# WATER RESOURCES AVAILABILITY IN THE CALEDON RIVER BASIN PAST, PRESENT AND FUTURE

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By

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# ABSTRACT

The Caledon River Basin is located on one of the most water-scarce region on the African continent. The water resources of the Caledon River Basin play a pivotal role in socio-economic activities in both Lesotho and South Africa but the basin experiences recurrent severe droughts and frequent water shortages. The Caledon River is mostly used for commercial and subsistence agriculture, industrial and domestic supply. The resources are also important beyond the basin's boundaries as the water is transferred to the nearby Modder River. The Caledon River is also a significant tributary to the Orange-Senqu Basin, which is shared by five southern African countries. However, the water resources in the basin are under continuous threat as a result of rapidly growing population, economic growth as well as changing climate, amongst others. It is therefore important that the hydrological regime and water resources of the basin are thoroughly evaluated and assessed so that they can be sustainably managed and utilised for maximum economic benefits.

Climate change has been identified by the international community as one of the most prominent threats to peace, food security and livelihood and southern Africa as among the most vulnerable regions of the world. Water resources are perceived as a natural resource which will be affected the most by the changing climate conditions. Global warming is expected to bring more severe, prolonged droughts and exacerbate water shortages in this region. The current study is mainly focused on investigating the impacts of climate change on the water resources of the Caledon River Basin.

The main objectives of the current study included assessing the past and current hydrological characteristics of the Caledon River Basin under current state of the physical environment, observed climate conditions and estimated water use; detecting any changes in the future rainfall and evaporative demands relative to present conditions and evaluating the impacts of climate on the basin's hydrological regime and water resources availability for the future climate scenario, 2046-2065. To achieve these objectives the study used observed hydrological, meteorological data sets and the basin's physical characteristics to establish parameters of the Pitman and WEAP hydrological models. Hydrological modelling is an integral part of hydrological investigations and evaluations. The various sources of uncertainties in the outputs of the climate and hydrological models were identified and quantified, as an integral part of the

whole exercise. The 2-step approach of the uncertainty version of the model was used to estimate a range of parameters yielding behavioural natural flow ensembles. This approach uses the regional and local hydrological signals to constrain the model parameter ranges. The estimated parameters were also employed to guide the calibration process of the Water Evaluation And Planning (WEAP) model. The two models incorporated the estimated water uses within the basin to establish the present day flow simulations and they were found to sufficiently simulate the present day flows, as compared to the observed flows. There is an indication therefore, that WEAP can be successfully applied in other regions for hydrological investigations.

Possible changes in future climate regime of the basin were evaluated by analysing downscaled temperature and rainfall outputs from a set of 9 climate models. The predictions are based on the A2 greenhouse gases emission scenario which assumes a continuous increase in emission rates. While the climate models agree that temperature, and hence, evapotranspiration will increase in the future, they demonstrate significant disagreement on whether rainfall will decrease or increase and by how much. The disagreement of the GCMs on projected future rainfall constitutes a major uncertainty in the prediction of water resources availability of the basin. This is to the extent that according to 7 out of 9 climate models used, the stream flow in four sub-basins (D21E, D22B, D23D and D23F) in the Caledon River Basin is projected to decrease below the present day flows, while two models (IPSL and MIUB) consistently project enhanced water resource availability in the basin in the future.

The differences in the GCM projections highlight the margin of uncertainty involved predicting the future status of water resources in the basin. Such uncertainty should not be ignored and these results can be useful in aiding decision-makers to develop policies that are robust and that encompass all possibilities. In an attempt to reduce the known uncertainties, the study recommends upgrading of the hydrological monitoring network within the Caledon River Basin to facilitate improved hydrological evaluation and management. It also suggests the use of updated climate change data from the newest generation climate models, as well as integrating the findings of the current research into water resources decision making process.

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# 1 INTRODUCTION

## 1.1 BACKGROUND OF THE STUDY

Water resources play a vital role in the socio-economic development activities in the Caledon River Basin as well as in the broader southern African region and are essential for agriculture, food security, industrialisation, energy production, urbanisation (Postel, 1997) and many other uses. The Caledon River Basin is located in one of the most water-scarce parts of the globe, prone to severe water shortages and recurring droughts, which have hindered the economic development and social well-being in the region. Therefore, comprehensive hydrological evaluation forms an integral part in the sound planning and management of water resources, especially in view of mitigating the impacts of droughts, curbing water shortages and boosting the economy of the region.

The quality and quantity of water resources are susceptible to various environmental and societal dynamics. While the impacts of environmental changes on water resources have been investigated for a relatively long time (Hibbert, 1967; Bosch and Hewlett, 1982), the relationship of societal issues and water resources has only received significant attention in recent years from the International Association of Hydrological Sciences (IAHS: Montanari *et al.,* 2013).Nevertheless, hydrological scientists continue to investigate the impacts of changes such as population growth (Vörösmarty *et al.*, 2000; Arnell, 2004) and migration (Roy *et al*., 2008; Wenger *et al*.,2009; Allen *et al.,* 2011) on water resources. Several studies (Calder *et al*., 1995; Legesse *et al.,* 2003; Jewitt *et al*., 2004; Warburton *et al*., 2012) have also investigated the hydrological impacts of land use changes.

Perhaps the most widely investigated threat to water resources is the phenomenon of climate change. Contemporary literature abounds with research into the possible changes in hydrological processes and regimes, as well as water availability at both regional and global scales. While only a few studies (Alcamo *et al.,* 2007; Gosling *et al*., 2011; Arnell and Gosling, 2013) have focused on the global impacts of climate change, many have investigated the regional and local impacts (Andersson *et al.,* 2006; Hughes *et al.,* 2011a; Tshimanga and Hughes, 2012; Wolski *et al.,* 2012). From both management and scientific perspectives, these impacts on, and other changes in, water resources need to be well understood so that they can be incorporated into hydrological simulations of the past and present, as well as for the predictions of future water resources.

While the current study takes into consideration the various changes affecting water resources in the Caledon River Basin which include, among others, the impacts of climate change. As it is widely accepted that the quality and quantity of water resources are impacted by regional climate variability and change, predictions about the future status of water resources relies heavily upon the predictions of future climatic conditions. Adequate understanding and reasonable simulations of the current state of water resource dynamics are necessary to achieve reliable predictions of the future. (Beven 1993; Nandakumar and Mein 1997).More confidence in the future predictions can be achieved if the past and the present are successfully simulated.

Hydrological models, in one form or the other, are the basic tools used for hydrological simulations of the present climate and land use conditions. Future hydrological predictions of the influence of climate change are achieved by driving the hydrological (and water resources) models with predicted climate data derived from the coupled atmosphere-ocean general circulation models (AOGCM's), otherwise known as global climate models (GCM's).

The accuracy and integrity of such future climate conditions and related water resource predictions are inevitably marred by the cascade and propagation of uncertainties emanating from various sources (Bastola *et al.,* 2011; Dobler *et al.,* 2012). Water scientists and managers are faced with the difficult task of incorporating such uncertainties in the decision-making process. It is therefore useful to assess, quantify and eventually attempt to minimise these uncertainties. Uncertainty has not always been included as part of general hydrological modelling and water resources assessment until fairly recently, when it has received increased consideration (Montanari, 2007). Nowadays almost every hydrological investigation published in internationally recognised journals includes estimation of uncertainty.

## 1.2 RATIONALE

Water resource projects usually involve huge monetary investments and careful planning is required in order to maximize benefits. Such planning should also be done well ahead of time. However, in an attempt to make hydrological plans, water resource managers and decision makers are faced with a number of uncertainties in terms of hydrology, water demands, allocations and environmental impacts (Hobbs *et al.*, 1997). Accurate projections of water resource status are inherently affected by various sources of uncertainties, more especially when the impacts of climate change are taken into consideration (Lempert *et al.*, 2004).

Uncertainties such as those related to climate change significantly affect the hydrological decision-making process. For instance, a decision on whether to construct a larger reservoir or a higher bridge will depend on the predicted impacts of global warming on the local water resources and the local hydrology. A larger dam would be constructed to conserve more water if lower flows are predicted, while anticipated increases in peak flows may lead to the re-design of bridges, dam spillways or urban drainage systems. The scale and magnitude at which a project is executed depends on the uncertainties involved and the related risks in order to avoid over- or under-design of hydraulic structures.

Even though hydrological uncertainties can have serious consequences, they are sometimes ignored or indirectly addressed. Uncertainties impact on reliability, resilience and vulnerability of water resource management systems. Hydrological predictions should be as reliable as possible and the related uncertainties should be assessed and used to provide information for the decision makers. The uncertainty estimates can be used for risk assessment in the decision-making process. Inadequate uncertainty evaluation can lead to poor and ineffective water resource management decisions. When decisions about water resources are taken, it is important therefore that the uncertainties are thoroughly understood (Ajami *et al.*, 2008).

## 1.3 RESEARCH OBJECTIVES

The study is aimed at enhancing the understanding of the water resources and hydrological dynamics of the Caledon River Basin. It will also investigate the potential hydrological impacts of climate change, using the Pitman and the WEAP models. Uncertainties related to hydrological modelling and climate models will be evaluated and quantified, and approaches to minimise them will be formulated. An adequate understanding of general hydrology and water resources of the Caledon River Basin will lead to better integrated water resource management strategies and help maintain sustainable use of the resources. The study and its findings will also be useful in informing the policy and decision-making process and will be applicable to nearby basins and possibly to other areas with similar physiographic and hydrological environments. The main objective of the study will be achieved through the following specific objectives:

1. Accounting for natural and artificial factors affecting the quantity of water within the basin.

2. Simulating the past and present hydrological regime of the basin as influenced by the current and past state of the physical environment, observed climate conditions and estimated water use.

3. Predicting the future status of water resources in the basin and evaluating the impacts of climate change under predicted future climate conditions.

4. Identifying and assessing major sources of uncertainty related to the use of both the hydrological and the climate models.

5. Establishing methods of reducing the uncertainties at various stages of the prediction process.

## 1.4 STRUCTURE OF THE THESIS

**Chapter 2** covers the contemporary literature on the latest hydrological, water resource systems and climate modelling concepts, with emphasis on related uncertainties. Methods used in the various stages of the investigations are described in **Chapter 3**, while the description of the study area is covered in **Chapter 4**. **Chapter 5** provides detailed results of hydrological simulations of the Basin using the Pitman and WEAP models. Results of climate change scenarios are outlined in **Chapter 6.** General discussion, conclusions and recommendations arising from the study are outlined in **Chapter 7.**

# 2 LITERATURE REVIEW

## 2.1. INTRODUCTION TO HYDROLOGICAL MODELLING

A hydrological model is, by definition, any simplified representation of a complex hydrological system with a set of physical, chemical and biological processes involved in the conversion of input climatic variables, such as precipitation, to hydrological output variables, such as river discharge and groundwater storage (Hughes, 2004a). Rainfall–runoff models have long been used by hydrologists for a variety of purposes, including investigating and representing the hydrological catchment processes that convert rainfall into river discharge (Clarke, 1973; Loague and Freeze, 1985; Jakeman and Hornberger, 1993; Singh and Woolhiser, 2002; Moradkhani and Sorooshian, 2008). Such representations of the hydrological systems can be in various forms. For instance, a model can be a physical scaled-down exemplification of the real catchment; it can be an analogue-electrical model with various electronic components representing different catchment processes, or it can be in mathematical form where a set of mathematical equations and logical statements are used to represent various hydrological processes that influence the catchment response to the climatic inputs (Alley and Emery, 1986; Konikow, 1986; Refsgaard and Storm, 1996). To date, mathematical models have been the most widely used form of hydrological models, mainly because of the advances in computer technology. The discussions that follow will therefore only refer to the mathematical form of rainfall–runoff models.

## 2.2 THE CONTINUUM OF HYDROLOGICAL MODELS

A variety of hydrological model models have been developed over the past several decades to represent the hydrologic response of catchments to meteorological inputs. The models vary significantly in terms of degree of complexity. Several criteria for classifying rainfall–runoff models have been proposed within the hydrological arena (Clarke, 1973; Wheater *et al.,* 1993; Singh, 1995; Hughes, 2004b). Nonetheless, a more simplified classification involves categorising the models into three classes according to how they represent the physical hydrological system, the hydrological processes and the catchment's spatial characteristics.

Traditionally, hydrological models were regarded as either deterministic or stochastic. A deterministic model represents a hydrological system in such a way that the same sets of inputs always yield the same output series, given identical conditions. Deterministic models traditionally did not account for any type of error or uncertainty in either the input or the output variables (Jain and Indurthy, 2004; Schuol *et al*., 2008). Many of the hydrological models in use today are of a deterministic nature (Beven, 2001) but many of them also include stochastic components in that they allow for uncertainty in either climate inputs or model parameters or both (Beven, 2001; 2010).

Stochastic hydrological models on the other hand, have at least one component of a random character which is not explicit in the model input, such that identical random input sequences may yield different outputs under similar conditions. This type of model considers the random nature of hydrological variables (Hirsch, 1981; Yevjevich, 1987; Vachaud and Chen, 2002). The basis of stochastic models is to establish model parameters from statistical relationships between the input and output variables. Recently, the issue of uncertainty in hydrological models has been widely acknowledged and it is now part of many modelling exercises (Refsgaard, 1996; Krzysztofowicz, 2001) and consequently the traditional distinction between stochastic and deterministic models is less clear.

Another classification approach for hydrological models is based on the amount of detail and degree of complexity used to describe hydrological systems (Hughes, 2004b). Figure 2.1 shows the variation of model complexity in three dimensions: structural, spatial and temporal. Figure 2.1 also provides a few examples of commonly used hydrological models and places them in a three dimensional 'complexity space' according to their various features.

Structural complexity in rainfall-runoff models is primarily determined by the extent and detail to which they represent and describe the various processes involved in transforming climatic inputs (e.g. rainfall and evaporative demands) into hydrological outputs (e.g. stream flow). While conceptually complex models explicitly represent individual processes such as interception, infiltration and groundwater movement, relatively simple models use fewer mathematical equations to implicitly account for dominant hydrological processes (Freeze and Harlan, 1969; Beven, 1989; Grayson *et al.,* 1992). For this reason, complex models inevitably use large numbers of parameters to describe the hydrological processes, while the simplified model structures comprise only a few model parameters. Similarly, the amount and detail of data required to inform a model increases with the level of model complexity. This can be demonstrated as presented by the direction of the arrow in Figure 2.1.

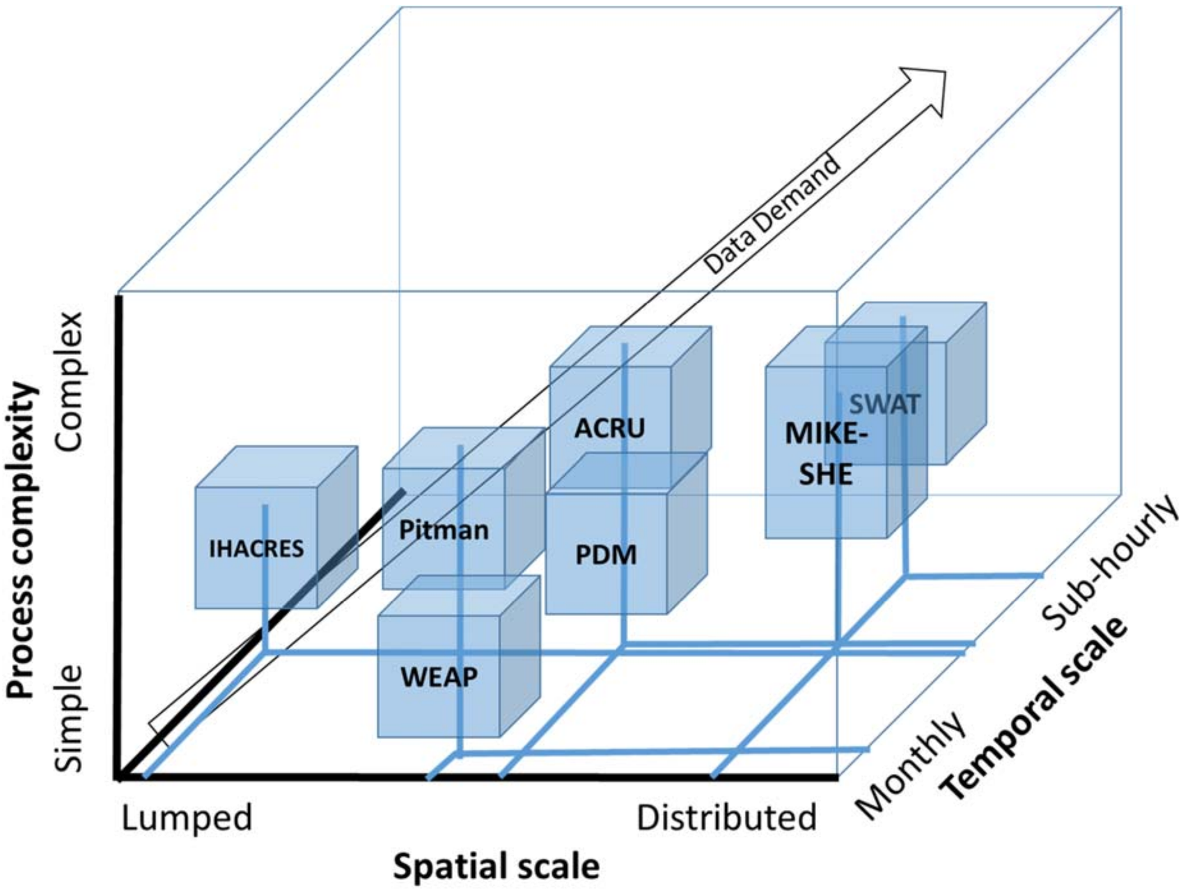



Figure 2.1 Illustration of a classification of hydrological model according to the level of complexity, with examples of commonly used models: IHACRES (Jakeman *et al*., 1990), Pitman (Hughes, 2004a), WEAP (Yates *et al.,* 2005), ACRU (Schulze, 1994), PDM (Moore, 2007), SWAT (Arnold *et al.,* 1998), MIKE-SHE (Abbott *et al.*, 1986).

The level of complexity and conceptual detail required in hydrological models has been a matter of considerable debate by hydrological scientists (Perrin *et al.* 2001; Das *et al.,* 2008; Rosero *et al.,* 2010). While some are of the opinion that simplified model structures may be sufficient to represent hydrological systems, others maintain that models should be complex enough to adequately represent many of the catchment hydrological processes. One of the advantages of the simple model structures is that they are easier to calibrate, while on the other hand a complex model with many parameters suffers from parameter interaction (Boyle *et al.,* 2000; Rosero *et al.,* 2010), equifinality (Beven, 2006) and the problem of parameter identifiability (Beven and Freer, 2001). Beven (1989) argues that a simple model with five or less parameters can sufficiently reproduce the hydrologic information of a system. The use of simple models has also been advocated by Hornberger *et al*. (1985) and Loague and Freeze (1985), both of whom found that simple models can out-perform complex model systems. Perrin *et al.* (2001)

demonstrated that simpler models can perform at a level similar to models with many parameters.

Spatial complexity defines the resolution with which a model represents spatial details of a hydrological system. In spatially simple models an entire catchment is considered to be a homogenous unit with input and output data and parameter sets being uniform throughout the catchment and runoff considered at the outlet of the catchment and not at sub-basin level (Refsgaard, 1996; Willems, 2001; Ruelland *et al.,* 2008). Very spatially simplified models do not account for heterogeneous spatial variations in physical characteristics of a watershed (such as slope, vegetation and geology). On the opposite end of the spatial complexity scale are the models which are described as fully-distributed. Spatially complex models are fully capable of incorporating the heterogeneous nature of the state variables, basin properties and meteorological forcing data. These are delineated and defined at grid cell scale, each of which are uniquely defined (Clark *et al.,* 2008; Immerzeel and Droogers, 2008; Bouma *et al.*, 2011). The role of spatial complexity in the performance of hydrological models has been investigated by several researchers (Refsgaard and Knudsen, 1996; Shah *et al.,* 1996; Boyle *et al*., 2001; Koren *et al,* 2003; Zhang *et al.,* 2004; Carpenter and Georgakakos, 2006; Das *et al.,* 2008). Even though spatially complex models are more realistic representations of the environment, many of these studies suggest that they are not superior over simplified model structures, as one might hypothesise. In fact, Das *et al.* (2008) concluded that models with intermediate complexity structures performed better than both fully distributed and lumped models.

Another dimension of complexity of hydrological models is the temporal resolution (Figure 2.1). This scale is based on the simulation interval and time duration at which input and output variables are defined. Bruneau *et al.* (1995) contend that time resolution of a hydrological model can have a significant impact on modelling results. The coarsest time interval usually used in models is the monthly time-step and there are also more complex models which simulate hydrological variables at finer temporal scales: daily, hourly and sub-hourly (Singh and Woolhiser, 2002; Bárdossy, 2007; Collischonn *et al.,* 2008). Some models use variable length time intervals to simulate rapid and slower hydrological responses of a watershed in an efficient manner (Hughes, 1993; Hughes and Sami, 1994; Zhang *et al*., 2008).

All hydrological models, regardless of the level of complexity (see Figure 2.1) require data and information to be able to adequately simulate the hydrological process of a basin (O'Connell, 1991). Less spatially complex models require sufficiently long observation data to enable the quantification of parameters through mathematical calibration and less detailed basin property data may be necessary (Brath *et al.,* 2004). On the other hand, highly complex models (e.g. in case of a fully distributed physically-based model structure) depend more on field data relating to physical basin properties to estimate the parameter values (Beven, 1989). These require extensive field surveys running over substantial periods of time for every grid cell. However, Beven (1989) contend that measurements and information representative for every grid cell are feasible only at the scale of small experimental watersheds. To mitigate the extensive data demands required for spatially distributed, physically-based modelling approaches, some modellers proposed that some of the hydrological processes be presented by means of simplified conceptual algorithms. This has consequently, given rise to a generation a mixed conceptual- physically-based model types (Brath and Montanari, 2000). While some parameters of such models are quantified through field investigations, others are estimated by mathematical calibration against historical data (Brath and Montanari, 2000; Brath *et al.,* 2004). Other models have incorporated probability distribution approaches to represent variability in a structure with a relatively low degree of spatial resolution (Moore, 2007).

The choice of a model to represent the basin's hydrological response to climate inputs should therefore be guided by the type and quantity of data available. Complex models are more appropriate to represent hydrological systems of catchments with high geometrical variation, such as the Caledon River Basin. However, lack of sufficient measured data in southern Africa (Hughes, 1997; Oyebande, 2001) presents a major challenge and results in substantial uncertainties in model predictions (Binley *et al.,* 1991). For this reason application of simpler models is more appropriate in data-scarce regions. In general, simpler models require less intense data and information than complex models, nevertheless their outputs will have a substantial uncertainty resulting from the more generalised model structure.

## 2.3 MODEL PARAMETERISATION

Rainfall-runoff models are characterized by parameter values which often represent physical processes of the catchment spatial hydrological processes. Parameters are typically designed to represent different components affecting runoff generation process, such as soil types, vegetation types, geological layers (Refsgaard, 1996), as well as the general hydrologic response of a catchment. Fewer model parameters imply a simpler calibration process but more parameters are required to represent the complex rainfall-runoff processes (Hughes, 2004a). The optimum level of detail and the number of parameters is therefore not easily determined and is dependent on the available data to quantify parameters or calibrate a model (Beven, 1989; Jakeman and Hornberger, 1993). Wheater *et al*. (1993) propose that model parameters should preferably be quantified from field measurements. Although this proposal is convincing and scientifically plausible, Beven (1989) recognised that this is precluded by the heterogeneity of process responses and the scale-dependence of parameters. To mitigate this challenge, several researchers developed simplified coefficients to quantify model parameters based on physical basin properties (Ao *et al*., 2006; Wagener and Wheater, 2006; Kapangaziwiri and Hughes, 2008). This approach is known as the *priori* estimation technique. An advantage with this approach is that the established quantitative relationships between model parameters and basin characteristics (e.g. topography, soil types and geology) can be applied to in poorly gauged and ungauged basins, where there are insufficient stream flow records to facilitate mathematical calibration (Refsgaard and Knudsen, 1996; Loague and Kyriakidis, 1997).

## 2.4 MODEL CALIBRATION

Hydrological models consist of parameters which define the hydrological response of the modelled catchment and thus determine the ability of the model to simulate and predict the catchment runoff. It is common practice to adjust parameter values so that the modelled output matches the observed records as closely as possible (Beven and Smith, 2014; Zhou *et al.,* 2014). The 'optimum' parameter values are determined based on the best model performance in terms of an established set of objective functions, which may be in the form of statistical coefficients, bias, visualisation of the hydrographs, as well as the use of scatter plots. Calibration is therefore aimed at obtaining a set of parameter values which yield the maximum or minimum value (whichever is the case) of the set objective function (Geem, 2014).

Ndiritu and Daniell (1999) describe calibration as an iterative procedure whereby the first step is to simulate using initial parameter values from a search space, followed by a new set that performs better than the previous one. The procedure is repeated until there cannot be any further improvements obtained for the simulated time series relative to the observed. The traditional idea of obtaining the optimum set of parameters may seem appropriate for parsimonious models (Perrin *et al.,* 2003; Basu *et al*., 2010) with a relatively few parameters, with minimum interaction. However, for models with many parameters, a combination of many different parameter sets can yield equally acceptable hydrological simulations, in which case there is no best single parameter set. This concept is known as *equifinality,* coined in the 1950`s by von Bertalanffy (1950) and later introduced to the hydrological world by Beven (1993, 1996, 2001). There are basically two ways in which calibration of model parameters can be achieved, i.e. either manually or automatically.

### 2.4.1 Manual Calibration

Traditional manual calibration requires the user to manually adjust parameters, usually one at a time, in a trial-and-error fashion. Adjustments are done until the best hydrograph fit is achieved, based on visual judgement and some form of performance measures. This procedure requires the expertise of a modelling hydrologist about the model structure being used as well as of the effects of individual parameters on a simulated hydrograph. Because parameters are adjusted one by one, the effect of each on the simulated hydrograph can easily be identified. However, the process can be tedious and time-consuming. This exercise is even more difficult in the case of a model with several parameters, which might also interact with each other in the way outputs are determined (Gupta *et al.,* 1998; Fenicia *et al.,* 2007; Boyle *et al.,* 2000). While manual calibration can give good results (Govender and Everson, 2005) and allows the user to pass judgement on the plausibility and validity of parameter values, its major disadvantage is that it is a subjective exercise and it may not always be able to cover the plausible parameter space (Kim *et al.,* 2007).

### 2.4.2 Automatic Calibration

The development of automatic methods of parameter calibration for hydrological models was mainly motivated by the drawbacks inherent in manual calibration. Automatic calibration uses mathematical algorithms to sample through the parameter continuum in search of optimum parameter values, based on a well-defined search procedure and one or more objective functions (Madsen, 2000). Automated calibration is suitable in structurally complex models with several parameters, where manual calibration might be extremely difficult. Automatic calibration takes advantage of high speed computer power and thus saves a lot time, compared to the manual method. Though automatic calibration offers a convenient means of obtaining optimal parameter values for hydrological modelling, there is a major concern about its lack of assessment of the physical plausibility of parameter values (Boyle *et al*., 2000; Madsen *et al*., 2002).

Some of the first developments of automated calibration were formulated in the mid 1960's and the late 1970's (Dawdy and O`Donnell, 1965; Chapman, 1970; Nash and Sutcliffe, 1970; Johnston and Pilgrim, 1976). Recently, there has been considerable interest in the use and improvement of automatic parameter calibration and as such, a large number of parameter optimization algorithms have been formulated. The use of some of the most popular globally-based optimization methods reported in the literature include the adaptive random search (Brazil, 1988), generic algorithm (Wang, 1991; Ndiritu, 2001), shuffled complex evolution (Duan *et al.,* 1992; 1993), multi-start simplex method (Sorooshian *et al.,* 1993), automatic calibration scheme for HBV (Zhang and Lindström, 1997) and simulated annealing (Sumner *et al.,* 1997).

The abundance of methods for automatic calibration makes it a challenging task for a hydrologist to select one particular method over others. This has motivated researchers to embark on studies with the aim of comparing the performance of some of the more popular frameworks. Such comparative studies may assist hydrologists in the difficult task of selecting a suitable method to meet their objectives. In one study, Madsen *et al*. (2002) compared the performance of three calibration methods. The authors concluded that none of the methods was superior to others in terms of general performance, but indicated that different methods perform differently on various performance indicators. On the other hand, a similar study by Goswami and O'Connor (2007) compared six automatic calibration routines and concluded that one method (simulated annealing) generally out-performed other competing methods. Numerous other comparative studies were also reported for example by: Gan and Biftu (1996); Cooper *et al*. (1997); Kuczera (1997); Franchini *et al*. (1998); Thyer *et al*. (1999); Vugrin (2005). Many of these studies concluded that the population-shuffle-based routines such as the shuffled complex evolution method (SCE-UA) developed by Duan *et al.* (1993) yielded the best results in terms of obtaining the closest fit to the observed.

Some researchers have proposed to combine the two calibration approaches (i.e. manual and automatic) to estimate model parameters (Gupta *et al*., 1999; Boyle *et al.,* 2000; Flipo *et al*., 2012). The so-called hybrid calibration takes advantage of the high-speed automatic calculations, at the same time involving the personal experience and skill of a hydrologist. In this case, a modeller would manually estimate parameter values based on prior experience and then 'fine tune' them using automatic calibration. Other studies compared the performance of manual against automatic calibration, with a variety of conclusions. For instance, Ndiritu (2009) compared the two approaches using the Pitman model and concluded that automatic calibration performed better in some catchments and worse in other catchments. Conversely, Madsen (2003) noted that automatic calibration provided better hydrological simulations than the expert manual approach. It is still therefore, inconclusive as to which of the two calibrations is superior to the other. They both have significant advantages and drawbacks. The hybrid approach may however, appear to be the more attractive choice as it makes use of the strengths of each procedure (Boyle *et al*., 2000; Madsen *et al*., 2002).

The entire calibration process, whether manual or automated, is commonly complicated by the inherent limitations in the quality and quantity of observed input data, complexity of the mathematical representation of the physical and hydrological processes occurring in the catchment, as well as an incomplete knowledge of the watershed characteristics (Immerzeel and Droogers, 2008). These result in hydrological model parameters, and the entire model predictions, being fraught with uncertainties.

## 2.5 MODEL EVALUATION

Hydrological models are the most powerful tools available to a hydrologist and thus play a critical role in hydrological sciences and water resource management. As such, the models need to be evaluated to gain confidence in their outputs. Model evaluation is normally based on its ability to simulate major hydrological processes in a watershed. Model performance assessment is normally carried out by comparing the model predictions at the basin outlet with the corresponding observed records (Wagener, 2003; Krause *et al*., 2005; Moriasi *et al.,* 2007). Of all the hydrologic variables that rainfall-runoff models simulate, river discharge is the most frequently used variable for evaluation because it is generally measured more often than other variables. Soil moisture content, groundwater levels, evapotranspiration and other components of catchment hydrology have also been used, albeit occasionally, as additional evaluation criteria for model performance (Anderton *et al*., 2002; Parajka *et al.,* 2006; Immerzeel and Droogers, 2008; Rakovec *et al.,* 2013). Heavy reliance on observed stream flow for model evaluation has recently been criticised for the fundamental reason that total output of a catchment can be simulated for the wrong reasons in the absence of other assessment measures of model performance (Kirchner, 2006).

There are a number of essential reasons why model evaluation should be performed. According to Krause *et al.* (2005), the main advantages of evaluating model performance are to quantitatively estimate the ability of the model to simulate the past, and possibly the future, hydrological response of a river basin and to allow, facilitate and monitor model improvements resulting from parameter and structural modifications.

Evaluation of model performance involves assessing the ‘goodness-of-fit’ of the simulated and the observed hydrological variables such as stream flow. This is usually achieved either by subjective visual inspection of the two hydrographs (Ewen, 2011) in terms of timing, rising and falling limb and base flow variations among others; or by objective mathematical methods. While visual inspection has no formalised standard procedure, it depends profoundly on the experience of a modelling hydrologist. However, objective model evaluation involves the use of mathematical estimation of the disparity between observed and simulated time series of a chosen output variable (Beven, 2001). Several mathematical objective functions have been developed and used over the years in hydrological modelling studies. The commonly used criteria include: the Nash-Sutcliffe efficiency (Nash and Sutcliffe, 1970), index of agreement (Willmott, 1981), coefficient of correlation (Wilcox *et al.,* 1990), and percentage bias. Traditionally, a modeller uses one of the objective functions to evaluate model performance. However, it is now widely acknowledged that using multiple objective functions is more appropriate as no single indicator can represent all the statistical aspects of a hydrological variable and may consequently lead to an inaccurate model assessment (Gupta *et al*., 1998; Wagener, 2003; De Vos and Rientjes, 2007).

A number of studies have compared the efficiency of different performance indicators (e.g. Krause *et al*., 2005).These comparison studies concluded that none of the evaluation criteria is superior to others, but emphasised that each has its own strengths and drawbacks. Therefore, more than one indicator may provide more information about the models' ability to represent the hydrological system response. Because there are a large number of model performance measures available to a hydrologist, it is difficult to justify the most appropriate indicator to use mainly because there are no clear and universally standardised guidelines on the quantitative evaluation of hydrological models (Moriasi *et al*., 2007). However, Legates and McCabe (1999) recommend that a proper hydrological model evaluation should include at least one dimensionless statistic, one absolute error index as well as a graphical analysis technique.

Both calibration of model parameters and the entire procedure of evaluating performance of hydrological models rely on the availability, quality and quantity of observation data (Boughton, 2007). Lack of sufficient hydrological and meteorological data is the main challenge facing hydrological modelling exercise in many parts of the world. Among others, Boughton (2007) and Li *et al.* (2010) assessed the effects of length of observation data series on calibration and performance of hydrological models. Whereas the former concluded that longer data sets produced improved model performance, the latter did not find any significant differences between data sets of varying lengths. The accuracy of hydrological modelling depends entirely on the observed hydrological and climate data, which is one of the major sources of uncertainty in hydrological predictions.

## 2.6 UNCERTAINTIES IN HYDROLOGICAL MODELLING

The accuracy and integrity of hydrological model predictions are inevitably affected by a cascade of uncertainties from various sources. Water scientists and managers are faced with the difficult task of incorporating such uncertainties in the decision-making process. It is therefore essential to understand, assess, quantify and, eventually minimise uncertainties in hydrological modelling at various phases as well as in the final model output.

The term ‘uncertainty’ does not appear to have a universal meaning in the context of hydrological science. However, in the context of the English language, ‘uncertainty’ refers to a state of having limited knowledge, where it is impossible to describe exactly the existing state, a future outcome or more than one possible outcome. Similarly, Zadeh (2005) defines uncertainty simply as ‘an attribute of information’. Uncertainty has not always been included as part of general hydrological modelling and water resources assessment until fairly recently, but since its inclusion, it has been receiving increased consideration (Montanari, 2004).

Hydrological model accuracy is affected by a number of sources of uncertainty including: errors in input data, parameter setting and model structure. When hydrological models are used to predict hydrological impacts of climate change, a predicted climate data set is used to drive them. Such data becomes an additional source of uncertainty.

### 2.6.1 Uncertainties in Observed Data

Rainfall–runoff models require, as input, several hydro-meteorological variables such as rainfall, potential evapotranspiration and snowmelt data. Other observation records that might be used to calibrate a model and quantify parameter values include stream flow volumes, groundwater heads and soil moisture content of the catchment being modelled (Kavetski *et al*., 2006a). Uncertainty in the hydrological modelling process is introduced by both systemic and random errors inherent in the values of these variables. Systematic errors in rainfall measurements may arise from factors such as strong winds (Nešpor and Sevruk, 1999) and evaporation from rain gauges which lead to under-estimation of rainfall depth (Habib *et al.,* 2001; Ciach, 2003). Poor rain gauge maintenance (leakage and damage) can also affect the estimation of rainfall in a catchment (Bartholomew, 2009).

Rainfall over any duration needs to be spatially interpolated from point data to obtain a representative estimate of catchment rainfall. There are a number of techniques used to convert gauge point measurements to areal data series. These include arithmetic average, Kriging and the Theissen polygon method which, because of their various assumptions, yield different average values (Buytaert *et al.,* 2006; Ruelland *et al.,* 2008). In many catchments especially in southern Africa, estimation of catchment rainfall is impacted by inadequate density of rain gauges which are not able to capture the high spatial and temporal variability

(Sawunyama and Hughes, 2007; Villarini *et al.,* 2008). Butts *et al*. (2004) contend that rainfall input is the major contributor of uncertainty in predicted flows.

Evapotranspiration (ET) is one of the most important constituents of the hydrological cycle in many environments and it comprises a major input in hydrological models (Droogers, 2000; Hargreaves and Allen, 2003). Accurate estimation of evapotranspiration is therefore critical in hydrological simulations and predictions. Inclusion of evapotranspiration data to drive hydrological models constitutes a major source of uncertainty in model outputs (Thompson *et al.*, 2014). One of the reasons for this is that ET is difficult to determine as it depends on many driving forces such as wind speed, temperature and other meteorological variables, which are also measured with a certain degree of error. There is a plethora of methods and models available for estimating potential evapotranspiration and according to Lu *et al.* (2005), there are more than 50 of such methods. Hargreaves and Samani (1982) and Lu *et al*. (2005) provide some of the commonly used ET estimation approaches. The Penman-Monteith method (Monteith, 1965) is one of the most widely used estimation methods in many hydrological models (Beven, 1979; Abbott *et al*., 1986; Arnold *et al*., 1998; Kay and Davies, 2008). The use of remote sensing for ET estimation is being tested globally in an attempt to explore methodologies of improving estimation as well as reducing model output uncertainties (McCabe and Wood, 2006; Cleugh *et al*., 2007; Kalma *et al.,* 2008; Mu *et al*., 2011).

One of the uncertainties in the estimation of ET stems from the method used, as well as the integrity of data of the atmospheric variables used in the estimation (Andréassian *et al.,* 2004). Given the fact that meteorological variables required for ET estimation are subject to systematic and random errors, it is inevitable that the resultant ET estimation will be uncertain. In southern Africa and other economically poor regions, such estimations are also affected by inadequate spatial distribution of meteorological stations. Oudin *et al*. (2005) have demonstrated that hydrological model outputs are sensitive to ET estimates and therefore uncertainties in the ET inputs are critical. Similarly, Middelkoop *et al*. (2001) adds that uncertainty in evapotranspiration becomes even more important during low river flows.

In some other regions, snowmelt is an important contributor to stream runoff. Snowmelt is not directly measured but is usually inferred from air temperature and albedo. Blöschl (1991) offers an example of the use of various models in determining the amount of snowmelt from air temperature and albedo. The author comments that uncertainty in albedo is a major contributor in snowmelt estimations. Another uncertainty in snowmelt arises from the fact that it is usually difficult to know how much snow is there to melt (Beven, 2001). The snowmelt component in hydrological modelling thus adds a significant uncertainty.

Runoff data and stream discharge records are typically used for model calibration and validation. Stream flow discharge is typically determined from river water levels, flow velocity and cross-sectional areas of a river channel, measurements of which are significantly uncertain (Pelletier, 1988; Herschy, 2002; Di Baldassarre and Montanari, 2009). The widely used stage-discharge relationships (rating curves) are established for river channels as a convenient estimation of stream flow from stage height records. Stream flow estimations by rating curves are affected by a number of uncertainties. Westerberg *et al*. (2011, citing Schmidt, 2000) suggest that uncertainties in discharge derived from rating curves can be categorised into three groups: i) natural uncertainties caused by geomorphological changes in river cross-section; ii) incomplete knowledge about physical processes and the assumptions in the stage-discharge model and iii) systemic errors in stage measurements.

Westerberg *et al.* (2013) and Guerrero *et al.* (2012) showed that stage-discharge relationships can have high temporal variation especially in alluvial river environments and that uncertainties in stream flow estimates can be substantially high for low flows. The implication is that rating curves need to be continuously updated to mitigate the uncertainty. There is an additional uncertainty when the rating curves are used to determine discharges beyond the range for which they were established (Di Baldassarre and Claps, 2010), especially during very high river flows. Considerable focus has recently been on quantification of uncertainty in stream flow estimation (Montanari, 2004; Baldassarre and Montanari, 2009) and the investigation of possible effects of uncertain stage-discharge relationship on the performance of hydrological models (Aronica *et al*., 2006; Thyer *et al*., 2009; McMillan *et al*., 2010).

In most environments, especially forested areas, rainfall interception is a significant part of the hydrological cycle and therefore is an important part of a rainfall–runoff modelling setup. However, there are no direct measurements of interception, instead there are several models developed for this purpose. Muzylo *et al.* (2009) comprehensively documented various models for calculating interception. Rainfall data and vegetation cover used as inputs in interception models introduce additional uncertainty in the calculated interception which is carried along in hydrological models.

Methods for determining soil moisture content are well documented in the literature: direct *in-situ* methods (Walker *et al.,* 2004; De Lannoy *et al.,* 2007; Hawke and McConchie, 2011) and remote sensing methods (Engman, 1991; Kostov, 1993; Njoku and Entekhabi, 1996). Uncertainty in soil moisture measurement arises from the various methods of measurement, assumptions made and variations in space and with depth. The soil moisture estimation component therefore gives rise to additional uncertainty in hydrological model output.

### 2.6.2 Model Structure Uncertainty

Hydrological models are a conceptual approximation, simplification and representation of a hydrological system. The efficiency of these conceptualizations is limited by the understanding of the hydrological processes, assumptions made, mathematical equations representing the processes, and the computer code thus developed (Uhlenbrook *et al.,* 1999; Wagener and Gupta, 2005). The models' ability to simulate and predict flow depends on its structure and any flaws in the structure representing the physical world will result in uncertainties in the model efficiency (Refsgaard *et al.,* 2006). Refsgaard *et al.* (2006) further contend that model structural inadequacies constitute a significant source of model output uncertainties. This view was also shared by Engeland *et al*. (2005) who showed that model structural uncertainty was larger than uncertainties related to parameters values.

Structural uncertainty in hydrological models does not appear to have been adequately dealt with like other sources (e.g. input data and parameter) of uncertainty and there is presently not as many formal frameworks developed to deal with it (Refsgaard *et al*., 2006). Since model structural uncertainty is not well understood, it is more difficult to assess as well as to characterise (Renard *et al.* 2010). Nevertheless, there are researchers who have attempted to address this source of uncertainty. For instance, Butts *et al.* (2004) evaluated different models using a set of performance criteria and contended that resulting variations in hydrological simulations were a result of uncertainty in model structures. Refsgaard *et al.* (2006; 2007) developed a framework dealing particularly with model structural uncertainties using a multiple conceptual rainfall–runoff model method. On the other hand, Renard *et al*. (2010) adopted a different strategy to isolate structural uncertainties from the total model predictive uncertainty using a statistical probability approach. It is widely acknowledged that structural uncertainty is much more difficult to quantify than other sources of model uncertainty (Rojas *et al.,* 2008; Warmink *et al*., 2010).

### 2.6.3 Model Parameter Uncertainty

In traditional hydrological modelling, models are usually calibrated to estimate optimal parameter sets. Calibration introduces parameter uncertainty because it is generally not feasible to estimate model parameters from field measurements or by *a priori* estimation (Beven, 2001). Most hydrological models are, to some extent, considered to be over parameterised (Jakeman and Hornberger, 1993) and as a result their parameters cannot be estimated with a high degree of confidence. In many cases many parameter sets provide equally good fits compared to observed records (Duan *et al.,* 1992; Freer *et al.,* 1996), and there is no single optimal parameter set. This problem is referred to as 'equifinality' (Beven, 2001). Parameter uncertainty arises from various aspects of modeling. These include the quality of data used for calibration (Kuczera and Williams, 1992; Fonseca *et al.,* 2014) as well as from the objective function used for optimisation (Sefe and Boughton, 1982; Bastidas, 1998; Silvestro *et al*., 2014). Parameter uncertainty has also been found to increase with the number of model parameters (Jin *et al*., 2010).

Quantification of parameter uncertainty in hydrological models has received considerable attention in the past years and there is a variety of approaches developed to deal with it (Jin *et al.,* 2010) some of these methodologies are discussed in the following sections.

## 2.7 METHODOLOGIES FOR EVALUATING UNCERTAINTIES IN HYDROLOGICAL MODELLING

The various sources of hydrological model prediction uncertainty need to be identified, assessed and quantified in order to be incorporated into the decision-making process and in the risk assessment procedure. A number of methods have been used to quantify and assess uncertainty in hydrological models. The general procedure used in these methods is to observe the model output while the source of uncertainty is used to perturb the model. While the developed approaches differ in various ways, such as the underlying assumptions, they make use of the various well-established sampling procedures. There are several sampling methods that have been developed in recent years which include: Monte Carlo simulation, Latin hypercube simulation (McKay *et al.*, 1979; McKay, 1992), Rosenblueth's point estimation (Rosenblueth, 1975) and Harr's point estimation method (Harr, 1989).

*Monte Carlo Sampling*

The Monte Carlo sampling (MCS) procedure was introduced in the 1940s by Ulam (Metropolis and Ulam, 1949) while working on the nuclear weapons projects. The procedure has since been applied in a wide range of fields, including hydrology. In hydrological modelling, the Monte Carlo procedure is generally used for sensitivity analysis, as well as for assessing uncertainty resulting from model parameter values (Krajewski *et al.,* 1991; Kuczera and Parent, 1998; Yu *et al*., 2001; Vrugt *et al.,* 2008). In this procedure a large number of realizations of model parameters are generated, based on the prior probability distribution function (e.g. normal, uniform). This is perhaps the most widely used method of sampling, and it is incorporated into many uncertainty analysis frameworks (discussed in the following section).

*Latin Hypercube Sampling (LHS)*

This statistical method generates a distribution from a possible range of values in a multi-dimensional distribution. When sampling a function of *N* variables, the LHS divides each variable into *M* equally probable intervals. The order of ranges is randomized and the calculation is executed *N* times with the random combination of each basic variable values from each range for each variable. The Latin hypercube sampling (LHS) technique has been extensively used in engineering and various fields of research (Helton, 1999; Hofer, 1999; Helton and Davis, 2003) and has consequently attracted some attention in the hydrological modelling arena, though it has not been applied to a great extent.

A few examples of the use of LHS available in the literature include Hossain *et al*. (2005) who used the sampling procedure to assess uncertainty resulting from satellite-based observations of flood predictions. Sieber and Uhlenbrook (2005) carried out a sensitivity analysis on a distributed 'tracer aided catchment' model using the Latin hypercube procedure. Similarly, the LHS technique was also used by Christiaens and Feyen (2002) to evaluate uncertainty and sensitivity measures for the physically-based MIKE SHE model and for a regional hydrological simulation model (Lal *et al.,* 1997). Yu *et al*. (2001) compared a number of sampling methods for uncertainty analysis for hydrological model predictions and concluded that LHS was a more efficient sampling methodology (than, for example, Monte Carlo) since it is less computationally demanding.

*Rosenblueth`s Point Estimate Method (RPEM)*

This is a probabilistic point estimate method which was first proposed by Rosenblueth (1975) to deal with uncertainty estimation of a model with correlated and symmetric random parameters. The method was later developed (Rosenblueth, 1981) to accommodate asymmetric random variables. Though the RPEM has not been extensively applied in hydrological modelling, some applications were reported by Yu *et al*. (2001). These authors present a good example of the use of this method in comparison with other sampling estimation methods. Similarly, Protopapas and Bras (1990) applied the method to the unsaturated flow model. The use of RPEM for estimating uncertainty has also been reported in other fields of research, for example, in water quality, environmental and structural engineering (Wang and Hao, 2002; McIntyre *et al.,* 2002; Tsai and Franceschini, 2005; Wang, 2012).

*Harr's Point Estimate Method (HPEM)*

Regarded as an improvement on RPEM, HPEM was introduced by Harr (1987) and is able to deal with multi-random variables. The method requires $2^p$ (where p is the number of parameters) model runs to estimate the statistical moments of the model output. The application of Harr's method in hydrology has been reported by authors such as Yeh *et al.* (1997) who used it to analyse uncertainty in the regionalisation of the unit hydrograph. Muleta and Nicklow (2005) have also applied the method for uncertainty analysis to investigate reliability of hydrologic model outputs.

## 2.8 UNCERTAINTY ESTIMATION FRAMEWORKS

Recently, there have been developments of a large number of frameworks dedicated to dealing with the assessment of uncertainty within the field of hydrological modelling. Many such uncertainty frameworks are basically parameter optimisation algorithms, such as those used for automatic calibration (discussed above), with the additional ability to account for various sources of uncertainties, such as input data errors and parameter uncertainties. As such, their common objectives are to locate optimal (or behavioural) sets of parameters while simultaneously evaluating various sources of uncertainty. Though the general concept behind the formulation of uncertainty frameworks is consistent, they differ in their general assumptions. They also differ in the sampling methodologies applied within the individual framework. Another basic difference is in the source of the uncertainty being evaluated. For instance, one framework may focus on addressing uncertainty resulting from input data, while another may deal with parametric uncertainty.

Some of the widely used uncertainty frameworks in hydrological modelling include: Generalised Likelihood Uncertainty Estimation (GLUE) introduced by Beven and Binley (1992), Bayesian Recursive parameter Estimate (BaRE) by Thiemann *et al*. (2001), Bayesian Total Error Analysis (BATEA) of Kavetski *et al*. (2006a; 2006b), Shuffled Complex Evolution Metropolis Algorithm (SCEM) developed by Vrugt *et al.* (2003), Maximum Likelihood Bayesian Model Averaging (MLBMA) of Neuman (2003), DYNamic Identifiability Analysis (DYNIA) by Wagener *et al*. (2003), Simultaneous Optimization and Data Assimilation (SODA) by Vrugt *et al*. (2005), Dual state-parameter estimation of Moradkhani *et al*. (2005), Integrated Bayesian Uncertainty Estimator (IBUNE) by Ajami *et al.* (2007). According to Ouyang *et al.* (2014), the most commonly used methods are GLUE (Beven and Binley, 1992) and the Bayesian-based methods (Thiemann *et al*., 2001; Kavetski *et al.,* 2006a; 2006b).

The current study uses an uncertainty framework based on the approach developed by Kapangaziwiri *et al.* (2009). This uncertainty assessment approach makes use of *a priori* parameter estimation based on physical characteristics of watersheds. They coupled this methodology with an independent Monte Carlo sampling procedure to generate output simulation ensembles from which behavioural sub-sets could be identified according to regional signatures of hydrological behaviour. While one advantage with this approach is that the established signatures are independent of the model structure, it however relies heavily on availability and quality of observed data to determine bounds of uncertainty (Kapangaziwiri *et al.,* 2009).

The importance of evaluation and estimation of a hydrological model's output uncertainty cannot be over-emphasised. Notwithstanding the fact that there are plenty of methodologies available for a hydrologist to select from, there are still no clear and explicit guidelines on the proper application of individual frameworks, or on the criteria for selection of any methodology to meet an individual hydrologist's objectives. It is also not clear which methodology is appropriate in a particular set of modelling and physical environment conditions. In light of such concerns, there is a need for more guidance on using such frameworks in such a way that they do not end up being inappropriately applied.

## 2.9 HYDROLOGICAL MODELLING IN SOUTH AFRICA

South Africa, and the SADC region as a whole, has a very high degree of climate variability, with some catchments experiencing wet tropical-type climate while others experience arid and semi-arid climates. This type of climate variability translates into stream flow variability as well. In general, South Africa is a water-scarce country and, as such, it is important that this limited but vital resource be well managed to achieve maximum benefit and to maintain sustainable use for generations to come. Hydrological modelling remains one of the most valuable tools for water resource management, especially for simulating hydrological information where data collection is not feasible and to reduce both labour and equipment costs.

The hydrological modelling exercise faces numerous challenges. One of the most important is lack of, or poor hydro-meteorological records such as rainfall, evaporation and stream flow. Such records normally require financial and political will to implement, maintain and sustain.

Until decision-makers recognise the importance of investing in upgrading and improving gauging and monitoring networks in the country, the problem may persist for quite a long time.

Within the context of South Africa, which might also be the case in other developing countries in southern Africa, Kapangaziwiri and Hughes (2008) contend that the main challenges that limit the applicability of hydrological models are: variation of climate and resultant river discharge in space and time; inadequate rainfall and stream flow records; general shortage of information on activities that impact on stream flow such as land use and water abstractions; inadequate scientific knowledge of hydrological processes, and more importantly, lack of trained personnel.

Hydrological modelling has proved to be one of the most important tools in the scientific understanding of the dynamic physical processes affecting the availability of water in South Africa and elsewhere. In recognition of hydrological models as invaluable water resource management tools, there have been a number of hydrological models developed in the country (e.g. Pitman, 1973; Schulze 1994; Hughes 2004b). The structures of these models were developed to suit the unique arid and semi-arid conditions of the country and the region as well. The conditions are commonly marked by high spatial and seasonal variations. The models were aimed at addressing some of the environmental and hydrological challenges that are faced by South Africa and the neighbouring countries, perhaps initiated and driven by development of water resources prompted by economic growth. The models were also useful for evaluating possible impacts of various water resources development options/scenarios, as well as feeling the hydrological data gaps resulting from inadequate monitoring networks, common in economically developing countries (Hughes 2004b).

*Pitman Model*

This model was introduced in the 1970's by Pitman (1973). It is a semi-distributed, conceptual model, with parameters which have physical relevance and can be inferred from characteristics of a catchment. The model runs on a monthly time step and there is also a version that runs on a daily time-step, but which is rarely used for practical purposes (Hughes, 2013). Since its inception, the model has been modified a number of times to include additional physical processes such as groundwater recharge and outflow, wetland and reservoir sub-modules and water abstractions (Hughes, 1997, 2004a; Hughes *et al.,* 2014a) which are significant and prevalent under southern African environmental conditions. The Pitman model has a relatively large number of parameters (see chapter 3 for a more detailed model structure) and might be considered to be over-parameterised (Jakeman and Hornberger, 1993). It is however, considered by Hughes (2013) to be a compromise between an adequate representation of a complex reality and “mathematical simplicity”. Of all the locally developed hydrological models, the Pitman model is arguably the most applied model both in the country and the wider region (Gan *et al.,* 1997; Andersson *et al*., 2003; Hughes *et al.,* 2006a, 2006b; Hughes, 2006; Wilk *et al.,* 2006; Tshimanga and Hughes, 2012). The commercial version of this model, named the Water Resources Simulation Model (WRSM 2000) is the model of choice of the South African Department of Water and Sanitation (DWS).

*ACRU Model*

The ACRU agrohydrological modelling system was developed at the University of KwaZulu-Natal by Schulze (1994). It is described by Jewitt and Schulze (1999) as an integrated physical conceptual model with a multi-purpose and multi-level capability. It is able to simulate stream flow, evapotranspiration and land cover impacts on water resources. The model runs on a daily time step and was designed for use in where there is no adequate stream flow data. This was achieved by having parameters which can be directly related to measurable physical characteristics of a catchment such as soil cover, vegetation and geology (Schulze, 1994). ACRU model has been used in South Africa for variety of purposes including the hydrological impacts of land use changes (Jewitt and Schulze, 1999; Gush *et al*., 2002; Görgens and van Wilgen, 2004; Jewitt *et al.,* 2004; Dye and Versfeld, 2007), design flood estimations (Smithers *et al.,* 1997; Boughton and Droop, 2003), agriculture (Martin *et al.*, 2000; Schulze, 2000) and water resource availability assessment (Schulze *et al*., 2001).

*VTI Model*

The variable time interval model is a daily step model developed by Hughes and Sami (1994), at the Institute of Water Research, Rhodes University. The model was originally aimed at studying the catchment response characteristics of a semi-arid catchment in South Africa. It has, nevertheless been successfully applied in other regions of South Africa, as well as in other countries in southern Africa (Hughes, 1995; Smakhtin *et al.*, 1997; Hughes, 1997). As the name suggests, shorter time modelling intervals can be applied depending on the objectives of the user. Based on the paucity of published documentations available in the mainstream electronic databases, the VTI model appears not to have received as much attention of water resources managers and hydrologists alike, compared to the other locally developed hydrological models (Pitman and ACRU).

*Internationally developed hydrological Models*

In addition to locally developed hydrological models, there has been a considerable interest in the application of models developed outside the southern African region. These models were used to achieve various scientific objectives. One of the examples is the use of a physically based distributed TOPographic Kinematic Approximation and Integration model (TOPKAPI) developed by Liu and Todini (1999). The model consists of five main modules: soil, overland, channel evapotranspiration, snow and can be run at hourly time-steps. TOPKAPI was tested for performance under South African environmental conditions by Vischel *et al.* (2008a) and was later used to simulate soil moisture content in a few catchments by Vischel *et al*. (2008b) and Sinclair and Pegram (2010).

The Identification of Hydrographs and Components flow Rainfall, Evaporation and Stream (IHACRES) (Jakeman *et al.,* 1990; Jakeman and Hornberger, 1993) is one of the simplified hydrological models that has been used in the South Africa. The model is based on the moisture deficit principles and uses a non-linear module to determine effective rainfall and a linear routing module to represent transport lags to convert effective rainfall to stream flow. Dye and Croke (2003) evaluated the model for stream flow simulation in two South African catchments. They found that the model is able to accurately simulate stream flow over a short duration (2-3 years), while it performed poorly for longer durations.

Govender and Everson (2005) used the Soil Water Assessment Tool- SWAT, to simulate the hydrological processes in two mountainous catchments, with different land covers, in the KwaZulu-Natal province of South Africa. The authors reported that SWAT performed reasonably well in simulating the major hydrological processes in the catchment. They however, observed that the model performed better in drier years than in wet periods. SWAT is a relatively complex, continuous daily time-step model developed at the United States Department of Agriculture (Arnold *et al.,* 1998). It is an integrated model with a comprehensive water balance, includes flood and sediment routing, water transfers as well as agricultural management and water quality components.

Another model of international origin that was used in southern Africa is the HBV (Bergström, 1992). HBV is classified as a semi-distributed conceptual model, with three main components consisting of subroutines for snow accumulation and melt; soil moisture accounting; response and river routing. The model was originally developed by the Swedish Meteorological and Hydrological Institute with the aim of simulating runoff (Lindström *et al*., 1997). Lidén and Harlin (2000) applied the HBV model in Zimbabwe and Tanzania with the objective of assessing its suitability and performance in catchments with varying climatic conditions. The authors reported that HBV performed better under wetter conditions and less climate variability. Their findings imply that the model might not be suitable for application in South Africa, as it was developed for humid Nordic conditions.

## 2.10 WATER SYSTEMS MODELLING

Water resources in any hydrological system are renewable but at the same time subject to limitations and subsequently have to be allocated to various, ever-increasing and competing interests. Water allocation needs to be done in a strategically and economically viable manner, while satisfying all the demands and needs. It therefore has to be managed in a way that aims to achieve sustainable use of the resource. In some cases, it may be necessary to have additional sources of water because of an inadequate available supply. Scientific and technological advancements have enabled efficient means of reusing and recycling waste water, which may further augment the limited available resources.

Recently, issues such as environmental and ecological water uses and requirements, which were previously not given much attention, are now being regarded as even higher priority than other uses. For instance, environmental flows, also termed instream flow requirements (Louw *et al*., 2000; Hughes and Louw, 2010) are legally binding in South Africa and any water-related project undertaken in the country must cater for such a requirement in order to maintain aquatic and other life forms dependent on water. The inclusion of the environmental flows as part of holistic water resources management (Hughes and Mallory, 2008) has rendered the allocation of water for uses such as irrigation, municipal, hydropower a daunting exercise for managers and decision makers, and as such requires careful integrated water resource management and planning. This has been achieved largely by the application of computer modelling tools known as water resources system models, or yield models.

### 2.10.1 Water Resources Systems Modelling Tools

Water resources system planning models include any of the several computer-based tools designed to deal with the management and allocation of available water resources within a given hydrological setting. These are also commonly known as decision support systems (Loucks, 1995) as they provide information that is useful to decision-makers and water managers. The concept of decision support systems was conceived in the early 1970's (Gorry and Morton, 1971), and they have since been developed and modified to assist in addressing some of the environmental and socio-economic challenges driven by the availability of water resources.

There are a number of such tools with varying frameworks, methodologies and approaches. They are however, commonly aimed at accounting for water demand for municipal, industrial and agricultural water uses as well as maintaining environmental and other instream flow requirements in relation to the available water resources. Such tools may incorporate the assessment of the impact of facilities such as the size and location of reservoir storage and water supply diversion (Muttiah and Wurbs, 2002) to seek the optimum operational solution with the highest possible economic returns.

Unlike hydrological models, most water resource system models do not attempt to simulate the various physical processes involved in the conversion of precipitation to stream runoff. This is of one of the major challenges in the use of water systems models in that they normally rely on the outputs from hydrological, reservoir hydraulics and water quality models for analytical calculations (Westphal *et al*., 2003). Thus, unavoidably inheriting any flaws and uncertainties inherent in the outputs of these models. Irrespective of such concerns, these models have been used quite extensively and are developed either as generalised or project-specific tools. Labadie and Sullivan (1986) suggest that a well-planned and properly designed decision support system can be successfully used to reduce operational costs, improving systems efficiency and production as well as increasing the system's reliability.

Even though these water resource system models have been widely used for decades for various specific and general purposes in many water resources projects and in solving water-related conflicts, the fact remains that it is still difficult to assess objectively the level at which they succeed or fail. The main reason for this, as pointed out by Mysiak *et al.* (2005) is that there is no clear, specified and universal definition of what actually constitutes the quality of a model-based decision.

### 2.10.2 Water Resources Systems Modelling in South Africa

There are a few models which have been locally developed and applied within South Africa in the last two decades. These include the Water Resources Yield model (WRYM), Water Resources Planning Model (WRPM), Water Situation Assessment Model (WSAM) and Water Resources Modelling Platform (WReMP). These models use, as inputs stream flow simulations from rainfall-runoff models, commonly the Pitman model. Additionally, stochastically generated stream flow sequences have traditionally been applied as inputs for predictions of future water resources availability. The sequences may be generated by independent statistical software. While this is aimed at accounting for hydrological input uncertainties, other sources of uncertainties such as water use and reservoir parameters are not included.

*Water resources yield model – WRYM*

The WRYM is the first and perhaps the most broadly applied decision support system in South Africa and the southern Africa region as a whole. It was developed by South Africa's DWAF and has been in use since 1985 to assist in decisions relating to the operation of water supply, mostly from artificial reservoirs. The WRYM model uses a network solver to analyse complex water resources systems under varying operation and management scenarios. It was originally designed for the Vaal river system supplying water to the Gauteng region (DWAF, 1989). Subsequent to the Vaal system, it has been successfully applied to other river systems (Mudd and Smith, 2006; Nyabeze *et al*., 2007; Juízo and Lidén, 2010). The fundamental objective of WRYM is to determine the quantity of water available for use after the Reserve (for both ecological and basic human needs) has been catered for (Louw and Birkhead, 1999).

The model operates on a monthly time step and has facilities to provide analysis for both short and long terms of up to 100 years. It uses a series of data sets, with each set comprising files for naturalised stream flow data, point rainfall data as well as water demand data (e.g. irrigation and afforestation). The system requires as input data, historical or stochastically generated stream flow sequences to calculate various outputs e.g. reservoir yield (McKenzie and van Rooyen, 2003) and thus, allow for the analysis of uncertainties in the model outputs. WRYM configures any given water resources system into reservoirs, channels and nodes. Although the system has been widely used within the southern Africa region, Juízo and Lidén (2010) raise a concern that the model is too complicated for users to be able to correctly interpret the results, and it is also difficult to use without advanced training.

*WRPM*

This model was developed by the Department of Water Affairs and Forestry (DWAF, 1989). WRPM is a monthly time-step network model for which the configuration is based on an existing WRYM set-up. The model is run with a large number of stochastically generated long term stream flow sequences, and accounts for growth in water demand and change, as well varying operating rules to the end of a given future target time horizon (Basson *et al.,*1994). For each year into the future the model superimposes the set of increasing system demands linked to that particular year and then simulates the sequential behaviour of the total system for set of stochastic stream flow. For each of the model runs, long term stochastic yield-reliability characteristics are used to maintain allocations to different users. One of the advantages of WRPM is that it allows shorter-term future scenario assessment based on stochastic projections and is used for one- year ahead reservoir management.

*Water Situation Assessment Model– WSAM*

This model was developed for the South African Department of Water Affairs and Forestry (DWAF) in the early 21$^{st}$ century by Schultz and Watson (2002). The model is suitable for use at variable spatial scales such as national, water management agency and quaternary levels. It is normally applied at the exploratory phase of water resources planning and management for scenario testing. WSAM is designed to provide a summary of the availability, supply and utilisation of water resources, which is vital information for any planned or existing water-related project.

The water situation assessment model incorporates a substantial data-base with more than 150 input parameters for all of the 1 946 quaternary catchments of South Africa, Lesotho and Swaziland. The database component of the water situation model has been continuously updated to better present the current water resources situation of the country (Lange *et al*., 2007).The model uses an annual water balance, reconciling the available water resources against the requirements at an assurance level of 98%, i.e. at the failure rate of 1 in 50 years. According to Schultz and Watson (2002), the model integrates about 20 sub-models which are sequentially executed to yield a final output. The sub-models include among others, the calculations for irrigation requirements, reservoir characteristics, hydropower and ecological water requirements.

The WSAM model has been mostly used in South Africa for various objectives in many projects. There are however, only a few reported studies available in the general literature. These include research by Görgens and van Wilgen (2004) and Cullis *et al.* (2007). Both of these studies used WSAM to investigate the impacts of invasive alien plant species on the availability of water resources in two watershed areas in South Africa. Similarly, Ncube and Taigbenu (2005) assessed the hydrological and water resources impacts of the changing land cover and use in the Oliphant’s catchment in Limpopo, using the WSAM. Other reported studies that used the model include those by Nel *et al.* (2007) and McCartney and Arranz (2007). One of the disadvantages about this model is that operates at the quaternary catchment level as its highest spatial resolution and thus, not offer enough details for projects of smaller scales.

*Water Resources Modelling Platform –WReMP*

The WReMP model (Mallory and van Vuuren, 2007) uses various water use input data sets which may consist of, for example, forestry and irrigation. The system configuration of WReMP is very similar in nature to that of the WRYM model, particularly in the way the physical reality is represented. The two models differ mainly in the in terms of software environment and user interface that enables WReMP to be more user-friendly.

The mainstream literature databases do not yield much about the published reports on the use and application of the WReMP model. One of the published reports includes that of Mallory *et al*. (2008). The authors used WReMP on the Algoa water supply system in the Eastern Cape to determine the firm yield. They reported that the model represented the real situation reasonably well. Nyabeze *et al.* (2007) compared the performance of the WReMP model and two others (WRYM and Mike Basin) in the operational analysis of a reservoir system of the Letaba River in Limpopo. The authors reported that their results could not clearly indicate which of the models performed better.

*Internationally Developed Water Resources System Tools*

MIKE-Basin and WEAP are two of the internationally developed water resources tools that are currently being applied in South Africa for water management and research purposes. Though the two models have minor differences in terms of design and utilities, they have a lot of features in common. Both are river basin planning and management models that use a network approach allowing simulation of water allocation and evaluate consequences of various development options on the availability of water resources within a river basin. The models have utilities to address reservoir operations and water quality issues. MIKE-Basin and WEAP are developed by the Danish Hydraulic Institute (DHI) and the Stockholm Environment Institute (SEI), respectively. Both models simulate water distribution according to user-specified priority settings. The two water resources systems models operate on the basic concept of conservation of mass to estimate yield. Although the two models have been globally used, they have been minimally applied within South Africa. The use of MIKE-Basin in the country has been reported by Nyabeze *et al*. (2007), Pott *et al*. (2008), Grové (2011) and Jackson *et al*. (2012). The reported application of the WEAP model includes the evaluation of water demand in the Olifants River Basin (Levite *et al.* 2003; Arranz and McCarthey, 2007; McCartney and Arranz, 2007). WEAP has also been used to investigate the impacts climate change on water quality and quantity in some South Africa catchments (Hughes *et al.,* 2011b; Slaughter *et al.,* 2011).

## 2.11 GLOBAL WARMING

Global warming is widely defined as the continuing rise in the average temperature of the earth's atmosphere and oceans caused by the increased concentrations of greenhouse gases (GHG). The emissions and the subsequent increase in the atmospheric greenhouse gases such as carbon dioxide, methane and nitric dioxide in the atmosphere from the last two centuries have been associated with an increase of the temperature of the earth's atmosphere (International Panel on Climate Change- IPCC, 2007).

The global warming phenomenon was first proposed in 1824 and later confirmed by 1859 (Weart, 2008). The impacts of GHG's on global warming are now widely acknowledged (IPCC, 2007). According to some projections, the global temperature may rise by 1 to 5 $^{o}$C during the next 100 years or so (Wuebbles and Jain, 2001). The potential impacts of global warming include rise in sea level, and changing global patterns in precipitation marked by increased frequency of droughts and floods (Arnell, 1999). Global warming might also be accompanied by an increase in extreme weather events such as heat waves, tropical cyclones and hurricanes. Climate change induced variability will inevitably affect the global and regional water cycles, general hydrological characteristics and water resource availability because various regions might experience altered water cycles resulting from changes in rainfall, temperature and evapotranspiration. It has been indicated that different regions will be impacted differently. Such changes have been suggested by many researchers, including Matondo *et al*. (2004), who suggested that rainfall amounts in some regions may increase by up to 20% while other regions may experience a decrease of the same magnitude.

Climate change impacts on hydrology and water resources are predicted by forcing hydrological models with predicted climate variables, usually derived from General Circulation Models (GCMs) (Döll, *et al.,* 2003; Singh *et al*., 2014). Global and regional climate projections depend on the GCM simulations of climate response to atmospheric concentrations of greenhouse gases. While the current generation of GCMs generally predict increased future temperatures, they typically disagree on the direction and magnitude of change of rainfall (Hughes *et al*., 2014b). The disparity in the projections of future rainfall constitutes a major uncertainty in the assessment of future water resources availability and hydrological impacts of climate change (Maurer, 2007; Minville *et al*., 2008; Chen *et al*., 2011).

## 2.12 CLIMATE CHANGE MODELLING

General circulation models are currently the best tools available for simulation of the past climate conditions and prediction of the future climate change. However, there is a major concern about the reliability of their outputs. It is widely observed that GCM predictions are generally biased relative to observed climatology, particularly rainfall (Leith and Chandler, 2010), to the extent that they cannot be directly used for hydrological application without any sort of bias correction.

The climate simulations from the GCMs are also subject to a number of errors and uncertainties. One of the most important and widely acknowledged challenge in the prediction of water resources availability is the fact that climate change science is marred with a significant degree of uncertainties (Arnell, 2004). Such uncertainties inevitably propagate through when climate change impacts on water resources are evaluated and these need to be assessed and incorporated in hydrological projections. Some of the known uncertainties in climate projections are discussed in details in the sections that follow. Uncertainties in the outputs of the GCMs emanate from several sources. While some of these uncertainties are known, there are also others which still remain largely unknown. The known uncertainties stem mainly from the climate model structures, greenhouse emission scenarios, internal variability and the downscaling approaches (Kay *et al.,* 2009). Though Wu *et al*., (2005), among others, recognise initial and boundary conditions as other sources of uncertainty in climate change modelling, these are often regarded as negligible in long term climate projections (Buizza 1997; Kalnay, 2003). To inform climate change policies, it is necessary that all the known uncertainties be assessed and quantified (Allen *et al.,* 2000; Webster *et al.,* 2003; Murphy *et al*., 2004; Tebaldi *et al.,* 2005; Millar *et al*., 2007). Such uncertainties should also be adequately presented to the scientific and non-scientific stakeholders, the general public and managers (Shackley *et al.,* 1998; Zehr, 2000). The ultimate aim may therefore be to account for, and reduce, the associated uncertainties (Araújo *et al.,* 2005; Hawkins and Sutton, 2009) and finally to incorporate them into impact assessment studies.

### 2.12.1 General Circulation Models

The earth's climate system is complex and limits the current scientific understanding of the various processes and the climatic forcings (McFarlane *et al*., 1992). Notwithstanding these concerns, the coupled general circulation models are by far the best tools currently available for simulating and studying the various dynamics of the earth's climate system, as well as to project future climate. However, there is inherent uncertainty in the outputs of the GCMs arising from various sources, including the model structure and model parameterisation (Pope *et al.*, 2000; Tebaldi and Knutti, 2007).

Models are a simplification of the real world and their structures differ in the way the earth's climate system is presented in the numerical computer code, according to how their developers conceptualise the physical climate system. Other structural differences occur because of inadequacies and imperfect scientific understating of some physical, biological processes and feedbacks that affect the climate dynamics (Collins *et al.,* 2011). This has led to some of the processes either being presented in a very simplified manner or being excluded altogether from the models, while other models present those processes in varying degrees of complexity (Jackson *et al*., 2004).

There is additional uncertainty involved in estimating and predicting the ocean circulation and dynamics (Manabe *et al.,* 1991). Several studies, including Washington and Meehl (1989), Stouffer *et al*. (1989) and Manabe *et al*. (1990) have asserted that oceans absorb and distribute heat energy contained in greenhouse gases, thereby impacting the atmospheric temperatures. Similarly, Ganopolski *et al*. (1998) pointed out that the reduction of circulation of the Atlantic Ocean causes an increase in atmospheric temperatures in the southern hemisphere. Incomplete scientific knowledge of the interaction between the ocean and the atmosphere is consequently reflected in the GCM structures, adding more uncertainty to the prediction of future global climate (Rayner *et al.,* 2006; Kent and Taylor, 2006). Because of such knowledge gaps, climate models cannot fully mimic the earth's climate system and are unable to simulate past climate conditions perfectly, reducing confidence in projecting future climate change even more (Smith *et al*., 2007; McWilliams, 2007; Knutti, 2008).

One of the approaches to statistically estimate the uncertainties related to the model structure is the use of multi-model ensembles. A number of studies (Cess *et al*., 1990; Hulme and Brown, 1998; Lambert and Boer, 2001; Prudhomme *et al*., 2003; Williams *et al*., 2006; Meehl *et al*., 2007; Weigel *et al.,* 2008) compared outputs from several GCMs and demonstrated significant variances in the simulations of the observed climatic variables and the climatic response to increased $CO_2$. Such divergences give rise to a critical question of how reliable the climate models are in projecting greenhouse gas-induced climate change (Räisänen and Ylhäisi, 2012), especially in view of the lack of a standardised approach for evaluating model performance (Gleckler *et al.,* 2008).

Figures 2.2 and 2.3 demonstrate model uncertainty in the temperature and precipitation simulations from several models under similar operating conditions. It can be seen that the uncertainty in both precipitation and temperature increases with the increasing time horizon projection. For instance, temperature is projected to rise by 1–2 $^{o}$C by the mid-21$^{st}$ century and by about 2–5 $^{o}$C by the end of the century (Figure 2.2). Similarly, the climate models used in Figure 2.3 suggest a 0–3 % increase in global rainfall by 2050. This range increases further (1–9%) by the beginning of the year 2100.

In dealing with model uncertainties, some researchers advocate the use of a simple arithmetic mean (Wang and Ding, 2006) to reduce the uncertainties, while others support the idea that a weighted mean of the ensemble members is a more effective approach (Robertson *et al*., 2004; Nohara *et al*., 2006; Min and Hensen, 2006; Weigel *et al.,* 2008). However, taking an ensemble mean does not reduce the uncertainties, but only ignores them. Whichever aggregation method is applied, there is a consensus within the climate modelling community that using the combined multi-model ensembles is a better way to quantify model uncertainties, while simultaneously achieving superior simulations to the individual members of the ensemble (Hagedorn *et al*., 2005; Palmer *et al.,* 2005; Thomson *et al.,* 2006; Weigel *et al*., 2008).

The other source of uncertainty in GCMs is related to model parameters. This occurs because some of the processes, such as cloud formation and plant-snow interactions in the climate system, are too complex to be explicitly resolved by mathematical equations in the model computer code. It is, therefore, common practice among model developers to present such processes by means of parameters. Parameterisation of processes adds a certain degree of uncertainty and different models may assign different parameters for the same process. For a given model structure, parameters are set within a plausible and accepted range of values, while some parameters are estimated based on observations (Webster *et al*., 2003; Murphy *et al.,* 2004; Zaehle *et al.,* 2005).

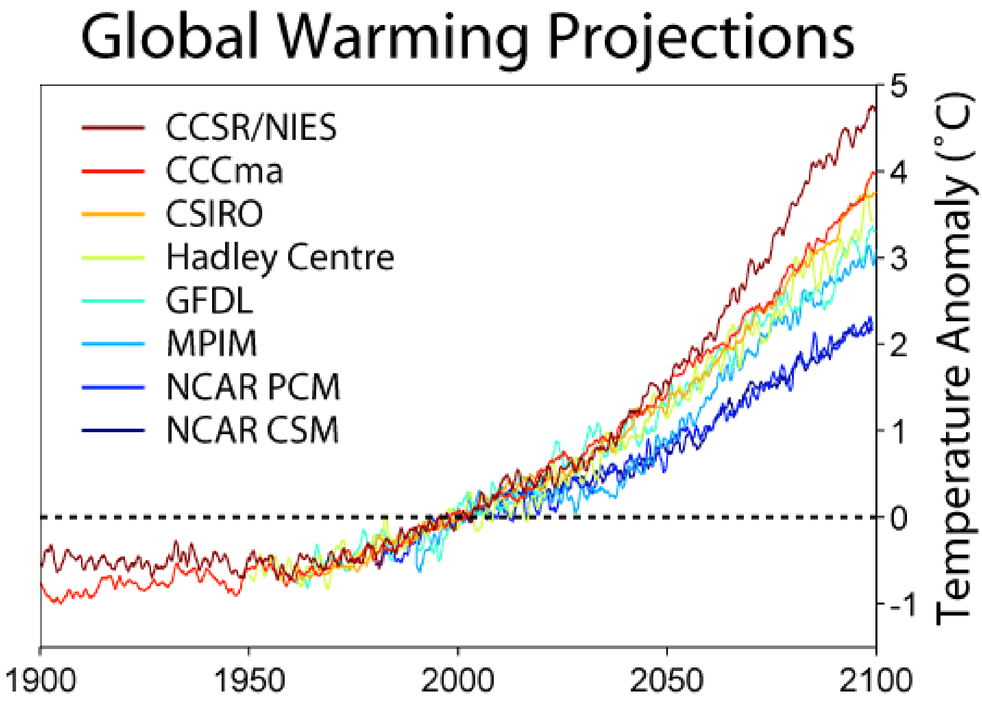



Figure 2.2 Uncertainty in global mean temperature as projected by various GCMs (Houghton *et al.*, 2001)

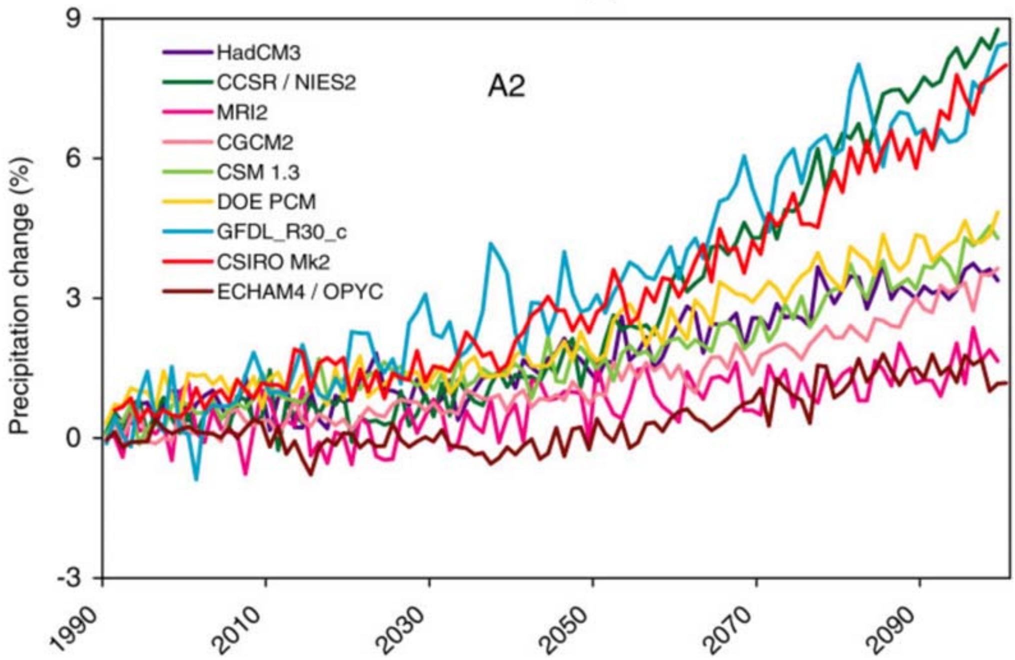



Figure 2.3 Uncertainties in the projections of global precipitation (Cubasch *et al.,* 2001).

Parameters are usually adjusted in a search for a set that yields the best or optimum simulation for a given variable (Annan *et al.,* 2005). Knutti (2008) notes that the uncertainty due to parameter adjustment increases if the selected range of values is not based on observed records. Parameter uncertainty in climate models has been substantially investigated especially through the use of 'perturbed physics ensembles' (Murphy *et al*., 2004; Stainforth *et al.,* 2005; Collins *et al.,* 2011). In this method, a model is run multiple times while varying the internal parameters to explore the full range of parameter space. The ensemble outcomes may be combined by various statistical approaches to quantify the parametric uncertainty within a given model structure (Annan *et al*., 2005; Murphy *et al*., 2007; Rougier, 2007).

### 2.12.2 Emission Scenarios

Projections of the future human-induced climate change depend on the assumed emissions and concentrations of the atmospheric greenhouse gases. To estimate these, the International Panel on Climate Change (McCarthy, 2001) developed sets of emission scenarios which are used to drive climate models for projections of future climate conditions. The currently used 'special report on emission scenarios' (SRES) scenarios replaced the 1990 IPCC scenario A (SA90) of the first assessment report (Houghton *et al*., 1992) and the 1992 IPCC scenarios (IS92) used during the third assessment report (Leggett *et al*., 1992). The SRES consists of forty (40) different scenarios based on possible future human activities that might affect the rate of emission of greenhouse gases. The 40 SRES scenarios emanate from the four qualitative storylines or 'families', namely, A1, B1, A2 and B2. The four storylines comprise six sets of scenarios, one from each of A2, B1, B2 and three from A1 (A1F1, A1B and A1T). Each of the scenarios makes different assumptions about issues such as future economic and technological advancement, world population and the consumption of fossil fuels. Nakicenovic *et al.,* (2000) summarises characteristics of the different emission scenario groups.

Uncertainties associated with emission scenarios occur when any individual scenario is considered for climate projections because the future is uncertain, especially in view of the assumptions made to formulate the emission scenarios. In other words, it is not known which of these scenarios will manifest. There are no probabilities assigned to the scenarios and they are therefore considered equally likely. It is also possible that none of the storylines and scenarios will actually occur. The adverse divergence of the greenhouse gases concentration for each scenario is shown in Figure 2.4, while Figure 2.5 shows the corresponding rises in predicted average global temperature.

There is significant uncertainty in the rate of emissions as proposed by the four scenarios. It is clear from Figure 2.4 that all but one scenario (B1) suggests an increase in greenhouse gases. The scenarios suggest a wide range of carbon dioxide emission between 5 and 28 Gt C/yr at the end of the $21^{st}$ century. This trend and uncertainty in emissions is translated by the climate models to average global temperature range of about 2–5 $^{0}$C at the end of the century. Figure 2.5 also indicates that the uncertainty in global temperature increases with the time horizon.

### 2.12.3 Internal Variability

Climate models are aimed at simulating long-term average conditions of the atmosphere as a result of anthropogenic greenhouse emissions. However, the earth's climate system is also influenced by short-term internal variability. These are caused by natural processes in the atmosphere and oceans. For instance, the phenomena such as the North Atlantic Oscillation (Hurrell *et al*., 2001; Wanner *et al*., 2001; Hurrell and Deser, 2009) and the Atlantic Meridional overturning circulation (Bingham *et al.,* 2007; Cunningham *et al*., 2007; Kanzow *et al.,* 2010) are known to cause significant fluctuations in precipitation over the high latitudes (Fowler and Kilsby, 2002; Folland *et al*., 2009). Researchers such as Genesio *et al*. (2011) and Wolff *et al.* (2011) reported a link between the El-Nino/ Southern Oscillation and the inter-annual rainfall variations in Africa. This natural climate variability adds more uncertainty in the climate projection since it is not adequately represented in the current generation of the GCMs (Hulme *et al.,* 2001). When quantifying the various sources of uncertainty in climate modelling, Hawkins and Sutton (2009) concluded that internal variability contributes a much smaller uncertainty than the other sources.

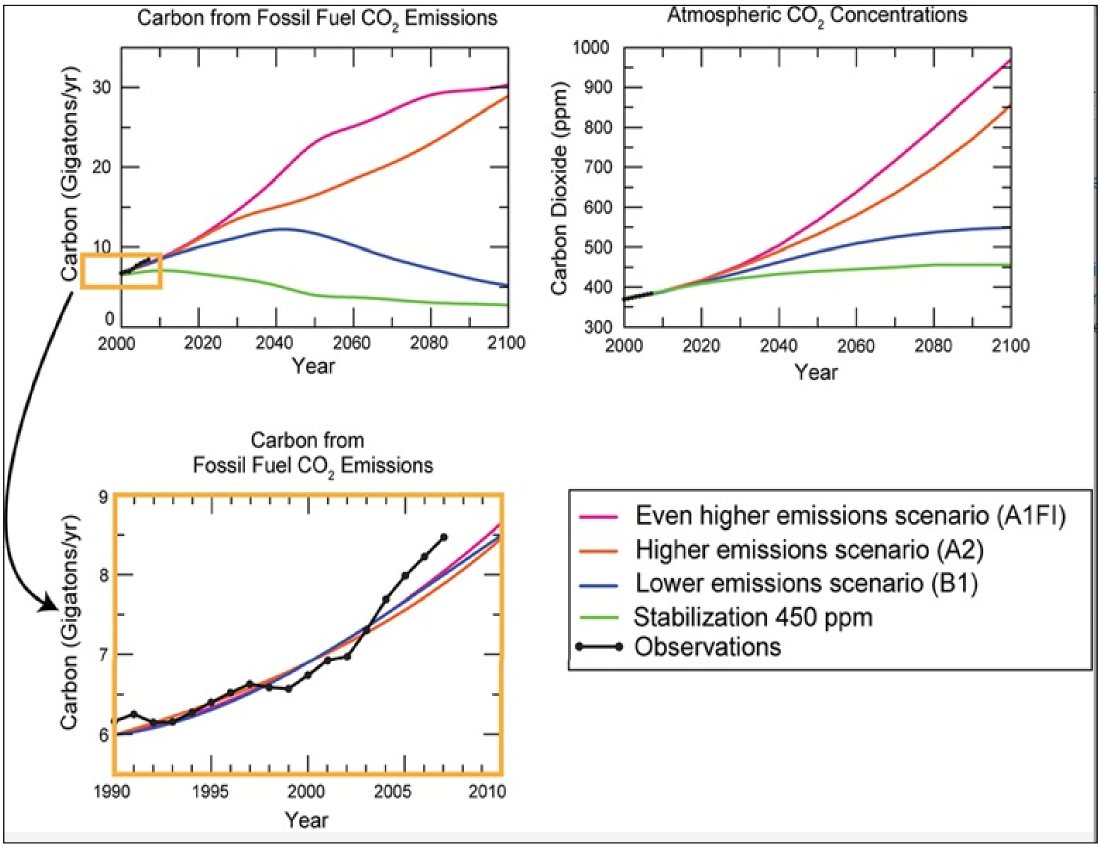



Figure 2.4 Emissions and concentrations of the greenhouse gases (equivalent of carbon dioxide) projected by the four SRES emission scenarios (Source: USGCRP, 2009)

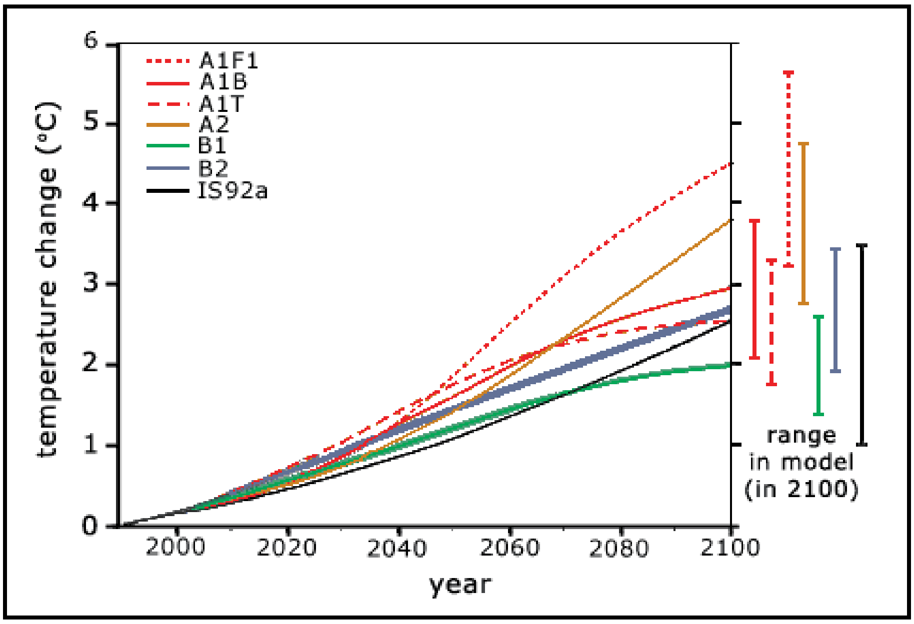



Figure 2.5Global mean temperature variations predicted under various emission scenarios (Source: McCarthy, 2001).

### 2.12.4 Downscaling Techniques

Because GCMs are designed for global scale simulations, they have spatial resolutions of hundreds of kilometres (Wilby *et al.,* 2004) and are too coarse (Grotch and MacCracken, 1991; Kidson and Thompson, 1998) to be used at regional and local scales for impact assessment such as hydrological and water resources. The outputs of the GCMs are normally downscaled to attain finer resolutions of tens of kilometres (Wilby *et al*., 2004), to extract local-scale information suitable for application with hydrological and other local impact assessment modelling tools. A choice of method for downscaling adds more uncertainty in the prediction of the impact of climate change because of limitations in the assumptions used in the methodologies.

Downscaling GCM data is normally achieved by using one of two techniques; dynamical or statistical approaches. A number of studies provide detailed reviews on the past and current developments and on the application of the two methods of downscaling (Hewitson and Crane, 1996; Wilby and Wigley, 1997; Zorita and von Storch, 1997; Xu, 1999; Wilby *et al.,* 2004; Hewitson and Crane, 2006; Fowler *et al.,* 2007; Teutschbein *et al.,* 2011). On the other hand, extensive research has focused on comparing and contrasting the general strengths and limitations of each of the two general downscaling techniques as well as quantifying their related uncertainties in the hydrological context (Kay *et al.,* 2009; Prudhomme and Davies, 2009; Quintana-Segui *et al*., 2010; Chen *et al.,* 2013).

*Statistical Downscaling*

The statistical (empirical) downscaling approach entails the use of any of several statistical techniques that map large-scale climate GCM ‘predictors’ and circulation characteristics to local or regional-scale meteorological ‘predictants’ (Xu, 1999; Wilby *et al.*, 2004; Ghosh and Mujumdar, 2008). Some of the widely applied statistical methodologies include regression methods, weather pattern-based methods, stochastic weather generators, artificial neural networks, continuous vorticity methods and self-organising maps. Even though these methods are substantially different in approach, they are based on the common premise that regional climate is influenced by both large-scale climate and local physiographic features (Timbal *et al.,* 2009) and as such, a statistical relationship can be derived based on observed historical data. The established relationships can then be used to predict future climate under different conditions indicated by a GCM.

Statistical downscaling considers several assumptions, including: i) there is a statistically significant relationship between large- and small-scale predictor variables; ii) the established relationship is constant and does not vary under future climatic conditions; and iii) the predictor variables and their changes are well characterised by the GCM (Karl *et al*,. 1990; Wigley *et al*., 1990; Wilby and Wigley, 1997; Wilby and Wigley, 2000). These assumptions introduce inherent uncertainties in the projection of future climate conditions. Details of the various empirical methodologies have been widely documented in the contemporary literature and some can be found in Wilby and Wigley (1997), Wilby *et al*. (1998) and Hewitson and Crane (2006).

According to Gachon and Dibike (2007), some of the main advantages of the statistical downscaling approach are that it is a relatively easy method to apply; it is not computer intensive, and it provides site-specific, high resolution climatic information. Another advantage noted by Hessami *et al.* (2008) is that the technique performs well in regions with highly heterogeneous environments. However, the approach has a major drawback since the fundamental assumptions cannot be verified, raising concerns that the established present-day statistical relationships may not be valid in future (Wilby and Wigley, 2000).

Statistical downscaling techniques have been widely used for regional climatic and impact assessment and their use has also been promoted for the reasons mentioned above. Some studies such as Wilby *et al*. (2004) and Schmidli *et al*. (2006) provide detailed guidelines on using statistical downscaling to develop climate scenarios, while other studies have evaluated and compared the performance of various statistical techniques (Heyen *et al.,* 1996; Huth, 1999; Busuioc *et al.*, 2001; Khan *et al*., 2006; Maurer and Hidalgo, 2008).

According to Khan *et al.* (2006), uncertainty in statistical downscaling arises from the concepts on which the downscaling models are based, as well as from the historical climate data used in the process. Dibike *et al.* (2008) evaluated the implications of uncertainties related to statistical downscaling, remarking that such uncertainties make it “difficult to have great confidence” in the output climate variable for “meaningful climate change impacts studies”. Contrary to that, Segui *et al*. (2010) indicated that uncertainties related to downscaling of GCM data are less important than uncertainties due to other sources, such as emission scenarios. This conclusion was later supported by Chen *et al.* (2011) who added that the downscale-related uncertainties are relatively minor.

*Dynamical Downscaling*

The basic aim of dynamic downscaling is to extract high resolution local-scale climate information from coarse resolution large-scale GCM data (such as the lateral boundary conditions, sea surface temperature and initial land surface conditions). This is generally attained by the use of limited-area models (LAMs) or regional climate models (RCMs). These are capable of achieving spatial resolutions of about $0.5^0$ (longitude, latitude) and can simulate regional climatic features including orographic precipitation and extreme climate events (Fowler *et al.,* 2007). Though the dynamical downscaling approach has the disadvantage of being computationally expensive and is strongly dependant on the parent GCMs' boundary conditions (Chen *et al*., 2011), the method is based on physically consistent atmospheric processes and is thus achieving reasonable simulations of the atmospheric flow at the regional scale (Caldwell *et al*., 2009).

There are several dynamical downscaling approaches and Xu (1999) (after Rummukainen, 1997) summarises some of the commonly used methods: i) running a regional climate model using data from a GCM as geographical or spectral boundary conditions, also known as 'one way nesting'; ii) performing global scale experiments with high resolution atmospheric regional climate models (RCMs) with data from GCMs as initial and boundary conditions; and iii) using a variable-resolution global model where the highest resolution is over the area of interest.

Uncertainties in dynamical downscaling arise mainly from the imperfect structures of the RCM, as well as from the driving GCM outputs (Rowell, 2006). Such uncertainties can either be significant or minor, depending on scale, season and the climate variable under consideration. For instance, according to Rowell (2006), the uncertainties in temperature simulations are less than those for precipitation. However, the uncertainties associated with the RCMs are less significant than those associated with the emission scenarios (Rowell, 2006). Déqué *et al*., (2007) suggest that the largest uncertainties in the RCMs climate outputs are due to uncertainties in the boundary conditions of the driving GCM rather than to the RCMs themselves.

Since many downscaling techniques have been developed, the choice of any particular one is critical when predicting climate change on local and regional scales and the results should be interpreted with great care (Chen *et al*. 2011). Concurrent application of several downscaling methods may yield a better understanding about the level of uncertainties relating to the downscaling approaches.

## 2.13 SUMMARY

Hydrological models are commonly used tools to simulate the different basins' hydrological processes. The above sections highlighted the pertinent technical aspects relating to the various forms of the models, ranging from rather simplified to sophisticated structures. The choice and application of any single model for hydrological investigations depends on the amount of detail required, as well as the data available to inform and drive the model. It is therefore important to select a model which is the most appropriate with regard to structure and data availability. In general, hydrological modelling is subject to a variety of uncertainties, and as such there are several approaches developed to evaluate and assess these uncertainties. Outputs of climate models constitutes an additional source of uncertainty in water resources projections under the influence of climate change, in which case climate projections are used to drive the hydrological models. It is important that all these technical issues be considered when estimating future status of water resources under climate change.

# 3 METHODS

## 3.1 INTRODUCTION

The main objectives of the study are to assess the historical, current and likely future water resources availability of the Caledon River Basin. Two hydrological models are used to achieve to these objectives, for the purpose of comparison. While the Pitman model (Pitman, 1973; Hughes, 2004a) has already been extensively applied in southern Africa, including the Caledon, the WEAP model has only recently been tested in this region. For this reason, the existing Pitman model set-up for the Caledon River Basin is used to guide the parameter estimation of the WEAP model. This process involved comparing the various functionalities of the two models representing the catchment hydrological processes, as well as the simulation outputs. The two models are used to simulate stream flow of the Caledon River influenced by a number of water uses and the predicted future climate conditions. Figure 3.1 illustrates the methodology adopted for this study. The methodology is divided into three main parts: firstly, to simulate the natural historical hydrology of the Caledon River Basin using the two hydrological models; secondly, to estimate the present-day stream flow by incorporating water uses and artificial modifications of the natural flow. The last part involves the estimation of future water resources availability under the influence of climate change.

Future availability of water resources in the Caledon River are predicted by forcing the two hydrological models with projected future rainfall and temperature data. The projected climate data were obtained from 9 climate models (GCM), downscaled by the Climate Systems Analysis Group of the University of Cape Town. The rainfall climate data was corrected for bias against historical data before being used in the hydrological models. Daily rainfall data were also analysed to detect any change in future rainfall characteristics at time scales of less than the monthly time step used in the hydrological models.

## 3.2 THE PITMAN MODEL

The Pitman hydrological model was first developed by Pitman (1973) with the core objective of simulating river flow from meteorological inputs for water resources planning in South Africa. The Pitman model is an explicit soil moisture accounting model and represents the main hydrological processes such as interception, soil moisture and groundwater storages. It has arguably become the most widely-used rainfall-runoff model in southern Africa.

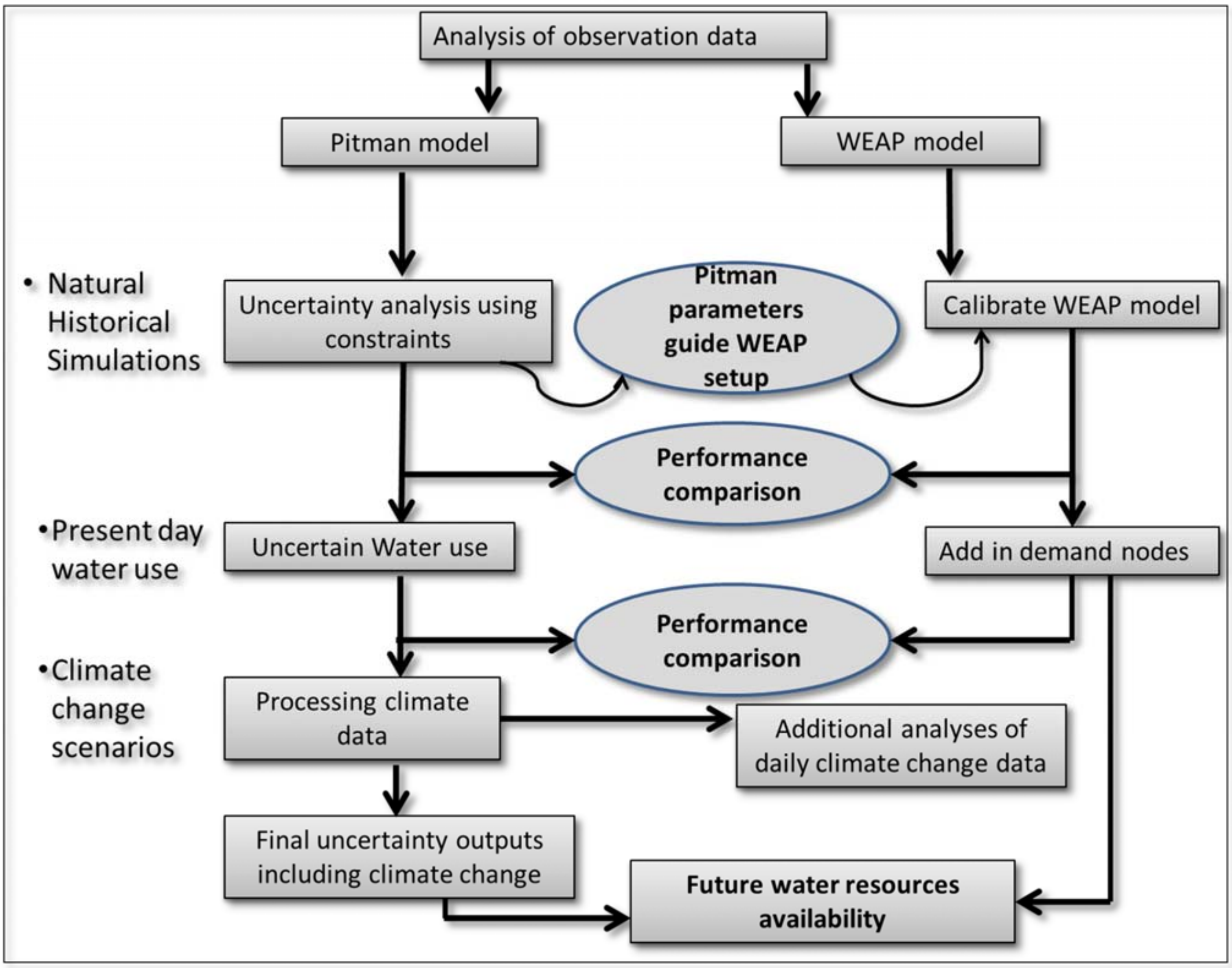



Figure 3.1 Flow diagram illustrating methodological procedure and the methods used in the study.

The model's development was specifically based on the environmental conditions of South Africa, but it has since been successfully applied elsewhere in the Southern Africa region and abroad. For example, the model has been used in the Okavango Basin shared between Angola, Namibia and Botswana (Andersson *et al.,* 2003; 2006; Wilk *et al.,* 2006; Hughes, *et al*., 2006a; 2006b; 2011), the Kafue River Basin in Zambia (Mwelwa, 2005), various rivers in Namibia (Hughes and Metzler, 1998), Mali (Grimes and Diop, 2003); Botswana (Meigh, 1995), Democratic Republic of Congo (Tshimanga and Hughes, 2012), India (Wilk and Hughes, 2002a; 2002b), China (Bharati and Gamage, 2010).

Though the basic structure of the model (Pitman, 1973) has been preserved, the model has been modified a number of times to incorporate some of the important hydrological processes that are significant and relevant to southern African environmental conditions. Some modifications were initiated by hydrological assessments of the Southern African Development Community (SADC) region during the Southern Africa FRIEND programme (Hughes, 1995; 1997). More explicit links between surface and groundwater including revised methods that account for groundwater recharge, discharge and abstractions were added by Hughes (2004a). Several other components and parameters have also been added to improve the functionality of the model (Hughes and Metzler, 1998; Görgens and Boroto, 2003; Hughes *et al.,* 2003; Hughes *et al*., 2014a). Hughes (2013) summarises the developments and applications of the model over the last 40 years or so.

The model now exists in a number of different forms and various modelling platforms. In the current study, the Pitman model is applied within an integrated software package referred to as SPATSIM (SPatial And Time Series Information Modelling) platform which was developed at the Institute for Water Research, by Hughes (2002) and has been continuously enhanced (Hughes and Forsyth, 2006). The SPATSIM version of the model is a semi-distributed, conceptual monthly rainfall–runoff model. The software package is coded in the 'Delphi' programming language, with ESRI MapObjects which affords easy links to spatial data as well as an integrated database for access to all the data typically required for hydrological modelling. It has the advantage of a more user-friendly graphical output display and easy-to-use data management for setting up models and analysing their outputs.

### 3.2.1 Structure of the GW-Pitman Model

The modified version of the model used in this study is known as GW-PITMAN and the main difference from the original model is that it incorporates explicit groundwater fluxes. It also includes a number of storages such as rainfall interception and soil moisture and model accounts for the dominant hydrological processes such as infiltration, evapotranspiration, surface runoff, soil moisture runoff and groundwater recharge. These processes are presented as a conceptual model structure in Figure 3.2. The methods for simulating the individual processes and the associated parameters have been presented many times in the literature and are summarised in the following sub-sections. The model requires monthly precipitation and potential evapotranspiration as input data for each sub-basin.

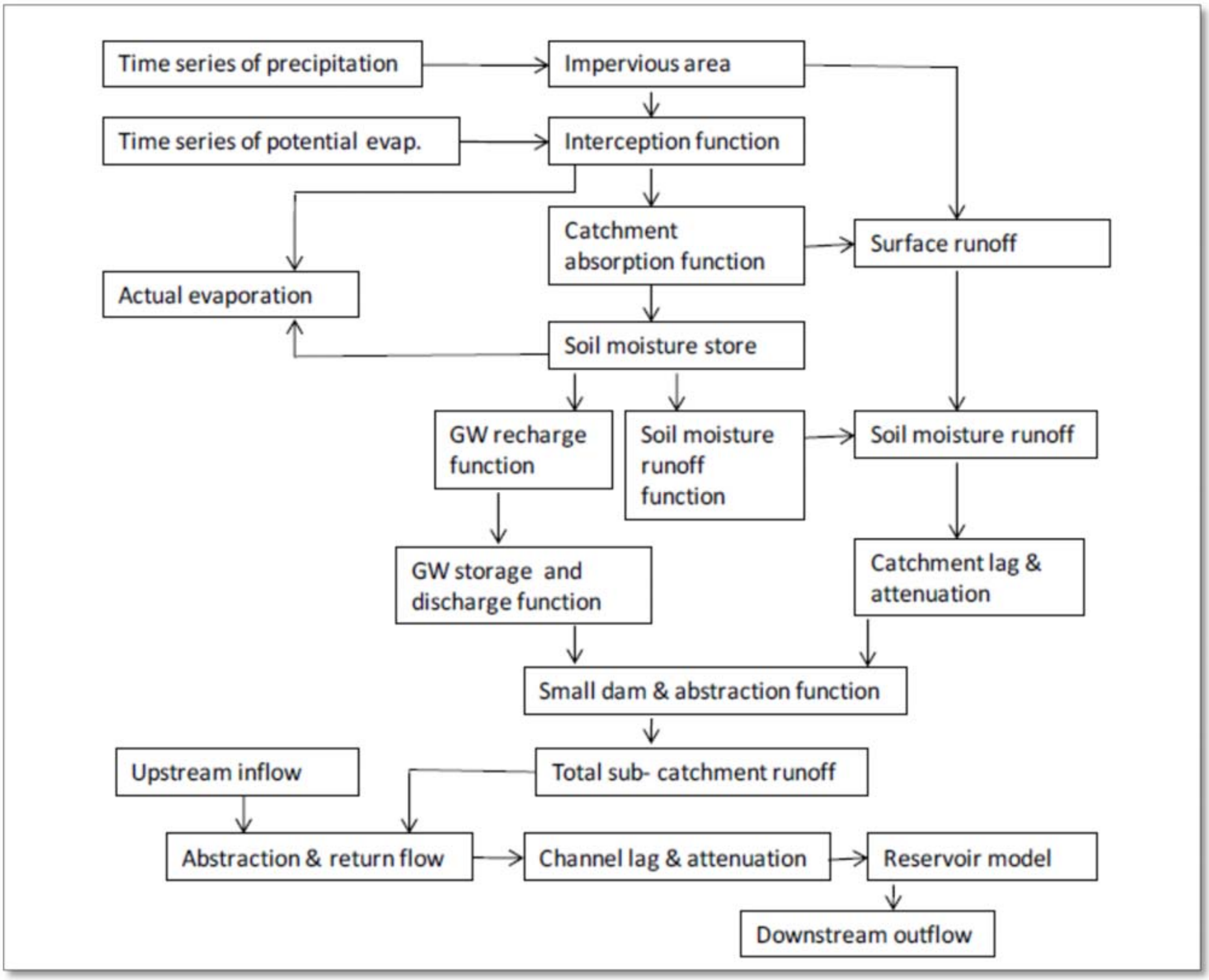



Figure 3.2 Flow diagram representing the structure of the modified Pitman model (Source: Hughes *et al.,* 2006a)

### 3.2.2 Parameters and Conceptual Functions

In attempting to represent known hydrological processes, together with possible water uses, the Pitman model has a total of 40 parameters. Of these, 28 influence the natural catchment hydrological response, while others are related to water use and abstraction. The 28 parameters represent the surface, sub-surface, groundwater processes as well as flow routing (Table 3.1) and some (PI1, PI2, ZMIN) can be seasonally variable. Each sub-basin in the distribution system has its own parameter set.

Table 3.1 Parameters of the Pitman model.

| **Parameter** | **Units** | **Parameter Description** |
|---|---|---|
| RDF | - | Rainfall distribution factor |
| AI | - | Impervious fraction of sub-basin |
| PI1, PI2 | mm | Interception storage for vegetation types (2) |
| AFOR | % | Percentage area with vegetation 2 |
| FF | - | Ratio of potential evaporation rate for veg2 relative to veg1 |
| PE | mm/year | Annual potential evapotranspiration |
| ZMIN | mm/month | Minimum sub-basin absorption rate |
| ZAVE | mm/month | Average sub-basin absorption rate |
| ZMAX | mm/month | Maximum sub-basin absorption rate |
| ST | mm | Maximum storage capacity |
| SL | mm | Minimum moisture storage below which no GW recharge occurs |
| POW | - | Power of moisture storage-runoff Equation |
| FT | mm/month | Runoff from moisture storage at full capacity |
| GPOW | - | Power of moisture storage in GW recharge Equation |
| GW | mm/month | Maximum groundwater recharge |
| RIP | % | Controls the riparian evaporation losses from GW storage |
| R | - | Evaporation-moisture storage relationship |
| TL | month | Lag of surface and soil moisture runoff |
| CL | month | Channels routing coefficient |
| D DENS | km/km$^2$ | Drainage density |
| T | m$^2$/day | Transmissivity |
| S | - | Storativity |
| GW Slope | - | Initial groundwater gradient |
| RWL | m | Groundwater rest water level |

*Rainfall distribution Factor (RDF)*

The rainfall distribution function accounts for the distribution of total monthly rainfall over four model iterations. The function depends on both rainfall amount and the value of the RDF parameter. Lower values of this parameter indicate a more even monthly rainfall distribution. The original model (Pitman, 1973) had a fixed value of 1.28.

*Interception (PI1, PI2)*

This function is used to represent the amount of rainfall intercepted by vegetation cover. The interception function is controlled by the interception parameters, PI, which are allowed to vary seasonally to cater for changes in vegetation cover throughout the year. Two different types of vegetation (PI1 and PI2) can be used to account for major vegetation differences and specifically to allow for managed forest plantations.

*Surface runoff (AI, ZMIN, ZAVE, ZMAX, ST)*

In the Pitman rainfall-runoff model, surface runoff is conceived as being generated in three ways: i) from an impermeable surface (AI), ii) when the rainfall amount is higher than the absorption capacity (ZMIN, ZAVE, ZMAX), and iii) when the maximum soil moisture storage (ST) is exceeded. The soil absorption capacity is controlled by a triangular distribution function defined by ZMIN, ZAVE and ZMAX.

*Soil moisture storage and runoff (ST, FT, POW)*

The depth of runoff from the soil moisture storage is determined by a non-linear relationship between runoff and relative storage. The power of this relationship is defined by POW, while FT represents the maximum runoff rate (mm month$^{-1}$) at maximum soil moisture storage (ST).

*Groundwater Recharge (ST, SL, GW, GPOW)*

The groundwater recharge function uses a similar non-linear relationship as the soil moisture runoff function, with GW representing the maximum monthly recharge rate (mm month$^{-1}$) at ST and GPOW the power of the relationship. Parameter SL is the soil moisture storage level (mm) at which recharge ceases.

*Evaporation from the soil moisture storage (ST, PE, R)*

The annual potential evaporation parameter (PE) is distributed into 12 monthly mean values (an additional model input). The actual evapotranspiration in any month is determined as a function of the current soil moisture storage level (relative to ST), the current monthly potential evapotranspiration value relative to the maximum monthly values and parameter R. R ranges from 0 to 1, where 0 implies higher evaporation that continues to low moisture storage levels. When R is 1, evaporation ceases at progressively higher moisture levels as the monthly potential evapotranspiration decreases. Low values of R therefore imply shallow rooting depths and less effective evapotranspiration.

*Groundwater storage and discharge (S, T, DDENS, GW Slope, RWL, RIP)*

Hughes (2004) describes the relatively simple geometry approach used to determine groundwater storage and discharge to the river. Groundwater recharge inputs, drainage outputs to the river, drainage to downstream catchments and evapotranspiration losses from the riparian strip (RIP) are used to update the assumed gradient of groundwater within a sub-basin. When the gradient is positive drainage to the channel occurs and is calculated from the gradient, transmissivity (T) and channel length (derived from sub-basin area and drainage density). When negative gradients occur, riparian strip evapotranspiration and downstream drainage are progressively reduced until groundwater storage reaches the level equivalent to the rest water level. Transmission losses from upstream channel flows can occur when the gradient is negative. More details can be obtained from Hughes (2004a) and Tanner (2014).

### 3.2.3 Parameter Estimation Approaches

The successful application of any hydrological model depends on its parameterization. Parameter values for many models are estimated by a trial-and-error process of calibration which is based on comparing the simulated hydrograph against the observed using visual comparisons or more quantitative objective functions. The challenge with such an exercise is that a model may yield similarly acceptable simulations with different parameter sets, thus leading to significant uncertainties in hydrological estimations. This complex issue in hydrological modelling is referred to by Beven (1996) as equifinality. The existence of equifinality in models with many processes also makes it difficult to obtain optimum parameter sets using automatic calibration methods.

One possible approach to reduce the equifinality is to make use of parameter estimation approaches based on an understanding of the conceptual structure of a model and physical sub-basin properties. These approaches were thoroughly explored for the Pitman model (Kapangaziwiri and Hughes 2008; Kapangaziwiri, 2010). An advantage with such an approach is that the parameter estimation established through a relationship with basin physical properties would lead to a more consistent methodology, especially when the role of each parameter in the hydrological response of a catchment is conceptually well-defined (Kapangaziwiri**,** 2010). Empirical relationships that transform physical basin characteristics to small scale model parameters values have been developed (Kapangaziwiri and Hughes, 2008; Hughes *et al.* 2010) for the Pitman model. The inherent uncertainties in the parameter estimations were defined in terms of the uncertainties and spatial variability in the data defining the sub-basin properties (Kapangaziwiri *et al.,* 2012).

The use of physical basin characteristics for estimating parameters of a hydrological model was also adopted by Schulze (1994) for another locally developed rainfall–runoff model (ACRU). Other studies that explored this approach include Duan *et al*. (2003) and Ao *et al.* (2006). The importance and effectiveness of estimating hydrological model parameters using *a priori* techniques has also been recognized by the International Association of Hydrological Sciences within its recent 10-year theme on “Prediction in Ungauged Basins” (Sivapalan *et al*., 2003).

### 3.2.4 Uncertainty Versions of the Pitman Model

Prior to and during the course of this study several uncertainty versions of the Pitman model were created (Kapangaziwiri *et al.,* 2012; Hughes, 2013; Tumbo and Hughes, 2015). All of the versions share the same basic approach using simple independent Monte Carlo sampling of the parameter space and generating ensembles (typically 5 000 to 10 000) of model simulations. The sampling space for each parameter can be defined by uniform or normal distributions. The differences between the approaches are mostly related to two major issues. The first is at what point in the whole modelling process are the ensembles assessed for their ability to represent the known hydrological response regime of the basin being modelled. The earlier versions of the model (Kapangaziwiri *et al.,* 2012) were based on doing this assessment after the ensembles had been generated (i.e. a form of post-processing filtering), while more recent versions have been based on doing this as part of the model run, using constraint indices (see section 3.2.5). The second issue is associated with the extent to which the parameter samples for each sub-basin in the total basin are independent of each other. One of the sub-objectives of this study was to evaluate some of the different uncertainty approaches in the relatively large Caledon River Basin that has 31 sub-basins.

### 3.2.5 Parameter Constraining Procedure

In the initial approach proposed by Kapangaziwiri and Hughes (2008) either *a priori* parameter estimation using physical basin properties or simple estimation of likely parameter ranges or distributions were used. During the model run each parameter value is sampled independently but groups of sub-basins with similar expected responses are sampled from the same parameter space, such that high (or low) values of a specific parameter will be similarly high (or low) in all the sub-basins in the same group. The reasoning behind this approach is that if all sub-basins are considered independent, then the degree of uncertainty substantially reduces as more and more sub-basins are combined at downstream locations. This reduction in uncertainty occurs as a result of different sub-basins generating different relative responses to the climate inputs such that the upstream uncertainties tend to be largely cancelled out at downstream sub-basins. Allowing groups of similar sub-basins to have parameters sampled from a similar space has been demonstrated to better preserve the upstream uncertainties in downstream sub-basins (Hughes, 2013).

During the initial approach, the ensemble outputs of the model runs were examined on the basis of expected constraints on runoff response (such as mean monthly runoff volume, recharge depth, slope of flow duration curves) and a decision is made about which ensembles are behavioural and which are not. However, the fundamental problem with this approach is that the selected behavioural ensembles at downstream sub-basins can be made up of a mixture of behavioural and non-behavioural ensembles in all of the upstream sub-basins (Hughes, 2013; Tumbo and Hughes, 2015). This could mean that ensemble outputs that are selected for further use in water resources management could be spatially inconsistent in terms of their representativeness relative to the known (or expected) ranges of hydrological response.

In the revised approach (Tumbo and Hughes, 2015) that was finally used in this study, not only are the parameter ranges defined as model inputs, but also the likely output constraints. The regional constraint bounds are therefore an additional input into the model. The constraint bounds are mainly based on observed streamflow within the region and reflect uncertainty in the available knowledge about the hydrological response of the different parts of the total basin and can be narrow if there are sufficient observation data available. The revised approach adopts a two-step procedure; the first step is aimed at identifying behavioural parameter sets (only for the natural hydrological response) for each sub-basin, while the second step involves using these parameter sets to simulate the basin response as a whole and can include uncertainty sampling of the parameters associated with water use and other anthropogenic impacts.

Step 1 of the approach is aimed at constraining only the parameters related to natural runoff in each sub-basin. The constraints apply to the incremental runoff in each sub-basin and step 1 does not simulate the cumulative flows in downstream sub-basins. The sub-basin response characteristics used for constraining or for deciding behavioural ensembles are: mean monthly runoff (MMQ), high (Q10), medium (Q50) and low (Q90) flow volumes of the flow duration curve relative to mean monthly flow, mean monthly groundwater recharge and percentage of time with zero flow. The mean monthly runoff and the flow duration curve characteristics are typically obtained from stream flow gauging data from catchments with similar physiographic characteristics to the ones being studied. Groundwater recharge estimates are established in South Africa from the Groundwater Resources Assessment study (GRA II- DWAF, 2005).

For each sub-basin the model is run up to 100 000 times with an independent Monte Carlo sampling procedure from pre-determined parameter distributions. The outputs are assessed against the constraints during each run of the model. If all constraints are satisfied the full parameter set is saved for further analysis. The model continues until a pre-defined number of parameter sets (2 000 to 5 000) are saved or until the maximum number of model runs (50 000 to 100 000) is reached.

A facility is available within SPATSIM (Figure 3.3) to examine the distributions of parameter values and constraints in the saved results to guide any decisions about whether to change the input parameter distributions or re-evaluate the constraint ranges to achieve the required number of behavioural parameter sets.


Figure 3.3 Illustration of the tool designed to help with determining appropriate parameter bounds.

Figure 3.4 illustrates three possible outcomes of the first step. Figure 3.4A shows a situation where the parameter bounds and constraint bounds are compatible, and the constraint bounds are compatible with each other. The required number of parameter sets is found and less than 100 000 test runs of the model are required. The results evaluation method (Figure 3.3) can be used to determine if the results are reasonably well distributed within the constraint bounds or whether the initial parameter bounds could be changed to achieve the required number of behavioural parameter sets more efficiently. In Figure 3.4B the constraint bounds are not compatible with each other and no ensembles meet all of the behavioural requirements. In this situation the constraint bounds have to be adjusted to ensure compatibility. Figure 3.4C illustrates a situation where all of the model simulations are inconsistent with the constraints and therefore either the constraints need to be re-evaluated, or the ranges of some of the parameters have to be modified to match the expected response (defined by the constraints).

There can be a number of intermediate situations between Figures 3.4B and 3.4C where some behavioural parameter sets are found but not enough before the total number of model runs is reached. The facility illustrated in Figure 3.3 is then used to identify which parameters require their ranges to be adjusted. In the example it can be seen that the Q10 constraint is always at the lower end of the input range and that ZMIN and ZMAX (surface runoff parameters) are also at the low ends of their input ranges. Shifting the range of one or both of these parameters downwards will generate more surface runoff, solving the problems with the Q10 constraint and increasing MMQ which is also under-simulated in the example provided.

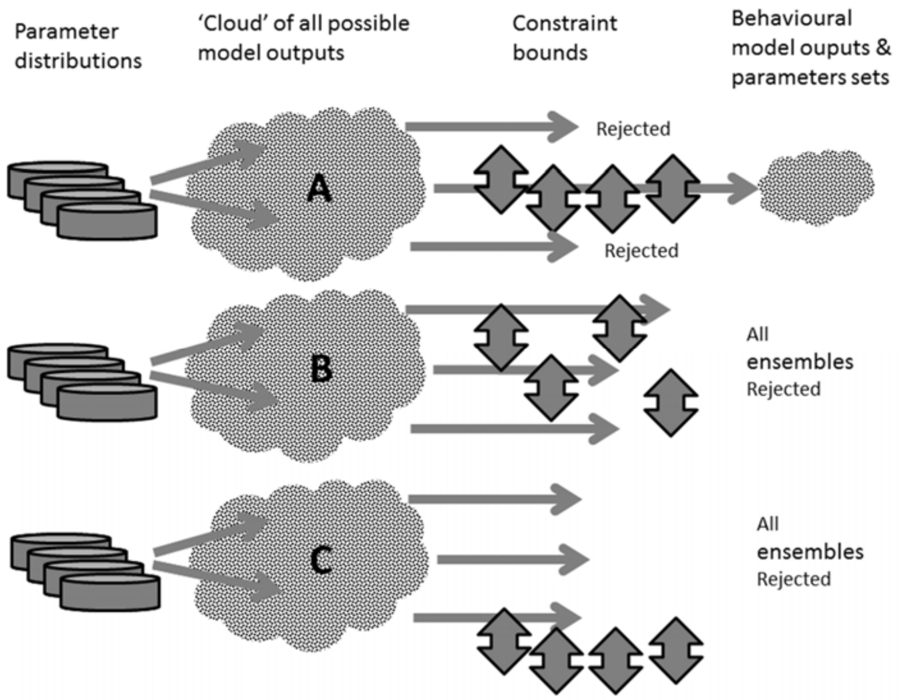



Figure 3.4 Step 1 in the revised approach to uncertainty estimation with the Pitman model (Source: Tumbo and Hughes, 2015).

Step 2 is only initiated after all of the sub-basins have the desired number (typically 2 000 or 5 000) of saved parameter sets. At the beginning of step 2 the saved behavioural parameter sets are sorted according to the 6 constraint values from wetter to drier conditions. The sub-basins are then grouped and random samples (typically 10 000) are drawn from the parameter sets using the same sub-basin group sampling dependency referred to in the description of the earlier uncertainty method. In this step all the model parameters are sampled and used with all sub-basins linked to generate cumulative streamflow simulations. While the parameters related to the natural runoff are randomly sampled from the saved parameter sets, the others (e.g.

those related to water use and land use changes) are sampled independently from their pre-defined input distributions. The main advantage with this approach is that, unlike the previous methods, it assures that all the incremental catchments have behavioural simulations relative to the constraints.

For sub-basins with stream flow records, a summary output file provides evaluations of all the ensembles based on four objective functions: Nash-Sutcliffe coefficient of efficiency and percentage bias in mean monthly flow for normal and natural log-transformed data.

### 3.3 THE WEAP MODEL

The Water Evaluation And Planning (WEAP) modelling software tool was developed in the 1990's by the Stockholm Environment Institute-Boston (Yates *et al*., 2005), and has undergone a number of modification phases and improvements over the years. The WEAP program provides a holistic and integrated representation of the water supply and demand system within a basin, suitable for varying user-specified physical, social and economic conditions at a monthly temporal scale.

WEAP is capable of graphically representing a variety of sources of water supply and points of water demand, through a GIS-based user interface. The water supply sources covered by the software include river systems, groundwater, wetlands, artificial reservoirs, etc. On the other hand, demand sources such as towns, irrigated areas and hydro-power can also be represented. Other water-related activities such as water and wastewater treatment facilities and water transfers can also be analysed within the WEAP modelling system.

The software program is relatively versatile and is able to handle simple, as well as complex watersheds or any other system such as agricultural and municipal systems, single catchments as well as complex river systems like the Caledon River Basin. Points and areas of water demand for both consumptive water uses and non-consumptive uses (e.g. environmental flow requirements) are also represented. Configuring a specific water resources system is achieved through a GIS interface (Figure 3.5) by adding objects or nodes to represent all of the different elements of the system such as catchments, reservoirs, water demands, transfers, return flows, etc.

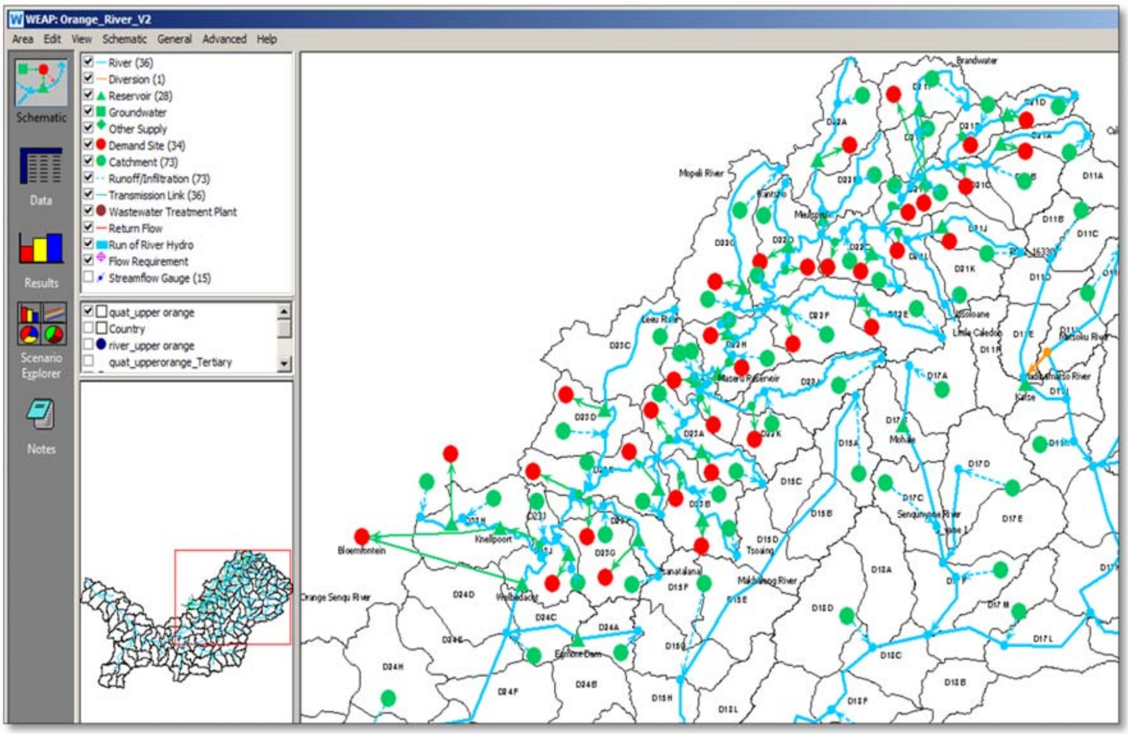



Figure 3.5 The Schematic view of the WEAP model.

Facilities are included in the model that allow time series data files (e.g. rainfall, temperature, observed streamflow) to be linked to the nodes, as well as entering variables (seasonal distributions of climate data, water use, etc.) and the model parameters. Variables and parameters can be entered as single numbers or as mathematical expressions. There are also a range of tools to graphically display (Figure 3.6) outputs and results and to export these to Excel spreadsheets for further analysis. The WEAP model allows for various scenarios to be simulated, making it a very useful tool for examining changing conditions of either water resources use or climate.

WEAP has been applied worldwide for various purposes, and in recent years, the modelling software has been popular for investigating the potential impacts of climate change on water resources (Yates *et al*., 2009; Hughes *et al*., 2011b; 2011c; Slaughter *et al*., 2011; Donley *et al*., 2012; McCartney and Girma, 2012). Applications of WEAP for other objectives have also been documented. For example, Levite *et al*. (2003), McCartney and Arranz (2009) and Droogers *et al*., (2012) used WEAP to study the impacts of population growth, economic development and environmental considerations on the availability of water supply to meet expected demands. WEAP has also been used as a decision support system (Le Page *et al*., 2012; Harma *et al.,* 2012). More details on the general use, application and publications related to the WEAP model are provided by the Stockholm Environment Institute (SEI), at their official website: www.weap21.org

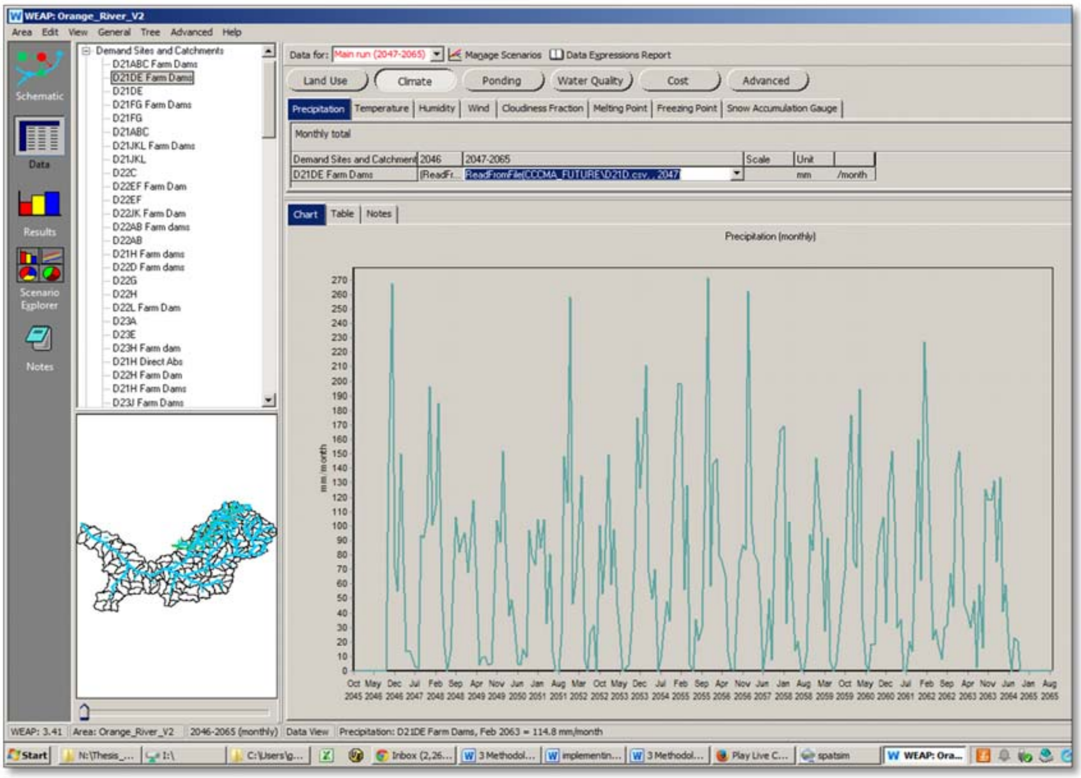



Figure 3.6 Snapshot of a result view window of the WEAP model.

In the current study, the WEAP model was used to simulate the natural stream flow and the flow impacted by various water uses within the Caledon River Basin, in the past, current and future climate conditions.

### 3.3.1 The Rainfall–Runoff Soil Moisture Method

While there are several options within the WEAP model for simulating streamflow, this study used the 'rainfall-runoff soil moisture' method. This method uses a two compartment soil moisture accounting structure that is designed to account for inputs of rainfall, losses through evapotranspiration and runoff generated as surface runoff, interflow (from the upper soil storage) and groundwater (from the lower storage). The model is therefore simpler than the Pitman model but also simulates the main water balance components of natural hydrological systems (Figure 3.7).

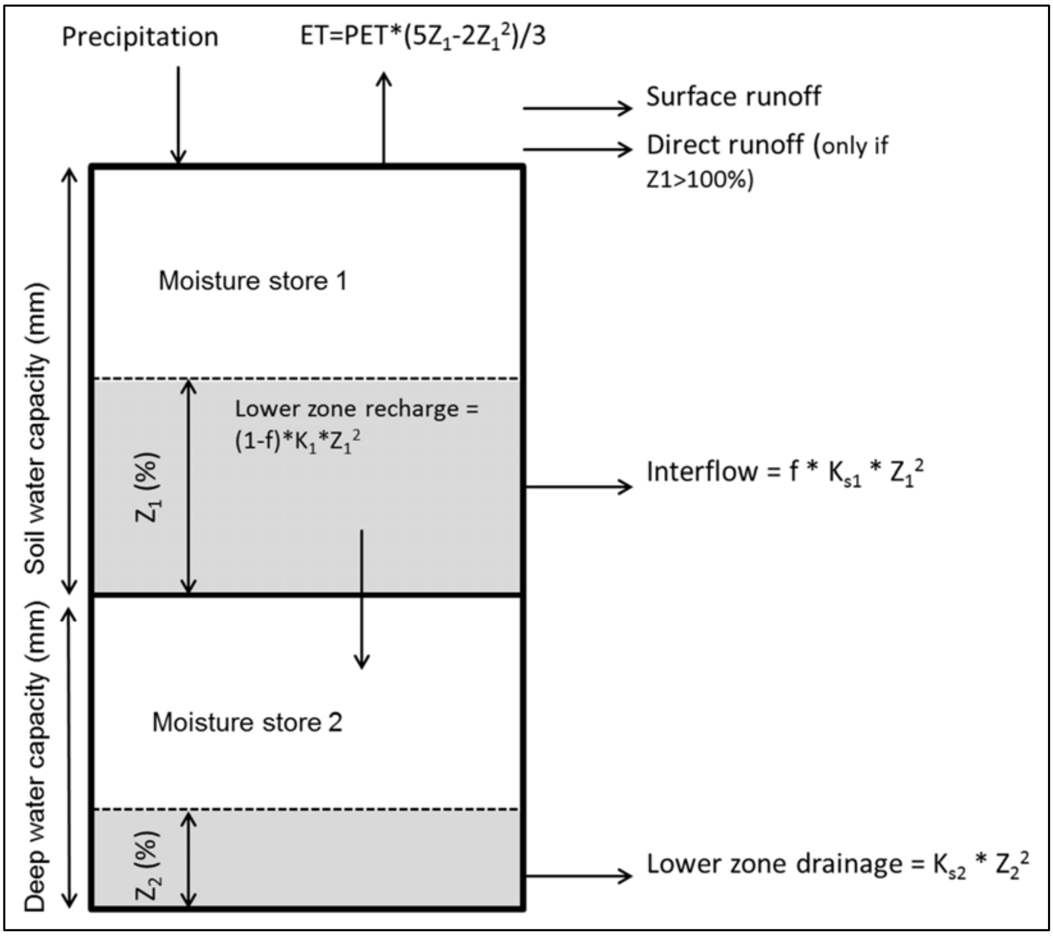



Figure 3.7 Conceptual diagram of the rainfall–runoff soil moisture model (Adopted from SEI, 2013).

Some of the default functionalities of the different components of the WEAP model have been modified by including some expressions in the parameter definitions to achieve simulations matching those of the Pitman model. The following sub-sections present a brief overview of the WEAP model components and compare them to the Pitman model.

#### 3.3.1.1 Evapotranspiration

There is no interception function within the WEAP model and therefore all atmospheric losses are dealt with in a single non-linear equation (3.1) that relates the relative soil moisture store and the proportion of potential evaporation that contributes to actual evaporation losses:

$$ET = PET * K_c * (5Z_1 - 2Z_1^2) / 3 \ldots \qquad \text{Equation 3.1}$$

Where:

PET = Potential evapotranspiration (seasonally variable)

$K_c$ = Crop coefficient (seasonally variable)

$Z_1$ = Current upper storage level (relative to maximum storage)

Figure 3.8 compares the estimations of actual evapotranspiration of the WEAP and Pitman models for PET values of 120 and 60 mm, assuming the Kc-value of 1 and the Pitman parameter R of 0. While the Pitman evapotranspiration increases proportionately with moisture content, the non-linearity relationship in the WEAP function implies that higher values of evapotranspiration will be generated for the same demand value (PE * $K_c$) and this will have the largest impact at moderate relative moisture storages.

*Kc,* the crop coefficient parameter, is a property of plants which can be used to predict evapotranspiration for a particular type of vegetation. It therefore varies with the type and stage of growth of a crop. The Z value in WEAP is similar to S/ST of the Pitman model.

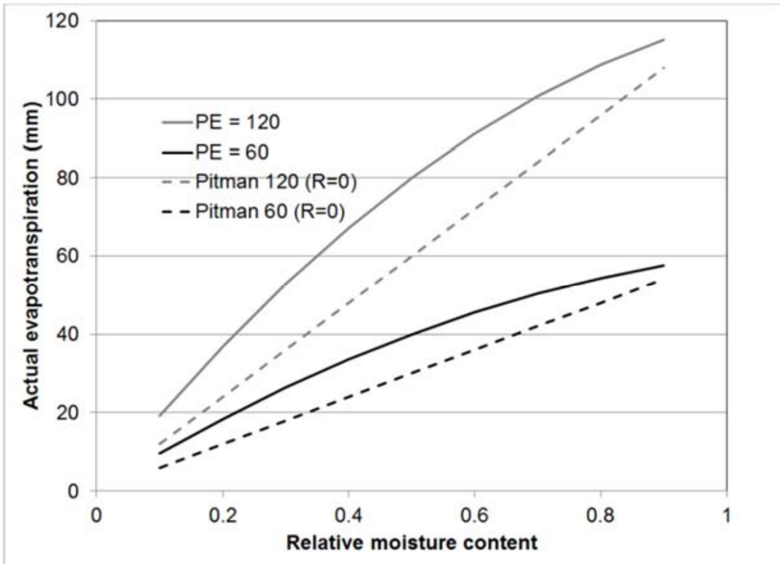



Figure 3.8 WEAP model actual evapotranspiration from soil moisture function.

#### 3.3.1.2 Surface Runoff

The default surface runoff (SQ) equation for WEAP is given by Equation 3.2, where P and Z are monthly rainfall and relative soil moisture content of the upper zone, respectively and RRF is the surface runoff parameter.

$$SQ = P^*Z_1^{RRF} \quad \ldots \qquad \text{Equation 3.2}$$

This implies that surface runoff is dependent not only on rainfall (as in the Pitman model) but also on storage level of the upper soil zone. This default equation also implies that surface runoff will occur at all rainfall depths, unlike in the Pitman model where rainfall has to exceed ZMIN. To better align the surface runoff calculations of the two models, an expression was developed for RRF rather than using a fixed value. This expression (Equation 3.3) was developed after various approaches were explored within an Excel spreadsheet.

$$\text{If P-Pmin}<0.5,\ 20,\ \text{N + Pmax/(P-Pmin)}^{(\text{Ln(P)/5})}\ ; \ldots \text{ Equation 3.3}$$

Where:

P = monthly rainfall depth (mm)

Pmin = monthly rainfall (mm) below which surface runoff is not expected

N = nominal RRF

Pmax = rainfall scale factor

Figure 3.9 compares the simulated surface runoff for the WEAP and Pitman models using various combinations of ZMIN, ZAVE and ZMAX (for Pitman) and Pmax, Pmin and N for different relative moisture contents in the WEAP model. Figure 3.9 suggests that the general shape of the surface runoff relationship for WEAP can be made similar to that of the Pitman model.

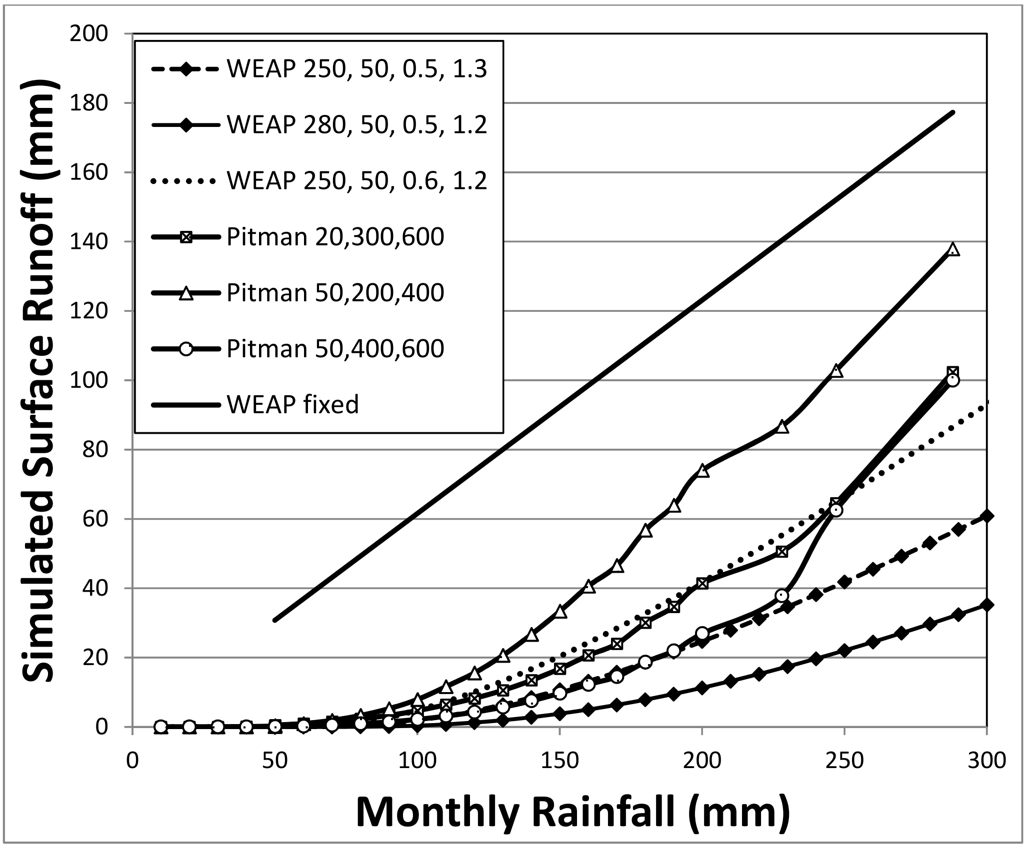



Figure 3.9 Differences in simulation of surface runoff between the two models. For WEAP the numbers refer to the rainfall scale factor, minimum rainfall, relative moisture content and nominal RRF; for Pitman the number refers to ZMIM, ZAVE and ZMAX.

#### 3.3.1.3 Interflow Function

The WEAP interflow function is used to determine both interflow and percolation to the lower storage zone and is based on two parameters; $K_{s1}$ (root zone conductivity in mm month$^{-1}$) and f (dimensionless fraction), the preferred flow direction (Equations 3.4 and 3.5).

$$\text{Interflow} = K_{s1} * f * Z_1^2 \quad \ldots \qquad \text{Equation 3.4}$$

$$\text{Percolation} = K_{s1} * (1-f) * Z_1^2 \quad \ldots \quad \text{Equation 3.5}$$

This is a similar function to that used in the Pitman model with $K_s$*f being equivalent to FT and POW is fixed at a value of 2. The percolation component is roughly equivalent to groundwater recharge in the Pitman model but is clearly less flexible in the WEAP model.

#### 3.3.1.4 Groundwater or Baseflow

The WEAP model baseflow function is based on a simple non-linear function (Equation 3.6) of the relative storage level of the lower zone ($Z_2$) storage using a single deep conductivity parameter ($K_{s2}$):

$$\text{Baseflow} = K_{s2}{*}Z_2^2 \quad \dots \quad \text{Equation 3.6}$$

This is clearly much simpler than the approach used in the Pitman model and therefore less flexible. One of the problems with the use of the WEAP model in semi-arid areas is that the default function does not allow for zero flows. The function was therefore modified using a conditional expression (Equation 3.7) for $K_{s1}$ and $K_{s2}$ based on either the upper ($K_{s1}$) or deep ($K_{s2}$) zone storage levels at the end of the previous time step (prevTSValue(Z%) and a threshold parameter (Zthresh).

If (prevTSValue(Z%) < Zthresh, 0, $K_{s1}$ * (prevTSValue(Z%) – Zthresh)/ prevTSValue(Z%))

…Equation 3.7

In ephemeral river systems Equation 3.7 would be used for the upper zone and $K_{s1}$, while the preferred flow direction parameter (f), and the deep storage zone capacity values would be set to 0. The Zthresh value could then be calibrated to ensure the correct duration and patterns of zero flow.

Within the Pitman model it is possible to have groundwater recharge as well as zero flow periods because of the riparian evapotranspiration function which can intercept the movement of groundwater towards the river channel system.

#### 3.3.1.5 Summary on Functionalities of the Models

There are substantial differences in the conceptual structures, assumptions and functionalities of the WEAP and the Pitman models. Some of the differences include surface runoff and drainage from storage functions. There are also a number of similarities in the processes the two models simulate and therefore some of the parameters (individually or combined) can be compared. Table 3.2 shows the processes and the related parameters of the two models. While some of the WEAP parameter values can yield similar results to the Pitman model outputs (given the same climate inputs), some WEAP expressions have to be used achieve comparable outputs from parts of the WEAP model. The WEAP model was ‘forced’ to produce similar outputs to Pitman mainly because the latter has been extensively used in the region and hence gained a lot of confidence, while the former is yet to be applied as much. Another reason is that the Pitman simulations are bound on constraints based on observed records.

Table 3.2 List of comparable parameters controlling similar hydrological processes of the WEAP and Pitman models.

| Process | Pitman | WEAP |
|---|---|---|
| Evapotranspiration | R | $K_c$ |
| Surface Runoff | ZMIN<br>ZAVE<br>ZMAX | RRF |
| Interflow | FT<br>POW<br>ST | $Ks_1$<br>f<br>Upper zone maximum storage |
| Groundwater | GW<br>GPOW<br>RIP | $Ks_2$<br>f<br>Lower zone maximum storage |

### 3.3.2 Setting up the WEAP Model for the Caledon River Basin

The same GIS layers used in setting up the Pitman model in SPATSIM (sub-basin boundary polygons and river network) were used as the basis for establishing appropriate nodes within the WEAP model. Apart from the major reservoirs towards the downstream end of the Caledon River Basin (see chapter 4), the major water uses in the basin are irrigation from either run-of-river abstractions or small farm dams. Each sub-basin was therefore represented by two catchment nodes, one representing the proportion draining into small farm dams and one with no reservoir storage. The latter were set to be downstream of the former, while run-of-river abstractions and demand sites were established at downstream nodes. Other water uses include rural and municipal domestic water supplies and these are treated in the same way as the abstractions for irrigation.

## 3.4 TIME SERIES DATA SETS

Both WEAP and the Pitman models require monthly rainfall data as an input for each of the quaternary catchments. The data used in this study were obtained from the surface water resources study of South Africa of 2005 (WR2005, Middleton and Bailey, 2008).

The two models use different approaches to estimate evaporation demands. While the Pitman model uses a mean annual value that is distributed by either a fixed seasonal distribution or by an additional time series input of monthly deviations (as fractions) from the fixed seasonal values, the WEAP model uses temperature, humidity and wind speed data together with the

Penman-Montieth estimation equation to generate reference evaporation. The Pitman model assumes that the evaporation demand is represented by S-Pan estimates. There were no wind speed and cloudiness fraction data available for this exercise. Therefore the default values of 2 m $s^{-1}$ and 1 (no clouds) were used for wind speed and cloudiness respectively. Latitude data are used in the WEAP model for adjustments of potential evaporation due to extraterrestrial radiation and daylight hours. The sub-basin latitudes were obtained from the SPATSIM GIS layers.

The initial temperature values used in this study were obtained from the Climate Systems Analysis Group (CSAG, 2012) of the University of Cape Town. Together with the temperature data, relative humidity data were set to reflect differences between wet and dry seasons. Both temperature and humidity data were then adjusted to achieve the potential evaporation seasonal variations that closely match those used in Pitman model.

Figure 3.10 illustrates some comparisons between the seasonal evaporation demands for one sub- basin of the Caledon River Basin based on WR90 Pitman model data (Midgley *et al.,* 1994) and several possible estimates of monthly temperature and relative humidity (see Table 3.3) using the WEAP model approach.

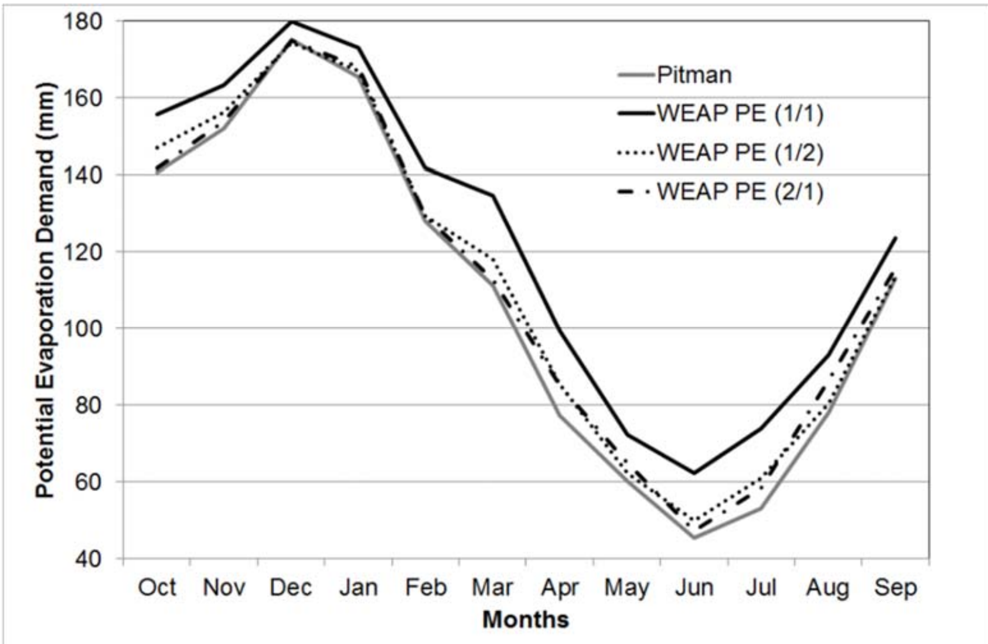



Figure 3.10 Graphical comparisons of seasonal evaporation demand estimates (in mm). The numbers in parenthesis for the WEAP series refer to the various combinations of temperature and relative humidity values given in Table 3.3.

Table 3.3 Comparisons of seasonal evaporation demand estimates (in mm). PE (1/1) is the evaporation demand calculated by WEAP using initial temperature (Temp1) and relative humidity (RH1) data; PE (1/2) and PE (2/1) are modified to approximate the Pitman evaporation values.

| | Oct | Nov | Dec | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Pitman | 140.8 | 152.0 | 175.2 | 165.4 | 128.2 | 111.3 | 77.2 | 60.3 | 45.5 | 53.2 | 78.0 | 113.0 |
| WEAP | | | | | | | | | | | | |
| Temp1 | 15.0 | 16.0 | 17.5 | 17.5 | 17.5 | 17.0 | 15.0 | 11.0 | 9.0 | 10.0 | 10.0 | 13.0 |
| RH1 | 53.0 | 65.0 | 7.0 | 75.0 | 78.0 | 75.0 | 70.0 | 65.0 | 55.0 | 50.0 | 45.0 | 45.0 |
| PE (1/1) | 155.7 | 163.5 | 180.0 | 173.0 | 141.9 | 134.7 | 99.3 | 72.4 | 62.3 | 73.8 | 93.2 | 123.6 |
| RH2 | 61.0 | 75.0 | 77.0 | 82.5 | 90.0 | 96.0 | 88.0 | 75.0 | 70.0 | 70.0 | 55.0 | 54.0 |
| PE (1/2) | 147.0 | 156.1 | 174.5 | 167.0 | 129.5 | 118.0 | 85.5 | 62.2 | 50.0 | 60.9 | 80.4 | 113.7 |
| Temp2 | 12.0 | 14.0 | 16.5 | 16.5 | 14.5 | 11.5 | 10.5 | 8.0 | 2.0 | 4.0 | 8.0 | 11.0 |
| PE (2/1) | 141.7 | 153.8 | 174.8 | 167.9 | 129.4 | 112.8 | 85.2 | 64.8 | 47.3 | 58.5 | 86.6 | 115.8 |

The same observed stream flow data (see Chapter 4) were used to calibrate (or assess the uncertainty ensembles in the case of the Pitman model) both models, while some of the Pitman model results were also used in ungauged sub-basins to guide the WEAP model calibration. This was justified on the basis of the far greater effort put into the Pitman model calibration that included uncertainty analysis.

### 3.5 CLIMATE CHANGE PROJECTIONS

Predictions in climate change and climate variability are essential for sound and meaningful water resources planning and management for future use. Global circulation models (GCMs) simulate the past climate and predict future global climate. While GCMs attempt to represent most mechanisms and processes of the earth’s atmosphere, ocean and land surface (Lambert and Boer, 2001), the outputs are too coarse a scale for use in hydrological models and require downscaling. There are also substantial differences in projections across different models due to different assumptions, boundary conditions and parameterisation of the physical processes of the climate dynamics (MacKellar *et al*., 2007) and therefore hydrological modelling studies should ideally use an ensemble of future predictions.

### 3.5.1 Downscaling the Climate Data

For use at river basin scales GCM data need to be processed to a finer spatial scale, normally tens of kilometres (Wilby *et al.,* 2004). This is commonly achieved by downscaling techniques. The data used in this study were statistically downscaled by the Climate Systems Analysis Group (CSAG), based at the University of Cape Town using the method of Hewitson and Crane (2006). The projections of future climate variability were attained by assuming the SRES A2 carbon emission scenario of IPCC (2007). Table 3.4 provides a list of the GCMs used to generate the data products provided by CSAG that were used in the current study. The climate models were selected solely on the basis of availability and not through any sort of objective selection criteria.

Table 3.4 List of general circulation models used in the study

| GCM | Source | References |
|---|---|---|
| CCCMA | Canadian Centre for Climate Modelling and Analysis | Flato *et al.* (2000) |
| CNRM | France Centre National de Recherches Meteorologiques | Salas-Melia *et al*. (2005) |
| CSIRO | Australian Atmospheric Research | Gordon *et al.* (2002) |
| GFDL | USA NOAA Geophysical Fluid Dynamics Lab | Wetherald and Manabe (1988) |
| GISS | USA Goddard Institute for Space Studies | Hansen *et al*. (1988) |
| IPSL | France Institut Pierre Simon Laplace | Marti *et al*. (2005) |
| MIUB | German Meteorological Institute of the University of Bonn | Min *et al*. (2004) |
| MPI | Max-Planck Institute For Meteorology | Jungclaus *et al*. (2006) |
| MRI | Japan Meteorological Research Institute | Tokioka *et al.* (1996) |

### 3.5.2 CSAG Data Products

Daily rainfall and temperature data sets are available from CSAG for baseline (1961-2000), near-future (2046-2065) and far-future (2081-2100) periods for each of the nine GCMs. The data are available at the 'quinary' catchment scale which is more detailed than the 'quaternary' scale used for the Caledon. The quinary catchments were first represented as a point GIS coverage (points located at the quinary centroid, Figure 3.11), and the raw CSAG data imported. The quinary scale data were then spatially interpolated using the inverse distance squared interpolation method (Equations 3.8 and 3.9) to cover the quaternary catchment scale. This interpolation approach forms a standard analysis procedure in the SPATSIM modelling framework. The SPATSIM procedure allows the user to specify the maximum number of points to use in the interpolation as well as the maximum radius of the search area away from the quaternary centroid. The interpolated time series can be at the same time step as the original data (daily) or cumulated to monthly totals.

$$Rp = \sum_{i=1}^{N} wiRi \quad \text{… Equation 3.8}$$

$$wi = \frac{di^{-2}}{\sum_{i=1}^{N} di^{-2}} \quad \text{… Equation 3.9}$$

Where:

$R_p$ – interpolated quaternary catchment rainfall

$R_i$ – rainfall at a quinary point

N – number of data points

$d_i$ – distance from the quinary points to the centroid of the quaternary catchment

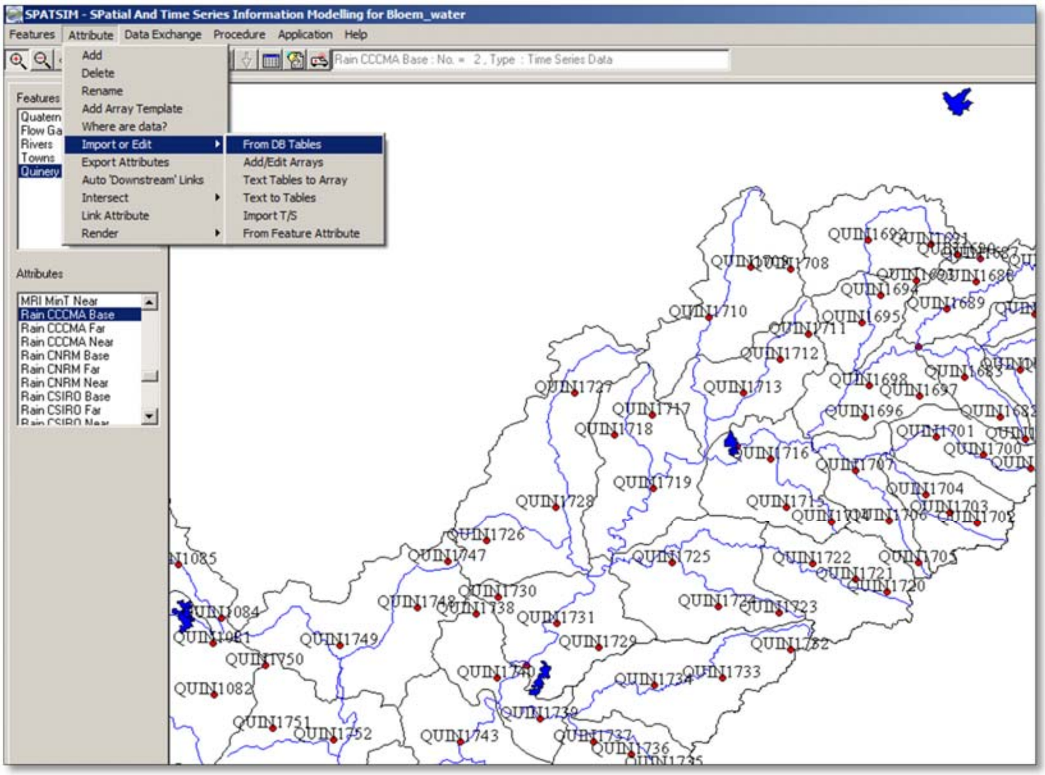



Figure 3.11 Snapshot of a SPATSIM window showing positions of quinary catchments (red dots).

### 3.5.3 Bias Correction of Downscaled Rainfall Data

It has been observed that most of the GCM products are biased (Ines and Hensen, 2006; Hageman *et al*., 2011), where there is a shift of baseline model simulations from the observed historical climate data. Bias is mainly due to systemic errors inherent in the GCMs and the models' inability to adequately represent some of the important climate components (Piani *et al*., 2010). To attain sensible results when using downscaled climate data, the model outputs should be bias-corrected before they are used for any impact assessment. This is particularly true when the GCM data are used with a hydrological model that has been calibrated using historical data and when several GCMs are to be used and compared. In an attempt to bridge the gap between the observed and the simulated climatology, a number of bias correction techniques have been developed.

The main objective of such methods is to achieve a GCM-simulated climatology with similar statistical characteristics to the historical observations. Most methods either establish a statistical or non-statistical relation, also known as a `transfer function', between the observed and the simulated climate. The same transfer function is then applied to the future climate scenarios. One of the main assumptions used in the bias correction methods is that the bias properties of the GCMs are not time dependent and subsequently the established transfer function remains unchanged in the future. Another assumption is that the observation records are perfect and free of measurement, random and systematic errors.

The characteristics of the downscaled baseline rainfall (point and interpolated) data for the Caledon River Basin were significantly different from the historical (WR2005) data, in terms of seasonal distribution and descriptive statistics. This therefore required the application of some mathematical transformation so that the GCM baseline output was statistically comparable to the observed rainfall data. The same correction factor was then applied to the future (near and far) rainfall data to remove bias in the statistical parameters, while maintaining the behavioural properties of individual GCMs outputs (Equation 3.10). Statistically, baseline temperature data from the GCMs were not substantially different from the observed data used in WR2005 (Hughes *et al*., 2014b). It was therefore not considered necessary to apply a bias correction procedure to the temperature data.

$$FRC_{ijk} = [WRM_j + WRSD_j{}^*(FR_{ijk} – BRM_{jk})/BRSD_{jk}]^2 \quad \text{… Equation 3.10}$$

Where:

$FRC_{ijk}$ – corrected future rainfall for month i and calendar month j in the time series of GCM k.

*$WRM_j$* - mean of WR 2005 rainfall for calendar month j (historical observed data).

*$WRSD_j$* – standard deviation of WR2005 rainfall for the calendar month j.

*$FR_{ijk}$* – future rainfall for month i and calendar month j in the time series of GCM k.

*$BRM_{jk}$* – mean of the baseline rainfalls for GCM k and the calendar month j.

*$BRSD_{jk}$* – standard deviation of the baseline rainfall for the GCM k and calendar month j.

All of the rainfall data bias corrections are based on square root transformations of the data as this was found to give the lowest skewness values (i.e. closest to normal distribution) across all data sets and all calendar months.

### 3.5.4 Estimation of Future Evaporation

The Pitman model typically uses fixed calendar month distributions of potential evaporation, but can also include time series of fractional deviates from the monthly means. The CSAG daily maximum and minimum temperature data for baseline and future scenarios were used to estimate time series of the temperature components of the Hargreaves (Hargreaves and Samani, 1982), equation (3.11).

The Hargreaves\` potential evapotranspiration estimation is given by:

$$PET = 0.0075 * R_a * C_t * \delta_t^{1/2} * T_{avg.d} \quad \text{… Equation 3.11}$$

Where:

PET – Potential evapotranspiration

$R_a$ – Total incoming extra-terrestrial solar radiation

$C_t$ – Temperature reduction coefficient which is a function of relative humidity

$\delta_t$ – Difference between the mean monthly maximum and mean monthly minimum temperatures

$T_{avg.d}$ – Mean temperature in the time step.

The temperature components are derived through Equation 3.12 below.

$$HC_{kj} = (Tmax_{kj} + Tmin_{kj})/2 * (Tmax_{kj} - Tmin_{kj})^{1/2} \quad \text{… Equation 3.12}$$

Where:

$HC_{kj}$ – Temperature component of the Hargreaves equation for GCM k, and month j

$Tmax_{kj}$ – Daily maximum temperature for GCM k and month j

$Tmin_{kj}$ – Daily minimum temperature for GCM k and month j

The mean calendar month $HC_{kj}$ values were computed for the baseline and near future periods for each GCM and the percentage changes calculated (Equation 3.13). The same percentage changes were then applied to the historical mean monthly potential evaporation values, while the annual potential evaporation value was left un-changed. While the sum of the historical mean monthly evaporation values always adds up to 100, the sums for the near-future will always be greater than 100 (assuming that all GCMs predict increases in temperature). The approach is therefore based on the assumption that changes in the temperature component of the Hargreaves equation (3.11) will dominate changes in future potential evaporation demand, and that the solar radiation and relative humidity effects can be ignored.

The time series of potential evaporation for the future scenarios therefore reflect GCM projected increase in evaporation demand based on temperature increases. The evaporation factors (Equation 3.13) from the GCMs are applied to the quaternary historical evaporation demands, which are expressed as a percentage of annual evaporation rates. The difference of future evaporation relative to historical for each GCM and for month j is given by Equation 3.14.

$$E_{kj} = 100 * (HC_{kjb} – HC_{kjf})/HC_{kjb} \quad \text{… Equation 3.13}$$

$$E_{diffj} = E_{kj} * E_{obsj} / 100 \qquad \text{… Equation 3.14}$$

Where:

Subscripts b and f stand for baseline and future climate scenarios respectively.

$E_k$ – evaporation factors derived from GCMs.

$E_{diff}$ – difference in future evaporation value relative to historical.

$E_{obs}$ – observed evaporation rates (historical WR90).

### 3.5.5 Daily Rainfall Variability Analyses

As part of this study new analysis routines were added to the SPATSIM framework to facilitate detailed daily rainfall analyses and quantify projected changes (baseline to near and far future) in daily rainfall characteristics. The three analyses included were:

- Annual and seasonal rainfall threshold changes.

- Changes in high rainfall at different probability of exceedence.
- Changes in the frequency of dry spells of different duration.

The objective of these analyses was to identify if there are projected changes in daily rainfall characteristics that might be masked when using a monthly time step in the hydrological model that was used to assess projected changes in streamflow and water resources availability.

#### 3.5.5.1 Annual and Seasonal Threshold Analysis

This analytical technique involves determining the maximum number of consecutive days with rainfall below the prescribed rainfall thresholds of 2, 5, 10, 15, 20 and 50 mm, for all the climate models and the three climate scenarios. These were carried out for selected quinary catchments and were analysed at seasonal and annual time scales. Seasons are defined only as summer (wet), spanning October to March, and winter (dry), which is April to September.

#### 3.5.5.2 Annual Probability of Exceedence

This method determines the probability that rainfall of a particular depth can occur or be exceeded. The values of all daily rainfalls are considered for the total period of each of the three climate scenarios. Comparisons were made for rainfall occurring less than 0.5, 1, 10 and 15% of the time.

#### 3.5.5.3 Frequency of Dry Spells

In this analysis, the frequency of occurrence of consecutive number of days ('dry spells') with rainfall below of the thresholds of 5, 10, 20, 50 mm are analysed. The method determines how often dry spells of 10, 30, 60, 180, 270, 360, 720, 1440, 1800, and >1800 days occur throughout the duration of each of the climate scenarios projected by each GCM. Figure 3.12 shows an example of the output of the annual frequency analysis from one the quinary points (the figure is abridged to show analysis for a rainfall threshold of 5 mm only).

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Annual frequency analysis | | | | | | | | | | | |
| Data outputs are frequencies of dry spells below 5, 10, 20, 50 mm | | | | | | | | | | | |
| | | | | | | | | | | | |
| QUIN | 1749 | | | | | | | | | | |
| | **Rainfall Threshold** | **5mm** | | | | | | | | | |
| **GCM** | **Length of dry spell** | **10** | **30** | **60** | **180** | **270** | **360** | **720** | **1440** | **1800** | **>1800** |
| CCCMA | Baseline | 64.5 | 26.9 | 6.7 | 1.9 | 0 | 0 | 0 | 0 | 0 | 0 |
| CCCMA | Near Future | 67.1 | 26.3 | 5.1 | 1.5 | 0 | 0 | 0 | 0 | 0 | 0 |
| CCCMA | Far Future | 66.9 | 27.9 | 2.8 | 2.4 | 0 | 0 | 0 | 0 | 0 | 0 |
| CNRM | Baseline | 77.3 | 17.9 | 3 | 1.8 | 0 | 0 | 0 | 0 | 0 | 0 |
| CNRM | Near Future | 78.5 | 17.6 | 2.2 | 1.7 | 0 | 0 | 0 | 0 | 0 | 0 |
| CNRM | Far Future | 81.9 | 13.7 | 3 | 1.4 | 0 | 0 | 0 | 0 | 0 | 0 |
| CSIRO | Baseline | 76.2 | 19.9 | 3.3 | 0.6 | 0 | 0 | 0 | 0 | 0 | 0 |
| CSIRO | Near Future | 76.6 | 21.2 | 1.7 | 0.5 | 0 | 0 | 0 | 0 | 0 | 0 |
| CSIRO | Far Future | 79.1 | 18.8 | 1.8 | 0.3 | 0 | 0 | 0 | 0 | 0 | 0 |
| GFDL | Baseline | 74.7 | 21.2 | 3.2 | 0.8 | 0 | 0 | 0 | 0 | 0 | 0 |
| GFDL | Near Future | 73 | 22.5 | 4 | 0.5 | 0 | 0 | 0 | 0 | 0 | 0 |
| GFDL | Far Future | 73.1 | 22.9 | 3.6 | 0.5 | 0 | 0 | 0 | 0 | 0 | 0 |
| GISS | Baseline | 80.3 | 16.1 | 2.9 | 0.7 | 0 | 0 | 0 | 0 | 0 | 0 |
| GISS | Near Future | 81.3 | 16.5 | 1.4 | 0.8 | 0 | 0 | 0 | 0 | 0 | 0 |
| GISS | Far Future | 83 | 14.6 | 1.8 | 0.6 | 0 | 0 | 0 | 0 | 0 | 0 |
| IPSL | Baseline | 64.5 | 27.1 | 6.7 | 1.8 | 0 | 0 | 0 | 0 | 0 | 0 |
| IPSL | Near Future | 69.6 | 24.6 | 5.2 | 0.7 | 0 | 0 | 0 | 0 | 0 | 0 |
| IPSL | Far Future | 64.9 | 28.3 | 6.4 | 0.4 | 0 | 0 | 0 | 0 | 0 | 0 |
| MIUB | Baseline | 70.3 | 23 | 5.5 | 1.2 | 0 | 0 | 0 | 0 | 0 | 0 |
| MIUB | Near Future | 72.9 | 23.1 | 3 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| MIUB | Far Future | 76.2 | 19.5 | 4.1 | 0.2 | 0 | 0 | 0 | 0 | 0 | 0 |
| MPI | Baseline | 70.3 | 23.7 | 4.6 | 1.4 | 0 | 0 | 0 | 0 | 0 | 0 |
| MPI | Near Future | 70.8 | 23.7 | 4.4 | 1.1 | 0 | 0 | 0 | 0 | 0 | 0 |
| MPI | Far Future | 72.4 | 21.8 | 5.1 | 0.8 | 0 | 0 | 0 | 0 | 0 | 0 |
| MRI | Baseline | 66.2 | 27.1 | 5.9 | 0.8 | 0 | 0 | 0 | 0 | 0 | 0 |
| MRI | Near Future | 69.7 | 24.5 | 5 | 0.8 | 0 | 0 | 0 | 0 | 0 | 0 |

Figure 3.12 A snapshot showing an example of an output of frequency analysis from SPATSIM.

### 3.6 SUMMARY

The aim of this chapter was to outline the various methodological approaches and models used to achieve the objectives of the study. Hydrological models are vital tools and are an integral part of water resources evaluation and hydrological investigations. Similarly, GCMs are currently the best generation of models for simulating and predicting future global climate. The output of any modelling exercise inevitably depends upon of the quality and availability of input data, in terms of both temporal and spatial representativeness. It is therefore important that climate and hydrological data sets are processed and analysed using methods with sound scientific bases. It is however, recognised that there are inherent methodological uncertainties related to extrapolation both in time and space.

# 4 THE CALEDON RIVER BASIN

## 4.1 INTRODUCTION

A thorough hydrological study of an area requires a full understanding and knowledge of the various physical and anthropological aspects of the basin under investigation. Further, a satisfactory description of a drainage basin depends on the various types of data and observational information recorded. The success of any hydrological modelling exercise depends on the quality and level of detail of the data available to describe the area. These data also provide the basis for a conceptualisation of the hydrological processes (Tetzlaff *et al*., 2008).

Remote-sensing products have proved to be a viable option when field data are not available and have recently gained popularity (Bøgh *et al*., 2004), though some ground-truthing is often necessary (Hughes, 2006; Soulsby *et al*., 2008). This innovative approach has in many cases alleviated the severe shortage of information in many areas, where ground monitoring networks are not feasible. The availability and quality of hydrologically relevant historical observation data is also extremely important in hydrological studies (Smakhtin *et al.,* 1997; Sivapalan *et al.,* 2003). However, developing countries are faced with the challenge of producing such data with the quality required by hydrologists.

This chapter describes the Caledon River Basin characteristics that are relevant to a hydrological understanding of the area. These include, but are not in any way limited to, topography, climate conditions, historical stream flow records, generalised geology and soil cover, as well as land and water use activities within the basin.

## 4.2 LOCATION OF THE CALEDON BASIN

The study area is the upper Caledon River extending for more than 250 km in length from the source at the Golden Gate Highlands (-28.5$^0$ lat, 28.65$^0$ long) at an altitude of about 2035 m to the Welbedacht dam (-29.9$^0$ lat, 26.86$^0$ long) at an altitude of about 1424 m. The Caledon River Basin is a transboundary watershed shared between the western lowlands and the north western regions of the Kingdom of Lesotho and the eastern part of the Free State province of the Republic of South Africa (Figure 4.1). The basin covers an estimated area of about 15 266 km$^2$. The Caledon River flows in a south westerly direction and forms part of the border between the two countries before entering the Free State province near the town of Wepener.

It then continues westwards into Welbedacht dam. The Caledon River Basin is one of Lesotho`s major drainage basins (Chakela, 1981) and is also a significant tributary to the Orange–Senqu River which drains the majority of the Kingdom of Lesotho, passes through the central regions of South Africa and flows into the Atlantic Ocean at the boundary between Namibia and South Africa.

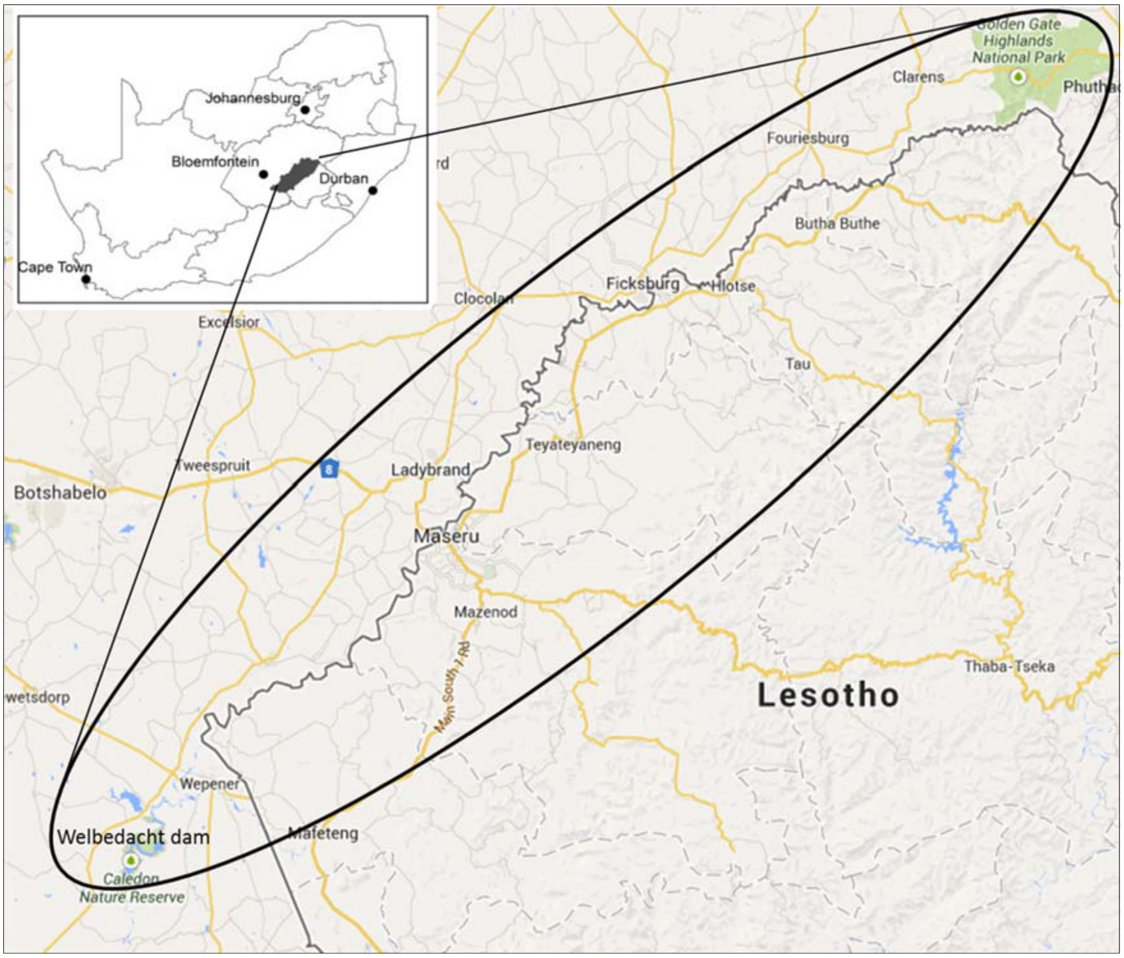



Figure 4.1 Location of the Caledon basin.

## 4.3 TOPOGRAPHY

Topography is one of the most important physical properties of a basin and, through its influence on hydraulic gradients, has a significant impact on hydrological processes and variability (Armstrong and Martz, 2003; Wu *et al.,* 2008). Topography has therefore often been used as a basis for developing physically meaningful methods for evaluating basin`s response to climatic inputs and in the development of rainfall–runoff models (Zhang and Montgomery, 1994; Beven *et al*., 1995). Kirkby (1988) contends that basin response can be categorised on the basis of topographic characteristics. The role of topography and associated drainage networks in hydrological studies has also been emphasised by Devito *et al.* (2005) who pointed out that topography is the basis of well-defined hydrologic response units (HRUs) and that topography influences flow rates as well as direction.

The Caledon River Basin is generally a gently sloping area, with vast areas having slopes of less than 8 degrees, mostly within the South African parts. The basin consists of undulating terrain throughout the entire western and south-western regions, marked by gentle and moderate slopes (Figure 4.2). The eastern and the north-eastern parts of the basin, mainly within Lesotho, consist of slightly sloping terrain towards the south and the middle regions. The steep rugged topography of the Drakensberg Mountains lying at around 2 400 m above mean sea level covers most of the upper half of the basin on the eastern side (Figure 4.2).

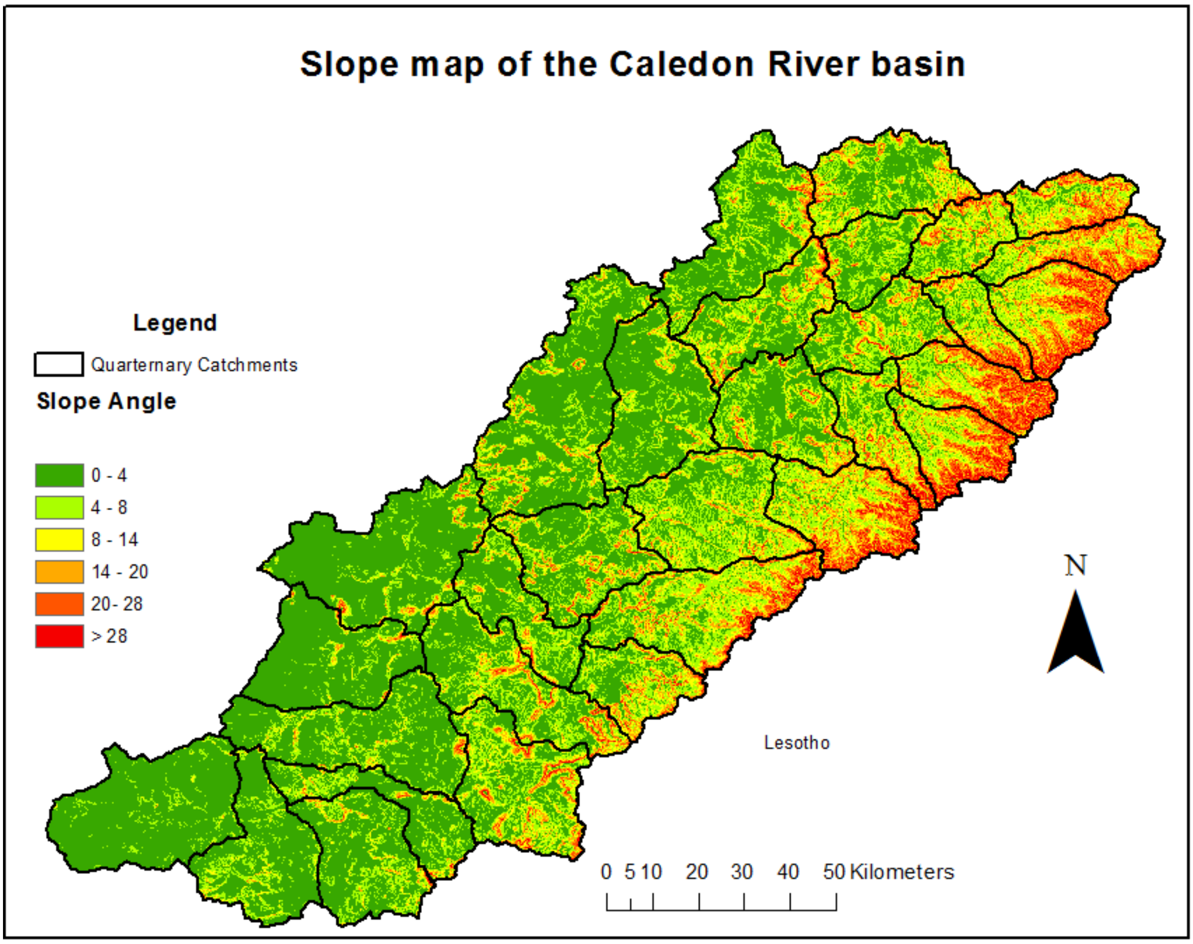



Figure 4.2 The slope map of the Caledon River Basin generated using SRTM digital elevation data at the resolution of 90 meters (http://srtm.csi.cgiar.org/Index.asp).

## 4.4 CLIMATE

The entire basin falls into the so-called ‘cold interior’ climatic zone, which is marked by generally dry and cold winters together with warm and humid summers. Winter months are May, June and July and temperatures occasionally drop below -3 $^0$C in the low lying areas and -8.5 $^0$C in the mountainous Drakensberg region (Lesotho Meteorological Services- LMS, 2013). Relatively small amounts of snow are common in winter in the eastern part of the basin, while frost occurs in the flat lower topographic regions in the west. The summer season extends from October to February, while January is the hottest month of the year with average temperatures of about 20 $^0$C in the mountainous regions to 30 $^0$C in the low-lying areas (LMS, 2013).

Figures 4.3A, 4.3B and 4.3C show average monthly rainfall and temperatures from three weather stations located at Fouriesburg in the north-east, Maseru in the centre and Wepener in the south-western part (see Figure 4.4 for the locations). These are based on a 30-year data record (1979–2000) obtained from the climate information platform of the Climate System Analysis Group (CSAG) based at the University of Cape Town (CSAG, 2014). Although there are some differences in absolute values for both temperature and rainfall, the three figures indicate very similar seasonal variations. The similarities in precipitation are not as marked as they are for temperature. However, it is clear that for the three stations under consideration, up to 70% of the rainfall in the basin occurs during the five-month period ending in February.

Based on the South African water resources study of 1990 compiled by Midgley *et al.* (1994), the mean annual precipitation within the Caledon River Basin varies from 1 000 to 1 500 mm in the north-eastern parts of the Drakensberg Mountains, and drastically decreases to between 500 and 600 mm in the lower south-western parts of the basin (Figure 4.4A). The rainfall patterns in the basin are very seasonal, with approximately 70% of the rain falling between November and March. The rainfall values used by Midgley *et al*. (1994) were derived from the network of rain gauges within the basin (shown in Figure 4.4A) with variable record periods spanning the period from 1920 to 1989.

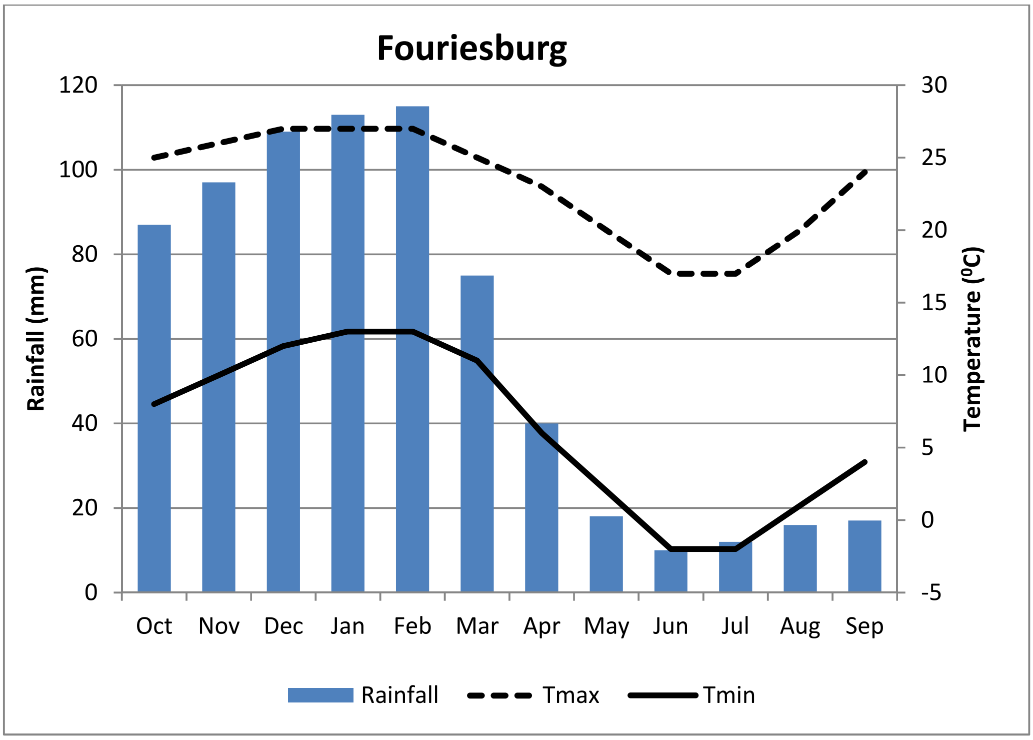



Figure 4.3A Average climate conditions in the Caledon Basin at Fouriesburg.

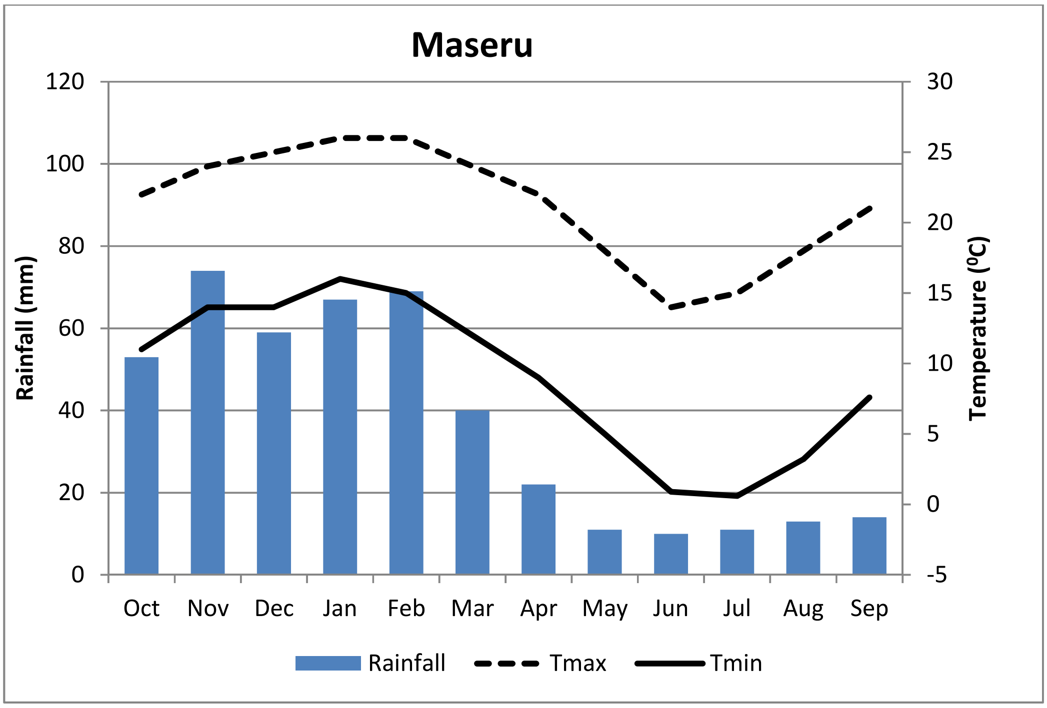



Figure 4.3B Average climate conditions in the Caledon Basin at Maseru.

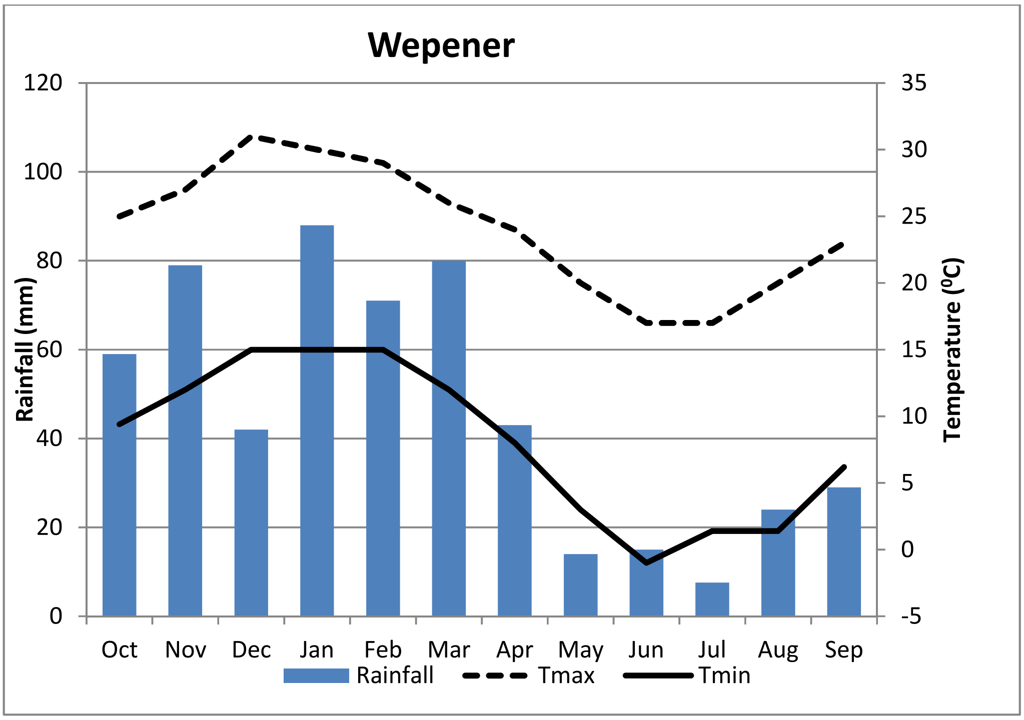



Figure 4.3C Average climate conditions in the Caledon Basin at Wepener.

The density of the evaporation network of stations in the Caledon River Basin is relatively low, with only a few of them located in the Lesotho side of the basin. There are about 10 stations recording evaporation rates from Symons pans, all of which are located in the lower lying areas and none in the mountain areas. Using the available information from the functional stations, Midgley *et al.* (1994) suggest that S-pan mean annual evaporation ranges from less than 1 200 mm in the mountainous headwaters of the basin and increases gradually to about 1 500 to 1 600 mm downstream (Figure 4.4B). It is apparent that the western sub-basins with lower rainfall amounts, also experience higher rates of evaporation, making the water scarcity severe in those areas. Just like many parts of water-stressed southern Africa, most parts of the basin have higher evaporative demands than can be satisfied by rainfall.

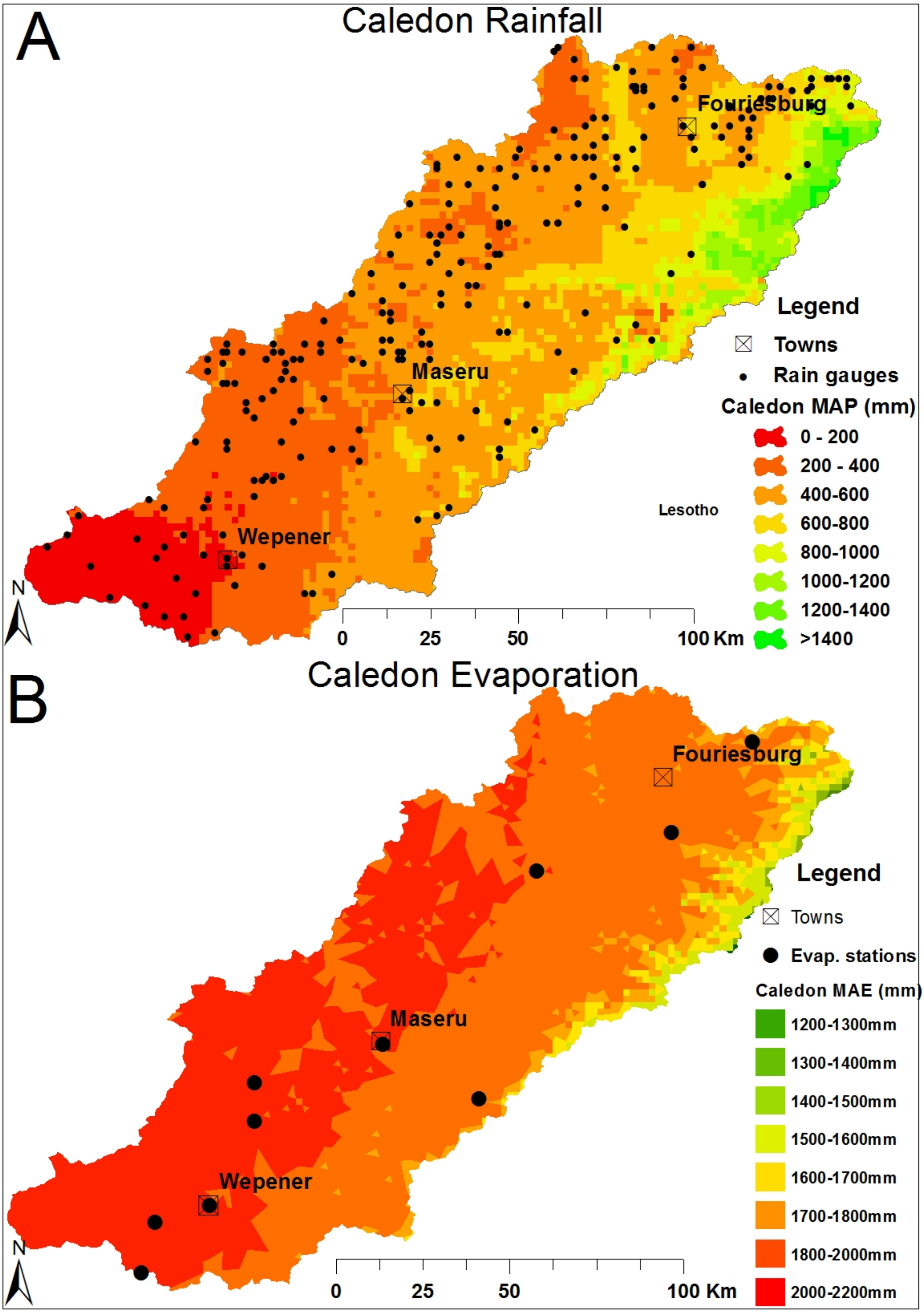



Figure 4.4 Mean annual precipitation (A) and mean annual evaporation (B) of the Caledon River Basin.

## 4.5 STREAM FLOW

With an estimated area of about 16 000 $km^2$, the Caledon River Basin is divided into 31 quaternary catchments (Figure 4.5). Quaternary catchments are the fourth order catchments which are the principal hydrological units used by the Department of Water and Sanitation, DWS (formerly known as the Department of Water Affairs and Forestry) for management purposes in South Africa. Each quaternary catchment has a relatively homogenous hydrological response, and has been assigned representative properties of various physical and climate characteristics such as soil properties, mean monthly temperature and potential evapotranspiration (Schulze and Maharaj, 1997). The whole country (including Lesotho and Swaziland) is demarcated into 1946 quaternary catchments, covering a total area of about 1.3 million $km^2$. The quaternary catchments comprising the Caledon have surface areas ranging from 200 $km^2$ to more than 900 $km^2$ (Table 4.1).

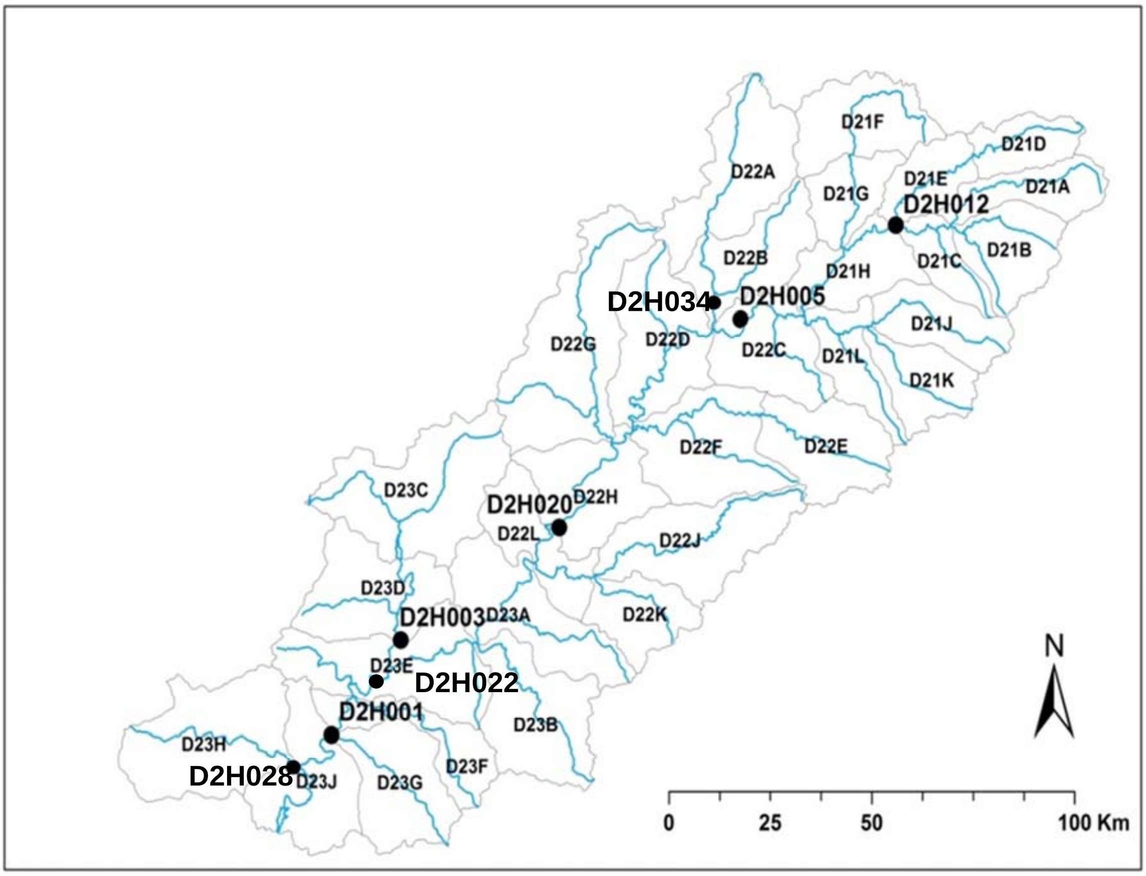



Figure 4.5 Quaternary catchments and key stream flow monitoring gauges in the Caledon River Basin.

Table 4.1 Quaternary catchments of the Caledon River Basin

| Catchment ID | Area ($km^2$) | Coverage (%) |
|---|---|---|
| D21A | 309 | 2.02 |
| D21B | 394 | 2.58 |
| D21C | 212 | 1.39 |
| D21D | 251 | 1.64 |
| D21E | 268 | 1.76 |
| D21F | 480 | 3.14 |
| D21G | 278 | 1.82 |
| D21H | 381 | 2.50 |
| D21J | 359 | 2.35 |
| D21K | 326 | 2.14 |
| D21L | 304 | 1.99 |
| D22A | 635 | 4.16 |
| D22B | 457 | 2.99 |
| D22C | 485 | 3.18 |
| D22D | 628 | 4.11 |
| D22E | 498 | 3.26 |
| D22F | 633 | 4.15 |
| D22G | 969 | 6.35 |
| D22H | 541 | 3.54 |
| D22J | 652 | 4.27 |
| D22K | 324 | 2.12 |
| D22L | 376 | 2.46 |
| D23A | 608 | 3.98 |
| D23B | 597 | 3.91 |
| D23C | 861 | 5.64 |
| D23D | 565 | 3.70 |
| D23E | 702 | 4.60 |
| D23F | 351 | 2.30 |
| D23G | 512 | 3.35 |
| D23H | 776 | 5.08 |
| D23J | 534 | 3.50 |
| **TOTAL** | **15 266** | **100.00** |

The density and the condition of the stream flow gauging network in the Caledon River Basin are not satisfactory. In a physiographic environment such as that of the study basin, the World Meteorological Organisation (WMO, 2008) recommends at least one gauging station every 1 875 km$^2$. However, there are only six partially functional stream flow gauging stations in the basin, with some gaps in recorded data (Figure 4.5, Table 4.2). A further problem with the current monitoring network is that the data records are short, cover different periods and have substantial amounts of missing data. Similarly, the stations do not measure the full range of high flows due to limitations with the rating curves.

An additional challenge in quantifying the stream flow characteristics of the basin is that upstream abstractions are poorly quantified. The combined uncertainties in the observed data make the basin effectively ungauged. The observed data may be useful for constraining some aspects of simulated flow data, but cannot be effectively used for conventional model calibration (Seibert and Beven, 2009; Hughes, 2013). There are two additional gauges (D1H006 and D1H032) which are not located within the Caledon but are useful for defining flow regime characteristics of the steep headwater catchments that can be used to establish regional flow constraints. These gauges are on the eastern side of the Drakensburg mountains and drain southwest towards the Orange- Senqu River.

### 4.5.1 Temporal Variations

Analysis of the stream flow records from the six gauging stations in the main channel and the tributaries indicate that peak flows generally occur during the months of January and sometimes in February, followed by gradually declining flows with minimum flow around the months of June and July (Figure 4.6). There are however, a few exceptions from this general trend. For instance, gauge D2H003 depicts a rather delayed maximum flow occurring in March, while D2H005 shows a bi-modal hydrograph with a second peak also occurring in March. There is a large monthly variation of river discharge in the Caledon River Basin. All the gauges indicate that more than 40% of the annual stream flow occurs in the period January to March.

The flow records of most of the gauges have significant missing data and comparisons between gauges are rather difficult since they also cover different time periods and are of varying lengths of observation. It is apparent that the flow trends shown by the seasonal distributions in Figure 4.6 do not necessarily reflect the natural hydrology of the catchment because the basin is heavily impacted by numerous water abstractions and impoundments constructed along the length of the main channel as well as in the tributaries (see section 3.7). Figure 4.7 presents the observed and simulated total annual stream flow at gauge D2H001 (1920-1977) and at the outlet of quaternary catchment D23F (1920-1989). Both indicate a steady increase in the long-term variation of stream flow in the basin, since 1920.

Table 4.2 Summary of properties of the stream flow gauges in the Caledon Basin.

| Gauge No. | Catchment area ($km^2$) | Records | Details | Missing data (%) |
|---|---|---|---|---|
| D2H012 | 518 | 1968–2011 | High flows poorly quantified; some farm dam and land use change effects. | 2 |
| D2H005 | 3 857 | 1941–1956 | High flows moderately well quantified; many farm dams, abstractions and land use impacts; some domestic return flows. | 1 |
| D2H020 | 8 399 | 1982–2010 | High flows moderately well quantified; large and poorly quantified impacts of Maseru city abstractions plus all upstream impacts. | 54 |
| D2H003 | 1 424 | 1934–1954 | High flows well quantified; some agricultural abstractions but assumed to be relatively small (note that the period of record is before the construction of a large dam). | 0 |
| D2H022 | 12 852 | 1988–2010 | Stable river section and subject to many uncertainties. | 7 |
| D2H001 | 13 421 | 1926–1978 | High flows very badly quantified in early parts of record; many accumulated upstream abstraction impacts. | 11.6 |
| D2H034 | 1 082 | 1992-2012 | Recent gauge with records since 1999. Highly impacted catchment with many farms dams and irrigation. | 0 |
| D1H006* | 2 969 | 1949-2013 | Located at the Makhaleng River in Lesotho. High flows fairly are quantified and it is impacted by relatively minimal upstream abstractions. | 12 |
| D1H032* | 1 074 | 1986-2013 | Senqunyane River – 16 years of record available prior to Mohale Dam construction. Relatively good quality data with little water abstraction. | 1.5 |

*Not located in the Caledon River Basin.

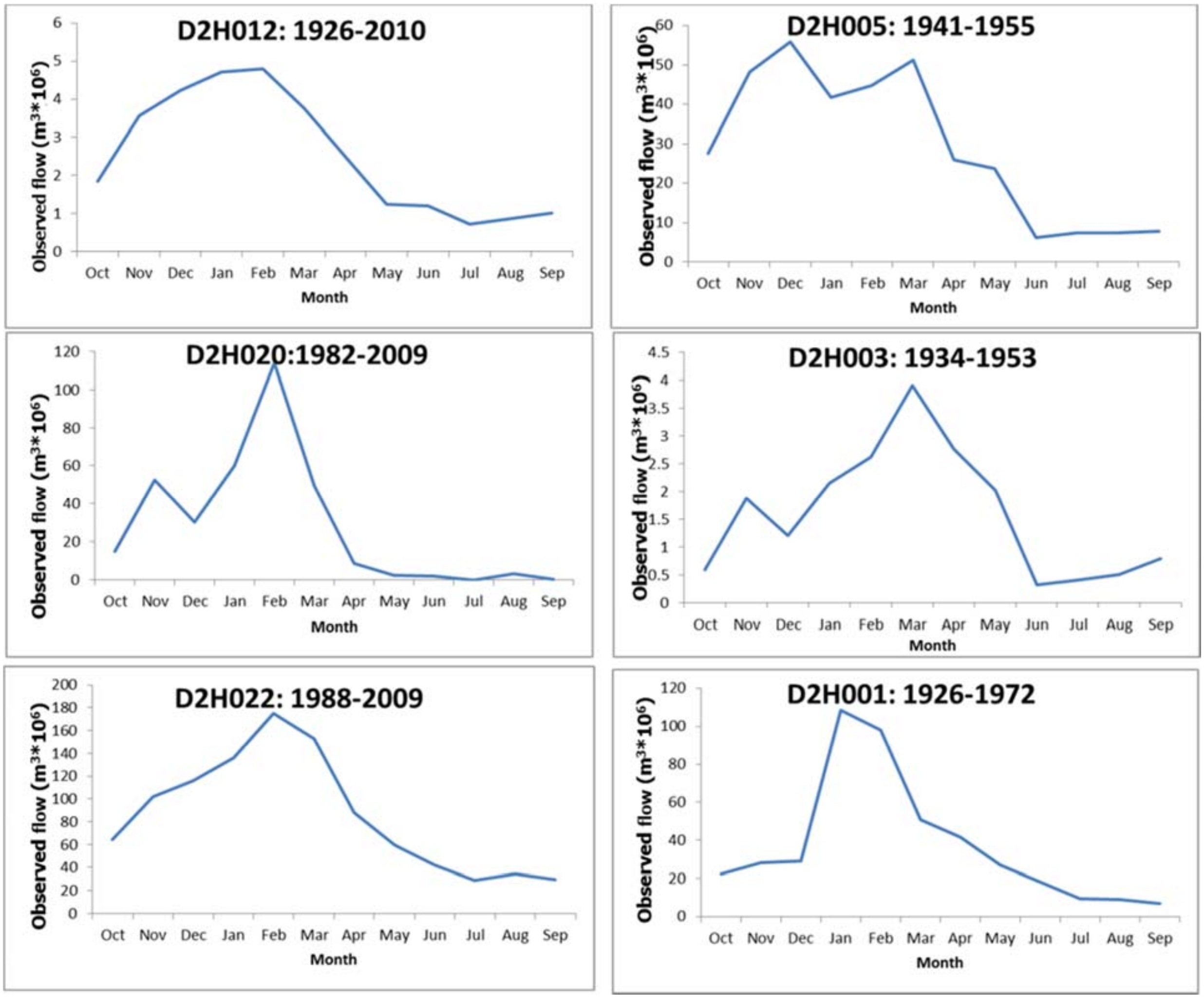
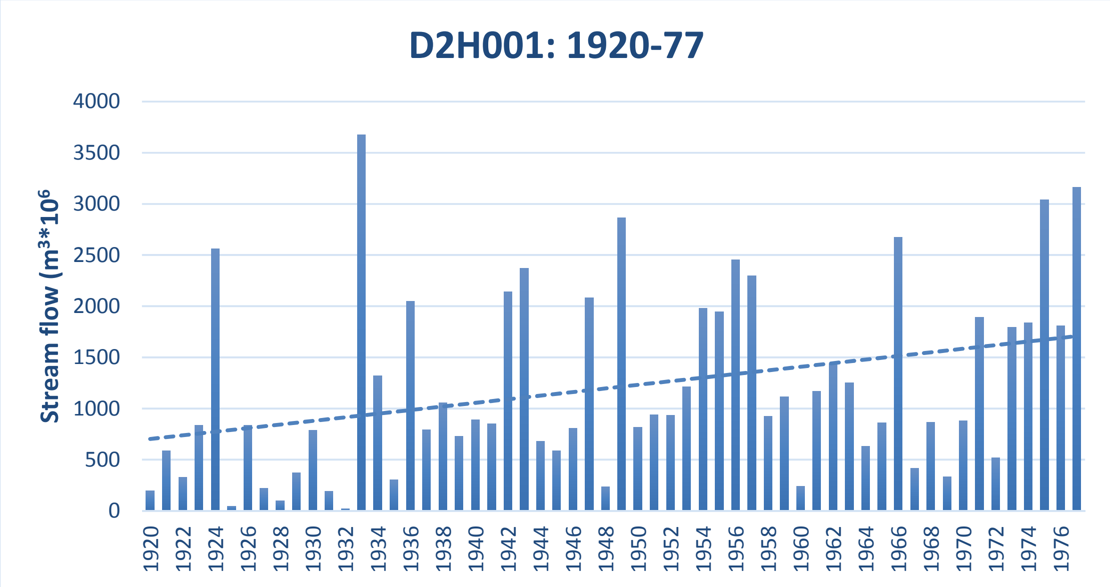



Figure 4.6 Observed monthly average stream flow from the gauging stations in the Caledon River Basin.



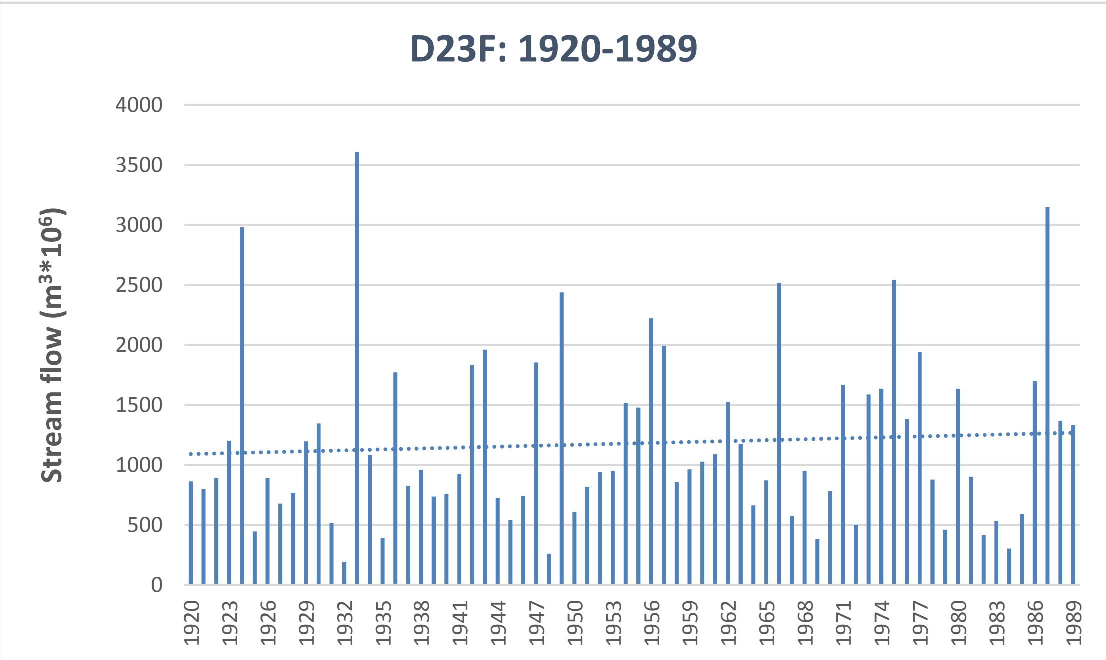




Figure 4.7 The temporal stream flow variations of the observed (gauge D2H001) and the simulated at the outlet of the D23F quaternary catchment.

### 4.5.2 Spatial Variations

There is high spatial variation in terms of normalised runoff across the length of the basin. According to the water resources study reports (Midgley *et al.*, 1994; Middleton and Bailey, 2008), the mean annual runoff ranges from above 500 mm in the headwater mountainous region to as low as below 50 mm in the downstream catchments. The majority (19) of the quaternary catchments of the Caledon River Basin produce annual average runoff between 50 and 100 mm. These sub-basins are located in the middle and the northern parts of the basin. Sub-basins in the western part contribute the least amount of runoff (20–50 mm) to the total basin discharge, which is reported by the Department of Water Affairs (DWAF, 2004) to be about 1 240 million $m^3$ per annum (81 mm).

## 4.6 GEOLOGY

Most of the western and northern parts of the Caledon River Basin lie within the Stormberg geological group of the Karoo super-group. In this area the Stormberg group of rocks consists of three geological formations namely, the Molteno, Elliot and Clarens (Figure 4.8). The three formations are basically sandstones which were formed through a variety of processes of cementation and lithification of sand grains. The Molteno formation sandstones are light-coloured, with fine to very coarse sand grains. This formation can be up to 100 m thick (Eriksson, 1984). The red coloured, argillaceous sandstones of the Elliot formation vary in thickness from about 30 m in some areas to more than 150 m in others (Eriksson, 1985). The Clarens formation of the Stormberg is dominated by light-coloured, fine sandstones with a combination of sand siltstones and mudstones (Smith *et al*., 1993; Holzförster, 2007). The Clarens formation can be 115-195 m thick.

In the north-eastern parts of the basin, geology is mainly composed of fresh basalts belonging to the Drakensberg geological group. These are a relatively young group of volcanic rocks, intruded by numerous dolerite dykes which resulted in the fracturing of the main rock body. The Drakensberg volcanic capping the Stormberg sandstones rocks are up to 1 000–1 400 m thick (Haskins and Bell, 1995; Moore and Blenkinsop, 2006).

The geological characteristics of an area play an important role in the hydrological regime of a watershed. The Stormberg geological formations, which mostly underlie the Caledon River Basin, are known to store and transmit appreciable amounts of groundwater (van Tonder and Kirchner, 1990). The southern and western parts of the Caledon basin sit on top of the Karoo sedimentary aquifer as illustrated by Cobbing *et al*. (2008).

The fractured basalts also play an important role in the percolation of rain water, which would otherwise contribute immediately to the stream flow as surface flow. The stored precipitation within the geological domain impacts the amount of baseflow (Bloomfield *et al*., 2009) in Caledon River. Such a geological setting would then affect the water balance and thus, the hydrological regime of the basin.  The role and contribution of groundwater (recharge and discharge) to stream flow has long been recognised (e.g. Hughes, 2004a). Consequently, in recognition of the importance of geology-driven groundwater, interaction of surface and groundwater has also received significant attention (Hughes and Sami, 1994; Kalbus *et al*., 2006; Tweed *et al*., 2009).

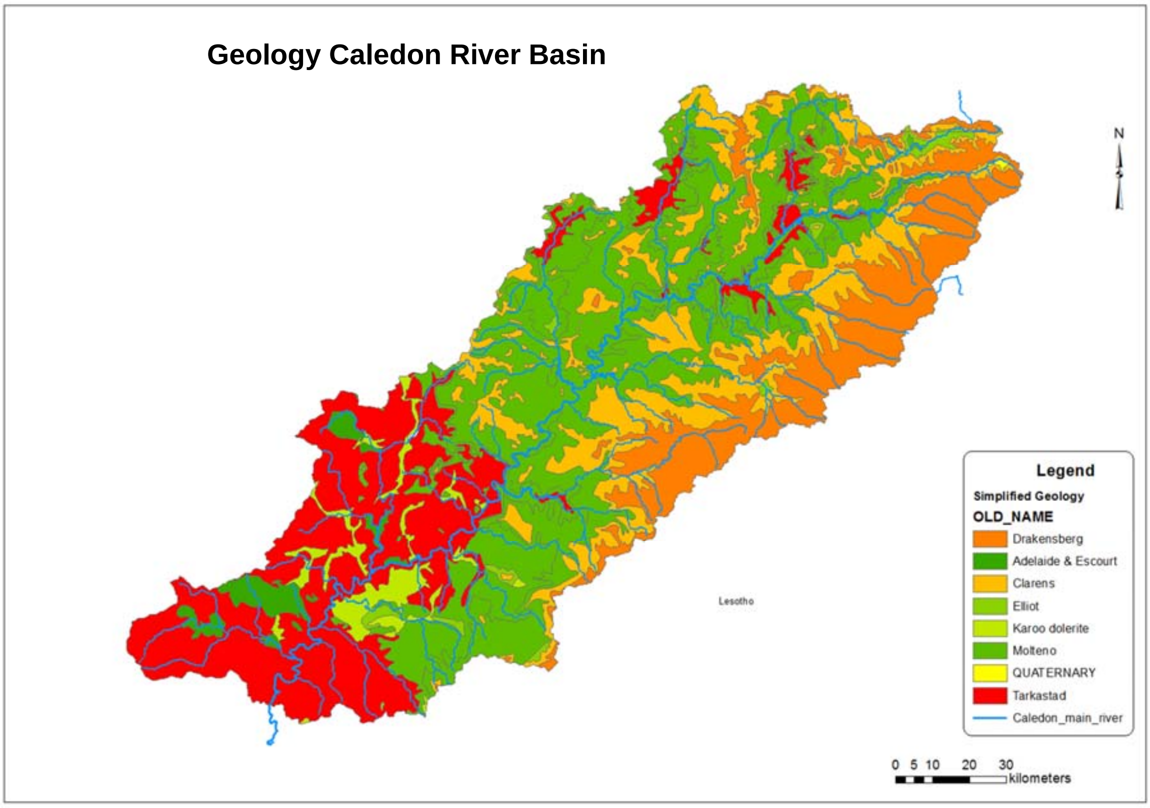



Figure 4.8 Simplified geology of the Caledon River Basin.

**4.7 SOIL COVER**

According to Midgley *et al.,* (1994), there are various types of soils within the catchment. The basin is mostly covered by moderate to deep sandy soils on the steep eastern and northern parts, down to the centre and towards the southern area. The sandy soils reflect weathering of sandstones in the area. There is also a strip of moderate to deep clayey soil material along the eastern border of the basin, stretching south to the downstream boundary of the catchment. These soils are on the steep terrain of the basin and are associated with the basalts of the Drakensburg series. The south-western sub-catchments with undulating terrain are characterised by clayey loam soils originating from the mudstones and the siltstones present in this part of the basin.

The South African Agricultural Geo-referenced Information System (AGIS, 2007) database describes various land types based on soil cover for the basin and the country as a whole.

According to the database, the basin is covered by various soils of different properties defined in terms of depth, top soil and sub-soil clay content, texture and depth limiting material for each soil series. Information on soil properties of basins can be used to quantify the runoff generation parameters of the Pitman model (Kapangaziwiri, 2010). Kapangaziwiri (2010) however, noticed that this information is too detailed and highly variable in many sub-basins, making it quite difficult to assimilate into a modelling exercise especially for a large basin like the Caledon.

## 4.8 WATER USES

### 4.8.1 Domestic water use

The water resources of the Caledon River Basin are locally important to sustain water supplies for many small and medium sized towns in South Africa and Lesotho. The Caledon River is used for various water uses including irrigation, and municipal and industrial use in two local municipalities namely, Dihlabeng and Mantsopa. According to the South African census of 2011, Dihlabeng municipality (six towns) has a total population of 128 704 people, while Mantsopa (5 five towns) has 51 056 people (Statistics South Africa, 2013).

The Lesotho capital, Maseru, relies on direct river abstraction (40 000 $m^3 d^{-1}$) from the Caledon River when the flow is high enough (i.e. > 2 $m^3s^{-1}$) and on storage in off-channel reservoir (Maqalika) at other times. The reservoir is used when the river flow is low or when the river water is too turbid. The abstraction is meant to meet the capital’s water demand, mainly for wet garment industries and the population of about 432 000 people. There are also other smaller towns such as Teyateyaneng, with 250 000 people (Bureau of Statistics Lesotho, 2006) which rely on the Caledon River for water. According to the water utility in Lesotho, Water and Sewage Company (WASCO, 2013) the minimum water allocation target set by the Lesotho government is 30 litres per capita per day; however, some social classes use up to 80 litres per person per day or more. There are also very small and scattered rural settlements located in the highlands of Lesotho. There are no developed water distribution facilities or reticulation systems in most of these villages and the water they use is mainly from natural springs and boreholes. The water is used primarily for domestic purposes.

The Caledon water resources are important even beyond the catchment. There is an inter-basin transfer scheme abstracting water from the Knellpoort and Welbedacht dams to Magaung municipality which comprises the cities of Bloemfontein, Thaba-Nchu, Botshabelo and others, and is located in the Modder River Basin in the north-western part of the Free State province and to the west of the Caledon River Basin. The Caledon-Modder scheme transfers about 5.6 *

$10^6$ $m^3$ per annum, mainly for municipal purposes and supplies more than 747 430 people with potable water (discussed further in section 4.9 below).

#### 4.8.2 Reservoir Infrastructure

There are seven major artificial reservoirs constructed within the boundaries of the Caledon River Basin on both sides of the international border (Table 4.3). The reservoirs have diverse storage capacities, ranging between 4 and 130 * $10^6$ $m^3$. While the majority of these reservoirs are located across tributaries (Leeu, Rietspruit and Phuthiatsana Rivers) of the main Caledon River channel, only Welbedacht and Maqalika dams receive water from the main channel as instream and off-channel reservoirs, respectively. Amongst the reservoirs in the basin, the Knellpoort dam presents a unique case, being both an instream and off-channel reservoir in that it simultaneously intercepts flow of the Rietspruit River and receives pumped water from the Caledon River. The main aim of these impoundments is to secure a more stable and reliable water supply for nearby urban centres and for industrial and irrigation purposes. Table 4.3 provides a brief summary of the reservoirs located within the catchment.

Table 4.3 List of large dams in the Caledon basin

| **Reservoir** | **River** | **Storage Capacity ($10^6$ $m^3$)** | **Quaternary** |
|---|---|---|---|
| Newbury[1] | Leeu | 5.6 | D23C |
| Armenia[1] | Leeu | 13.0 | D23C |
| Knellpoort[1] | Rietspruit | 130.0 | D23H |
| Welbedacht[1] | Caledon | 9.6 | D23J |
| Maqalika[2] | Caledon | 3.7 | D22H |
| Metolong*[3] | Phuthiatsana | 63.7 | D22J |

*Under construction.

Sources: [1] DWAF (2013); [2]Letsie (2005); [3]Metolong Authority (2013).

There are also many small and moderate sized farm dams (Figure 4.9) in the basin which have a direct impact on the total runoff of the river. Midgley *et al*. (1994) list a total of 53 impoundments with a combined storage capacity of approximately 202 * $10^6$ $m^3$, compared with the river's estimated mean annual runoff of 1 244 * $10^6$ $m^3$. There is no doubt that small and large impoundments offer some sort of socio-economic benefit, but they impact significantly on the hydrological regime of the watershed which might complicate studying and understanding the contemporary and future hydrological characteristics of the Caledon River.

The impacts of small farm dams on the hydrological regimes have been reported by many researchers including Schreider *et al*. (2002), Hughes and Mantel (2010), and Nathan *et al*. (2005). Similarly, hydrological changes of rivers brought about by large dams, such as those in the Caledon basin, have been investigated (Maingi and Marsh, 2002; Magilligan and Nislow, 2005; Graf, 2006).

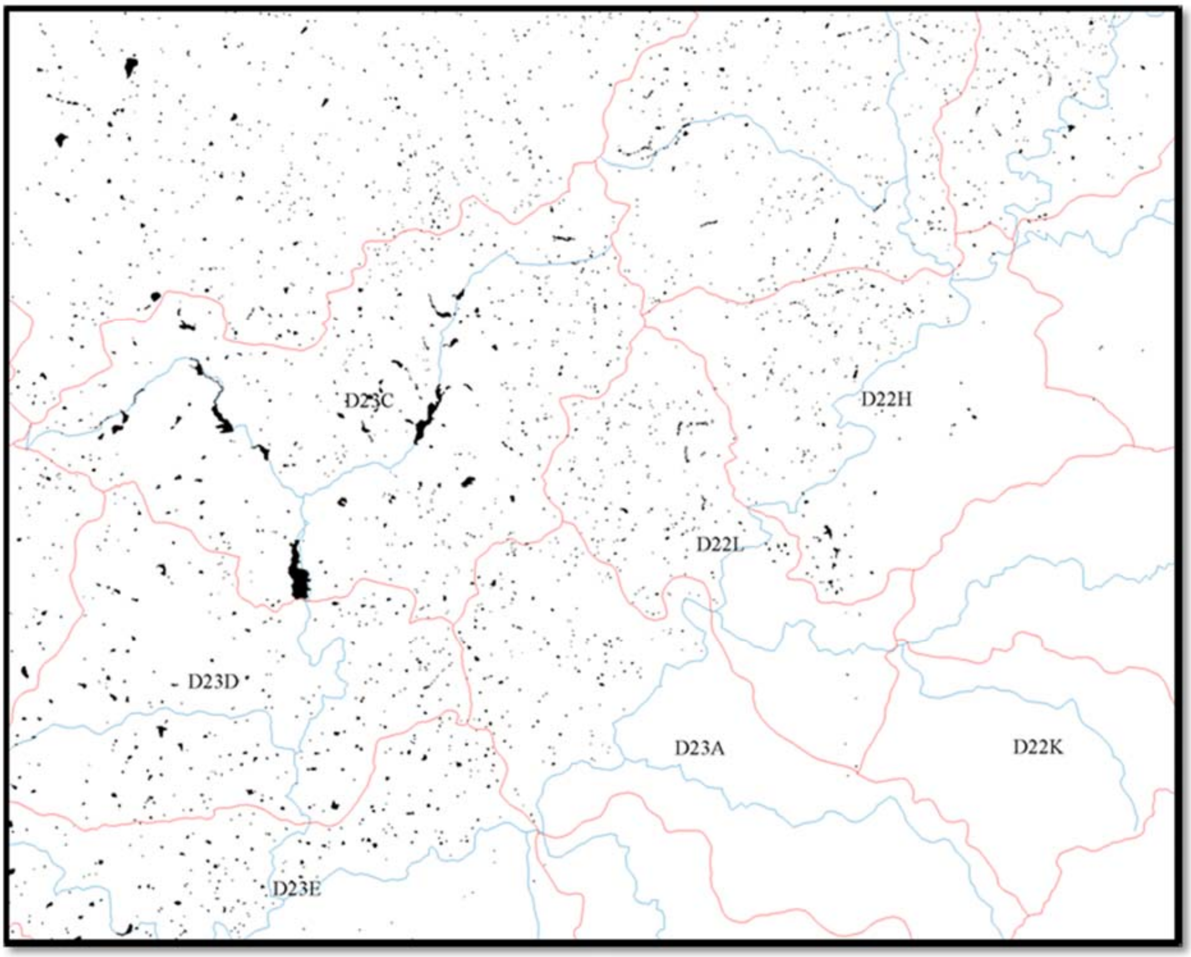



Figure 4.9 Distribution of farm dams and other impoundments, both represented by black shaded areas, in parts of the Caledon River Basin. Quaternary catchments and river network are shown by red and blue lines, respectively.

### 4.8.3 Water Development Projects

There are two major water development projects designed to supply the Bloemfontein area through an inter-basin transfer scheme, and an additional scheme that supplies the Lesotho capital of Maseru. The other water developments projects are much smaller and designed to supply either local municipalities with domestic water or irrigation schemes. These include many privately owned farm dams.

#### 4.8.3.1 Caledon-Modder River Government Water Scheme

The Caledon-Modder River Government Water Scheme (CMRGWS) was commissioned in 1974 to transfer potable water from the Caledon to the Modder River through a 115 km long pipeline in order to meet the water demand of Bloemfontein and neighbouring urban areas. To achieve this, the 32-metre high Welbedacht dam was constructed with an original storage capacity of approximately 115 * $10^6$ $m^3$. Severe siltation in the Caledon reduced the dam's capacity to about 16 * $10^6$ $m^3$ some 20 years after completion (DWAF, 2012). The transfer pipeline has a discharge capacity of about 1.16 $m^3\ s^{-1}$. Because of the high sediment content, the water was first treated at a purification plant, located downstream of the dam, before being transferred. The plant has average and maximum capacities of 1.68 $m^3\ s^{-1}$ and 1.85 $m^3\ s^{-1}$, respectively.

#### 4.8.3.2 Novo Transfer Scheme

As silting reduced the storage capacity of the Welbedacht Dam from 115 million $m^3$ to about 10% of that, the water demand of Bloemfontein and other towns could no longer be satisfied. The Novo transfer scheme was therefore inaugurated in 1988 and was expected to deliver water with the maximum capacity of 150 million $m^3$ by the year 2030. The scheme comprises the construction of the Knellpoort Dam on the Riet River (tributary to the Caledon), with a maximum storage capacity of 137 million $m^3$.

The 50 m high dam was completed in 1988. The dam also receives water from the Caledon River, as off-channel storage, through a pumping facility at Tienfontein. Water from the Caledon is delivered through a 2 km long canal to the Knellpoort Dam from the Tienfontein pumping station which is equipped with four pumps with a combined maximum pumping capacity of about 3.7 $m^3\ s^{-1}$. The transfer channel was designed to trap and minimise siltation of the Knellpoort Dam to avoid a similar situation to that of the Welbedacht Dam. From the Knellpoort Dam, water is then pumped into the Modder River. Figure 4.10 gives a schematic view of the Novo transfer scheme. Slabbert (2007) investigated the potential impacts that the Novo water transfer scheme might impose on the integrity of the both the Caledon and the Modder Rivers.

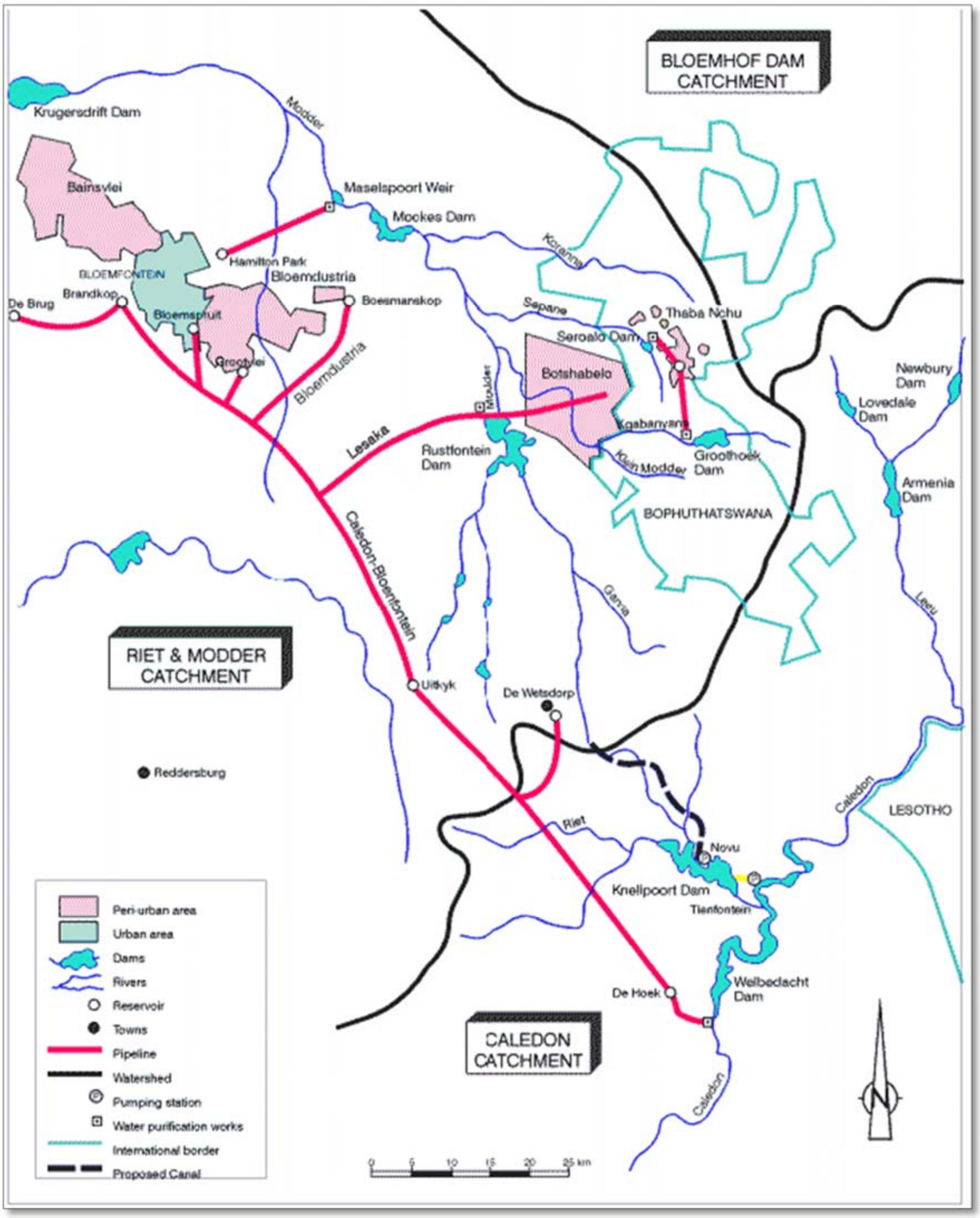



Figure 4.10 The Novo water transfer scheme (Source: DWAF, 2012).

### 4.8.3.3 Maqalika Reservoir

The Maqalika reservoir is located on the outskirts of the Lesotho capital, Maseru, and collects the runoff of the Mejametalana stream which drains a 44 km$^2$ catchment. The sole purpose of the dam was to supply the rapidly developing city with a stable potable water supply. With a 25 m high zoned clay core embankment, the reservoir initially had a maximum storage capacity of 3.7 million $m^3$ which is however, dwindling because of the high rate of sedimentation (Letsie, 2005). Maseru was previously supplied by water pumped directly from the Caledon River to the nearby water treatment facility. However, during dry seasons, the flow can be very low, thus failing to meet the city's water demand. The construction of the Maqalika reservoir was aimed at stabilising the supply. The reservoir was constructed in 1983 as a temporary measure to ease the ever-increasing water demand of Maseru, and was intended to be operational till 1995, while more sustainable alternatives were being sought. The reservoir is still being used at the moment. During high flows in the Caledon River, water is pumped into the reservoir, which is located less than 100 m away (Figure 4.11). Caledon water inevitably adds more sediment to the already silted reservoir resulting in a decreased capacity.


Figure 4.11 Arial view of the location of the Maqalika Reservoir and the Caledon River.

## 4.9 LAND USES

The Caledon River Basin on the South African side is sparsely populated, with an average of 21 persons $km^{-2}$ and relatively small areas are urbanised. The available land is used for agricultural purposes in the form of stock farming (mainly beef, dairy cattle and sheep), as well as for growing cash crops (mainly maize, sorghum and wheat) (Figure 4.12A). The agriculture is predominantly rain-fed but there are also irrigation activities abstracting water either from the farm dams or directly from the streams. However, it is not always straightforward to identify which areas are regularly irrigated and it is possible that some areas are irrigated opportunistically when water is available.

By contrast, the Lesotho side of the basin is one of the most densely populated zones of the country (Figure 4.12B). This is where most major urban areas, including the capital of the country are situated. Subsistence agriculture is sporadic and maize is the major crop, mostly dependent on rainfall (Figure 4.12C). There is, however, minor run-of-river irrigation in the northern parts of the basin. Cattle, sheep and goat rearing are a common practice among the local population and largely uncontrolled, leading to massive over-grazing and subsequent soil erosion. Deep gully erosion is evident in most parts of the basin (Figure 4.12D). This has been associated with poor land use practices, geology and slope gradient, among other factors (Seitlheko, 2003; van Zijl *et al.,* 2013). Stromquist *et al.* (1985) contend that gully erosion is the most important source of the sediments in the Caledon River.

## 4.10 SUMMARY

The Caledon River Basin is located in a generally dry and cool region. The basin has quite a diverse physiography, with the northern parts largely marked by steep slopes of the Drakensberg Mountains, while the central and southern regions are gentle and flat. The basin experiences high rainfall variability. The northern regions are mostly wetter relative to the southern and western parts. Hydrology and water resources availability in the basin is influenced by several factors including soil cover, topography, geology and water uses. For successful hydrological assessment and predictions, it is important that the physical characteristics of the Caledon Basin and the water-related anthropological activities are well understood. This chapter highlighted important features of the basin which are useful in developing a comprehensive hydrological model of the basin.

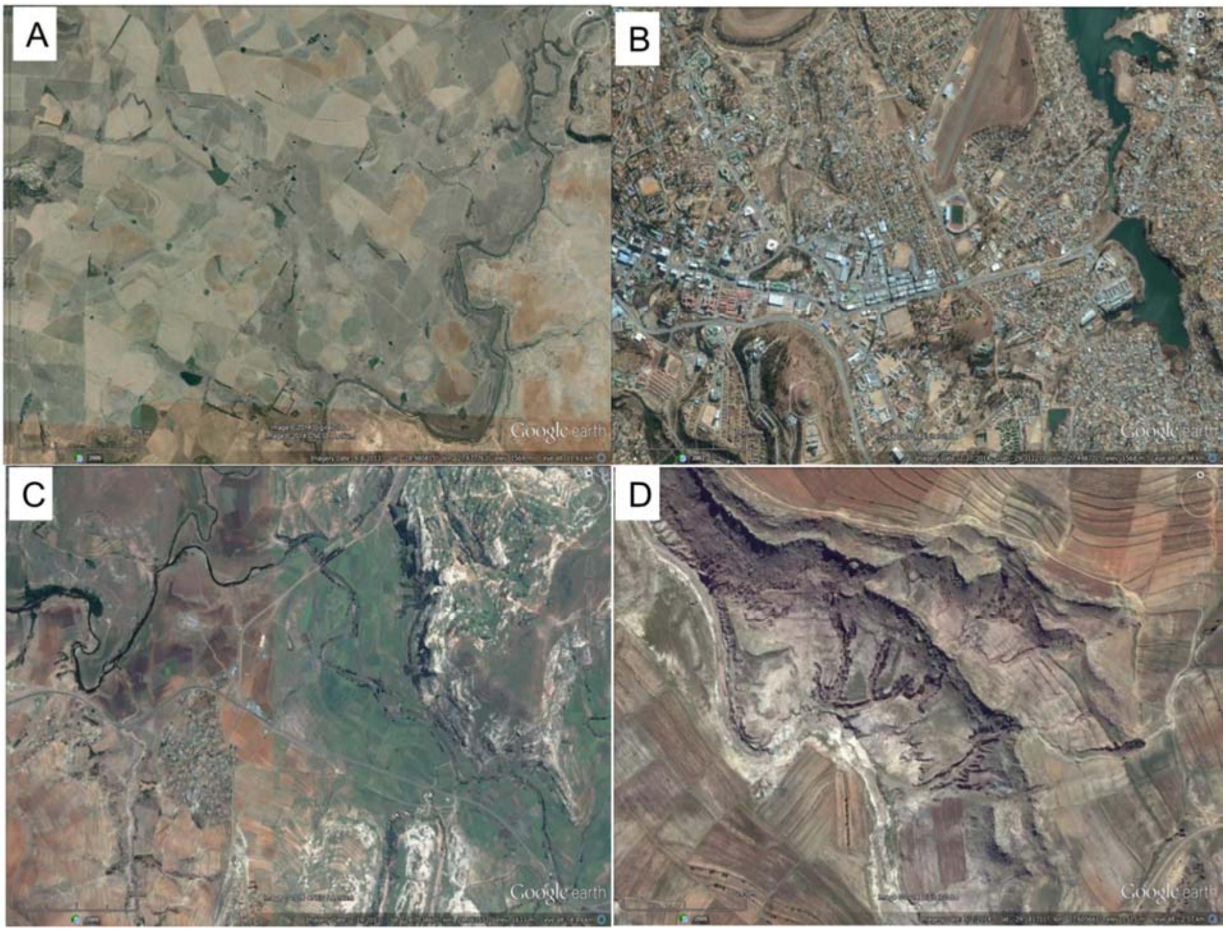


Figure 4.12 Land use types in the Caledon River Basin. A is an irrigated commercial farming area located in D23C; densely populated area in D22H; C shows a mainly rain-fed agriculture with possible small-scale run-of-river abstractions in D21A; D (in Sub-basin D22F) depicts the extent of soil erosion typical in most parts of the central and southern parts of the basin.

# 5 HYDROLOGICAL SIMULATIONS OF THE CALEDON RIVER BASIN

## 5.1 INTRODUCTION

Any hydrological model is a simplification and interpretation of highly complex river basin systems and hence no model is expected to generate simulations without some degree of uncertainty. The Pitman model has been successfully applied for hydrological research and practical purposes within South Africa and elsewhere in southern Africa and confidence has been gained in its ability to successfully simulate hydrological systems. However, despite the popularity of the model, the level of uncertainty of these simulations has rarely been quantified. On the other hand, the WEAP model has not been sufficiently applied and tested for hydrological assessment under the environmental conditions of southern Africa (Levite *et al*., 2003). The current study therefore focusses on applying the Pitman model within an uncertainty framework and investigates the application of the WEAP model in the South African context using the Pitman model setups as a point of reference for assessment.

The main differences between the models are the level of detail included within the structures and the number of hydrological processes that are explicitly included. Both are conceptual models, but the Pitman model includes more processes, while the WEAP model has somewhat more parsimonious parameter requirements. The other main difference is that there is a great deal more documented experience of the use of the Pitman model within the region. One of the sub-objectives of this study was to determine if quantitative links between the parameters of the two models could be identified in an attempt to develop guidelines for transferring parameters from existing Pitman model setups to new WEAP model setups and then take advantage of the water use functionality of the WEAP model. Another objective was to outline the differences between the two models as well as the likely impacts of the differences on the simulation results of the Caledon River.

In this chapter, the two models are used to quantify and characterize the hydrology (both natural and with existing anthropogenic modifications) of the Caledon River Basin. The Pitman model parameters were estimated using the uncertainty framework discussed in Chapter 3, whereas the WEAP model was established using more traditional manual calibration approaches, using the limited observed stream flow data and the Pitman model outputs to quantify the WEAP model parameters and assess the outputs. Hydrological simulations using the two models were carried out under natural conditions and present day conditions for the historical period (1920 to 2005). Chapter 6 reports on the results of the climate change assessments which used the two calibrated hydrological models together with climate projections data for the mid-21st century (2046-2065) (rainfall and temperature) downscaled from nine general circulation models (GCMs).

Some of the objectives of this study, namely the quantification and reduction of hydrological model output uncertainties contribute to the international trends in hydrological science reflected by the themes of the two science decades of the International Association of Hydrological Sciences (IAHS). The PUB (Predictions in Ungauged Basins) decade ended in 2012 and had a very large component of uncertainty analysis (Hrachowitz, *et al.,* 2013; Blöschl *et al.,* 2013) and addressed some aspects of uncertainty in practice (Pomeroy *et al.,* 2013). The new science decade was launched in 2013 with the theme of 'Everything Flows (Panta Rhei)' and is designed to address change in hydrology and society (Montanari *et al.*, 2013), but also emphasises the value of putting science into practice. Inevitably it retains some of the uncertainty issues that came out of the PUB programme.

From a practical perspective, it is important to establish realistic uncertainty ranges. A low range of uncertainty may imply false confidence, while unrealistically high uncertainty may preclude the use of the outputs in making decisions about future developments of water resources. Therefore, the main purpose in dealing with the quantification of realistic uncertainty bounds is how uncertainty can be reduced to the extent that it can be included as part of practical water resources assessments.

## 5.2 QUANTIFYING UNCERTAINTIES IN HYDROLOGICAL SIMULATIONS

### 5.2.1 Strategies for Reducing Uncertainty in the Parameter Ensembles

The two-step approach for including and constraining uncertainty in the modelling of large basins with many sub-basins that was explained in Chapter 3, has been applied in this study. The first step involves the use of regional or local constraints to identify the parameter sets that can be considered behavioural in the simulation of natural (un-impacted) incremental flows for each sub-basin. These parameter sets are then used with uncertain water use parameters sampled independently in the second step when the cumulative flows at the outlet of all sub-basins are simulated. One of the advantages of the approach is that where there are high confidence gauged data, the constraints can be set with very narrow uncertainty bounds, while in ungauged areas these bounds are expected to be much wider. The approach therefore allows for different levels of uncertainty to be included in basins where the hydrological response in some areas is well understood and known, but where other areas have much higher uncertainty. The approach was largely designed to allow realistic uncertainty bounds to be established throughout a large river basin.

### 5.2.2 Constraining Natural Flow Simulations

The Caledon River represents a complex example of uncertainty analysis for several reasons. The first reason is that there is a great deal of distributed water use, such as irrigation from farm dams and directly from the river, coupled with some municipal supplies within the catchment. These water-use activities impact on the interpretation of the observed stream flow data. The observed flow data are also very limited and there are no gauges to represent, for instance, the steep mountain sub-catchments that drain the Lesotho parts of the basin. A further level of complexity is associated with the differential effects of upstream sub-basin uncertainty on the uncertainty outputs of the downstream sub-basins. The first step of the constraint analysis, is only applied to simulating the incremental flows of individual sub-basins without including inflows from upstream areas and therefore avoids any problems associated with cascading uncertainty from upstream simulations.

There are not enough observed stream flow data to establish individual constraints for all of the sub-basins and therefore one of the important issues is the grouping of the 31 quaternary catchments of the Caledon River Basin into groups that are assumed to have similar hydrological responses, constraints and directions of uncertainty. Table 5.1 lists the quaternary catchments, their groupings and some of the characteristics that have been used to determine the groupings and guide the quantification of the constraints. Table 5.2 lists the stream flow gauging stations that are available within the Caledon River Basin and nearby catchments, some of which were used to develop the regional constraints. Table 5.2 also includes some notes about the quality of the stations and data, as well as some indications of the extent to which the available data can be used to represent natural flows. It is clear that there really are not enough reliable observed data to quantify the constraints without a relatively high level of uncertainty.

Table 5.1 Uncertainty groups for the Caledon River Basin and the characteristics used to group them.

| Groups | Quaternary catchment | Mean annual rainfall (mm) | Characteristics |
|---|---|---|---|
| 1 | D21A, B, C, D, J, K, L | 839 – 1021 | Steep eastern headwaters in the Lesotho Maluti mountains. Possibly some stock grazing. |
| 2 | D21E, F, G, H<br>D22A, B, C, D | 682 – 782 | Undulating topography in the northern headwaters with some steep areas. Intensive agriculture in the valley bottoms. |
| 3 | D22G<br>D23C, D, H | 519 – 688 | Dry south western tributaries with undulating to flatter topography and intensively cultivated. |
| 4 | D22E, F, J, K<br>D23B, F, G | 705 – 817 | Undulating topography with some steep headwater areas. Extensively cultivated in South Africa and dense rural populations with over-grazing in Lesotho. |
| 5 | D22H, L<br>D23A, E, J | 541 - 730 | Lower basin valley bottom areas with generally flatter topography and intensively cultivated. |

It was decided to use uniform distributions to represent the parameter uncertainty, thus avoiding the need for any assumptions about mean values, the shapes of the distributions (normal or log-normal) and the extent of any outliers. Table 5.3 lists the minimum and maximum values of the constraints that were used (excluding the % zero flow constraint). The groundwater recharge data were obtained from DWAF (2005) and the range of uncertainty was based on the two lowest recharge estimates of the three that are available in the GRAII (DWAF, 2005) database for the quaternary catchments falling into each group. The choice of the lowest two estimates was based on previous experience of using the GRAII database (Kapangaziwiri *et al.,* 2012). The recharge constraints given in Table 5.3 are expressed as percentages of mean annual rainfall, which are then dimensionalised for use with individual quaternary catchments by the mean monthly rainfalls of the time series used in the simulations (WR2005 data). Similarly, the mean monthly flow constraint is expressed in mm and dimensionalised using the catchment areas of the sub-basins (quaternary catchments).

Table 5.2 Stream flow gauging stations available for use in developing the regional constraints (see Figure 4.5 for the station locations).

| Gauge No. | Catchment area ($km^2$) | Records | Groups | Details |
|---|---|---|---|---|
| D2H012 | 518 | 1968-2011 | 1 & 2 | High flows poorly quantified; some farm dams and land-use change effects. |
| D2H005 | 3 857 | 1941-1956 | 1 & 2 | High flows moderately well quantified; many farm dams, abstractions and land-use impacts; some domestic return flows. |
| D2H020 | 8 399 | 1982-2010 | 1, 2 & 4 | High flows moderately well quantified; large and poorly quantified impacts of Maseru city abstractions plus all upstream impacts. |
| D2H003 | 1 424 | 1934-1954 | 3 | High flows well quantified; some agricultural abstractions but assumed to be relatively small (note that the period of record is before the construction of a large dam). |
| D2H022 | 12 852 | 1988-2010 | All | Stable river section and subject to many uncertainties. |
| D2H001 | 13 421 | 1926-1978 | All | High flows very badly quantified in early parts of record; many accumulated upstream abstraction impacts. |
| D2H034 | 1 082 | 1992-2012 | 2 | Recent gauge with records since 1999. Highly impacted catchment with many farms dams and irrigation. |
| D1H006 | 2 969 | 1949-2013 | 1 | Makhaleng River in Lesotho. |
| D1H032 | 1 074 | 1986-2013 | 1 | Senqunyane River – 16 years of records available prior to Mohale Dam construction. |

Table 5.3 Constraints developed for the quaternary catchment groups of the Caledon River Basin.

| Group | **Mean monthly flow (mm)** | | **Mean monthly recharge (% mean monthly rainfall)** | | **Flow duration curve constraints (values are fractions of mean monthly flow)** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | **Q10** | | **Q50** | | **Q90** | |
| | Min. | Max. | Min. | Max. | Min. | Max. | Min. | Max. | Min. | Max. |
| 1 | 10.0 | 17.0 | 3.5 | 8.0 | 2.5 | 3.0 | 0.35 | 0.55 | 0.04 | 0.08 |
| 2 | 2.5 | 7.0 | 2.5 | 3.7 | 3.0 | 4.0 | 0.15 | 0.30 | 0.02 | 0.05 |
| 3 | 1.2 | 3.2 | 0.8 | 2.5 | 2.0 | 2.5 | 0.15 | 0.25 | 0.02 | 0.05 |
| 4 | 6.0 | 10.0 | 1.2 | 7.2 | 2.5 | 3.0 | 0.35 | 0.55 | 0.04 | 0.08 |
| 5 | 1.2 | 3.2 | 1.2 | 4.2 | 2.0 | 2.5 | 0.15 | 0.25 | 0.02 | 0.05 |

Note: The % time of zero flow constraint were set at the range 0 – 8 % for the 5 groups of sub-basins.

Analyses of the data from the flow gauges within the basin and in the nearby catchments were used for quantifying the mean monthly flow and flow duration curve constraints (including the duration of zero flows). These were also supported, to a certain extent, by examining the existing simulations available from the WR90 (Midgley *et al.*, 1994) and WR2005 studies (Middleton and Bailey, 2008). Gauge D2H012 has a relatively long record, but is affected to some extent by poor high flow measurements and abstraction impacts on low to moderate flows. It also covers two of the quaternary groups, being at the outlet of D21E (group 2), which includes D21D (group1). The observed (after some corrections to account for missing high flow observations) mean monthly flow depth of 5.4 mm is expected to be an under-estimate but more representative than the simulated data reported in both WR90 (9.3 mm) and WR2005 (5.9 mm). The under-estimation is expected to effect the low flow Q90 estimates the most.

D2H005 and D2H020, both on the main Caledon River, have a number of problems with uncertainties in the accuracy of the gauged flows and are heavily impacted by intense water uses within the upstream parts of the basin. They were therefore not considered useful for developing constraints. While D2H001 appears to have a relatively good record (after some adjustments to high flows based on data from a nearby flood section), it represents the accumulation of flows from most of the quaternary catchments and therefore cannot be used for constraints. Nevertheless, it is useful to compare these records with the total uncertainty outputs from D23F which is close to the basin outlet. However, it must be remembered that this gauging record reflects many upstream water uses that have varied over time.

Gauge D2H003 represents group 3, the driest parts of the catchment, and has a record that pre-dates any of the large dams constructed in the upstream quaternary catchments. However, it is assumed that some distributed agricultural water use occurred even before 1934 and therefore the observed data are expected to under-estimate flows, particularly low to moderate flows. The mean monthly observed flows of 1.6 mm are substantially lower than the values given in either WR90 (3.8 mm) or WR2005 (3.1 mm) and it is difficult to justify an almost doubling in mean volume on the basis of the likely agricultural water use in the 1940s and 1950s.

Gauge D2H034 (representing group 2) is heavily impacted by distributed agricultural water use and therefore the 2.9 mm mean monthly flow will definitely be an under-estimate. WR90 and WR2005 suggest that the values should be in the region of 4.6 to 6.0 mm $month^{-1}$.

Gauges D1H006 and D1H032 drain the eastern slopes of the Lesotho Mountains and have very large mean monthly runoff values of 16.8 mm and 29.6 mm, respectively. Both of these catchments have more consistently steep and mountainous terrain than the Group 1 Caledon catchments and even more so for the Group 4 catchments. WR90 and WR2005 suggest mean monthly flows of between 13 mm and 22 mm for the quaternary catchments that are gauged by D1H006 and D1H032, respectively. Developing constraints for Groups 1 and 4 is therefore problematic.

The flow duration curve (FDC) constraints were based on the same gauges (with the same problems of interpretation) and all the constraint values are given in Table 5.3 (as unit runoff values or non-dimensional values relative to mean monthly flow). Given the lack of reliable and representative observed data, it is inevitable that most of the constraint boundaries are subjective. However, attempts have been made to ensure that they are at least realistic. Group 5 is made up of catchments in the lower parts of the catchment through which the main Caledon River flows and has been allocated runoff and FDC constraints that are the same as Group 3, but with a wider range of recharge.

### 5.2.3 Caledon River Basin Hydrology Under Natural Conditions

Establishing the initial uncertainty parameter ranges and then ‘calibrating’ the ranges to ensure compatibility with the outputs constraints discussed in the previous section firstly involved some trial runs of the single-run version of the model (i.e. no uncertainty ensembles) to approximately establish the likely range of parameter values that would generate some outputs that are consistent with the constraints. This was followed by running Step 1 of the main uncertainty model that only simulates incremental flows and tries to find (and save back to the database)

2 000 behavioural parameter sets (out of 50 000 total model runs) that generate outputs that are within the constraint ranges given in Table 5.3.

This process started with some sub-basins from each group and then progressed until all sub-basins were successfully simulated, where success mean that 2 000 parameter sets were saved. An analysis utility (incorporated into SPATSIM, and illustrated in Figure 3.3) was used to revise the parameter ranges for individual sub-basins when the total of 50 000 model runs were completed without reaching 2 000 so-called 'behavioural' parameter set solutions. Typically, this process involves identifying which parameters have values at one end of the input range within the saved behavioural parameter sets and adjusting the input range, such that a repeat of the model run will identify saved sets that are more evenly distributed within the input range. This 'calibration' process can also involve adjusting the input parameter ranges even when 2 000 sets are saved, particularly if the output values of the constraints associated with the 2 000 saved sets are not reasonably distributed within the input ranges of the constraints given in Table 5.3.

Table 5.4 provides a range of values for a list of parameters resulting from the two-step uncertainty analysis of the Pitman model. Ranges are the minimum and maximum values yielding behavioural flow ensembles for uncertain parameters. Single values are assigned to those parameters which are considered not to be uncertain.

Step 2 of the uncertainty model involves running the complete model (i.e. routing upstream incremental flows through downstream sub-basins and generating total cumulative flow at all sub-basin outlets). However, the natural stream flow simulations are almost impossible to evaluate because almost none of the available observed stream flow data can be considered representative of natural conditions. It was therefore considered more appropriate to include the development impacts before undertaking comparisons with observed data and evaluating the model performance.

### 5.2.4 Caledon River Basin Hydrology Under Developed Conditions

There are a number of water use activities impacting on the flow volumes and patterns of the Caledon River, the most notable of which are direct abstractions for irrigation and municipal use, construction of farm dams and irrigation from farm dams, and storage by large reservoirs. It is essential that such activities are quantified and incorporated in the modelling exercise.

Table 5.4 Final input parameter ranges (minimum: maximum) for the 5 catchment groups.

| Parameter | Group 1 | Group 2 | Group 3 | Group 4 | Group 5 |
|---|---|---|---|---|---|
| RDF | 1.280 | 1.280 | 1.280 | 1.280 | 1.280 |
| PI1 | 1.50 | 1.50 | 1.50 | 1.50 | 1.50 |
| PI2 | 4.0 | 4.0 | 4.0 | 4.0 | 4.0 |
| ZMIN | 10:150 | 10: 150 | 10:150 | 10:150 | 10:150 |
| ZAVE | 250 | 300 | 300 | 300 | 400 |
| ZMAX | 200:2000 | 200:2000 | 200:2000 | 200:2000 | 200:2000 |
| ST | 60:300 | 60:300 | 60:300 | 60:300 | 80:300 |
| POW | 1.5:5.0 | 1.5:5.0 | 1.5:5.0 | 1.5:5.0 | 1.5:5.0 |
| FT | 2:20 | 2:20 | 0:10 | 1.0:20 | 0:10 |
| GPOW | 4.0:6.0 | 4.0:6.0 | 4.0:6.0 | 4.0:6.0 | 4.0:6.0 |
| GW | 0:100 | 0:100 | 0:100 | 0:100 | 0:100 |
| R | 0.3:0.7 | 0.3:0.7 | 0.3:0.7 | 0.3:0.7 | 0.3:0.7 |
| TL | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 |
| D Density | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
| T | 5:50 | 5:50 | 5:50 | 5:80 | 5:50 |
| S | 0.004 | 0.001 | 0.001 | 0.001 | 0.004 |
| GW Slope | 0.011 | 0.011 | 0.011 | 0.011 | 0.010 |
| RSF | 0.2:2.0 | 0.2:2.0 | 0.2:2.0 | 0.2:2.0 | 0.2:2.0 |

#### 5.2.4.1 Abstractions for Irrigation

The irrigation areas were initially based on an assumption that the annual yield of the farm dams would be the same as their maximum stored volume. However, a large part of the irrigation is assumed to be supplied from direct abstractions from the river and these areas were based on an analysis of Google Earth imagery through the identification of parcels of land that appeared to be under irrigation (distinguishable by green patches of land) and were within reach of major river channels (either the main Caledon channel or major tributaries).

Additional information provided from WRP Consulting (pers. comm, 2013) suggests that the original estimates of irrigation areas could be considerably under-estimated. The WRP study was largely based on the registration of existing water uses and rights that formed part of the transformation of national water management in the post-Apartheid era, and also included some attempts to validate the estimates of the individual landowners who had registered water rights. The extent to which this is likely to impact on downstream flows largely depends on whether the WRP estimates are realistic, and whether the estimates of farm dam volumes or river flows (in the case of run-of-river direct abstractions) can support such expanded irrigation areas. This also depends, to a certain extent, on the seasonal distributions of water use. If the majority of the seasonal water use for irrigation is during the dry winter months, then it will largely have to be met from storage with minimal inflows. However, if part of the requirement is within months of higher flow, then wet season storage will be used and more upstream inflows will be intercepted by the farm dams, causing reduced downstream flows.

It is evident, however, that the WRP estimates are extremely high in many areas (Table 5.5). In revising the water use estimates, a more detailed assessment of Google Earth images was employed together with a comparison between the original estimates and the WRP estimates. The overall conclusion was that a large degree of uncertainty remains in any of the estimates as it is not always possible to distinguish between dry land farming and irrigated agriculture. It is also not always possible to determine whether the irrigation abstractions are derived from small dam storage or from direct channel abstractions.

The detailed examination of Google Earth suggests that many of the areas included in the data obtained from WRP are not permanently irrigated. The evidence for this is partly based on the visual signal of the fields (dry conditions) and partly on the lack of a clearly available water source in the vicinity, either from a perennial river or from farm dams. It is possible that some ‘dry’ fields are irrigated at times of the year other than those covered by the Google images; however, the second source of evidence (no water source) is much more difficult to account for. The final minimum and maximum irrigated areas have been approximately quantified to represent the overall uncertainty in expected irrigation water use.

The crops are dominated by pasture/lucerne (25%), maize (25%), maize/wheat (18%) and wheat (13%) (WRP, pers. comm, 2013). It is possible that many of the summer grain crops are in fact not irrigated most of the time. The seasonal distribution of irrigation requirements that was used in the present-day uncertainty analysis was therefore a weighted distribution dominated by lucerne and wheat (based on WR90 data; Midgley *et al.*, 1994) and is given in Table 5.6. It is, however, accepted that the validity of this distribution is substantially uncertain.

#### 5.2.4.2 Farm Dams

The volume of the farm dams was estimated using a GIS coverage (which includes data on surface area at full capacity) which was used together with regional estimates of the relationship between surface area and volume (using an approach similar to that of Hughes and Mantel, 2010). However, these estimates are largely uncertain as there are no field measurements to support the establishment of the relationships. Volume estimates for farm dams in each of the sub-basins are included in Table 5.5. A normal uncertainty distribution has been assumed for the farm dam volumes and it is specified by the mean and standard deviation (subjectively assumed to be approximately 10% of the mean).

The Pitman model includes a function that allows a proportion of each incremental runoff sub-basin to contribute to the storage in these dams, while the remainder of the simulated runoff is unaffected by that specific type of development impact. The portion of the sub-basin contributing to storage was estimated using GIS information including a sub-basin polygon layer (used in the Pitman model), the farm dam polygons, river network line layer and a contour layer. The approach also uses details on the density of farm dams and their position within the sub-basins.

The WEAP model does not include such a function and the farm dams have to be dealt with using the normal on-channel reservoir function. Therefore, in practice, this means that all of the catchment nodes need to be divided up into two – those that contribute to reservoir inflow and those that do not. To achieve this without doubling the catchment nodes, pairs of quaternary catchments in the Pitman model setup have been combined. One of these is used to represent the part of the combined catchment area that is assumed to contribute to the total farm dam storage, while the other is assumed to be downstream. Any direct run-of-river abstractions for irrigation or other uses are assumed to be from the downstream catchment and therefore will be impacted by the effects of the farm dams. This is thought to be the most realistic way in which these development effects can be incorporated into the WEAP model. The WEAP model has been set up using similar water demand (farm dams and abstractions) data that were used in a present day uncertainty run of the Pitman model.

#### 5.2.4.3 Abstraction for Domestic Water Use

There are a number of small to medium sized towns within the Caledon River Basin, both in South Africa and Lesotho which depend on the river for their water supplies. Information on the rural and town populations were not directly available (and would change over time) and therefore all of these estimates for this study are uncertain and quite subjective. Although it is fairly clear that the Lesotho capital of Maseru uses water from both the off-channel storage facility and the river, it is not clear how many of the South African towns (Clarens, Fouriesburg, Ficksburg, Ladybrand, Wepener and others) abstract directly from the channel or rely on local reservoirs. Patterns of abstraction for Maseru are also difficult to determine despite having water consumption data for the city as a whole. This is because there are no data on how much is abstracted from the river, and when, to replenish the off-channel storage.

The volumes of use for towns and the rural areas in the basin are therefore based on rough estimates of population coupled with consumption of water of 100 l $person^{-1}$ $d^{-1}$. Detailed information about the population estimates was not readily available. The mean value estimates of the water use are given in Table 5.5, while the range was based on approximately 50% of the mean (i.e. mean ± mean * 0.25), reflecting the very high uncertainty (but relatively low volumes of water use). The seasonal distribution of use has been slightly biased toward summer, partly to account for influxes of tourists in some of the towns and partly based on an assumption of garden watering during the hot summer months.

#### 5.2.4.4 Large Reservoirs

There are 5 quaternaries where large reservoirs, with storage capacity of at least $1*10^6$ $m^3$ have been added as part of the present day model set up. D22B has a reservoir with 2.6 * $10^6$ $m^3$ storage and 3 * $10^6$ $m^3$ annual water use to account for the Meulspruit dam that possibly supplies Ficksburg, while D23C has a reservoir (Newbury) with 5.6 * $10^6$ $m^3$ storage and 2 * $10^6$ $m^3$ annual water use that is assumed to be used for downstream irrigation.

A relatively small channel storage volume (1 * $10^6$ $m^3$) has been allocated to D22H to allow for the fact that Maseru may pump some water from river pools, even when the river stops flowing. Annual water use has been set to 12 * $10^6$ $m^3$ but this would not be obtainable from the available storage and this value has been used to ensure that the instream pool storage is pumped dry, as evidenced by the number of months with zero flow at gauge D2H022. Reservoir storage has also been added to D23H to represent the Knellpoort Dam with estimated storage capacity of 137 * $10^6$ $m^3$. Some of the large reservoirs in various sub-basins are shown in Figure 5.1 and the information on their storage volumes and water use has been mainly based on Midgley *et al*. (1994).

Table 5.5 Farm dam volumes ($m^3 * 10^6$), percentage area of sub-basin contributing to storage and irrigation areas ($km^2$) estimated by different methods (direct abstractions are in $m^3 * 10^3 y^{-1}$).

| | **Dam Vol.** ($m^3 * 10^6$), | **% Area above dams** | **Direct abstraction** | | | **WRP** | **Google** | **Final** | |
|---|---|---|---|---|---|---|---|---|---|
| | | | **Domestic** | **Irrig.** | **Dams Irrig.** | | | **Min** | **Max** |
| D21A | 391 | 50 | 100.0 | 0.0 | 0.35 | 1.23 | 0.40 | 0.35 | 0.50 |
| D21B | 0 | 0 | 100.0 | 0.0 | 0.00 | 0.00 | 0.10 | 0.00 | 0.00 |
| D21C | 240 | 20 | 100.0 | 0.0 | 0.20 | 0.50 | 0.03 | 0.10 | 0.40 |
| D21D | 630 | 50 | 400.0 | 0.0 | 0.50 | 9.40 | 1.10 | 0.50 | 1.50 |
| D21E | 2660 | 70 | 0.0 | 2.5 | 2.20 | 13.70 | 4.40 | 2.50 | 5.00 |
| D21F | 4440 | 70 | 0.0 | 0.0 | 3.50 | 36.30 | 2.20 | 2.20 | 4.00 |
| D21G | 2200 | 50 | 0.0 | 0.0 | 1.80 | 11.80 | 1.30 | 1.30 | 2.50 |
| D21H | 3130 | 20 | 275.0 | 0.0 | 2.50 | 11.50 | 0.75 | 1.00 | 3.00 |
| D21J | 35 | 5 | 75.0 | 0.0 | 0.03 | 0.00 | 0.00 | 0.00 | 0.10 |
| D21K | 60 | 5 | 80.0 | 0.0 | 0.07 | 0.00 | 0.00 | 0.00 | 0.10 |
| D21L | 1200 | 20 | 100.0 | 0.0 | 1.00 | 0.00 | 0.00 | 1.00 | 2.00 |
| D22A | 10595 | 90 | 0.0 | 0.0 | 8.80 | 29.80 | 3.70 | 5.00 | 10.00 |
| D22B | 8300 | 85 | 0.0 | 0.0 | 6.50 | 33.60 | 1.70 | 5.00 | 10.00 |
| D22C | 4000 | 90 | 120.0 | 0.0 | 3.00 | 5.50 | 0.30 | 1.00 | 4.00 |
| D22D | 12000 | 85 | 90.0 | 8.4 | 12.50 | 53.40 | 14.50 | 10.00 | 20.00 |
| D22E | 0 | 0 | 65.0 | 0.0 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| D22F | 280 | 10 | 225.0 | 0.0 | 0.22 | 0.00 | 0.00 | 0.00 | 0.50 |
| D22G | 21000 | 90 | 0.0 | 0.0 | 15.00 | 57.80 | 3.90 | 5.00 | 20.00 |
| D22H | 7900 | 70 | 14000.0 | 0.0 | 6.00 | 18.30 | 3.10 | 3.50 | 7.00 |
| D22J | 0 | 0 | 110.0 | 0.0 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| D22K | 0 | 0 | 110.0 | 0.0 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| D22L | 6600 | 60 | 5000.0 | 0.0 | 5.50 | 11.30 | 1.10 | 1.50 | 6.00 |
| D23A | 10000 | 80 | 0.0 | 0.0 | 6.00 | 5.60 | 1.40 | 1.50 | 7.50 |
| D23B | 20 | 5 | 65.0 | 0.0 | 0.02 | 0.00 | 0.00 | 0.00 | 0.10 |
| D23C | 41600 | 100 | 0.0 | 0.0 | 30.00 | 48.60 | 25.00 | 25.00 | 40.00 |
| D23D | 22000 | 85 | 0.0 | 0.0 | 19.00 | 39.40 | 28.00 | 19.00 | 32.00 |
| D23E | 14500 | 60 | 1000.0 | 0.0 | 10.00 | 22.70 | 6.20 | 6.00 | 12.00 |
| D23F | 3500 | 100 | 0.0 | 0.0 | 3.20 | 1.70 | 2.30 | 2.00 | 3.50 |
| D23G | 9600 | 70 | 200.0 | 0.0 | 6.00 | 6.10 | 0.50 | 1.00 | 6.00 |
| D23H | 19000 | 85 | 0.0 | 0.0 | 15.00 | 38.30 | 3.90 | 5.00 | 20.00 |
| D23J | 14000 | 85 | 0.0 | 0.0 | 10.00 | 28.20 | 6.20 | 7.00 | 15.00 |

Table 5.6 Seasonal distribution of irrigation requirements (mm) for Lucerne and wheat obtained from WR90

| Oct | Nov | Dec | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 67 | 47 | 56 | 48 | 36 | 28 | 19 | 15 | 18 | 30 | 61 | 92 |

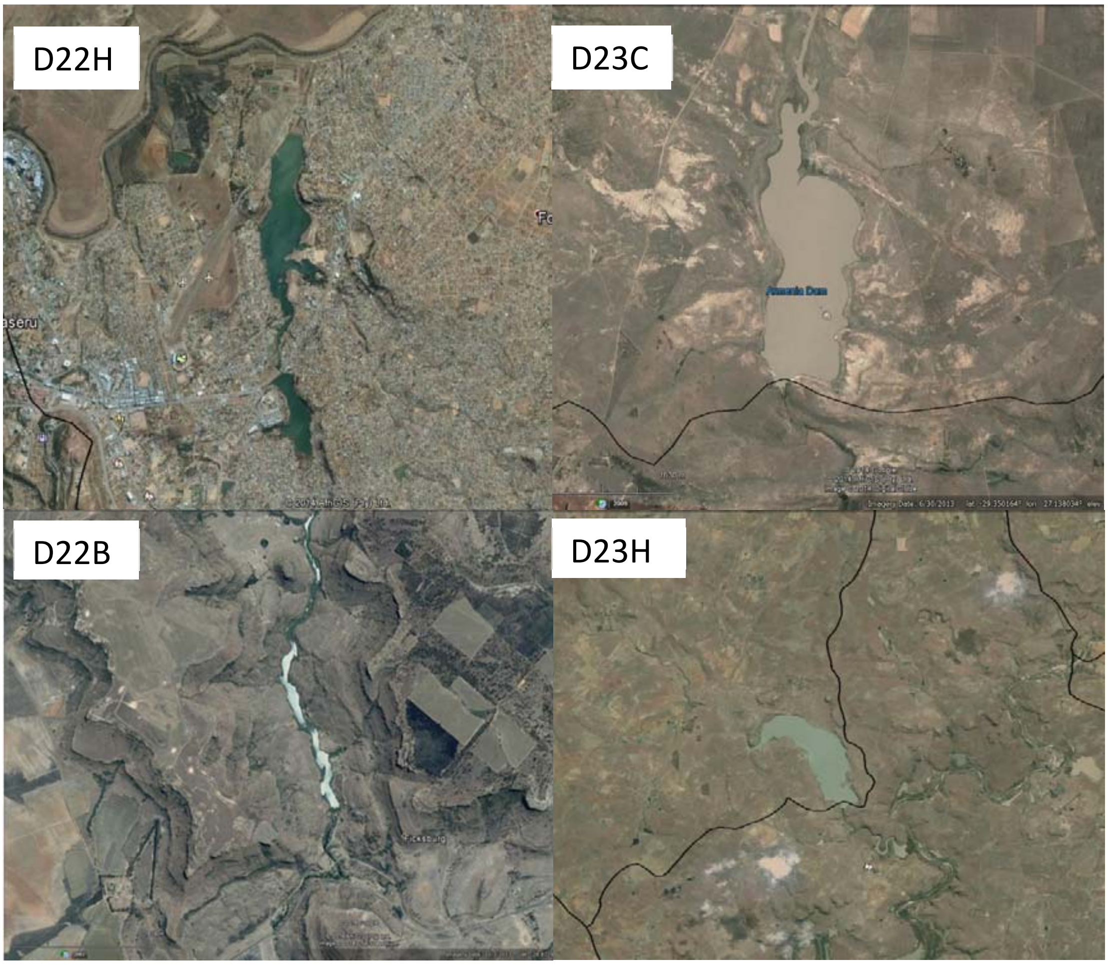



Figure 5.1 Examples of the large reservoirs in the Caledon River Basin.

### 5.2.5 Present Day Flow Simulation Results

#### 5.2.5.1 Present-day results at D21E

Figure 5.2 compares the flow duration curves of the simulated natural and present day flow, with the observed records of gauge D2H012 located at the outlet of D21E, while Table 5.7 compares several quantiles of the flow duration curves of the modelled and the observed. Comparisons of the simulated flow against the observed are based on four objective functions: the Nash-Sutcliffe coefficient of efficiency of the normal and natural logarithm values, NSE and NSE{ln}, and percentage bias of normal and natural logarithm values, %Bias and %Bias{ln}. An index was formulated that identifies the best (based on the overall performance on the four objective functions) of the 10 000 generated flow ensembles. The 'best fit' index ensemble is given by: 100 * (NSE + NSE{ln}) / (abs %Bias + abs %Bias). Figure 5.3 compares the variations of the four objective functions with the best fit index for the full ensemble set. As expected, the high values of the index correlate well with the better values of % bias (normal and natural logarithmic values), as well as with the ensembles of better NSE values.

The very high flows (occurring at less than 10% of the time) are under-represented in the observed data due to poor high-flow gauging. There are some indications that the lower estimates of water use (Table 5.5) are perhaps more appropriate than the higher values, however, the observed data also represent non-stationary abstractions since 1966. Overall, the simulated ensembles bracket the observed flows very well, despite the fact that the objective function values are frequently poor. This outlet represents two of the catchment groups (1 and 2) and therefore it is difficult to make any firm conclusions about the constraints that were used for these groups. The generally high positive bias values are partly a reflection of the poor high flow gauging, while it is also possible that the Q50 and MMQ constraints for the upstream sub-basin are too high.

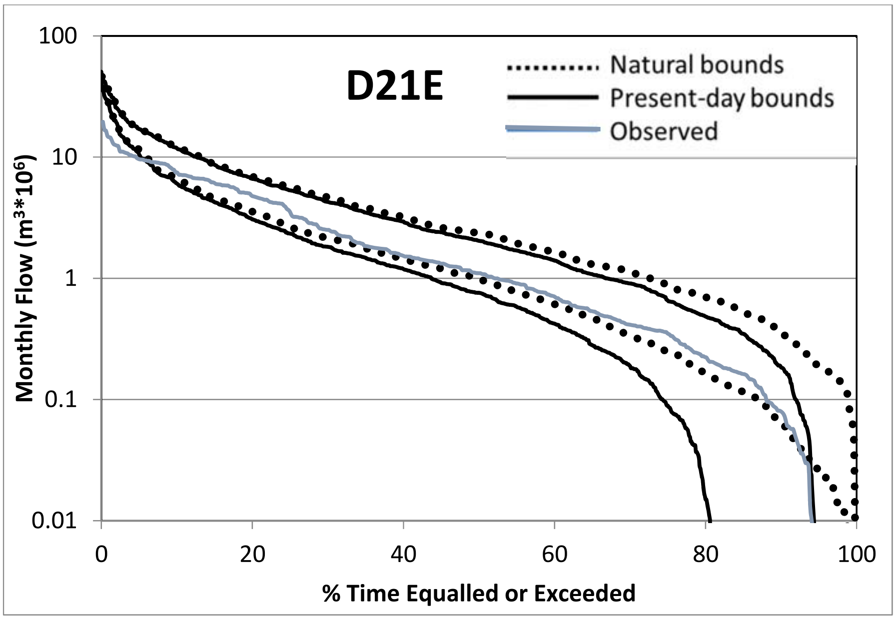



Figure 5.2 Simulations of the natural and present day flows compared to the observed flow.

Table 5.7 Simulation results compared with observed flows for sub-basin D21E and gauge D2H012 (Q- values are in $m^3 * 10^6$ $month^{-1}$, zero flow in percentages).

| | Natural simulation range | P-day simulation range | Observed |
|---|---|---|---|
| Q10 | 6.555 to 12.275 | 6.07 to 11.80 | 7.46 |
| Q50 | 1.002 to 2.363 | 0.76 to 2.04 | 1.10 |
| Q90 | 0.064 to 0.359 | 0.0 to 0.18 | 0.08 |
| Zero flow (%) | 0.3 to 1.5 | 5.95 to19.41 | 5.94 |

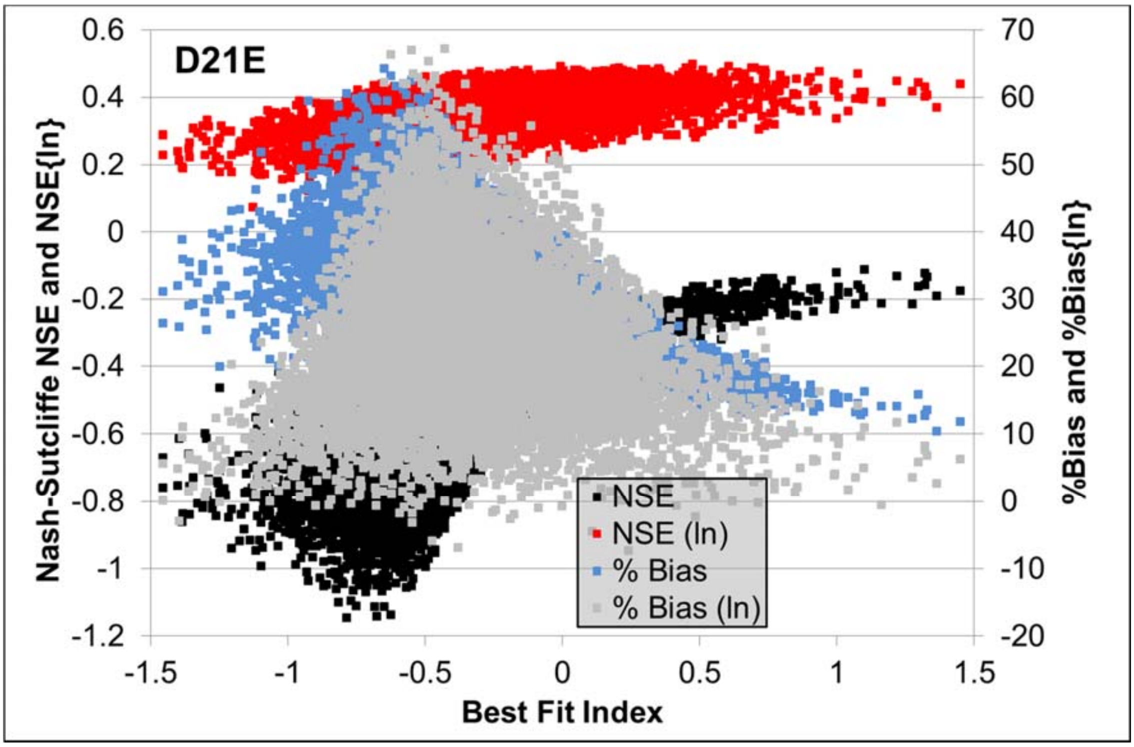



Figure 5.3 The best fit index versus the four objective functions for the 10 000 simulated present day flow ensembles in the sub-basin D21E.

#### 5.2.5.2 Present day results at D22B

Gauge D2H034 was built in 1991, reflecting present day conditions, and observation data obtained from it was used to assess the results for the two quaternary catchments at the outlet of D22B. Both sub-catchments D22A and D22B have a large number of farm dams and apparently a substantial amount of irrigation. Most of the water use has been assumed to be extracted from farm dams, while the percentage catchment area contributing to the dams has been set to 90% and 85% for D22A and D22B respectively. This means that large volumes of water are abstracted as reflected by the quite extended periods of zero flows (Figure 5.4 and Table 5.8). It is possible that some of the irrigation requirements are satisfied by pumping directly from the river. Meulspruit Dam, with a full supply capacity of 2.6 * $10^6$ $m^3$ (Midgley *et al*., 1994), supplying water to Ficksburg has been included in the simulation at the outlet of D22B and has a significant impact on low flows and this is also reflected by the zero flows in the present day simulations as well as the observed flow records. The observed data values for Q10 and Q50 fall within a rather large uncertainty range for the present day flow simulations as show by both Figure 5.4 and Table 5.8.

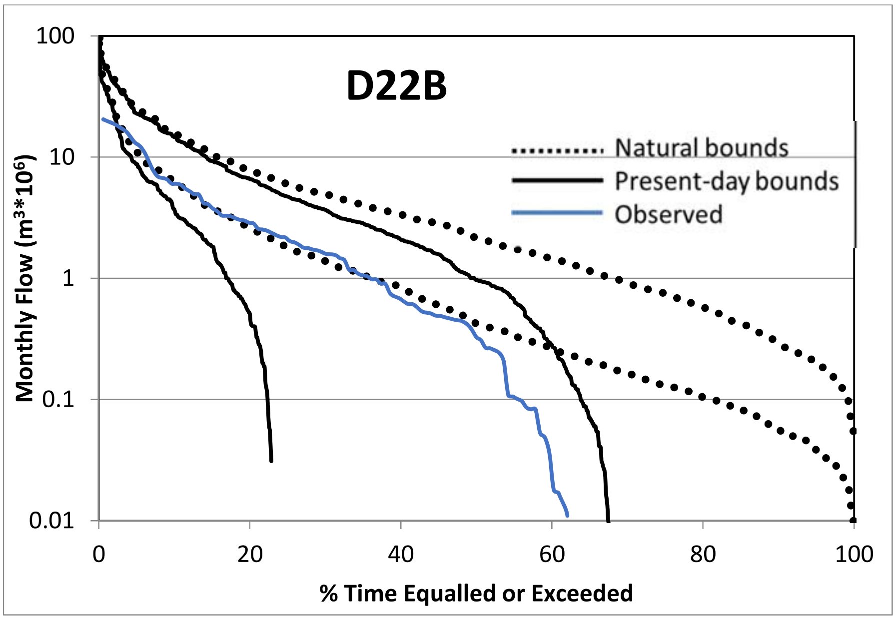



Figure 5.4 Simulations of the natural and present day flows compared to the observed flow.

Table 5.8 Simulation results compared with observed flows for D22B and D2H034 (Q- values are in $m^3 * 10^6$ $month^{-1}$, zero flow in percentages).

| | Natural Simulation range | Present-day Simulation range | Observed |
|---|---|---|---|
| Q10 | 6.137 to 15.715 | 3.71 to 14.6 | 5.9 |
| Q50 | 0.426 to 2.167 | 0.0 to 1.0 | 0.30 |
| Q90 | 0.057 to 0.293 | 0.00 | 0.00 |
| Zero flow(%) | 0 | 32.65 to 77.16 | 38.0 |

As with the other gauges in the Caledon River Basin, the high flows are not well-gauged due to limitations of the rating curve and therefore the high flow simulations are not expected to follow the observed data (Figure 5.4). In other respects, the simulated present day flows bracket the observed, but with a high degree of uncertainty. It is therefore possible that the higher estimates of water use and farm dam volumes are excessive, despite being substantially lower than the WRP estimates (Table 5.5).

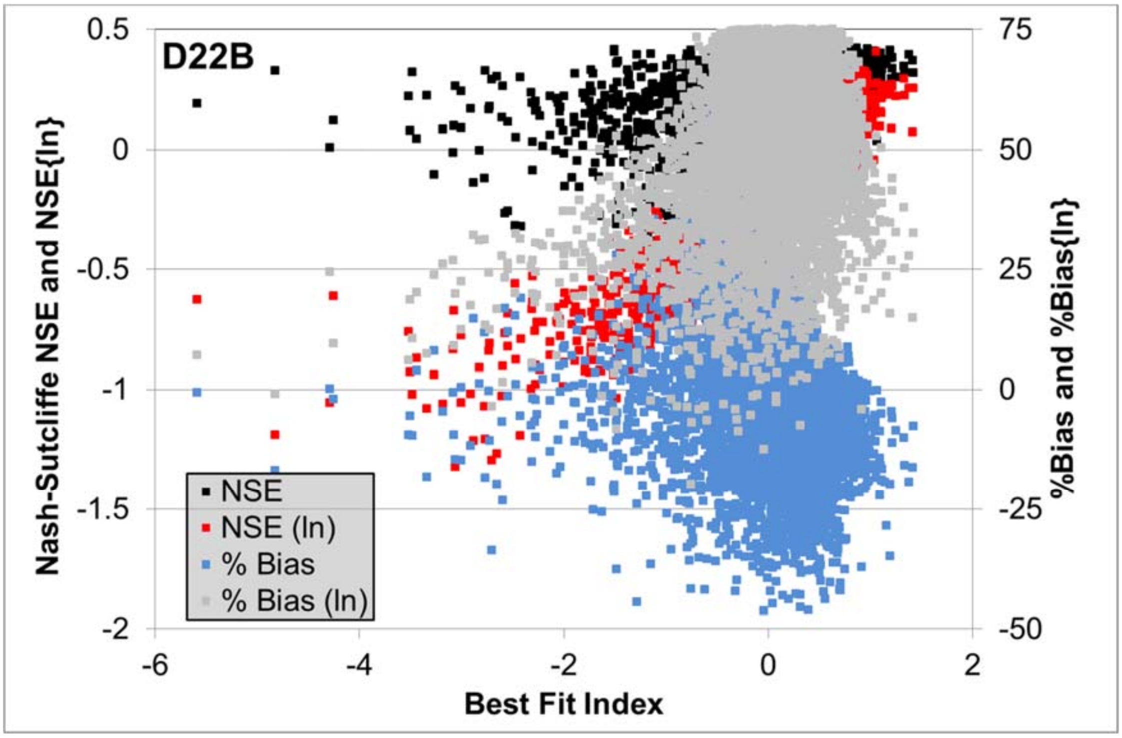



Figure 5.5 The best fit index versus the four objective functions for the 10 000 simulated present day flow ensembles in the sub-basin D22B.

Figure 5.5 indicates that a large number of the ensembles fall within the region of a relatively high 'best fit' index (0 – 2) and a significant number with relatively high NSE values close to 0.5. The figure also shows that there is quite substantial bias (both negative and positive) based on untransformed flows. The NSE{ln} and %Bias{ln} values are more difficult to interpret given the quite large differences in the number of months with zero flows (not used in the calculations based on log transformations) between the observed data and some of the ensembles. Figure 5.5 also suggests that the best ensembles are not clearly identifiable, unlike in the above case of D21E.

#### 5.2.5.3 Present-day and natural results at D23D

The observed record at D2H003 is an old record (1934-1954) and it is not expected to reflect present-day conditions. It also has very poor high flow observations with many periods when the daily flow measurements are truncated at the maximum rating curve value. Figure 5.6 clearly indicates that there are huge differences between the simulation of the medium and low flow and the observed records (Table 5.9). It is most likely that the current water uses in catchments D23C and D23D have substantially increased since the 1950's. As might be expected in this intensively cultivated area, the differences between natural and present day are very large, even for the very high (Q10) flows, indicating substantial water use mainly for irrigation. There are a number of major reservoirs in this part of the Caledon River Basin. These include Newbury Dam (constructed in 1892) with a maximum capacity of 5.587 * $10^6$ $m^3$ and Armenia Dam which was constructed in 1954 with a full supply capacity of 14.2 * $10^6$ $m^3$. There are also other smaller reservoirs with capacities of less than 1 * $10^6$ $m^3$.

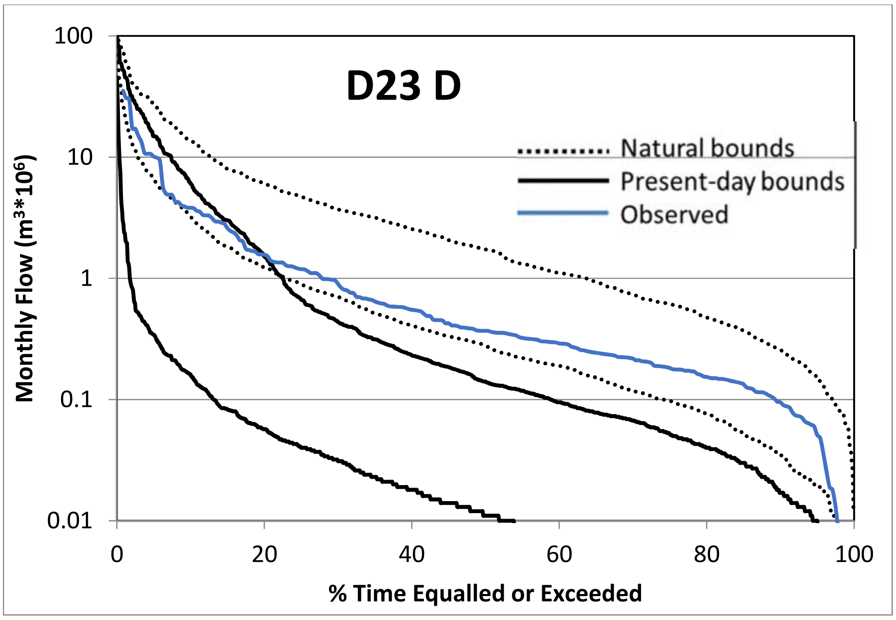



Figure 5.6 Simulations of the natural and present day flows compared to the observed flow.

With respect to comparisons between the simulated and observed data, it is more difficult to be conclusive as the records are from 1935 to 1954 when there would have been some water use but much less than today. It is also unlikely that high flows have been measured with a great deal of accuracy, leading to under-representation of flow volumes at Q10 (as illustrated in Figure 5.6). Most of the observed flow is much higher than the bounds of the present day simulation. This is the only region of the basin with such a severe mismatch and bias between the modelled and the observed records (Table 5.9). As with D21E, there is not enough information to validate the model results adequately, or to reduce the uncertainty any further. However, it is interesting to note that there is much more agreement between the different sources of information about irrigation areas for these catchments than in most of the other parts of the basin.

Table 5.9 Simulation results compared with observed flows for D23D and D2H003 (all values given in $m^3 * 10^6 month^{-1}$).

| | Natural simulation range | Present-day Simulation range | Observed |
|---|---|---|---|
| Q10 | 3.189 to 13.853 | 0.16 to 6.23 | 3.61 |
| Q50 | 0.274 to 1.734 | 0.011 to 0.140 | 0.360 |
| Q90 | 0.035 to 0.258 | 0.001 to 0.017 | 0.088 |
| Zero flow (%) | 0.1 to 2.6 | 5.5 to 47.16 | 2.5 |

It can be seen from Figure 5.7 (based on comparisons between observed and the natural flow simulations) that for D23D, the best fit index is highly insensitive to variations of all the four objective functions. While relatively fewer natural flow ensembles show a slight negative bias, a large number are highly positively biased. It is also evident from Figure 5.7 that there is a quite distinct correlation between the two NSE and the two %bias statistics. The reduced scatter for similar values of the index (horizontal axis) is largely a consequence of using the constrained natural flow simulations. All of the other example sub-basins include the independently uncertain water use that will increase the scatter. However, there are also high NSE values (close to 0.6) that are coupled with relatively lower NSE{ln} values, as well as not very good bias statistics. This implies that some ensembles may simulate some parts of the hydrograph well, but not others. There are rapid changes of both objective functions at low values of the index, which tend to flatten out with increasing values of the index. This is a very positive result in terms of supporting the constraint ranges for natural flows, something that could not be tested at the other gauging sites. A more detailed examination of these results could be used to reduce the range of some of the constraint values. However, it is impossible to determine whether such changes could be considered equally applicable to the other sub-basins within this group.

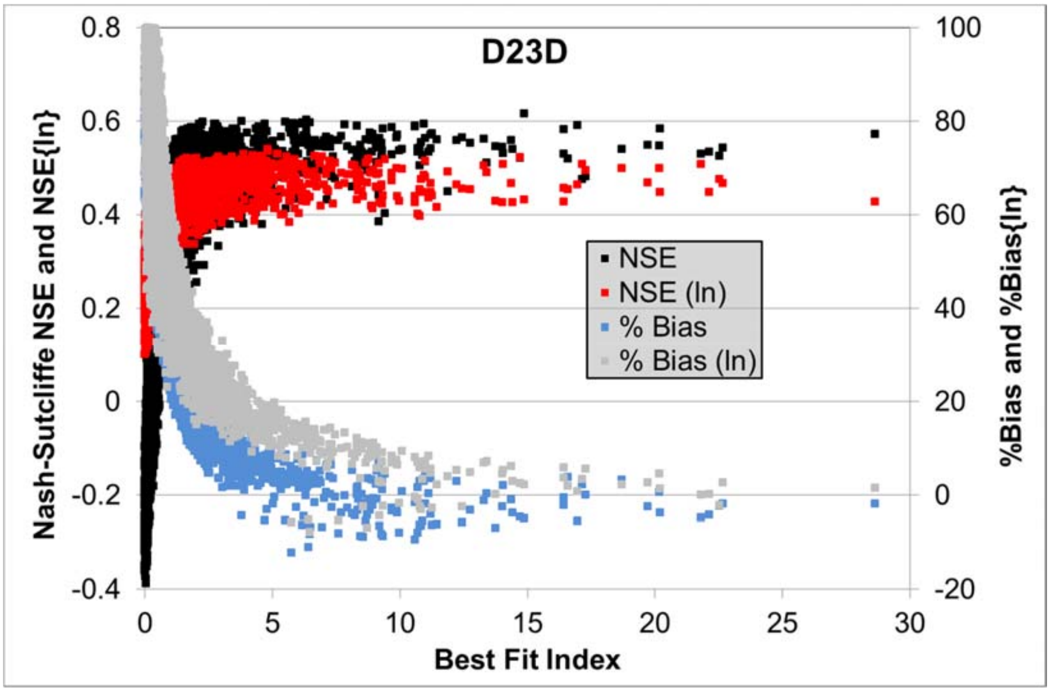



Figure 5.7 The best fit index versus the four objective functions for the 10 000 simulated natural flow ensembles in the sub-basin D23D.

#### 5.2.5.4 Present-day results at D23F

Sub-basin D23F and gauge D2H001 in the downstream part of the basin, and is the nearest gauge to Welbedacht Dam which is the lowest part of the basin covered by this study. It therefore represents the combinations of water use activities and natural runoff uncertainties for almost the entire basin. The gauging record appears to be of reasonably good quality and represents the longest record period of all of the flow gauging stations in the basin. The observed data record used represents data that has been partially patched for high flows using the nearby high flow rated section (gauge D2H020) that was operational from 1983 to 2010. Figure 5.8 illustrates that apart from the lower flows, the correspondence between the lower uncertainty bound and the observed flows is reasonably good. This is also indicated by the comparisons given in Table 5.10.

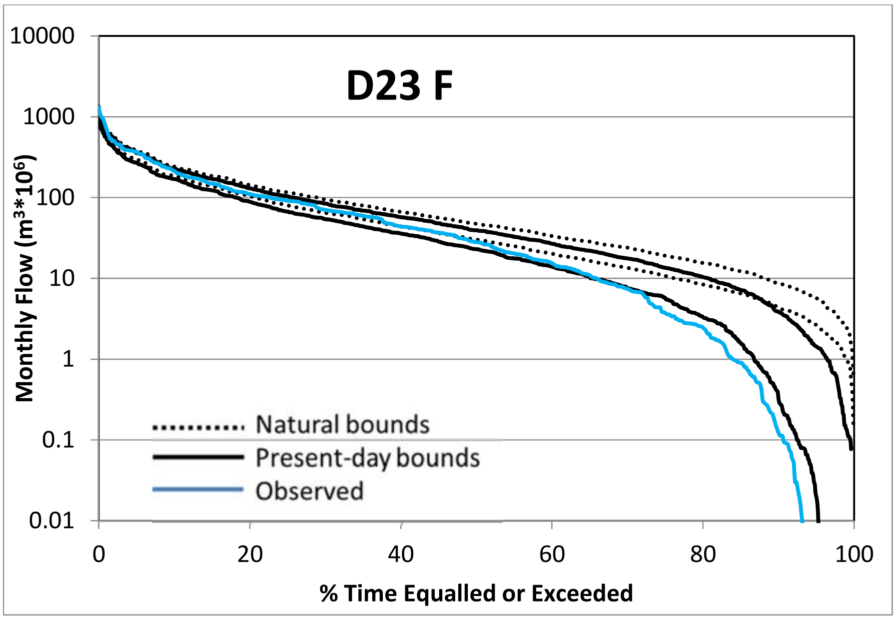



Figure 5.8 Simulations of the natural and present day flows compared to the observed flow.

Table 5.10 Simulation results compared with observed flows for D23F and D2H001 (all values given in $m^3 * 10^6 month^{-1}$).

| | Natural Simulation range | Present-day Simulation range | Observed |
|---|---|---|---|
| Q10 | 188.04 to 241.81 | 169.47 to 226.64 | 221.7 |
| Q50 | 30.20 to 46.99 | 22.97 to 39.30 | 28.12 |
| Q90 | 4.47 to 8.77 | 0.321 to 3.87 | 0.114 |
| Zero flow (%) | 0 | 0 to 3.14 | 6.88 |

Despite the assumed limitations of the observed data in terms of representing present-day conditions it is nevertheless useful to look at the range of objective functions of the full ensemble sets (Figure 5.9). Given the very large uncertainties that have been included as part of the model, the results at this downstream sub-basin are quite good. All the flow ensembles occupy a high range of NSE (normal) values (0.7 to 0.8). The best fit index appears to increase with improving values of %bias. The much lower NSE{ln} values are partly associated with all of the combined uncertainties in water use within the upstream basin (coupled with unknown non-stationarity effects in the observed data series). Unfortunately, it is not possible to separate these uncertainties from those associated with the simulations of natural low flows.

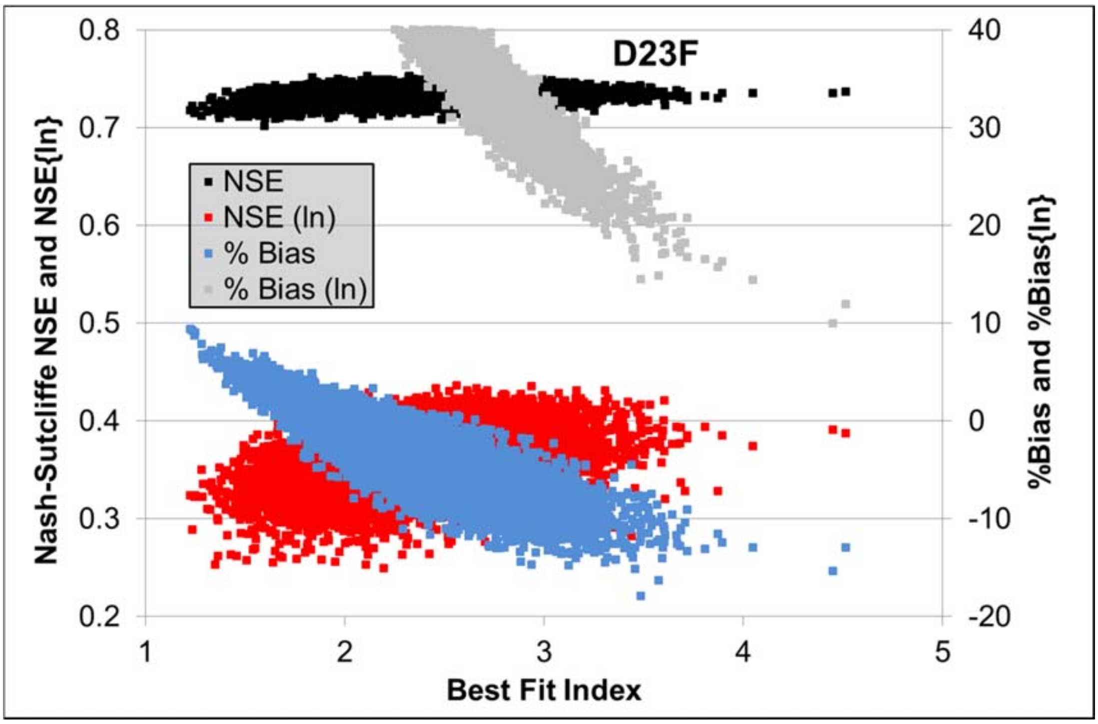



Figure 5.9 The best fit index versus the four objective functions for the 10 000 simulated present day flow ensembles in the sub-basin D23F.

Figures 5.10 to 5.12 illustrate some of the outputs of the model for the Caledon River Basin using frequency distributions of standardized indices of three of the constraints (MMQ, Q10 and Q90). The standardized indices on the horizontal axes are based on the fractional deviations of the simulated values for all of the 10 000 ensembles from the ensemble mean for the natural flow simulations for that sub-basin. The graphs include the simulations of natural conditions as well as present day conditions which are largely based on uncertainty in the volume and abstractions from farm dams. The observed values are also indicated by arrows on the graphs.

The uncertainty bounds shown by mean of flow duration curves show the full range of uncertainty, but not how the uncertainty is distributed throughout the entire set of ensembles. Figures 5.10 to 5.12 provide more details of the frequency distributions of certain key flow indices and compare them to the observed data.

The observed values for the constraints do not always fall within the simulated present day frequency distributions, partly because of the uncertainty in terms of what conditions the observed data represent, as well as other problems with the observed data and, of course, the combined uncertainties in all of the upstream flow simulations.

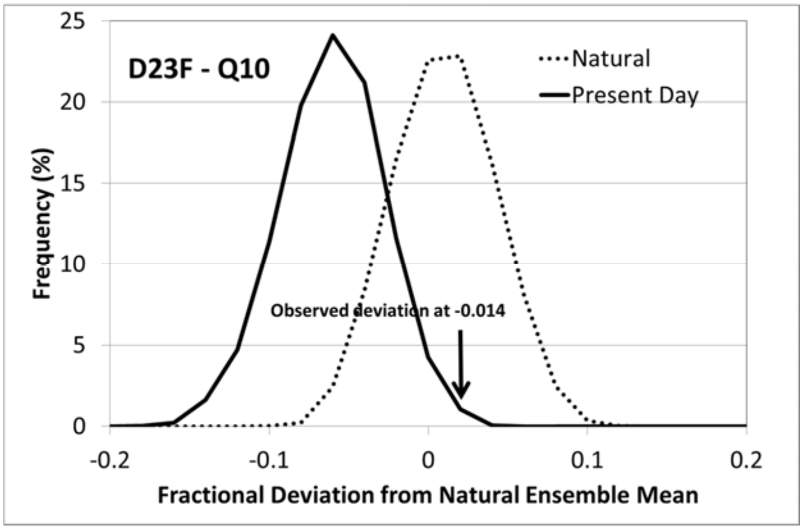



Figure 5.10 Example outputs using standardized flow indices for Q10 (high flows) at a downstream (D23F) sub-basin.

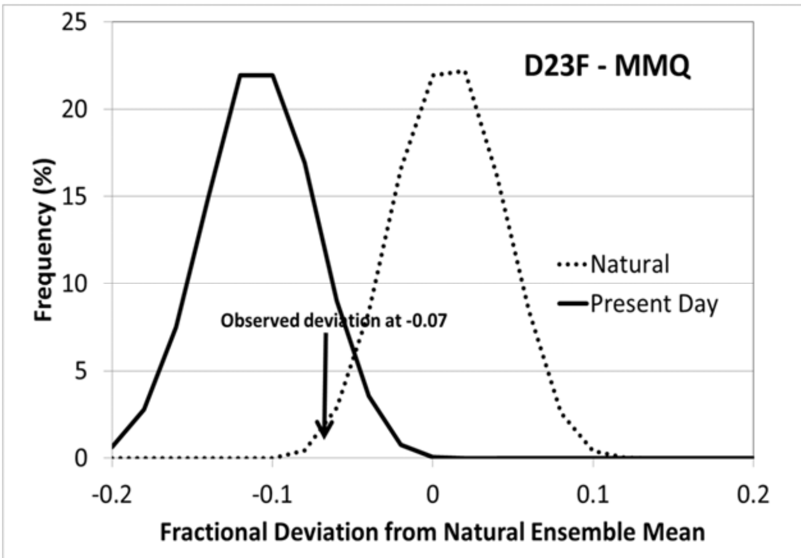



Figure 5.11 Example outputs using standardized flow indices for MMQ at D23F.

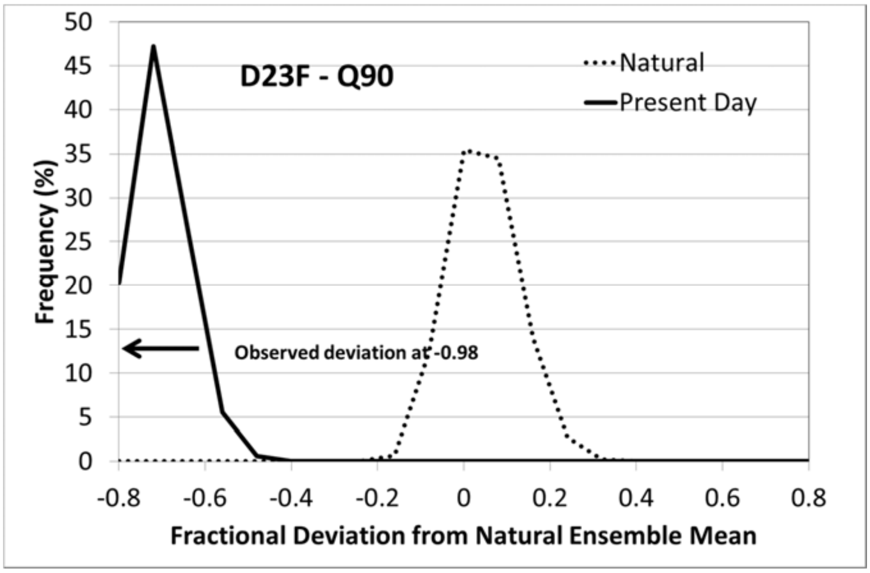



Figure 5.12 Example outputs using standardized flow indices for Q90 (low flows) at D23F

In general terms, the Pitman model simulates the hydrology of the Caledon River Basin sufficiently. Modelling results for the four example sub-basins indicate that the both the present day and the natural flow simulations are comparable to the observed flow from the various flow gauging records in the basin. There still remains a challenge with regard to flow records, which are fraught with missing data and short records. It is recognised that high flows (Q10) are mostly not well simulated and the observed flows are generally not within the simulated uncertainty bounds. One possible explanation for this is the high degree of error in measuring high river flows. While most of the uncertainty ranges for the natural flows are satisfactorily narrow, there is still a need to improve on the present day simulations. This might prove to be a challenging task as most of the developments within the basin are not adequately quantified.

### 5.3 COMPARISONS OF THE PITMAN AND WEAP MODELS

For both models it is possible to examine the time series of internal storage or flux components so that not only can the final result be compared in terms of downstream runoff, but the reasons for any differences between the two models can also be identified. The detailed comparisons are based on sub-basin D21E in the upper parts of the Caledon River Basin. The simulation comparisons are for the major hydrological processes common to both models, namely: evapotranspiration, surface flow, soil moisture flow and groundwater flow. The rainfall inputs are based on the WR2005 data used for the Pitman model for the period October 1920 to September 2004.

The comparisons are aimed at identifying any possible quantitative links between the parameters of the two models, with the objective of developing guidelines for the transfer of parameters from existing Pitman model setups to establish the WEAP model. Another aim is to detect the differences in their functionalities and to establish possible reasons for differences in the resultant simulations of the two models. Table 5.11 lists the initial parameter values that were used in the comparison tests, which were mainly designed to assess the sensitivity of the WEAP model outputs (compared to the Pitman model outputs) to changes in the WEAP model parameters.

### 5.3.1 Actual Evapotranspiration (ETa)

Actual evapotranspiration will vary with the crop factor ($K_c$) as well as with many of the parameters that affect the water balance in the upper layer of the WEAP model. Within the Pitman model, parameter R controls ETa, as well as any other parameters that affect the main moisture storage. Figure 5.13 illustrates the effects of changing the $K_c$ value from 0.9 to 0.7 while keeping all the other WEAP parameter values fixed at values listed in Table 5.11.

Table 5.11 Initial parameter values of the two models (some of the groundwater parameters of the Pitman model are not listed and were not changed during the model runs).

| Pitman | | WEAP | |
|---|---|---|---|
| ZMIN (mm) | 50.0 | Min Rain (mm) | 50.0 |
| ZAVE (mm) | 300.0 | Nominal RRF | 0.7 |
| ZMAX (mm) | 600.0 | $K_c$ | 0.9 |
| ST (mm) | 150.0 | Upper Zone Max. (mm) | 150.0 |
| R | 0.5 | Lower Zone Max. (mm) | 200.0 |
| FT (mm) | 4.0 | Ks1 (mm) | 16.0 |
| POW | 3.0 | Ks2 (mm) | 2.0 |
| GW (mm) | 15.0 | f | 0.5 |
| GPOW | 5.0 | | |
| Riparian Factor | 0.5 | | |

Figure 5.13 illustrates that the WEAP model generally produces a smaller range of ETa than the Pitman model with an R value of 0.5. Using a $K_c$ value of 0.9, yields results which are more similar to the Pitman simulations (Figure 5.13). Figure 5.14 indicates that the WEAP model

simulates generally lower moisture levels than the Pitman model, but the variations in actual evapotranspiration are much more similar.

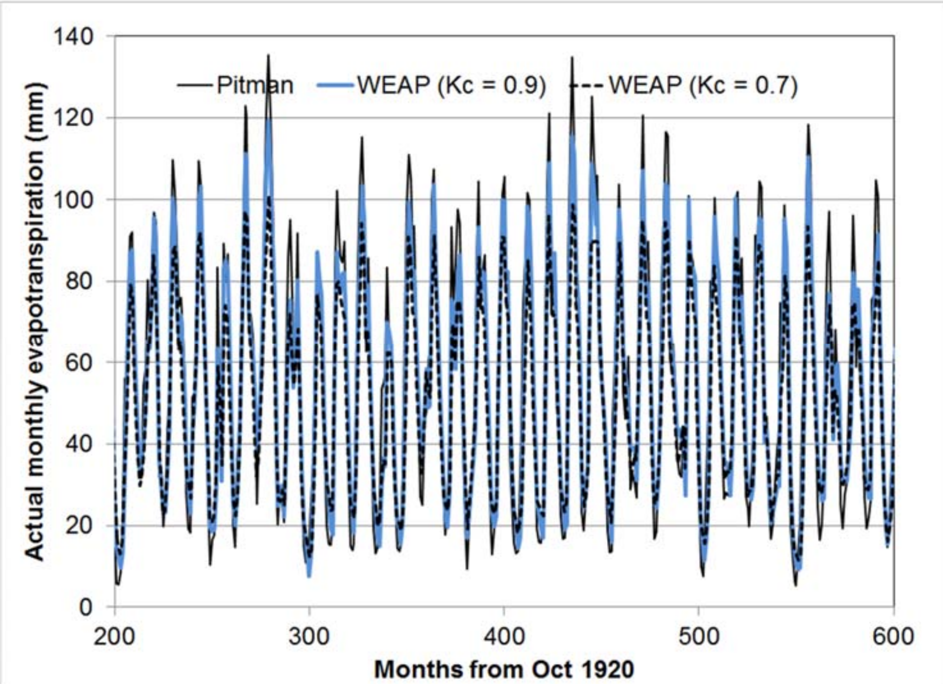



Figure 5.13 Comparison of Pitman and WEAP model estimates of actual evapotranspiration for WEAP $K_c$ = 0.9 and 0.7.

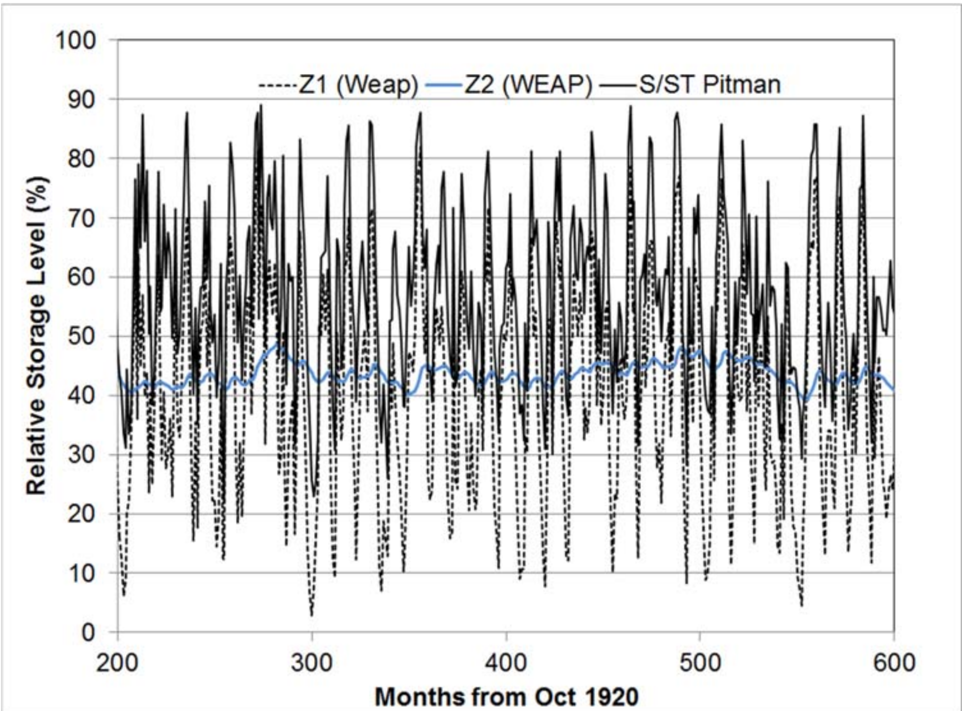



Figure 5.14 Comparison of Pitman and WEAP model estimates of relative moisture storage (Using parameter values listed in Table 5.11).

### 5.3.2 Surface Runoff

The surface runoff function of the Pitman model is controlled by the three parameters: ZMIN, ZAVE and ZMAX. There is no surface runoff generated at low monthly rainfalls less than ZMIN, while at higher rainfalls the triangular distribution defined by the three parameters determines the proportion of the rainfall that will be generating surface runoff and at what rate. Additional surface runoff can be generated when the part of the rainfall that is assumed to infiltrate the soil is added to the soil moisture storage and when this additional water results in the maximum storage depth (parameter ST) being exceeded. The parameter AI represents the impermeable portion of the catchment that will immediately generate runoff even at very low rainfall amounts. However, AI was set at zero throughout the simulations for this study. Figure 5.15 illustrates the surface runoff output from the Pitman model (with no exceedence of ST) for the ZMIN, ZAVE and ZMAX values given in Table 5.11. Within the WEAP model, the default surface runoff function is based on the rainfall input (P), a runoff resistance factor (RRF) and the current relative content (Z) of the upper moisture storage using the equation:

$$\text{Surface runoff} = P * Z^{RRF}$$

However, this approach could generate quite substantial depths of surface runoff even at low rainfalls. In this study the function was modified so that RRF varies more directly with rainfall depth. This was achieved by adding a rainfall threshold, below which the RRF parameter is assumed to be very high (say 20) and above which it is expressed by a conditional natural logarithmic equation (Equation 5.1), which makes RRF less dependent on Z.

$$\text{If}(P\text{-}Pmin<0.6,20,N+(Pmax/(P\text{-}Pmin))\text{^}^{(Ln(P)/5)})\ldots \text{ Equation 5.1}$$

Where: P - monthly rainfall (mm)
Pmin - monthly rainfall (mm) below which surface runoff is not expected
N - nominal RRF parameter
Pmax - rainfall scale factor (mm)

Figure 5.15 clearly suggests that the general shape of the surface runoff relationship is very different when the standard WEAP function is used, but that it can be made more similar to the Pitman model with the revised approach (Equation 5.1). The assumption that surface runoff varies only with storage (Z) in the default WEAP model makes it impossible to establish parameter values for a constant RRF value that will give similar outputs as the Pitman model. It is also evident that surface runoff simulated by WEAP is substantially sensitive to changes in the value of Z (Figure 5.15). The WEAP model allows the relative soil moisture to exceed 1.0 and this implies that all outputs, including surface runoff, can increase significantly during very wet periods.

Figure 5.16 repeats some of the WEAP model relationships from Figure 5.15, but the Pitman model simulations now include the surface runoff generated from the exceedence of the maximum soil moisture parameter (ST) as well as from the triangular absorption function. It is clear from Figure 5.16 that the two models can produce very similar variations of surface runoff. However, it is evident that the WEAP model tends to over-estimate surface runoff relative to the Pitman model, for the set of parameters used in Equation 5.1. An RRF value of 0.7 for the standard WEAP equation has been used in Figures 5.15 and 5.16 and the results suggest that the approach to scaling the RRF (Equation 5.1) is more consistent with the outputs of the Pitman model than using a constant (default) RRF value.

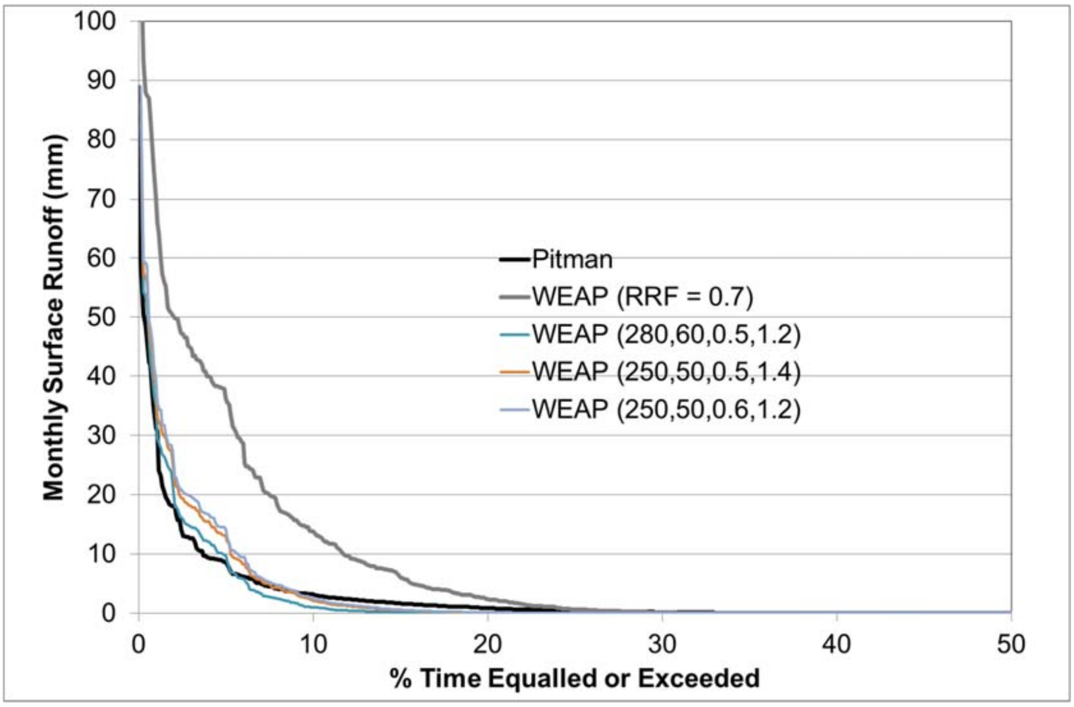



Figure 5.15 Differences in simulation of surface runoff between the two models. Values in the brackets for WEAP stand for rainfall scale factor, minimum rainfall, relative moisture, nominal RRF respectively.

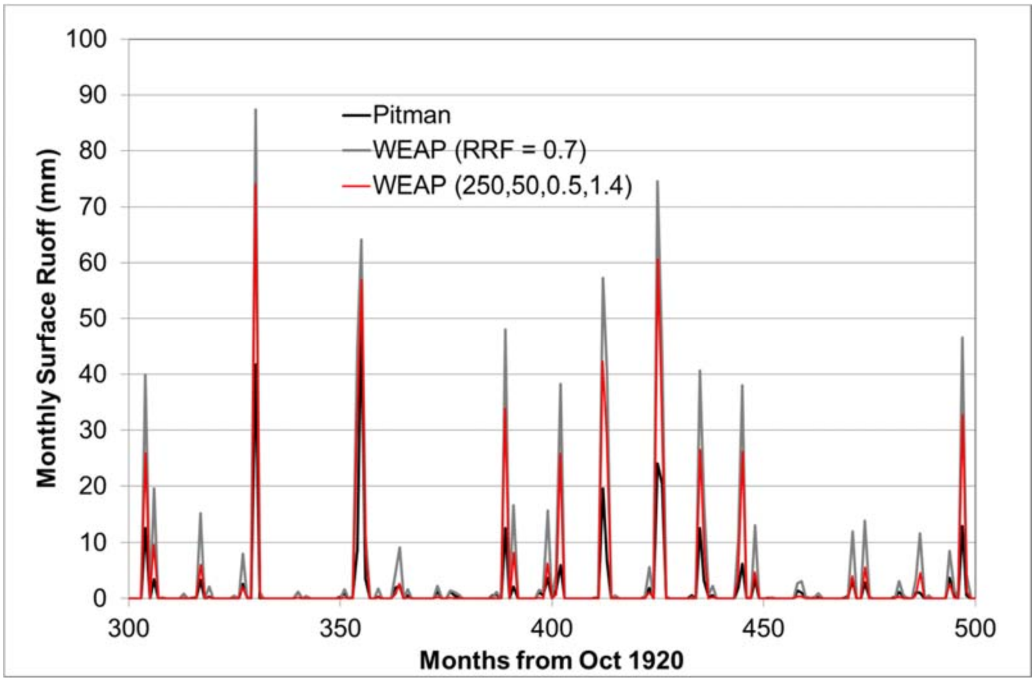



Figure 5.16 Comparison of Pitman and WEAP model estimates of surface runoff time series. Values in the brackets for the WEAP model refer to rainfall scale factor, minimum rainfall, relative moisture, nominal RRF respectively.

### 5.3.3 Interflow and Groundwater Discharge

Figure 5.17 illustrates the results for interflow and groundwater outflows using the parameter values given in Table 5.11 and it is apparent that the Pitman model groundwater outputs are much more variable than the WEAP model drainage flows from the lower (deep) storage zone. This is related to the very high storage used for this zone (200 mm) which was therefore identified as unlikely to realistically represent groundwater storage. Additional runs of the WEAP model were therefore made with the other parameters remaining at the same values, but reducing the lower zone or deep storage depth. While, the rather high and very variable groundwater outflows from the Pitman model are not necessarily realistic, the purpose of this comparative exercise was to identify which WEAP model parameter values should be used to match the Pitman model outputs.

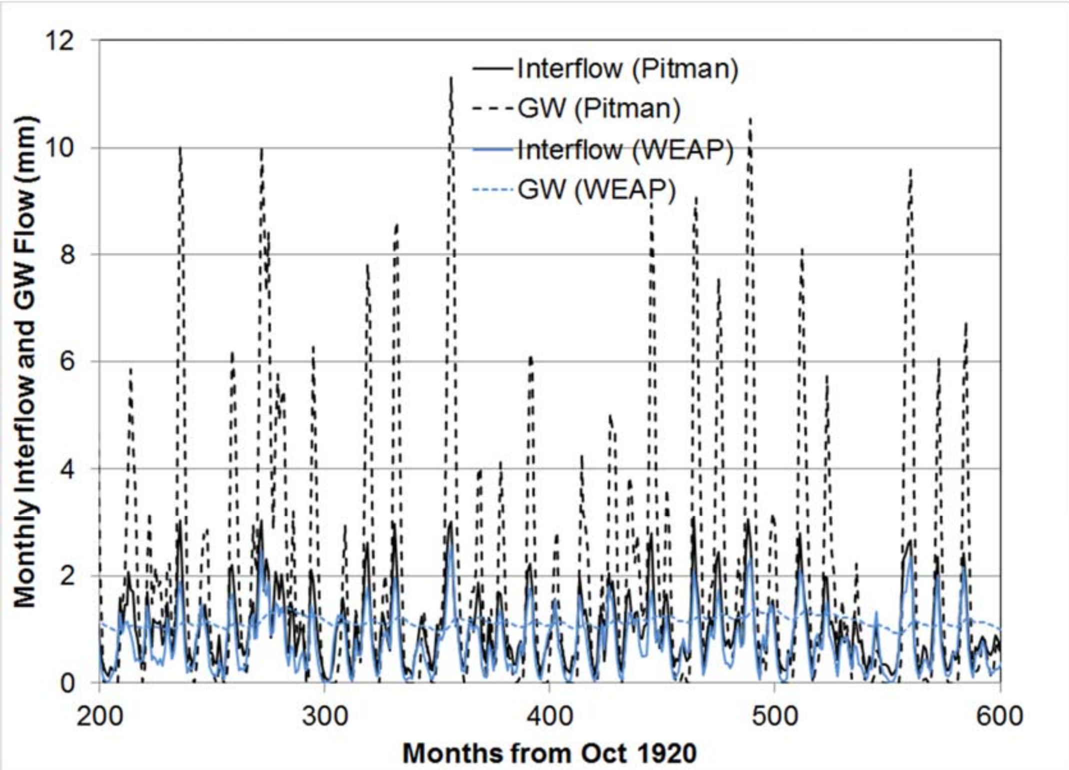



Figure 5.17 Comparison of Pitman and WEAP model estimates of interflow and groundwater flow (original parameter values).

Though simulations of interflow variations for the two models match closely (Figure 5.17), the differences in groundwater simulations are substantial. For this reason, it is almost impossible to get the WEAP model to emulate comparable patterns of groundwater outputs as the Pitman model. However, adjusting some of the WEAP parameter values from the original set yields slightly improved results relative to the Pitman model. Figure 5.18 illustrates the situation using values of Ks1 = 20, Ks2 = 10 and f = 0.25 with a deep zone capacity of 25 mm. The WEAP model interflow remains similar to the Pitman model and the groundwater outflow is much more variable. However, the groundwater outflow always remains above 0.45 mm in the WEAP model, while it drops down to 0 mm in the Pitman model, mainly because groundwater drainage is the only loss from the deep storage zone in the WEAP model, while the Pitman model includes a component of riparian evapotranspiration from groundwater. What can be inferred from these results is that if lateral drainage from the storage zones is assumed to be non-continuous, then the effects of the deep storage part of the model should be minimised.

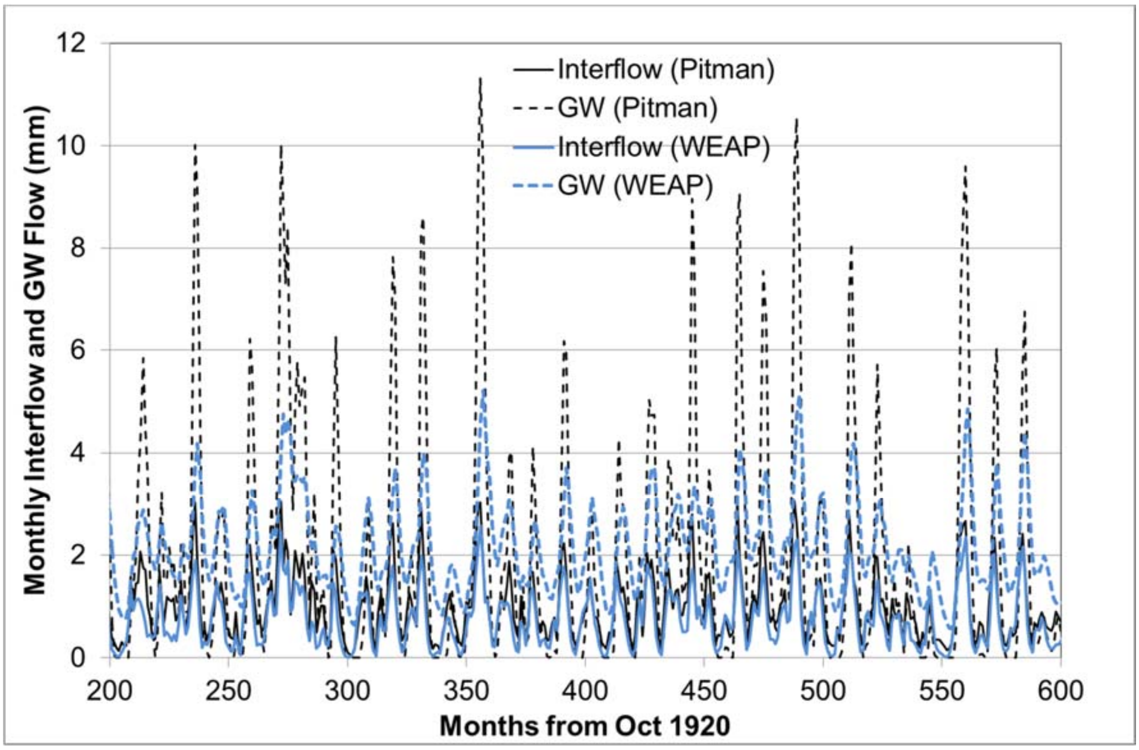



Figure 5.18 Comparison of Pitman and WEAP model estimates of interflow and groundwater flow (WEAP: Ks1 = 20, Ks2 = 10, f = 0.25 and deep zone capacity = 25).

Figure 5.19 illustrates one result with the deep storage zone effectively turned off by reducing the rate of drainage from the upper layer and making the Ks2 value as small as possible. The full range of total Pitman baseflow (interflow and groundwater flow) is not reproduced, but the pattern of variation of the two sets of simulations yielded a close match which is a great improvement, particularly with regard to low flows. This could be important in terms of eventually getting zero flows after the effects of water-use scenarios, such as small farm dams and direct abstractions from the river, are accounted for. Since there is extensive use of water from the main Caledon channel as well as within its tributaries, these are very important effects within the Caledon River Basin.

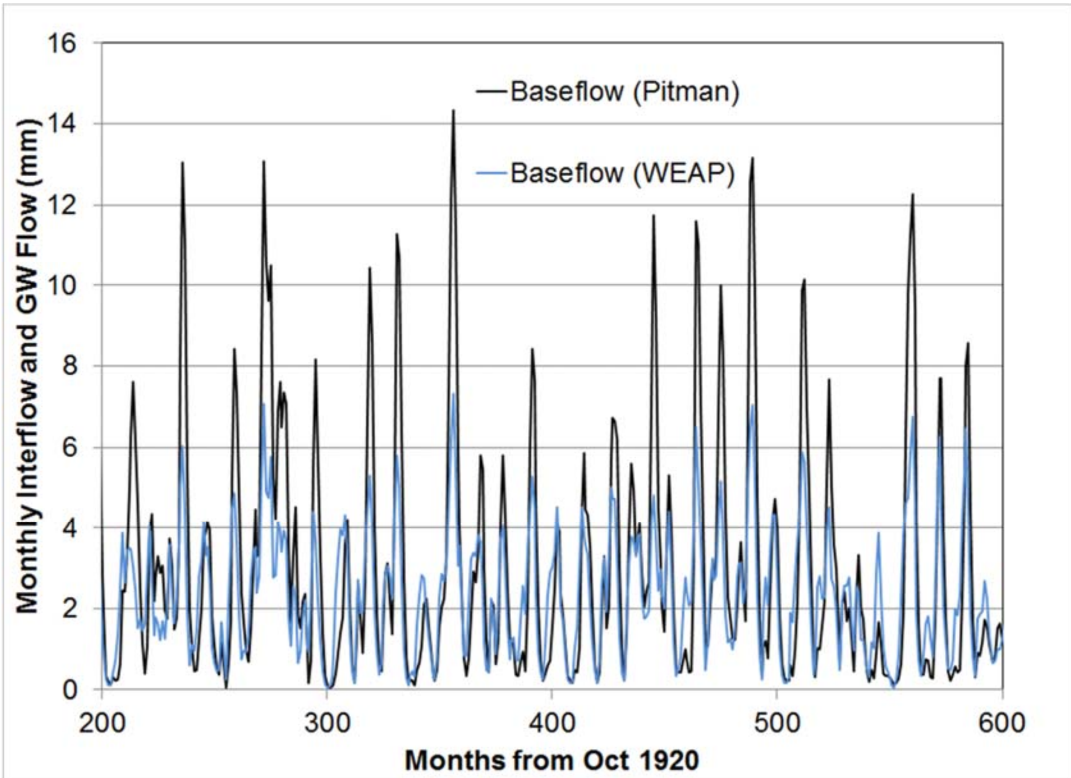


Figure 5.19 Comparison of Pitman and WEAP model estimates of total baseflow (WEAP: Ks1 = 16, Ks2 = 0.1, f = 0.99, deep zone capacity = 25).

### 5.3.4 Natural Streamflow Outputs

The ultimate objective of the application of hydrological models is to reliably estimate the quantity and timing of river discharge. This is attained by analysing and quantifying the storages and fluxes embedded in various components of the models. One of the problems with testing the individual components of the WEAP model against the Pitman model equivalents is that changes made to one part of WEAP will inevitably affect other parts. This is because all the WEAP components, such as surface runoff, depend on the content of the upper root zone soil moisture storage, while the surface runoff in the Pitman model is independent of soil moisture store. Figure 5.20 illustrates this problem and the final comparison of stream flow outputs for the two models, under natural conditions. The Pitman model simulations are based on uncertain model parameters, while the WEAP simulations are based on the parameter values given in Table 5.12 and discussed in the sections above. It is clear from the flow duration curve shown in Figure 5.16 that the moderate to low flows simulated by WEAP are very similar to the uncertainty range simulated by the Pitman model. However, the changes made to the interflow parameters have clearly had a major secondary impact on the WEAP surface runoff results and it was initially thought that these parameters could be further adjusted to reduce the very high runoff values. However, this was not very successful as it also affects the interflow results as more water is added to storage. The other notable point is that the default version of the WEAP model cannot simulate zero stream flow even for short periods of time.

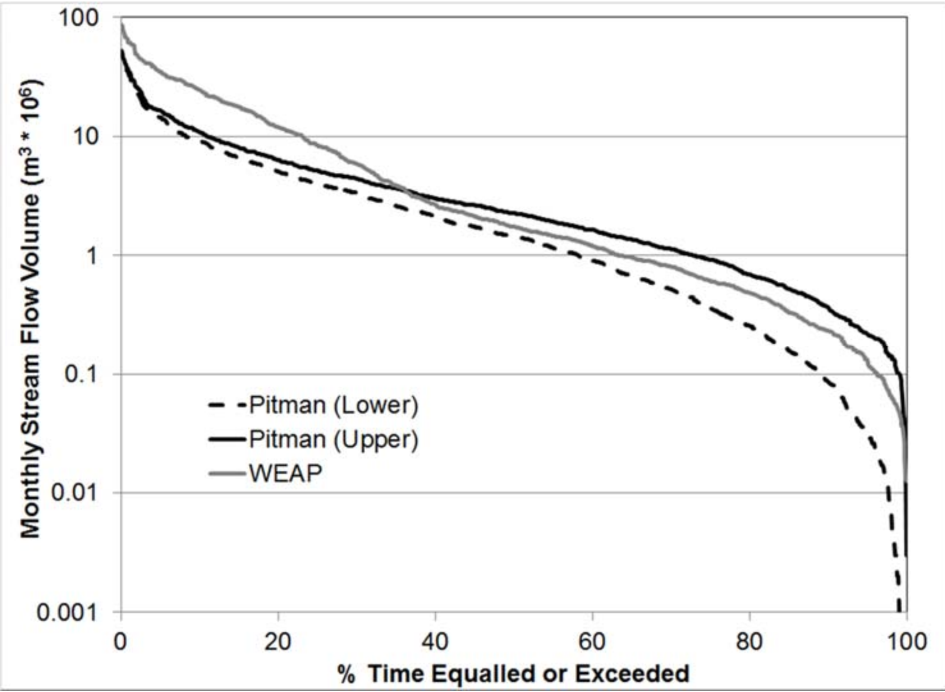



Figure 5.20 Comparison of simulated stream flows at the outlet of D21E by the WEAP model and the uncertainty range simulated by the Pitman model (natural conditions).

Table 5.12 Final parameter values used for the two models. Parameter values for the Pitman model are ranges for the uncertainty version.

| **Pitman** | | **WEAP** | |
|---|---|---|---|
| ZMIN (mm) | 10:150 | Min Rain (mm) | 50.0 |
| ZAVE (mm) | 300 | Rainfall Scale Factor | 250 |
| ZMAX (mm) | 200:2000 | Nominal RRF | 1.2 |
| ST (mm) | 60:300 | Z | 0.6 |
| R | 0.3:0.7 | $K_c$ | 0.9 |
| FT (mm) | 2:20 | Upper Zone Max. (mm) | 150 |
| POW | 1.5:5.0 | Lower Zone Max. (mm) | 25 |
| GW (mm) | 0:100 | Ks1 (mm) | 16 |
| GPOW | 4.0:6.0 | Ks2 (mm) | 0.1 |
| Riparian | 0.2:2.0 | f | 0.99 |

### 5.3.5 Incorporating Farm Dams and Direct Run-of-River Abstractions

The Pitman model includes a function that allows a proportion of the runoff from each incremental sub-basin to contribute to storage in small farm dams, while the remainder of the simulated runoff is unaffected by that specific type of development impact. The WEAP model does not include such a function and the farm dams have to be dealt with using the normal on-channel reservoir function. Therefore, in practice, this means that all of the catchment nodes need to be divided into two, those that contribute to reservoir farm dam inflow and those that do not. To achieve this without doubling the catchment nodes, pairs of quaternary catchments in the Pitman model setup have been combined.

One of these catchments is used to represent the part of the combined catchment area that is assumed to contribute to the total farm dam storage, while the other is assumed to be downstream of the farm dam and thus does not contribute any water to it. Any direct run-of-river abstractions for irrigation or other uses are assumed to be from the downstream catchment and therefore will also be impacted by the effects of the farm dams. This is thought to be the most realistic way in which these development effects can be incorporated into the WEAP model.

The WEAP model has been set up using the mean of the uncertainty ranges of the water demands as used in the Pitman model, in terms of estimated farm dam volumes and rates of water abstraction. These are the data sets that were used in a present-day uncertainty run of the Pitman model. A comparison between the natural and present-day situations for the WEAP model is given in Figure 5.21. The effects of the demands from farm dams and direct abstraction appear to be smaller for the WEAP model than the Pitman model.

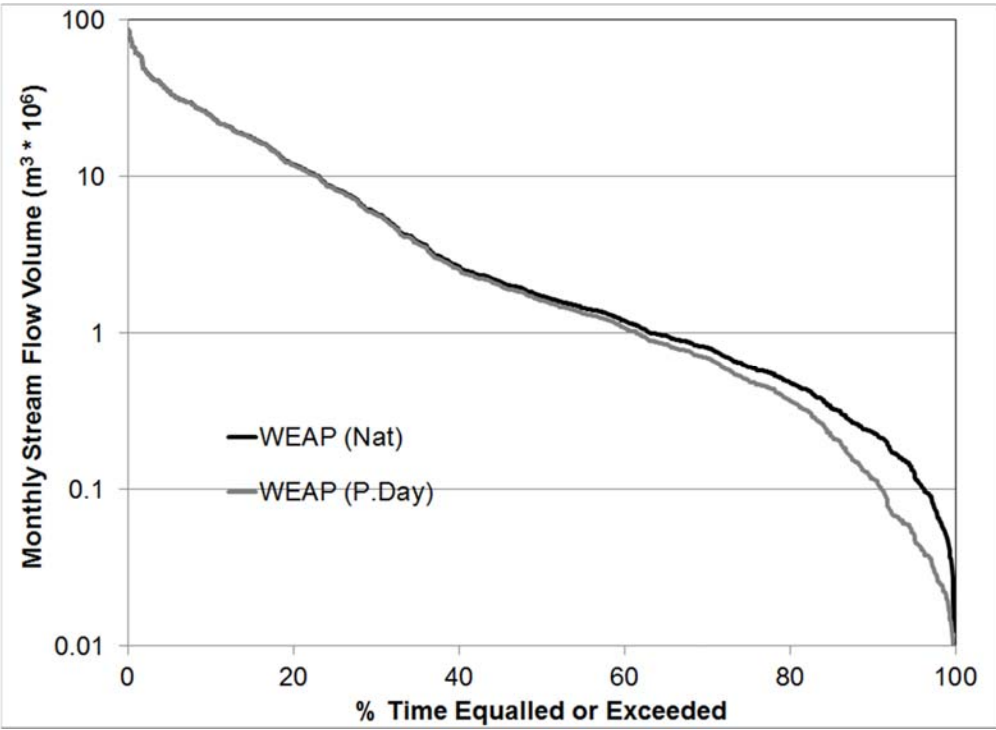



Figure 5.21 Comparison of simulated stream flows at the outlet of D21E by the WEAP model for natural and present-day demand conditions.

Figure 5.22 shows the WEAP model results compared to the Pitman flow simulation uncertainty bounds for the present-day demand situation and the observed stream flow records at both the upstream (D21E) and further downstream (D23F) sub-basins. It is observed from Figure 5.22 that the WEAP model simulates substantially higher streamflow values compared to the observations and over-simulates high and very low flows relative to the Pitman model. For D21E sub-basin, WEAP suggests that there will not be any zero flows, whereas Pitman and the observed records indicate dry conditions for at least 5% of the time. On the other hand, an opposite scenario is observed for the downstream sub-basin (D23F), whereby the WEAP model consistently under-simulates streamflow relative to both Pitman and the observations (except for the very high flows).

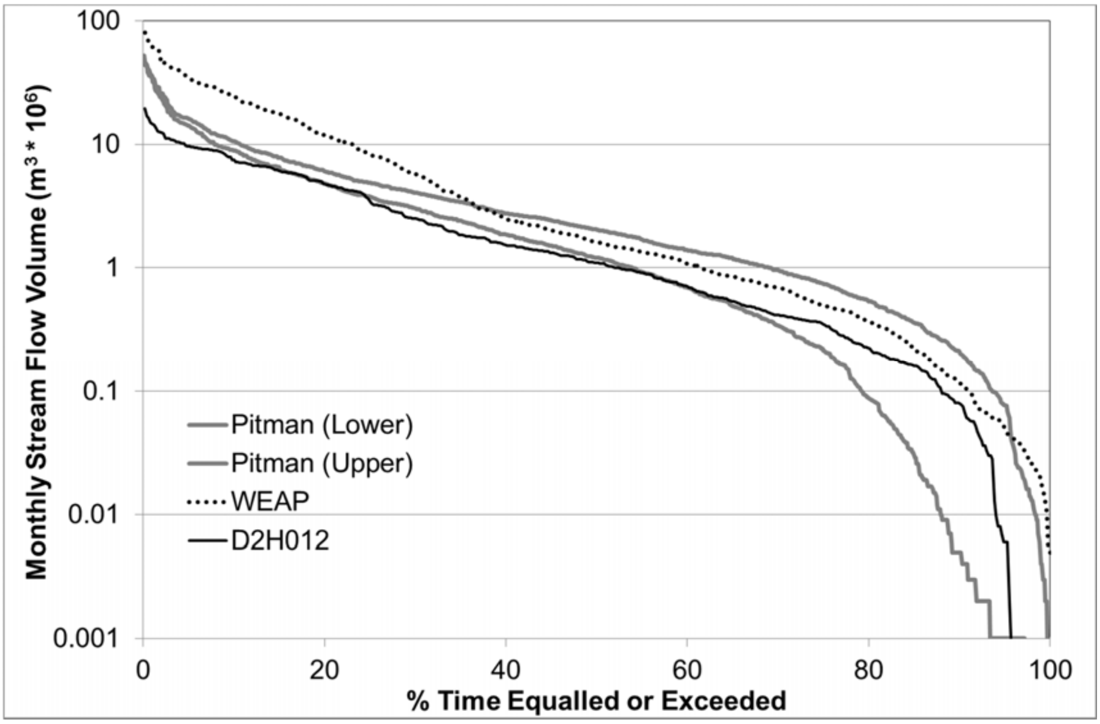



Figure 5.22a Comparison of simulated stream flows at the outlet of D21E by the WEAP model and the uncertainty range simulated by the Pitman model (present-day demand conditions).

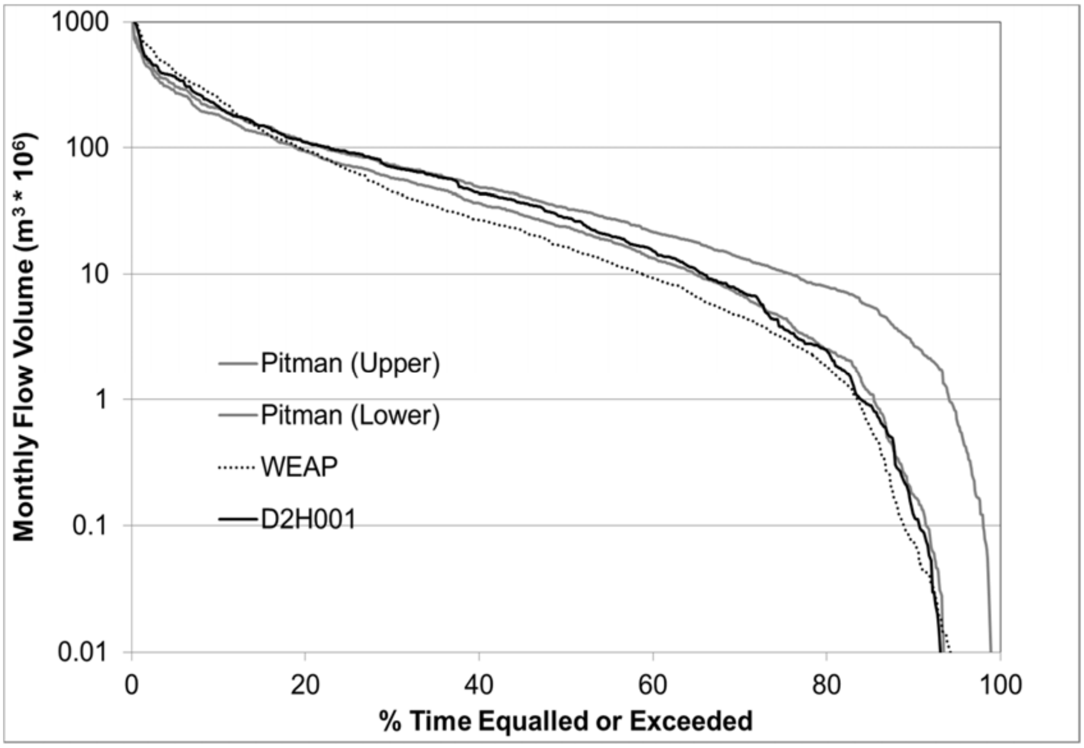



Figure 5.22b Comparison of simulated stream flows at the outlet of D23F by the WEAP model and the uncertainty range simulated by the Pitman model (present-day demand conditions).

## 5.4 SUMMARY

### 5.4.1 Uncertainties in Hydrological Modeling for the Caledon

In the Caledon River Basin there are many sources of uncertainty and very little observed data to resolve the uncertainties. The sub-sections below summarise the main uncertainties as well as the attempts that have been made in this study to reduce them.

*Rainfall:* There are many uncertainties in the rainfall inputs for the mountainous Lesotho parts of the basin, but these have not been dealt with as there are no additional data to either define the uncertainties or reduce them.

*Evapotranspiration demands:* There are also very few data to define the uncertainties in evapotranspiration. However, it would be useful to try and apply some of the remote sensing techniques such as MODIS to this basin to establish if it is possible to identify spatial variations in actual evapotranspiration that could be linked to either natural processes or the use of irrigation water.

*Natural hydrology parameter values:* The report has detailed a three-stage process that involved the use of four constraints on the model outputs and a detailed examination of the parameter space for behavioural and non-behavioural ensembles. The initial parameter ranges could be reduced quite significantly and the number of behavioural ensembles increased. Examining the outputs at downstream sub-catchments is much more complex because of the large number of sub-catchments and the interactions between them. This process was, however, made slightly easier by grouping the sub-basins on the basis of their physical properties and expected hydrological response.

*Present-day water use:* The data that are available to quantify farm dam volumes, water use from these dams, as well as direct abstractions from the river (for irrigation, rural domestic use and town use) are not adequate to properly define the necessary parameter values of the model. While uncertainty in most of these has been included, it is very difficult to know if the range of uncertainty is appropriate or not.

*Observed flow data:* In many catchments, the practical reduction of uncertainty can be achieved by using local observed data to constrain the model outputs. However, this is complicated by the short record lengths of most gauges, the inaccuracies in the observation of high flows (or high flows simply not measured) and the poor knowledge of actual water use. Thus, it is almost impossible to understand exactly what the gauge records represent in terms of the mix of natural and impacted conditions. The records are expected to be highly non-stationary, but there is not enough additional information to define the variations over time.

The above section concentrated on detailed uncertainty reduction attempts in the Caledon River (31 sub-basins) basin. It is essential to note that these assessments resulted in some reduction in uncertainty but involved a considerable amount of detailed analysis of the simulation ensembles (both parameter space and output results). There is simply a large uncertainty space (even without uncertain climate inputs) that resolving the interactions and the inter-dependencies is almost impossible. One of the main deductions is that, while there are approaches that can be used to reduce uncertainty, they can be quite time-consuming and would involve substantial amounts of field data collection which was beyond the scope of this desktop study.

### 5.4.2 Comparisons of Pitman and WEAP Models

The differences between the main processes and rainfall-runoff generation algorithms of Pitman and WEAP models were examined. The main purpose of the comparison was to establish possible links and therefore to suggest guidelines for setting the WEAP model parameters on the basis of the already existing Pitman model setup for the Caledon River Basin, with the possibility of applying these parameters elsewhere in similar physical and environmental conditions. The analysis revealed that there are some components of the WEAP model where such guidelines can be suggested. However, there are other parts of the model where there were no guidelines established. These would likely require more trial runs of the models and more vigorous comparisons of their component outputs because of the interactions between the storage and output functions, which will be different between the two models.

There appear to be a number of similarities in the way in which the two models operate, but there are also some important differences that need to be taken into account:

- The surface runoff function of the WEAP model partly depends on the storage state of the upper zone, while the Pitman model function depends entirely on rainfall. This is important, not only because of the effects on simulated surface runoff, but also because any changes made to the WEAP parameters related to this function will affect other parts of WEAP as well (evapotranspiration and interflow). This adds an additional component of equifinality (parameter interaction) to the WEAP model compared to the Pitman model.

- The drainage from storage functions (interflow and groundwater) of the WEAP model do not allow for the simulation of zero flows implying that there will always be a small amount of water draining from both the upper and lower zones, even if their storage states are very low. This could be solved by the use of an expression for the conductivity parameters for both storage zones that includes the storage (in the last time interval) and therefore sets the conductivity parameters to zero below a certain storage state.

The results of model comparisons indicate that there are many similarities between the two models that can be very useful in setting up the WEAP model based on existing Pitman model setups. Hence, there is a potential for WEAP to be incorporated as part of hydrological assessment and water resource availability investigations in the region. Compared to the Pitman model, WEAP is relatively easy to implement because of its rather parsimonious structure and user-friendly interface. The model also requires less data and information to run, which makes it appropriate, especially in this data-scarce region. WEAP has several other advantages including the analysis of water use management and development options. It also incorporates many functions representing the engineered components (e.g. reservoirs, water treatment works) of the water system relevant to the region. In addition to the water resources evaluation, WEAP includes a water quality component and financial cost-benefit function.

# 6 CLIMATE CHANGE SCENARIOS FOR CALEDON BASIN

## 6.1 INTRODUCTION

This chapter discusses the future climate scenarios in the Caledon River Basin as predicted by the downscaled global circulation models outputs from the Climate System Analysis Group (CSAG) based at the University of Cape Town. Nine GCMs (based on availability) are used in this study which are part of the coupled model inter-comparison project (CMIP3) multi-model datasets used during the fourth assessment report of the Intergovernmental Panel on Climate Change (IPCC, Solomon *et al.*, 2007). The model outputs used are based on the high A2 carbon emission scenario (Nakicenovic *et al*., 2000) and consist of empirically downscaled daily temperature (maximum and minimum) and rainfall data. The climate conditions were computed for three scenario periods: baseline (1961-2000), the near future (2046-2065) and the far future (2081-2100). Other meteorological variables were derived from the temperature data.

The chapter is divided into three sections. The first section deals with the analysis of observed data and the models' baseline monthly rainfall data. Four sample quaternary catchments, namely: D21B, D22A, D23C, D23H are used for discussion and illustration and are selected to represent the different climate and hydrological conditions of the Caledon River Basin. In this section, the statistical bias of rainfall simulated by the climate models is established and an appropriate bias correction methodology is introduced. The second section deals with the statistical analysis of daily rainfall in order to determine any changes in the future climate conditions with reference to current climate patterns, and considers uncertainties associated with the prediction outputs of the climate models. The bias-corrected future rainfall and future evaporative demands are then used to force the Pitman hydrological model (established in chapter 5 using historical observed data) to evaluate the impacts of climate change on the hydrology and water availability of the Caledon River Basin.

### 6.1.1 Climate Model Data and Observations

The historical rainfall data used in this study were obtained from the South African surface water resources assessment study (WR2005) of Middleton and Bailey (2008) and consist of monthly totals for each of the quaternary catchments for the whole of South Africa, Lesotho and Swaziland. The rainfall data from the WR2005 study are the best available historical data series in the country, although they are not perfect because the density and coverage of the gauging network are not adequate in many regions. The observed historical data set used in this study spans the period from 1920 to 2005 and has been accepted to represent the long term climate patterns of the region (Middleton and Bailey, 2008).

The downscaled climate data sets comprise daily maximum and minimum temperatures and rainfall at the quinary catchment scale. Within the South African hydrological and water management system, there are at least three quinary points within each quaternary catchment. The GCM climate simulation data was scaled down using an empirical statistical procedure (Hewitson and Crane, 2006). The model simulations used here cover three climate scenario periods: baseline (1961-2000), near-future (2046-2065) and far-future (2081-2100). The quinary scale baseline daily rainfall data were interpolated to the quaternary catchment scale using the inverse distance squared method and then summed to monthly values for comparison with the historical WR2005 data. The climate model data do not represent real historical sequences of rainfall and each model depends on the initial boundary conditions. It is therefore not possible to compare the climate model time series data with each other, nor with the historical WR2005 data. The comparisons and bias correction methods (Chapter 4) are therefore mainly based on calendar month statistical properties (means, standard deviations and skewness).

The GCM-simulated baseline annual rainfalls for the four sub-basins are substantially biased relative to the observed rainfall. The bias varies significantly in both magnitude and direction. Table 6.1 shows that while some GCMs are biased by as much as 68% others severely under-simulate rainfall, by up to -35%. The annual rainfall bias of the GCMs seems to increase with increasing rainfall amounts. While the GCMs show a generally negative bias in the wettest region (D21B), the opposite is true in the driest part (D23H). However, rainfall simulations by CCCMA and IPSL show a consistent negative bias across all sub-basins, whereas GISS consistently show the highest positive bias in the four sub-basins.

Figure 6.1 provides more detailed comparisons of the calendar month mean rainfall values and the deviations from the observations for the baseline simulations of the nine GCMs. One immediate observation is that the percentage deviation varies in both time and space. There is higher deviation during the dry winter period (May to September), as well as in the drier sub-basins, with the high summer rainfall amounts being generally under-estimated and the lower winter rainfalls being over-estimated. The deviation values range between approximately 250% (in June) to about -50% (in January). Figure 6.1 suggests that there is generally a negative deviation during the rainy season and that the range of uncertainty appears to be greater in the drier area (D23H) than in the wetter parts of the basin (D21B and D22A). However, the general differences in percentage bias between the nine GCMs appear to be quite consistent across the four example sub-basins.

Table 6.1 Percentage bias (PBIAS) of the annual rainfall simulated for the baseline scenario by the climate models relative to the observed.

| Catchment | D21B | D22A | D23C | D23H |
|---|---|---|---|---|
| Historical rainfall (mm) | 1013 | 679 | 633 | 517 |
| CCCMA | -35.8 | -23.9 | -19.52 | -2.0 |
| CNRM | -13.2 | 2.3 | 11.24 | 35.3 |
| CSIRO | -15.5 | -11.3 | 10.53 | 22.8 |
| GFDL | -13.6 | -7.0 | 8.62 | 21.3 |
| GISS | 4.5 | 23.9 | 31.64 | 68.6 |
| IPSL | -31.9 | -20.0 | -17.54 | -9.7 |
| MIUB | -24.7 | -11.8 | -3.58 | 18.6 |
| MPI | -23.1 | -9.1 | -1.54 | 19.5 |
| MRI | -27.7 | -15.3 | -6.60 | 17.4 |

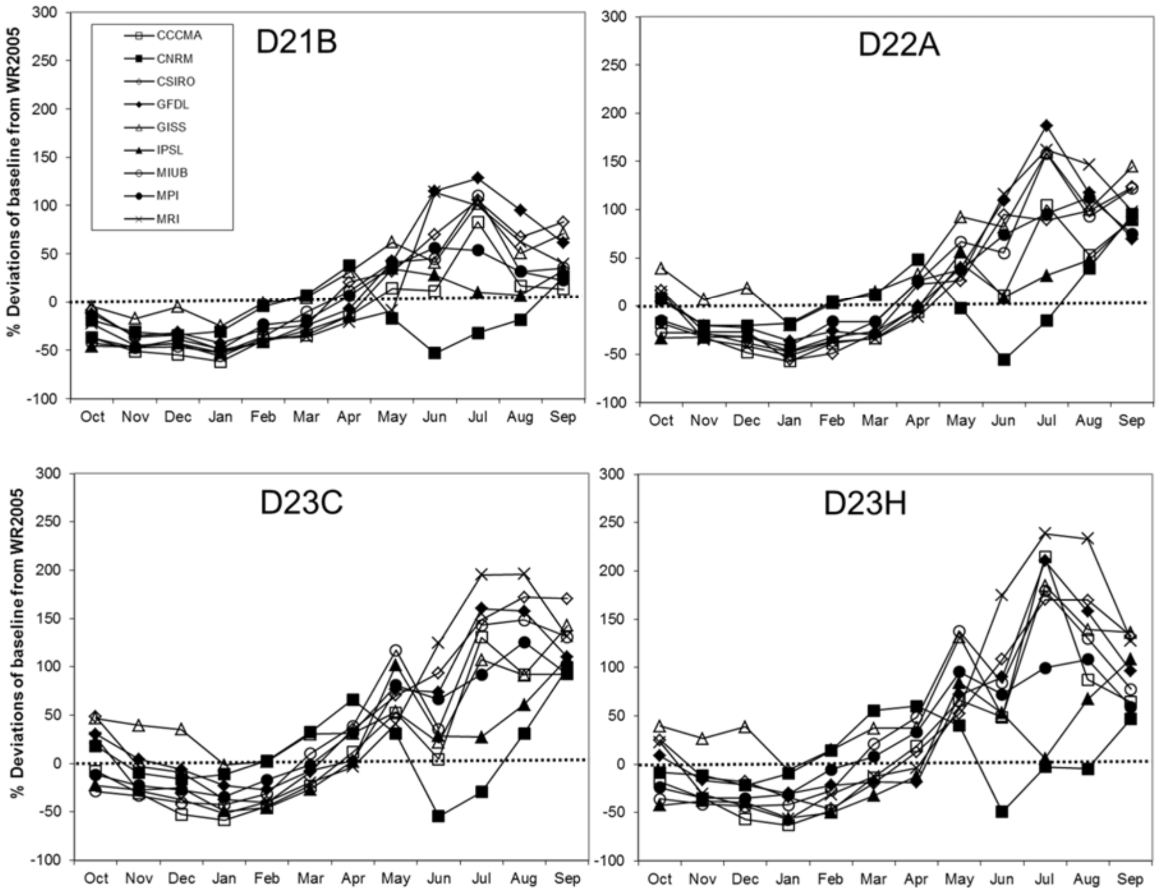



Figure 6.1 Percentage deviation of the simulated baseline monthly rainfall from the observed rainfall.

### 6.1.2 The Bias Correction Method

In the preliminary analysis of the GCM baseline rainfall data, several calendar month statistical measures were used to compare the characteristics of the climate models with the observed WR2005 rainfall records. The analyses indicate that the GCM baseline data differ significantly against the observations, in terms of the various statistical indicators used (see Table 6.1 and Figure 6.1). These discrepancies indicate that the outputs of the future climate scenarios cannot be directly applied for any impact assessment without some form of bias correction if sensible results are to be attained from a model previously established using climate forcing data based on historical data.

In the current study, a bias correction method introduced by Hughes *et al*. (2014b) is used to adjust the statistically downscaled precipitation data sets (see Chapter 4). The bias correction method is based on the use of the calendar month means and standard deviations and relies to a certain extent on the frequency distributions of the rainfall data to be near-Normal. Preliminary analyses of all of the rainfall data sets suggested that a square root transformation would produce the closest approximation to Normal distributions in all cases. There are some situations where the requirement for low skewness values after transformation is still not met in the dry winter months, however, this was not considered to be a critical problem as the rainfall values are almost always very small and have little influence on the hydrological modelling results. In the bias correction method the future rainfall estimates are expressed in terms of standard deviates of the baseline scenario monthly distributions and the standard deviates are scaled with the monthly distributions of the historical rainfall data. The bias correction method was presented in detail in Chapter 4.

The application of the bias correction removes bias in the monthly rainfall means and standard deviations between the historical and the GCM simulated baseline data. At the same time, the bias correction method is able to preserve the differences between the GCM baseline and future scenario predictions.

### 6.1.3 Performance of the Bias Correction Method

The results of applying the square root transformation bias correction method to the future climate scenario is demonstrated using the observed, control baseline and future climate simulation for the four example quaternary catchments of the Caledon Basin. For this purpose, precipitation simulations of the two climate models namely, CCCMA and CNRM are used to show how the application of the bias correction methodology impacts the future rainfall predictions (Figure 6.2a and b). It was demonstrated in Figure 6.1 that the seasonal distributions of the historical and baseline data differ significantly and Figure 6.2 further reinforces this fact. It is also evident from Figure 6.2 that the distributions of the mean monthly raw (uncorrected) future scenario rainfall are not very different to that of the equivalent baseline distributions for these two climate models, suggesting relatively small climate change effects on rainfall. Further details of the future predicted rainfall patterns for all of the GCMs are provided within the next section of this chapter.

It would generally be expected that the differences between the baseline and uncorrected near-future distributions would be reflected in similar differences between the historical and corrected near-future distributions. However, there are some month/GCM/quaternary combinations where this is not the case (e.g. Nov, Dec and Jan for CCCMA and D21B or Jan, CNRM and D21B). This is almost certainly associated with inadequacies in the square root transformation of one or more of the rainfall time series leading to adverse effects of some rainfall outliers. While the baseline time series are 40 years in length, the near-future predictions are based on a 20 year time series, within which single outlier rainfall values can have a substantial effect on the distribution statistics. Fortunately, this does not occur very frequently in the full set of results for all climate models and quaternaries, but does highlight a potential problem with this relatively simple bias correction method. This problem was noted to be far worse if a logarithmic transformation was used for all of the rainfall rime series. As noted in Hughes *et al.* (2014b), alternative bias correction techniques (such as quantile-quantile transformations) were not able to preserve the seasonality and the changes in the statistical properties of the rainfall between the baseline and near-future scenarios and it was concluded that the simple bias correction method used here, in combination with a square-root transformation, achieved the most realistic results.

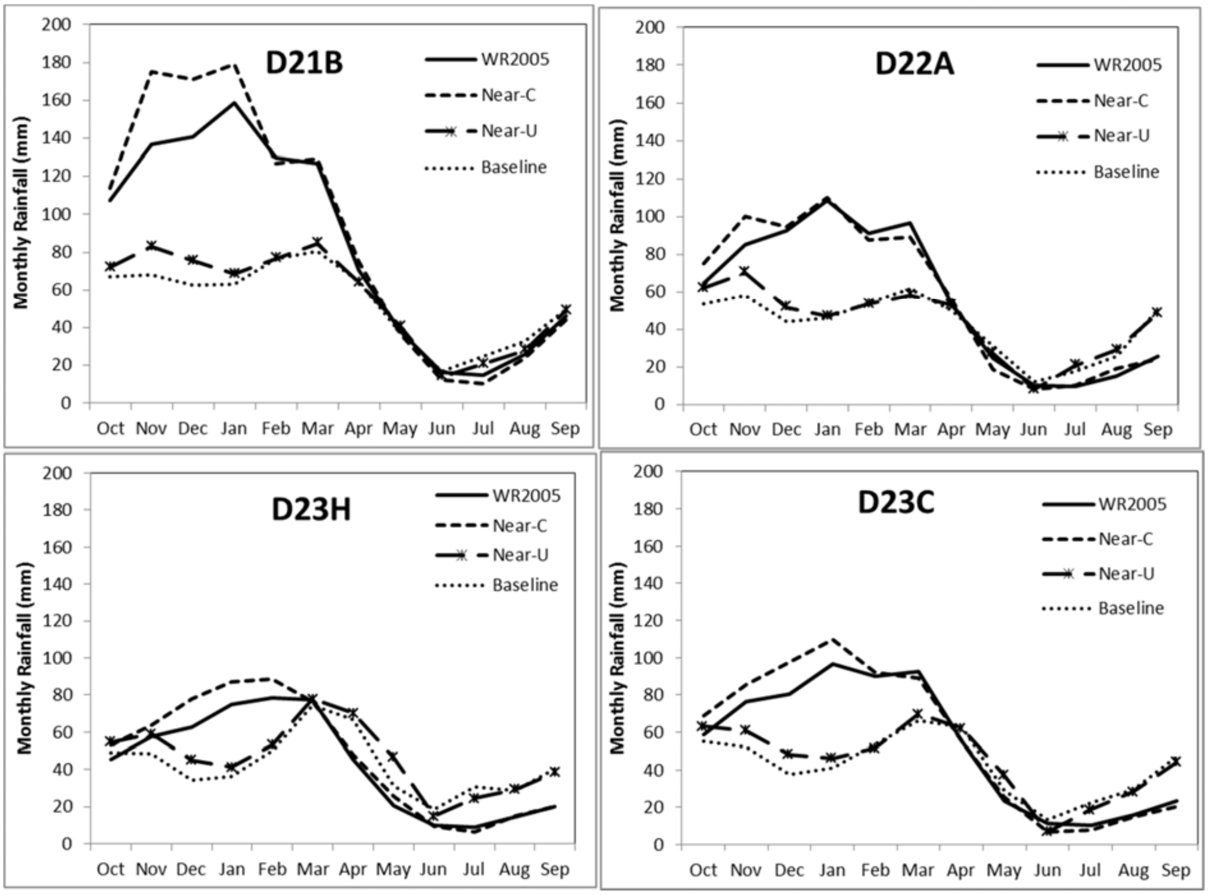



Figure 6.2a Comparison of observed (WR2005, 1961-2000), Baseline climate scenario (Baseline, 1961-2000), raw future rainfall (Near-U, 2045-2065) and the corrected future rainfall (Near-C, 2045-2065) from the downscaled CCCMA model simulations.

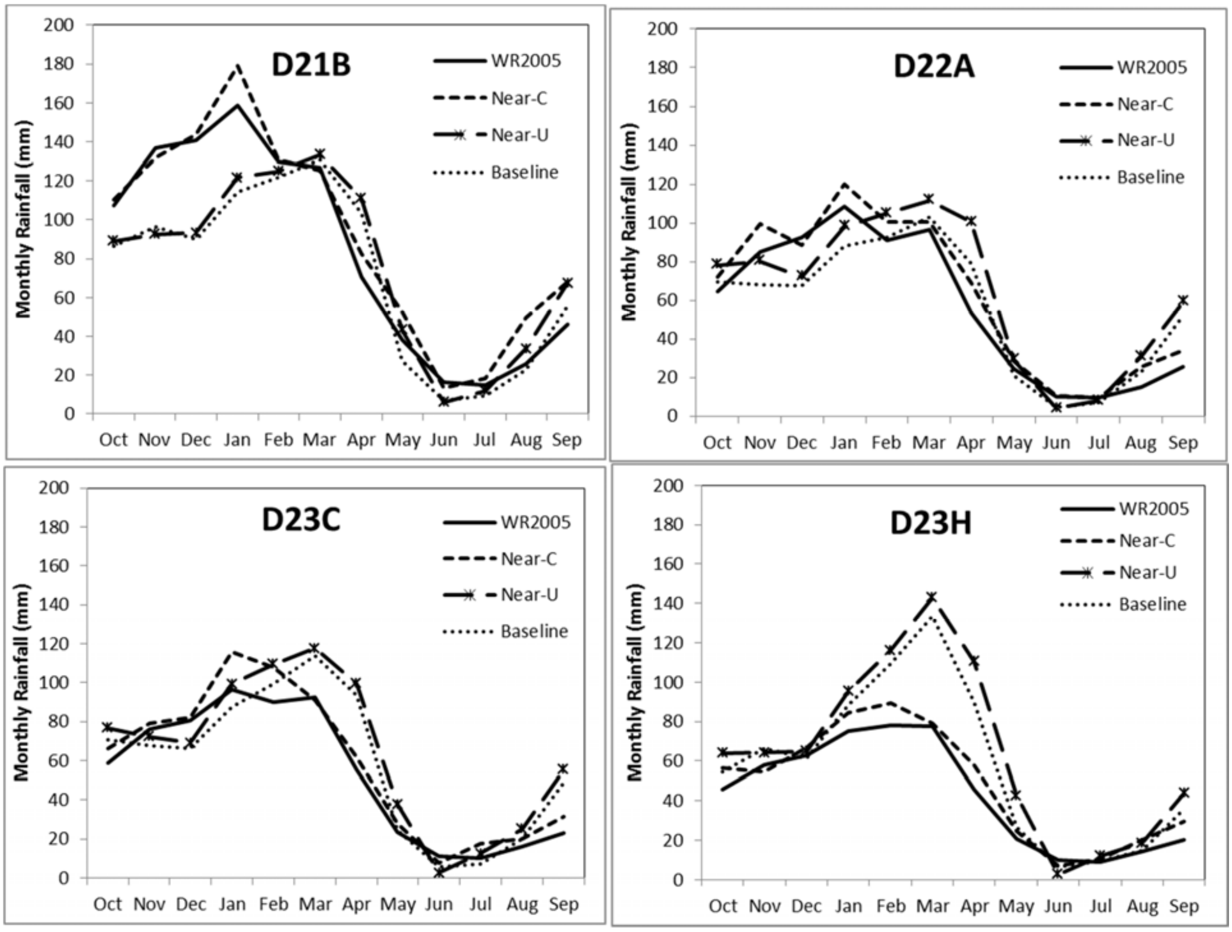



Figure 6.2b Comparison of observed (WR2005, 1961-2000), Baseline climate scenario (Baseline, 1961-2000), raw future rainfall (Near-U, 2045-2065) and the corrected future rainfall (Near-C, 2045-2065) from the downscaled CNRM model simulations.

### 6.1.4 Future Climate Conditions

Future climate conditions (temperature and rainfall) are predicted by nine climate models for the near-future and far-future climate scenarios of the period spanning from 2046–2065 and 2081-2100 respectively. Future evaporative demands of the basin were estimated by using the derived temperature component of the Hargreaves equation.

#### 6.1.4.1 Future Rainfall

The results of the predicted future rainfall of the study area are illustrated using the four sample quaternary catchments in the basin. According to Figure 6.3, the bias-corrected data from the set of nine climate models of the predicted future rainfall (2046–2065) display a fairly consistent seasonal variation across the four sample catchments. The seasonal variation also closely matches the observed historical rainfall (WR 2005, 1961-2000). However, it is also evident that there is a wider margin of uncertainty in the projected rainfall during the wet summer season. Although the uncertainty seems to diminish during the winter season when lower rainfall is experienced, the GCMs do not agree on the magnitude and direction of change of rainfall, relative to the historical records.

There is an indication that the driest region of the basin (D23H) will be drier during the period 2046–2065, with the majority of the models predicting decreased amounts of summer rainfall (Figure 6.3). The opposite is true for the wetter mountainous part of the basin (D21B) where most models predict increased rainfall during the summer season. For the two intermediate rainfall catchments, D23C and D22A, some models predict increased summer rainfall, while almost the same number suggests a decrease. The models do not provide a clear trend in terms of magnitude and direction of change in winter rainfall for all four catchments. All the models appear to indicate a stationary seasonal variation in future rainfall, although there is a suggestion of a slight delay of peak rainfalls in catchment D23H where most models predict highest rainfalls will occur in February–March instead of January.

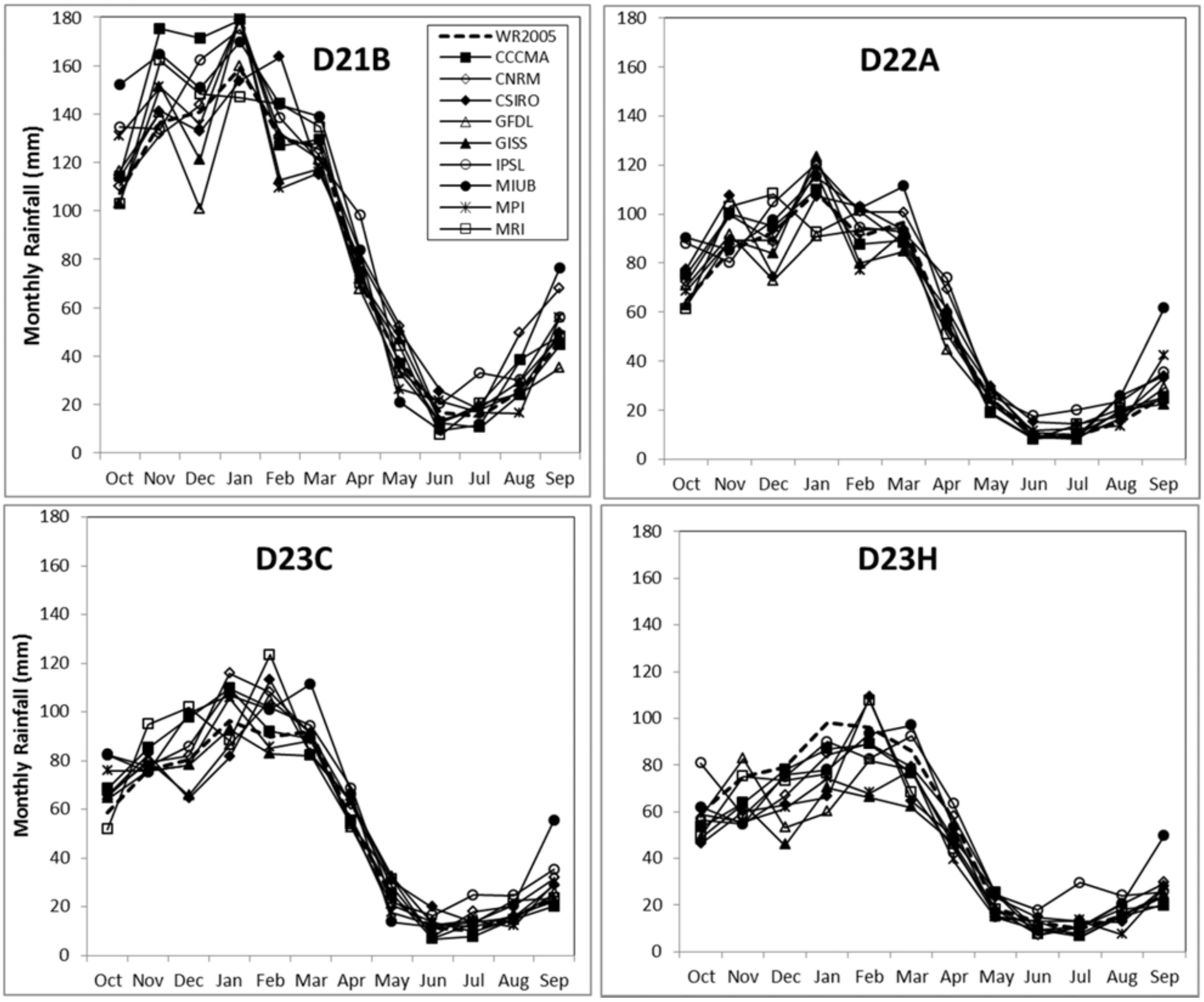



Figure 6.3 Monthly rainfall variation of the corrected GCM near future scenario (2045–2065) and the observed rainfall (1961–2000).

The predicted amounts of rainfall in terms of maximum, minimum and median of future rainfall relative to the observed amounts for each calendar month from all the GCMs are shown in Figure 6.4. There is a significant disparity amongst the GCMs with regard to both the magnitude and signs of the predicted rainfall changes (Figure 6.4). The GCMs generally indicate that the highest percentage increase in future rainfall will occur during the winter season in all the catchments, except D22A which will occur in September. According to Figure 6.4 some models suggest more than a 100% increase in rainfall for the month of July. Relatively smaller increases are also suggested for the rainy months. However, given the low values of the historical rainfall data for the dry winter season, the large percentage changes are unlikely to be important from a hydrological response perspective.

Quaternary catchments receiving lower annual rainfall amounts appear to be the ones expected to experience the highest changes, with one GCM predicting a decrease of 25% in D23H and one indicating an increase of 20% in D23C. On the other hand, the wetter catchments (D21B and D22A) are expected to have a narrower range of rainfall change. The models indicate that both catchments are expected to receive between -5% and +15% increase in annual rainfall. In general, there is a higher degree of change in future rainfall in low rainfall months than in the wetter season. Additionally, there is no indication of significant changes in total annual rainfall amounts between the observed data and the bias corrected near-future GCM simulations. If the median value is used as a statistic indicator, as is the case in many studies (e.g. Murphy *et al.,* 2004; Schulze, 2012), the immediate observation would be that catchments D23C, D21B and D22A will receive a slightly increased (<10%) total rainfall amount, while only D23H will experience reduced amounts of future rainfall.

The nine climate models used in this study predict varying future changes in the amount of rainfall within the Caledon Basin. Monthly rainfall probability curves in Figure 6.5 present the range of expected changes across the nine GCMs expected to occur at given probabilities. Most of the time, the observed rainfall falls between the projected range of change. This indicates that for almost all of the time there is at least one climate model that predicts a decreased future rainfall amount and one an increase in rainfall.

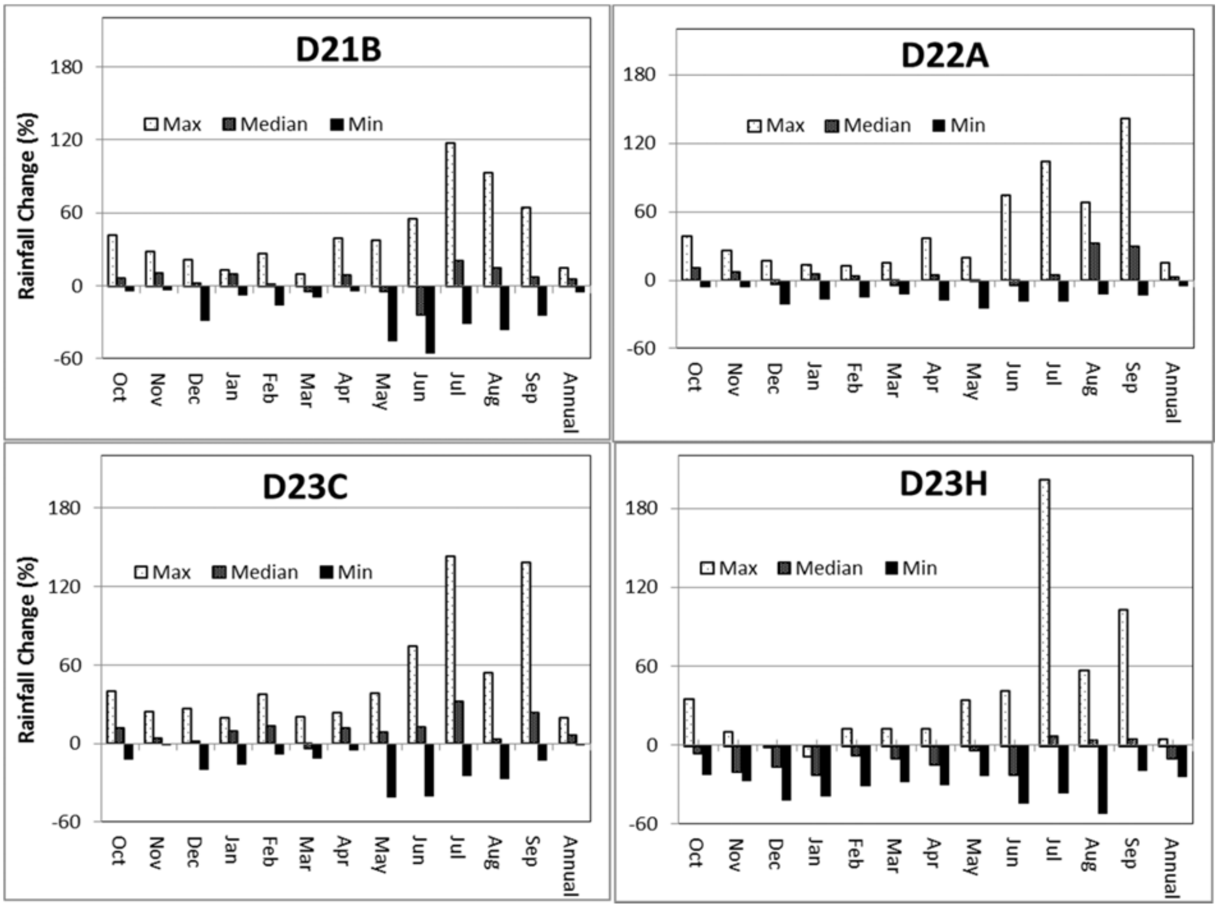



Figure 6.4 Percentage change of corrected future (2045-2065) from the historical (1961-2000) rainfall aggregated for all the nine GCMs.

Figure 6.5 also shows that the probability curve of the observed rainfall lies below the predicted range of change at rainfall depths of about 10 mm and below. This suggests that the climate models unanimously agree that there will be a slight increase in the low rainfall amounts that are equalled or exceeded about 75 to 99% of the time. The degree of discrepancy amongst the models appears to vary across the catchments as the uncertainty bands (difference between the minimum and the maximum) of predicted rainfalls appear to be narrower in the wettest catchment (D21B) and widest in the drier part of the basin (D23H).

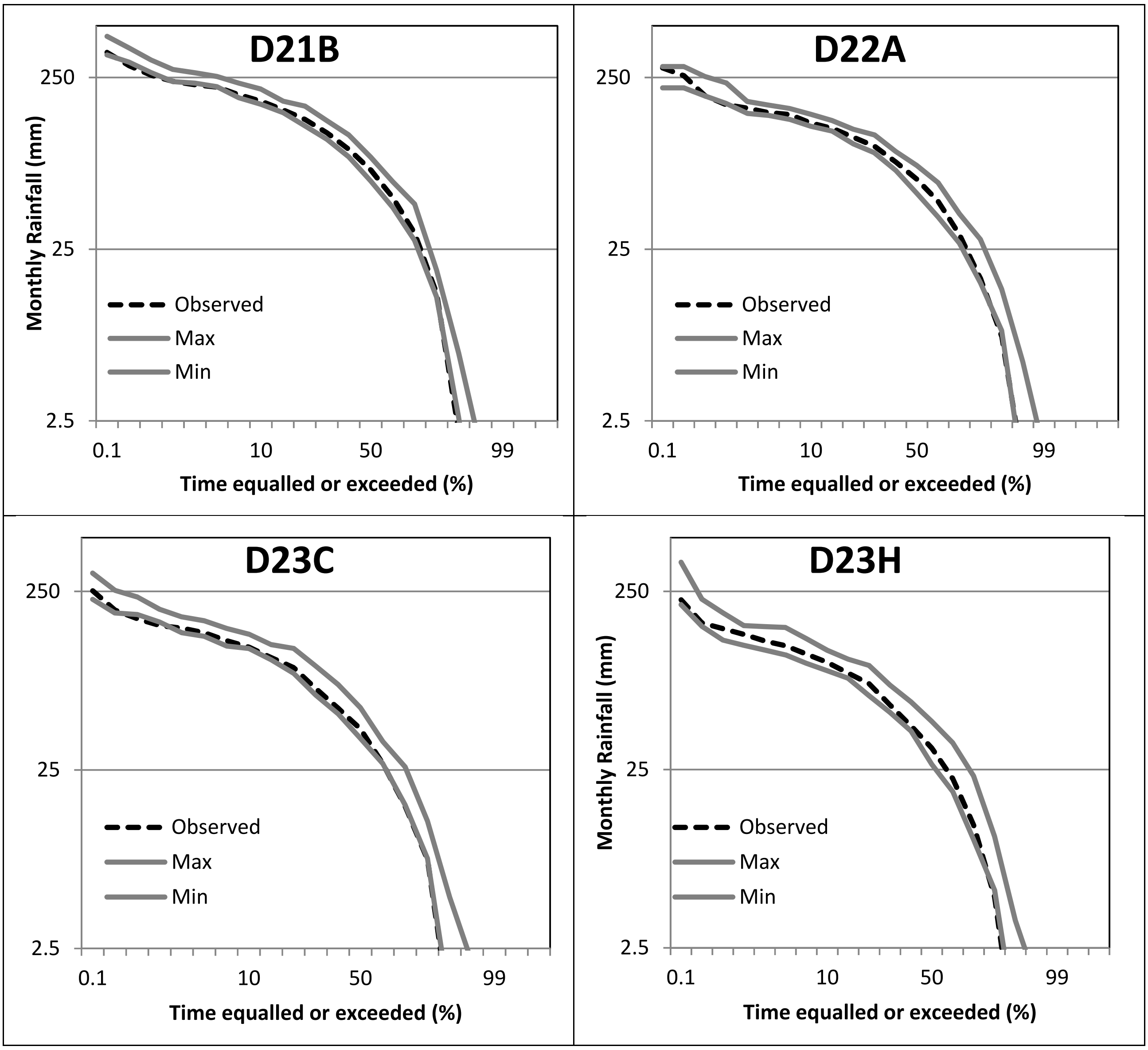



Figure 6.5 Comparison of the observed (1920-2005) monthly rainfall to the range of future climate scenario (2045-2065) aggregated from the nine climate models.

#### 6.1.4.2 Temperature and Evapotranspiration

The historical runs of the hydrological model are based on fixed mean monthly evaporation demands (PE: potential evapotranspiration) taken from studies such as WR90 or WR2005 and no allowance for time series variations in PE were included (although these can be catered for by including time series inputs of deviations from the monthly means, if such information is available).

There are several methods for estimating evapotranspiration developed over many decades. The methods are generally classified into different groups including: water-budget (Guitjens, 1982), mass-transfer (Harbeck, 1962), radiation (Priestley and Taylor, 1972), and temperature-based methods (Thornwaite, 1948; Hargreaves, 1975). A relatively simple approach has been adopted here. Maximum and minimum temperature data for the baseline and future climate model scenarios were used to determine the temperature component of the temperature-based Hargreaves method (Allen *et al*., 1998) as explained in Chapter 4. The percentage increases in these values, from baseline to future, were then used to scale the historical seasonal distributions of potential evaporation when running the Pitman hydrological model for future scenarios.

The approach adopted in this methodology ignores the other components of the Hargreaves equation (relative humidity and wind speed), which are assumed to remain unchanged between the baseline and future scenarios. While this assumption may not be valid, no information is currently produced through the standard downscaled meteorological variables to estimate the differences between baseline and future conditions. The daily values are used to compute mean monthly values for all calendar months and a seasonal scaling factor computed for changes for the individual GCMs from baseline to near-future scenarios (see Chapter 4 for further details).

Figure 6.6 illustrates the results for two of the GCMs (CCCMA and CNRM) and compares the Hargreaves-based evaporation demand results with the change results based on mean temperature only. For the four quaternary catchments used as examples, the variations and increases in both temperature and evaporation are generally close to each other, with the exception of minor differences between the two variables. However, some differences are noted in the patterns of temperature change between the two models. There is an indication from Figure 6.6, as suggested by both climate models, that the Caledon Basin is likely to experience substantial increases in both temperature and evaporation demands.

The climate models predict an increase of evaporation of up to 30% during the dry winter season, while the rainy season is expected to experience lower increases (12–18%). Even though only two GCMs and four sample sub-basins are used here to represent the spatial variability of both climatic and physiographic conditions over the Caledon, there is an indication that the entire basin is likely to become drier and warmer in the near future (2046–2065). One of the possible consequences of such a condition is a decrease in the magnitude of streamflow and hence less water resources available in an already water-scarce region of southern Africa. The increases in evaporative demand during the dry season may have little impact on the stream flow simulations as actual evapotranspiration is more likely to be determined by water availability than evaporative demand. However, higher dry season temperatures and evaporative demand might heavily impact on water demands for irrigation.

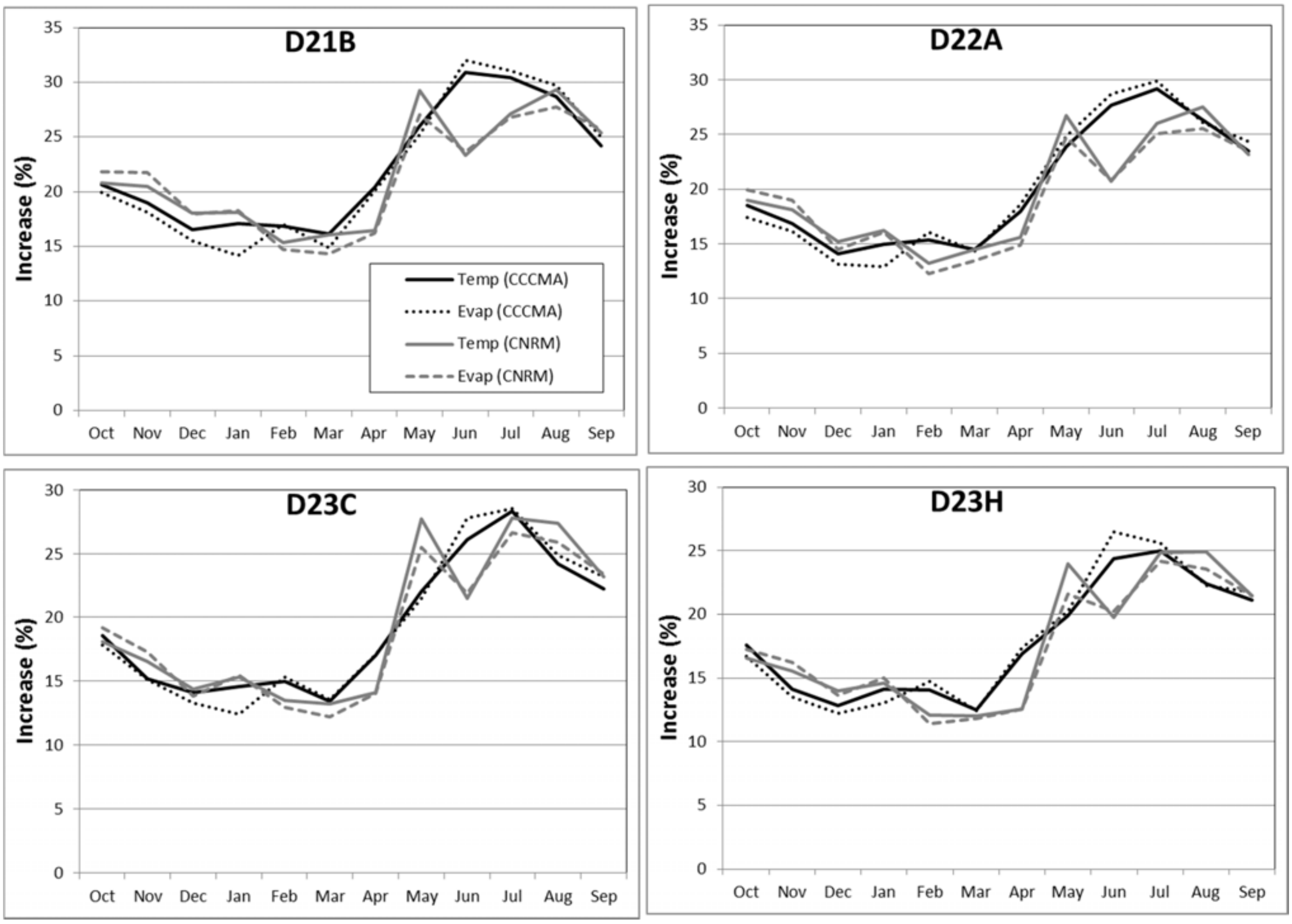



Figure 6.6 Change in future (2046-2065) mean monthly temperature and evapotranspiration predicted by CCCMA and CNRM climate models.

### 6.2 DAILY RAINFALL ANALYSES

In the previous section of this chapter, future climate change scenarios were discussed in terms of monthly variations in keeping with the monthly time-step hydrological models used throughout this study. However, monthly data sets can potentially mask some possible changes and signals in climate signatures that may occur at shorter temporal scales. This section therefore analyses the original daily rainfall data sets (at the quinary scale) for the nine GCMs to identify if there are any predicted changes that might be obscured by the use of a monthly hydrological model. These assessments are based on the differences predicted by the nine

GCMs between their baseline and future scenarios without any reference to historical observed data.

The CSAG downscaled rainfall data from the 9 GCMs, for the near-future (2046–2065) and the far-future (2081–2100) climate scenarios are compared to the equivalent climate model baseline data (1961-2000). Because the objective of this section is to compare the rainfall changes predicted by each of the GCMs, in this analysis, rainfall data sets are used in a raw format and have not been corrected for bias with reference to the WR2005 rainfall characteristics. The raw CSAG data are based on quinary catchments and two sample quinary catchments are selected from the different quaternary catchments of the Caledon Basin referred to in the previous section of this chapter.

The two quinary catchments are 1749 and 1676 located in quaternary catchments D23C and D21B, respectively. Quinary 1749 lies within the more arid westerly parts, while 1676 is within the wetter mountainous Lesotho parts of the basin in the northeast. These quinaries do not in any way fully represent the climate situation in the Caledon River Basin as a whole but are used to illustrate any diversity in the predictions from the climate models, as well to showcase the degree of uncertainty in their outputs.

Three analytical methods were used to detect any statistical variation in the daily rainfall characteristics of the baseline and near future climate scenarios as predicted by the nine climate models. The three methods are: annual and seasonal threshold analysis, probability of exceedence analysis, frequency of occurrence of dry spells.

### 6.2.1 Annual and Seasonal Threshold Analyses

For hydrological studies as well as water resources planning purposes, different rainfall thresholds represent different issues of importance. While low rainfalls and the amount of time between their exceedance may be used to represent agricultural drought conditions, higher rainfall thresholds are likely to be more important with respect to stream flow droughts. In this part of the study the maximum number of days of ‘dry spells’, defined as cumulative rainfall below several prescribed thresholds of 2, 5, 10, 15, 20 and 50 mm were determined for all the models for the three climate scenarios. The maximum lengths of the dry spells were analysed using all the data (annual time scale) as well as separate seasonal analyses, based on summer (October– March) and winter (April–September).

*Quinary 1676*

Analysis of the results for this region of the Caledon Basin revealed that 6 out of 9 models predict a decrease in the maximum number of consecutive days with rainfall less than the prescribed thresholds of 2, 5 and 10 mm, for the two future scenarios. IPSL predicts the highest rate of decrease for most of the thresholds in the near-future (Figure 6.7). On the other hand, the majority of the models predict a reduced maximum period of dry days below 10 and 15 mm (Figure 6.7). On the annual scale, there is a trend amongst the GCMs that the dry spell durations may decrease in the near-future and more into the far-future, with an exception for the 50 mm threshold where the durations are shown to mostly increase from the near-future to the far-future.

While the dry spell durations are shorter for the wet season compared to the dry season (Figures 6.8 and 6.9), there is a similar general trend of decreasing length of dry spells from the baseline to the two future scenarios (with few exceptions). This trend does not persist from the near to the far future, in which case there is a substantial disagreement amongst the GCMs.

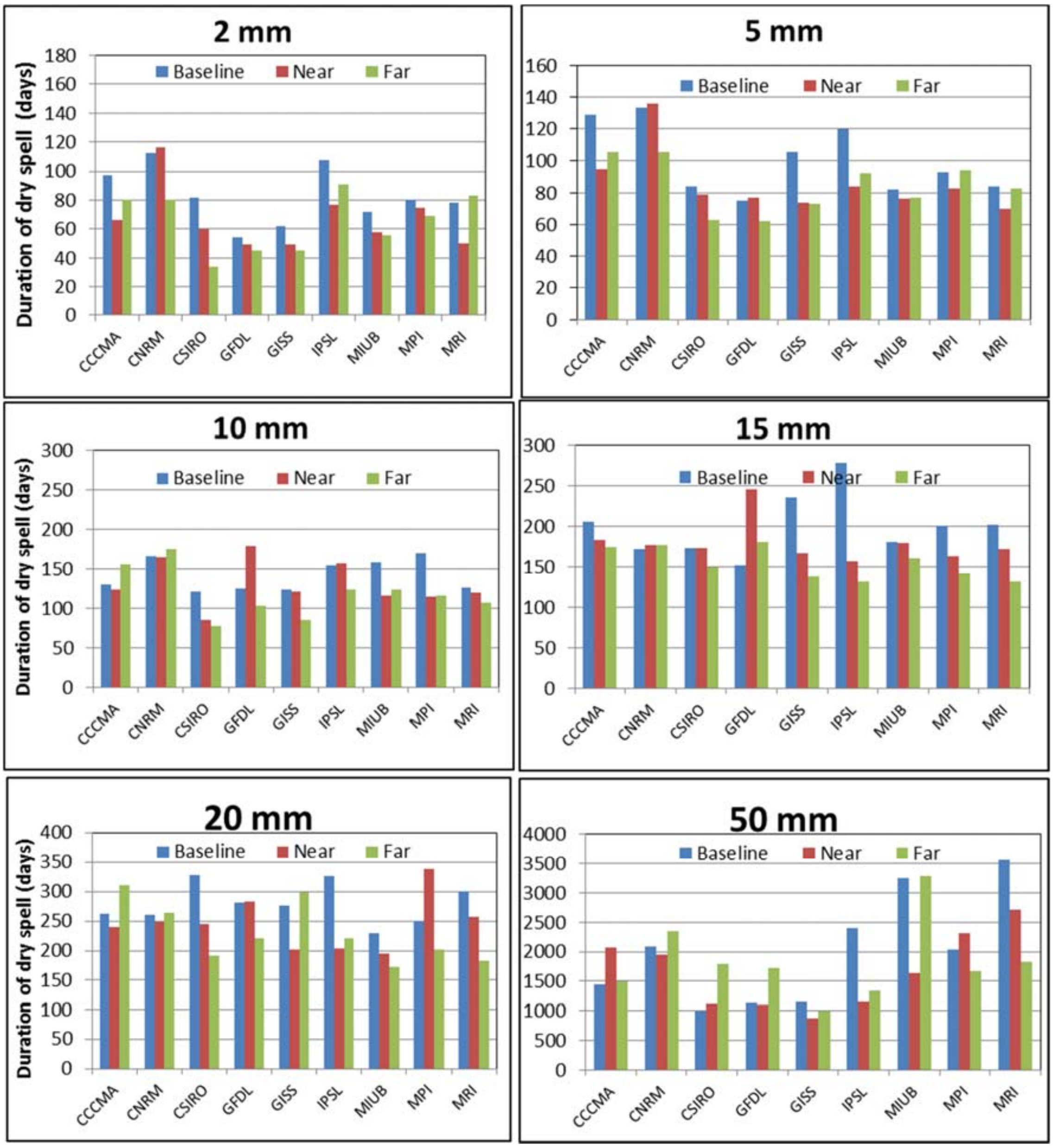



Figure 6.7 Length of dry spells with rainfall below the specified thresholds for an annual time scale at Quinary 1676.

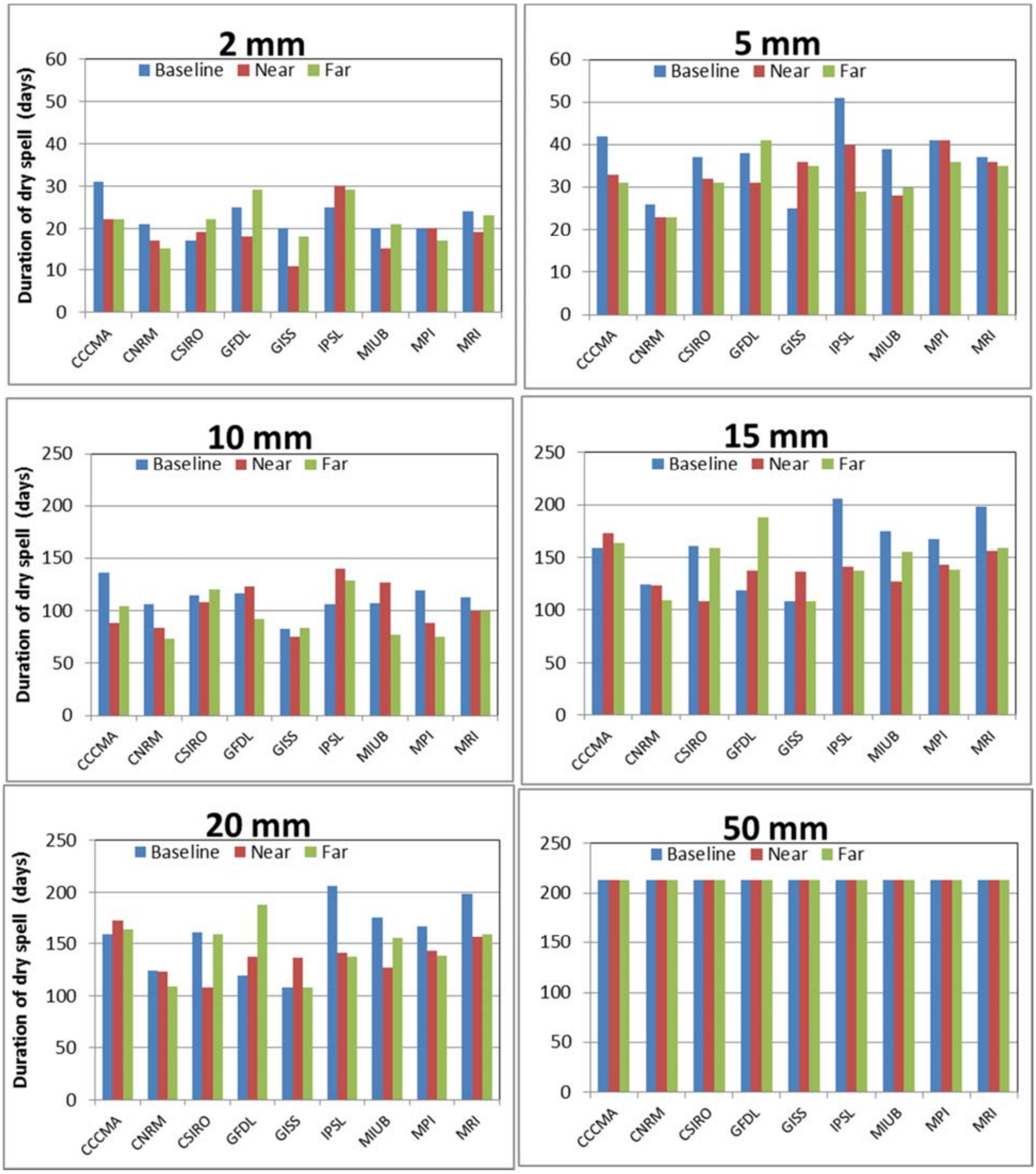



Figure 6.8 Duration of dry spells below the specified rainfall thresholds at Quinary 1676 for the wet summer season.

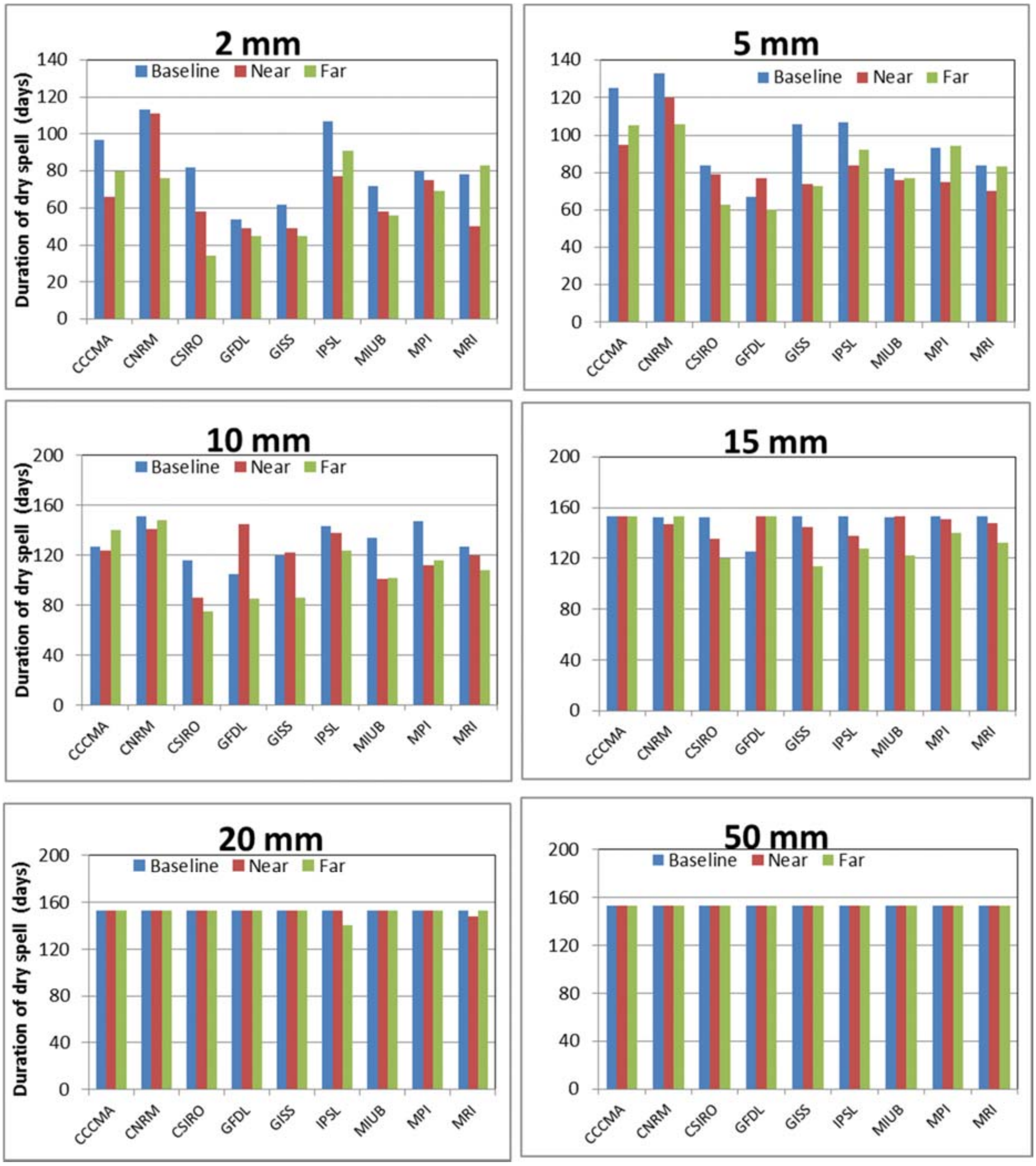



Figure 6.9 Duration of dry spells below rainfall of the specified thresholds at Quinary 1676 for the dry winter season.

*Quinary 1749*

For this portion of the Caledon basin, eight out of nine GCMs predicted that the duration of the maximum number of consecutive days with rainfall less than 2 and 5 mm would decrease during the far-future climate scenario. MRI indicates a progressive prolonged dry-day durations for the 2 mm and 5 mm thresholds, from the baseline to the near future and more to the far-future (Figure 6.10). Similarly, CNRM is the only model that consistently suggested that such dry periods would be marginally increased in either of the two future climate scenarios for almost all of the rainfall thresholds. For the higher rainfall threshold of 15, 20 and 50 mm the models do not clearly depict which direction the dry day durations would adopt in the future. It is however, noticeable that IPSL consistently indicated the sharpest decreases in the lengths of dry day duration periods and that GFDL showed a remarkable decrease in dry days for the 15 mm threshold.

Within the Caledon Basin, the data for Quinary 1749, which is in the drier part of the basin, suggested a reduction in the duration of dry spells below the low rainfall thresholds of 2 and 5 mm during the wet season (Figure 6.11). However, it is very difficult to make any generalisations for either of the Caledon sample points. The general trend of decreased lengths of dry spells indicated in the annual and the wet season analyses appeared to prevail even in the dry winter season (Figure 6.12) although there was some degree of uncertainty where some models appeared to predict an increase in the duration of the dry spells. The overall conclusion is that there are few consistencies in the direction and magnitude of change in maximum spells below defined rainfall thresholds. This lack of consistency applies across the different GCMs.

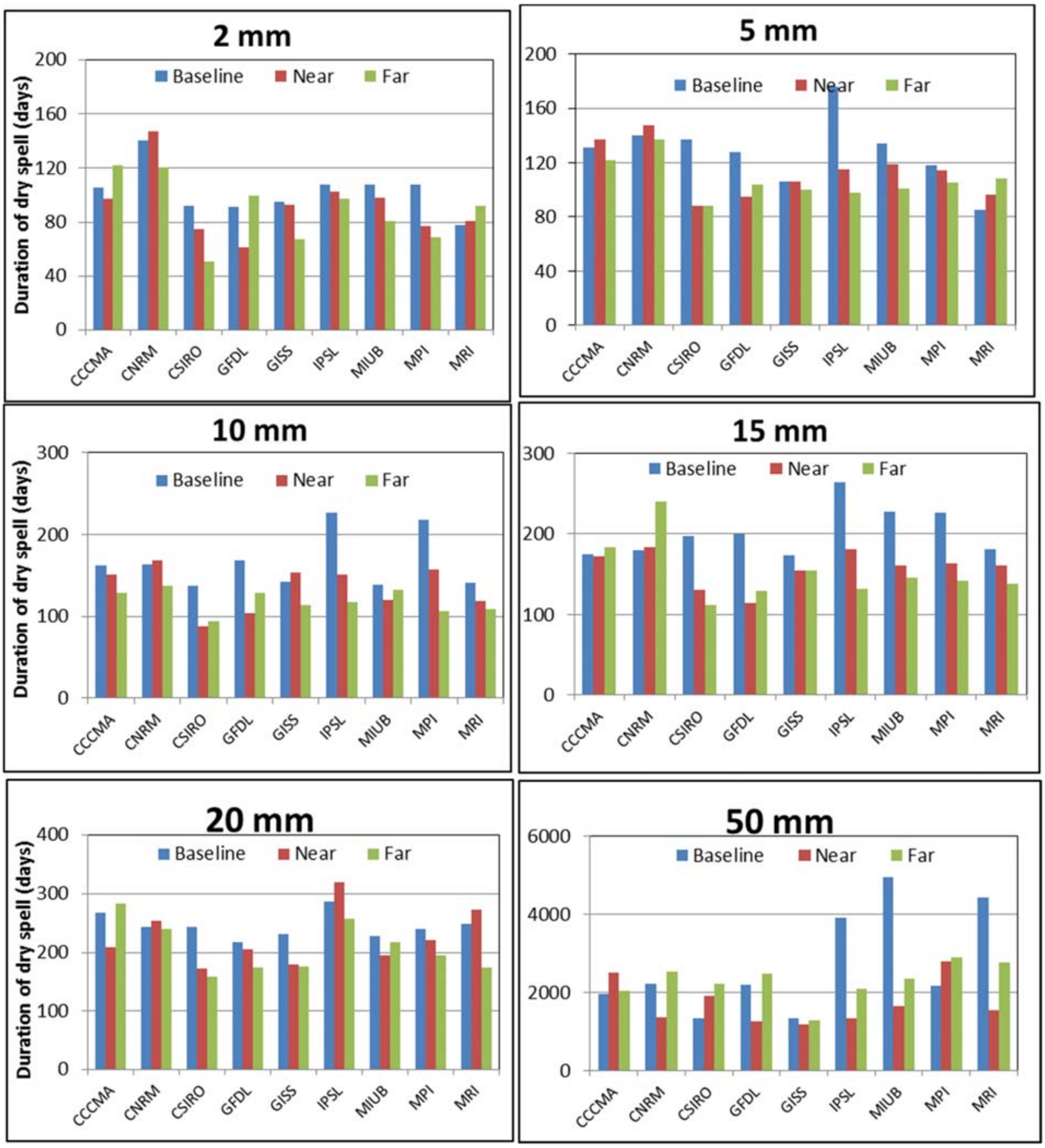



Figure 6.10 Duration of dry spells below rainfall below the specified thresholds at Quinary 1749, on the annual time scale.

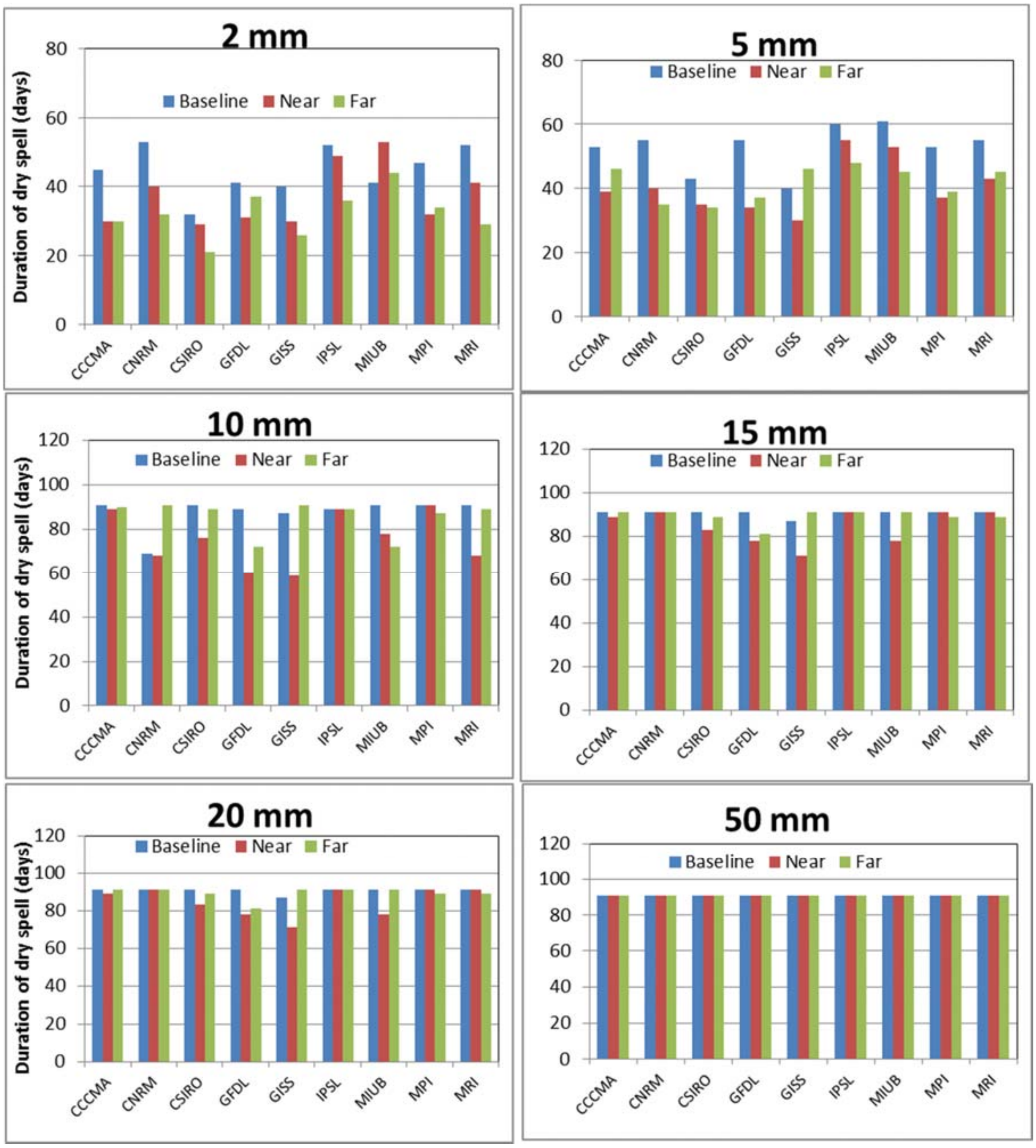



Figure 6.11 Duration of dry spells with rainfall below the specified thresholds at Quinary 1749 for the wet season.

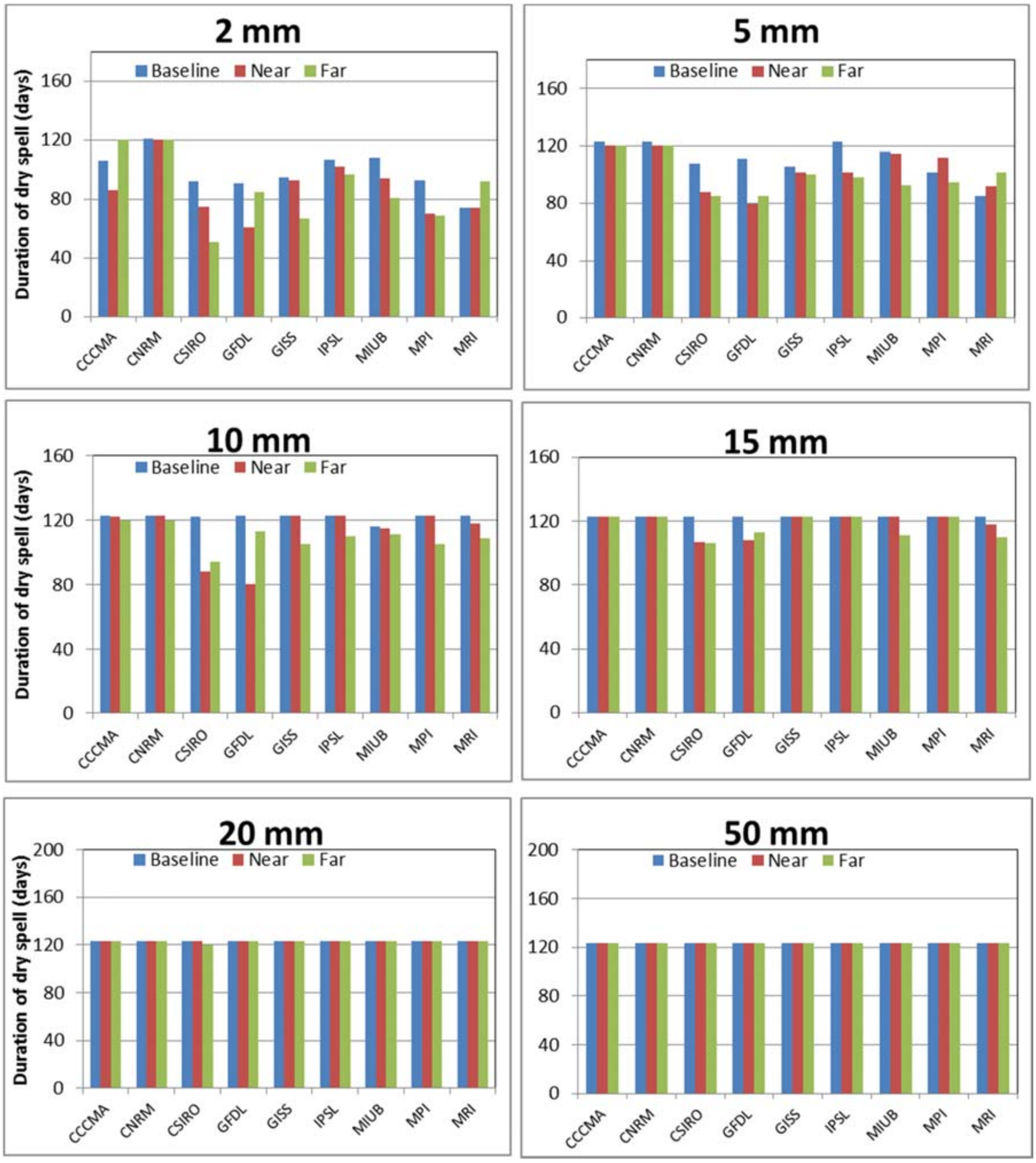



Figure 6.12 Duration of dry spells with rainfall below the specified thresholds at Quinary 1749 for the dry season.

### 6.2.2 Frequency of dry spells

This analysis involves quantifying the frequency of dry spells, defined by cumulative rainfall below thresholds of 5, 10, 20, 50 mm, with durations of 10, 30, 60, 180, 270, 360, 720, 1440, 1800, and more than 1800 days. The results shown in Figure 6.13 are for the quinary 1676. The results indicate that the frequency of relatively short dry spells below the rainfall thresholds of 5 and 10 mm could increase slightly in the two future climate scenarios. The trends of predicted changes for dry spells below higher rainfall thresholds of 20 and 50 mm are somewhat inconsistent. Some models predict increased occurrence, while at the same time, others predict contradictory results.

Results for the quinary 1749 (not shown), in a drier portion of the basin, indicate generally similar trends, with a rather clear trend and agreement with regard to the occurrence of dry spells below the threshold of lower rainfall. Similarly, the pattern of predicted change for the 20 and 50 mm threshold are inconsistent with significant differences between the climate models for the near and far future scenarios.

As with the previous assessments of dry spells, there is little agreement between the different GCMs. However, within individual GCMs there is some level of consistency, such that a predicted increase (or decrease) in frequency of occurrence of dry spells for the near-future typically continues into the far-future.


Figure 6.13 Frequency of occurrence of dry spells for prescribed rainfall thresholds for quinary 1676.

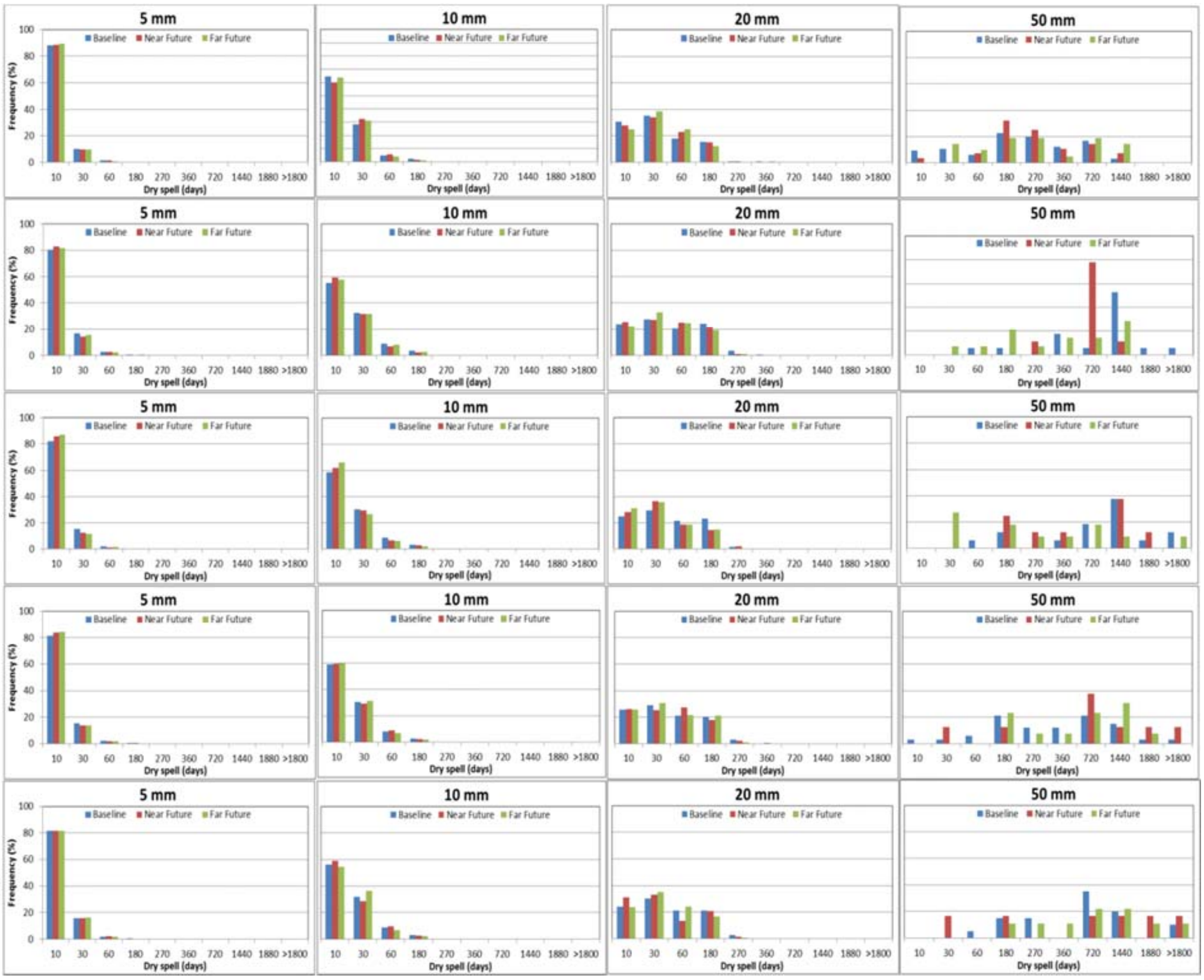



Figure 6.13 (cont.) Frequency of occurrence of dry spells for prescribed rainfall thresholds for quinary 1676.

### 6.2.3 Probability of Exceedence of Rainfall

This part of the analysis addresses the issue of potential changes in high daily rainfalls and is focussed on the changes in the rainfall depths for two percentiles (0.5 and 1.0%) of the exceedance frequency curves of daily rainfall. Two additional percentage points (10 and 15%) have been added to represent moderate to low daily rainfalls, Table 6.2 illustrates that the percentage change of rainfall exceeded in the four percentiles from baseline to near-future and baseline to far-future for quinaries 1676 and 1749. The table shows a substantially high degree of disagreement amongst the climate models. While some models suggest significant increases in the extreme and high rainfalls (exceeded 0.5 and 1% of the time), other GCMs suggest decreases. For the relatively wetter part of the basin (quinary 1676) most of the models predict a slight decrease of up to 10% in both extreme and high rainfall levels. However, there are a few which predict that quinary 1676 may experience an increase in extreme rainfalls, with the highest increase predicted being about 16%. All the climate models agree on an increase in rainfalls exceeded 10% and 15% of the time in the far-future, while there is only one model (GFDL) that indicates a small decrease within the near-future climate scenario.

Quinary 1749 is located on the drier portion of the Caledon Basin than quinary 1676. The rainfall predictions for this sample point show a rather similar trend in terms of changes during the two future scenarios compared to the baseline. Nevertheless, Table 6.2 shows that the predicted increases in all categories of rainfall are of a much larger magnitude. Some models predict as much as a 40% increase in both moderate and low rainfalls in the near-future scenario, while some models predict about 100% increase in low rainfall for the far-future.

As with the previous assessments of dry spells, there is little agreement between the different GCMs, especially with regard to changes in extreme and high rainfalls in terms of direction and magnitude of rainfall change. Conversely, with regard to moderate and low rainfall amounts, the models tend to be unanimous that there will be an increase, though they differ when it comes to the magnitude of the increase. However, there is more consistency within individual GCMs, such that a predicted increase (or decrease) in extreme rainfall for the near-future typically continues into the far-future. It is also of great interest to note that two models, IPSL and MIUB, have almost constantly predicted increases across all rainfall categories, for both future scenarios and within both quinary catchments.

The daily rainfall probability curves for the two quinary catchments simulated by the nine climate models for the three climate scenarios are shown in Figures 6.14 and 6.15. The figures clearly depict that there are more rainy days in quinary 1676 than 1749 and this will persist into the near-future and far-future periods. This prediction is also in line with the historical data records for the two zones which indicate that quinary 1676 receives the highest amount rainfall, whereas quinary 1749 is located in one of the driest parts of the basin.

Table 6.2 Percentage change of rainfall exceeded 0.5, 1, 10 and 15% of the time for near-future and far-future climate scenarios relative to the baseline scenario.

**Quinary 1676**

| % Exceedence | NEAR- FUTURE 0.5 | 1 | 10 | 15 | FAR- FUTURE 0.5 | 1 | 10 | 15 |
|---|---|---|---|---|---|---|---|---|
| CCCMA | 5.9 | -2 | 7.7 | 9.6 | -2.3 | -4.5 | 11.9 | 14.8 |
| CNRM | -2.4 | -0.1 | 11.2 | 6.6 | 1.4 | 0.8 | 19 | 13.6 |
| CSIRO | 0.3 | 2 | 8 | 8.4 | -2 | 2.3 | 18.9 | 16.5 |
| GFDL | -1.4 | -0.3 | -7.7 | -6.2 | 0.4 | -1.1 | 5.5 | 1.7 |
| GISS | -0.8 | -2 | 1.7 | 3.7 | -5.9 | -2.8 | 7.3 | 8.1 |
| IPSL | 15.8 | 7.7 | 15.8 | 14 | 17.8 | 6.9 | 14.1 | 14.9 |
| MIUB | -6.2 | 1.9 | 11.5 | 12 | 1.1 | 5 | 18.1 | 18 |
| MPI | -4.6 | -11.5 | 5.2 | 7.4 | 2.5 | -1.6 | 9.3 | 13.8 |
| MRI | 2.6 | 6.4 | 4.2 | 3.9 | -0.3 | 2.7 | 4.8 | 5.6 |

**Quinary 1749**

| % Exceedence | NEAR- FUTURE 0.5 | 1 | 10 | 15 | FAR- FUTURE 0.5 | 1 | 10 | 15 |
|---|---|---|---|---|---|---|---|---|
| CCCMA | 0.6 | 2.8 | 11.8 | # | -3.3 | 5 | 13.8 | # |
| CNRM | 3.6 | 0.7 | 17.6 | 46.2 | 2.2 | 3.5 | 29.8 | 103.8 |
| CSIRO | -0.4 | -7.2 | 14.3 | 21.1 | -0.7 | -2.5 | 26.4 | 64.5 |
| GFDL | 3.7 | 1.2 | -2.6 | 11.6 | 0.6 | -0.3 | 9.2 | 32.6 |
| GISS | -0.6 | -4.6 | 6.7 | 32.3 | 1 | -0.1 | 7.3 | 45.3 |
| IPSL | 10.3 | 13.3 | 41.5 | # | 3.8 | 5.6 | 30.2 | # |
| MIUB | 1.5 | 6 | 25.2 | # | 0.03 | 1.5 | 46.1 | # |
| MPI | 2.6 | -5.2 | 3 | # | -0.3 | 1 | 9.6 | # |
| MRI | 6.4 | 4.9 | 15.1 | # | 3.8 | 4 | 12.9 | # |

# Represents calculations involving zero rainfall values.

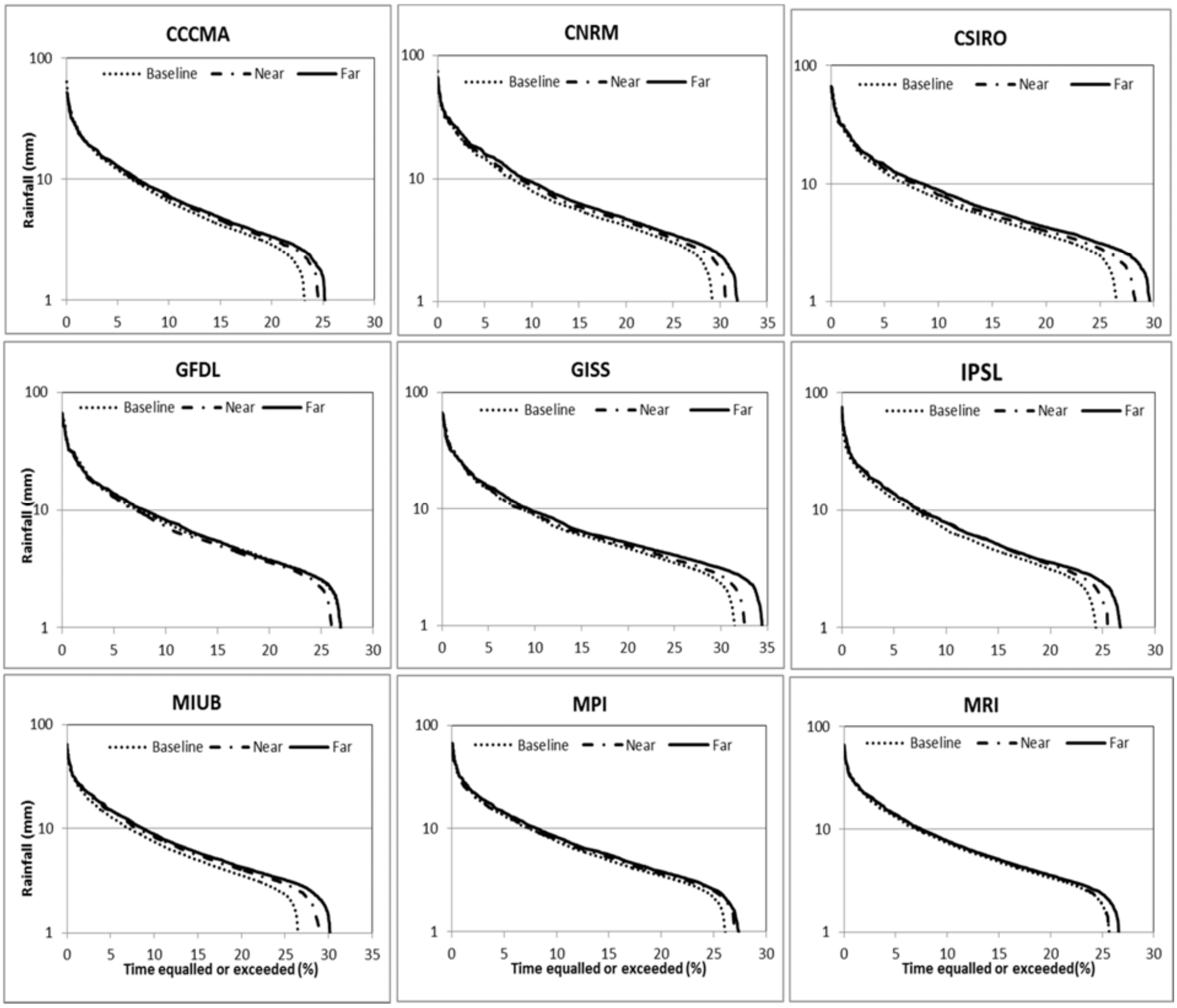



Figure 6.14 Probalility charateristics of daily rainfall simulated by a set of climate models for baseline and near- and far-future climate scenarios in quinary 1676.

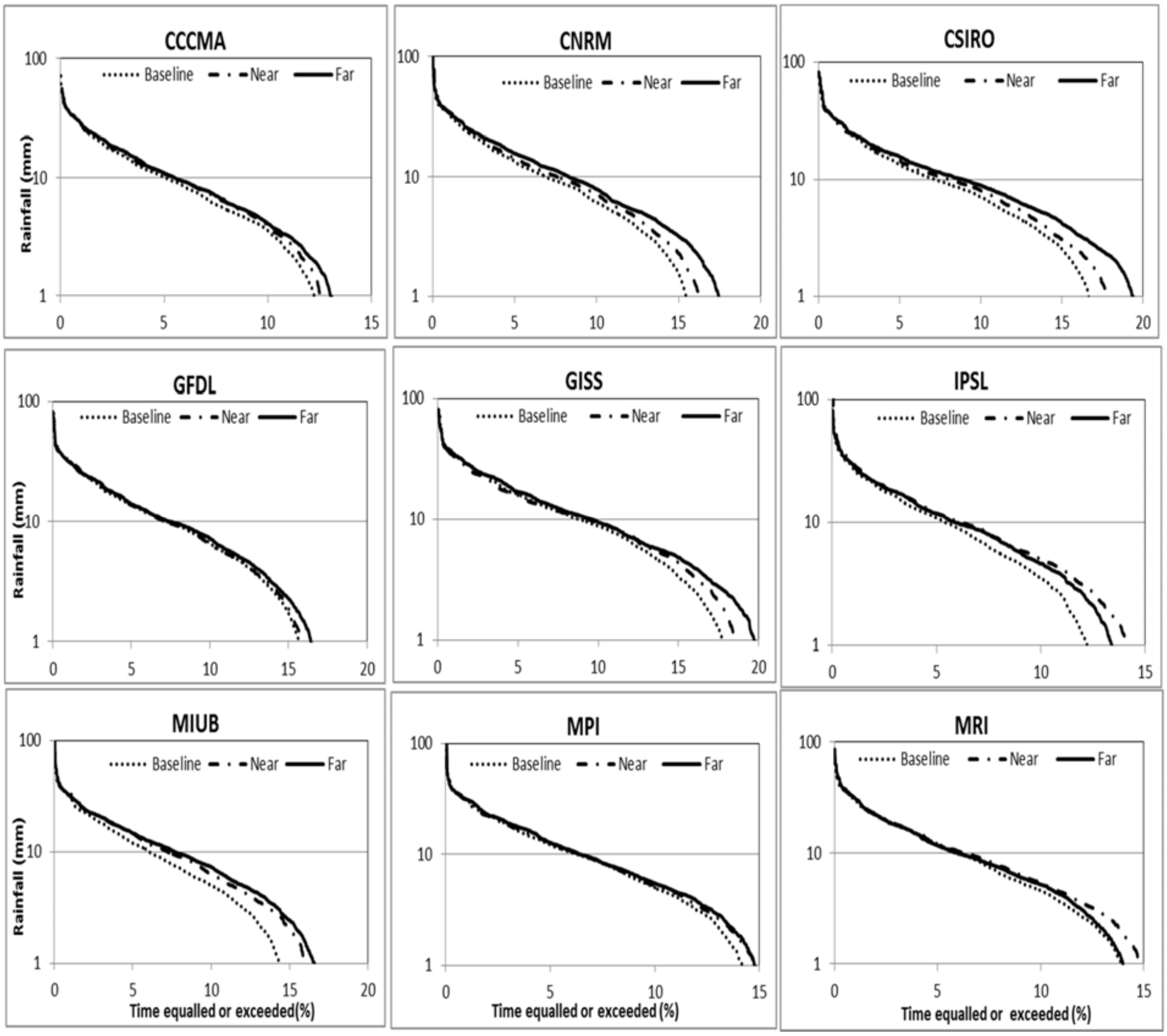



Figure 6.15 Probalility charateristics of daily rainfall simulated by a set of climate models for baseline and near and far-future climate scenarios in quinary 1749.

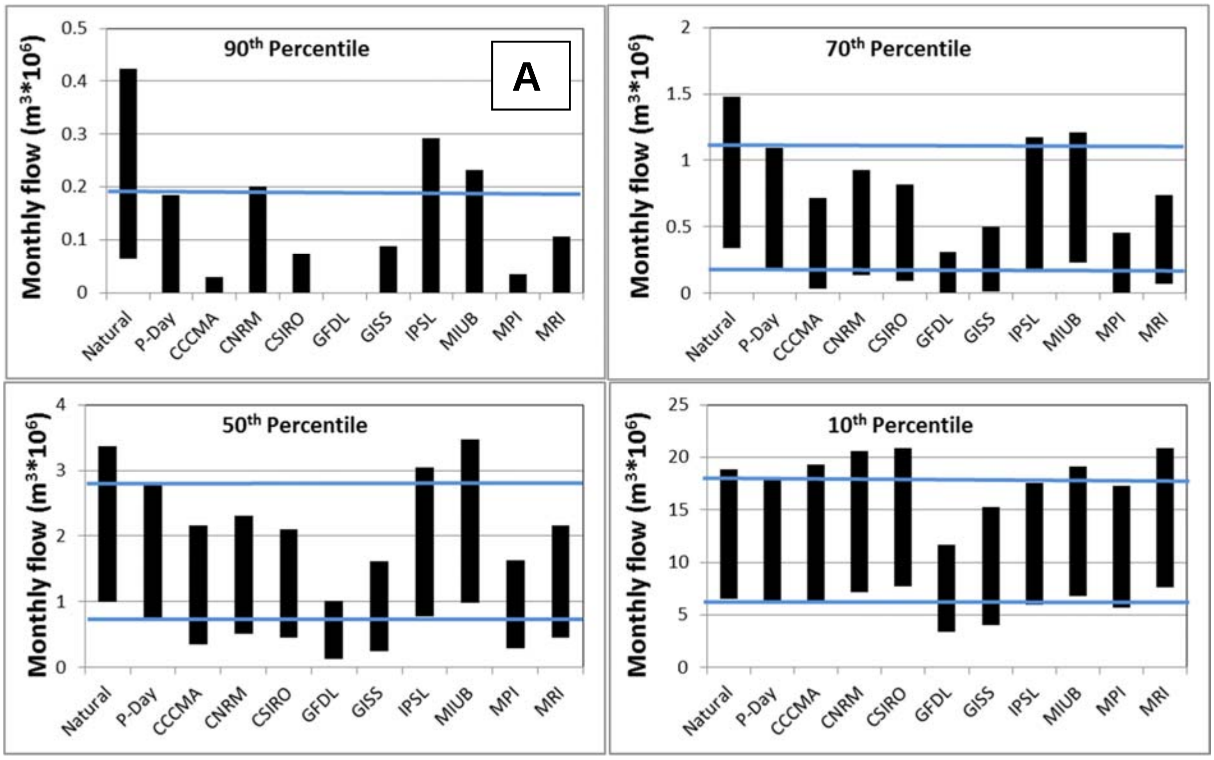
There is a great deal of uncertainty in the analysis of the occurrence and lengths of dry spells, such that there is no decisive conclusion on whether and how the hydrological conditions of the Caledon River Basin will change in the future or not. The GCMs do not predict a unanimously clear pattern of the characteristics of the future occurrence of dry spells. Similarly, the GCMs also disagree on the amount of change of heavy rainfall (occurring at 0.5 and 1.0% of the time) of future (near and far) climate scenarios relative to the baseline. However, the GCMs consistently agree that moderate and low rainfalls (occurring at 10 and 15% of the time) will increase in the future, though they differ on size of the change. There is no clear indication about such changes from the near to the far-future. Generally speaking, the daily rainfall analyses do not seem to provide any more significant information of hydrological relevance than the monthly rainfall analyses. This is mainly due to the fact that there is a great deal of uncertainty in the rainfall output of the GCMs.

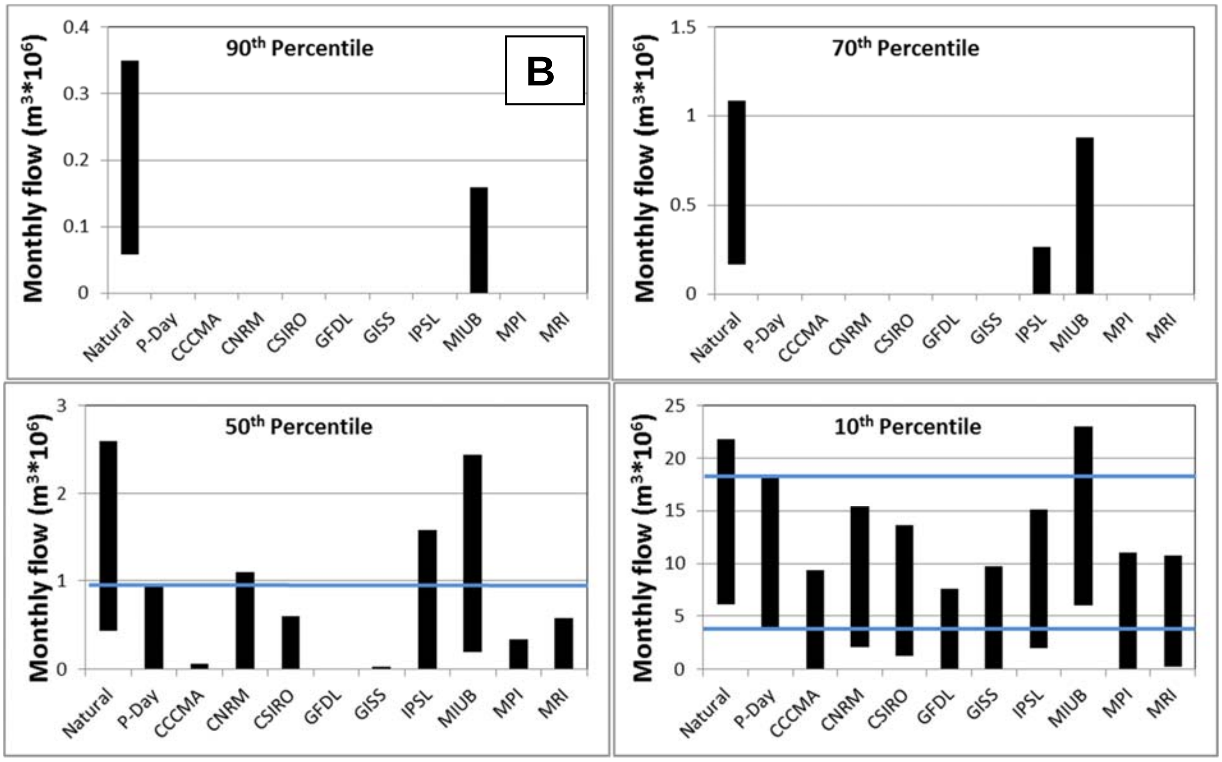
## 6.3 CLIMATE CHANGE IMPACTS ON HYDROLOGY

Prediction of future hydrological conditions of the Caledon River Basin involves the use of predicted climate change data (rainfall and evaporative demands) as inputs to the hydrological models that have already been parameterised for current climate and water use conditions. The first step in this procedure entailed establishing a set of behavioural parameter uncertainty bounds using the historical data sets (as discussed in chapter 5). This is then followed by replacing the historical climate inputs with time series representing possible future conditions, and assuming (at this stage of the analysis) that water use demands will remain stationary into the future. While the assumptions that both the model parameter values and the water use will remain the same into the future are almost certainly not valid, it was beyond the scope of this study to speculate on how these would change in response to future climate regimes. It would be necessary to add further information on crop growth under different temperature and soil moisture regimes in order to determine how natural vegetation (Gao *et al.,* 2014) and irrigation demands might change into the future. Some of this information may be obtained from the climate change simulations presented below and used to change the uncertainty bounds of some of the natural hydrology and water use model parameters. This issue will be further addressed in the final chapter of the thesis.

### 6.3.1 Predictions of Future Streamflow

There are substantial uncertainties in the prediction of future stream flow and water resources availability in the Caledon River based on the projections of climate change used. Stream flow simulation results and observed records from the four example sub-basins across the basin are presented in Figures 6.16 and 6.17. The results indicate that the majority of GCMs used in the current study predict a slight decrease, though they do not agree on the amount of this decrease (Figure 6.16), with GFDL projecting the largest decrease across all the flow levels. On the other hand, only two GCMs (IPSL and MIUB) project a significant increase of low and medium stream flows and slight increases in high flows relative to the historic present day flows (Figure 6.16). As might be expected the variations across the GCM projections are greater for the lower flows than for the higher flows. The effects of these low flow changes are exacerbated when the present day water uses are included in the modelling and within the drier sub-basins (see Figures 6.16b and 6.16c for the high percentiles). Where the future climate impacts suggest lower and zero flows at high percentiles it is likely that some of the required water uses will not be met and therefore the impacts on water resources might be even greater than is indicated by Figures 6.16 and 6.17. Even though some of the climate models had projected increased rainfall amounts, the effects have been offset by increased rates of evapotranspiration resulting from increased temperatures. It is worth noting that while there is a strong disagreement amongst the GCMs on direction and magnitude of change of rainfall, they are far more consistent in their projections of increases in temperature, and hence evaporative demands. The combined uncertainties across all of the GCM predictions are shown in Figure 6.17. It is evident from Figure 6.17 that the uncertainty margin of GCM predictions is much wider than the historical uncertainties. For example, if the outputs of all the GCMs are considered to be equally plausible, there is a possibility that median flows (occurring at least 50% of the time) can increase by as much as 50% relative to present day simulations, as predicted by the MIUB model, or might decrease by the same amount according to GFDL (Figure 6.16).




B
90th Percentile
70th Percentile
50th Percentile
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Monthly flow (m3*106)
Natural
P-Day
CCCMA
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GFDL
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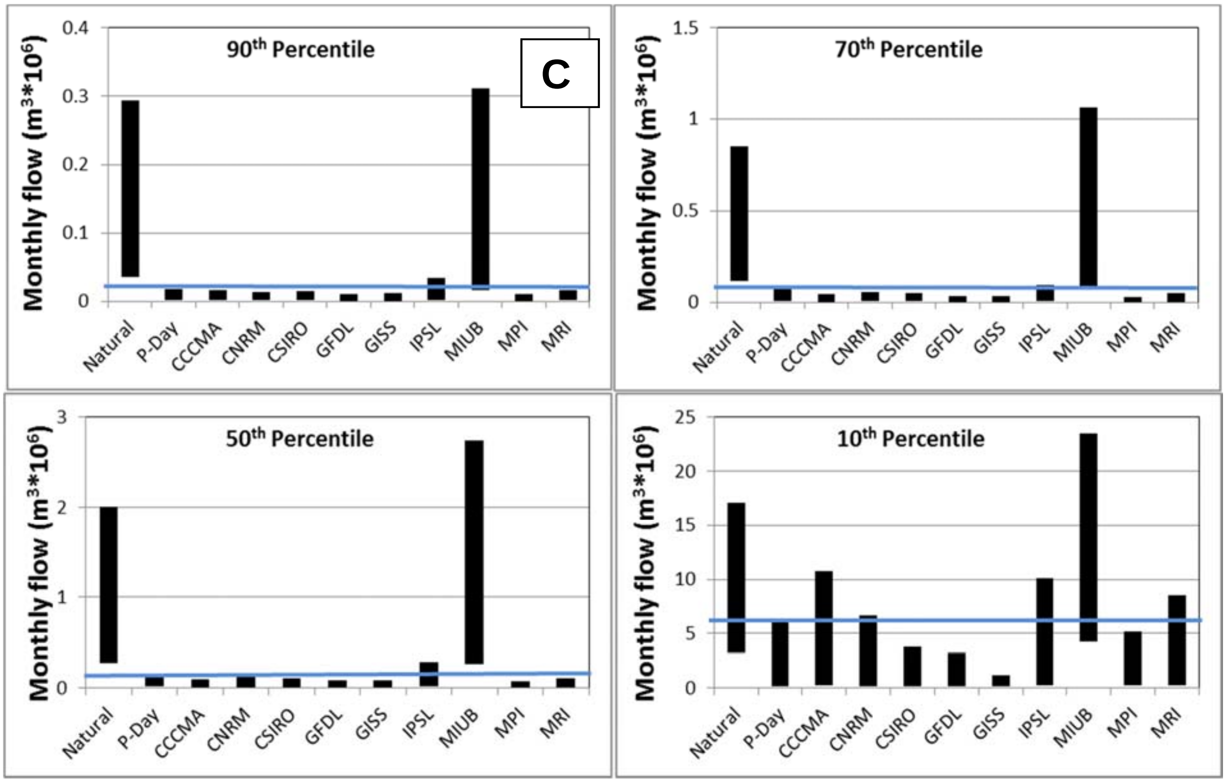
IPSL
MIUB
MPI
MRI


C
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Monthly flow (m3*106)
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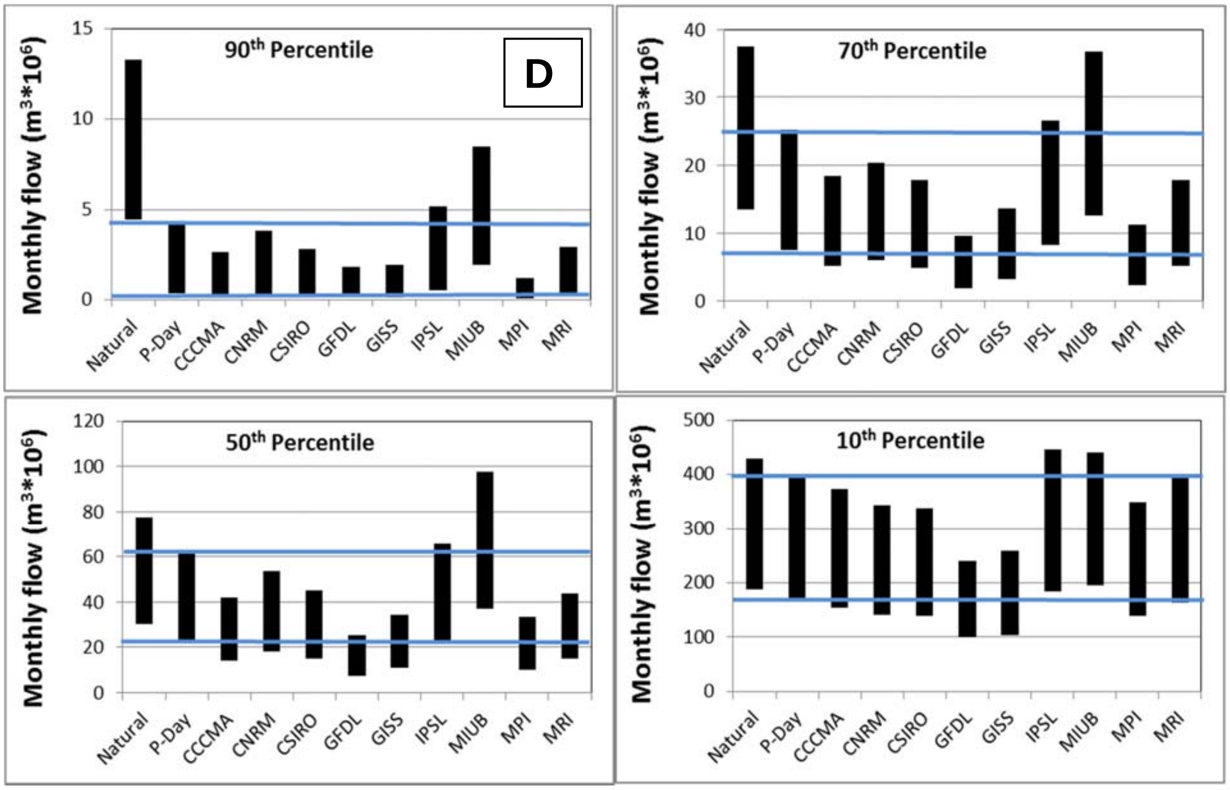


Figure 6.16 Uncertainty bands of selected quantiles of the flow duration curves for flow simulations at sub-basins D21E(A), D22B(B), D23D(C) and D23F(D) . The natural and present day simulations are for 1920 to 2005, while those based on the GCMs are for 2046 to 2065. The blue horizontal lines represent the uncertainty bounds of the present day simulations.

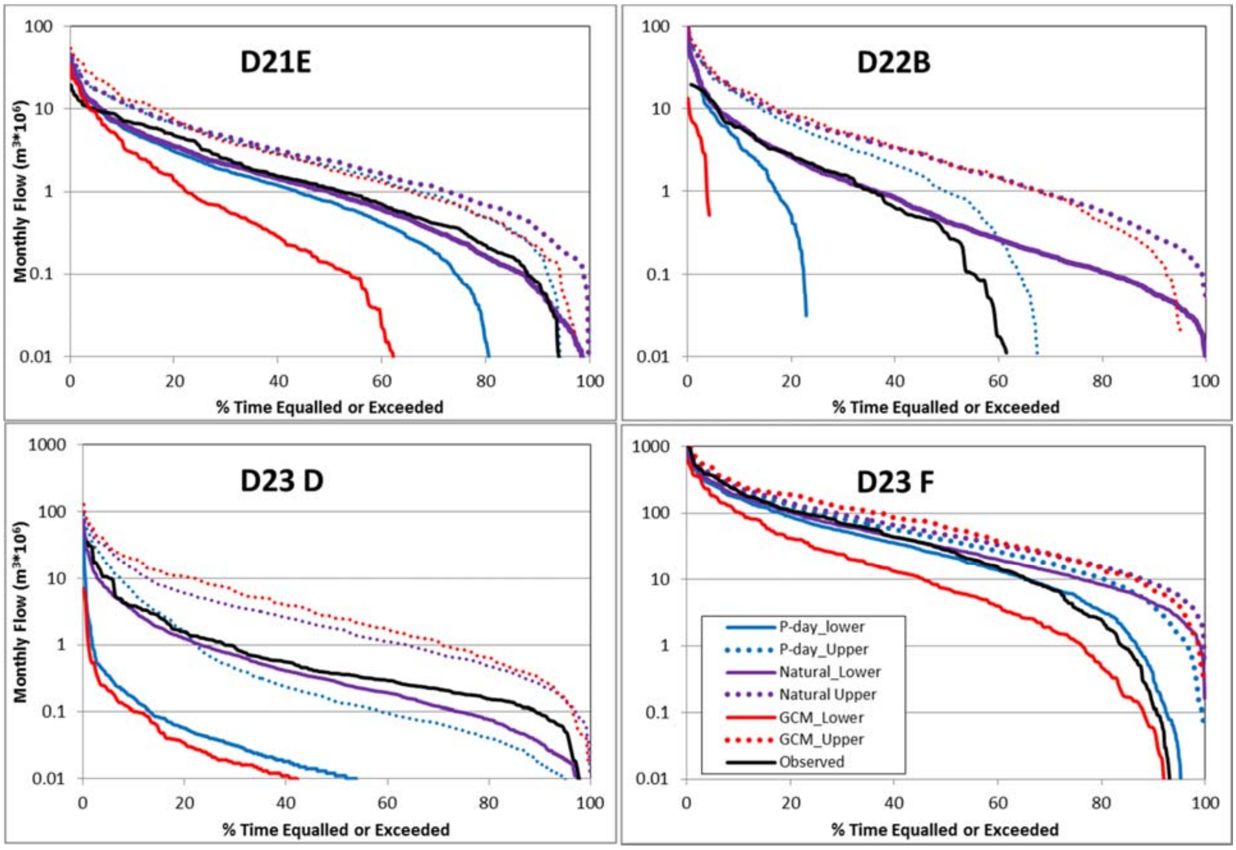


Figure 6.17 Current and predicted future streamflows at four quaternary catchments simulated by the Pitman model, under possible future evaporatranspiration and rainfall regimes projected by 9 climate models.

## 6.4 SUMMARY

The bias-corrected future monthly rainfall predictions from all the nine GCMs showed inconsistent results. The models disagree on the magnitude and direction of change in future rainfall for the study area. While some of the models predict decreased rainfall, others indicate an increase in the future rainfall. Similarly, the analysis of daily rainfall did not yield a consistent change of rainfall patterns for the future climate scenarios compared to the baseline. However, the models are unanimous on two issues: firstly, the occurrence of short-duration (10 days) dry spells below 5 and 10 mm rainfall is likely to increase by approximately 5%; secondly, that low daily rainfalls (that is, those which are exceeded 10 and 15% percent of the time) are likely to increase in the two future scenarios. However, they disagree on how much this increase will be.

In spite of the possible increase in rainfall predicted by some GCMs, the general trend across all of the GCMs is for somewhat lower stream flow volumes and this is related to the effects of higher evaporation demand resulting from increased temperatures. Converse to these findings, a study by Graham *et al.* (2011) suggests an annual increase of runoff for the Thukela River Basin, which is located relatively close to the Caledon River in Kwazulu-Natal province of South Africa. For the same evaluation period (2046 – 2065), the South Africa Risk and Vulnerability Atlas of Archer *et al.* (2010) predicts the annual stream flow in the region of the Caledon River Basin to potentially decrease by 10% in some sub-basins and increase by about more than 30% in others. Their study compared the future stream flow to the baseline period (1971 – 1990). Kusangaya *et al.* (2014) reviewed several climate change studies for southern Africa and concluded that stream flow will generally decrease by the middle of this century. These varying inferences bring attention to the degree of uncertainty in the future status of water resource under the influence of climate change.

The results indicate that evapotranspiration in the Caledon River Basin is likely to increase in the future as a result of increased temperatures. There will be more increase during the dry winter seasons than in summer. The assumption that evaporation demand will increase in close relation to temperature is not totally supported by some measurements of evaporation from various parts of the globe. For instance, Roderick and Farduhar (2002; 2004; 2006) reported a decreasing trend in pan evaporation observations over New Zealand and Australia. Similarly, Eamus and Palmer (2004, 2007) and Hoffman *et al*. (2011) reported declining evaporative demands in South Africa. The best explanation for the decreasing pan evaporation can be attributed to decreased wind speed, solar radiation caused by increased cloud cover and atmospheric aerosol content (Roderick *et al.,* 2007). These components of the relationship between meteorological conditions and evaporative demand have not been included in this study as data for both past and future conditions were not available. This therefore constitutes an additional source of uncertainty in the prediction of future water resources availability..

The basic assumption made in the analysis of future stream flow simulations under the influence of climate change is the stationarity of the factors influencing the hydrological processes in the basin. It has been assumed that the parameter ranges established for historical conditions will also be applicable in the future and are not affected by the changing climate patterns in the basin. Additionally, it is assumed that the current rate of water use, monthly distribution and abstractions will remain the same. However, it has been argued that hydrological response, as well as the associated model parameters depends on the climatic conditions (Wagener, 2007; van Werkhoven, 2008; Gao *et al.,* 2014).

While it is acknowledged that the rate of water use might increase to meet the possible increase in irrigation demand due to increased evapotranspiration rates, it is not possible to accurately quantify such increases. Similarly, some parameters used in the Pitman model are related to factors such as land use and cover, both of which are likely to change in adapting to climate change. This will, in turn, have an impact on the parameters used. At this stage it is also not possible to establish the new parameter sets under the influence of climate change. Even though the results indicate a general decreasing tendency, the overall indication is that the estimated stream flow and future water resources availability in the Caledon River Basin is substantially uncertain. Many previous studies have clearly demonstrated the importance of uncertainties in rainfall and evapotranspiration demand data and have attempted to improve the quantification of climate variables through analysis of the existing data (Lynch, 2004) or using satellite observations (Hughes and Mallory, 2008; Sawunyama and Hughes, 2008). However, the fact remains that it is very difficult to reduce the uncertainties without additional data and, unfortunately, these are simply not available.

# 7 DISCUSSION, CONCLUSION AND RECOMMENDATIONS

## 7.1 INTRODUCTION

The Caledon River Basin is located in a generally water-stressed region of the South Africa, with sporadic rainfall patterns and high evaporative losses. The basin and the region as a whole are prone to frequent occurrence of droughts with prolonged periods of rainfall shortage (Rouault and Richard, 2003; Reid and Vogel, 2006). It is widely expected that the area will experience more frequent and severe droughts in the future as a result of climate change (Reason *et al.*, 2005; Stringer *et al.*, 2009; Mirza, 2011). Thus, shortage of available water resources in the basin is expected to be exacerbated. This will potentially lead to negative impacts on, and deterioration of, various socio-economic activities such as agriculture and domestic (rural and urban) water supply. Proper planning for future water resources in the basin requires a comprehensive quantification of the hydrological impacts of climate change, as well as the uncertainties associated with any future predictions.

With adverse hydrological impacts of climate change envisaged, it is necessary to fully understand the current hydrological dynamics and characteristics of the Caledon River Basin in order to obtain sensible predictions for the future. While assessing the current hydrological status and predicting future hydrological changes, there are uncertainties related to various stages of the modeling process. There are also uncertainties introduced by the different projections of future climate conditions from different GCMs. It is therefore essential that such uncertainties be identified, evaluated, quantified and possibly reduced so that they can be incorporated into the decision-making process. This task necessitates the use of appropriate modelling tools and advanced methodological approaches to achieve realistic results. While this study is entirely focused on the Caledon River Basin, the issues of uncertainty in water resources assessments in relatively data scarce areas are common to many other basins, not only in South Africa, but also in many other parts of southern Africa.

## 7.2 HYDROLOGICAL AND CLIMATE CHANGE MODELLING TOOLS

The Caledon River Basin is a relatively large basin in South Africa and consists of more than 30 sub-basins of varying areal extent, topography and physiographic, as well as water use characteristics. For this reason, it is a considerable task to represent the basin in the form of a hydrological model. Selection and identification of appropriate hydrological models for investigation of water resources of the Caledon River Basin is a critical issue. The study used two hydrological models namely, Pitman and WEAP for the hydrological and water resources assessment of the basin. The Pitman model has been successfully applied in South Africa for more than 40 years (Hughes, 2013) and it incorporates the known major hydrological processes relevant to the Caledon Basin. It is also available in different formats, including those that allow for the incorporation of uncertainty ensemble modelling using simple Monte Carlo sampling of the feasible parameter space. On the other hand, the WEAP model presents a rather simpler conceptual structure with fewer parameters to quantify, but includes more components to allow for the simulation of water resources development infrastructure than are available in the Pitman model. This model has not been substantially applied in the region.

The study demonstrated the potential for the WEAP model to be calibrated based on existing Pitman model setups for the Caledon River Basin. The two models performed reasonably well against the available stream flow observations, however, it has to be recognised that these observations are very limited and therefore the quality of the simulations remains highly uncertain. The somewhat reasonable performance of the parsimonious WEAP model was not unexpected as it has been demonstrated by several studies (e.g. Jones *et al*., 2006) that simple models can yield comparable, and sometimes better, results than more sophisticated models. However, the choice of a hydrological model constitutes another source of uncertainty in hydrological modelling. The use of more than one model for hydrological assessment has the advantage of offering more robust results and it has been demonstrated that multi-model predictions are more accurate than individual models (Duan *et al.*, 2007). Establishing the WEAP model also offers an additional advantage because of its additional functionalities (which are not present in the Pitman model) that are essential from the water resources management and planning perspectives.

The 2-step approach of the uncertainty version of the Pitman model used in the current study, which is based on a progressive reduction of uncertainty, ensures that all of the simulated natural incremental flows are behavioral, according to the established local and regional constraints and reflect a catchment's hydrological responses. Thus, the resultant downstream flows comprise only behavioral upstream ensembles. One of the advantages with the 2-step approach is that it enables the constraints can be set with very narrow uncertainty bounds where there is a good quality of observed data. However, there is still substantial uncertainty in ungauged and poorly gauged sub-basins. The approach therefore allows for different levels of uncertainty to be included in basins where the hydrological response in some areas is well understood and known. The approach yielded satisfactory results and was successful in constraining the model parameter ranges. Though the simulated natural stream flow uncertainty bounds were narrow for many sub-basins, they were much wider in others. This is a reflection of the lack of observed stream flow data to represent either the natural or present day development flow regimes of some parts of the basin. One of the critical issues in the approach is the dependence on observed data to set the output constraints. Data quality, quantity and spatial representation still remain a major challenge in the basin. Most of the stream flow records are of relatively poor quality, some with a lot of missing data, most with inadequate recording of high flows and with non-stationary and largely unquantified water abstraction impacts. These limitations make it very difficult to establish appropriate constraints on the model outputs and to assess the validity of the model outputs. High flows have been identified as being poorly quantified as a result of limitations of the stream-discharge rating curves, while assessments of the simulations of low flows are affected by the large uncertainties in water uses.

In estimating the water use within the Caledon River Basin, the study carried out a detailed investigation of the extent of irrigation demands for the main crops cultivated within the basin. This involved estimating the cultivated area using satellite imagery (from Google Earth). One of the major limitations with this approach was the lack of a means of verification and confirmation. For instance, in some areas it was difficult to distinguish between rain-fed and irrigated areas as they both appear the same. Other water abstractions were estimated based on population and assumed water demands for the towns and rural areas on both sides of the South Africa/Lesotho border. This approach is also uncertain and it could be improved by field work, data collection surveys and information gathering from the responsible local authorities. However, this would have been expensive and time-consuming.

The study reveals that the water resources of the Caledon River are heavily impacted by a number of water use activities in the basin. The main water uses in the basin are artificial impoundments in the form of a few large dams and many ubiquitous small farm dams. Both kinds are used for various purposes such as municipal and industrial water supplies as well as irrigation. Such impoundments in the Caledon River Basin have affected the natural hydrology of the watershed as they decrease the magnitude and timing of the stream flow. The major challenge in this regard is an inadequate quantification of the amount of water abstracted from the streams and the main river channel. As a result stream flow characteristics change over time even if the meteorological inputs and other natural processes in the basin remain the same.

There are some situations where the observed data lie outside the simulated present day uncertainty bounds and these are mostly at very high flows or at very low flows. To improve the confidence (and reduce the uncertainty) in the model outputs, it would be necessary to obtain more observed data of flood flow events through extension of the rating curves at the gauging sites. In terms of low flows, improvements in the model outputs would mostly rely on improved quantification of the patterns of water use.

### 7.3 DATA QUALITY AND ANALYSES

Modelling a large river basin such as the Caledon requires an extensive amount of observation data collected over a sufficiently long period, covering as much of the basin as possible and without gaps. Data required by the Pitman and WEAP models include meteorological inputs to force the models and catchment land surface and sub-surface data to help quantify model parameters. Stream flow and groundwater data are also important to evaluate the final model output and to ensure that sub-surface water storages and fluxes are simulated appropriately. One of the major challenges facing hydrological investigations and modelling of the Caledon River Basin was found to be inadequate spatial distribution of meteorological and stream flow gauging stations. As with many developing areas in the region and globally, maintenance of monitoring networks in the basin appears to be declining, with several gauges either ceasing to operate or having substantial data gaps and incomplete records. The required data sets and information were obtained from various databases and previous studies undertaken in the basin, particularly the Groundwater Resource Assessment-GRAII (DWAF, 2005), Agricultural Geo-Referenced Information System (AGIS, 2007), Water Resources of South Africa-WR2005 (Middleton and Bailey, 2008), stream flow observation data from the Department of Water and Sanitation (DWS) official website, and the downscaled climate change data from the Climate System Analysis Group (CSAG) of the University of Cape Town. Though such data sets are not perfect and are uncertain, they are the best available.

During the course of the study, the raw climate change data was subjected to a series of modifications and transformations to attain suitability and to meet the intended use. It is common practice for point rainfall measurements to be spatially interpolated to area data, when using a semi-distributed hydrological model such as the Pitman model. The inverse distance weighting interpolation method was used in this study. This approach is one of the widely used spatial interpolation methods and it has provided reliable results (Willmott and Robeson, 1995; Yasrebi *et al.,* 2009). However, like any other approach of this type, there is always a degree of uncertainty involved. The uncertainties are even more severe in the northern parts of the basin (highlands region of Lesotho) where the density of the rainfall gauging network is sparse. The high spatial and temporal rainfall variability is not adequately reflected in the rainfall data used as input to the hydrological models.

The study demonstrated that rainfall data from the GCMs' baseline rainfall data for the Caledon River Basin are biased relative to the observed rainfall (WR2005). The bias properties of climate model outputs are generally well-known. For this reason a bias correction method (Hughes *et al.*, 2014b) was applied to the downscaled near-future rainfall data. The bias correction was considered essential as the future rainfall and evaporation demand data were used with a model calibrated against the historical data (Andersson *et al.*, 2006). However, it is also noted that the bias correction method is based on some assumptions about the statistical properties of the square root transformed rainfall data that are almost certainly not met for all of the data sets used. While this introduces some additional uncertainties in the validity of the future climate inputs to the hydrological model, these are expected to be relatively small compared to the differences between the projections across the nine GCMs. The alternative approach would have been to calibrate the model nine times using the individual GCM baseline data and then run the model with each GCM near-future data. This would have involved a substantial amount of additional work and would have added uncertainties related to the differences in the calibrations based on the nine baseline outputs of the GCMs. It is therefore concluded that the bias correction approach used in this study is appropriate for the purposes of quantifying the future uncertainties in water resources availability in the Caledon River Basin.

### 7.4 UNCERTAINTIES IN THE PREDICTION OF FUTURE HYDROLOGICAL CHANGES

The amount of water resources available within the Caledon River Basin is likely to decrease in the future as a result of increased evapotranspiration caused by rising temperatures, even though many GCMs predict increased rainfall amounts. The GCMs substantially disagree on the amount and direction of change of future rainfall. They do however, consistently predict rising temperatures and consequent evaporative demands during the middle and end of the century. The study concludes that uncertainties in the predictions of hydrological and water resources availability emanate from several sources at various levels of hydrological and climate change modelling. Uncertainties in hydrological modelling output originate from the imperfect climate inputs and imperfect structures and parameter sets of the Pitman and WEAP hydrological models which do not adequately represent the complicated hydro-climatic system of the basin. Further uncertainties are related to the model representation of existing water uses and the lack of sufficiently reliable observed stream flow data to calibrate and evaluate the model outputs.

Predictions of the future water resources availability in the Caledon River Basin involved two stages. The first step was to establish an appropriate range of behavioural parameter sets using historical data and then replacing historical data with GCM-predicted future climate data as input (rainfall and evapotranspiration) to the Pitman model. This is a rather standard approach. However, it has several uncertainties and limitations. Perhaps the most important of the uncertainties stems from the rainfall outputs of the climate models. One of the important observations in this study is that there is large uncertainty in the prediction of rainfall, with some models predicting an increase while others suggest a decrease compared to the observed. The study concurs with the general view within recent and contemporary literature that GCMs constitute the largest uncertainty in future hydrological predictions (Giorgi and Francisco, 2000; Tebaldi *et al*., 2005; Deque *et al*., 2007; Buytaert *et al.,* 2009; Kay *et al*., 2009; McMahon *et al.,* 2014; Peel *et al*., 2014). The absence of consensus amongst climate models in terms of change of future rainfall is inevitably reflected in the uncertainty in the estimations of predicted stream flow.

While it is assumed in this study that projections of individual GCMs are equally likely, some climate change impact assessment studies have selected only those which are deemed to be more credible than others, based on their 'skills' to simulate past climatologies (Min and Hense, 2006; Hughes, *et al.*, 2014b; Watanabe *et al*., 2014); others have used an unequal weighting approach (Klocke *et al.,* 2011; Sunyer *et al.*, 2014).. Some of these studies have also found a small difference in outcomes when using all models, only skilful ones and a weighted approach (Hughes *et al.,* 2014b). Multi-model means have also been applied in studies such as Thomson *et al.* (2006), and Wolski *et al*. (2012). A disadvantage with the ensemble mean approach is that it ignores the uncertainty inherent in the various climate models and it is highly susceptible to extreme model simulations. The advantage of using several GCMs over a single model is that uncertainties in projections are better quantified as more GCMs provide additional information. Considering many possible outcomes should lead to robust decision making for future climate change impacts. As one of the objectives of the study was to quantify the uncertainties, the assumption of equal likelihood for individual GCM projections was considered to be the most appropriate approach.

The predictions of future stream flows presented in this study are mainly based on the current state of the basin's physical characteristics, as well as current water uses. The basin`s physical characteristics are primarily subject to land use (and cover) changes, while the rate of water uses depend on factors such as population, irrigation requirements and socio-economic development. Land use and cover changes have been shown to affect hydrological regimes and stream flow in many catchments throughout the world, including South Africa (Schulze, 2000). It is possible that in the Caledon River Basin there will be significant changes in land use practices and cover in the future and this will affect some of the Pitman model parameters. For example, urbanisation will increase the portion of impervious portion of the basin thereby affecting the value of the parameters that determine surface runoff, while changes in land cover would lead to changes in the interception storage and actual evapotranspiration parameters. While these are some of the more obvious likely changes, there is insufficient knowledge or information available to predict the extent of such changes within the basin, as well as to sufficiently establish new parameter sets under changed conditions. While, the general physical characteristics of the Caledon River Basin and its response to climate inputs are likely to change in future, these changes could not be quantified with sufficient confidence to warrant their inclusion in this study. Whether or not the current uncertainty bounds of the model output constraints and the model parameters are wide enough to include the effects of climate induced physiographic changes therefore remains a question for future research.

Another critical aspect and an additional source of uncertainty in the prediction of future stream flow is the rate of population change and related water uses. The current domestic water use estimates are based on approximate estimates of the number of people living in various sub-basins. Domestic water use constitutes a significant portion of the total water use within the basin. Therefore more precise data on the current rate of domestic use and the demographics are crucial in simulating the present day stream flows. However, there still remains significant uncertainty in the estimations of the two variables. This problem escalates when future water resources availability is evaluated. Though change in population growth (rate per annum) is normally established through census and other methods, it becomes more difficult to make projections in time scales similar to those used in climate change particularly in this study. Additional uncertainty in such estimates is brought about by migration. Changes in population might also reflect in the intensity of agriculture to meet the changed demands, this in turn affects the magnitude of water use for agricultural purposes. Such issues impose more complications in the prediction of water resources availability in the Caledon and in any other basin for that matter.

The predicted stream flows of the Caledon River Basin are based on current irrigation water use, which is a major consumer of water in the basin. It is assumed in this study that climate change will likely cause the evaporative demands within the basin to increase in future as a result of increased temperatures. This change will result in increased irrigation water requirements for optimum crop production. From this premise, it is therefore conceivable that there will be more (than current) water allocated for irrigation. On the other hand, it has been argued by agronomists, among others, that enhanced concentrations of carbon dioxide in the atmosphere stimulate a reduction in plants stomatal conductance and hence reduced water loss by transpiration (Doll, 2002; Fischer *et al*., 2007). These two issues clearly result in opposing effects on the consequent water use and highlight one of the challenges in predicting hydrological impacts of climate change. It is not yet clear which of the two will have more impact. Though the assumption of stationary irrigation water is somewhat flawed, it forms a credible basis until more research can be carried out with regards to implications of climate change on plant growth.

The issue of irrigation is closely related to that of evapotranspiration (ET) which the present study estimates an increase of up to 30% for the climate scenario 2046-2065, as result of rising air temperature. This deduction is in line with the findings of several other studies (e.g. Andersson *et al.*, 2011) that southern Africa will be faced with more severe droughts and is going to be increasingly drier, worsening the water situation in the region. Though the assumption that evapotranspiration will increase with increasing air temperature is plausible, it is contrary to several studies which reported that observed pan evaporation has been decreasing simultaneously with increasing temperatures in many part of the world (Nicholls, 2003; Roderick and Farquhar, 2004; 2005) and more importantly in some parts of South Africa (Eamus and Palmer, 2007). While ET correlates with temperature, there are also other important variables which affect the rate of ET. These include: net radiation (which is affected by cloudiness and aerosol concentrations), humidity and wind speed. Doll (2002) suggests that ET would also be affected by decreased plant transpiration due to decreased stomatal conductance in response to increased $CO_2$ concentration.

Results of the current study are based on the assumption that other factors affecting ET (other than temperature) will remain constant into the future and were therefore factored out of the calculations. This is one of the most serious limitations of the study as ET constitutes a major component of the hydrological cycle in the Caledon River Basin. However, the contention is that even if these omitted variables were included in the estimation of ET, it would be extremely difficult to predict them and as such would constitute additional uncertainties in hydrological predictions. This would be exacerbated by lack of or inadequate observations in this part of the world to bias correct predictions and it would be almost impossible to establish credible estimations.

## 7.5 CONCLUSIONS

The study presented an assessment of the uncertainties related to modelling the natural hydrology as well as the impacts of various water use activities affecting the quantity of flow in the basin. These include farm dams, irrigation and domestic water supply. This was to attain sensible model outputs with results comparable to the observed flows. The two-step approach was used to generate flow ensembles based on regional and local constraints of mean monthly flow, groundwater recharge and three flow duration curve quantiles. The constraints were basically aimed at limiting the parameter sets to those that generate model results that can be considered behavioral under natural conditions. The approach led to the establishment of appropriate parameter uncertainty ranges for individual sub-basins and the results are generally satisfactory except for very high and low flows. The study achieved reasonably low ranges of uncertainty that can be assimilated as part of decision-support for water resources planning and management.

The study demonstrated that there are substantial variations in the projections of future climate based on the downscaled rainfall and temperature outputs from nine climate models. While the climate models tend to agree that temperature will increase in the future, they contradict on the direction and magnitude of change in future rainfall patterns. This observation has also been reported in many other studies (Hughes *et al.,* 2014b; Klutse *et al*., 2015). The contradicting projections of rainfall from the climate model tend to be reflected in the characteristics of projected stream flow. The majority of the climate models predict a decline in stream flow at the outlets of the four sub-basins (D21E, D22B, D23D and D23F) used to illustrate the results. On the other hand, only two models (IPSL and MIUB) consistently predicted increased water resources availability for the four sub-basins in the Caledon River Basin. The stream flow uncertainty range (of all GCMs) indicates increased high flows (occurring more than 90% of the time) and decreased moderate and low flows relative to the present day flow simulations.

Though there still remains a large degree of uncertainty in the prediction of future stream flow in the Caledon River Basin, it is concluded that the study used regionally appropriate modelling tools. It should be further emphasised that the quality and length of observation data are major limiting factors in undertaking modelling exercises in this basin. Some of the uncertainties could be reduced in the future through improved hydro-climatic monitoring together with some targeted detailed field investigations, particularly to address the uncertainties in water use. However, there will always be remnants of ‘unknowable’ uncertainties.

## 7.6 RECOMMENDATIONS

The study`s focus was on understating the hydrological dynamics and characteristics of the Caledon River Basin during the past, current and possible future climatic conditions, while recognizing and evaluating the related uncertainties. Predictions of the future hydrology and water resources availability is particularly important for sound water resources planning and management. During the tenure of the study there are a number of observations and contemplations that were recognized, and based upon these the following recommendations are made:

- One of the major challenges the study encountered was availability, quality and length of recorded data which proved to be inadequate to fully yield credible information. It is therefore recommended to the relevant authorities in South Africa and Lesotho that there be financial investments aimed at upgrading and improving data gathering facilities (meteorological and hydrological stations) within the basin.

- The two governments, regional organizations such as ORASECOM and SADC-HYCOS may invest more into the new technology of acquiring data. There has recently been innovative developments in science and technology with regard to remote sensing products (e.g. MODIS) that can be used to collect more accurate and spatially representative meteorological, data and information on physical catchment properties. These can improve the parameter estimation process which is based on physical basin characteristics (for the Pitman model). The use of such products will certainly yield fruitful results (Sharma *et al.,* 2015, and references therein), and will likely improve the results of predictions of future water resource availability and hence sound planning and management.

- It is advisable that decisions on water resources planning based on the findings of this thesis should account for the uncertainty ranges that have been simulated. Considering all the known possibilities when making decisions on the future state of water resources would avert the situation whereby the excluded outcomes manifest and is much safer than considering only one outcome. Additionally, the possibility of a decision to fail is relatively low if all uncertainties are borne in mind. For this approach to succeed, it will be necessary to adopt decision-making processes that can account for uncertainty (Matrosov *et al*., 2013; Usitalo *et al.,* 2015).

- The current study identified climate change data as a major limiting factor in predicting future water resources availability in the Caledon River Basin. The climate change data used in the study were produced and downscaled several years ago (Hewitson and Crane, 2006). Since then there have been subsequent generations of more complex climate models which are expected to provide improved climate projections (Knutti *et al.,* 2013; Arnell and Lloyd-Hughes, 2014). For this reason it is recommended that future climate change impact studies use the most recent climate change data available.

- The current hydrological investigations of the Caledon River Basin has brought to light some of the pertinent issues. These issues require more resources and further research and as such could not be resolved during the present study. This section provides a brief recommendations on the additional investigations and approaches that can be carried out.

  i. Further studies may investigate approaches that would more accurately estimate future evapotranspiration using temperature and perhaps other climate model products. The temperature-based Hargreaves approximation approach used in this study ignores several other important factors that affect evapotranspiration. Therefore the implication here is that evapotranspiration will increase due to increase in climate change-induced air temperature. This conclusion is however, contrary to observations made by some researchers (Roderick and Farquhar, 2004; 2005) that evaporation has actually been decreasing while temperatures are increasing. Thus, there is a need for more precise estimations that would reduce such uncertainties.

  ii. It is also recommended that further studies for hydrological and water resources investigations consider customising the structure of the Pitman model to suit the individual quaternary catchments of the Caledon River Basin with highly contrasting physical features such topography, land cover and climate. This approach is likely to improve the hydrological simulations at various points of the basin and the main outlet.

  iii. The observed stream flow data for many gauges in the entire Caledon River Basin are substantially uncertain. It is therefore recommended that future studies for the basin assess the degree of uncertainty of the observed flow and apply an approach such as the limits-of-acceptability such that the uncertainty in the observed flow is included as part of the modelling procedure.

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