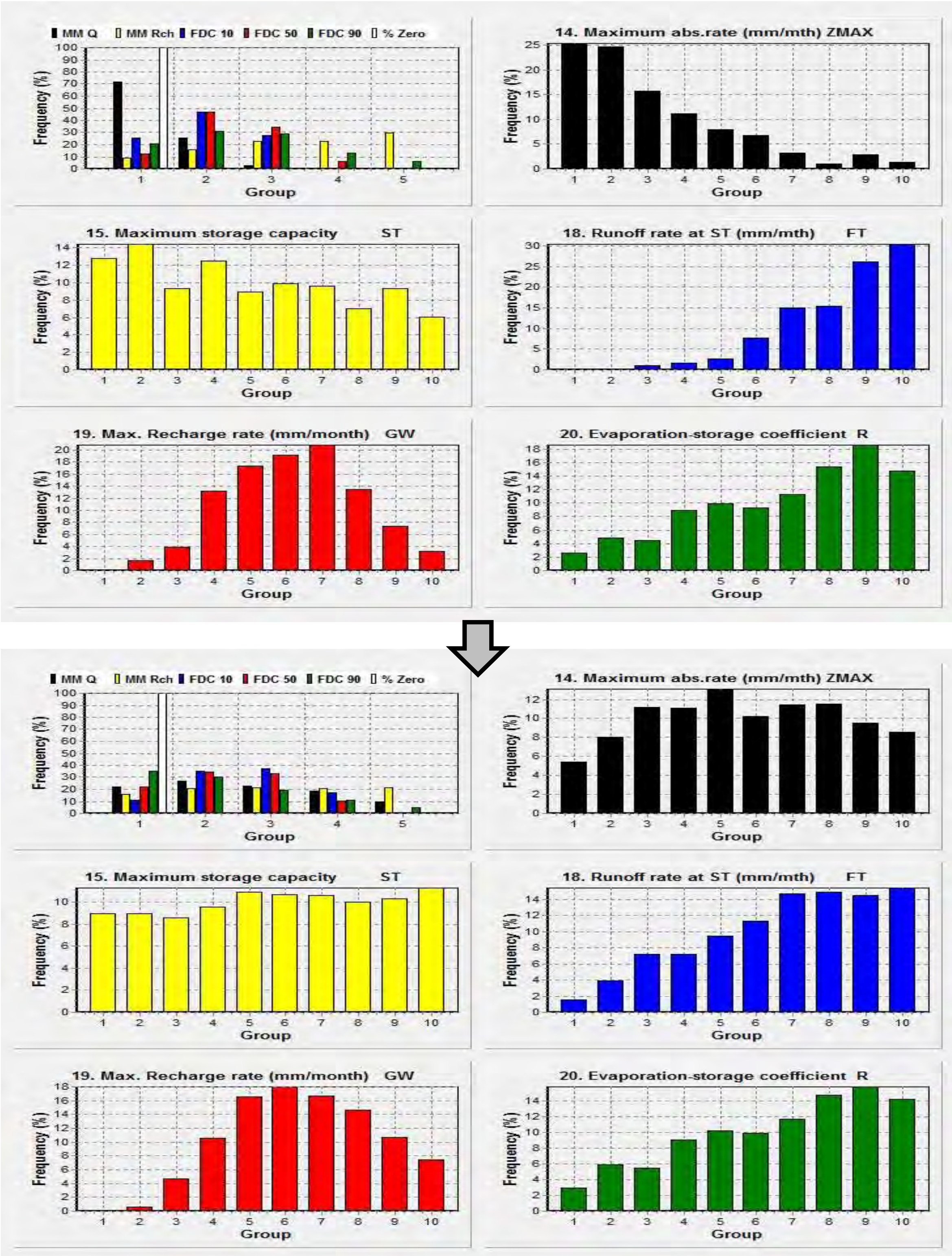

Figure 4.11: Progressive improvement of simulations by aligning parameters with constraints. In this case, parameters ZMAX and ST were reduced while FT was increased. This was coupled with the reduction of MMQ and Q10 constraints, for instance (upper diagram). These

adjustments resulted in the final output of a well-distributed set of constraints and parameters (lower diagram).

4.5.3.2 Step two: cumulative uncertainty run

In step two, the model is run with the same climate inputs as in step one, but with all the downstream linkages incorporated (i.e., it also includes routing parameters) to generate cumulative flows at all sub-basin outlets. Where appropriate, water use functions and associated parameter values are also included. Each model run is based on random sampling from the parameter sets that were saved during step one (only parameters affecting the incremental natural hydrology) together with independent random sampling from the ranges of any other parameters (routing, water use, etc.) that are considered uncertain. The number of model runs used (for both steps) represents a compromise between effectively sampling the uncertain parameter space and the total time taken to run the model (Kapangaziwiri et al., 2012; Hughes, 2013).

The model can be run under 'natural' (or near-natural) conditions and the ensemble results can be compared with any observed stream flow data that represent such conditions. The outputs from step two include a set of comparative statistics (Nash-Sutcliffe efficiency, bias, etc. as outlined in subsection 4.7) for each ensemble and each sub-basin where observed data are available. However, the observed data are not used to condition or constrain the model, they are simply used to assess the results of each ensemble.

While observed data for headwater sub-basins may have been used to calibrate the WR90/2005 version of the model and therefore establish the constraints, downstream gauged data can be used in step two of the process to check that the constraints for upstream ungauged sub-basins are also realistic. The iterative loop in Figure 4.1 illustrates that the observed data are used to check constraints and therefore refine them (or revise parameters) in gauged sub-basins before (and/or after) any water use parameters are included in the model. The overall objective is to establish natural flow simulations with realistic and behavioural uncertainty bounds that are consistent with the constraint indices.

In the lower part of Figure 4.1, any water uses or land use changes (both with uncertainty) are included in the model setup, which then allows for comparisons (and evaluation using suitable objective functions explained earlier) with observed data that represent impacted conditions. In some cases, the available observed data may represent both natural and impacted conditions (Hughes, 2015). In these situations, the early part of the observed record may be used for the first level of constraint refinement (natural conditions), while the more recent observed data may be used with the second level of refinement. Inevitably, the refinement process in any set of linked sub-basins must start upstream so that any changes made can be included in the downstream assessments.

4.6 Parameter uncertainties

Some of the natural hydrology parameters of the model are not directly measured from the field and are highly uncertain. The degree of uncertainty assigned to each parameter depends, among others, on the amount of information that is available to appropriately define that parameter. For example, some water use parameter values can be easily estimated from GoogleEarth images, for instance, and this may result in low uncertainty as opposed to some natural hydrology parameters (such as groundwater parameters) which may be difficult to measure or estimate. All the parameters in Table 4.2 can be set to be uncertain in the model setup. However, in this study, only the parameters affecting the main water balance are considered uncertain in step one of the approach. These include the surface runoff (ZMIN and ZMAX), soil moisture storage (ST), interflow, groundwater recharge (FT, POW, GW and GPOW) and evapotranspiration loss (R, RSF) components. One of the advantages of the use of constraints is that issues of parameter identifiability and equifinality are largely side-stepped, because the model outputs and the parameter sets that can be considered behavioural are constrained by the ranges of the hydrological indices. In step two, most of the water use parameters (for run-of-river abstraction and farm dam storage) were considered uncertain due to the limited amount of information to accurately define the anthropogenic impacts on stream flow. All the reservoir parameters are fixed during the model run and some were modified in subsequent runs.

4.7 Model performance evaluation

The first level of evaluating simulations involves visual assessment of the simulated hydrograph against the observed flows through SPATSIM. This includes the assessment of seasonal flow distributions, long-term flows and the analysis of flow duration curves. A scatter plot can be viewed and assessed to determine how well the observed flows are simulated. The second level is the use of statistics (i.e., the objective functions computed by the model) which can be combined to assess the outputs against observed flow data and to further evaluate the model simulations objectively. The untransformed and natural log-transformed coefficient of determination (R^2) which measures how well the observed series is replicated by the model is expressed as:

$$R^2 = \frac{[\Sigma(Q_O - \overline{Q_O}) * (Q_S - \overline{Q_S})]^2}{[\Sigma(Q_O - \overline{Q_O})^2 * (Q_S - \overline{Q_S})^2]}, \quad \text{(Eq. 4.3)}$$

where Q_o is the observed flow, $\overline{Q_o}$ is the mean of the observed flows, Q_s is the simulated flow and $\overline{Q_s}$ is the mean of the simulated flows. The Nash-Sutcliffe coefficient of efficiency (NSCE) is calculated as:

$$NSCE = 1 - \left[\frac{\Sigma(Q_O - \overline{Q_S})^2}{\Sigma(Q_O - \overline{Q_S})^2}\right]. \quad \text{(Eq. 4.4)}$$

and is used to assess the predictive power of the model. The percentage bias:

$$\%BIAS = 100 * \left[\frac{(\overline{Q_s} - \overline{Q_o})}{\overline{Q_o}}\right] \quad \text{(Eq. 4.5)}$$

is critical in the assessment of model residuals and has implications on the overall band of uncertainty in the model output.

4.8 Summary

Generally, the main justification of using the Pitman model is its previous experience of its use in southern Africa. This is characterised by its relevance in southern Africa which has contributed to advances in science and research in the region. The two-step modelling approach allows for the estimation of sub-basin hydrological response based on stream flow indices and setting up of appropriate initial constraint ranges and their regionalisation. In this study, six constraints were used in the two-step uncertain Pitman model approach to ensure behavioural simulations at both upstream and downstream locations are generated through a progressive procedure. The initial constraint analysis is based on previous simulations, and these are refined through assessments against the available observed data. Additional constraints could be included where this is considered appropriate to reduce uncertainty in simulation and this is mainly dependent on data availability. As with many studies in southern Africa, the data used in this research were expected to be limited and inaccurate. This was expected to affect the degree of uncertainty in the simulated flows. However, the uncertainty approach presented in this study aims to enable realistic modelling in the presence of such data issues.

CHAPTER FIVE: RESULTS AND DISCUSSIONS

The results are presented according to the steps outlined in Figure 4.1. The first part of the results chapter deals with establishing the regional patterns of response signatures and their ranges that are used to constrain the initial model outputs (refer to Figures 4.1 and 4.7). The second part deals with the results of the model simulations and the adjustment of the regional constraint ranges in specific sub-basins. In the second part of the results chapter, the testing and validation of the modelling approach in a few sample sub-basins is presented first before the results of the application of the modelling method to the rest of the study area is presented. Finally, the discussion of the results, conclusions and recommendations are presented.

5.1 Constraint index analysis

Initially, the sub-basins were subjectively classified into five topographic zones (LV, MV, FHV, ES, and SM) as seen on Table 5.1 after a pre-analysis of the WR2005 incremental stream flow simulations, mainly using the shape of the flow duration curves to guide the classification. Inevitably, the climatic variations across the region also influenced the classification as they are reflected in the WR2005 stream flow simulation results. The use of elevation, elevation range and slope as an additional guide to the topographic classification of the individual sub-basins resulted in six zones that were intuitively sensible and geographically cohesive. However, further analysis suggested that the characteristics of the LV sub-basins were quite variable, partly because of the influence of the Lubombo Plateau, and this group was further divided into LV and SLV (Table 5.1). However, some catchments which were classified as SLV were then later reclassified as LV because they are located in the Lowveld (based on further analysis of the topography) yet influenced by climatic conditions of the Lubombo Plateau. Other changes made to other groups are: SM to ES, LV to MV, and ES to FHV. These changes were made because of elevation for the first one, and also slope in some instances (for the last two groups).

Figure 5.1 illustrates the final classification, while Table 5.1 lists the full names of the zones or regions, as well as some of their key characteristics. There is little doubt that some sub-basins are difficult to classify as they share similar characteristics with more than one region. This is particularly true for some of the sub-basins along the borders of the different regions. The key issue is that this classification is only used to establish the initial constraint ranges which will then be assessed during the application of the model, as illustrated in Figure 4.1.

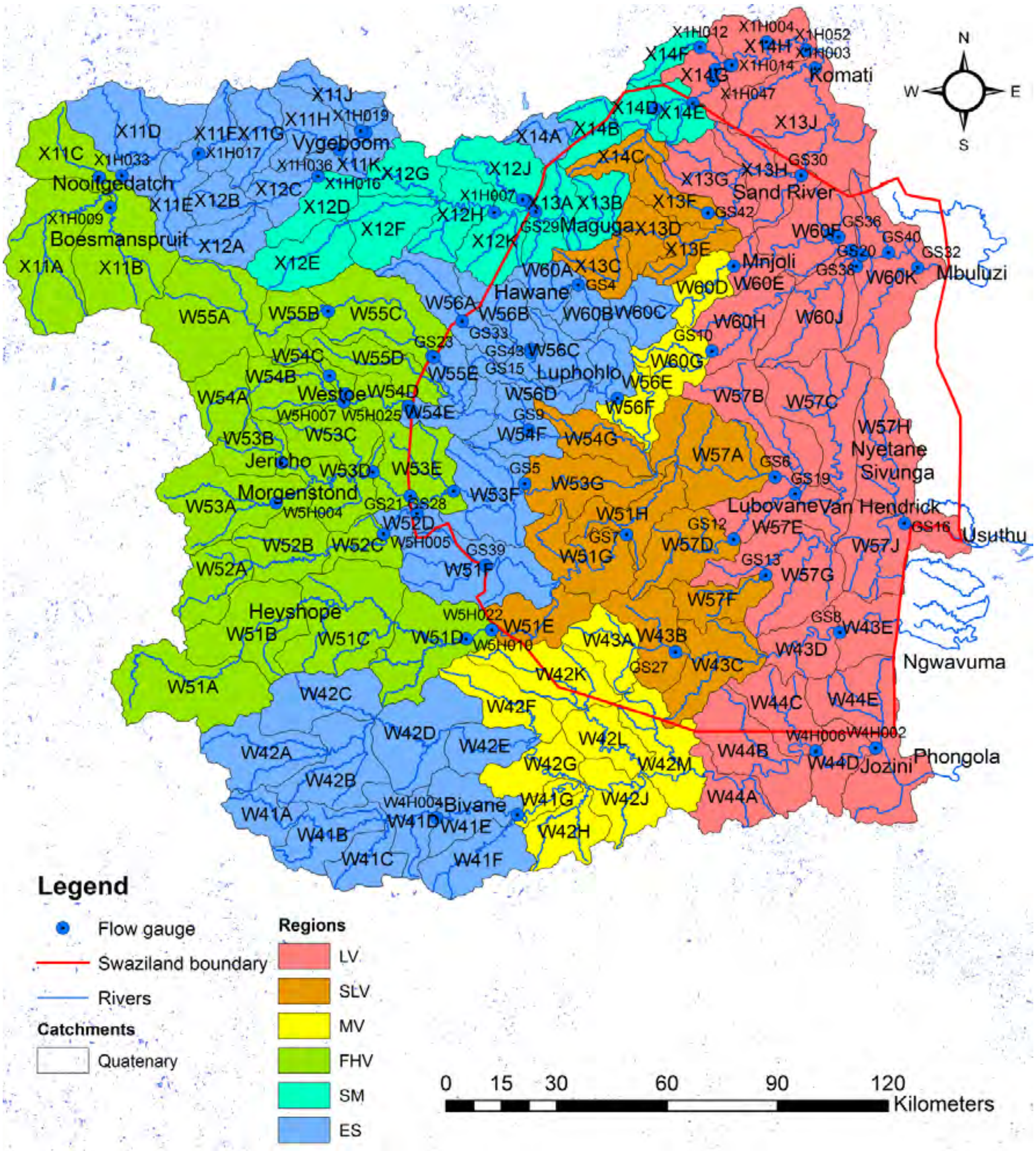

Figure 5.1: Identified regions for the study area

Figures 5.2 and 5.3 and Table 5.2 summarise the hydrological response characteristics (whose values were based on previous simulations and therefore reflect the whole previous calibration approach) and results of the constraint analyses. Figure 5.2 suggests that there are some consistent relationships between AI and the mean monthly flow (MMQ) constraint (plotted as the runoff ratio to avoid sub-basin scale effects) for most of the topographic regions (with R^2 values of >0.8), while the MV and particularly the SLV region show more scatter. This is largely a consequence of the difficulties of assigning sub-basins to these two intermediate regions and also related to the likely differences in the regionalisation scheme in this study compared to the one used in WR2005 to assign regional parameter values. The constraint ranges are based on the regression equations and either ±15% or ±20% uncertainty ranges depending on the degree of scatter in the relationships for the six regions (Table 5.1).

Table 5.1: Description of the topographically-classified hydrological response zones

Region ID	Name	Altitude Range (m)	Average slope (%)	Range of aridity index (PE/P)	Comments
SM	Steep mountains	151 to 319	1.08	1.15 to 1.65	Humid and consistently steep sub-basins.
ES	Escarpment	102 to 225	0.80	1.15 to 1.95	Humid and generally steep, but with some low topography areas in headwaters on top of the escarpment.
FHV	Flat Highveld	32 to 203	0.53	1.55 to 2.1	Semi-arid and dry sub-humid sub-basins with generally low topography, but with steeper headwater areas in some sub-basins.
MV	Middleveld	97 to 284	1.19	1.5 to 2.05	Semi-arid and dry sub-humid sub-basins with generally moderate topography, but with steeper headwater areas in some sub-basins.
SLV	Steep Lowveld	120 to 237	1.05	1.1.5 to 2.0	Dry sub-humid but generally similar to LV but with some steep areas associated with the Lubombo mountains (border between Eswatini and Mozambique).
LV	Lowveld	73 to 269	0.84	1.7 to 2.7	Semi-arid and mostly low topography, but with some sub-basins containing small steep areas.

In general terms, the relative shapes of the relationships between the hydrological indices and the aridity index are intuitively sensible:

- All of the general trends show reductions in the hydrological indices with increases in the aridity index.
- The highest runoff ratios are associated with the steep escarpment region (ES), while the lowest with the flat and more arid Lowveld (LV) region, as well as the relatively low topography of the Flat Highveld (FHV) region.

However, there are also a few surprises in the results, including the relatively low runoff ratios for some of the steep mountain areas in the north of the total region (Figure 5.1). At least some of these are quite heavily covered by plantation forestry and it is possible that these land use effects could have been included in the WR2005 simulations, such that they do not properly represent natural flow regimes. As noted earlier, this type of potential anomaly can be checked during the initial simulations runs, assuming that there are sufficient gauged data to assess the initial constraints in these areas, and assuming that it is possible to isolate the impacts of afforestation from the natural flow regime. These issues are dealt with later in this chapter.

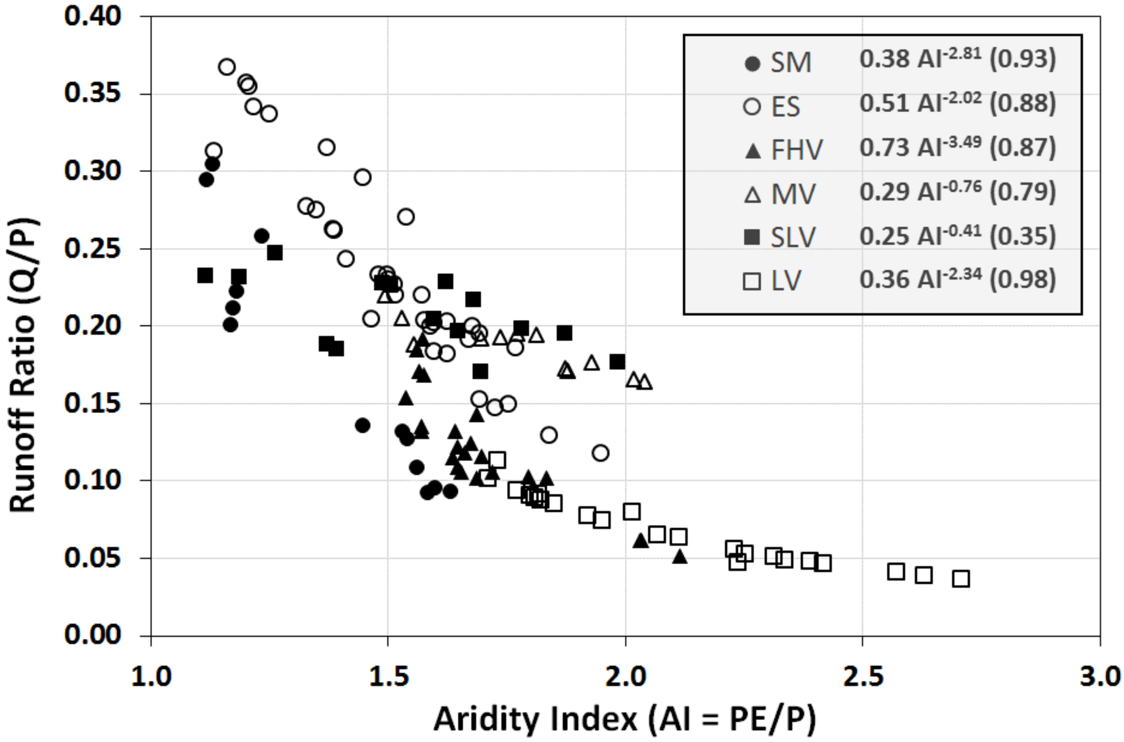

Figure 5.2: Regional analysis for the MMQ constraint using runoff ratio plotted against aridity index for the identified physiographic zones

There are few identifiable trends in the relationships between the three flow duration curve indices (Q10, Q50 and Q90, expressed as fractions of MMQ) and AI (Figure 5.3). The exception is some weak relationships for the Q50 constraint and the ranges for these are based on similar regression equations as for the runoff ratio (and hence MMQ) using ±20% uncertainty ranges. All the other FDC constraint ranges are based on fixed minima and maxima (Table 5.2), approximately based on the ranges of scatter shown in Figure 5.3.

The mean monthly recharge constraint ranges were extracted from the GRAII database (DWAF, 2005) using the two lowest of the three estimates provided, on the basis of past experience of using the values from this database for calibrating the recharge parameters of the Pitman model (Hughes, 2004; Tanner and Hughes, 2015). Finally, most of the sub-basins outside the Lowveld region are not expected to experience zero flows under natural conditions, while the Lowveld range of 0 to 10% zero flows was based on the WR2005 simulations.

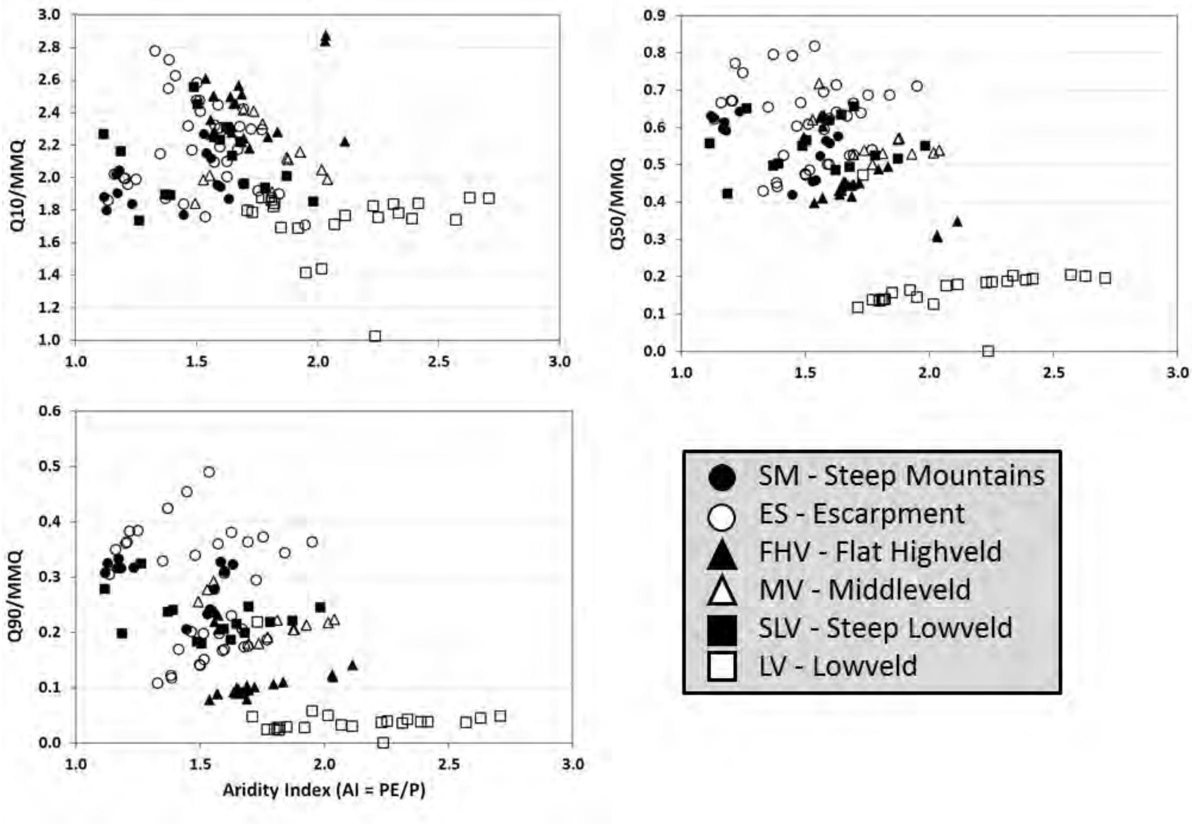

Figure 5.3: Regional analysis for the flow duration curve constraint indices (Q10/MMQ, Q50/MMQ and Q90/MMQ) all plotted against aridity index for each of six physiographic zones

Table 5.2: Initial constraint indices

Region ID	Runoff ratio	Q10/MMQ	Q50/MMQ	Q90/MMQ	MMR (mm)	% Zero flows
SM	As defined through the regression equations with the aridity index (AI) given in Fig. 5.2 and with ±15% or ±20% (SM & ES) uncertainty bounds	1.8 to 2.8	$0.66 * AI^{-0.56}$ with ±20% bounds.	0.2 to 0.35	Based on the two lower recharge estimates given in the GRAII (DWAF, 2005) report.	0
ES		1.8 to 2.8	0.4 to 0.8	0.1 to 0.25		0
FHV		2.1 to 2.6	$0.95 * AI^{-1.43}$ with ±20% bounds.	0.08 to 0.15		0
MV		1.8 to 2.5	$0.94 * AI^{-0.9}$ with ±20% bounds.	0.15 to 0.3		0
SLV		1.8 to 2.6	0.4 to 0.7	0.15 to 0.3		0
LV		1.6 to 1.9	0.1 to 0.22	0 to 0.08		0 to 10

**NB: Runoff ratio is converted to the MMQ using the sub-basin mean monthly rainfall*

5.2 Hydrological modelling

The initial ranges for the uncertain parameters, and the fixed values for the other parameters (Appendices 1 – 6), were based on previous experience of simulating basins in the escarpment areas of South Africa and Swaziland and the uncertain ranges were further refined during step one of the modelling approach for sample sub-basins of each topographic region using the utility program referred to in Chapter 4. The key point is that the initial parameter ranges can be quite large because the most appropriate parameter sets are determined through the constraining process (Figure 4.7, Step one). The utility program is mostly used to improve the efficiency of the uncertainty model runs by changing the parameter minimum and maximum values to achieve fewer non-behavioural results (i.e., those that do not match all of the constraint index ranges).

Apart from identifying appropriate parameter ranges to achieve simulations that match the constraint ranges, the eventual objective for the study was to validate and/or refine the constraint indices (using the structure outlined in Figure 4.1) for all 122 sub-basins in order to simulate both natural and impacted stream flow conditions. Some of the gauges can be considered to represent natural flows with minor development impacts. Some also represent headwater sub-basin responses, while many represent downstream cumulative flows from two or more sub-basins (Table 4.1).

The first objective of the constraint index adjustment process is to ensure that the sub-basin constraints used in step one (and uncertain water use data used in step two) generate behavioural responses at all points in the basin where this can be checked using the observed stream flow data. The second objective is to determine if the sub-basin constraint ranges can be reduced in some sub-basins where there is less uncertainty in the hydrological response due to the availability of at least some observed data.

5.2.1 Testing of the approach

A detailed illustration of the application of the method according to Figure 4.1, using the Mbuluzi, Ngwavuma and two headwater sub-basins of Usuthu basin, is given before the results of individual sub-basins are presented and discussed. This illustration follows the order:

- Checking and refining the constraints against observed data that represent natural headwater flows.
- Similar checks for headwater catchments with anthropogenic impacts
- Checks at downstream stations, where adjustments are made in some sub-areas to achieve an acceptable result downstream. This applies to both natural and impacted conditions.

Including the gauge names in Figure 5.1 is difficult, however reference can be made to the quaternary catchment numbers (e.g., W60D) to locate the position of all of the results shown in the following diagrams of this chapter.

5.2.1.1 Mbuluzi River basin

Table 5.3 summarises the constraint index changes for the Mbuluzi sub-basins and the results are presented in Figure 5.4, including the comparisons of the simulations before and after the changes. The top-left part of Figure 5.4 illustrates the uncertain bands of the FDC using the original constraints and the revised constraints for the headwater sub-basin W60A (in the ES region). An explanation of the additional value of including highly impacted gauges for model refinement is illustrated in Figures 5.7 to 5.9 and Table 5.6 and 5.7. The top-right part of Figure

5.4 illustrates the situation at W60D (MV region) after some additional changes to the constraints for this sub-basin and the upstream ungauged W60B and W60C sub-basins.

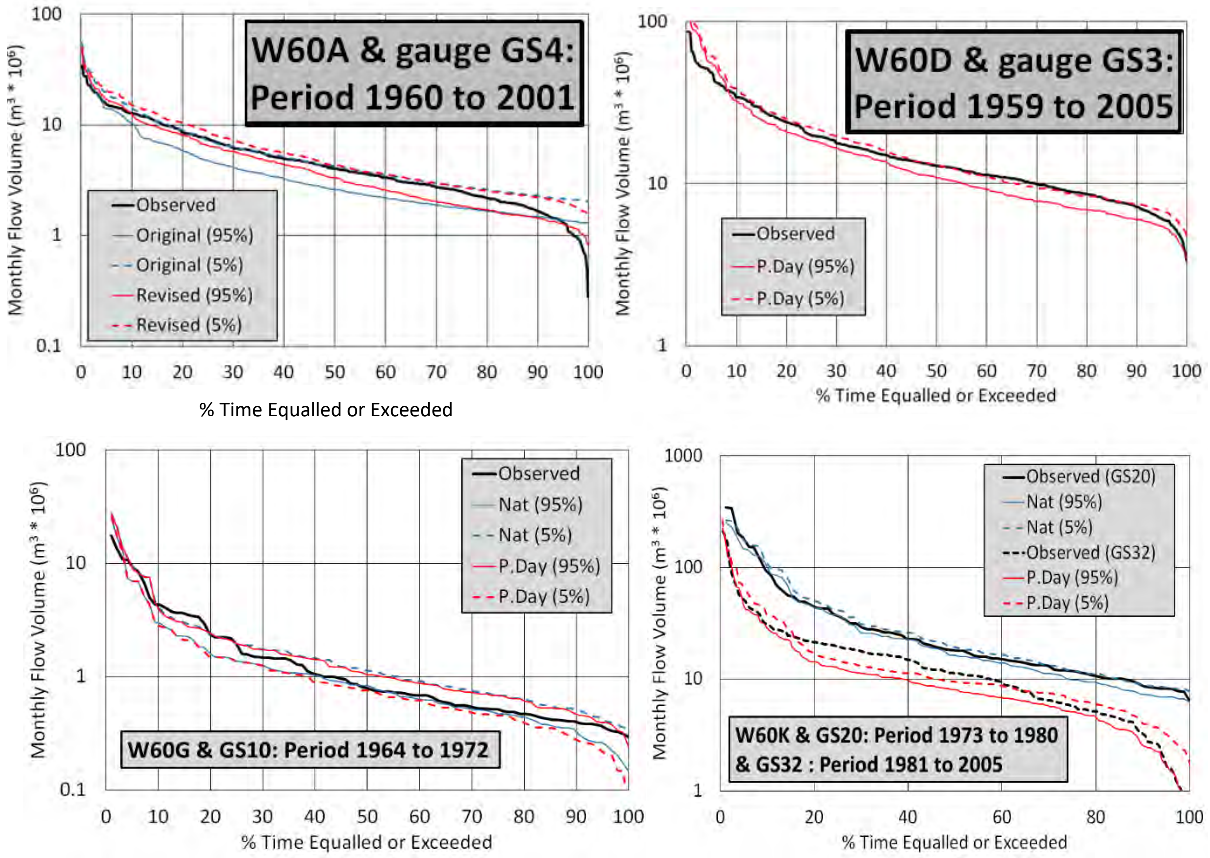

Figure 5.4: FDCs comparisons between model outputs and observed data using periods representing natural (Nat) and present day (P.Day) conditions for the sub-basins in the Mbuluzi catchment

The bottom-left part of Figure 5.4 refers to W60G (southern headwaters in the MV region) where the original constraints for MMQ and Q50 were substantially reduced by some 40%. There is no evidence to suggest that these changes in W60G are related to water use and it does not seem to be miss-classified (as MV). This sub-basin therefore appears to have an anomalous response relative to the others analysed in the Mbuluzi basin. The bottom-right of Figure 5.4 shows the FDCs for before and after the construction of Mnjoli Dam in 1980 based on gauges GS20 (located at the upstream end of W60K with a record from 1973 to 1980) and GS32 (lower part of W60K with records from 1981 to the present day). However, the source of these water use data are not always credible. Therefore, the data for these sub-basins are inaccurate and, in many cases, do not exist.

Table 5.3: A summary of constraint index changes in Mbuluzi made after comparisons of simulations with observed flow data

Gauge and sub-basin	Region	Constraint index changes made after comparisons with observed data
GS4 (W60A)	ES	Increase in lower MMQ bound and reductions in Q10 & Q90 constraints as a reservoir and some irrigation could not account for under-simulations. (Figure 5.4).
GS3 (W60D)	MV	Some reductions in the MMQ & Q10 constraints were made to W60C (ES, upstream), while some small changes were made to W60D to align the simulations to the observed data and reduce the uncertainty (Figure 5.4).
GS10 (W60G)	MV	Small amounts of irrigation, but largely natural and the MMQ and Q50 constraints were substantially reduced by some 40% (Figure 5.4).
GS20 & GS32 (W60K)	LV	Gauge GS20 was used to validate all upstream constraint changes under more-or-less natural conditions prior to the construction of Mnjoli Dam in 1980 (Figure 5.4). Gauge GS32 was used to assess the downstream result after the early 1980s. The main problems are associated with the definition of the Mnjoli Dam operating rules and the true patterns of irrigation abstractions for the large sugar cane plantations (Figure 5.4).

Both the bias in MMQ (%Bias) and a mean bias based on log transformed flows (%Bias{ln}) of the final ensemble set for W60A have reasonable ranges. More than half the ensembles (for W60A) have Nash-Sutcliffe efficiency values (NE) better than 0.5 and 11% better than 0.6. Apart from W60K, the objective function ranges across the 10 000 ensembles (NE, NE{ln}, %Bias, %Bias{ln}) for all the W60 sub-basins are generally similar to those given for W60A above. The bias values are generally between -20 and +20% (and often better) while the best NE values are between 0.4 and 0.65, and log transformed NE{ln} values typically better than 0.65.

The over-simulation of very high flows at W60D and GS3 is not repeated downstream at W60K and GS20. This could be related to under-measurement of the monthly high flow volumes at gauge GS3. The water use and operation of Mnjoli Dam, as well as the water use within W60K, are very uncertain and it was difficult to reproduce the shape of the observed FDC. This result could also be related to a high degree of non-stationarity in the volumes of water use from 1981 to the present day.

The simulation results are, to a large extent, a reflection of the water resources developments that exist in the basin. Abstractions increase in the whole basin towards the Lowveld sub-basins. Mnjoli Dam, in the Mbuluzi River basin (within W60E and constructed in 1980), provides canal flows and controlled releases for a large area (over 200 km^2) of sugar cane plantations downstream in sub-basin W60K. Some of the sugar cane is clearly irrigated from the canal leading from the dam, some from direct abstractions from the Mbuluzi River and some from an IBT from the Komati River catchment to the north. However, data for such water uses are inaccurate and often unavailable.

5.2.1.2 Ngwavuma River basin

There is some afforestation (15% of the sub-basin) in W43A and small amounts of irrigation in W43A to W43D, with a much larger area of sugar cane (i.e., about 21km^2) irrigation in W43C.

However, the effects of the sugar cane irrigation could not be assessed without a downstream gauge. Figure 5.5 illustrates the final results for sub-basins with gauges; W43B (GS27) and W43D (GS8). No constraint changes were made to W43A and W43B. Minor changes were made for W43C and W43D (Table 5.4). Only MMQ constraint index for W43C and W43D was reduced. Only Q50 constraint for W43C and W43D was increased.

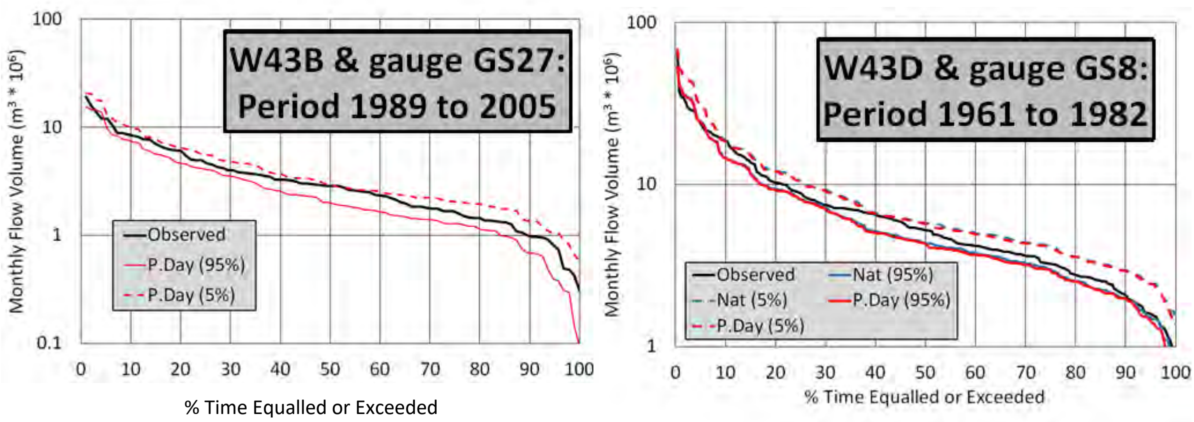

Figure 5.5: FDCs comparisons between model outputs and observed data for W43B and W43D sub-basins

Table 5.4: A summary of constraint index changes in Ngwavuma River basin made after comparisons of simulations with observed flow data

Gauge and sub-basin	Region	Constraint index changes made after comparisons with observed data
GS27 (W43B)	SLV	No changes to constraints. Inclusion of small–scale irrigation and afforestation in upstream W43A generates acceptable results (Fig. 5.5).
GS8 (W43D)	LV	W43C & W43D are not very impacted by abstractions. Tendency for over-simulation in most ensembles suggests that the MMQ constraints for W43D & W43C (upstream) should be reduced & Q50 slightly increased (Fig. 5.5).

The bias values are range between -15 and +15% and the best NE values are between 0.5 and 0.6, and log transformed NE{ln} values better than 0.6. The results are acceptable with the small inclusion of water use in the sub-basins. These can be improved further with some changes to constraints for the most downstream sub-basins.

5.2.1.3 Headwater sub-basins of Usuthu River basin

Figure 5.6 presents the uncertainty bands of the FDC based on minor constraint adjustments for the downstream headwater sub-basins of the Usuthu. W57D and W57F are the only gauged headwater sub-basins of Usuthu catchment within eSwatini. W57D has about 13km^2 of irrigation. The MMQ constraint was reduced by 15% while the Q10 index for W57D was slightly increased by a similar amount to achieve the results shown in Figure 5.6. No changes were made to the W57F constraints, which has been considered to be largely natural. However, the right side of Figure 5.6 suggests that there could be some small direct abstractions from the river that have not been accounted for and this is supported by evidence of quite intensive agricultural activity in the valley bottom areas of the lower parts of the sub-basin.

Table 5.5: A summary of constraint index changes in headwater sub-basins of Usuthu River basin made after comparisons of simulations with observed flow data

Gauge and sub-basin	Region	Constraint index changes made after comparisons with observed data
GS12 (W57D) GS13 (W57F)	SLV SLV	10 – 15% reduction in MMQ as over-simulations could not be attributed only to known water use (Figure 5.6). No changes to original constraints and simulations are generally satisfactory, except for very low flows. There is evidence for some direct abstractions in the lower parts of the sub-basin (Figure 5.6)

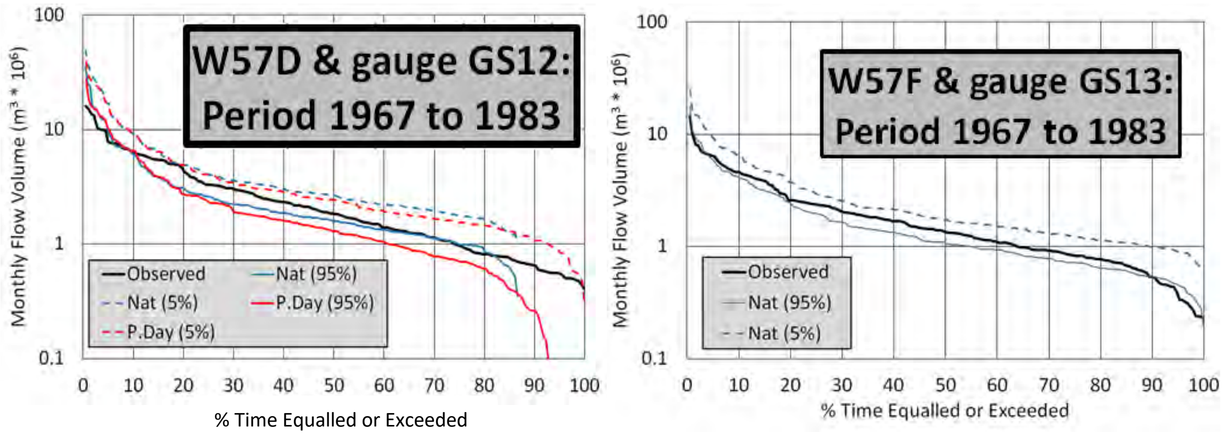

Figure 5.6: FDCs comparisons between model outputs and observed data for W57D and W57F sub-basins.

5.2.1.4 Summary of constraint adjustments and model performance

There are no clear regional patterns or trends in the changes that were made to the constraint indices (Tables 5.3 – 5.5). However, it has been necessary to make some adjustments to the specific sub-basin constraints in order to match the observed stream flow data FDCs. In addition, the constraint uncertainty ranges have been reduced in some sub-basins. With the exception of W60G, most of the required constraint changes were relatively small and of the order of 10 – 15%.

The model performance has been largely assessed using visual comparisons between the observed FDCs and the simulated FDC ranges. The objective function values of the 'best' ensemble results have also been assessed to ensure that the monthly time series patterns of the simulated data are acceptable. The Nash-Sutcliffe efficiency values for untransformed (CE) data are typically above 0.5 and for log transformed (CE{ln}) data typically above 0.6. However, there are some sub-basins where these values are lower (e.g., W43B). Part of the problem almost certainly lies in the difficulties of accurately representing the spatial variations in monthly rainfall depth in such a topographically diverse region and with such a limited gauging network. Other problems could be related to inconsistencies in the actual patterns of abstraction relative to the fixed patterns included as part of the model setup.

5.2.1.5 Discussion

The approach adopted here is quite different to many previous regional modelling studies in that it has been largely based on previous simulations using a similar version of the same model. One of the critical assumptions is that the original model results have made the best use of the available observed data. The previous model setups were based on manual calibration against naturalised observed stream flow data followed by subjective parameter regionalisation for ungauged sub-basins (Middleton and Bailey, 2011). These simulations therefore include the information content of the observed data, but it is recognised that this content is uncertain. In the absence of sufficient regional coverage from observed stream flow data that represent un-impacted conditions, the previous simulation results were used to establish the initial uncertainty ranges of the indices used to constrain the new simulations of hydrological response. The relationships illustrated in Figures 5.2 and 5.3 and Table 5.2 are therefore largely a reflection of the calibration approach that was used to generate the previous simulations (Middleton and Bailey, 2011). Figure 5.2 and Table 5.2 suggest that the previous simulations show clear regional patterns of variation for the MMQ index. However, for some of the other constraints (Q10, Q90 and Q50 for some topographic regions) the previous simulations do not offer very clear guidelines for setting constraint ranges.

It was found to be quite straightforward to establish parameter uncertainty bounds that would efficiently generate 5 000 behavioural ensembles from 100 000 sample model runs. The initial parameter bounds were quantified from experience of using the model in similar regions and a thorough understanding of the sensitivity of the simulations to different parameter value changes. For example, the main interflow and groundwater recharge parameters are expected to have higher values for those sub-basins with higher groundwater recharge and Q90/MMQ constraint values. Similarly, the surface runoff parameters are expected to reflect greater volumes in the steep and wet mountain areas relative to the flat Lowveld sub-basins. The critical point is that the use of hydrological response indices to constrain the model outputs and identify behavioural parameter sets, precludes the need to be precise in the quantification of the initial parameter ranges. If the initial parameter ranges are not consistent with the constraints, a model utility is used to identify where the problem lies and which parameter ranges to adjust. The same utility can be used to reduce the uncertainty ranges of some parameters and achieve the required number of behavioural results more efficiently (i.e., fewer rejections of non-behavioural results).

The results reported so far are confined to assessments of the constraint index ranges for the two rivers lying entirely within Eswatini (Mbuluzi and Ngwavuma) plus a further two sub-basins in the Usuthu River basin. To a large extent, the initial constraint ranges are consistent with the observed stream flow data, after the available information on water use is incorporated into the model simulations. As might be expected, there were some sub-basins where relatively small changes (up to 15%) to some of the constraints were necessary to reduce the bias in the simulations. This is encouraging and suggests that the likely bias of the regional estimates in at least some of the totally ungauged sub-basins is unlikely to be excessive. However, there was one sub-basin (W60G) where the observed data suggested a much greater change in the values of the constraint indices. It has not been possible to identify any reasons for this apparent anomaly at this stage, but this issue will be re-visited after simulations for all of the other sub-basins have been assessed against the available observed stream flow data.

These preliminary simulation results, including the model performance measures, are acceptable given the level of uncertainty of the available information used to set up the model. Considering the uncertainty bounds of the FDC, the flow simulations are sensibly representative, except for W60K where the problem certainly lies with the unavailability of water use data. The pattern of uncertainty for the flow gauges is acceptable. An exception is the two headwater gauges of the Usuthu basin whose uncertainty level for low flows is high. This can be further improved provided more water use information is available.

5.2.2 Model application to the rest of the study area

A summary of the constraint adjustment (key differences between the final and original constraints) for the rest of the study area are presented in Tables 5.8, 5.10 and 5.12. It is worth noting that changes to the constraint ranges do not always have to be accompanied by changes to the input parameter ranges; a lot depends on how wide the parameter ranges are and whether different parameter groupings can still generate a sufficient number of behavioural ensembles (i.e., ones that satisfy all constraints). Figures 5.10 to 5.20 illustrate the simulation results for all individual sub-basins/gauges using flow duration curves. All the flow duration curve plots are based on using only those months of the simulated records for which there are observed flow data. Appendices 7 to 14 are example time series plots of observed against simulated stream flow data covering the six regions of the study area.

Figures 5.7 to 5.9 demonstrate the procedure of reducing uncertainty that was followed in the simulation of stream flow (for all the basins) as well as associated results for the two flow gauges in the Komati basin which are given as an example. These two gauges are downstream of the Nooitgedacht Dam where data on natural stream flow and information on how the reservoir is operated are not available. A brief explanation of the progressive procedure of adjusting parameters and constraints to resolve uncertainty is given in Tables 5.6 and 5.7.

Both parameters and constraints were revised to improve simulation of observed cumulative flows for gauge X1H033 at X11C. Minor changes to some natural hydrology parameters (i.e., ZMAX and GW) did not improve the simulation at X11C. Increase in run-of-river abstraction at X11A and X11B as well as reduction of reservoir abstraction at sub-basin X11C improved the simulation at gauge X1H033 (X11C). A notable improvement is on the upper bound at FDC10 due to the adjustments made to Q10 and MMQ constraints (Figure 5.7b and Table 5.6).

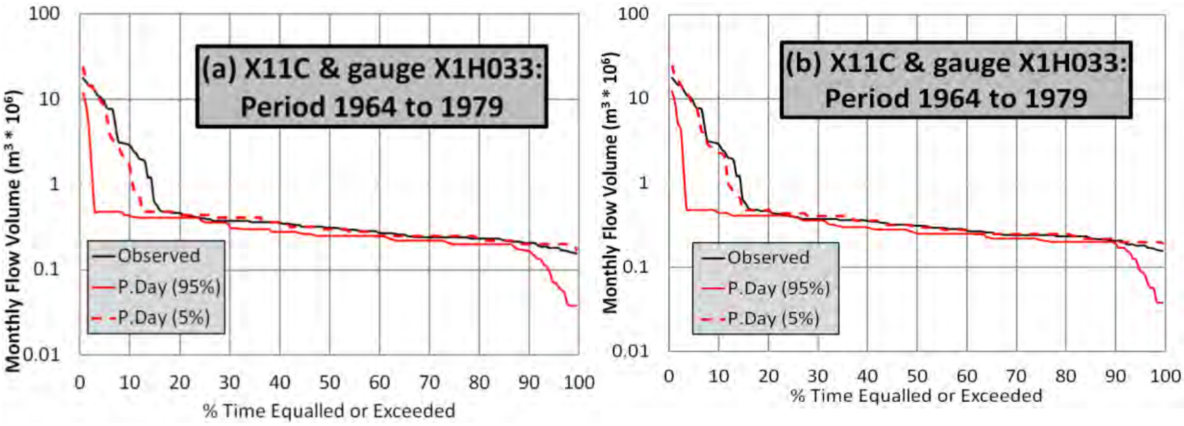

Figure 5.7: Initial simulation of observed flows (a) at gauge X1H033 and effects of these changes (b) as shown in Table 5.4

Table 5.6: Summary of the progressive procedure followed to resolve uncertainty in X11C (gauge X1H033) flow simulation

	Adjustment			Outcome
Parameter	X11A	X11B	X11C	
Main water use parameters				
Irr. Area from dam	0 to 2 to 0 to 6			Notable improvement in reduction of peak flows and notable improvement in low flow simulations. Zero flows simulations are extended to mimic the observed FDC. Peak flows are reduced.
AIRR	0 – 2 to 0 – 5	0 – 0.6 to 0 – 5		
Constraints				
MMQ			0.88 – 1.36 to 0.96 – 1.50	Slight changes on high flow simulation (Figure 5.7a and 5.7b).
Q10			2.20 – 2.70 to 2.20 to 2.75	
Reservoir parameters				
Annual abstractions			50 to 46	Significant improvement on the upper bound of FDC (esp. Q5 to Q20). Refer to illustration in Figure 5.8(a).
Compensation flows			0.48 to 0.60	Improvement resulting in reduction of uncertainty in the lower bound of Q10 and increase of upper bound (from ~Q20 to ~Q25: see illustration in Figure 5.8(b)

**NB: X11A and B constraints were considered appropriate (on the basis of the utility for checking constraint distribution) and were not changed. Only MMQ and Q10 constraints for X11C were slightly modified, based on the utility and visual assessment of the FDC in order to generate the maximum number of behavioural ensembles (5 000 out of 100 000 samples). The water use parameters for X11A to X11C were adjusted in order to correct the simulated shifts towards the left in the FDC of X11C (Figure 5.7a) and the results of this are illustrated in Figure 5.8c.*

Figure 5.8 illustrates the effects of further adjustments made on the water use parameters. An improvement on the upper bound of the FDC (especially from Q5 to Q20) is shown in Figure 5.8a. Figure 5.8b shows a final improvement of the uncertainty bound (i.e., at lower bound of Q10 and between Q20 and Q25 of the upper bound), based on independent sampling while Figure 5.8c shows the similar FDC improvement based on dependent sampling of parameters (refer to section 4.5.2 for the types of sampling).

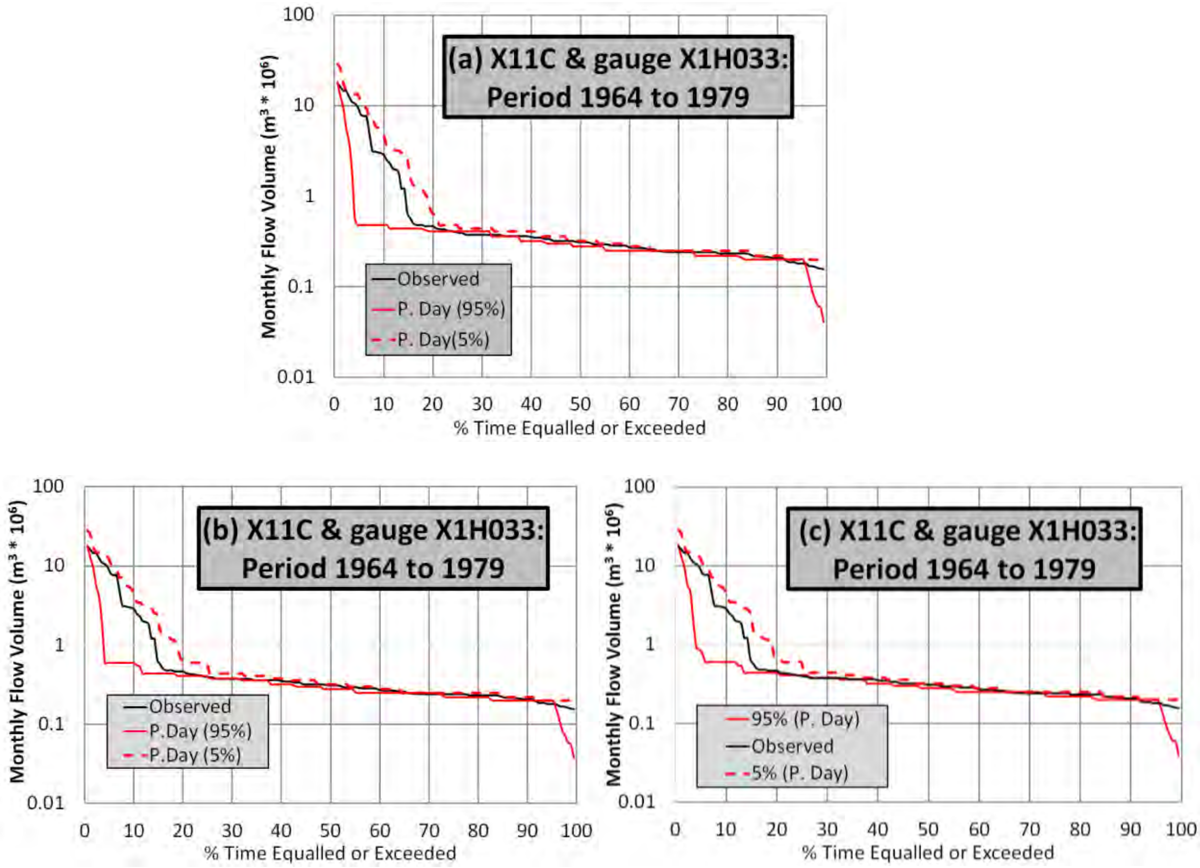

Figure 5.8: Effects of the further adjustments in Table 5.6.

Figure 5.9 illustrates the effects of the constraints and parameters changes (to the FDC) applied in order to improve simulation of observed flows for the further downstream gauge (X1H017) at X11E. In this case, changes were made to the natural hydrology and water use parameters as well as all the FDC constraints of X11D and X11E sub-basins. Changes to the Q50 and Q90 constraints, and water use parameters resulted in significant improvement in the simulation (Table 5.7 and Figure 5.9).

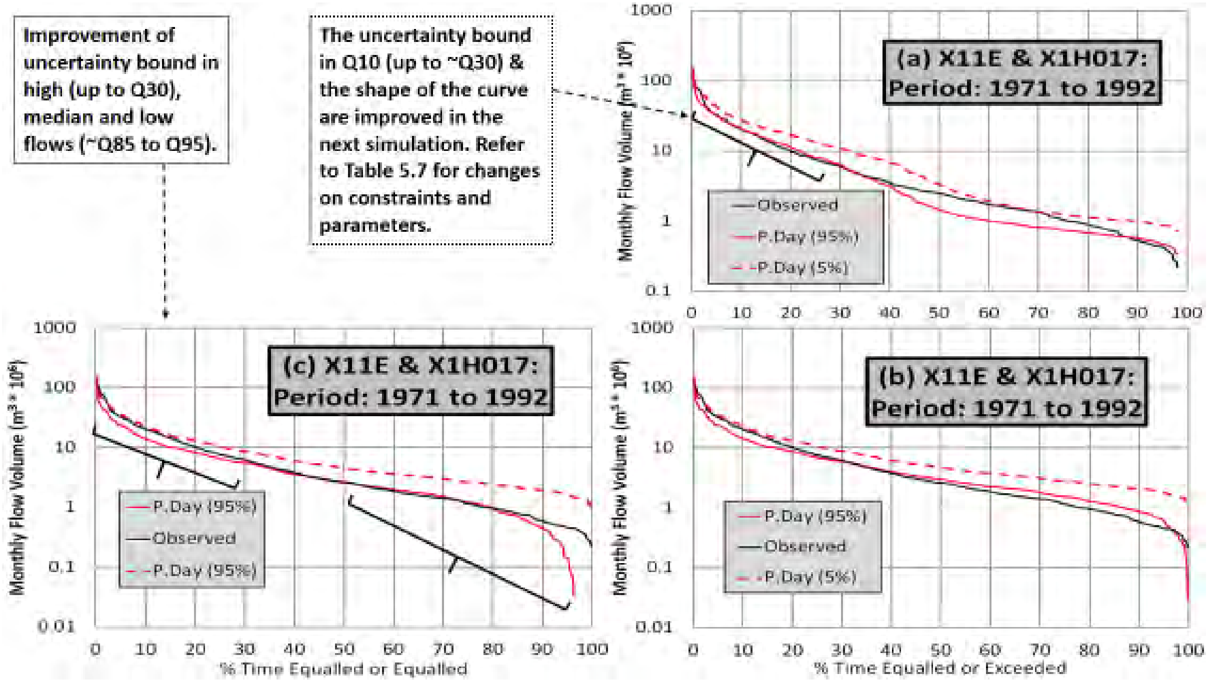

Figure 5.9: Initial simulation of observed flows (a) at gauge X1H017 and the effects of the adjustments (b and c) as shown in Table 5.7.

Table 5.7: Summary for the progressive procedure followed to resolve uncertainty in X11E flow simulation

	Adjustment level 1		Outcome
Parameter/constraints	X11D	X11E	
Water use parameters			
AIRR	0.4 – 3 to 0.4 5	0 – 5 to 0 – 10.	Uncertainty bound in FDC10 (up to ~FDC40) is improve: see Figure 5.9 (b)
Irr. area from dam	5 – 20 to 5 – 25	2 – 13 to 2 – 15	
	Adjustment level 2		
Constraints			
1. Q50	0.35 – 0.8 to 0.38 – 0.85	0.435 – 0.855 to 0.425 – 0.845	Significant improvement of uncertainty bound up to Q100. See Figure 5.9(c)
2. Q90	0.22 – 0.38 to 0.216 – 0.374	0.24 – 0.39 to 0.2 – 0.375	
	Adjustment level 3		
Water use parameters			
1. AIRR		0 – 10 to 0 – 15	Further significant improvement of uncertainty bound up to Q100. See Figure 5.9(c)
2. NON IRR DD		0 – 0 to 50 – 500	
3. IRR area from dam		2 – 15 to 2 – 17	

**NB: Changes to constraints and water use parameters for X11D and X11E sub-basins were made concurrently based on the utility for checking constraints and parameters as well as on FDC assessment, respectively, in order to generate maximum number of behavioural model outputs and improve low and high flow simulation for gauge X1H017 at X11E.*

In cases where the sub-basins are heavily impacted by dams (e.g., X11A – X11C) it is difficult to distinguish between the uncertainties in the model constraints and those related to water use and reservoir operating rules. The wide band of uncertainty for very low flows at X11C where there is a reservoir is repeated downstream at X11E. The reason for the poor simulation might be due to lack of information about how the dam has been set up (at X11C). This has been based on very uncertain information.

5.2.2.1 Komati River basin

Figure 5.10 illustrates the uncertainty bands of the FDC using the revised constraints for the upstream sub-basins based on the changes in Table 5.8. Minor decreases or increases of MMR, Q10 and Q50 constraints were made for a few sub-basins. Other adjustments include moderate increases on the Q90 constraints (e.g., X11H) to improve low flow simulation. Major constraint changes made (greater than 40%) for these sub-basins include a decrease of Q90 constraints for X11F and X11G and an increase of the Q90 constraints for X11J in order to improve low flow simulation. X11F and X11G appear to have a response that is inconsistent with the other sub-basins.

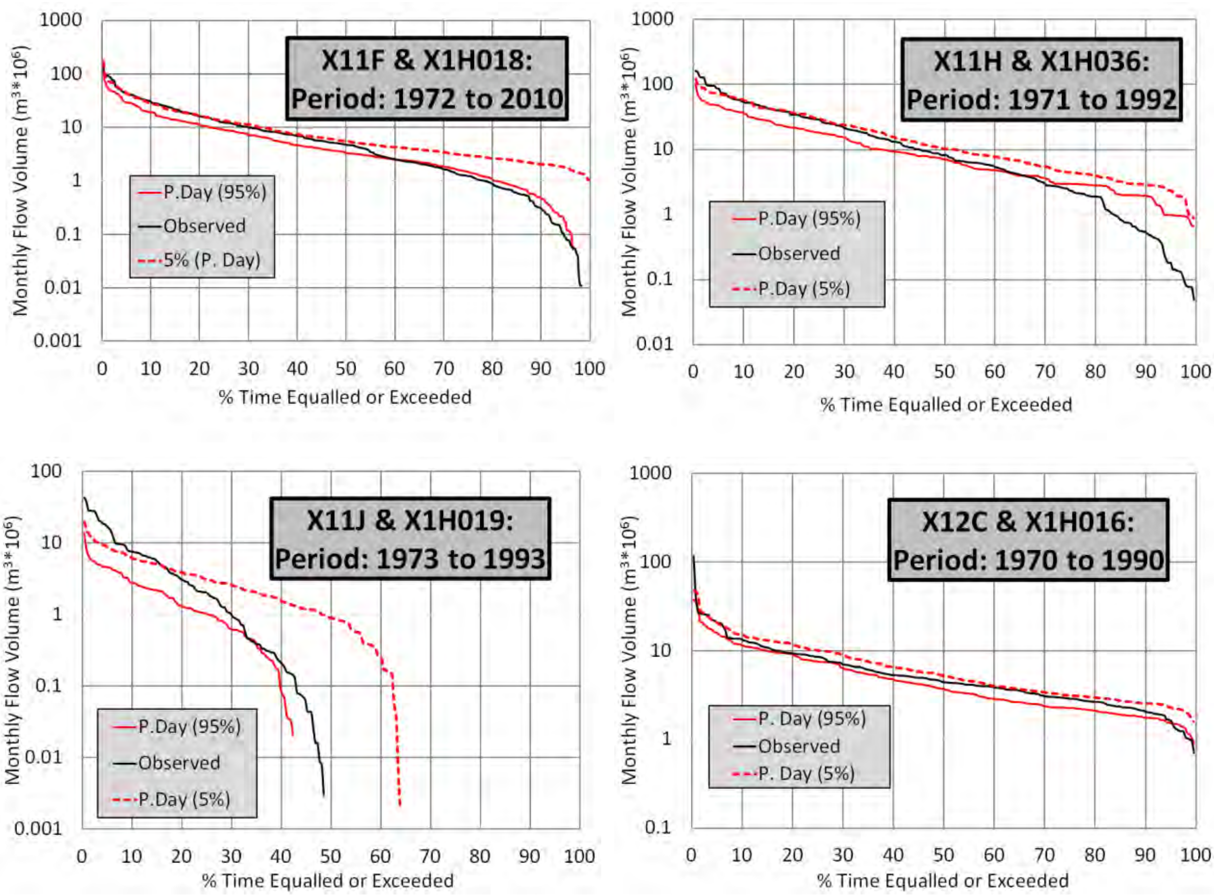

Figure 5.10: FDCs comparisons between model outputs and observed data for the upper sub-basins. X11J is a headwater sub-basin.

Figure 5.11 presents the simulation of cumulative flows for sub-basins in the mid-section of the Komati catchment. Changes made to these sub-basins include some minor decreases of Q10 for all the sub-basins. Others include increase of Q50 for most sub-basins. Minor increase of Q90 were made on X13A only.

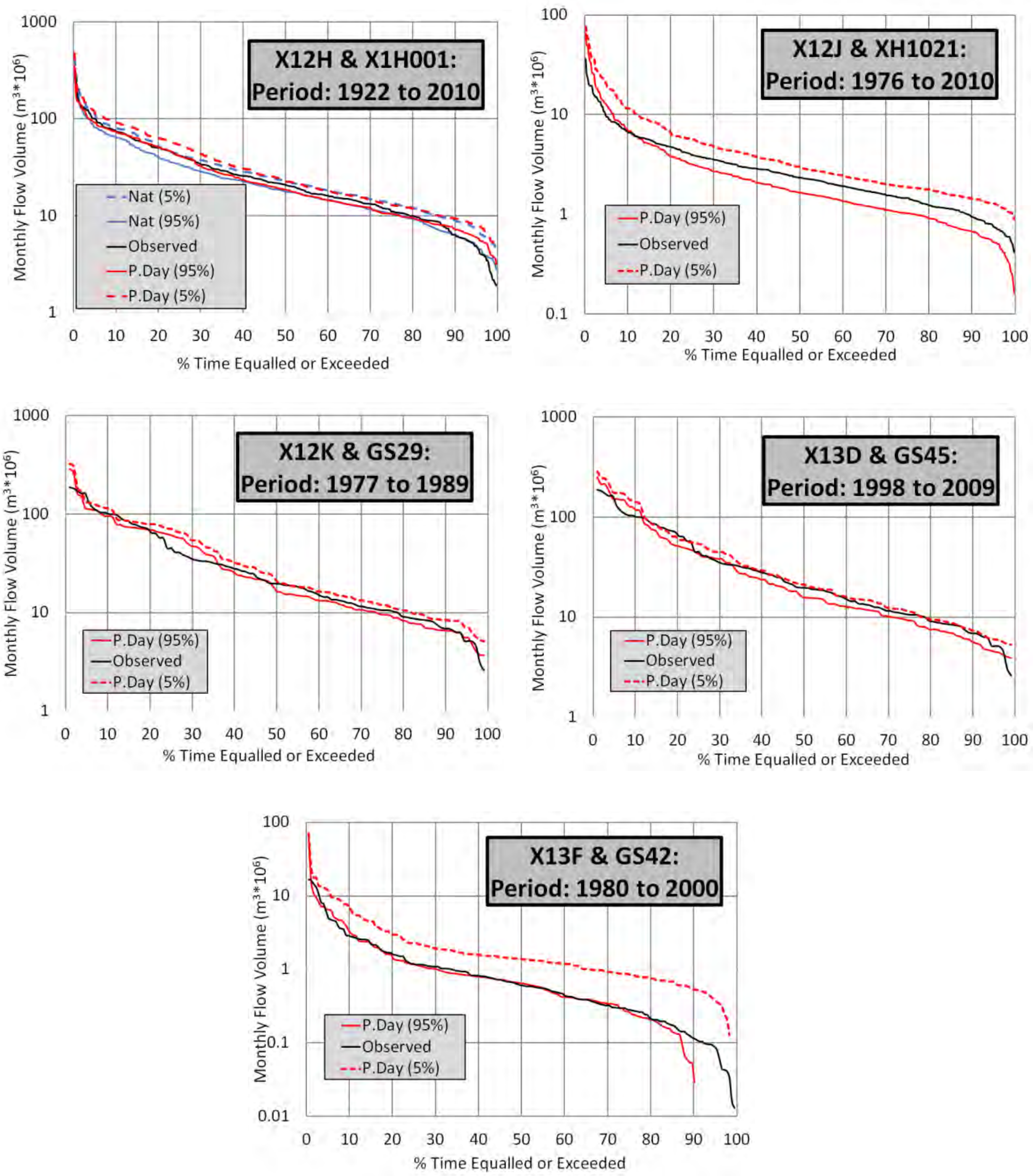

Figure 5.11: FDCs comparisons between model outputs and observed data for the sub-basins in the mid-section of the Komati catchment. X12J and X13F are afforested headwater sub-basins.

Figures 5.12 and 5.13 illustrate the situation in the most downstream sub-basins. Reasonable results were achieved without any adjustments to the original constraints for the downstream sub-basins, except for X14A X14B, X14D, X14E and X14F.

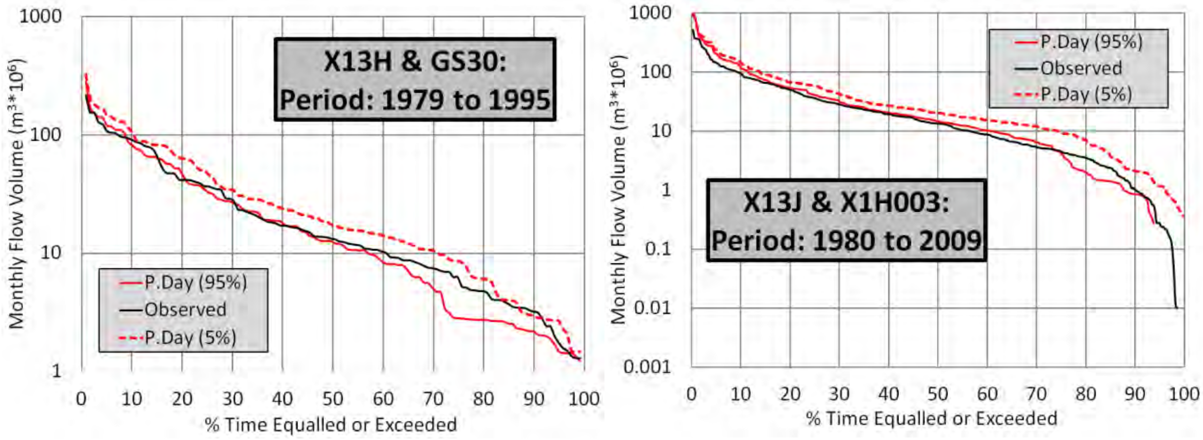

Figure 5.12: FDCs comparisons between model outputs and observed data for the most downstream sub-basins.

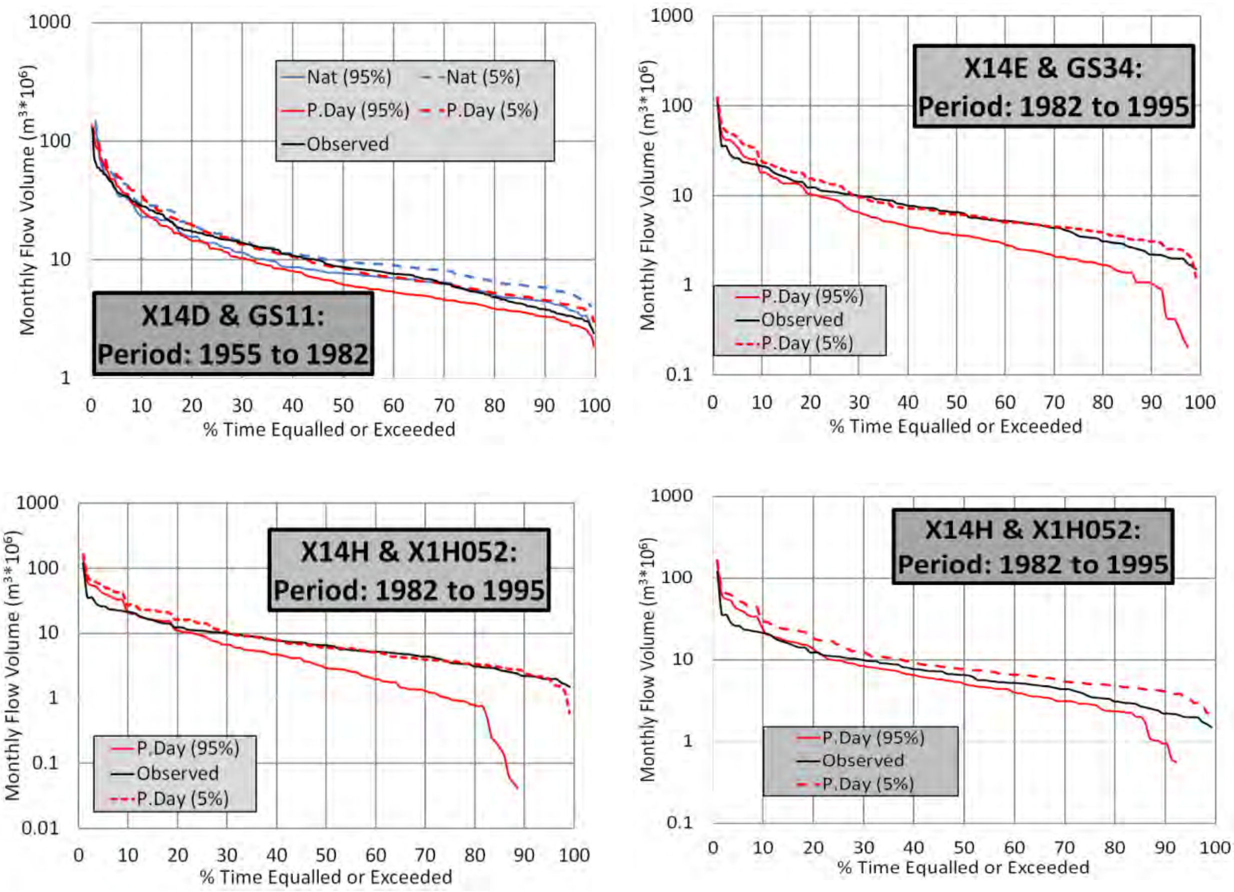

Figure 5.13: FDCs comparisons between model outputs and observed data for the lower sub-basins of the tributary of the Komati catchment. The bottom graphs of X14H show the

simulation based on independent (left) and dependent sampling (right) of uncertain parameter space.

Table 5.8: A summary of constraint index changes in Komati made after comparisons of simulations with observed flow data

Simulated (and affected) gauge	Region	Constraint index changes made after comparisons with observed data
X1H033 (X11C)	FHV	MMQ: increase by 10% for X11C Q10: Some 20% increase on lower bound and 2 % increase on upper bound for X11C
X1H017 (X11E), X1H036 (X11H), X1H019 (X11J), X1H016 (X12C).	All gauges in ES	MMR: increase by some 1.5% for X11E; reduce by 2% for X11H MMQ: 2% increase on X11F; 5% increase on X11J; reduce by 13% for X12J Q10: 3% reduction of lower bound for X11D, E; 10% increase of bounds for X11F, H, J; 1% increase of bounds for X11G. Q50: 13% decrease in lower bound for X111D, 13% increase on lower and 7% increase on upper bound for X11E; 6% increase on bounds for X11F; 1.3% decrease of bounds for X11G; 50% reduction for lower bound and 25% reduction for upper limit for X11H; 13% reduction of lower limit for X11J. Q90: 6 – 13% decrease of bounds for X11D & E; 80% reduction of lower bound and 6%) reduction of upper bound for X11F; 40 – 50% increase of bounds for X11G; 15 – 30% increase on bounds for X11H; about 40% increase of bounds for X11J.
X1H001 (X12H), X1H021 (X12J), GS29 (X13A)	All gauges in SM	Q10: 5 – 15% reduction of bounds for X12D-K, X13A and B. Q50: Increase of bounds by 3% for X12E,F,G,K; increase of bounds by 3 – 5% for X12H; increase bounds by about 15% for X12J, 20% increase for X13A. Q90: Increase bounds by 10 – 15% for X13A.
GS42 (X13F)	SLV	Q10: no changes made Q50: no changes made Q90: no changes made
GS30 (X13H), X1H003 (X13J), X1H052 (X14H)	All gauges in LV	Q10: no changes made Q50: no changes made Q90: no changes made
GS11 (X14D), GS34 (X14E).	All gauges in SM	Q10: 5 – 15% reduction of bounds for X14B,D,F; 5 – 20% decrease of bounds for X14E Q50: About 5% increase of bounds for X14B,D,E,F Q90: More than 50% increase of bounds for X14A.

Table 5.9 shows the model performance statistics (%Bias, %Bias{ln}, NE and NE{ln}) of the final ensemble sets. Generally, the ranges in Bias in each ensemble vary significantly, while the best NE and NE{ln} values do not vary much. The Bias varies greatly especially in those gauges whose stream flow is highly impacted by water resources developments (e.g., X11C, X11J, X11H, X13D, X13F, X13H, X14G and X14H). Poor and low NE and NE{Ln} values are noted in about six of these gauges that are affected by major water resources developments. The record of the stream flow gauge at sub-basin X13D is not representative of the cumulative flows since the gauging station is not located at the outlet of X13D.

Table 5.9: Best NE values and variation of % Bias of the ensembles in each corresponding flow gauge of the Komati catchment

Gauge and sub-basin	Bias		NSCE	
	% Bias	% Bias {ln}	CE	CE{ln}
X1H033 (X11C)	-51 to 80	-29 to 9	0.37	0.41
X1H017 (X11E)	-34 to 31	-27 to 90	0.39	0.61
X1H018 (X11F)	-36 to 13	-52 to 114	0.50	0.43
X1H036 (X11H)	-21 to 22	42 to 150	0.30	0.53
X1H019 (X11J)	-78 to -14	-67 to 127	0.16	0.22
X1H016 (X12C)	-18 to 25	-20 to 37	0.62	0.72
X1H001 (X12H)	-11 to 12	-18 to 11	0.49	0.63
X1H021 (X12J)	-11 to 59	-38 to 45	-0.33	0.64
GS29 (X12K)	-9 to 15	-12to 18	0.22	0.60
GS45 (X13D)	-10 to 7	-4. to 18	0.07	0.02
GS30 (X13H)	1 to 44	-22 to 45	0.07	0.25
X1H003 (X13J)	-21 to 7	-46 to 4	0.21	0.30
GS11 (X14D)	-26 to 16	-44 to 11	0.63	0.62
GS34 (X14E)	-38 to 22	-68 to 19	0.56	0.63
X1H052 (X14H)	78 to 181	-27 to 107	-5.03	-0.90

The simulation of flows in sub-basins X11C, X11H and X11J of Komati could not be further improved with the limited water use information. There is a pattern of high flow simulation in X11C and X11H. The under-simulation of very low flows in X11C are repeated in X11H.

The problems of stream flow simulation resulting in poor results and model performance in the Komati basin are associated with high levels of water use that are unknown. The whole basin is heavily modified by water resources developments. In the upstream part, for example, information on the operation of the Nooitgedacht and Vygeboom reservoirs are not available in order to represent well the abstraction levels at X11C and X11H, respectively, in the model setup. The difficulty in establishing representative water use parameters for X11J is attributed to dense afforestation and unknown levels of water use for the mining operations existing in the sub-basin. A similar situation is in the most downstream sub-basins due to an interbasin transfer scheme supplying irrigation water to Mbuluzi River basin and also due to unknown operating rules for the Driekoppies Dam.

5.2.2.2 Usuthu River basin

Figures 5.14 presents the uncertainty bands of the FDC for the gauges in W51B, W51D and W51G sub-basins of the Usuthu catchment based on the constraint changes shown in Table 5.10. Table 5.10 applies to all the sub-basins in Usuthu basin reported in this section. The record for both W51D and W51G was split in to two: one which reflects near-natural conditions and one representing an impacted stream flow condition. The adjustments in these sub-basins are associated with increases and decreases of all the constraints, except for W51E and W51G where only two or three constraints were revised. Decreases and increases of MMQ range were less than 30%. MMR was moderately reduced or increased in most sub-basins. Q10 and Q50 were either slightly reduced or increased while the adjustment of Q90 varied between 5 – 30%.

Figure 5.15 to 5.17 illustrate the uncertain bands for the gauges in W53, W54 and W55 sub-basins. MMQ range was increased by more than 30% while MMR was moderately reduced or increased in some sub-basins. Q10 and Q50 were either slightly reduced or increased while the adjustment of Q90 varied between 5 – 30%.

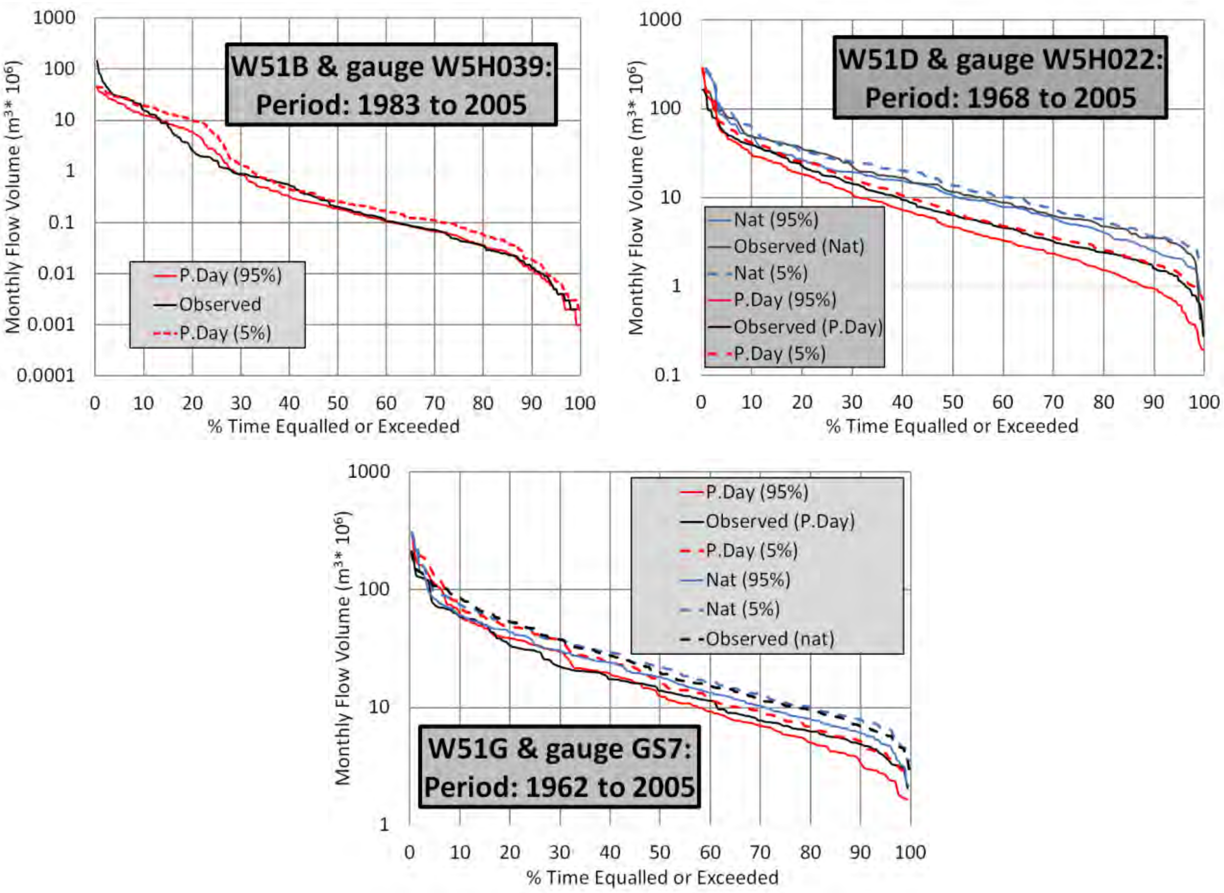

Figure 5.14: Observed and simulated FDCs for W51B, W51D and W51G sub-basins. The record for W51D and W51G for near-natural conditions is up to the 1980s while for impacted conditions is beyond 1980.

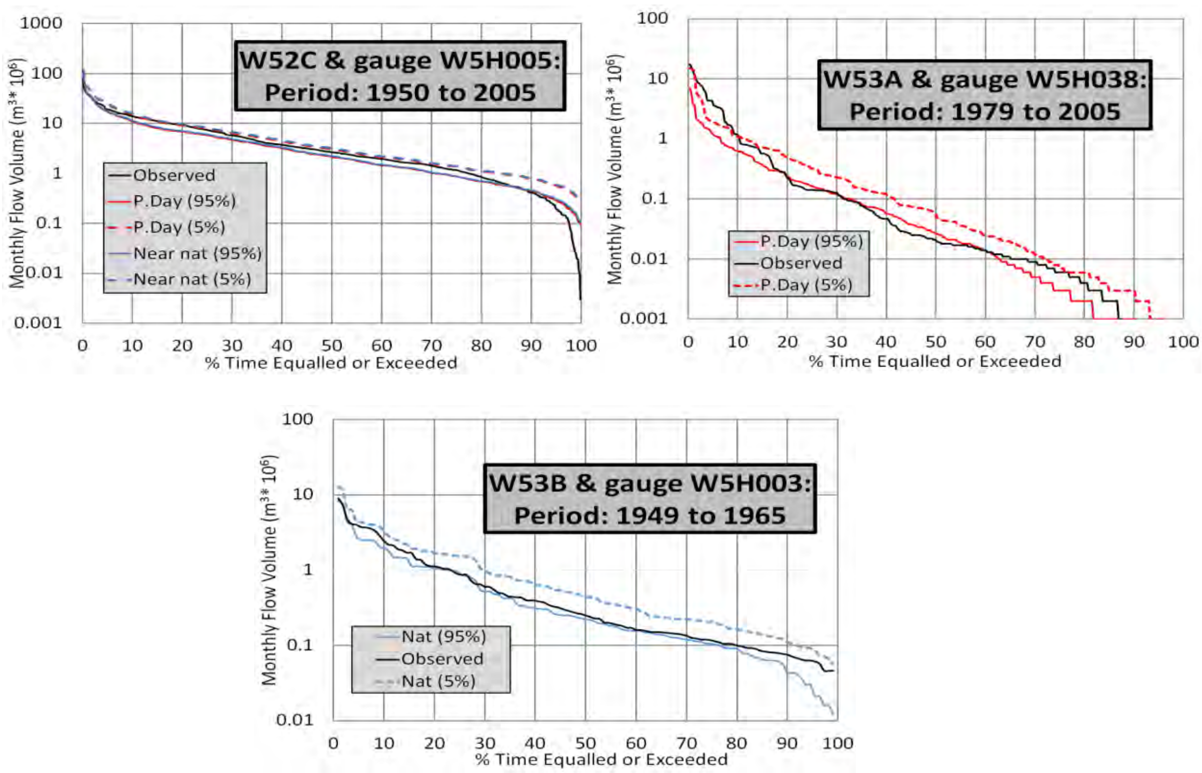

Figure 5.15: Observed versus simulated FDCs for W52C, W53A and W53B sub-basins

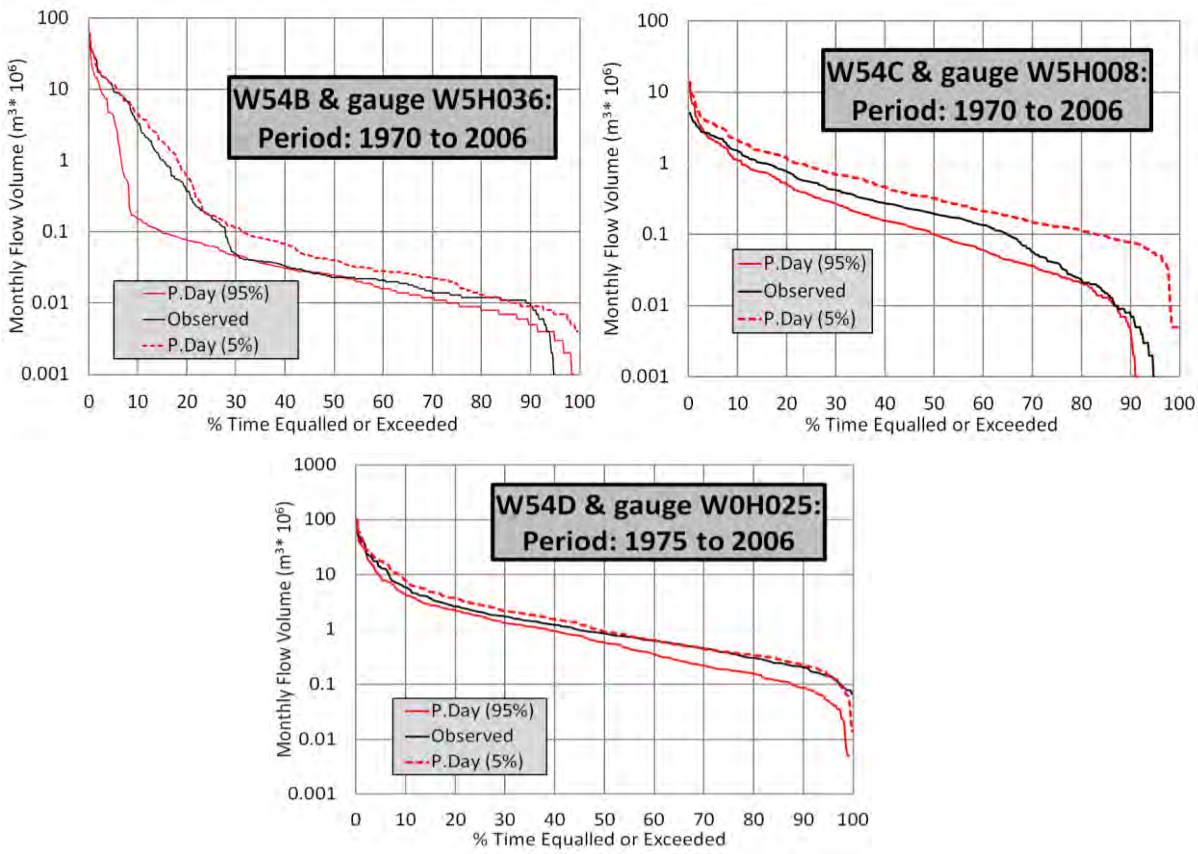

Figure 5.16: Observed and simulated FDCs for W54B, W54C and W54D sub-basins

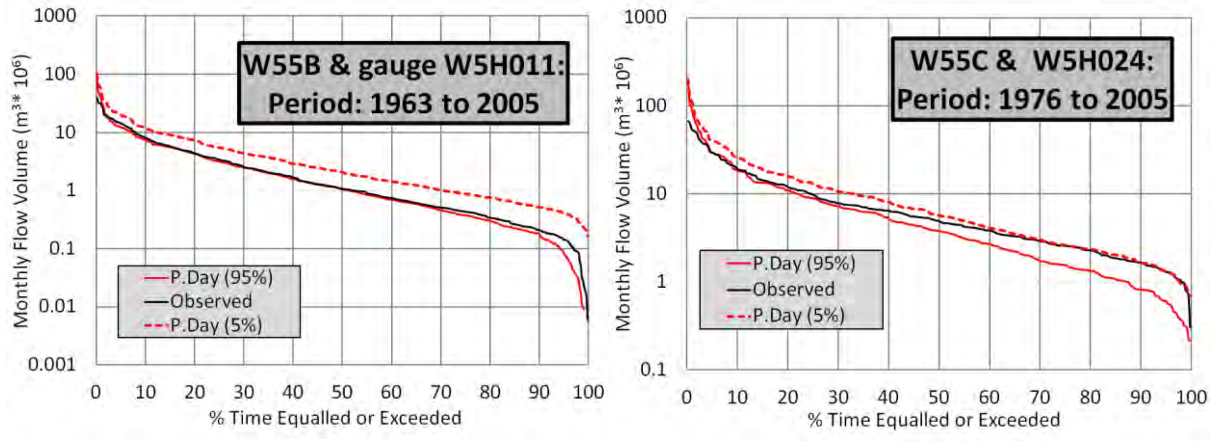

Figure 5.17: Observed versus simulated flow duration curves for W55B and W55C sub-basins

Figure 5.18 presents the uncertain bands of the FDC for W56B and W56E sub-basins. The constraint revision included substantial increases of Q90 in a few sub-basins as well as small changes to the other constraints. The reduction of MMR ranges between low and high. Adjustments (decrease or increase) of MMQ and Q10 constraints range between low to moderate. Increases of Q50 are relatively low while those of Q90 vary from low to high in some sub-basins and are high in others.

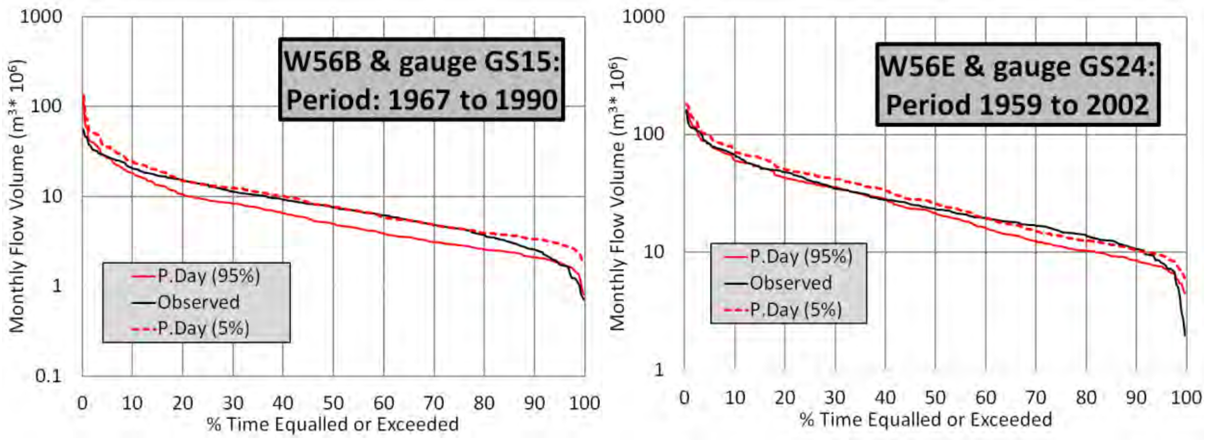

Figure 5.18: FDCs comparisons between model outputs and observed data for W56B and W56E sub-basins

Table 5.10: A summary of constraint index changes for Usuthu made after comparisons of simulations with observed flow data

Simulated (and affected) gauge	Region	Constraint index changes made after comparisons with observed data
W5H039 (W51B), W5H022 (W51D), GS7 (W51G), W5H005 (W52C), W5H038 (W53A), W5H003 (W53B), W5H036 (W54B), W5H008 (W54C), W5H025 (W54D), W5H011 (W55B), W5H024 (W55C).	All gauges in FHV	MMQ: 5 – 15% decrease bounds for W55A, W55B, W55D; 10 – 13% increase on bounds for W54A, W55C; 20% increase on bounds for W54C, 23 – 28% decrease on the upper bound for W53A, W53B; 40 – 50% increase on bounds for W53C, W53D; 5 – 10% decrease on bounds for W51A, W51D, W52A,B,C; 10 – 15% reduction of bounds for W51G. MMR: About 20 – 30% decrease on bounds for W51A, W53B, W55A, W55C, W55B, W54D, W54B, W54C; 33% decrease on lower and 55% decrease on upper bound, 43% decrease on lower bound and 63% decrease on upper bound for W53A; 10 – 15% increase on bounds for W51B, W51D, W53D; 10 % increase on upper bound for W51C; 30% decrease of upper bound for W51G. Q10: 4 – 9% decrease of the bounds for W51C, W51D, W53E, W54A and W54C; 2 – 7% increase on the bounds for W53A and W54B; 8 – 14% reduction of bounds for W51B; 3 – 10% increase of bounds for W51E and W51G. Q50: 2% increase of upper bound for W55C; 5% reduction of upper bound for W54A, W53D, W53E, W53E; 5 – 15% reduction of bounds for W55B, W52B, W54C, W53B, W53A, W52A, W52C, W54B, W53C, W54D, W51B, W51C, W51D; 20% reduction of bounds for W55A; 10% increase of bounds for W54G, W53G, W51H, W57A; 25% increase of lower bound for W51E. Q90: 5 – 13% reduction of bounds for W54A; 25 – 35% reduction of bounds for W53C, W53D and W54B; 50% reduction on lower bound and 20% increase on upper bound for W54C; 50% reduction of lower bound and 27% reduction of upper bound for W53E; 20% reduction of upper bound for W53A;
GS15 (W56B), GS24 (W56E)	Both gauges in ES	MMQ: about 30% increase of bounds for W56A, W56B, W56C, W56D and W56E; 5 – 15% increase of bounds for W53F, W54E and W55E; 6% decrease of bounds for W51F MMR: 10% decrease on bounds for W56A; 10% decrease on bounds for W56B; 7% decrease on bounds for W53F; 15% decrease on bounds for W51F; 20 – 30% decrease of bounds for W54E, W56C, W56D and W56E; 40% decrease on bounds for W55E and W54F. Q10: 3 – 10% increase of bounds for W54E, W55E, W56A, W56B, W56C, W56D and W56E; 14% increase of bounds for W54F; 3 – 5% reduction of bounds for W53F; 23% reduction of upper bound for W51F Q50: 10 – 15% increase of bounds for W56A, W56B, W56C, W56D, W56E, W55E and W54F; 18% increase of lower bound for W54E; 15% increase of lower bound and 5% increase of upper bound for W53F; 13% increase on the lower and 6% increase on the upper bound for W51F. Q90: more than 40% increase of lower bounds and about 20 – 30% increase of lower bounds for W56A, W56B, W56C, W56D, W56E, W54E, W54F, W53F; 10% increase of bounds for W55E.
No gauges	MV	MMQ: 5% increase of bounds for W56F Q10: 3% increase of lower bound and 10% increase on upper bound for W56F Q50: 14% increase of lower bound and 29% increase on upper bound for W56F Q90: 10% increase of bounds for W56F
GS6 (W57A),	All gauges in SLV	MMQ: 5% increase of bounds for W53G and W57A; 5% increase of lower bound and 6% decrease of upper bound for W51H; MMR: 10% decrease for bounds for W54G; 30% decrease of bounds for W53G and W57A; 10% decrease of upper bound for W51H. Q10: 3 – 10% increase of bounds for W54G, W53G, W51H and W57A. Q50: 10% increase of bounds for W54G, W53G, W51H, W57A. Q90: 10% increase of bounds for W54G, W53G, W51H, W57A
No gauges	LV	MMQ: no changes MMR: no changes Q10: no changes Q50: no changes Q90: no changes

Table 5.11 shows the model performance statistics (%Bias, %Bias{ln}, NE and NE{ln}) of the final ensemble sets. Both the bias in MMQ (%Bias) and a mean bias based on log transformed flows (%Bias{ln}) of the final ensemble set for the sub-basins across the regions vary from small to large. More than 40% of the gauges have best Nash-Sutcliffe efficiency values (NE) greater than 0.5. More than 70% of the gauges have best Nash-Sutcliffe efficiency values (NE{ln}) better than 0.5, and 50% are on average equivalent to 0.7. The bias values are generally between -30 and +30%. The best NE values are between 0.3 and 0.6, and log transformed NE{ln} values are typically greater than 0.6.

Table 5.11: Best NE values and variation of % Bias of the ensembles in each corresponding flow gauge of the Usuthu catchment

Gauge and sub-basin	Bias		NSCE	
	% Bias	% Bias {ln}	CE	CE{ln}
W5H011/W55B	7 to 93	0 to 144	0.28	0.70
W5H024/W55C	-2 to 54	-30 to 38	0.18	0.73
GS15/W56B	-6 to 55	-20 to 51	0.20	0.74
GS24/W56E	-11 to 19	-17 to 15	0.66	0.63
W5H036/W54B (nat.)	-27 to -2	30 to 109	0.60	0.72
W5H036/W54B (imp.)	-87 to -42	-97 to -79	0.51	-0.34
W5H008/W54C (nat.)	-39 to -8	-52 to -11	0.58	0.67
W5H008/W54C (imp.)	-31 to 62	-49 to 104	0.13	0.37
W5H025/W54D	-4 to 64	-31 to 50	0.05	0.69
W5H039/W51B	-34 to 16	-19 to 67	0.33	-0.48
W5H022/W51D	-12 to 28	-35 to 17	-0.14	0.52
GS7/W51G (nat.)	16 to 42	-4 to 28	-0.74	0.59
GS7/W51G (imp.)	-26 to 1	-33 to 2	0.50	0.68
W5H005/W52C	-37 to 17	-44 to 33	0.38	0.62
W5H038/W53A	-62 to 34	-42 to 84	0.33	-0.28
GS6/W57A	-8 to 7	-14 to 3	0.73	0.78

Many simulations for the Usuthu appear to be acceptable but the CE (untransformed) are generally poor. The upper part of the Usuthu River basin is characterised by a complex IBT system that is supposedly connected to more than two basins. Unfortunately, detailed information about the IBT scheme is not available. The downstream flow gauging stations are unreliable as they have a lengthy missing record and cannot be used to evaluate the impacts of the sugar cane irrigation in the lower parts of the catchment.

5.2.2.3 Phongola river basin

Figure 5.19 illustrates the uncertainty bands of the FDC using the revised constraints for W41D, W41E and W42M sub-basins after the modifications summarised in Table 5.12. Reductions of MMR for these sub-basins were very high. Moderate increases and decreases were made on MMQ constraint indices. Q10 and Q50 constraints were either reduced or increased by about 2 – 10%. Q90 constraints were substantially reduced.

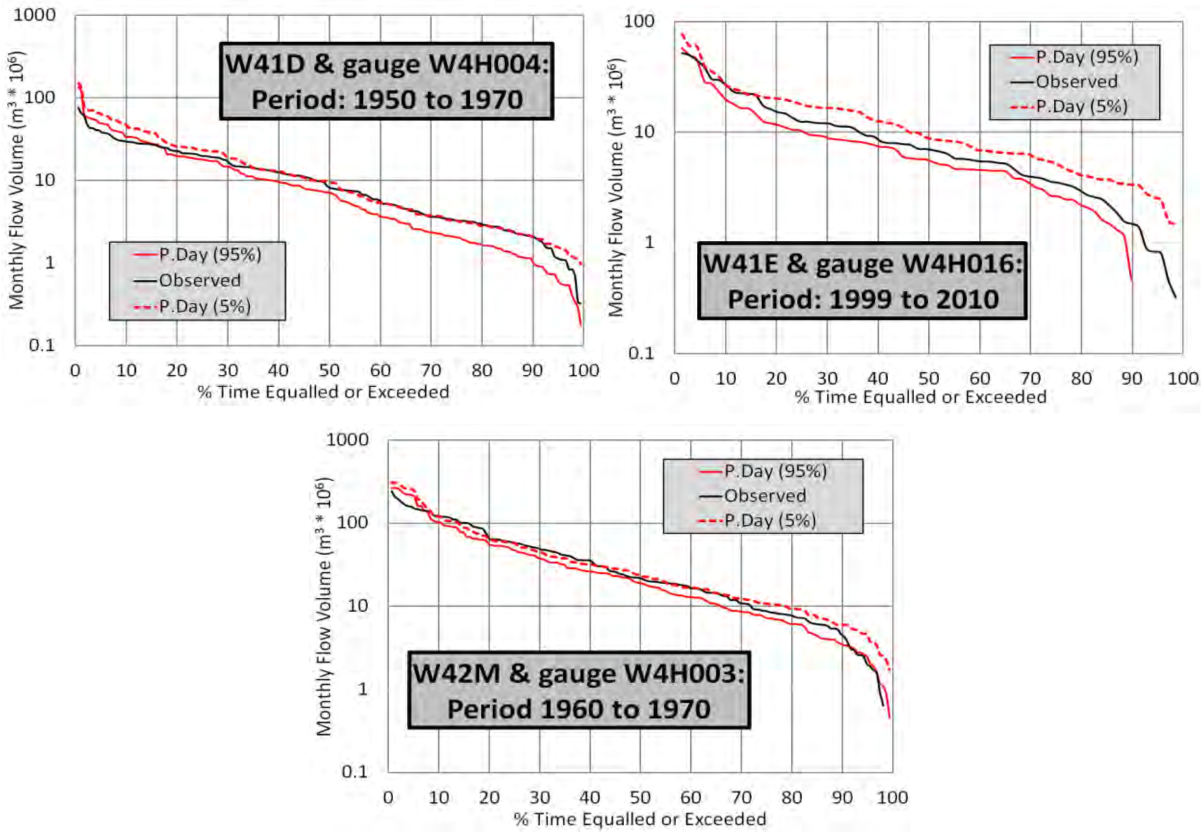

Figure 5.19: FDCs comparisons between model outputs and observed data for W41D, W41E and W42M.

Figure 5.20 illustrates the situation for the most downstream area after some changes to the constraints for W44C and W44D sub-basins. Inconsistent changes were made to MMQ and Q10 constraints: in some sub-basins, changes to the limits of these constraint resulted in an increase/decrease of the constraint bounds. Large increases in some sub-basins and decreases in others were made for MMR and Q90 constraints. A large increase of the upper bound of Q50 was made.

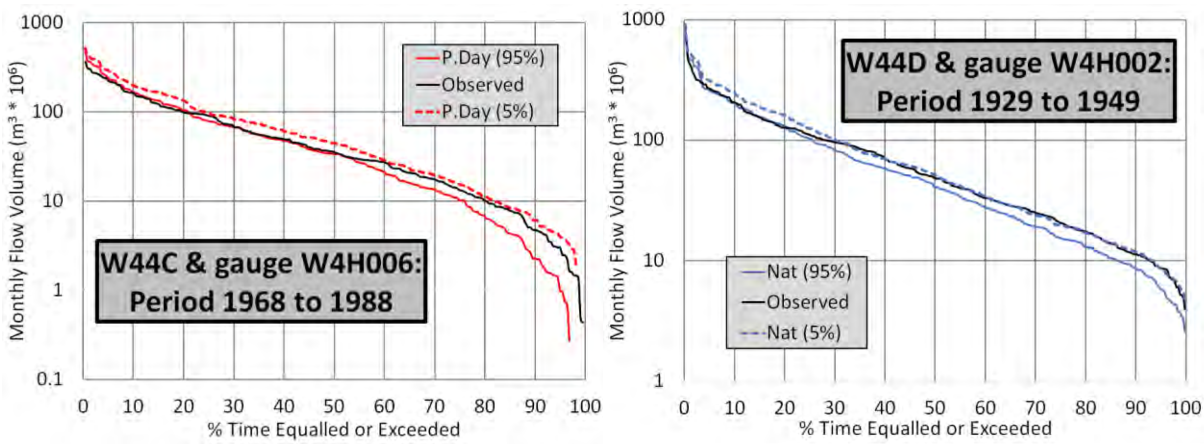

Figure 5.20: FDCs comparisons between model outputs and observed data for W44C and W44D sub-basins

Table 5.12: A summary of constraint index changes in Phongola made after comparisons of simulations with observed flow data

Simulated (and affected) gauge	Region	Constraint index changes made after comparisons with observed data
W4H004 (W41D), W4H016 (W41E),	Both gauges in ES	MMQ: 19% decrease on lower bound and 24% increase on upper bound for W41A; 30 – 40% increase or decrease of bounds for W41B; about 20 – 30% decrease or increase of bounds for W41C – W41F. MMR: more than 40% reduction of bounds for all W41 sub-basins. Q10: 10 – 13% increase of upper bounds and a maximum of 3% decrease of lower bounds for W41A – W41F and W42A – W42E. Q50: 5 – 10% decrease of lower bounds and increase of upper bounds for W41A – W41E and W42A – W42E. Q90: more than 30% decrease of bounds for W41A – W41E, W42A – W42E.
W4H003 (W42M),	MV	MMQ: About 20 – 30% decrease or increase of bounds for W42A – W42C; more than 40% increase of upper bounds and 10 – 20% decrease or increase of lower bounds for W42D and W42E; about 30% decrease of lower and more than 50% increase of upper bounds for W42F – W42M. MMR: more than 30% reduction of bounds for W42F – W42M; more than 40% reduction of bounds for W42A – W42E. Q10: 10 – 13% increase of upper bounds and a maximum of 3% decrease of lower bounds W42A – W42E; 1 – 3% reduction of lower bounds and 15 – 25% increase of upper bounds for W42F – W42M. Q50: 5 – 10% decrease of lower bounds and increase of upper bounds for W42A – W42E; 1 – 6% reduction of lower bound and 10 – 30% increase of upper bounds for W41G, W42F – W42M. Q90: more than 30% decrease of bounds for W42A – W42E; more than 40% decrease of lower and increase of upper bounds for W41G, W42F – W42M.
W4H006 (W44C), W4H002 (W44D)	Both gauges in LV	MMQ: more than 40% decrease of lower and increase of upper bounds for all sub-basins in W44. MMR: more than 30% reduction of bounds for all sub-basins in W44. Q10: 38% reduction of lower bound and 5% increase of upper bound for all sub-basins in W44. Q50: 11% increase of lower bound and more than 40% increase on upper bound for all sub-basins in W44. Q90: more than 40% increase of upper bound for all sub-basins in W44.

Both the bias in MMQ (%Bias) and a mean bias based on log transformed flows (%Bias{ln}) for all the gauges range between about -20 to 60% (Table 5.13). The best NE values are between 0.4 and 0.7, and log transformed NE{ln} values between 0.65 and 0.8.

Table 5.13: Best NE values and variation of % Bias of the ensembles in each corresponding flow gauge of the Phongola catchment

Gauge and sub-basin	Bias		NSCE	
	% Bias	% Bias{ln}	CE	CE{ln}
W4H004 (W41D)	-18 to 65	-34 to 56	0.40	0.80
W4H016 (W41E)	-4 to 69	-30 to 57	-0.35	-0.20
W4H003 (W42M)	-23 to 8	-12 to 28	0.71	0.81
W4H006 (W44C)	16 to 63	33 to 92	0.55	0.65
W4H002 (W44D)	-25 to 1	-37 to -9	0.58	0.73

A major challenge in setting up constraints was encountered in the Phongola River basin where the consistency in making constraint changes that was applied to the other basins (refer to section 4.5.3) proved to be irrelevant and unsuccessful. In some instances, the final constraint ranges in the Phongola basin were increased while they were decreased in some sub-basins in order to generate sensible model simulations. Data reflecting un-impacted stream flow conditions are not available for this basin, making it difficult to appropriately adjust model output constraints.

The simulation results and model performance for the Phongola basin are satisfactory. The basin is less impacted by water resources developments. There are no major water resources developments for the simulation period. Estimating water use parameters was simple, and resulted in sensible simulations of stream flow for impacted conditions in the catchment.

5.2.2.4 Summary of constraint changes and model performance

Similar to the constraint changes made for the test sub-basins, there are no straightforward regional patterns or trends in the changes that were made to the constraint indices. It was therefore necessary to make some major, and in many cases minor adjustments, to the certain sub-basin constraints in order to match the FDCs for observed data. This resulted in the reduction of the constraint uncertainty ranges in many sub-basins. Some of the required constraint changes were substantial but many were relatively small and of the order of 5 to 20%. No changes to the constraints were for most of the sub-basins in the SLV region (the Komati and Ngwavuma catchments). Constraints for many sub-basins in the LV regions were unchanged. Consistency was maintained on the changes made to constraint limits in all the basins except for the Phongola catchment where the changes were not straightforward, and it was very difficult to establish constraints that match with the observed flows.

The model performance was primarily assessed using visual comparisons between the observed FDCs and the simulated FDC ranges, and the objective function values of the 'best' ensemble results were also assessed to ensure that the time series patterns of the simulated data are satisfactory. The Nash-Sutcliffe efficiency values for untransformed (CE) data are typically above 0.5 and for log transformed (CE{ln}) data typically above 0.6. In some sub-basins, such as X11J and X13H, these values are lower. This could be due to the difficulty in representing the unknown patterns of abstraction in the model setup for those sub-basins.

5.3 Discussion and conclusion

The adopted uncertainty approach has been tested, validated and applied in all the transboundary basins of Eswatini with success and a few limitations in some sub-basins. The success and challenges can be attributed to the application of the same model in previous modelling studies. The previous simulations were very informative in terms of guiding the setting up of initial constraints and parameter ranges in order to simulate various stream flow conditions.

The importance of the use of hydrological response characteristics to constrain model outputs has been demonstrated in this study. The uncertainty approach applied in this study ensures that the estimated parameters are consistent with the established constraints on hydrological response, and that uncertainty is reduced both in the estimation of constraints and parameter ranges. The overall aim is to generate sufficient behavioural flow ensembles (5 000) for both 'natural' and impacted conditions. Generating the required number of behavioural ensembles after sensible parameter and constraints ranges have been established was generally straightforward for most river basins. However, the main challenge throughout the whole study was establishing constraints that are consistent with the model parameters. This challenge could also be related to the difficulty in incorporating non-stationarity in hydrological response indices.

Establishing water use parameters (i.e., in Step two of the model run) for most basins was also challenging. The stream flow (for all, except for Phongola) is heavily impacted by water resources developments with little information on the abstraction levels and reservoirs whose operating rules are unknown. In some instances, such as the Phongola sub-basins, water use parameter estimation was quite straightforward as the level of water use and developments is lower compared to the other basins.

The results of the assessments of the constraint index ranges and simulations of 'natural' and impacted stream flow conditions for all the transboundary rivers of eSwatini are generally satisfactory. To a large extent, the initial constraint ranges are consistent with the observed stream flow data, after the available information on water use was incorporated into the model simulations. In some sub-basins, constraints were not changed. As might be expected, there were some sub-basins where relatively small changes (up to 20%) to some of the constraints were necessary to reduce the bias in the simulations. Some changes were moderate, in the order of 20 to 30%. However, there was some sub-basins (e.g., in the Komati, Usuthu and Mbuluzi) where the observed data suggested a much greater change in the values of the constraint indices. In Phongola, specifically, more effort was spent on revising constraints so that they match with the observed hydrological response.

A few key regions and data sources, where existing uncertainties might impact adversely on water allocation management decision-making, were identified. Some uncertainties may be related to the anomalies in constraint changes made in the ES and MV regions. Others may be related to the inconsistent constraint changes applied to the Phongola basin, which were totally different from the other basins.

There are some identified sources of uncertainties which could have some detrimental effects on decision making. Identified data sources critical to water allocation management decision-making are associated with both rainfall and stream flow. Topographically diverse regions such as the SLV present some uncertainties in representing the spatial variation in monthly rainfall depth. The flow data at X14F, for example, are also suspicious as they are inconsistent with other relevant data. Other gauges do not capture high flows well, and their flow patterns are inconsistent with other flow patterns in neighbouring gauges whose catchment characteristics are similar. Water use data are inaccurate, and in many cases do not exist.

It is recognised that some simulations presented here are poor based on the visual assessment of FDCs and model performance measures. The reasons for some of the poor results (i.e., based on performance measures) may be due to huge gaps in the data and some challenges of observations to capture non-stationarities in data. However, some of these simulations which appear to be poor are generally acceptable based on the visual assessment of the time series plots (Appendices 7 – 14). The results demonstrate that the use of regionalised model output constraints is important in modelling that attempts to address uncertainty, regardless of the difficulty in establishing the constraints. Firstly, equifinality is reduced. Secondly, this approach ensures that behavioural model outputs are obtained before water use influences are incorporated in the model set-up. Therefore, given more observed flow data for natural conditions in headwater sub-basins, uncertainty can be constrained better. More detailed information on anthropogenic influences is useful to further represent well the water use component of the model in order to estimate uncertainty realistically. However, the use of pre-existing simulations has proved to be a potential complementary data source in areas with limited data, such as Eswatini.

CHAPTER SIX: CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

Water resources are becoming scarce. In addition, development is escalating globally and therefore threatening the natural environment. These trends require the development of practices that are based on adequate data about natural resources availability, including spatio-temporal variability of the resources as well as up-to-date information on current and future uses. However, the practical application of hydrological models for water resources assessments that incorporate uncertainty in many countries, including Eswatini, has yet to be realised. The aim of the study was therefore to develop a water resource assessment system that is based on both observed and simulated information and that includes uncertainty. This aim was achieved by applying a 2-step uncertainty modelling approach in which the simulations are based on behavioral model outputs that are constrained by suitable hydrological indices in order to generate realistic uncertainty estimates. Another key objective was to find out if the initial constraint regionalisation could be improved after calibration of the constraints against all the observed data. The conclusion is that the patterns of constraint changes are quite varied. Based on the variation of the constraint adjustments made and the attempt of regionalising parameters, it is found that a new regional pattern could not be established.

It is evident from the collected data that Eswatini is faced with problems of data-scarcity in terms of water resources information, and this crisis is expected to continue in the future (see Hughes, 2019). Appendix 11 illustrates a typical example of stream flow data issues in Eswatini. The stream flow observation networks have deteriorated over the past 50 years. From the data that have been collected for the purpose of modelling all the transboundary basins of Eswatini, it can be concluded that these basins are data-scarce. This situation of inadequate data should be considered as an opportunity for models to fill existing gaps and produce valuable information for water resources planning and management (Hughes, 2010a) of the transboundary basins of Eswatini. This kind of modelling, aimed at filling gaps and providing information for decision making, would require cooperation between scientists, decision makers and water users in order to ensure sustainable water resources management (Hughes, 2019). In addition, it might necessitate strong reliance on available global and local, observed and simulated information to enable reliable and appropriate water resources assessments.

It was straightforward to set up the model parameter ranges for natural hydrology, as opposed to establishing water use parameters. However, it was difficult to establish some of the constraints used in this study on the basis of the available previous simulations, for example flow duration curve (FDC) constraints, and mean monthly recharge. Among other reasons for this difficulty is because the stream flow records are typically less than 30 years and not a reflection of the entire natural flow conditions. Secondly, there are few gauged headwater catchments that are characterised by natural flow conditions. Thirdly, some of the datasets used to establish the constraints are known to be inaccurate. Lastly, water use data are rarely sufficient, and often unavailable.

In any practical water resources assessment that includes uncertainty, a key question will always be 'what are realistic uncertainty bounds'? This is a difficult question to answer as it will partly depend upon the critical water management issues (Beven and Alcock, 2012) and partly upon the confidence that can be expressed in the accuracy of the observed flow data and what level of water resources development (abstractions, reservoirs, etc.) these data really represent. Given the lack of available information on the maintenance of the flow gauging stations (all concrete weir or flume structures), as well as the poorly documented non-stationarities in the available water use data in the basins, it is clear that the observed flow data are uncertain, but it is not clear to what extent they are uncertain. A simple metric of uncertainty is the % difference between the extremes of the plotted ensembles divided by the mean value of the ensemble set. Some sub-basins are characterised by realistic patterns of uncertainty and reasonable metrics of uncertainty, such as W60A and W60D in the Mbuluzi basin; X12C and X12J in the Komati basin; W51D and W51G in the Usuthu basin; W43B and W43D in the Ngwavuma basin; and W44C and W44D in the Phongola basin. For sub-basin W60A (Figure 5.4), for example, which is reasonably representative in terms of uncertainty bounds, this metric increases almost linearly from about 6% for high flows to about 50% for very low flows. A case within the Mbuluzi that is similar to this one is W60G (GS10) and others include X11E (Komati basin), W54D (Usuthu basin) and W41E (Phongola basin). For water resources developments that depend upon storage, this pattern of uncertainty (less in the moderate to high flows) may be acceptable. For other water resources developments based on run-of-river abstractions, the level of uncertainty in low flows may make decision making very difficult. An attempt to simulate flows based on dependent parameter sampling was made and this did not really reduce the uncertainty band of the flow duration curve. The only improvement of the uncertainty band is noted at gauge X1H052 of X14H, in the Komati basin.

Based on the accuracy of model forcing data and the information about levels of water resources developments used, most of the estimates of uncertainty shown in the FDCs can be considered realistic: they are consistent with all available knowledge and data. In addition, the approach of constraining model output used in this study to generate these uncertainty estimates is related to other widely-accepted rigorous approaches such as the 'limits of acceptability' by Beven (2006). Realistic estimates of uncertainty in any water resources assessment are required to promote the analysis and ultimately reduce likely risks in decision making. As a result, the goal of hydrological process understanding must be interconnected to the purpose of decision making in water resources management (Beven, 2019). Water resources decision making must therefore be based on model predictions that are producing acceptable results for right reasons (Kirchner, 2007; Beven, 2019).

The overall conclusion is that the modelling approach adopted is appropriate for the quantification of available water resources in the region represented by the river basins that cover Eswatini. It makes use of relatively simple approaches for including uncertainty in the application of a hydrological model, coupled with regionalised indices, or signatures, of runoff response that constrain the model to produce behavioural outputs. These findings are consistent with findings from other studies that applied this approach of constraining model output based on the use of hydrological indices (e.g., Dunn, 1999; Gharari et al., 2014; Hrachowitz et al., 2014; Nijzink et al., 2018; Wambura et al., 2018). The general approach should be applicable anywhere, and with a similar type of hydrological model. However, the specific approach adopted here to establish the ranges of the constraint indices is likely to be unique as it relies on the availability of previous simulations which are available for the whole of South Africa, Eswatini and Lesotho. In other situations, the constraints may need to be developed from other data that can be used to quantify regional variations in sub-basin hydrological responses.

6.2 Recommendations

The following are recommendations based on the research findings:

- In the future, an in-depth examination of the constraint analysis may be necessary in the regions where there were substantial changes to the initial constraint ranges. It may also be necessary that an analysis be conducted in the other instances where the constraint changes were not consistent with the changes made in other areas.
- The use of additional constraints in the model, for example, Q30 (30^{th} percentile of the flow duration curve) and Q70 (70^{th} percentile of the flow duration curve) may be necessary to further improve stream flow simulation. Other suitable constraints may be considered.
- The adjusted MAP values by Pegram (2016) may be tested on the Ngwavuma basin where it is assumed that the rainfall stations are inadequate to capture the rainfall patterns in the topographically complex terrain.
- This study identified water use as a major source of uncertainty. It is therefore necessary for accurate water use data to be provided to allow for representative modelling of the basins of Eswatini to improve decision making.
- There is an over-simulation of high flows in many gauges. Some gauges do not measure daily extreme flows and this impacts differently on monthly flow volumes. This issue requires further examination. In some gauges, for example, the high flows are not captured well even in well-known events of excessive rainfall. Rating tables may be necessary, in situations where they are unavailable, to support and validate stream flow observations. Where they are available, they need to be assessed for accuracy and modified (if need be) to enable more reliable estimation of streamflow.
- A few gauges are characterised by flow pattern that is inconsistent with other related data. Therefore, in the absence of rating tables, flow data should be analysed before their usage. A thorough review of observed data, which was beyond the scope of this limited-duration study, is recommended.

- Since the term “uncertainty” is used by different groups of professionals and scientists in disparate ways (Fischhoff, 1995) and this affects the way uncertainty is communicated between professionals, the following are recommendations with respect to the application of these results in practical decision making:
  - (i) efforts are required to promote mutual understanding of the term ‘uncertainty’ among professionals and to ensure it is communicated effectively to decision makers in order to increase confidence in the uncertainty and to ultimately pursue the best decision;
  - (ii) decision makers should be involved in the development of model assumptions to gain confidence in the basic science and data used which might result in interrogative analysis in order to possibly narrow down the bands of uncertainty;
  - (iii) carefully evaluate the model performance indices, before applying these model results in decision making;
  - (iv) future-based water resources planning and decision making should take in to consideration non-stationarity assumptions;
  - (v) consider different water resources developments when applying the uncertainty results in decision making;
  - (vi) addition of measures of decision impact, such as costs of incorrect decisions, to give more objective and more readily appreciated bases for decisions (Pendrill, 2014)

  This approach should result in better science and better decision making (Fischhoff and Davis, 2014), i.e., having credible and useful bounds resulting in robust and more publicly acceptable decisions (McMillan et al., 2017). This can also lead to assessing the value of reducing the uncertainty, and yield positive outcomes, as long as the bounds are an honest expression of uncertainty.

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APPENDICES

Appendix 1: An example of uncertain parameter values used in the model for sub-basin X11H of Komati River basin (ES region)

Parameter	Parameter values for sub-basin		Parameter values across all sub-basins in the region	
	Minimum	Maximum	Minimum	Maximum
ZMIN	10	50	0	50
ZMAX	500	800	410	850
ST	100	300	70	300
POW	1.5	2.5	1.5	2.5
FT	5	35	3	45
R	0.2	0.7	0.2	0.7
GW	10	40	5	44
GPOW	2.5	3.5	2.5	3.5
RSF	0.2	1	0.2	1

Appendix 2: An example of uncertain parameter values used in the model for sub-basin W55C of Usuthu River basin (FHV region)

Parameter	Parameter values for sub-basin		Parameter values across all sub-basins in the region	
	Minimum	Maximum	Minimum	Maximum
ZMIN	10	80	0	80
ZMAX	600	900	450	900
ST	150	250	125	250
POW	2	3	2	3
FT	2	10	2	28
R	0.2	0.7	0.2	0.7
GW	8	15	5	15
GPOW	3	4	3	4
RSF	0.2	1	0.2	1

Appendix 3: An example of uncertain parameter values used in the model for sub-basin W60J of Mbuluzi River basin (LV region)

Parameter	Parameter values for sub-basin		Parameter values across all sub-basins in the region	
	Minimum	Maximum	Minimum	Maximum
ZMIN	0	100	0	50
ZMAX	700	1000	410	850
ST	100	300	70	300
POW	2.5	3.5	1.5	2.5
FT	0	5	3	45
R	0.2	0.7	0.2	0.7
GW	5	15	5	44
GPOW	3	4	2.5	3.5
RSF	0.2	1	0.2	1

Appendix 4: An example of uncertain parameter values used in the model for sub-basin W42L of Phongola River basin (MV region)

Parameter	Parameter values for sub-basin		Parameter values across all sub-basins in the region	
	Minimum	Maximum	Minimum	Maximum
ZMIN	0	50	0	50
ZMAX	550	850	550	900
ST	150	300	150	300
POW	2	3	2	3
FT	5	20	3	25
R	0.2	0.7	0.2	0.7
GW	5	30	5	30
GPOW	2.5	3.5	2.5	3.5
RSF	0.2	1	0.2	1

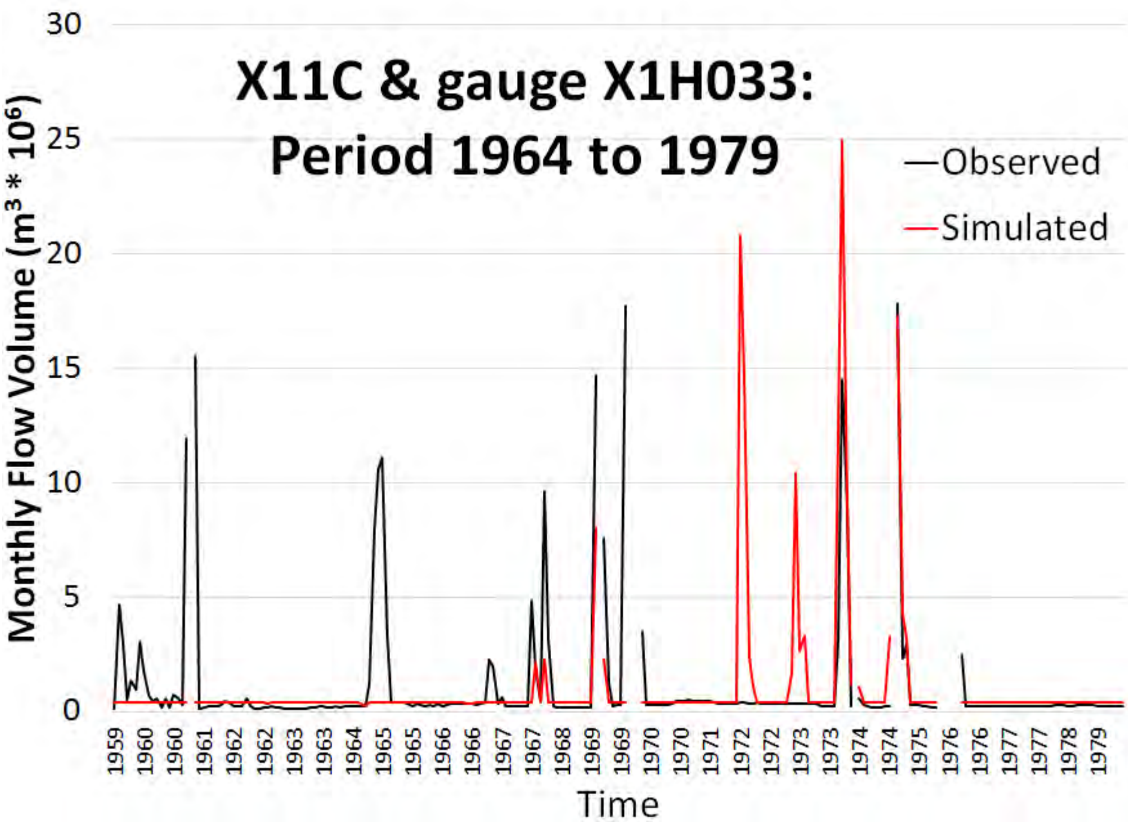
Appendix 5: An example of uncertain parameter values used in the model for sub-basin W43B of Ngwavuma River basin (SLV region)

Parameter	Parameter values for sub-basin		Parameter values across all sub-basins in the region	
	Minimum	Maximum	Minimum	Maximum
ZMIN	0	80	0	80
ZMAX	400	800	400	800
ST	150	400	125	400
POW	1.5	2.5	1.5	2.5
FT	1	20	1	27
R	0.2	0.7	0.2	0.7
GW	5	30	5	30
GPOW	2.5	3.5	2.5	3.5
RSF	0.2	1	0.2	1

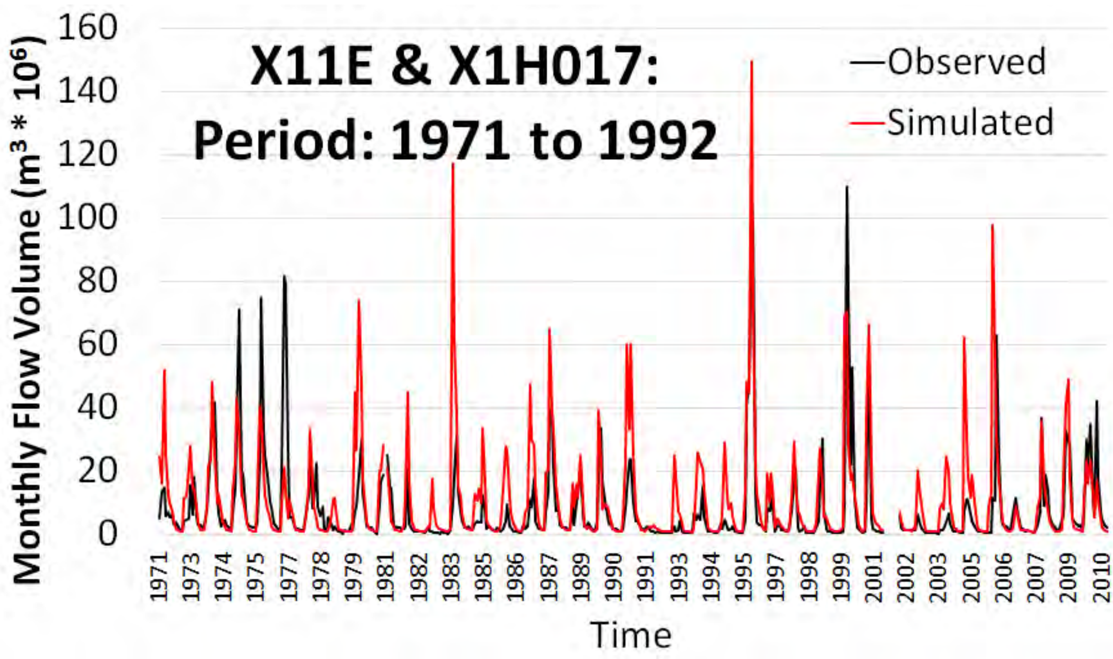
Appendix 6: An example of uncertain parameter values used in the model for sub-basin X12H of Komati River basin (SM region)

Parameter	Parameter values for sub-basin		Parameter values across all sub-basins in the region	
	Minimum	Maximum	Minimum	Maximum
ZMIN	0	100	0	100
ZMAX	500	800	500	800
ST	200	500	200	525
POW	2	3	2	2.5
FT	3	25	1	25
R	0.2	0.7	0.2	0.7
GW	5	30	5	35
GPOW	2.5	3.5	2.5	3.5
RSF	0.2	1	0.2	1

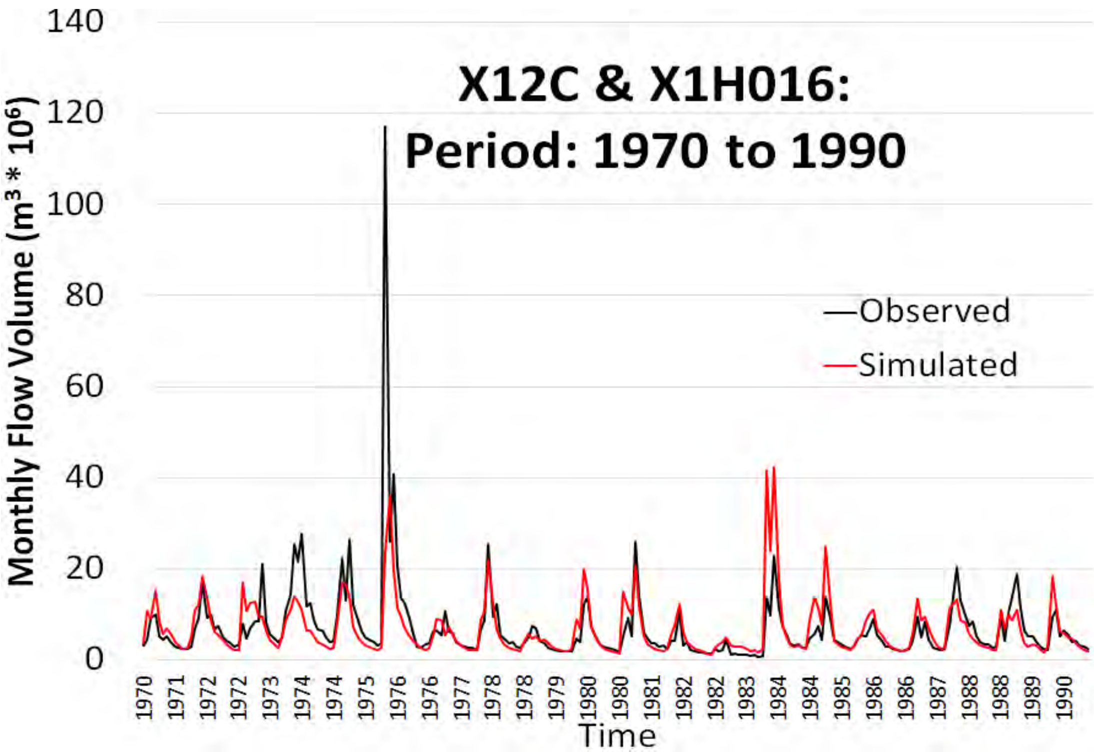
Appendix 7: Observed vs. simulated time series for X11C under impacted stream flow conditions



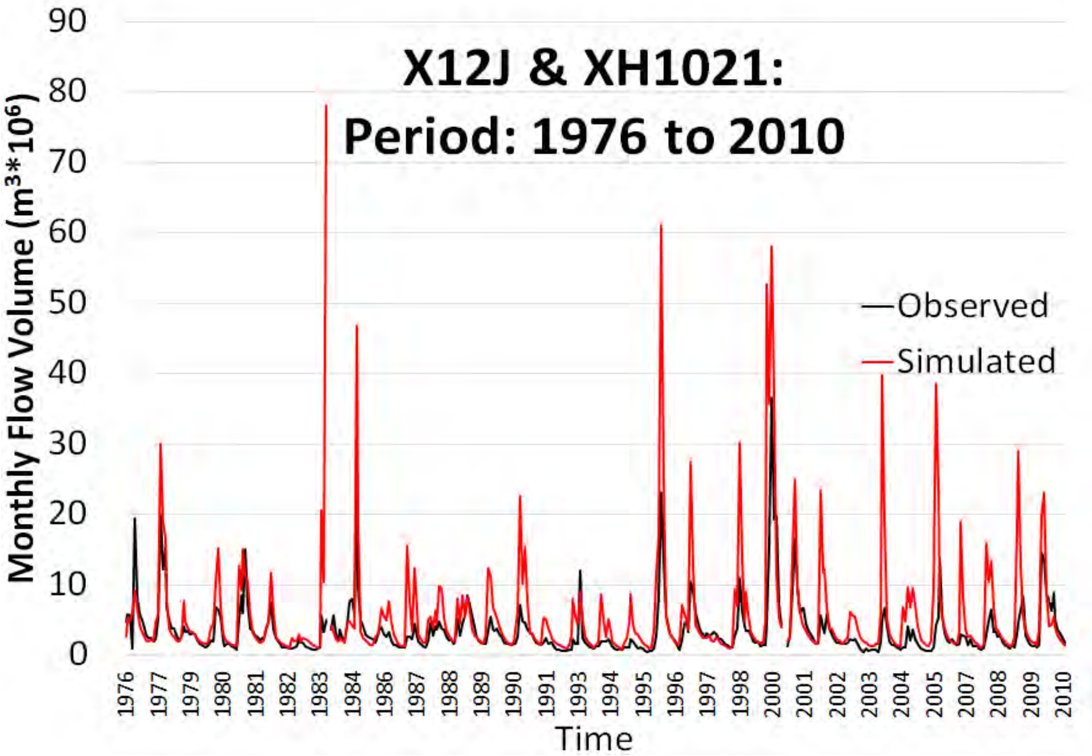
Appendix 8: Observed vs. simulated time series for X11E under impacted stream flow conditions



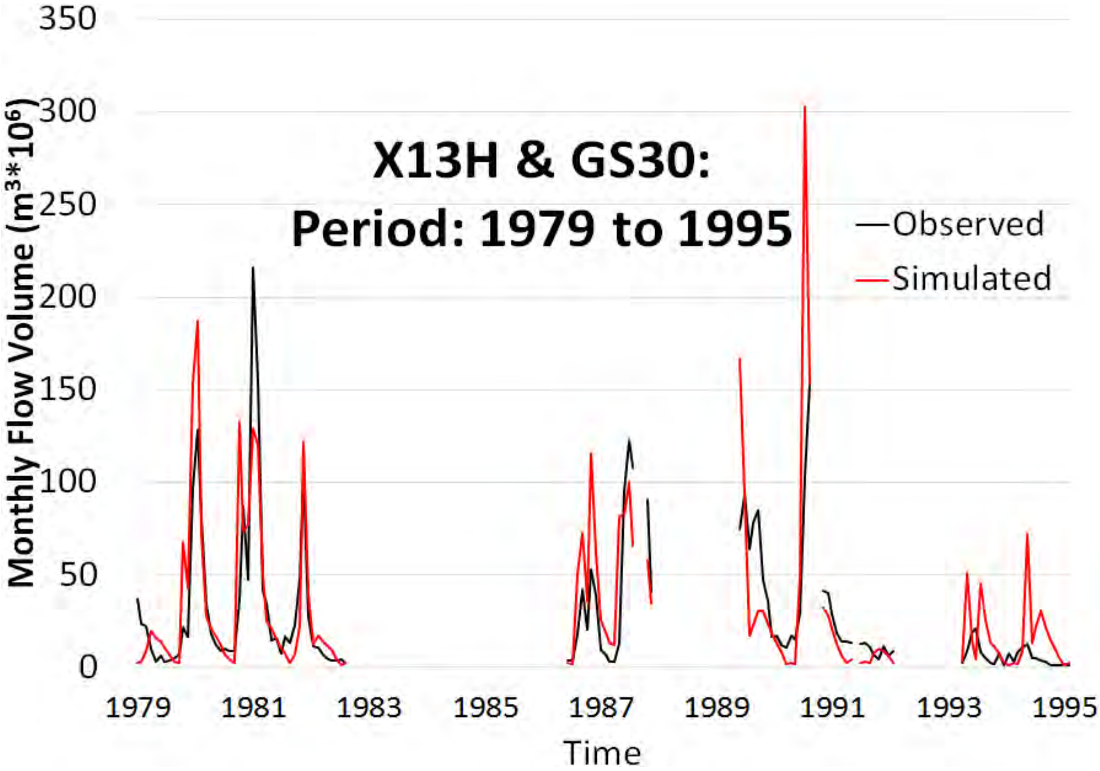
Appendix 9: Observed vs. simulated time series for X12C under impacted stream flow conditions



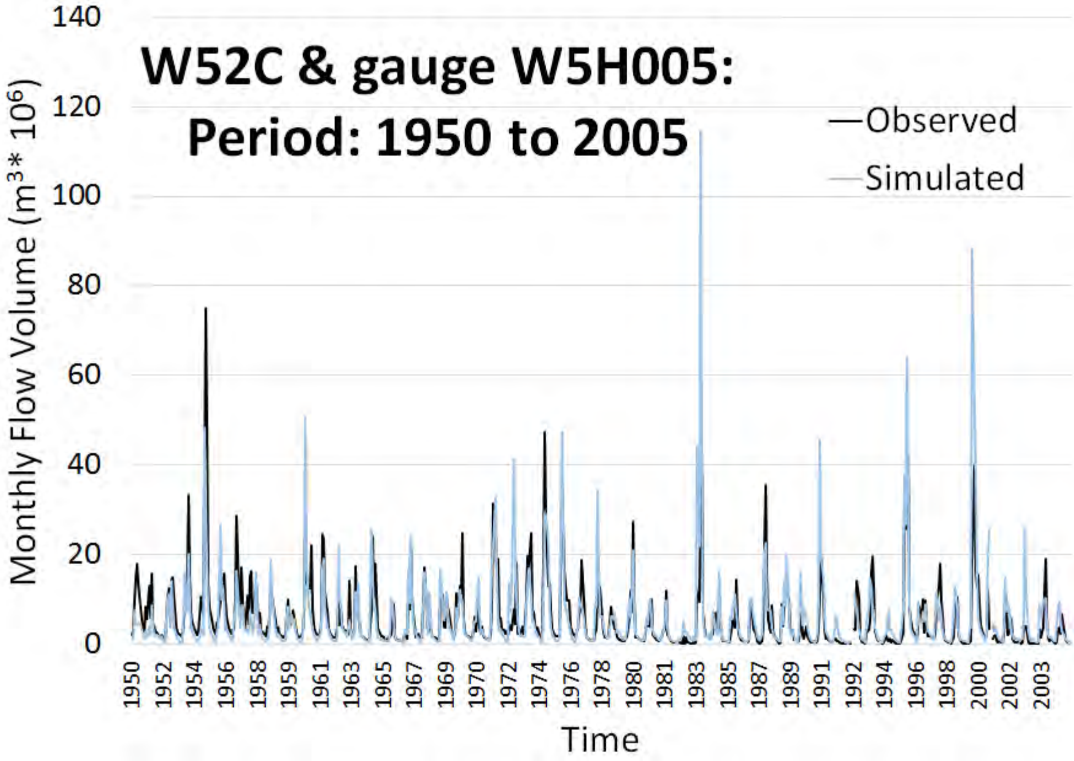
Appendix 10: Observed vs. simulated time series for X12J under impacted stream flow conditions



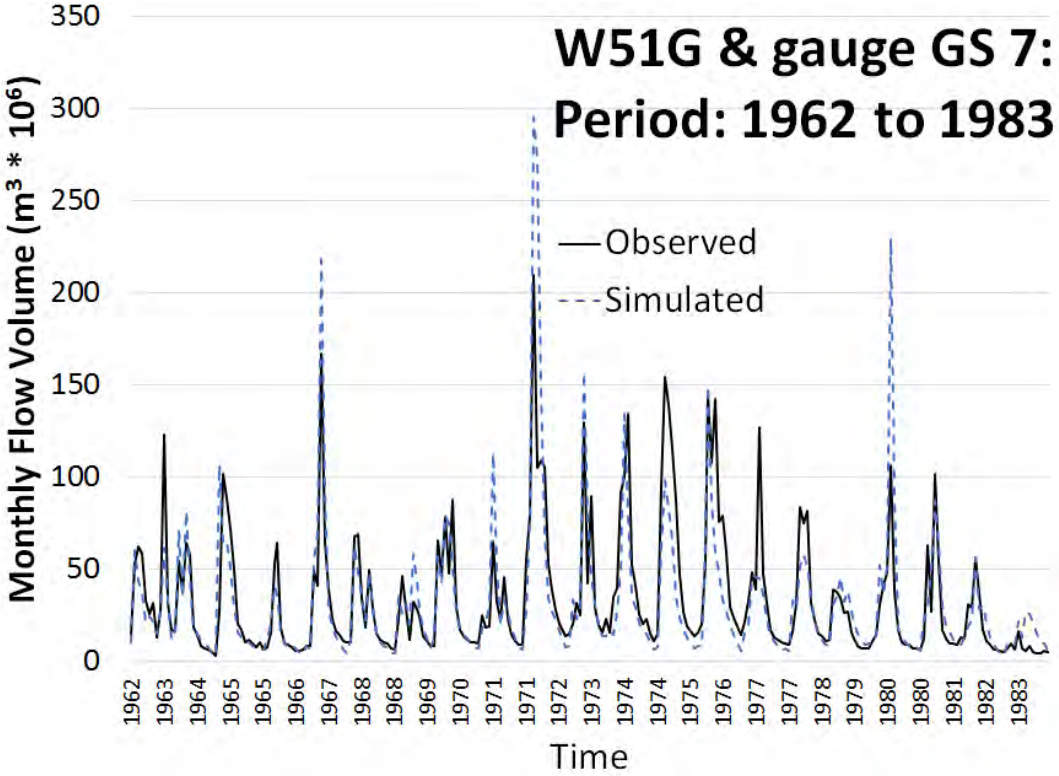
Appendix 11: Observed vs. simulated time series for X13H under impacted stream flow conditions downstream of Sand River Dam



Appendix 12: Observed vs. simulated time series for W52C under near-natural stream flow conditions



Appendix 13: Observed vs. simulated time series for W51G under near-natural stream flow conditions



Appendix 14: Observed vs. simulated time series for W42M under impacted stream flow conditions