QUANTIFICATION OF WATER RESOURCES UNCERTAINTIES IN TWO SUB-BASINS OF THE LIMPOPO RIVER BASIN

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Nadia Oosthuizen

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Nadia Oosthuizen

SUPERVISOR
PROF D.A. HUGHES INSTITUTE FOR WATER RESEARCH, RHODES UNIVERSITY

CO-SUPERVISORS
DR E. KAPANGAZIWIRI COUNCIL FOR SCIENTIFIC AND INDUSTRIAL RESEARCH
DR J. MWENGE KAHINDA COUNCIL FOR SCIENTIFIC AND INDUSTRIAL RESEARCH

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ABSTRACT

The demand for water is rapidly growing, placing more strain on access to the resources and subsequently its management. For sustainable management, there is a need to accurately quantify the available water resources. Unfortunately, the data required for such assessments are frequently far from sufficient in terms of availability and quality, especially in southern Africa. In the absence of historical observed data, models are generally used to describe the different hydrological processes and generate data and information that will inform management and policy decision making. Ideally, any hydrological model should be based on a sound conceptual understanding of the processes in the basin and be backed by quantitative information for the parameterization of the model. Such data is however, often inadequate in many sub-basins necessitating the incorporation of the uncertainty related to the estimation process. Model parameter estimation and input data are significant sources of uncertainty that should be quantified. Also, in southern Africa water use data are unreliable because available databases consist of licensed information and actual use is generally unknown. In this study, the water resources of two sub-basins of the Limpopo River basin – the Mogalakwena in South Africa and the Shashe shared between Botswana and Zimbabwe – are estimated. The study assessed how uncertainties in the Pitman model parameterisation and input water use data affect the estimation of surface water resources of the selected sub-basins. Farm reservoirs and irrigated areas data from various sources were collected and used to run the Pitman model. Results indicate that the total model output uncertainty is higher for the Shashe sub-basin which is more data scarce than the Mogalakwena sub-basin. The study illustrates the importance of including uncertainty in the water resources assessment process to provide baseline data for decision making in resource management and planning. The study reviews existing information sources associated with the quantification of water balance components and gives an update of water resources of the sub-basin. The flows generated by the model at the outlet of the basin were between 22.6 Mm^3 and 24.7 Mm^3 per month when incorporating uncertainty to the main physical runoff generating parameters. The total predictive uncertainty of the model increased to between 22.2 Mm^3 and 25.0 Mm^3 when anthropogenic water use data such as small farm and large reservoirs and irrigation were included. The flows generated for Shashe was between 11.7 Mm^3 and 14.5 Mm^3 per month when incorporating uncertainty to the main physical runoff generating parameters. The predictive uncertainty of the model changed to 11.7 Mm^3 and 17.7 Mm^3 after the water use uncertainty was added. However, it is expected that the uncertainty could be reduced by using higher resolution remote sensing imagery.

KEYWORDS: Data availability, Farm reservoir, Hydrological modelling, Irrigated areas, Mogalakwena sub-basin, Pitman model, Shashe sub-basin

Declaration

I declare that the dissertation, QUANTIFICATION OF WATER RESOURCES UNCERTAINTIES IN TWO SUB-BASINS OF THE LIMPOPO RIVER BASIN, which I hereby submit for the degree, Masters in Hydrology at Rhodes University, is my own work. I also declare that this dissertation has not previously been submitted by me for a degree at this or any other tertiary institution and that all the sources that I have used or quoted have been indicated and acknowledged by means of complete references.

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Nadia Oosthuizen

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CHAPTER 1
Introduction and study overview

1.1 BACKGROUND

The continued socio-economic development of riparian countries of the Limpopo River basin increase pressure on water resources. The management of water resources is therefore critical to avoid conflict and ensure equity and accessibility for both urban and rural populations of the large basin. There are also various other competing water users such as the environment (environmental water requirements), livestock, irrigation, and mining operations. There are several challenges within the Limpopo River basin, including shortages of water caused by droughts (Gebre and Getahun, 2016), flooding that occur especially in the Mozambique part of the basin (Maposa *et al.,* 2014; Manhique *et al.,* 2015) and deteriorating water quality e.g. in the Oliphant's sub-basin in South Africa (Thiam *et al.,* 2015; Thomas, 2015). Climate change is an additional threat to water security within the River Basin (Conway *et al.*, 2015; Nkhonjera, 2017). An identification of key hydrological processes, water use and a better understanding of their linkages; will improve water resources estimation, a requisite for better resource management, and help solve these problems. However, in the absence of historical observed data (large parts of the basin are virtually ungauged) of the different hydrological aspects of the basin such as streamflow, hydrological models are used to generate data that will inform management and ultimately policies.

Hydrological modelling should be based on sound conceptual understanding of the processes operating in the basin and should be backed by quantitative information that can be used for the parameterisation of the model (Hughes *et al.,* 2006; Hughes *et al.,* 2010). However, these data are often inadequate in most sub-basins, necessitating the quantification of the uncertainty related to the estimation process. Given the diversity of data availability and quality between and across the four riparian countries, a framework that incorporates estimates of uncertainty must be applied to deal with this challenge. The Pitman model which has been widely used for water resources assessment in the southern Africa region since its initial development in the early 1970s (Wilk and Hughes, 2002) will be set up to quantify water resources of the transboundary Limpopo River basin. The model was used for three studies that looked at the main stem of the basin (Matji and Görgens, 2001, LIMCOM 2013) and this study would contribute towards the updating of the hydrology and water resources of the Limpopo basin, including estimates of the uncertainty related to the modelling process.

1.2 PROBLEM STATEMENT

Water resources estimation is the prerequisite for proper planning, development, distribution and optimum use. If water resources availability of a particular area is not quantified or at least estimated, its proper management thereof cannot be achieved. Currently, large gaps exist on the understanding of the processes affecting water availability and management. The lack of access to observations and models that allow water resource managers to monitor and eventually predict key hydrological variables affecting the countries sharing the Limpopo River basin has led to constraints in the estimations of the water resources of the basin. Although these constraints are evident in the entire basin, this study will focus on two sub-basins. The two sub-basins were chosen because they are: physically and socio-economically contrasting; located in different countries and subject to different data quality and accessibility. It is thus important to quantify the water resources uncertainties on Mogalakwena and Shashe to gain some perspective on how the availability and accessibility of data from various countries impact the resultant water resources estimations.

1.3 STUDY AIM AND OBJECTIVES

1.3.1 Study aim

The aim of this study is to provide improved estimates of the water resources of the Limpopo River basin that can be used as a basis for planning and management of the basin both for the present and future.

1.3.2 Study objectives

To address the above aim, the following objectives have been identified:

- Estimate water resources using historical data
- Estimate the uncertainty related to water use data
- Quantify the uncertainties related to water resources estimation based on available water use data.

1.4 STRUCTURE OF THE THESIS

The dissertation is presented in seven chapters as summarised below:

- Justification for the study is discussed in Chapter 1 including the aim and objectives.
- Chapter 2 reviews input data needed to assess water resources of selectec basins. It further discusses hydrological models in general and the Pitman model in particular.
- The third chapter describes the Mogalakwena and Shashe sub-basins and highlights their differences.
- The methods, data collection process and a description of the model set up are presented in Chapter 4. The model runs consist of (i) water estimations based on current climate data; and (ii) water quantity estimations based on current climate and water use data.
- A detailed discussion on the Pitman model is the focus of Chapter 5.

- In Chapter 6 the results are displayed and discussed in detail with the main focus on comparing the uncertainty results of the two sub-basins.

Chapter 7 summarises the findings of the study and formulates recommendations for further work.

CHAPTER 2
Review of Literature

2.1 RAINFALL-RUNOFF MODELLING

2.1.1 Classification of hydrological models

Hydrological models are a mathematical representation of the processes involved in the transformation of climate inputs, such as precipitation, solar radiation and wind, through surface and sub-surface transfers of water and energy into hydrological outputs Hughes (2004). They are a simplified representation of the real world required to represent complex natural systems. However, many processes and interactions that occur in nature are lost when modelled (Davie, 2008). Rainfall-runoff models are classified based on their structure according to Clark (1973):

- Empirical models (black box) which represents the relationships of input-output observed data rather than physical principles and include antecedent precipitation (API) models, regression models, time series models, artificial neural network (ANN) models, fuzzy logic models, and frequency analysis models (Xu *et al.,* 2017).
- Conceptual models (grey box) which include some understanding of hydrological processes in the model formulation and mimic the results of detailed hydrodynamic models. In conceptual modelling, mathematical relationships are used to explicitly represent the elements. The basin is perceived as consisting of several moisture storages through which rainfall inputs are routed by a process of moisture accounting which eventually produce a streamflow output (Beven, 2001a). These models are very well

suited for applications that require long term simulations or a large number of model iterations (Meert *et al.,* 2016).

- Physically-based models (white box) which are based on physical laws such as the laws of thermodynamics, conservation of mass, momentum and energy (Beven, 2002).

Most rainfall-runoff models are used for research purposes, to deepen our understanding of hydrological processes that govern a real world system (Moradkhani and Sorooshian, 2008).

2.1.2 Model development

The history of rainfall-runoff models started in the 1880's and models have evolved over the last few decades from simple empirical, through conceptual, to complex physically-based models (Dooge, 1959; Binley *et al.,* 1991) and back to simpler or parsimonious models (Perrin *et al.,* 2003). This was largely due to the search for appropriate modelling tools that can be used to develop models with a level of complexity that reflects the actual need for modelling results (Jakeman and Hornberger, 1993). Hydrological processes can only be understood if the model is able to describe them and a good fit of a model to observe data may be obtained by parameterisation of the different processes involved (Beven, 1989). The use of appropriate parameters that reflect the fundamental governing mechanisms involved in the basin is therefore important for the model to achieve reliable predictions (Perrin *et al.,* 2003; Lazzarotto *et al.,* 2006). The main problems seems to be related to model complexity relative to data availability, choice of objective functions and the associated difficulties in identifying the chosen model structure and estimating its parameters (Yew Gan, *et al.,* 1997). Today, these issues still constitute the largest obstacle to the successful application of water resources estimation models for both gauged and ungauged basins (Sawunyama, 2008). This has led to the introduction of new modelling approaches and initiatives including fuzzy modelling techniques

(Kundzewicz, 1995), top-down uncertainty estimation in rainfall-runoff modelling (Beven, 2001a) and the Prediction in Ungauged Basins (PUB) initiative (Sivapalan *et al.,* 2003). The new approaches and initiatives are being introduced in recognition of the difficulties and limitations to the successful application of the current hydrological models to aid in decision making.

2.1.3 Model application

The International Association of Hydrological Sciences PUB decade led to improvements in both the science of hydrological modelling and the tools and approaches needed for model applications in ungauged basins (Blöschl *et al.,* 2013; Hrachowitz *et al.,* 2013). Despite these achievements, the usefulness of a model's ability to address water resources management problems under changing conditions, including land use, climate, and spatial variabilities, are still challenging (Montanari *et al.,* 2013; Hughes, 2010; Hughes, 2013). Various rainfall-runoff models are available to compensate for the need to adequately model water resources. The Pitman, Agricultural Catchment Research Unit (ACRU) and the Soil and Water Assessment Tool (SWOT) hydrological models are some of the models that are widely used in southern Africa. Pitman is a conceptual, semi-distributed monthly time-step model whereas the ACRU model is a conceptual, physically-based daily time-step agro-hydrological modelling system that has frequently provided information that is valuable for water managers (Sawunyama, 2008). These models vary in terms of the time-step, data requirements, the number of parameters, and at times the purpose that they serve (Sawunyama, 2008). SWAT is an agro-hydrological model designed to simulate the potential impacts of alterations on water fluxes and crop yields and it has been successfully applied in a wide range of scales and environmental conditions (Andersson *et al*., 2012).The selection of rainfall-runoff models depends on how processes are represented, the time and space scale that are used, and what methods of solution to equations are used (Singh, 1995). The most common rainfall-runoff models are data driven. The representation of spatial variabilities in models is achieved by using fully distributed models, which describe each hydrological response through parameters related to physical basin properties (Tumbo, 2014). These models tend to better simulate the hydrology off small watersheds. The difficulties in obtaining good quality data for large basins make these models more conceptual. Even so, data availability and quality for small watersheds can lead to model bias when the data does not provide an adequate representation of the physical system from the outset which may affect model predictability (Haerter *et al.,* 2010; Tshimanga, 2012; McMillan *et al.,* 2013). In contrast to conceptual models, where observed data is used for parameter estimation, the parameters of fully physically-based models are expected to be directly measurable from basin physical characteristics. Lumped models treat the catchment as a single homogenous unit (catchment or sub-basin level). In this modelling approach, the modeller tries to relate the forcing data, mainly precipitation inputs, to system outputs without any consideration for the spatial processes, patterns, and organisation of the characteristics that govern the processes (Moradkhani and Sorooshian, 2008). However, according to Beven (2000), lumped models cannot be used for the analysis of event scale processes unless the focus is on discharge prediction only. Also, lumped models are inadequate for calibration in ungauged basins, due to the spatial variability of landscapes, mainly because the parameters used in lumped models are averaged and cannot be compared to field measurements (Beven, 2001b; Sivapalan *et al.,* 2003; Tshimanga, 2012; Wang *et al.,* 2012). Alternatively, the use of distributed models is an attempt to take into account the spatial variation of hydrological responses within a watershed, which is treated as a discrete unit (Abbott *et al.,* 1986; Abbott and Refsgaard, 1996; Beven, 2001b).

2.2 CALIBRATION AND VALIDATION OF RAINFALL-RUNOFF MODELS

2.2.1 Model calibration approaches

Manual and automatic calibration approaches are used to calibrate rainfall-runoff models (Sawunyama, 2008). Manual calibration requires an experienced user to adjust parameters interactively in successive model runs to improve results. The quality of the model fit to observed time series, human judgements, and one of more objective functions (e.g. the Nash-Sutcliffe Efficiency) is used during manual calibration (Nash and Sutcliffe, 1970).

A computer algorithm is used during the automatic procedures to search the parameter space by performing multiple runs of the model for example the Shuffled Complex Evolution method (Duan *et al.,* 1992; Vrugt *et al.,* 2003). Ideally, this calibration approach should be able to define an optimum parameter set which normally cannot be achieved with manual calibration. Both the manual and automatic model calibration approach have advantages and disadvantages (Table 2.1).

Table 2.1. Advantages and disadvantages of model calibration approaches (Moradkhani and Sorooshian, 2008).

Calibration approach	Advantage	Disadvantage
Manual	Parameter values can be selected so that they are hydrologically meaningful	Inherent subjectivity, Derived parameters are biased with no clear point at which the calibration process is said to be complete
Automatic	Computer does most of the work The procedure is objective	Numerical exercise that produce parameters that may lack meaning

2.2.2 Model validation approaches

Hydrological model validation is the process where the calibrated model is run with an independent set of data or an independent period of the same data record, after the calibrated parameter values are generalised and assessed to find whether or not they are suitable (Kapangazwiri, 2008). The model is said to be validated when there is an acceptable fit between the simulated and the observed streamflow (Sawunyama, 2008).

2.3 HYDROLOGICAL SIMULATIONS IN UNGAUGED BASINS

2.3.1 Uncertainty in hydrological modelling

Understanding, quantifying as well as reducing uncertainty are the three critical aspects to be considered in order to adequately address uncertainty in hydrologic modelling and prediction (Liu and Gupta, 2007). Uncertainty in hydrological modelling may arise from several sources, whether it is from only one source at a time or a combination of them all, they include: model structure, parameters, initial conditions as well as the input data used to drive and evaluate the model (Liu and Gupta, 2007). However, it is often difficult to separate model structure uncertainty from parameter value uncertainty because the parameters are not independent of the model structure (Beven and Binley, 1992).

The use of extremely approximated information, future projections (specifically climate projections), lack of good observed data, a lack of a good understanding for reducing uncertainties as well as large basins with many sub-catchments are all causes of water resource assessments uncertainties (Kapangaziwiri, 2010). A major cause of uncertainty noticed in the available data is the uncertainty associated with scale. Raster format data (usually collected by satellites) have different resolutions and the data is usually shown at a global scale. Global scale data is usually shown at low resolution, therefore data quality is lost if the user decides to focus on a small area on that map. The user should therefore ensure that the data with the highest resolution are used. Another reason for data uncertainty is the exclusion of some data layers during the initial creation of a specific data layer. However, this form of uncertainty is usually difficult to avoid due to the lack of data as well as the complexity of creating one data layer from various other data sources. Good quality observation data, or even just observed data in general, can be difficult to obtain. Missing data and gaps within data were also sources of uncertainty, but most of this data can be fixed through data processing, such as patching.

2.3.2 A typology of uncertainty in hydrological modelling

Uncertainties in hydrological modelling are a result of the natural complexity and variability of hydrological systems as well as a lack of knowledge of the hydrological processes (Kundzewicz, 1995). Uncertainty differs from error because; the latter represents a specific departure from "reality" (Beven, 2000).

2.3.2.1 Definitions of uncertainty

Various definitions of uncertainty have been proposed (Moellering, 1988; Taylor and Kuyatt; 1993; Goodchild, 1994; Klir and Wierman, 1999; Mowrer and Congalton, 2000). However there has been little consensus on a universally accepted definition. Mowrer and Congalton (2000) defined spatial uncertainty as "the estimation of errors in the final output that result from the propagation of external (initial values) uncertainty and internal (model) uncertainty." Zimmermann (2000) suggested "uncertainty is a phenomenon, a feature of real world systems, a state of mind or a label for a situation in which a human being wants to make statements about phenomena." Another question is "whether uncertainty is an objective fact or just a subjective impression which is closely related to individual persons?" Sayers *et al.* (2002) defines uncertainty as a general concept that reflects our lack of sureness or knowledge about outcomes which may be important in decision making. This study will use the definition by Sayers *et al.* (2002) which is arguably less complex.

2.3.2.2 Types of uncertainties

Plate and Duckstein (1987) classified uncertainties into data uncertainties (e.g. measurement errors), sampling uncertainties (e.g. sample size errors), parameter uncertainties or model structural uncertainty (empirical equations and scaling laws), while Bernier (1987) distinguished between natural uncertainty, technological uncertainty, sampling errors and model structure uncertainty. Melching (1995) distinguished between uncertainties related to: (1) natural variability of climate and hydrological data; (2) errors in input data including precipitation, evapotranspiration and temperature; (3) errors in data that was used for model calibration and validation; (4) use of inappropriate model parameters; and (5) making use of an incomplete or imperfect model structure. The source of uncertainties for (1), (2) and (3) is dependent on the quality of the data source and are independent of the model, whereas (4) and (5) are more model dependent (Sawunyama, 2008). All those sources of uncertainties influence the disagreement between the observed and simulated outputs in hydrological modelling. Another typology of uncertainty proposed by the Environmental Agency (as cited by Sawunyama, 2008) is shown in Table 2.2.

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Table 2.2. A simple typology of uncertainty (Sawunyama, 2008).

Type of uncertainty		**Sources of uncertainty**
Real world environmental uncertainty		• Randomness observed in nature • Inherent variation in natural hydrological response systems
Knowledge uncertainty (this is a reducible form of uncertainty and is associated with ignorance or incomplete information)	Model input data uncertainty	Climate data and hydrological data • Missing/inaccurate records • Non-representative spatial and/or temporal data • Inappropriate spatial/temporal resolution • Data processing
	Model structural uncertainty	Conceptual framework • Spatial and temporal averaging of a model • Ambiguous boundary conditions • Wrong process presentation
	Parameter uncertainty	Lumping of parameters and scale issues • Parameter estimation process • Choice of objective functions • Use of inappropriate parameters • Parameter sensitivity and interactions

A discussion of the main sources of uncertainty is presented in the next sections.

2.3.3 Input data uncertainty

Data sparse regions such as southern Africa have high levels of uncertainties associated with the main climate inputs to hydrological models (Görgens, 1983; Hughes, 1995; Sawunyama and Hughes, 2008). Unfortunately this is unavoidable to a large extent because of the low gauging densities and the rainfall gradients associated with the steep topography of mountainous areas (Hughes and Mantel, 2010). Data scarcity as well as a decline in hydro-meteorological networks causes high uncertainty in regional hydrological predictions. This may also lead to the introduction of errors when interpolation methods are applied across space and time based only on data from a few available observation stations or periods (Jung *et al.,* 2012). Input data used to force (rainfall and evaporation) and calibrate (discharge) hydrological models are associated with errors due to measurement and estimation errors.

- Precipitation data - The spatial and temporal variability in rainfall contribute to uncertainty in precipitation data (Pechlivanidis *et al.,* 2011). Generally, precipitation uncertainty is regarded as the dominant source of uncertainty in rainfall-runoff modelling (Gupta *et al.,* 2005).
- Evaporation input data - Potential evaporation is calculated from variables such as temperature, wind speed, relative humidity and radiation. In turn, uncertainties in the evaporation data arise from the data used in the calculations as well as the methods used for the calculation (Sawunyama, 2008). However, uncertainties in precipitation are considered to be more serious than uncertainties in evaporation, in most of the applications used today (Gupta *et al.,* 2005).
- Discharge data - Even though discharge values are not direct measurement, but instead estimates of the real and unknown discharge values, their uncertainty in practical applications are rarely presented (Herschy, 2002).

2.3.4 Model structural uncertainty

Models are inevitably imperfect approximations of complex natural systems since they are a simplification of the real world (Liu and Gupta, 2007). Given that rainfall-runoff models are simplified representations of the real world, the choice of model assumptions for process descriptions are often a key aspect in the model structure (Beven, 1989). The assumptions may exist in the conceptualisation and mathematical formulations of the model structures as well as the computer coding. Conceptualisation without appropriate approximations and omissions can result in large errors in the conceptual structure of a numerical model. These errors are usually also poorly understood. Structure errors are also caused by the mathematical implementation, such as spatial and temporal discretisation, that transforms a conceptual model into a numerical model (Neuman, 2003).

2.3.5 Parameter uncertainty

Model parameters are often conceptual and must therefore be estimated indirectly (Liu and Gupta, 2007). Model parameters are classified as physical or process parameters (Sorooshian and Gupta, 1995; Figure 2.1). Physical parameters can be measured directly independent of the observable river basin responses while; process parameters cannot be measured directly and need to be inferred by indirect means (Gupta *et al.,* 1998). The term parameter estimation is synonymous with other terms, such as model calibration, parameter optimisation, data assimilation, inverse problems and parameter tuning amongst others (Liu and Gupta, 2007). A model needs to be calibrated in order to simulate the observed response of a river basin for an historical period for which forcing data (rainfall) and system output data (runoff) are available (Moradkhani and Sorooshian, 2008). Even though a wide variety of model calibration techniques have been developed, the trial and error procedure, or so called manual calibration, is the most basic approach to obtain the model parameters (Moradkhani and Sorooshian, 2008).

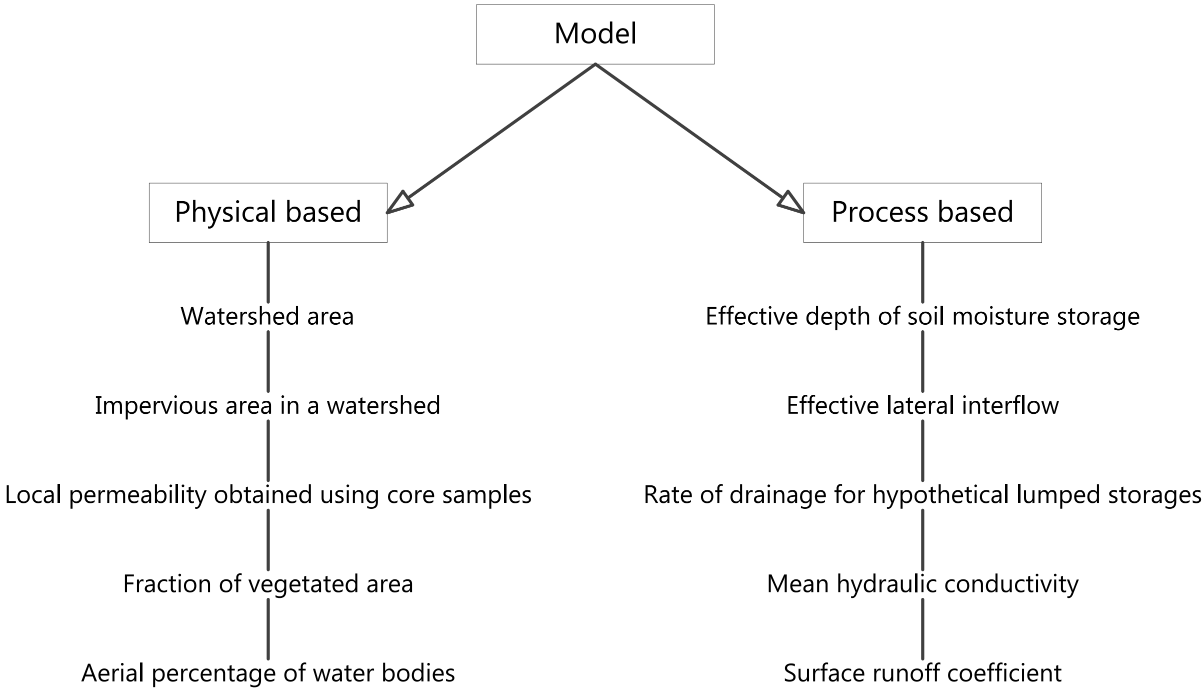

Figure 2.1. Classification of model parameters (Source: Moradkhani and Sorooshian, 2008).

2.4 AN OVERVIEW OF UNCERTAINTY ESTIMATION APPROACHES

2.4.1 Sensitivity analysis

Sensitivity analysis is an attempt to identify the key parameters that affect model performance. It plays important roles in model parameterization, calibration, optimization, and uncertainty quantification (Sawunyama, 2008; Song *et al.*, 2015); and it is used to decide where focus should be placed to reduce uncertainty. Sensitivity analysis studies of rainfall-runoff models assessed the sensitivity: (1) to rainfall input data (Andréassian *et al.*, 2001; Fekete *et al.*, 2004); (2) to potential evapotranspiration input data (Andréassian *et al.*, 2004; Oudin *et al.*, 2005; Xu *et al.*, 2006), as well as; (3) to model structure and parameter values (Butts *et al.*, 2004; Vrugt *et al.*, 2005). While uncertainties caused by input data and parameters seem to be the most important; model performance may be more influenced by model structure uncertainty (Sawunyama, 2008). Thus far, there are many studies of sensitivity analyses for the southern Africa region (see Montanari, 2007; Hughes *et al.*, 2010; Kapangazwiri *et al.,* 2012), however, there is a need for further research by making use of models developed in the region that are applicable to a wide range of climate conditions and spatial scales.

2.4.2 Approaches of estimating uncertainty in hydrological modelling

Various approaches are used to quantify uncertainty in hydrological model outputs. They include (Sawunyama, 2008):

- Monte Carlo Simulation (MCS) – uniform random sampling of parameters and the subsequent determination of model outputs (Beven and Binley, 1992).
- *Latin hypercube simulation (LHS)* – a stratified approach that efficiently estimates the statistics of an output by dividing a probability distribution of each basic variable into N ranges with an equal probability of occurrence (1/N) (Helton and Davis, 2003).
- Rosenblueth's point estimation method (RPEM) – a point-probability distribution is used to estimate the statistical moments (mean and covariance) of an output (Rosenblueth, 1981; Binley *et al.,* 1991).
- Harr's point estimation method (HPEM) – the estimation of the statistical moments of the model output for a given number of parameters and model runs (Harr Milton, 1989).
- The first order uncertainty analysis method – a Taylor series expansion approximate linearization (MFORM) that uses the mean of a parameter range (Melching *et al.,* 1990). There is also an improved approach (AFORM) that uses a 'likely' point and not the mean (Melching, 1992).
- Bayesian uncertainty analysis methods – estimate model uncertainty by combining prior information regarding the uncertainty of model inputs with the ability of different parameter sets so that the available data on state variables can be described (Sawunyama, 2008).

- Multi-objective approaches – the evaluation of uncertainty by making use of predictions that are based on some Pareto "optimal" parameter sets (Gupta *et al.,* 1998; Yapo *et al.,* 1998).
- The Generalised Likelihood Uncertainty Estimation (GLUE) – it rejects the concept of an "optimal" parameter set in favour of the equifinality concept (Beven and Binley, 1992). This allows for multiple acceptable models or parameter sets that is based on some likelihood measures and performance thresholds (Sawunyama, 2008). It has been developed in the context of multiple sources of uncertainty in real problems and an expectation that the structure of the errors is complex and non-stationary (Jin *et al.,* 2010).

Unfortunately, most of the aforementioned estimation methods do not separate the different sources of uncertainty in rainfall-runoff modelling because their primary emphasis is on parameter estimation uncertainty. However, appropriate procedures are being developed to estimate and capture the propagation of different sources of uncertainty into model output uncertainty (Sawunyama, 2008). They include:

- Simultaneous data assimilation and parameter estimation (Moradkhani *et al.*, 2005);
- Simultaneous uncertainty estimation of input data and parameter estimation (Kavetski *et al.*, 2003);
- Bayesian total error analysis to capture the combined impacts of input data, parameter and model structure uncertainty (Kavetski *et al.,* 2006; Kuczera *et al.*, 2006).
- The Integrated Bayesian Uncertainty Estimator (IBUNE) approach to capture input, parameter and model structural uncertainties (Ajami *et al.,* 2007).

2.5 REDUCING UNCERTAINTY IN HYDROLOGICAL MODELLING

Uncertainty in rainfall-runoff modelling outputs can only be quantified and reduced once the uncertainty in all of the different uncertainty sources, as well as the relationships between them, are understood. There are three main areas where actions can be taken to reduce uncertainty in hydrologic predictions (Liu and Gupta, 2007):

i. Acquisition of more improved and higher quality hydrological data by developing improved measurement techniques and observation networks;

ii. Development of improved hydrologic models by incorporating better representations of physical processes and using better mathematical techniques;

iii. Development of efficient and effective techniques that can better extract and assimilate information from the available data via the model identification and prediction processes.

2.5.1 Reducing input data uncertainty

Spatial representation and point measurement accuracy is some of the critical issues with the most important hydrological inputs, such as rainfall (Sawunyama, 2008). Unfortunately, adding to the issues is the relative sparseness and continuous decline of observation networks in southern Africa (Hughes, 2004). Spatially averaged information should be improved to reduce uncertainty related to incomplete spatial coverage of in-situ measuring networks and accuracy methods of interpolating data from point observations. So far, several studies on the use of radar-based (Moore and Hall, 2000, Borga, 2002, Carpenter and Georgakakos, 2004) or satellite-based (Hsu *et al.,* 1999; Koster *et al.,* 1999; Sorooshian *et al.,* 2000; Grimes and Diop, 2003) information to derive rainfall estimates have been reported. Satellite-based estimates are particularly favourable because, they are generally freely available and, provide direct basin spatial averages in sparsely gauged areas.

2.5.2 Reducing model structural and parameter uncertainty

The dynamic multiscale interactions among different hydrological processes might not be captured adequately in any particular model structure. Displacement of errors from structure to parameters can occur when calibrating single models for dynamic catchments because of the multiple dominant processes that exist there. This will in turn lead to over-correction and biased predictions (Moges *et al.,* 2016). Current hydrological research, such as the Prediction in Ungauged Basins (PUB) initiative of the International Association of Hydrological Sciences (IAHS), strongly focuses on the reduction of model structural and parameter uncertainty as part of any model evaluation (Refsgaard *et al.,* 2006; Hrachowitz *et al.,* 2013). It is necessary to go beyond finding justifiable assumptions about the model structure, to select a set of parameters that satisfy some conditions of model acceptability. It is, therefore, important to develop improved model structures that are based on a better understanding of physical processes and a better mathematical representation (Sivalapan *et al.,* 2003). While a number of studies have quantified model structural uncertainty (Yapo *et al.,* 1998; Vrugt *et al.,* 2003), very few have attempted to reduce it (Sawunyama, 2008). Instead, a lot of effort has been put on reducing parameter uncertainty (Beven and Binley, 1992; Thiemann *et al.,* 2001; Vrugt *et al.,* 2003; Kapangazwiri *et al., 2012).* The approaches used to reduce parameter uncertainty are dependent on the methods of calibration or regionalisation (for ungauged basins) as well as the model structure and the objectives of a specific study (Sawunyama, 2008). The following methods are used to reduce parameter uncertainty:

- Physically-based parameter estimation (e.g. Yadav *et al.,* 2007; Kapangazwiri and Hughes, 2008);

- Using alternative information such as remote sensing (Franks *et al.,* 1998; Boegh *et al.,* 2004);
- Data assimilation – using more information to constrain parameters (Moradkhani *et al.,* 2005; Vrugt *et al.,* 2005).
- General Probabilistic Framework (GPF) for uncertainty and global sensitivity analysis of deterministic models – the results of the framework can be used in a loop for model improvement, parameter estimation or model simplification (Baroni and Tarantola, 2014).
- The Integrated Parameter Estimation and Uncertainty Analysis Tool (IPEAT) – an input error model and modified goodness-of-fit statistics to incorporate uncertainty in parameter, model structure, input data as well as the calibration/validation data in watershed modelling (Yen *et al.,* 2014).

2.6 THE PITMAN MODEL

The Pitman model is a conceptual type that has been used extensively in southern Africa, and many studies have been published about the development and testing of the uncertainty approaches for the application of the model (Hughes, 2016). The model operates on a sub-basin or nodal distribution scheme and each of the sub-basins have their own climate inputs and parameter sets (Hughes, 2013). The Spatial and Time Series Information Modelling (SPATSIM, Hughes and Forsyth, 2006) version of the Pitman model (Pitman, 1973) was used in this study. The modelling framework facilitates the storage and management of the types of data used in the environmental modelling and also provide direct links to various models and procedures for data analysis (IWR, 2017).

CHAPTER 3
Study Areas

3.1 BACKGROUND

The Mogalakwena and Shashe sub-basins are modelled at the quaternary catchment and sub-zone scale, respectively. A quaternary catchment, or fourth order catchment, is a hierarchal classification system in which the primary catchment is the major unit. They are on average approximately 650 km^2 in size (Nel *et al*, 2011). It is the smallest operational unit and, until very recently, the finest spatial level of data resolution (Maherry *et al.,* 2013). The sub-zone scale is generally used in Zimbabwe and refers to divisions within a planning area which are usually centred on a focal point (Data.gov.sg, 2014). In this case the focal point would be runoff stations. Both delineations are used for general planning purposes and the level of the quaternary catchments constitute the lowest, i.e. most detailed, level of operational catchments (Midgley *et al.,* 1994). Unfortunately, only South Africa, together with the geographical enclaves of Swaziland and Lesotho has been delineated by the Department of Water and Sanitation (then the Department of Water Affairs and Forestry) into a hierarchical system of catchments, including quaternary catchments. Therefore, the same hierarchical system was not available for Botswana and Zimbabwe. Both sub-basins are therefore modelled at the lowest spatial level for water resources planning and management. However, even though these spatial units have different names, depending on the country in which they are situated, they will be referred to as catchments in this study.

The Shashe sub-basin, which straddles between Zimbabwe and Botswana, is drained by the Shashe River, a left bank tributary of the Limpopo River (Figure 3.1). The Mokgalakwena sub-basin is entirely located in South Africa and is drained by the

Mokgalakwena River, a right bank tributary of the Limpopo River (Figure 3.1). Because the sub-basins are located in different countries, both data availability and accessibility differ.

In South Africa, most hydrological data are freely accessible from the 1990, 2005 and 2012 Water Resources Studies , the Department of Water and Sanitation (DWS) and the Department of Agriculture, Forestry and Fisheries (DAFF). In both Botswana and Zimbabwe, there is a cost for accessing hydrological data. Moreover, the data is often outdated, records contain missing values, and large areas do not have data. The two sub-basins were therefore chosen due to the difference in data availability, accessibility, and the impact that the lack of input data might have on the model outputs.

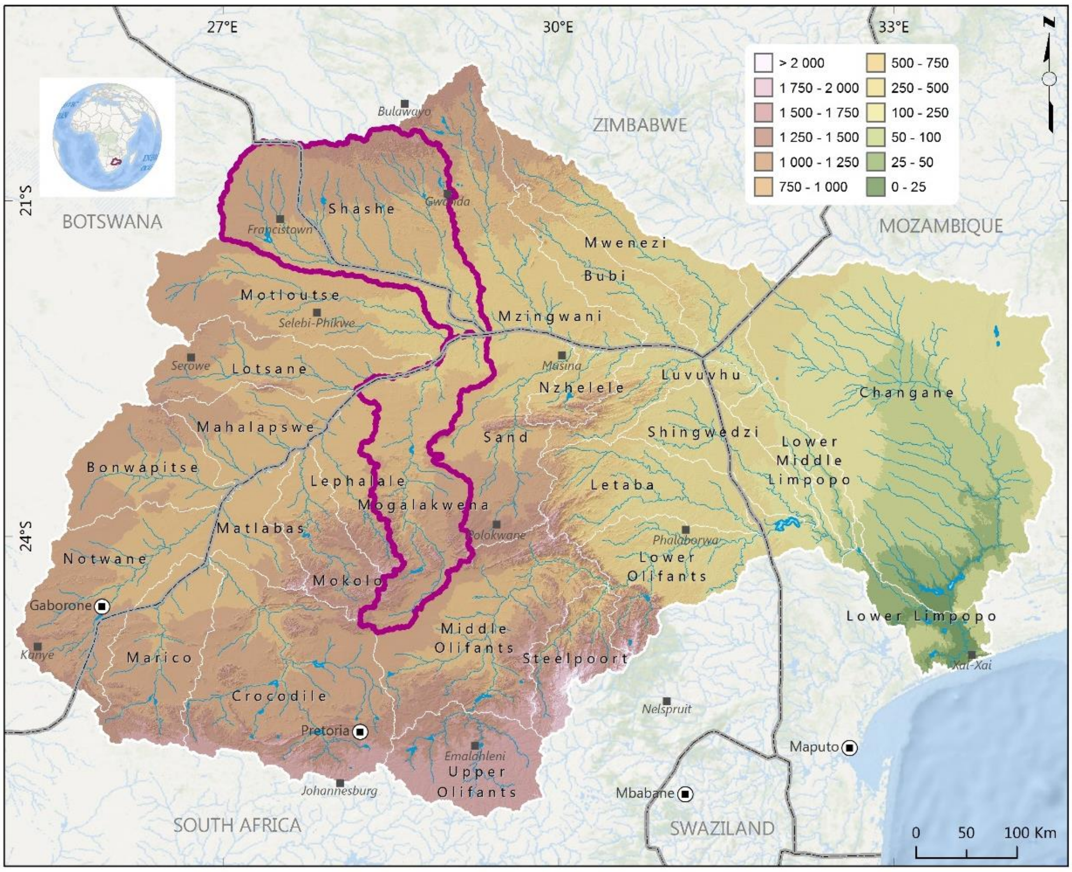

Figure 3.1. Location of the Mogalakwena and Shashe sub-basins.

3.2 THE MOGALAKWENA SUB-BASIN

The Mogalakwena sub-basin is located in South Africa and has an extensive drainage area of 19 400 km^2. It rises as the Nyl River south of Mokopane and is joined by the Sterk River (itself rising in the Waterberg Mountains) and flows northwards into the Limpopo River (Busari, 2008). The sub-basin is densely populated and industrialised and includes the towns of Modimolle, Mookgopong, Lephalale and Mokopane (Figure 3.2).

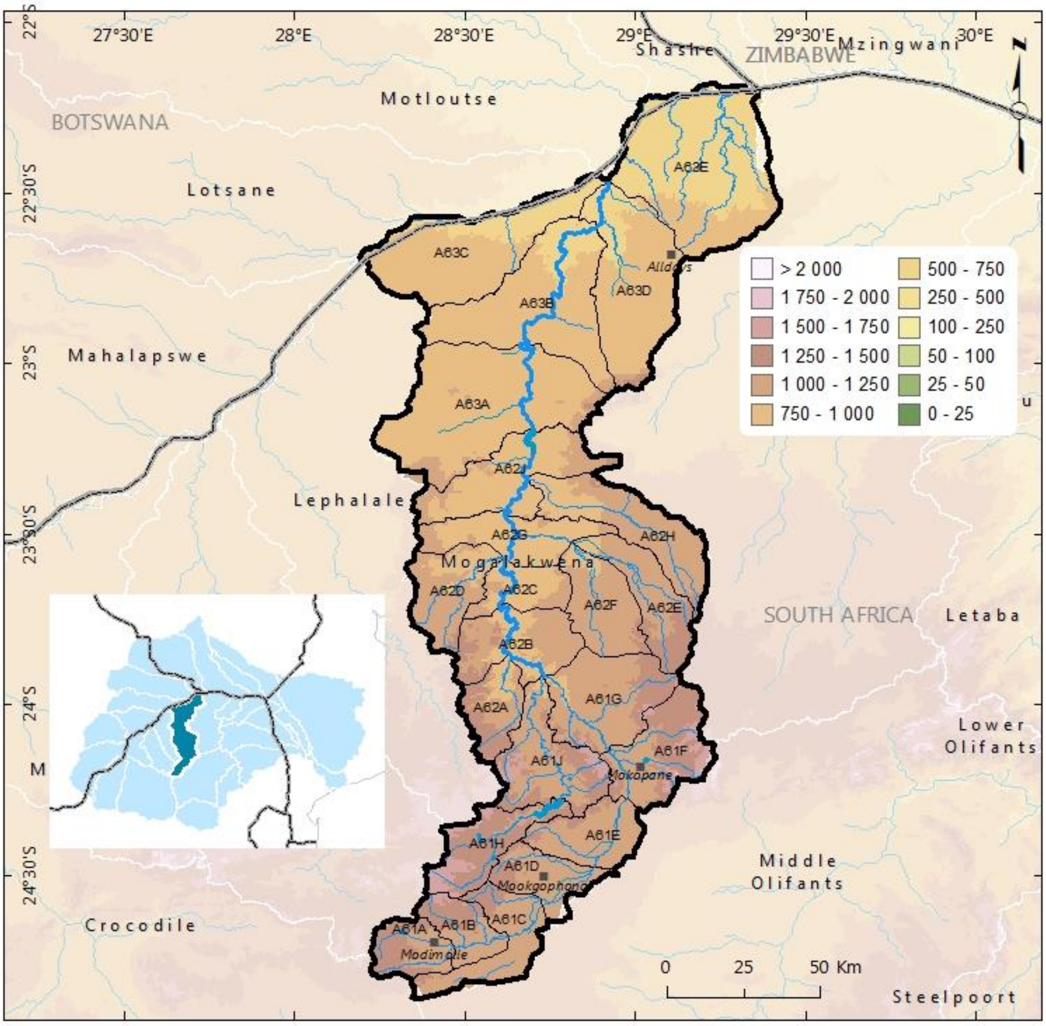

Figure 3.2. Location of the Mogalakwena sub-basin and its catchments (source: Bailey and Pitman, 2015).

3.2.1 Climate of the Mogalakwena sub-basin

Mogalakwena falls within the summer rainfall region (October – March). The Mean annual precipitation (MAP) decreases in the Northern direction towards the Limpopo River main stem from 800 to 300 mm a^{-1} (Bailey and Pitman, 2015). The mean annual potential evapotranspiration (MAE) ranges between 1700 to 2050 mm a^{-1} (Bailey and Pitman, 2015; LIMCOM, 2013).

The temperature correlates with the topography (Schulze, 1997). Summer and winter daily average temperatures decrease as the altitude increases. The summer temperatures range between 20 - 25^{o}C for the upper catchment where the altitude is highest and increase between 25 - 29.5^{o}C towards the Limpopo River main stem as the altitude decreases. Even though winter daily average temperatures are a lot lower than the daily summer temperatures, the same general pattern is observed. The mean winter temperature of the sub-basin ranges between 6.5 – 18^{o}C (LIMCOM, 2013).

3.2.2 Hydrology of the Mogalakwena sub-basin

3.2.2.1 Surface hydrology

The area of the Mogalakwena sub-basin is drained by the Mogalakwena River along with its tributary streams, most notably the Nyl River that is located in the upper reaches. The river system flows in a northerly direction originating in the area around Modimolle (Nylstroom) and joins the Limpopo River downstream of the Laphalala River (Figure 3.2). The flow patterns are variable and are influenced by either rainfall (average 540 mm) or dry spells during the winter season. However, the rivers only dry up during severe droughts. Most of the tributary streams only flow during the summer months. The Nylsvlei is the most important wetland in the sub-basin and is situated between Modimolle and Mookgopong and is South Africa's largest ephemeral floodplain. It has been declared a RAMSAR wetland site because of its international conservation importance and birdlife (Lombaard and Pieterse, 2015). It plays an important role in attenuating the flows from the Nyl River to the Mogalakwena River (Ashton *et al.,* 2001).

The distribution of the runoff clearly reflects the distribution of the rainfall and evaporation of each catchment. The runoff is higher for the upper part of the Mogalakwena catchment. However, high variations are observed with some quaternary sub-basins experiencing very low runoff values with adjacent quaternary sub-basins experiencing much higher values (e.g. A62B and A62C). It is, therefore, important to model at a catchment scale because each catchment is influenced differently by natural and anthropogenic activities/processes such as dam constructions, agricultural activities, vegetation cover, rainfall, etc. These activities/processes will, in turn, affect the total amount of runoff that reaches the Limpopo River main stem.

3.2.2.2 Subsurface hydrology

Meyer and Hill (2013) calculated the percentage of the recharge capacity by considering the aquifer types within a catchment. The calculation was based on the assumption that the soil thickness is less than 5 m thick for 50% of the catchments and over 5 m thick for the remaining 50%. An average slope of 5% was used and the resultant recharge values were calculated as a percentage of the MAP (Meyer and Hill, 2013). Because groundwater recharge is dependent on rainfall volumes, a change in rainfall variability is therefore associated with an even larger variability in recharge volumes (Bredekamp *et al.,* 1995).

3.2.3 Geology of the Mogalakwena sub-basin

The geology of the Mogalakwena sub-basin is complex and varies between different types of formations as well as age. The upper reaches of the sub-basin are mostly underlain by a variety of porous consolidated and partially consolidated sedimentary strata, predominantly sandstones, quartzites and felsites of the Waterberg and Soutpansberg Groups. Acidic and basic granites and lavas of the Bushveld Igneous

Complex and the Transvaal Sequence intruded the Waterberg and Soutpansberg Groups, which in turn overlie the crystalline rocks of the Basement Complex (Anderson *et al.,* 2001). The upper reaches of Mogalakwena are, therefore, mainly underlain by harder igneous and volcanic rock. Areas of different types of sandstone, siltstones, and shales, which are favourable geology types for aquifer development and in turn, groundwater storage, are also present.

The Karoo Sequence which is dominant further downstream, consists of sequences of silicified sandstones and quartzites, followed by carbon-rich mudstones and shales, and then basalts. Large areas of the central parts of the sub-basin are overlain by recent (Quaternary) deposits of unconsolidated or poorly consolidated sandy material (Ashton *et al.*, 2001).

3.2.4 Pedology, land cover and land use

Soils in the sub-catchment can be divided into two distincts groups. Moderately deep sandy soils are found on the sloping and undulating terrain in the upper reaches of the sub-basin (Ashton *et al.,* 2001). Relatively shallow, coarse-grained sandy soils and silt deposits in flat and undulating terrain in the lower reaches of the sub-basin, particularly along the flood terraces of streams (Ashton *et al.,* 2001). Mosaic vegetation/croplands cover most of the sub-basin (

Table 3.1, 45.4%), followed by closed to open grassland (29.6%) and closed to open shrubland (11%). Although there is no afforestation in the sub-basin (Bailey and Pitman, 2015), alien vegetation cover about 239.4 km^2 of the total area.

Table 3.1. Land cover/use of the Mogalakwena catchment (Bontemps *et al.*, 2011)

Description	% of total area
Rainfed croplands	0.00
Mosaic Croplands/Vegetation	0.00
Mosaic Vegetation/Croplands	45.41
Closed broadleaved deciduous forest	0.71
Open broadleaved deciduous forest	8.17
Open needleleaved deciduous or evergreen forest	0.00
Mosaic Forest-Shrubland/Grassland	4.67
Mosaic Grassland/Forest-Shrubland	0.07
Closed to open shrubland	10.95
Closed to open grassland	29.56
Sparse vegetation	0.12
Artificial areas	0.19
Bare areas	0.00
Water bodies	0.11

3.2.5 Water use of the Mogalakwena sub-basin

In Mogalakwena, additional water supplies include the Modimolle Urban Regional Water Supply Scheme (RWSS) that is used to supply water to Modimolle via the Magalies Water pipeline from the Roodeplaat Dam (located in the Crocodile West River catchment) and additionally by the Donkerpoort dam (located near Modimolle). Mookgopong is mainly supplied by water from the Nel well-field and the Welgevonden Dam as part of the Mookgopong RWSS. The Mokopane RWSS gets water from the Doorndraai Dam and groundwater resources and is used to provide water to Mokopane, Mahwelereng and the AMPLAT Mogalakwena Platinum Mine along with other denser settlements. The Roodeplaat Dam (situated in the Crocodile West River catchment) is used to transfer an additional 2 million m^3/year to the Mogalakwena sub-basin, and approximately sixteen other smaller schemes are also identified (Lombaard and Pieterse, 2015).

3.2.5.1 Dams and water transfers of the Mogalakwena sub-basin

Many dams are located in the Mogalakwena sub-basin, ranging from large dams to hundreds of small farm dams that are used to supply water for domestic and irrigation purposes as well as livestock watering (Görgens and Boroto, 1999). Despite their size, these small farm dams are responsible for most of the reduced flows that now characterise the Mogalakwena River (Ashton *et al.*, 2001).

Table 3.2. Characteristics of the large dams located in the Mogalakwena sub-basin.

Dam name	Closest Town	watercourse	FSC* (1000 m^3)	Source
Doorndraai	Mokopane	Sterk river	46500	DWS
Glen Alpine	Tolwe	Mogalakwena River	18900	DWS
Haaskloof	Naboomspruit	Hanskloofspruit	20160	FAO
Rooiwal	Potgietersrus	Sterk river	-	FAO
Gert Combrink	-	-	-	DWS
Donkerpoort	Nylstroom	Klein Nyl	34200	FAO

* Full Supply Capacity

The large dams that are located in Mogalakwena are listed in Table 3.2 and Figure 3.3 shows several major dams and farm dams in the Mogalakwena catchment, mostly in the upstream areas.

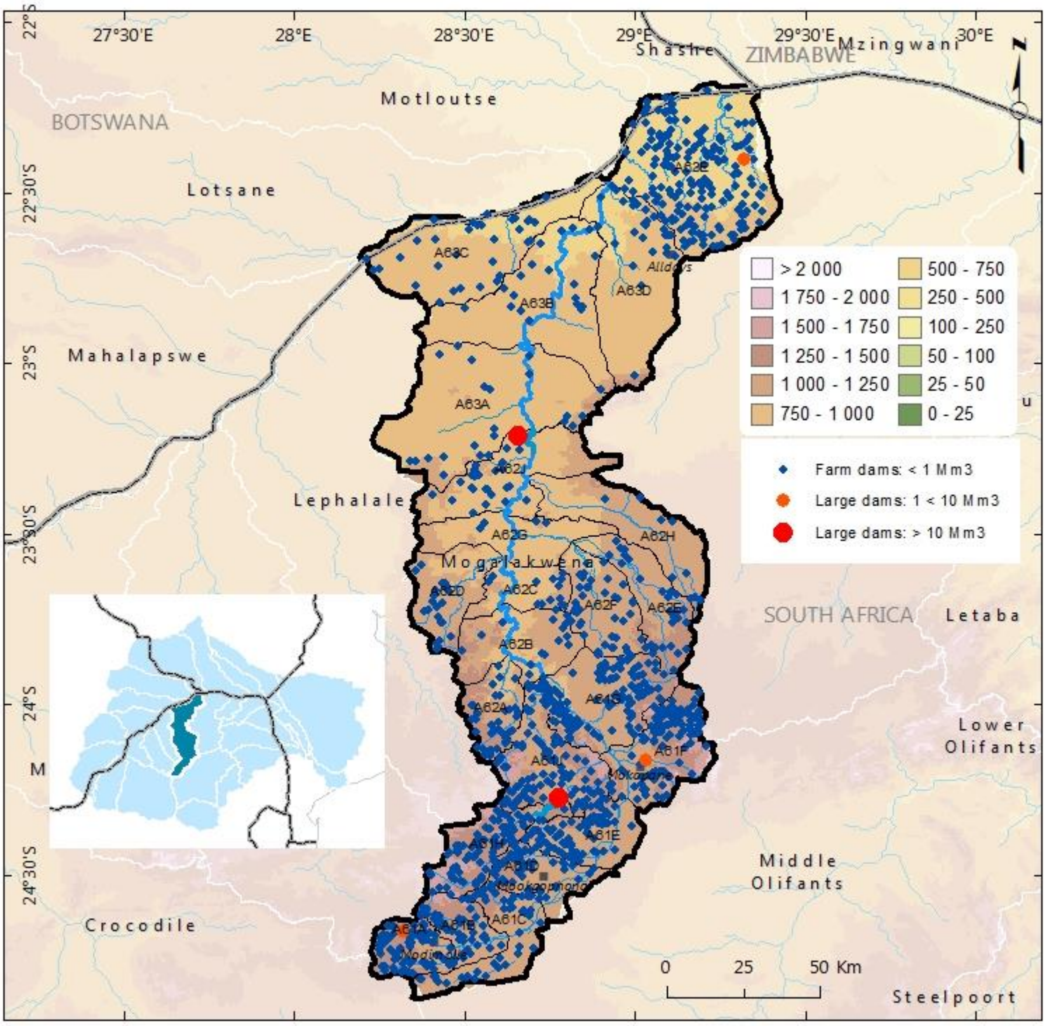

Figure 3.3. Major and farm reservoirs of the Mogalakwena sub-basin.

3.2.5.2 Irrigation in the Mogalakwena sub-basin

Extensive irrigation areas along the Mogalakwena River consume most of the water used in the central and upper reaches of the sub-basin. Subsistence farming are dominant in the central and eastern portion of the sub-basin and they rely on boreholes and hand-dug wells for their water supplies (Ashton *et al.,* 2001).

The surface water resources in Mogalakwena are limited. Therefore the irrigation sector extensively exploits the large groundwater resources of the catchment. It has two large dams; Doorndraai Dam that supplies domestic and irrigation requirements and Glen Alpine Dam that supplies only irrigation water. Irrigation areas are concentrated in the Moorddrift area near Mokopane, the central part of the catchment (Gillimburg area) and the areas surrounding the Glen Alpine Dam, and groundwater is used to supply water to approximately 60% of the irrigation in the catchment (Lombaard and Pieterse, 2015). The total irrigated area for Mogalakwena is 147.54 km^2 (Bailey and Pitman, 2015), but these values differ between sources.

3.2.6 Catchment delineation of the Mogalakwena sub-basin

The Mogalakwena has a total of 23 quaternary catchments (Table 3.3).

Table 3.3. Characteristics of the catchments of the Mogalakwena sub-basin (after Bailey and Pitman, 2015).

Sub-basins	Area (km^2)	MAP ($mm\ a^{-1}$)	MAPE ($mm\ a^{-1}$)	MAR ($mm\ a^{-1}$)	Recharge as 4% of MAP ($mm\ a^{-1}$)
A61A	381	629	1700	22.01	25.16
A61B	362	625	1700	11.11	25
A61C	587	608	1741	7.84	24.32
A61D	456	630	1734	11.89	25.2
A61E	547	615	1738	11.23	24.6
A61F	789	597	1800	16.72	23.88
A61G	927	585	1800	16.05	23.4
A61H	585	636	1700	29.94	25.44
A61J	818	631	1750	33.36	25.24
A62A	428	610	1800	17.56	24.4
A62B	710	529	1850	16.31	21.16
A62C	385	478	1900	5.8	19.12
A62D	603	489	1900	9.11	19.56
A62E	621	460	1850	5.51	18.4
A62F	620	478	1850	3.35	19.12
A62G	627	437	1900	6.22	17.48
A62H	871	439	1900	5.88	17.56
A62J	930	450	1950	6.25	18
A63A	1928	433	1950	13.64	17.32
A63B	1505	394	2000	9.01	15.76
A63C	1323	378	2050	6.61	15.12
A63D	1319	412	2000	5.57	16.48
A63E	1992	358	2050	8.36	14.32

The catchments represent different climate regimes and physical properties. However, some of the differences are very small due to the small size of the catchments. Therefore, different hydrological response characteristics are considered. The main characteristics of the sub-basins that will be modelled is listed in Table 3.3.

3.3 THE SHASHE SUB-BASIN

The Shashe sub-basin (18 991 km^2) is shared between Botswana and Zimbabwe, with the largest portion of the catchment situated in Zimbabwe (Figure 3.4). The Shashe River, also known as the Shashi River, rises on the border between Botswana and Zimbabwe. It flows south, past Francistown, and then southeast along the border for about 362 km until it flows into the Limpopo River where Botswana, Zimbabwe and South Africa meet. The confluence is at the site of the Greater Mapungubwe Transfrontier Conservation Area. Major tributaries of the Shashe River include the Simukwe, Shashani, Thuli, Tati and Ramokgwebana rivers.

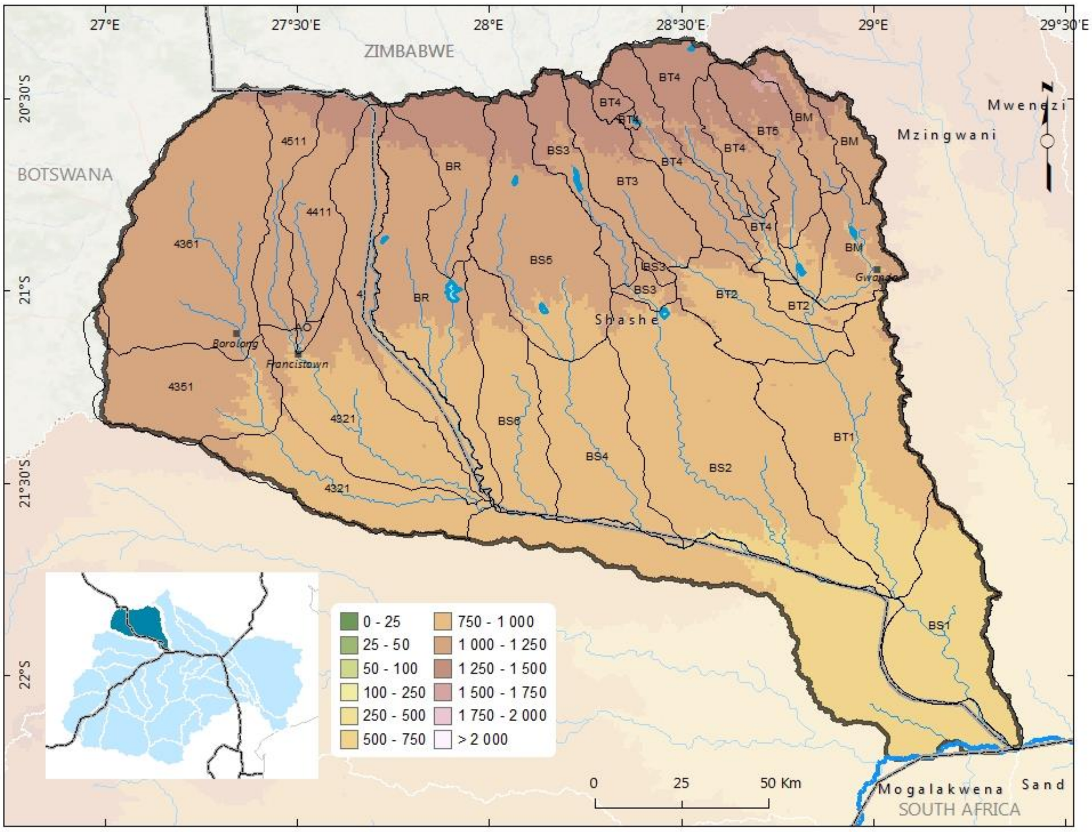

Figure 3.4. Map of the Shashe sub-basin and its catchments

3.3.1 Climate of the Shashe sub-basin

Shashe is located in a low rainfall region especially the part located in Botswana which experience rainfall of around 400 mm a^{-1}. In the Zimbabwean portion of the sub-basin, MAP varies between 350-600 mm a^{-1} (LIMCOM, 2013). The rainfall is highest in the upstream areas for both catchments and decreases towards the Limpopo River main-stem. The mean annual potential evapotranspiration (MAE) ranges between 1800 to 2600 mm a^{-1} (LIMCOM, 2013). Potential evapotranspiration rates are highest in the Botswana portion of the sub-basin which reflects drier conditions in that area. MAE exceeds rainfall which is typical of semi-arid regions. The sub-basin experiences temperature similar to those of the Mogalakwena sub-basin.

3.3.2 Hydrology of the Shashe sub-basin

3.3.2.1 Surface hydrology of the Shashe sub-basin

The flow pattern in this river is variable as a result of the prevailing low and unpredictable rainfalls (average 540 mm) though the river is normally perennial and only dries up during severe droughts. Summer rainfalls cause a dramatic increase in the flows of this river, though most of the tributary streams are highly seasonal and tend to flow only during the summer months. The Mogalakwena sub-basin goes through a five-year rain cycle in which the river is virtually dry for five years, followed by another five years in which there is sufficient water flow. The Nylsvley floodplain, a 242.5 km^2 Ramsar site, attenuates the flows contributed by the Nyl River to the Mogalakwena River (Ashton *et al.,* 2001).

Major tributaries of the Shashe River include the Simukwe, Shashani, Thuli, Tati and Ramokgwebana rivers (Ashton *et al.,* 2001). The Shashani is dammed at Gulameta, the Chavezi, a tributary of the Thuli, is dammed near Silobi, and the Ingwezi, a tributary of the Ramakwebana, is dammed near Domborefu. Small water supply dams on the Shashe River provide water for local communities and mining operations in Botswana, as well as small-scale irrigation farms (Ashton *et al.,* 2001).

3.3.2.2 Subsurface hydrology of the Shashe sub-basin

It is estimated that 65% of Botswana's water resources are derived from groundwater due to limited surface water resources (FAO, 2004).

3.3.3 Geology of the Shashe sub-basin

The Zimbabwe Craton underlies most of the sub-basin, including the Botswana portion. Important formations include: Gwanda Greenstone Belt, Lower Gwanda Greenstone Belt, Mphoengs Greenstone Belt and granitic terrain. The south is underlain by Limpopo Belt gneisses, and the far south (Thuli Village area) by Karoo basalts. Archaean granites and gneisses are intruded by numerous Greenstone belts, with associated Karoo System rocks and silicified sandstones in the western (Botswana) portion of the sub-basin (Ashton *et al.,* 2001).

3.3.4 Pedology, land cover and land use

Soils in the sub-basin can be divided into five groups ranging from moderate to very shallow depths:

- Moderately shallow, coarse-grained kaolinitic sands, derived from the granites;
- Very shallow to moderately shallow sandy loams, formed from gneisses;
- Very shallow to moderately shallow clays, formed from the Greenstone Belts;
- Shallow, clay soils with high sodium content in internally draining areas; and
- Very shallow sands, derived from the basalts (DRSS, 1979).

In the Shashe catchment (Table 3.4), mosaic vegetation/croplands has the highest surface area (34.81%), followed by closed to open grassland (33.1%) and closed to open shrubland (16.5%).

Table 3.4. Land cover/use of the Shashe catchment (Bontemps *et al.*, 2011)

Description	% of total area
Rainfed croplands	0.00
Mosaic Vegetation/Croplands	34.81
Closed broadleaved deciduous forest	2.82
Open broadleaved deciduous forest	6.89
Mosaic Forest-Shrubland/Grassland	5.37
Mosaic Grassland/Forest-Shrubland	0.03
Closed to open shrubland	16.52
Closed to open grassland	33.01
Sparse vegetation	0.04
Artificial areas	0.07
Bare areas	0.00
Water bodies	0.43

The Matobo National Park is located in the upper reaches of the Thuli River. Commercial farming, as well as private and resettlement land, is located south of the park. In the Botswana side of the catchment, land use consists of commercial farming of livestock and small irrigation areas along the rivers, with game ranching such as the Tuli Safari that is located in drier areas (Ashton *et al.,* 2001).

3.3.5 Water use in the Shashe sub-basin

The Botswana's North-South Carrier Water Transfer Scheme consists of two Phases. Phase-1 of the North-South Water Carrier Project transfers water from the Shashe Dam via Selebe-Pikwe to Gaborone (completed in 1999). Local water resources of the main towns including Palapye, Mahalapye, Palla Road and Mmamabula are supplemented on-route. Construction for Phase-II was estimated to start in 2012 and feeds on various dams, existing or newly emerging from the first phase. The pipeline is expected to deliver 45 Mm^3 of water per year (Bigen Africa Services, 2012).

3.3.5.1 Reservoirs and water transfers in the Shashe sub-basin

Shashe has predominantly large dams along with many small reservoirs and farm dams. The large dams, along with the smaller dams, supply practically all of the irrigation and urban water use (LIMCOM, 2013). Eight large dams are located in the Shashe catchment. However, even though these dams were identified, necessary information such as their purpose is not always available (Table 3.5).

Table 3.5. Large dams in the Shashe sub-basin (after LIMCOM, 2013)

Dam name	Closest settlement	Watercourse	Purpose	FSC (1000 m^3)
		Botswana		
Shashe	Tonota village	Shashe	Urban water supply	87.9
Ntimbale	-	Tati	Rural water supply	26.4
Dikgatlhong	Robelelavillage	Shashe	Urban water supply	400
		Zimbabwe		
Tuli Makwe	Gwanda	Tuli	-	6.1
Shashani	-	Shashani	-	27.3

* Full Supply Capacity

Also, many of the small reservoirs and farm dams had to be captured by making use of remote sensing methods accompanied by manual digitizing. Unlike Mogalakwena, the farm dams in Shashe are dispersed all over the sub-basin (Figure 3.5).

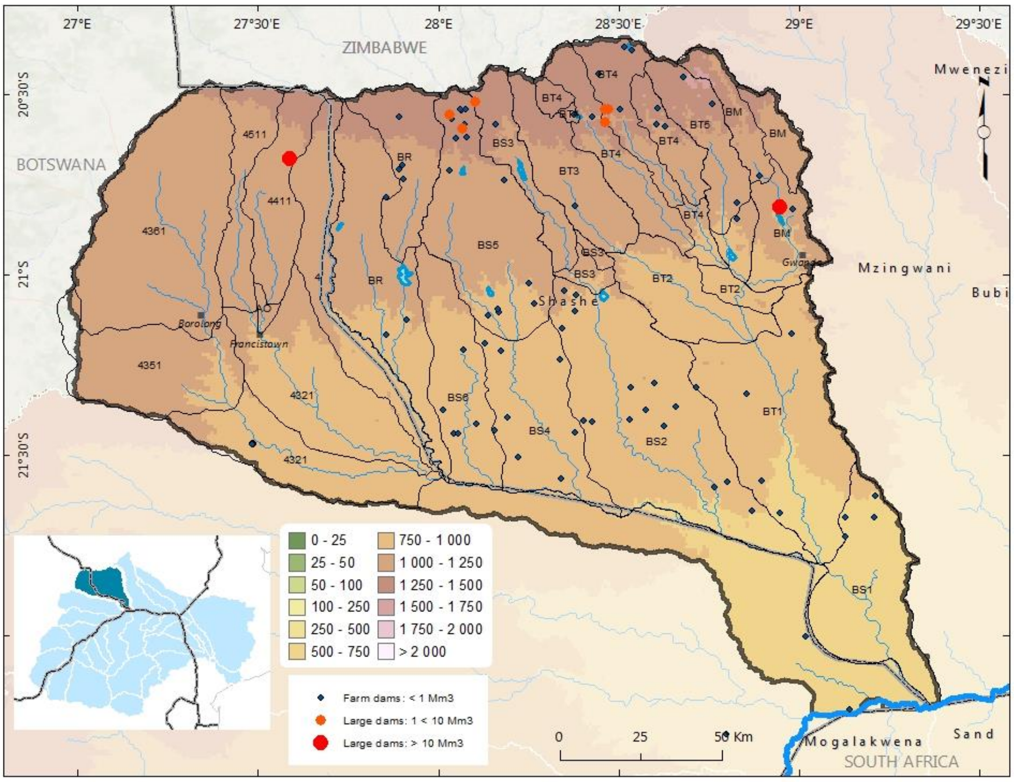

Figure 3.5. Locations of the dams in Shashe.

3.3.5.2 Irrigation in the Shashe sub-basin

In the Botswana portion of the Shashe catchment, some irrigation takes place along the Limpopo River main-stem. In Zimbabwe, irrigation water-use is shared by urban (towns), rural (primary) and industry (LIMCOM, 2013). The total irrigated areas for the Shashe catchments are listed in Table 3.6.

Table 3.6. Total irrigation areas for Shashe (LIMCOM, 2013)

Country	Sub-basin	Total Irrigated Area (km^2)
Zimbabwe	Ramakwebana	22.0
	Sansukwe	1.0
	Simukwe	11.0
	Shashani	30.0
	Tuli	36.8
Botswana	Shashe Upper	0
	Shashe Middle	0
	Shashe Lower	21
	Dati Upper	0
	Dati Middle	0
	Dati Lower	0
	Ntse	0

3.3.6 Catchment delineation of the Shashe sub-basin

The sub-basin is subdivided into 28 catchments. Table 3.7 shows the main characteristics of the catchments.

Table 3.7. Characteristics of the catchments of the Shashe sub-basin (LIMCOM, 2013).

Sub-basins	Area (km^2)	MAP ($mm\ a^{-1}$)	MAPE ($mm\ a^{-1}$)	MAR ($mm\ a^{-1}$)	Recharge as 4% of MAP ($mm\ a^{-1}$)
Zimbabwe					
BR-B64/72	818.1	537	1895	17.24	21.48
BR-Rest	1471.2				
BS6	1090.1	492	1902	-	19.68
BS5	1720.0	502	1904	-	20.08
BS4	1459.6	495	1904	-	19.8
BS3-Shashani	330.5	553	1910	16.63	22.12
BS3-B77	392.8				
BS2-B86	1582.4	500	1906	44.87	20
BS2-Kafusi	502.2				
BS1	408.3	415	1946	-	16.6
BT3	525.1	559	1919	-	22.36
BT4-B81	797.2	584	1939	17.68	23.36
BT4-B80	527.1				
BT4-B83	377.2				
BT4-B7	148.0				
BT5	766.5	582	1896	39.22	23.28
BM	944.0	575	1861	-	23
BT2-B87	877.4	528	1897	25.46	21.12
BT2-B31	534.4				
BT2-B9	488.6				
BT1-B85	1843.3	493	1912	193.7	19.72
BT1-Rest	1446.7				
Botswana					
Shashe Upper	3753.1	500	215.98	37	20
Shashe Middle	1021.7	400		-3	16
Dati Upper	408.0	500		59	20
Dati Middle	176.6	500		42	20
Dati Lower	1648.4	420		15	16.8
Ntse	840.7	500		34	20

CHAPTER 4
Datasets and general methods

4.1 INTRODUCTION

There are many parts of the Limpopo River basin where both observed rainfall and stream flow data are limited in terms of spatial coverage and lengths of record. There is little that can be done about the stream flow data, and it is inevitable that hydrological simulations will be difficult to validate and are therefore highly uncertain. Over the years technological advances such as remote sensing have been made in the methods used to collect data; computers also became more powerful and are now able to process vast amounts of data. In turn, the amount of data available for hydrological modelling has increased dramatically (Hughes, 2004). Moreover, the availability and accuracy of the data utilised by models have not kept pace with recent model developments and models are frequently expected to produce predictions based on insufficient and flawed data (Tanner and Hughes, 2015). With datasets originating from different sources, it is a daunting task to decide which one will provide the most accurate results when used in hydrological models. Input data uncertainties have been identified as a key problem in accurate modelling (Kleidorfer *et al.,* 2009).

This chapter discusses the various data collected and collated to set up and calibrate the Pitman model and the methods used to quantify uncertainties. The datasets used include climatic (rainfall and evaporation), hydrological (streamflow), physiographic (geology, soils, vegetation, and topography) and water use data (farm reservoirs, water abstractions, and irrigated area). Whenever possible, the data collection methods and sources will be identified and discussed.

Several organisations and private individuals provided data for the Mogalakwena sub-basin in South Africa. These include the South African Weather Service (SAWS), DWS, the Department of Agriculture, Forestry and Fisheries of South Africa (DAFF) and the Water Resources Studies of South Africa (WR2012, WR2005 and WR90). Data for the Shashe catchment, which straddles between Botswana and Zimbabwe, was inaccessible. Data from the Limpopo River Basin Monograph Study (LIMCOM, 2013), was assumed to be the least uncertain compared to data from other sources.

There are many parts of southern Africa where both observed rainfall and stream flow data are limited in terms of spatial coverage and lengths of record. There is little that can be done about the stream flow data, and it is inevitable that many of our hydrological simulations will be impossible to validate and are therefore highly uncertain.

4.2 HYDROLOGICAL AND CLIMATIC DATA

Input data and model parameters used to set up the model for both Mogalakwena and Shashe (Table 4.1) were sourced from the Limpopo River basin monograph study (LIMCOM, 2013) and were already assessed.

Table 4.1. Climatic and streamflow data analysed or used in this study.

Data type	Dataset	Country	Custodian	Availability	Used
Climatic	Rainfall	ZA	SAWS		No
		ZIM	LIMCOM	LIMCOM, 2013	Yes
	Evaporation	ZA	DWS		No
	Areal Rainfall	ZA	Public domain	WR2012	Yes
Stream flow	Runoff	ZA	LIMCOM	LIMCOM, 2013	Yes
		BOT	Department of Water Affairs		No

Nonetheless, not all of water use data including monthly irrigation demands and monthly water demands (e.g. for industrial/mining or domestic activities), was available and in turn the simulated flows are over simulated (Figure 4.1). Also, the only runoff station (A6H009) that provides adequate observed flow data is located at a large dam and large irrigation areas which in turn will have an impact on the recorded observed data due to various water abstractions. As a result, the difference between the long-term mean monthly simulated flows and observed flows is quite significant.

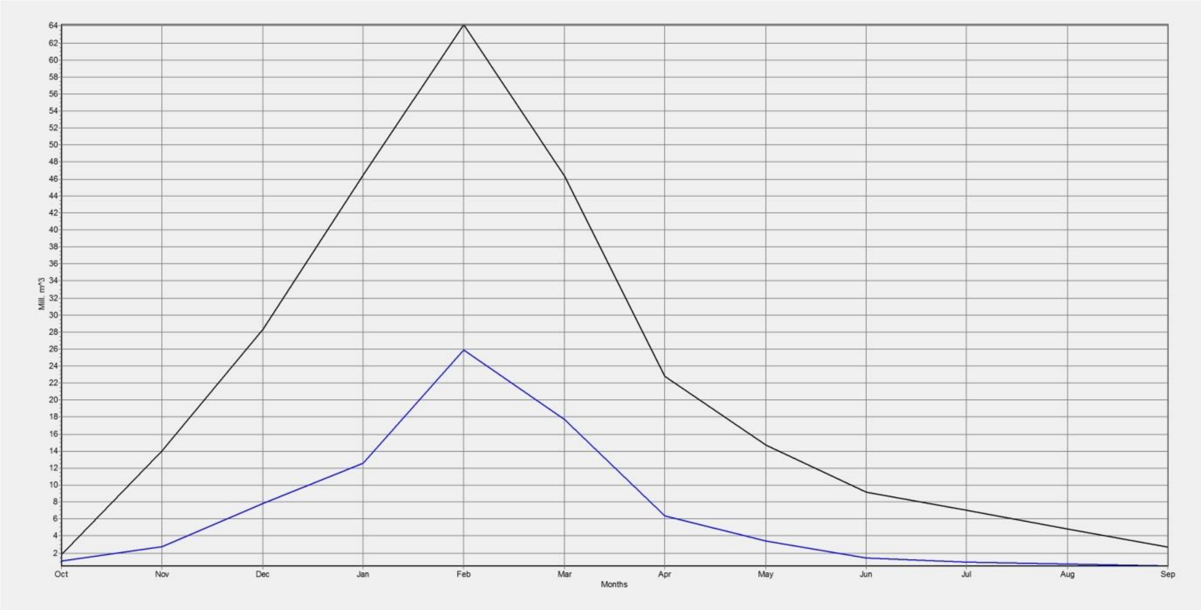

Figure 4.1. Monthly distribution of the Observed (blue) and simulated (black) flows for the Mogalakwena sub-basin.

4.2.1 Observed streamflow of the Mogalakwena and Shashe sub-basins

Monthly streamflow data required to calibrate the model is available from the DWS website. For modelling purposes, both WR2012 and LIMCOM (2013) downloaded the data and patched the missing values. They also discarded stations with too many missing values (Figure 4.2).

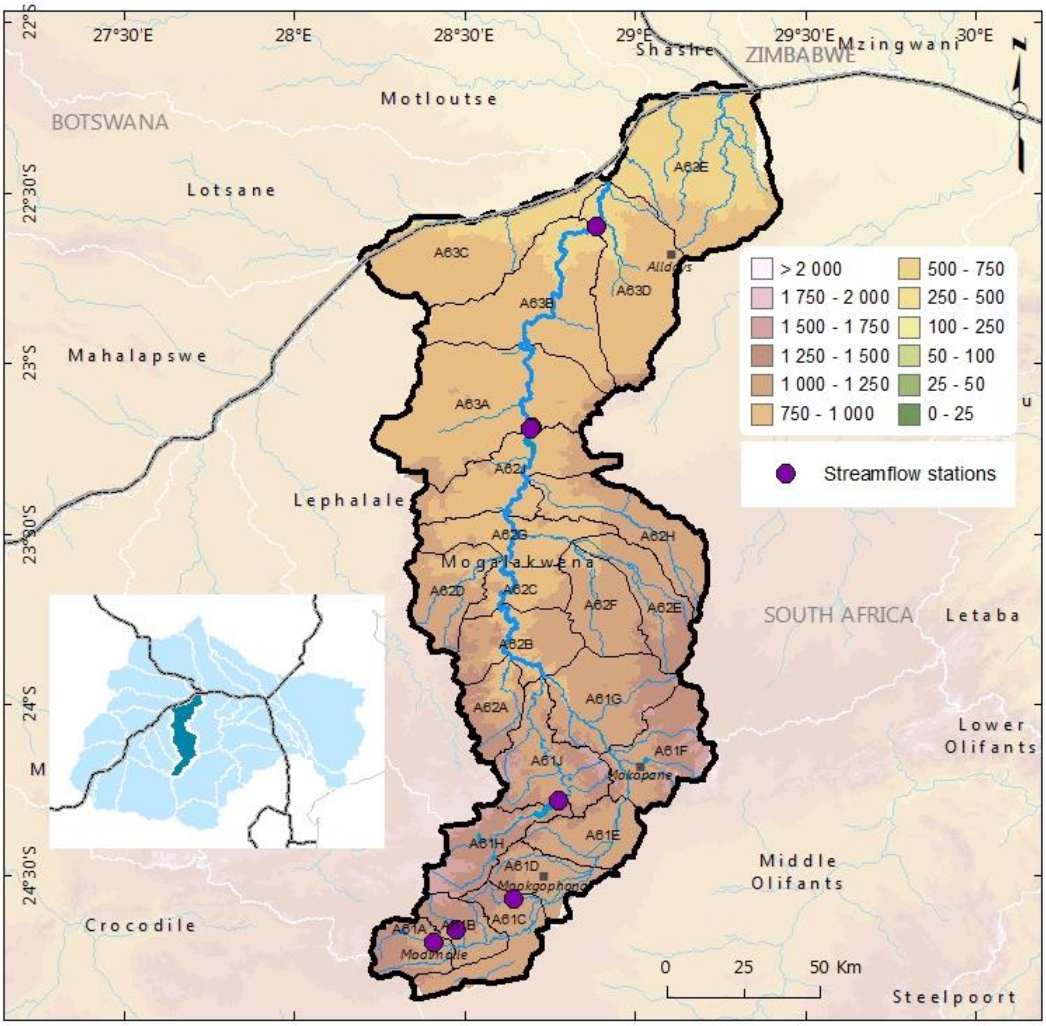

Figure 4.2. Streamflow stations in the Mogalakwena sub-basin

The observed streamflow data for the Shashe sub-basin (Figure 4.3) was obtained from LIMCOM (2013) which was in turn collected from other sources namely:

For Botswana:

- Botswana Department of Water Affairs;
- WR2005 Study (Middleton and Bailey, 2009);
- Limpopo River Hydrological Model Study (Boroto and Görgens, 1999); and
- Limpopo River Hydrological Model Update Study (Matji and Görgens, 2001).

For Zimbabwe:

- Zimbabwe National Water Authority; and
- Limpopo River Hydrological Model Study (Boroto and Görgens, 1999).

LIMCOM (2013) found that many records contain excessive periods of missing data and can therefore not be used for model calibration. The records that were used for the LIMCOM study, and in turn this study, had to be patched.

The observed flow data was patched by making use of Manual infilling of the streamflow records (where possible) followed by Statistical infilling/patching software for streamflow records (PATCHS) program on the aggregated monthly stream flows. The following general comments were provided for the Botswana part of the sub-basin (LIMCOM, 2013):

- The Shashe River was the only catchment where cross-patching of various sequences could be applied.
- Wherever the patched value was lower than the observed value, the observed value was retained (LIMCOM, 2013).

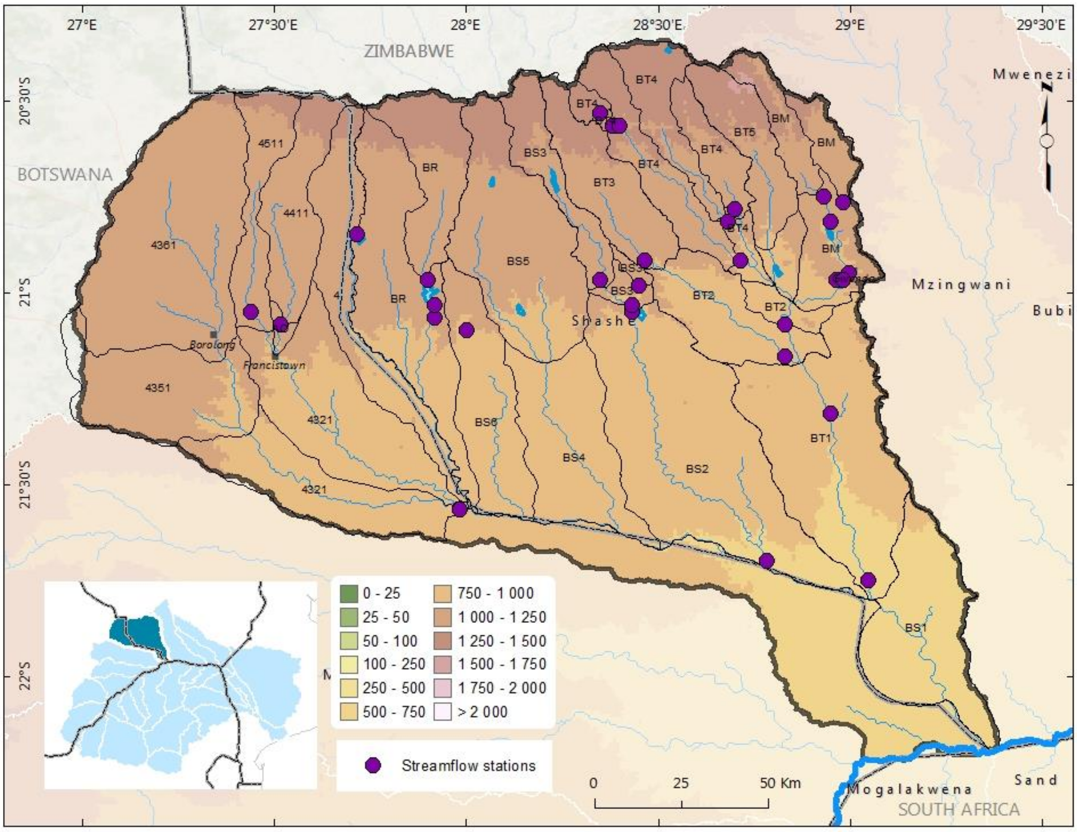

Figure 4.3. Location of the streamflow stations in the Shashe sub-basin (source: LIMCOM, 2013).

4.2.2 Rainfall gauges of the Mogalakwena and Shashe sub-basins

Spatially averaged monthly time series of rainfall data were obtained from the Limpopo River Basin Monograph study (LIMCOM, 2013). The rainfall database of the Mogalakwena sub-basin was constituted by extending rainfall files in the WR2005 configurations (Middleton and Bailey, 2009) with rainfall files, for the period 2004 – 2010, sourced from the DWS' Water Resources Information Management System (LIMCOM, 2013). The locations of the rainfall stations used are displayed in Figure 4.4.

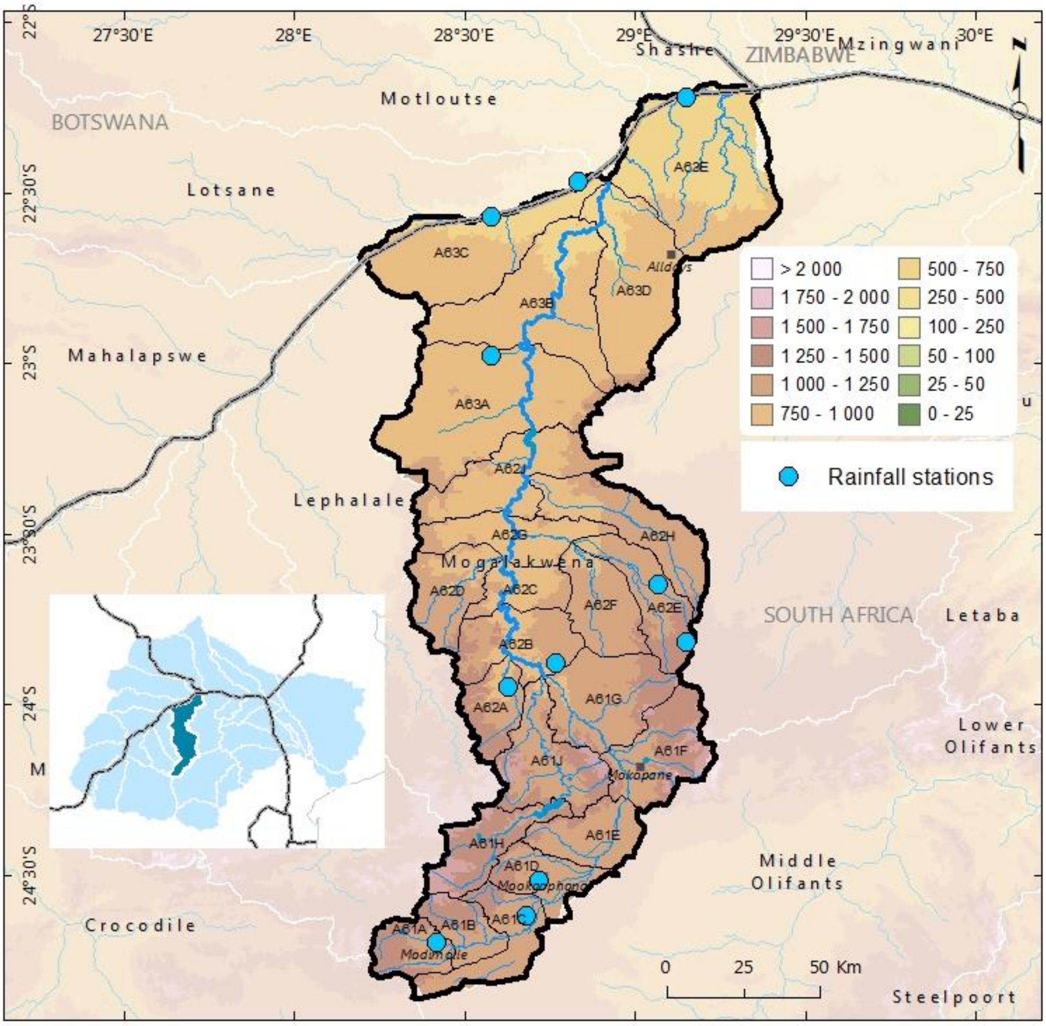

Figure 4.4. Location of the rainfall stations in the Mogalakwena sub-basin used to produce catchment rainfall sequences.

The average rainfall data the Mogalakwena catchments are presented in Table 4.2.

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Table 4.2. Long-term Mean Monthly Precipitation (MMP) for the catchments of the Mogalakwena sub-basin for the time period 1920-2010.

Catch.	MMP (mm a^{-1})	Sub-basin	MMP (mm a^{-1})
A61A	52.6	A62D	41.3
A61B	52.3	A62E	39.2
A61C	50.8	A62F	40.8
A61D	52.6	A62G	37.3
A61E	51.3	A62H	37.5
A61F	49.6	A62J	38.4
A61G	48.6	A63A	36.5
A61H	53.1	A63B	33.2
A61J	52.5	A63C	31.8
A62A	51.5	A63D	34.7
A62B	44.6	A63E	30.1
A62C	40.3		

Rainfall database of the Shashe sub-basin were assembled from a number of data sources (LIMCOM, 2013): (1) Botswana Department of Water Affairs; (2) WR2005 Study (Middleton and Bailey, 2009); (3) Limpopo River Hydrological Model Study (Boroto and Görgens, 1999), and (4) Limpopo River Hydrological Model Update Study (Matji and Görgens, 2001). The spatial location of the rainfall station used is displayed in Figure 4.5.

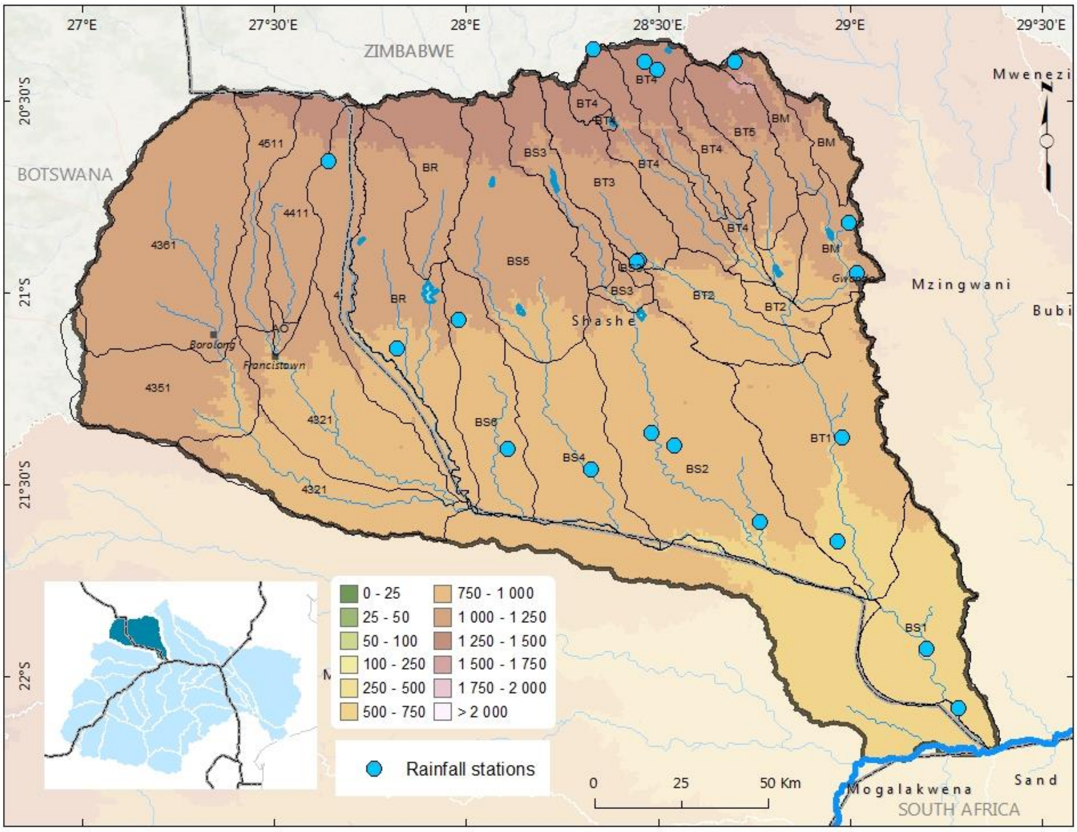

Figure 4.5. Location of the rainfall stations in the Shashe sub-basin used to produce catchment rainfall sequences.

The average rainfall data the Shashe catchments are presented in Table 4.3.

Table 4.3. Long-term Mean Monthly Precipitation (MMP) for the catchments of the Shashe sub-basin for the time period 1920-2011.

Catch.	MMP (mm a^{-1})
BT1	41.8
BT2	44.8
BT3	47.5
BT4	49.6
BT5	49.4
BM	48.8
BS2	42.2
BS3	46.6
BS4	41.9
BS5	42.5
BS6	41.6

4.2.3 Evaporation gauges of the Mogalakwena and Shashe sub-basins

The locations of the four evaporation stations in Mogalakwena are displayed in Figure 4.5. Evaporation plays an important role in the water budget of a sub-basin, however, data regarding the water lost through vegetation cover and water surfaces is limited. The unavailability of data from each individual source that influence evaporation makes it difficult to provide adequately representative measurements of the potential evaporation demand for input in hydrological models (Sawunyama, 2008). Only the data from two sources was used for this study (Table 4.4 and Table 4.5).

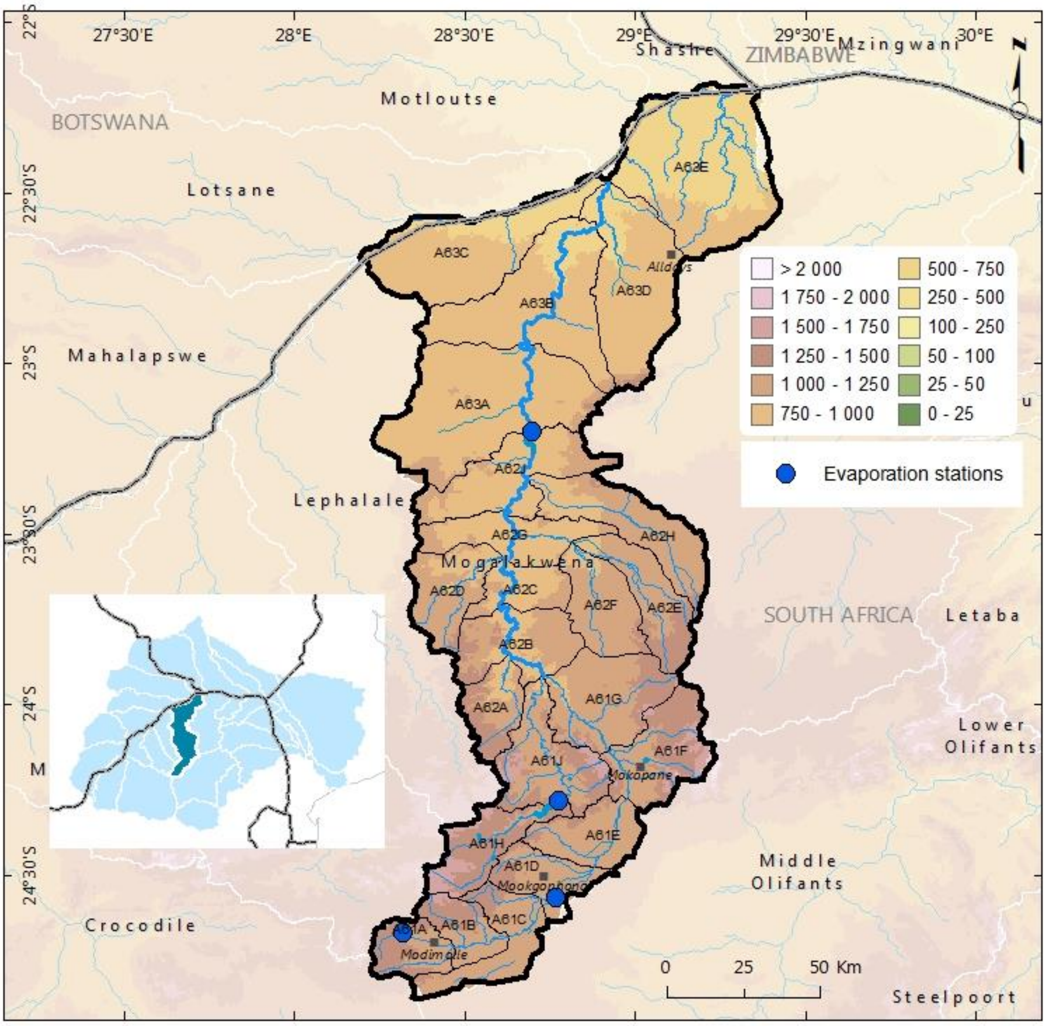

Figure 4.6. Location of the evaporation stations in the Mogalakwena sub-basin (source: LIMCOM, 2013).

Table 4.4. S-pan Mean Monthly Evaporation (MME) as a percentage of MAE for catchments of the Mogalakwena sub-basin (LIMCOM, 2013).

Catch.	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
A61A-63E	11.1	10.3	11.0	11.0	9.2	8.9	6.9	5.7	4.7	5.0	7.0	9.3

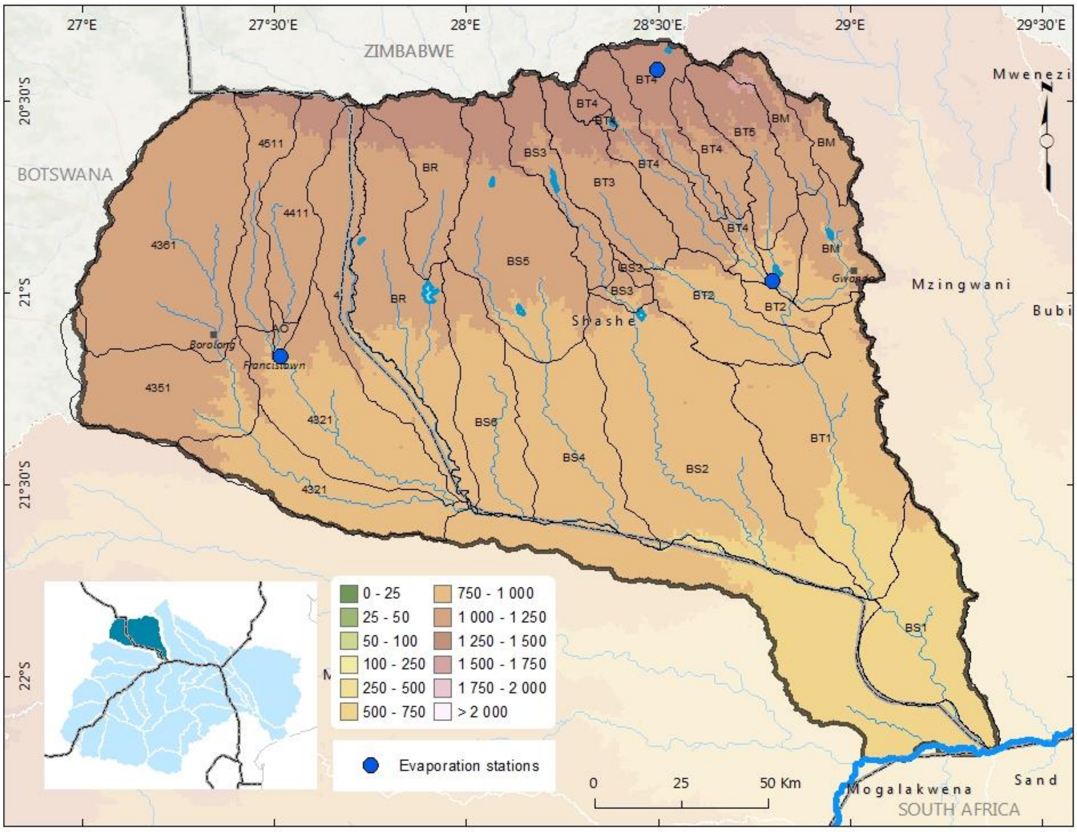

Figure 4.7. Location of the evaporation stations in the Shashe sub-basin (source: LIMCOM, 2013).

Table 4.5. Patched Mean Monthly Evapotranspiration (MME) as a percentage of MAE for catchments of the Shashe sub-basin (LIMCOM, 2013).

Sub-basin	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
BT1	10.8	10.6	11.0	11.0	9.5	8.9	7.1	5.8	4.6	5.1	6.9	8.8
BT2	9.5	7.6	7.9	9.5	7.6	7.9	9.5	7.6	7.9	9.5	7.6	7.9
BT3	7.7	10.3	8.7	9.1	7.6	7.9	7.1	6.4	5.7	6.4	8.4	10.6
BT4	11.8	10.3	8.7	9.1	7.6	7.9	7.2	6.4	5.7	6.3	8.5	10.6
BT5	11.8	10.3	8.7	9.1	7.6	7.9	7.2	6.4	5.7	6.3	8.4	10.6
BM	11.8	10.3	8.7	9.1	7.6	7.9	7.1	6.4	5.7	6.3	8.4	10.6
BS2	9.6	7.6	7.9	9.6	7.6	7.9	9.6	7.6	7.9	9.6	7.6	7.9
BS3	11.7	10.3	8.7	9.1	7.6	7.9	7.2	6.4	5.7	6.3	8.4	10.6
BS4	9.6	7.6	7.9	9.6	7.6	7.9	9.6	7.6	7.9	9.6	7.6	7.9
BS5	11.8	10.3	8.8	9.1	7.6	7.9	7.1	6.4	5.7	6.4	8.5	10.6
BS6	9.6	7.6	7.9	9.6	7.6	7.9	9.6	7.6	7.9	9.6	7.6	7.9

4.3 WATER USE IN THE MOGALAKWENA AND SHASHE SUB-BASIN

Anthropogenic activities can reduce or augment natural flows. Therefore, water use data is essential for water resources estimation of a catchment, but it is very difficult to assess due to the availability thereof. Collecting past, present and future water use estimates is thus important. Such water uses include land use modification including irrigation schemes, river abstractions and return flows (e.g. mining activities), and the distribution of small farm dams and large dams because they influence the amount of runoff that reach a river and evaporation losses of the catchment. Chapter 3 describes the water transfer schemes and other water users in more detail.

Since the Mogalakwena and Shashe catchments are located in different riparian countries of the larger Limpopo River Basin, different databases had to be used for this study. However, water use information for Zimbabwe and South Africa produced by the ZINWA and WARMS database is uncertain. Verification and validation of the agricultural water use had to be undertaken by making use of the WR2012 (Bailey and Pitman, 2015) study for Mogalakwena and LIMCOM, 2013 for Shashe. LIMCOM (2013) used remote sensing techniques to determine the extent of the cropped area. However, google earth, combined with data provided by ZINWA, had to be used to determine the crop type. Even though this approach is not without its own uncertainties, it is less time-consuming than visiting individual farms to collect data and the methods still provide reasonable estimates.

Information regarding the irrigation water use for both sub-basins are also provided by the FAO GeoNetwork (http://www.fao.org/geonetwork) and FAO AquaMaps. However, this data is generally at a larger scale, therefore, it was only used as a guideline in determining the crop type and area of irrigation at a sub-basin scale. For example the gridded data from FAO GeoNetwork shows the area actually irrigated as a percentage of the area equipped for irrigation in a 5 arc minutes (0.833 decimal degrees) grid cell in the year 2005 (Siebert *et al.*, 2013).

4.3.1 Farms dams in the Mogalakwena and Shashe sub-basins

Farm dam data was collected from sources such as Bailey and Pitman (2015), LIMCOM (2013), manual digitizing and remotely sensed imagery. Farm dams are generally less than 1 million m^3 and large dams are larger than 1 million m^3 (Bailey and Pitman, 2015). Many farm dams were identified and digitized in the upper and lower areas of the Mogalakwena catchment. Other sources such as the DWS's Water Authorization and Registration Management System (WARMS) database had to be used to collect the water use data, where possible. At first, the data was collected at a catchment scale where after the areas of all of the dams for each sub-basin was added together and represented separately. The dam areas were then used to calculate the total dam capacity per catchment.

Farm dams are mainly located in the upstream areas of the Shashe catchment. LIMCOM (2013) was the only source that provided farm dam data. However, they did not find any farm dams in the Botswana part of the catchment. The data was thus verified by digitizing Google Earth images and using remote sensing methods. It was found that there were farm dams in the Botswana part of the catchment. Unfortunately, the use of the dams could not be determined other than visual inspection which in itself does not provide a definite use for all the dams.

4.3.2 Irrigation in the Mogalakwena and Shashe sub-basins

The delineation of irrigated area and the irrigation water use for both sub-basins was obtained from the various sources, some of which are listed in Table 4.6.

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Table 4.6. Repositories used to determine irrigated areas and

Repository	Description	Relevant data	Spatial resolution	Sub basin	Sources
FAO GeoNetwork	Global map of irrigation areas	Irrigated areas, crop type and irrigation water demand	± 10km grids	Mogalakwena, Shashe	Siebert *et al.,* 2013
FAO AquaMaps	Global spatial database on water and agriculture		-	Mogalakwena, Shashe	FAO AquaMaps: http://www.fao.org/nr/water/aquamaps/
Limpopo Management Information System	Monograph Study of the Limpopo River Basin	Rainfall, Evaporation, Observed Flows, Model parameters	-	Mogalakwena, Shashe	LIMCOM, 2013
WR2012	Water Resources Study (2012)	Irrigation and farm dams	-	Mogalakwena	Bailey and Pitman, 2015
WARMS	Water use registration	Irrigated areas	-	Mogalakwena	DWS, 2016
DAFF	Field Crop Boundaries	Field Crop Boundaries	-	Mogalakwena	DAFF, 2011
USGS	LandSat 8 OLI images of study area	Imagery (2015)	30 m	Mogalakwena, Shashe	USGS, 2015

The Primary water use datasets that was used in this study is the WR2012, LIMCOM (2013) and DAFF (2011). Irrigation datasets (2011 and 2015) was provided by the Department of Agriculture, Forestry, and Fisheries (DAFF) and was used as the preferred source for irrigation information since both the total irrigation area and the areas dependent on water from dams are included in the dataset. Both total irrigation area and the area from the dam (in km^2) are requirements in the model. Other sources such as the WARMS database also provide irrigation data and it should be the most reliable source for information related to water used for irrigation. Unfortunately, checks and balances are not effective. Secondary datasets, includes Global datasets such as FAO GeoNetwork and FAO AquaMaps and were only used as a guideline when the locations of the irrigated areas were identified. Google Earth images were also used for verification purposes and to identify irrigated areas, digitise polygons of irrigated areas and provide irrigation data at a quaternary catchment scale manual digitising of Landsat 8 OLI imagery and Google Earth was therefore used to collect irrigation data.

The primary dataset for irrigation data for Shashe was LIMCOM (2013). The irrigated areas were originally identified by making use of maps, imagery and relevant reports. This data was verified in Google Earth and more irrigation areas were found. However, the irrigation areas dependent on water from dams was not provided by LIMCOM (2013) and Google Earth was used to make the best-educated guess. This was done by visually locating irrigation areas in the vicinity of farm and large dams. The same secondary data sources that were used for Mogalakwena was used for Shashe and the same digitizing methods were used.

There will be a total of two datasets for both Mogalakwena and Shashe after verification, one mapping farm dams and the other one mapping irrigation areas.

4.4 DESKTOP ASSESSMENT OF FARM AND OTHER SMALL DAMS

Farm dams play an important role in farming businesses because they provide water for irrigation and other farming activities. Nevertheless, these dams intercept surface flows if they are constructed on a river course and in turn reduce the availability of water to downstream areas. However, even though some dams are not located on watercourses, the water that they hold still has to be considered in water resources studies since the volume of water they hold is part of the catchment's water budget. It is, therefore, important to capture the volumes of all of the dams in each study area, but the data sources that provide information on the dams are often outdated or incomplete. Other data collection methods including remote sensing and manual digitizing will be used in this study to find all possible small farm dams along with other dams that might have been left out in other studies.

4.4.1 Scope of the assessment

- All licensed and unlicensed water storages identifiable as dams on satellite images in both sub-basins.
- Water storages not identifiable in the imagery due to the spatial resolution and dam delineations outside the defined boundaries.
- Waterbodies such as wetlands were excluded.

For over 30 years, Landsat imagery have been used to provide information for managing natural resources. Landsat 8 OLI imagery was therefore used in this study to delineate far dams (see Table 4.7 and Table 4.8). These images where acquired from USGS (2015).

Table 4.7. The Landsat 8 OLI imagery that was used to collect farm dam data in the Mogalakwena sub-basin.

	Path	Row	Date
Main	170	77	14 July 2015
Peripheral	170	76	12 June 2015
Peripheral	170	75	12 June 2015

Table 4.8. The Landsat 8 OLI imagery that was used to collect farm dam data in the Shashe sub-basin.

	Path	Row	Date
Main	172	74	12 July 2015
Peripheral	172	75	12 July 2015
Peripheral	171	74	5 July 2015
Peripheral	171	75	5 July 2015
Peripheral	170	75	12 June 2015

There are several types of digitizing methods. The type of digitizing used in this study is known as heads-up digitizing, also referred to as on-screen digitizing. It is the method of tracing geographic features from another dataset (in this case satellite imagery) directly on the computer screen. Google Earth was used to identify and digitize the dams (and irrigation areas). The dams identified through remote sensing methods were imported into Google Earth (dated between 2003 and 2016 for both Mogalakwena and Shashe) where after they were delineated according to the imagery and dams were identified and delineated if it was not identified through remote sensing methods.

4.4.2 Identifying farm dams using remote sensing methods

In recent years, remote sensing became a tool that is widely utilised for quantifying land surface water resources (Bastawesy *et al.,* 2008). The advantage of remote sensing, when compared to *in situ* measurements, is that spatial and temporal views of the surface water are provided over large areas (Giardino *et al.,* 2010). Even though imagery from Landsat satellites has a low spatial resolution (30 m) it has a higher spectral resolution than is obtained from other satellites. Therefore, Landsat imagery is the most common imagery used for the examination of natural phenomenon such as water bodies (Mustafa and Noori, 2013). A number of methods have been developed over the years to quantify water resources by using remote sensing (Wang *et al.,* 2008; Ji *et al.,* 2009; Jawak *et al.,* 2015). However, problems such as not considering spectral characteristics (e.g. Wang *et al.,* 2008) as well as accuracy and operational problems occur in the proposed methods (Malahlela, 2016). The algorithm most commonly used for quantifying dams is a multi-band index developed by McFeeters (1996) and later modified by Xu (2006). The algorithm is now known as the normalized difference water index (NDWI) and is designed to maximize water reflectance in the green and near-infrared bands as follows:

$$\mathrm{NDWI} = \frac{\mathrm{R_{GREEN}} - \mathrm{R_{NIR}}}{\mathrm{R_{GREEN}} + \mathrm{R_{NIR}}}$$ Equation 4.1

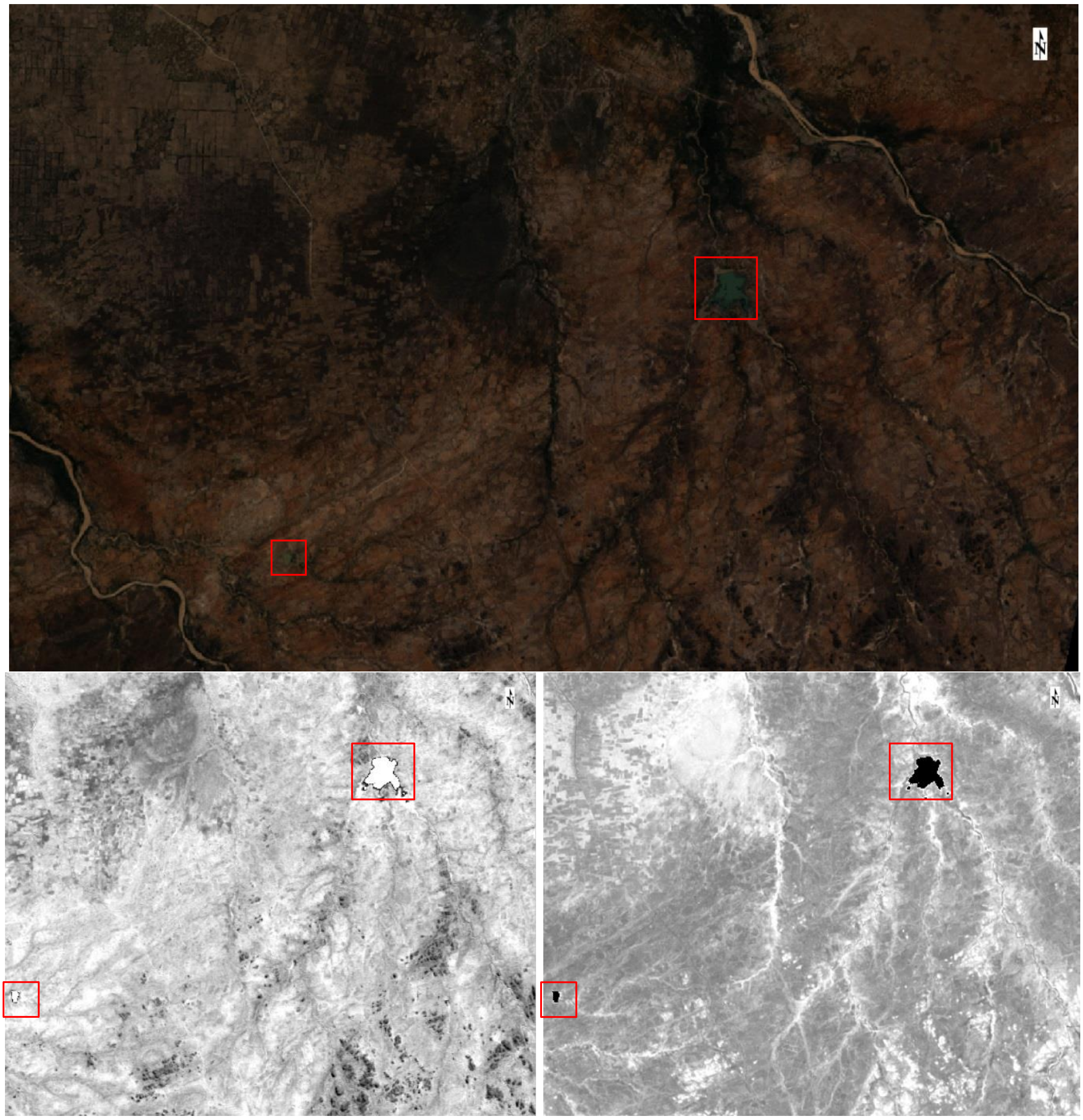
where: *R_{GREEN} = the reflectance value of the green band (0.53-0.59 μm), and R_{NIR} = the reflectance value of the near-infrared band (0.85-0.88 μm).*

A modified water index by Xu (2006) was intended to reduce noise associated with the NDWI image, which is often mixed-up with built-up land features (Malahlela, 2016). The following equation is used for the modified normalized difference water index (MNDWI):

$$\mathrm{MNDWI} = \frac{\mathrm{R_{GREEN}} - \mathrm{R_{SWIR1}}}{\mathrm{R_{GREEN}} + \mathrm{R_{SWIR1}}}$$ Equation 4.2

where: R_{GREEN} *= the reflectance value of the green band (0.53-0.59 μm), and* R_{SWIR1} *= the reflectance value of the shortwave infrared band (1.57-1.65 μm).*

Even though both algorithms can be used to identify water bodies from imagery on which water are not easily identified (see Figure 4.8 below), more misidentification took place when the MNDWI algorithm was used. MNDWI has been shown to subdue the confusion of water pixels by built-up areas (Xu, 2006); however, the algorithm did misclassify shadows (especially from clouds and mountains) for much larger areas than the NDWI algorithm (see Figure 4.9 for an example). The NDWI algorithm was therefore used to extract reservoir data for this study. It should be noted that even though other algorithms are also used to detect water bodies e.g. the simple water index (SWI) and automated water extraction index (AWEI), analysing each algorithm is beyond the scope of this study.



NDWI *MNDWI*

Figure 4.8. Comparison between two of the different algorithms that can be used to extract dam data from remotely sensed imagery.

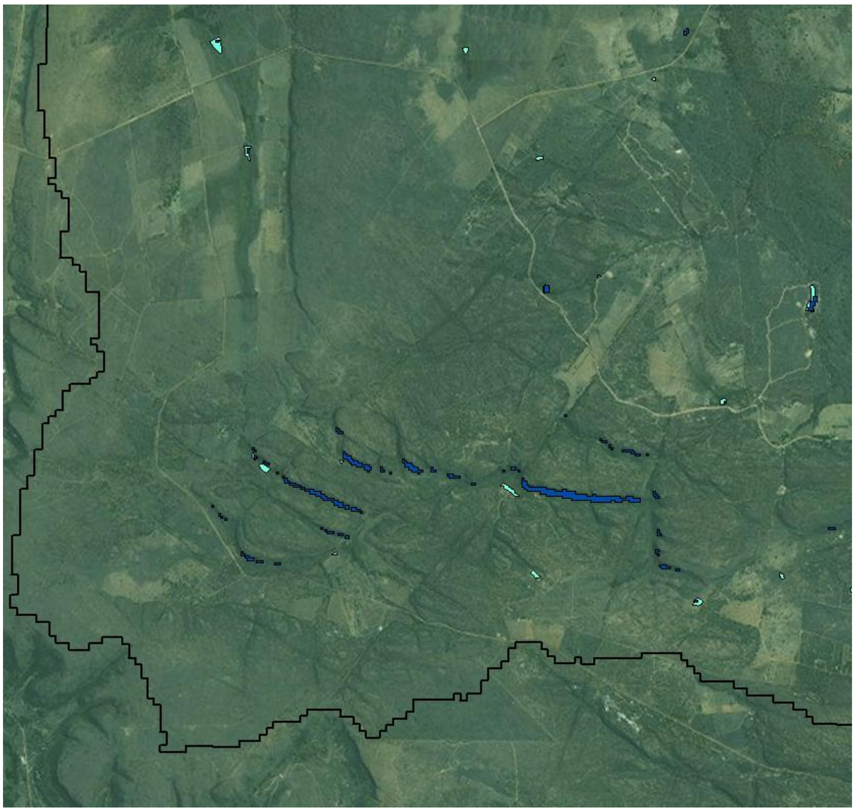


Figure 4.9. The difference between dams identified by manual digitizing (light blue) and remote sensing (dark blue). The areas identified by remote sensing methods are actually shadows of mountains and not dams.

4.4.3 Comparison between data obtained from manual digitizing and remote sensing

Even though remote sensing methods provide a quick and easy way to capture farm dams, issues such as misclassification do occur. Since the classification of farm dams is based on the thresholds that were manually selected, shadows are also classified as dams because their thresholds fall within the boundaries that were selected in the ENVI software. The remotely sensed data, therefore, had to be visually inspected and 'cleaned' by removing misclassified areas. An area in Mogalakwena where dam data from remote sensing methods and manual digitizing is compared during the data cleaning process is shown in Figure 4.10. It was found that not only were there areas that were wrongfully classified as dams in the remotely sensed data; the dam areas are also different from the manually digitised dams. The difference in dam area is caused by the spatial resolution of the imagery that was used to classify the dam. The remote sensing software can therefore not be used to estimate the exact area of a dam and manual digitizing is required. However, it was found that some dams were identified by remote sensing, but missed during the manual digitizing process. Remote sensing and manual digitizing were therefore used together to identify the number of dams in both sub-basin as accurately as possible.

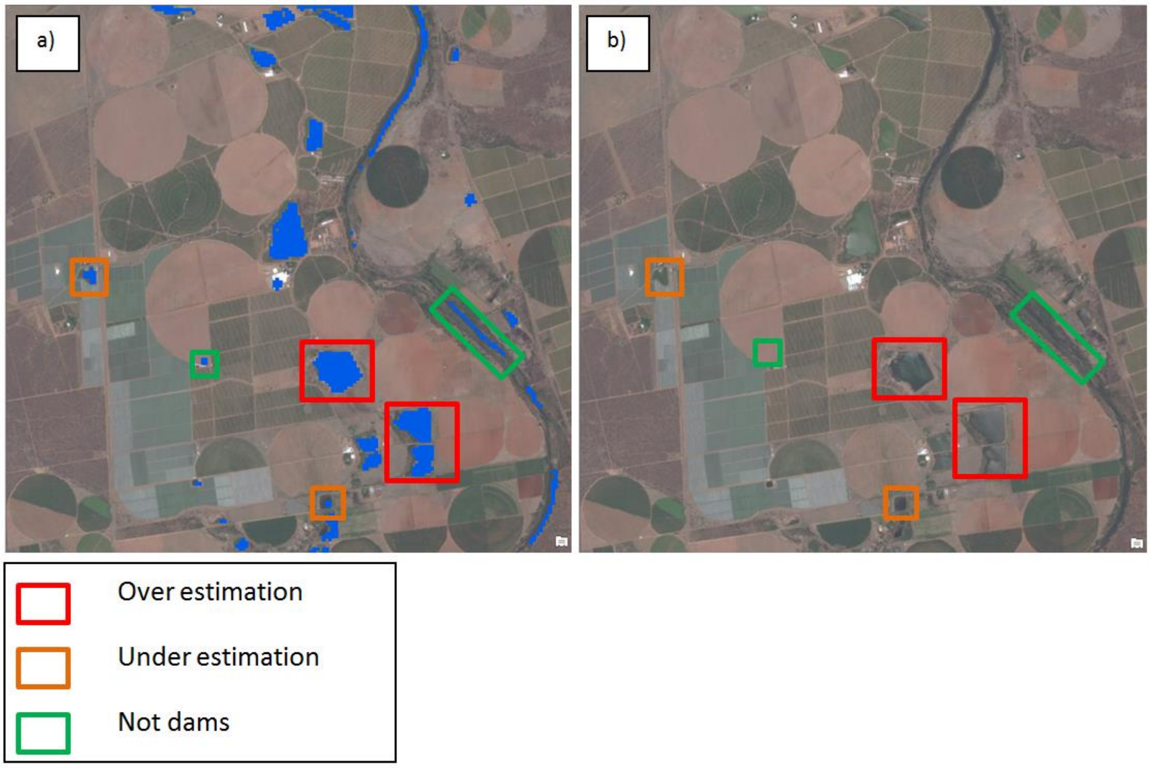


Figure 4.10. Water bodies identified in the Mogalakwena sub-basin by making use of the NDWI algorithm and Landsat 8 OLI imagery. The classified dams (a) are very different from the dams seen on satellite imagery (b) since remote sensing methods identify spectral signatures at a pixel level.

4.5 HYDROLOGICAL MODELLING

Identifying sources of uncertainty in hydrological modelling was the overall objective of this study. The objective, in turn, consisted of two sub-objectives:

- To quantify the degree of uncertainty for individual sources; and
- To assess their combined impact on the model outputs for each sub-basin.

The details of the methods are briefly discussed in section 4.3.2 and Chapter 5. The focus of this study is the uncertainty associated with simulations of the natural hydrology and water use. Therefore, additional sources found in water resources management, as well as operational planning, are beyond the scope of this study.

4.5.1 Model selection

SPATSIM (Spatial and Time Series Information Modelling) version of the Pitman model was the preferred software. The model input requirements such as rainfall and evapotranspiration have been taken from the WR2012 study and were fixed throughout the analysis. The two-steps model in SPATSIM was used for uncertainty analysis in this study. The first step of the model focuses on the parameters which is physically based and includes the natural hydrology of the Luvuvhu (e.g. runoff). The second step includes the impact of non-physical input data such as water use. The output model uncertainty is displayed for both the parameter and water use data separately and is compared to the actual flows obtained from WR2012. Chapter 5 provide a more detailed description of the Pitman model as well as the model setup for this study.

4.5.2 Quantifying uncertainty

Several reported methods such as the Bayesian Total Error Analysis (Kavetski *et al.,* 2006) and the Integrated Bayesian Uncertainty Estimator (Ajami *et al.,* 2007) have attempted to account for all sources of uncertainty. Unfortunately, these methods are not appropriate for data scarce regions such as southern Africa because they are statistical or data driven approaches (Sawunyama *et al.,* 2011). In this study the uncertainty was quantified in two steps:

Step One – the Pitman model parameters related to the physical processes of runoff generation are analysed;

Step Two – include the assessment of the contribution of anthropogenic water use data (farm dams and irrigation) uncertainty to the simulated runoff uncertainty.

4.5.2.1 Analysis of the Pitman model parameters

The parameters that were considered for uncertainty were restricted to ZMIN (minimum absorption rate in mm/month), ZMAX (maximum absorption rate in mm/month), ST (Maximum soil moisture storage capacity in mm a^{-1}), FT (runoff rate at ST in mm/month) and POW (power of soil storage-runoff curve). The approach that was used to quantify parameter uncertainty involves using different assumptions about the physical properties of the basin to derive the 'best guessed' parameters as well as the lower and upper bounds for the sub-basins. It is based on physical basin statistics from which the parameter values were constrained. Expected behavioural outputs are generated and compared to the actual flows from the WR2012 Study for Mogalakwena and the simulated flows from the Limpopo River Basin Monograph Study (2013) for Shashe.

4.5.2.2 Assessment of impacts on uncertainty in water use data

The extended version of the Pitman model includes several components that represent anthropogenic (i.e. water use) impacts such as small farm dams, large dams, water abstractions and return flows and irrigation. The focus was placed on farm dams and irrigation in particular because they represent important components of the present day water balance. Nevertheless, data on these water use components are very unreliable hence the need to estimate the uncertainty related to available data and to incorporate it into the model.

CHAPTER 5
The Pitman model

5.1 THE SPATSIM MODELLING FRAMEWORK

In this Chapter, focus will be placed on the uncertainty approach of the Pitman model through the use of the SPATSIM software interface used to apply the model. The SPATSIM software incorporates a comprehensive data management system with a Geographical Information System (GIS) interface. Therefore, data can be used in a spatial context (Sawunyama, 2008). Management of the data is done through a spatial interface by using of GIS shapefiles (referred to as the features) which are linked to any number of data attributes. The user decides on the attributes which occur in a wide arrange of data such as text information, single values, tabular information and time series data. The SPATSIM software allows the user to import, view, graphically display and share different types of data as well as further processing of data to create new information. The SPATSIM software has been developed mostly by Prof. D.A. Hughes and Mr. D.A. Forsyth at the Institute for Water Research (IWR) at Rhodes University and is available for download at no cost from the website of the IWR (http://iwr.ru.ac.za/iwr/software/spatsimupdate.php). The Delphi programming language (Software Developing Kit) was used to write the model, and a Paradox database structure is used for data sorting (IWR, 2017). A large part of the structure of the original Pitman model is preserved in the SPATSIM version. Some recent developments that are designed to improve the general applicability of the model in different physiographic settings of the southern Africa region are included (Hughes, 1997; Hughes *et al.,* 2006) and to handle multiple model runs that are required to consider uncertainty issues (Kapangaziwiri *et al.,* 2012). The version of the model used in this study has explicit surface-ground water interaction routines (Hughes, 2004) and a wetland function. Since it is a conceptual type of model, parameters that are associated with components that represent the main hydrological processes (and human impacts) that operate at a sub-basin scale are included (Hughes *et al.*, 2010). A flow diagram of the Pitman model used in this study is presented in Figure 5.1.

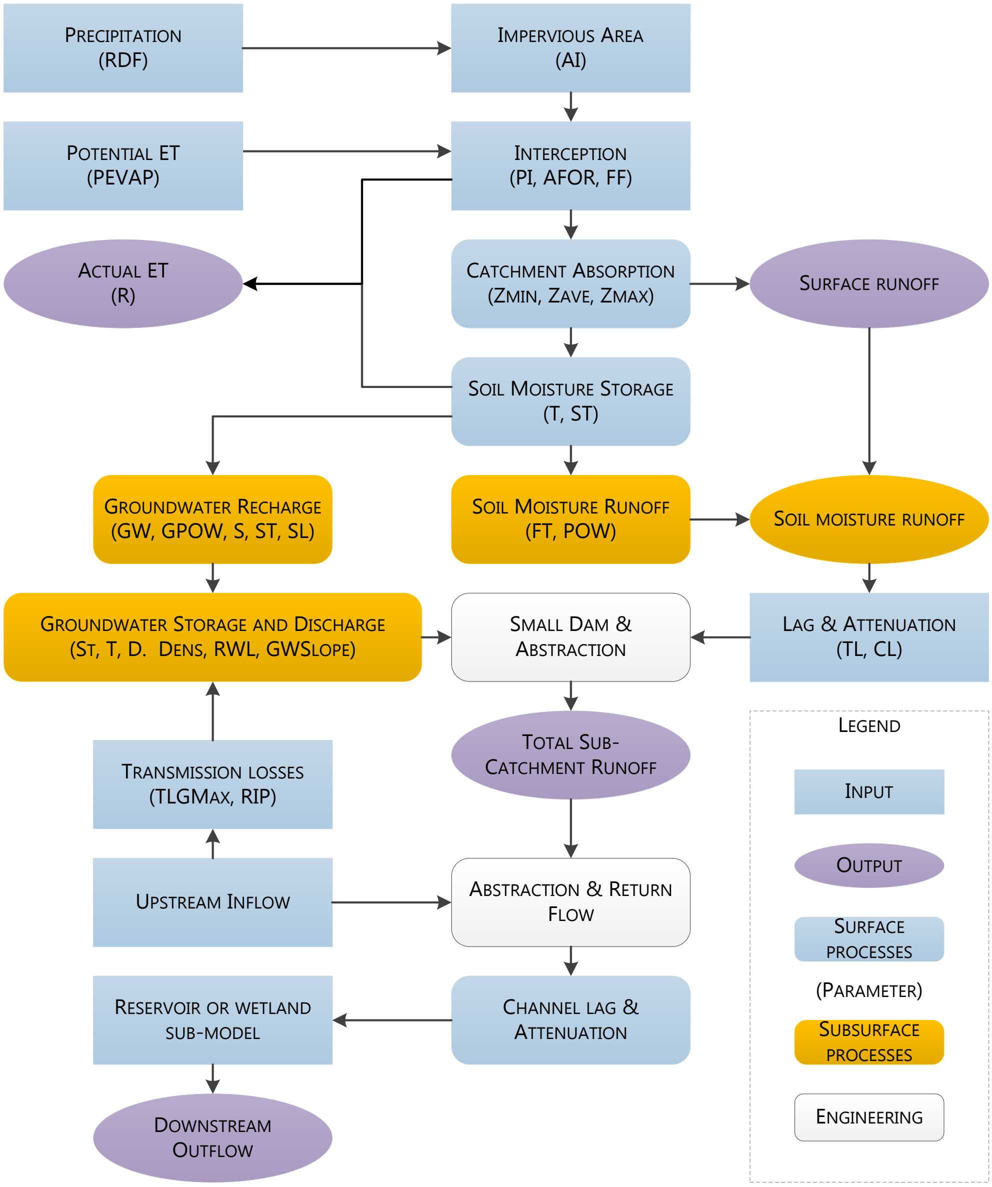


Figure 5.1. A flow diagram of the Pitman model, indicating the main components of the model including the parameters given in brackets (After Kapangaziwiri *et al.*, 2012).

The SPATSIM software consists of internal facilities (routes for data viewing, graphical display, data editing etc.) and also has links with external models (Figure 5.2). The models that are linked to SPATSIM have different purposes and are developed as separate computer programs and for this study the Global Options Threaded Model was selected for the uncertainty analysis. An external time series analysis program known as TSOFT is also linked to SPATSIM (Hughes *et al.*, 2000). TSOFT can be used to display all types of time series data graphically or statistically. The software is designed for the assessment of observed data, comparing observed and simulated data and the detailed investigation of model outputs.

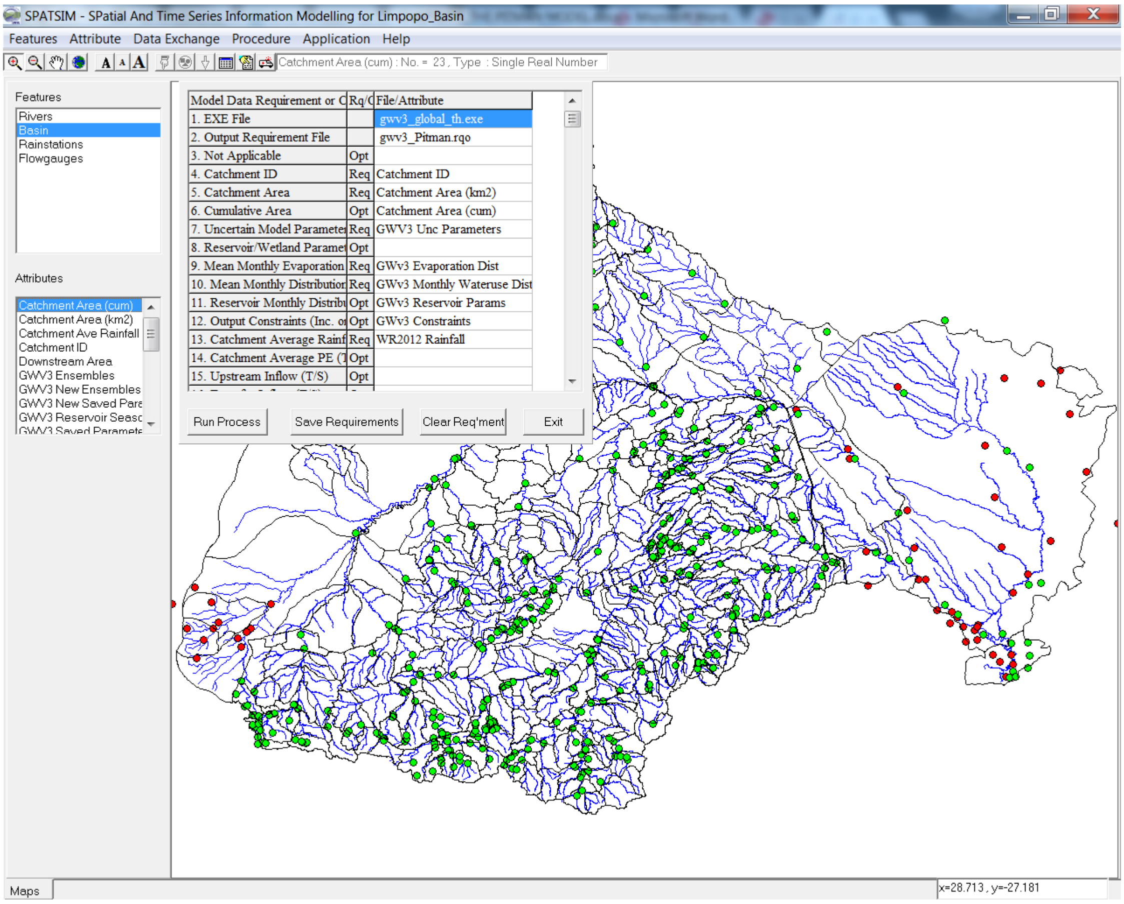


Figure 5.2. Screen shot of the SPATSIM software that also includes the model setup interface.

5.2 UNCERTAINTY ANALYSIS

The uncertainty analysis focused on the impact of parameters and water use uncertainties on estimated sub-basin water resources. The parameter uncertainties were modelled first, before the incorporation of water use uncertainties. The main parameters of the model are shown in Table 5.1. Runoff is mainly generated by two model functions. The first is an asymmetrical triangular distribution of catchment absorption rates defined by parameters ZMIN, ZAVE, and ZMAX.

Table 5.1. A list of the parameters of the Pitman model including those of the reservoir water balance model (Hughes *et al.*, 2006).

Parameter	Unit	Parameter description
RDF	-	Controls the distribution of total monthly rainfall over four model iterations
AI	Fraction	Impervious fraction of sub-basin
PI1 and PI2	mm	Interception storage for two vegetation types
AFOR	%	% area of sub-basin under vegetation type 2
FF	-	Ratio of potential evaporation rate for Veg2 relative to Veg1
PEVAP	mm	Annual sub-basin evaporation
ZMIN	mm month^{-1}	Minimum sub-basin absorption rate
ZAVE	mm month^{-1}	Mean sub-basin absorption rate
ZMAX	mm month^{-1}	Maximum sub-basin absorption rate
ST	mm	Maximum moisture storage capacity
SL	mm	Minimum moisture storage below which no GW recharge occurs
POW	-	Power of the moisture storage- runoff equation
FT	mm month^{-1}	Runoff from moisture storage at full capacity (ST)
GPOW	-	Power of the moisture storage-GW recharge equation
GW	mm month^{-1}	Maximum ground water recharge at full capacity, ST
R	-	Evaporation-moisture storage relationship parameter
TL	months	Lag of surface and soil moisture runoff
CL	months	Channel routing coefficient
DDENS	-	Drainage density
T	m^2 d^{-1}	Ground water transmissivity
S	-	Ground water storativity
GWSlope	%	Initial ground water gradient
AIRR	km^2	Irrigation area
IWR	Fraction	Irrigation water return flow fraction
EffRf	Fraction	Effective rainfall fraction
NIrrDmd	Ml a^{-1}	Non-irrigation demand from the river
MAXDAM	Ml	Small dam storage capacity
DAREA	%	Percentage of sub-basin above dams
A, B	-	Parameters in non-linear dam area-volume relationship
IrrAreaDmd	km^2	Irrigation area from small dams
CAP	Mm^3	Reservoir capacity
DEAD	%	Dead storage
INIT	%	Initial storage
A, B	-	Parameters in non-linear dam area-volume relationship
RES 1–5	%	Reserve supply levels (percentage of full capacity)
ABS	Mm^3	Annual abstraction volume
COMP	Mm^3	Annual compensation flow volume

The second function determines the drainage rate from the main moisture storage (S, with a capacity of ST, mm). This storage is depleted by evapotranspiration, interflow and groundwater recharge. The maximum interflow (FT, mm month^{-1}) and recharge (GW, mm month^{-1}) rates occur at ST, while two power functions (parameters POW and GPOW) determine these rates at lower values of moisture storage (S, mm). Recharge is routed through a groundwater storage function that accounts for evapotranspiration losses, drainage to other sub-catchments and contributions to baseflow. The model also has functions to simulate the impact of human activities like small farms dams or large reservoirs and irrigated agriculture in managed basins (see Table 5.1).

5.3 MODEL SETUP

The general approach adopted in this study is illustrated in Figure 5.3 below and follows similar procedures as the ones discussed in Tumbo and Hughes (2015). The modelling used accounts for uncertainties arising from the quantity and quality of the input data in a two-step approach in the SPATSIM version.

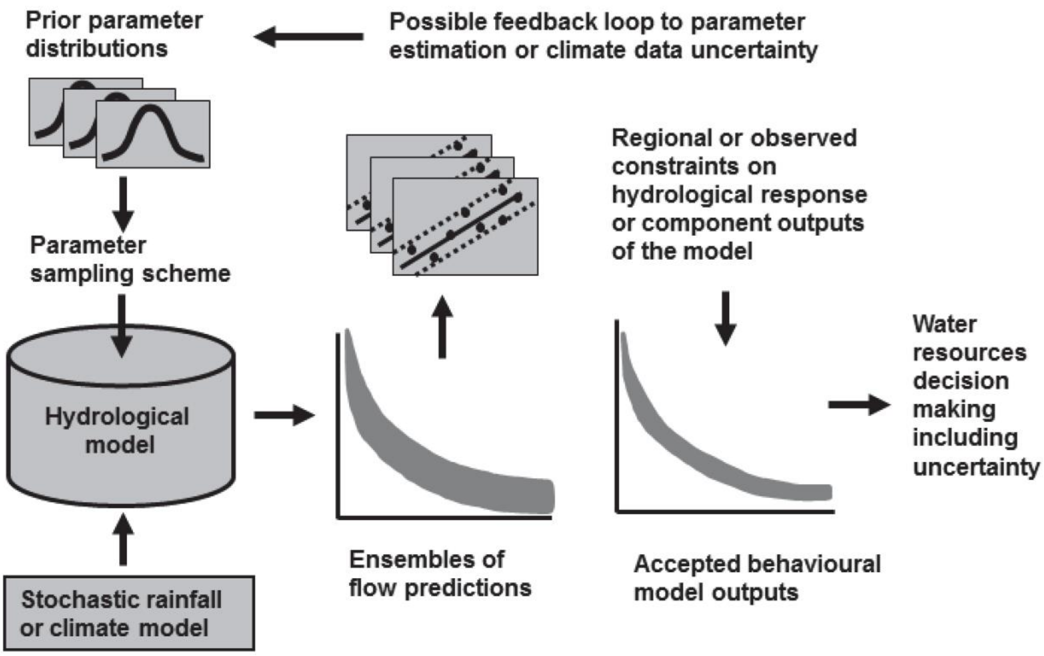


Figure 5.3. The process that was followed during the two-step uncertainty analysis modelling.

5.3.1 Analysis of the Pitman model parameters

The first step involves the use of constraint filters to get parameter sets that could be considered behavioural in the simulation of the incremental natural flows of each sub-basin. The physical parameters for generation of runoff that were considered for uncertainty were restricted to ZMIN, ZMAX, ST, FT and POW. The behavioural parameter sets are saved and then used with the uncertain water use data in the second step of the model when the cumulative flows were simulated. The first step (incremental uncertainty) runs the model 10 000 times (but can go up to 100 000 times) only on the incremental sub-basins and compares the simulated output to six constraints ranges (see Figure 5.4):

- Mean monthly streamflow (m^3*10^6);
- Groundwater recharge (mm);
- Three points on the flow duration curve at 10%, 50% and 90% (FDC10, FDC50 and FDC90); and
- % time of zero flows.

In this study, the parameter values for each run of the model are independently randomly sampled from the inputs by making use of a Normal (defined by the mean and standard deviation) frequency distribution. As soon as a parameter set generates a simulation that satisfies all of the constraints, it is saved to the SPATSIM database (Ndzabandzaba and Hughes, 2017). However, when 1 000 output behavioural parameter sets have been found the model terminates. Since the constraints define the uncertainty in the hydrological response behaviour of each of the selected sub-basins (Yadav, *et al.,* 2007; Westerberg *et al.,* 2011; Westerberg *et al.,* 2014) all of the saved parameter sets represents behavioural responses (Beven, 2012). The parameters that were considered for uncertainty were restricted to:

The surface runoff parameters (ZMIN, ZAVE and ZMAX mm/month), also known as the infiltration parameters, quantify the surface runoff/absorption capacity responses to rainfall. The model also makes use of a triangular distribution of catchment absorption rates, hence why the parameter values will vary from a minimum value of ZMIN to a maximum value of ZMAX and an average value of ZAVE (Kapangaziwiri and Hughes, 2008). Therefore, areas with deep soils and low slopes will have a ZMIN of over 100 mm (lower than 100 mm occur in semi-arid regions) and more tropical areas will have a variation of between 200 and 1 200 mm for ZMAX and will experience very little runoff. ZAVE can be calculated as follows: ZAVE = (ZMAX+ZMIN)/2.

The maximum moisture storage (ST in mm) represents the maximum storage depth of the unsaturated zone. All of the rainfall that does not get intercepted or diverted to surface runoff will be added to this storage. Evapotranspiration, drainage and groundwater recharge are outputs. The typical value ranges from 100 mm in arid areas where the soils are thin to over 1 000 mm in areas that contain deep soils or deep weathered rock material.

The non-linear relationship between the interflow runoff and the relative moisture storage is defined by *the interflow parameters (FT in mm month^{-1} and POW)*. The maximum runoff at ST is defined by FT and POW represents the power of the function.

The groundwater recharge parameter (GW in mm month^{-1}) represents the non-linear relationship between the groundwater and relative moisture storage by making use of the same type of function as for interflow. However, an additional parameter that defines the moisture content below which recharge ceases (SL) is added.

The approach that was used to quantify parameter uncertainty involves using different assumptions about the physical properties of the basin to derive the 'best guessed' parameters as well as the lower and upper bounds for the sub-basins. It is based on physical basin statistics from which the parameter values were constrained. Expected behavioural outputs are generated and compared to the actual flows from the WR2012 Study (Bailey and Pitman, 2015) for Mogalakwena and LIMCOM, (2013) for Shashe. Table 5.2 and Table 5.3 below list the parameter variations that were used for the uncertainty analysis. The assumption is that certain parameters cover the range of likely values for the sub-basins while other parameters such as the routing parameter (TL) remain fixed.

Table 5.2. Parameter ranges of the catchments in the Mogalakwena sub-basins.

Catch.		ZMIN	ZMAX	ST	POW	GW	RSF	Catch		ZMIN	ZMAX	ST	POW
A93E	MIN	40	950	180	2.9	32.5	0.1	A62B	MIN	40	950	150	2.8
	MAX	60	1050	220	3.1	37.5	2.0	MAX	MAX	60	1050	170	3.2
A93C	MIN	40	900	190	2.8	15	0.1	A62C	MIN	40	950	150	2.8
	MAX	70	1200	220	3.2	18	1.0	MAX	MAX	60	1050	170	3.2
A61A	MIN	0	0	140	2.8	18	0.1	A62D	MIN	40	950	150	2.8
	MAX	0	0	160	3.2	22	1.0	MAX	MAX	60	1050	170	3.2
A61B	MIN	0	0	135	2.8	13	0.1	A62E	MIN	40	950	150	2.8
	MAX	0	0	155	3.2	17	1.0	MAX	MAX	60	1050	170	3.2
A61C	MIN	50	500	180	2.8	23	0.1	A62F	MIN	40	950	150	2.8
	MAX	100	1000	200	3.2	27	1.0	MAX	MAX	60	1050	170	3.2
A61D	MIN	50	500	180	2.8	20	0.1	A62G	MIN	40	950	150	2.8
	MAX	100	1000	200	3.2	24	1.0	MAX	MAX	60	1050	170	3.2
A61E	MIN	50	500	180	2.8	17	0.1	A62H	MIN	40	950	150	2.8
	MAX	100	1000	200	3.2	21	1.0	MAX	MAX	60	1050	170	3.2
A61F	MIN	0	0	130	2.8	21	0.1	A62J	MIN	40	950	150	2.8
	MAX	0	0	150	3.2	25	1.0	MAX	MAX	60	1050	170	3.2
A61G	MIN	0	0	190	2.8	21	0.1	A63A	MIN	40	900	290	2.8
	MAX	0	0	210	3.2	25	1.0	MAX	MAX	60	1100	310	3.2
A61H	MIN	0	0	90	2.8	4.5	0.1	A63B	MIN	40	900	290	2.8
	MAX	0	0	110	3.2	6.5	1.0	MAX	MAX	60	1100	310	3.2
A61J	MIN	0	0	190	2.8	5	0.1	A63D	MIN	40	950	190	2.8
	MAX	0	0	210	3.2	10	1.0	MAX	MAX	60	1050	210	3.2
A62A	MIN	40	950	150	2.8	5	0.1						
	MAX	60	1050	170	3.2	10	1.0						

*Riparian Strip Factor

However, their values have to be restricted to sensible ranges that are based on previous experience and specific physical basin properties which, for this report, are mainly provided by the Water Resources Study of 2012 (Bailey and Pitman, 2015) and the Limpopo River Basin Monograph Study, 2013 (LIMCOM, 2013).

Table 5.3. Parameter ranges of catchments of the Shashe sub-basin that were modelled.

Catch.		ZMIN	ZMAX	ST	POW	GW
BS2	MIN	90	1150	500	3.1	2.5
	MAX	110	1250	600	3.3	30
BS3	MIN	90	1150	400	2.1	2.5
	MAX	110	1250	500	2.3	3.0
BS4	MIN	40	400	300	1.4	2.0
	MAX	60	500	400	1.6	2.5
BS5	MIN	90	1150	650	2.9	5.5
	MAX	110	1250	750	3.1	7.5
BS6	MIN	90	900	650	2.9	2.5
	MAX	110	1000	750	3.1	5.5

The parameter ranges (excluding the Groundwater parameter) were used to produce 10 000 ensembles each of which was constrained using MMQ, MMRchg, FDC10, FDC50, FDC90 and the % Zero Flows to determine behavioural ensembles (see Figure 5.4).

Figure 5.4. An illustration of the parameter set tool that helps with the determination of appropriate parameter bounds. The graph in the top left corner shows the distribution of the six behaviour ensembles and the other graphs shows the parameter ranges. This is an example of a successful sub-basin where 1002 out of 10000 behavioural ensembles was found, and both the constraints and parameter ranges are good.

5.3.2 Assessment of impacts on uncertainty in water use data

Adding the value for the water use parameters, with or without uncertainty, is the key issue of the second stage of the model. At this stage the results can be compared with available observed data that will inevitably include these impacts. However, in this study, uncertainty bounds will be added to the parameters. The extended version of the Pitman model includes several components that represent anthropogenic or water use impacts, such as small farm dams, large dams, water abstractions and return flows and irrigation. The focus was placed on farm dams and irrigation in particular because they represent important components of the present day water balance. A total of six water use related parameters can be used; however, only irrigation area (km^2), irrigation area from dams (km^2) and maximum dam storage (m^3*10^6) will have uncertainty bounds (minimum and maximum values).

The Irrigation area (km^2) parameter is used to represent direct abstraction from the river for irrigation purposes; and

The irrigation area from dams (km^2) parameter is used to represent the demands on the small dams for irrigation purposes.

Maximum dam storage (m^3*10^6) is the sum of the storage capacity of all of the small dams within a single sub-basin.

The % catchment area above dams is a representation of the portion of the sub-area that can contribute to the small dam storage.

A in area volume relationship is the constant parameter in the relationship between reservoir surface area.

B in area volume relationship is the power parameter in the relationship between reservoir surface areas.

The second stage of the model (cumulative uncertainty) samples from the saved parameter sets at random. They include parameters controlling the incremental sub-basin natural response, as well as independent random sampling of the range of the other parameter. This stage generates 10 000 ensembles of cumulative stream flow at all sub-basin outlets. Therefore, all of the downstream ensemble outputs are made up of behavioural inputs (within the range of the constraints used in the first stage) of each of the sub-basins of a larger catchment.

5.4 LIMITATIONS OF THE PITMAN MODEL AND SPATSIM SOFTWARE

One of the main motivations for using the SPATSIM approach in this study is because it has been adopted as the core modelling environment and used for the update of the South African water-resource information system (WR90 and WR2012). It also became one of the most widely used monthly time-step rainfall-runoff models within southern Africa (Hughes *et al.*, 2006). However, the software and the Pitman model do have some limitations that had to be overcome. Model calibration is dependent on good quality data which is at times difficult to obtain due to, for example in the case of southern region, warfare and economic limitations of the present and past that have largely preluded the collection of spatially and temporally representative water resource information (Hughes, 1997). In turn, the model cannot be adequately optimised if good quality input data with associated observed flows are absent. Remote sensing methods were used to collect farm dam and irrigation data to compensate for the lack of data is some catchments of the Mogalakwena and Shashe sub-basins. Observed streamflow data was also missing for most of catchments for both Mogalakwena and Shashe, therefore, the model was set up for the gauged catchments where after the methods were applied to ungauged catchments. In conclusion, despite limited data access, the model were able to represent the hydrological responses of other basins like the Okavanga Delta (Hughes *et al.*, 2006) which made it the ideal model to use for this study due to the lack of good quality data, especially for the Shashe sub-basin.

CHAPTER 6
Results and discussion

This chapter reports presents and discusses the results in the following order:

- Estimate water resources using historical data; and
- Quantify the uncertainties related to water resources estimation based on available water use data.

The combined effect of sources of uncertainty in input data on total output uncertainty for the catchments of the Mogalakwena and Shashe sub-basins are explored.

6.1 HYDROLOGICAL MODELLING AND UNCERTAINTY ANALYSES

The farm dam and irrigation datasets developed in this study as well as the irrigation data collected from DAFF was compared to the LIMCOM Study, 2013. LIMCOM (2013) was chosen because the study used the latest data available e.g. the WR2012 Study for South Africa. Therefore the data did not have to be sourced from various different sources. The data were collected at the sub-basin scale. For purposes of simplicity in this study and also based on the model to be used, the individual small farm dams in each quaternary sub-basin were added up to form one dam at the outlet of the quaternary, whose parameters (e.g. full supply capacity and area) were then subsequently specified and the level of uncertainty where necessary. Only the surface areas of the identified farm dams were estimated from the remote sensing and through the digitizing processes and dam capacities had to be calculated using a generalised relationship between capacity and area provided by LIMCOM (2013). While many approaches to the estimation of dam capacities could be used (e.g. Sayl *et al.,* 2016; Hughes and Mantel, 2010 and Sawunyama *et al.,* 2006) this equation was chosen since it was applied successfully in the whole of the Limpopo basin, and is given as:

$A = 0.4 \times C^{0.7}$ Equation 6.1

where: *A = Surface area of the farm reservoir [km²] and C = Capacity of the farm reservoir [m³]*

The volumes obtained from the equation were also compared to data from previous national regionalised databases and was found to be similar and was thus therefore adequate to use. The range of variation was then used in the Pitman model. Irrigation data for Mogalakwena sub-basin in South Africa was provided by LIMCOM (2013), which was in turn collected from the national water resources database (WR2012) and compared to the data received from DAFF. For the Shashe catchment data from LIMCOM (2013) was compared to areas that were digitized in Google Earth. A huge difference between the irrigation coverage was observed for the Mogalakwena quaternary catchments giving a relatively large uncertainty distribution (Table 6.2). However, the difference between the irrigated areas in Shashe which were also provided by the LIMCOM (2013) compared to the areas digitized in Google Earth is small. Nevertheless, the uncertainty still had an impact on the water resources availability especially the low flows (regardless of their size).

In Table 6.1,Table 6.2 and Table 6.3 the uncertainty values represents the percentage differences between the minimum and maximum dam volumes or irrigation areas and is given by: [maximum average – minimum average)/maximum average value] x 100 (Sawunyama *et al.,* 2011). The total farm dam volumes (in Ml) and the range (min and max) of variability (uncertainty) used in the model simulations for the BS2, BS3, BS4, BS5 and BS6 subzones which are part of the Shashe in Zimbabwe were so small that they did not impact the uncertainty of the model outputs. Therefore, their uncertainty % was not calculated.

The uncertainty distribution for Mogalakwena is given in Table 6.1. The uncertainty distribution shows a high overall uncertainty, averaging over 50%, for the farm dam data in Mogalakwena with relatively low uncertainty, averaging below 50%, for the irrigation data (except for a few catchments).

Table 6.1. Total farm dam volumes (in Ml) and the range (min and max) of variability (uncertainty) used in the model simulations for each of the quaternary catchments of the Mogalakwena sub-basin

Catchment	LIMCOM (2013)	Alternative source*	Uncertainty %
A63E	9310	15240	39
A63C	1610	5870	73
A61A	-	7590	100
A61B	-	9740	100
A61C	1210	1170	3.3
A61D	1410	5230	73
A61E	1320	12290	89
A61F	-	14450	100
A61G	3220	5640	43
A61H	8830	12040	27
A61J	-	12430	100
A62A	460	4680	90
A62B	-	-	0
A62C	-	540	100
A62D	200	2150	91
A62E	-	6550	100
A62F	390	4500	91
A62G	-	-	0
A62H	-	1220	100
A62J	-	3950	100
A63A	60	5120	99
A63B	750	1620	54
A63D	460	1900	76

**Remote sensing, etc*

The uncertainty distribution for Shashe is displayed in

Table 6.3. There is no uncertainty for most sub-zones and high uncertainty values for a small number of sub-zones for both farm dam and irrigation. However, in this study the uncertainty values are only based on comparing data from LIMCOM (2013) to remotely sensed data. Comparing other sources could have had completely different results, but that was beyond the scope of this study.

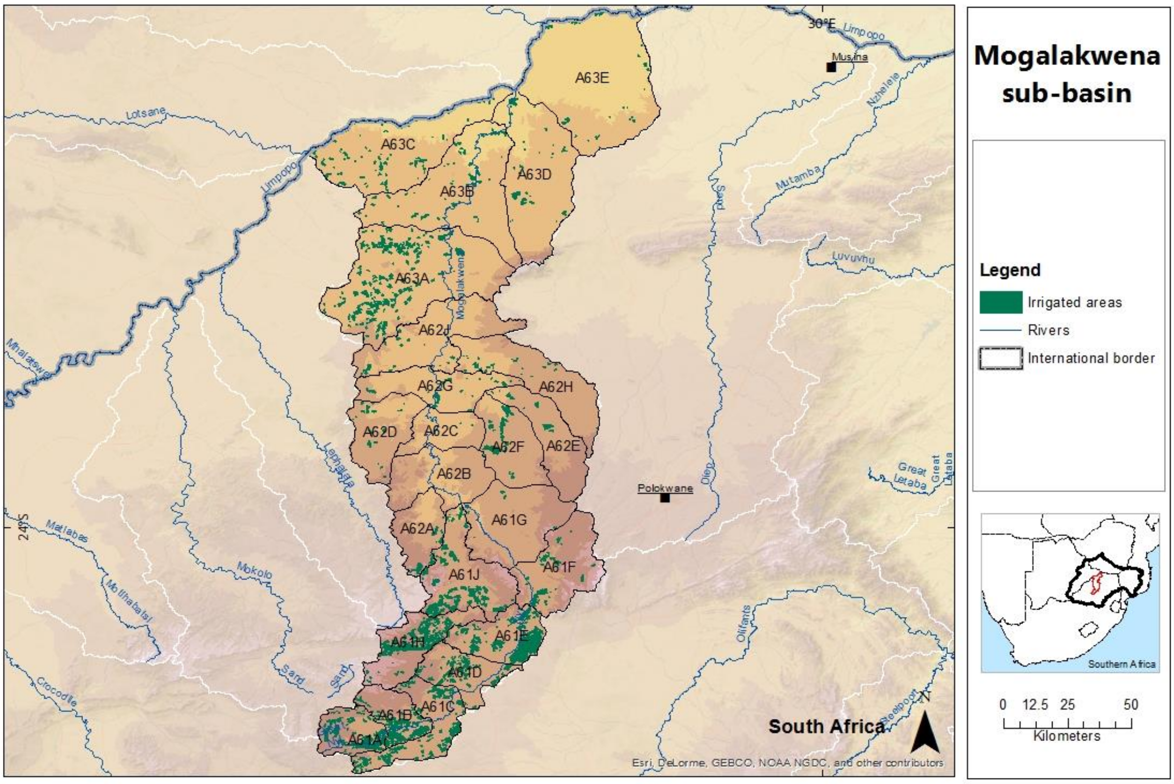


Figure 6.1. Distribution of irrigated areas in the catchments of the Mogalakwena sub-basin.

Table 6.2. Total irrigated areas (km^2) and the range of variability (uncertainty) for each of the quaternary catchments of the Mogalakwena sub-basin.

Catchment	LIMCOM, 2013	DAFF, 2011	Uncertainty %
A63E	40	52.91	24
A63C	2.67	7.28	63
A61A	6.81	7.66	11
A61B	3.34	5.59	40
A61C	4.56	4.9	7
A61D	2.93	3.35	13
A61E	17.75	9.63	46
A61F	8.6	5.41	37
A61G	7	1.16	83
A61H	8.38	33.63	75
A61J	18.93	14.04	26
A62A	3.54	2.28	36
A62B	0	0	0
A62C	0.1	0	100
A62D	1.16	0.66	43
A62E	1.49	0	100
A62F	4.41	3.86	13
A62G	0.74	0.04	95
A62H	0.55	0.03	95
A62J	0.53	0.53	0
A63A	3.43	24.98	86
A63B	8.7	6.25	28
A63D	1.91	6.46	70

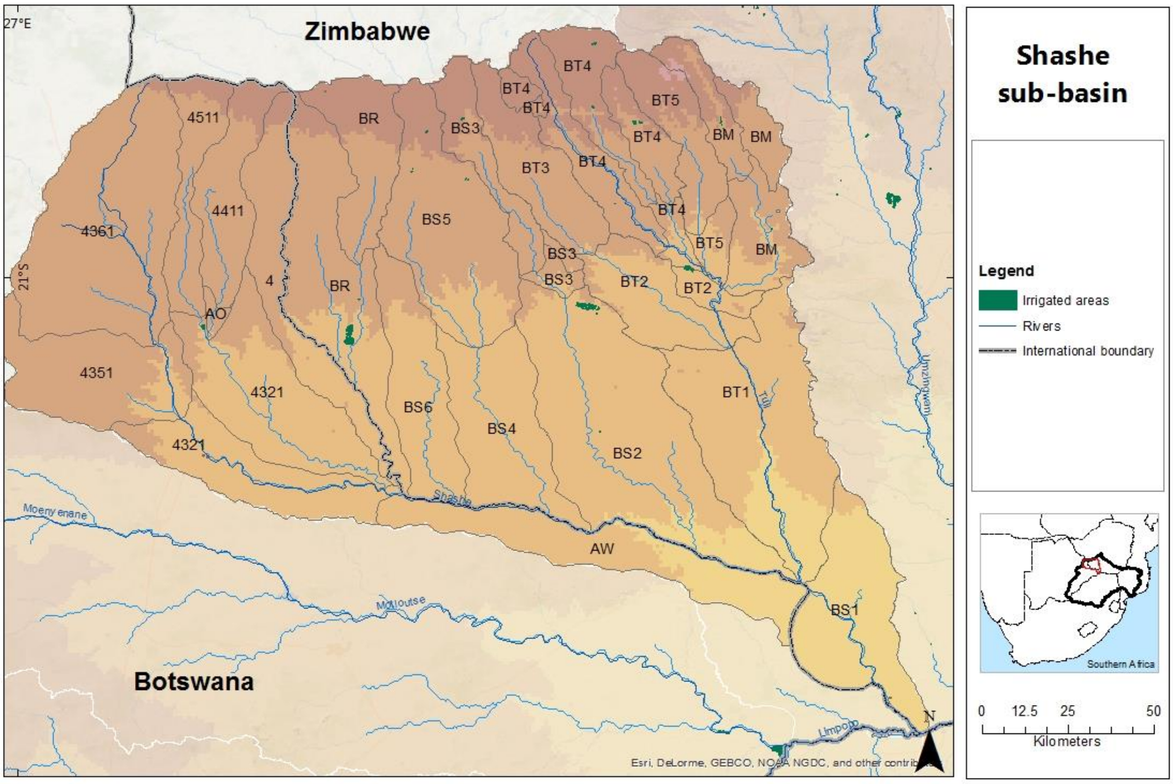


Figure 6.2. Distribution of irrigated areas in the Shashe sub-basin.

Table 6.3. Total irrigated areas (in km^2) and the range of variability (uncertainty) for each of catchments of the Shashe sub-basin.

Catchment	LIMCOM, 2013	Manual digitising in Google Earth	Uncertainty %
BS1	-	0.71	100
BS2	3.33	3.33	0
BS3	0.08	0.21	62
BS4	-	-	0
BS5	0.17	0.17	0
BS6	-	-	0
BR	4.58	4.67	2
BM	0.16	0.67	76
BT1	0.003	0.003	0
BT2	0.54	0.54	0
BT3	-	-	0
BT4	0.38	0.411	8
BT5	-	-	0
AW	-	-	0
AE	-	-	0
4321	-	0.448	100
AO	-	-	0
4411	-	-	0
4511	-	-	0
4351	-	-	0
4361	-	-	0

6.2 QUANTIFY THE UNCERTAINTIES AND MODEL CONTRASTING OF THE LIMPOPO RIVER BASIN

Three steps were taken to ultimately present the flow duration curves in Figure 6.3 and Figure 6.4. Firstly, the naturalised flows were simulated based on the data provided by LIMCOM (2013). Secondly, naturalised flows were simulated for a range of model parameters related to natural processes and lastly, water uses (small dams and irrigation were added) with their ranges of uncertainty. The parameter uncertainty is mainly caused by uncertainty associated with the inability to accurately relate physical properties data to the parameter values and how the Pitman model responds to these effects. Water use uncertainty, will only be affected by the relative contribution of each source (as displayed in Tables 6.1 – 6.3).

6.2.1 Results at the outlet of the Mogalakwena sub-basin, the A63D catchment.

The simulated mean monthly flows were 22.6 Mm^3 whereas the maximum mean monthly flows for the uncertainty related to the natural parameters were estimated to be at 24.7 Mm^3 and a minimum of 21.5 Mm^3. The results show that the whole range of flows (i.e. high, medium and low flows) is impacted when uncertainty related to natural parameters is considered (Figure 6.3). The minimum value for the expected total uncertainty when the natural and anthropogenic (water use) parameters are summed up together was the same as the natural parameters uncertainty only, but the maximum mean monthly flows were estimated to be at 25.0 Mm^3 and the minimum flows were estimated to be 22.2 Mm^3. The results show that the upper bound slightly increases once water use uncertainty is added, whereas the lower bound stays almost the same except for at the low flows where the bound increases slightly.

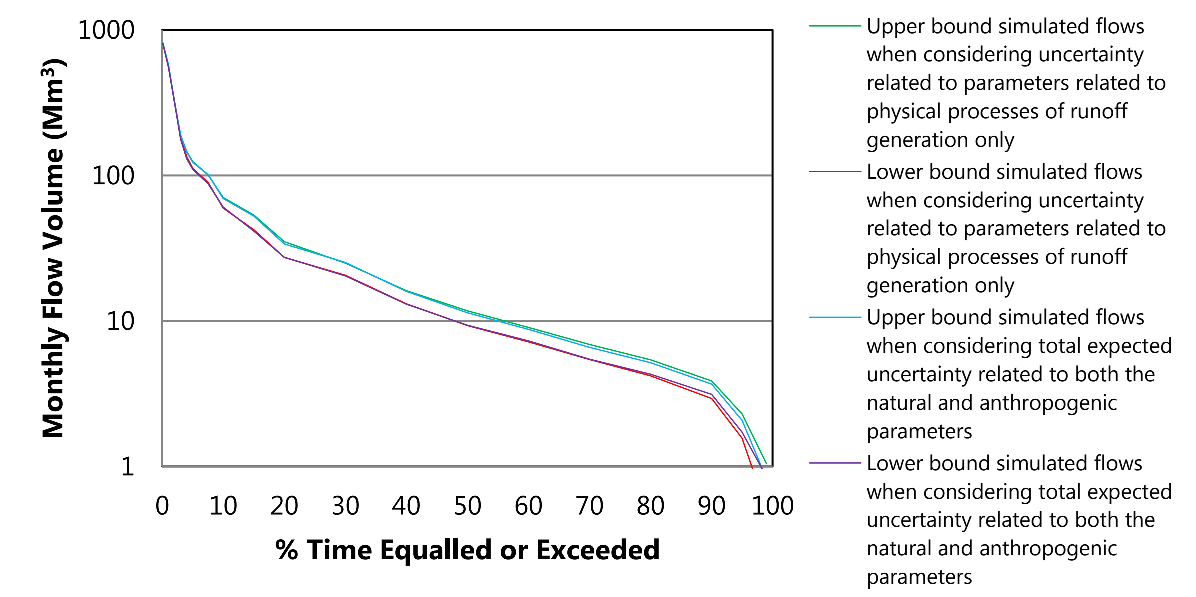


Figure 6.3. The variation of the flows at the outlet of the A63D catchment based on the uncertainty in the natural model parameters as well as total expected/calculated uncertainty range of both natural and anthropogenic water use (farm dams and irrigation) parameters.

6.2.2 Results for the Shashe sub-basin

The simulated mean monthly flows were 14.5 Mm^3 whereas the maximum mean monthly flows for the uncertainty related to the natural parameters were estimated to be at 18.0 Mm^3 and a minimum of 11.7 Mm^3. The results show that the whole range of flows (i.e. high, medium and low flows) is impacted when uncertainty related to natural parameters is considered (Figure 6.4). The minimum value for the expected total uncertainty when the natural and anthropogenic (water use) parameters are summed up together was the same as the natural parameters uncertainty only, but the maximum mean monthly flows were estimated to be at 17.7 Mm^3. The results show that the upper bound slightly increases once water use uncertainty is added, whereas the lower bound stays almost the same.

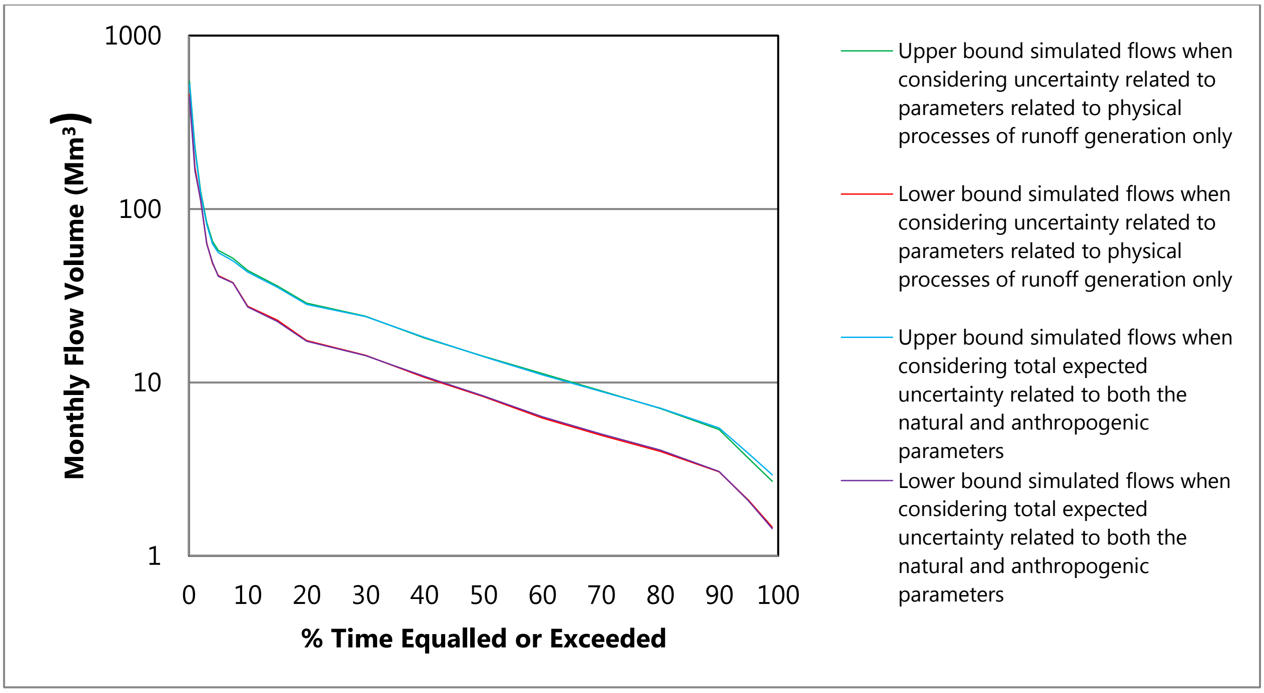


Figure 6.4. The variation of the flows at the outlet of the BR1 catchment based on the uncertainty in the natural model parameters as well as total expected/calculated uncertainty range of both natural and anthropogenic water use (farm dams and irrigation) parameters.

CHAPTER 7
Conclusions and recommendations

The purpose of this chapter is to summarize the main findings of the study and relate them to the study objectives. Some important recommendations for future research are also highlighted. The main idea of this study was to assess the impact of the addition of uncertainty related to generation of water resource estimates using available information since no formal recognition of uncertainty is used in the practical application of hydrological models in southern Africa. However, international research does provide many examples of different approaches that account for uncertainty in hydrological modelling. These approaches have not yet been used in practice in southern Africa mainly due to the differences in models calibration approaches, the willingness of practicing hydrologists to adopt new methods and the differences in the availability and quality of data in this region.

While formal uncertainty analysis of rainfall and runoff data did not form part of this study, impacts on model results were clearly observed. In this study, and also in modelling applications in southern Africa, general modelling were hampered by several factors, which include:

- A high degree of spatial and temporal variation in rainfall, evaporation and runoff data.
- A lack of long or continuous time series records of rainfall, evaporation and particularly runoff stations, resulting in many basins being ungauged.
- Uncertainty in the parameter estimation methods due to the high possibility of human error, especially in ungauged basins.
- Poor quantification of land and water use changes, particularly dams and irrigation areas. Observed runoff data are therefore often residual record.

This study therefore provides a first step towards employing uncertainty principles in water resource assessment studies by looking at the expected uncertainty related to the natural parameters of flow generation and those related to anthropogenic activities in basins.

6.3 CONCLUSIONS

Much of the discussion in this study focuses on the uncertainty related to the input data, specifically parameters of physical and anthropogenic (such as farm dams and irrigation) processes, and how it affects the model outputs. The main objective was to be able to demonstrate that estimated water resources are thus capable of spanning a wide range of plausible or probable values. This study gives insight into how the water resources of the Mogalakwena and Shashe sub-basins would be expected to vary when such uncertainty is accounted for in the estimation process. It can be concluded that uncertainty (in this case related to natural parameters and water use data) plays an important role in the estimation of water resources as demonstrated in the sub-basins. The uncertainty related to the estimation of water use data tends to affect both the high and low flows when compared to only uncertainty related to natural flow generation processes. Farm dams would absorb the peak flows during the rainy season, whereas irrigation would be important during the low flow season as water is abstracted for irrigation to supplement drier low rainfall conditions. This study provides a limited illustration of how the identification and quantification of uncertainties can provide insight into the possible impacts of using a database such as the national water resources assessment study (WR2012) without further examining the quality of the data. This study also contributes by providing water resources estimations that include uncertainties based on the data that are routinely used in the modelling processes.

6.4 Recommendations and limitations

6.4.1 Recommendations for the input data

Comparing all data sources of input data for Mogalakwena and Shashe was beyond the scope of this study. Also, input data such as climate data and other water use data (e.g. mining activities, groundwater abstractions) were not analysed in this study. Future studies can include:

- A comparison of other input data such as mining activities, industrial activities and other water abstractions to give an idea of the expected range of uncertainty related to these activities before the data could be used in water resources estimation studies.
- Comparing the uncertainties of various sources to find the expected impacts on the simulation of water resources. These simulation results are used in policy making and day-to-day decision making in management, planning and development processes. It is therefore imperative to have a sense of how the data, tools and science used for information generation can be relied upon.

6.4.2 Recommendations for the representation of the model outputs

How to present the results to decision makers was beyond the scope of this study. However, the importance of incorporating uncertainty in estimating water resources cannot be ignored. Also, strong connections between decision making risks with financial implication exist. Further studies can include:

- Analysing various methods in which the uncertainty can be presented. An important factor to consider is whether or not the decision maker will accept and be able to utilise data that show the upper and lower bounds of the estimated water or if they would prefer a single estimated value.
- An evaluation of the impact of the presentation of the uncertainty results to decision makers of various sectors, e.g. how does the presentation of upper

and lower bounds of uncertainty impact the calculations of constructing a large dam compared to just using an average value of the estimated water resources that is available in a sub-basin? There are obvious financial implications related to over or under- designing such infrastructure.

- Analysing how climate change, with its accompanying uncertainties, will impact the decision and/or policy making along with the uncertainties in the present day water resources estimation.

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