INCORPORATING UNCERTAINTY IN WATER RESOURCES SIMULATION AND ASSESSMENT TOOLS IN SOUTH AFRICA

Report to the
WATER RESEARCH COMMISSION

by

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EXECUTIVE SUMMARY

The main objective of the project was to contribute to the incorporation of uncertainty assessments in water resource decision making in South Africa, thereby quantifying the risks associated with specific decisions about planned future water resource developments. This objective was supported by several specific aims:

1. Develop an understanding of uncertainty and associated risks in water resource management on the basis of literature and known practices, nationally and internationally.

2. Identify and characterise the main sources of uncertainty (focusing on current South African practice and typical situations of data availability).

3. Develop techniques and guidelines for quantifying the uncertainty associated with different models. This will include uncertainty in all relevant areas (hydrological, climate, economic, social, etc.).

4. Determine the effects of uncertainty on water resource management and identify what level of uncertainty is acceptable.

5. Develop guidelines for the communication of uncertainty and the impacts to various stakeholder groups involved within water resource planning and management. This aim will need to address the issue of the links between uncertainty and risk.

6. Develop guidelines for incorporating uncertainty and the associated risk into water resource decision making processes.

7. Identify those areas of uncertainty that can be realistically reduced and which will have the greatest impact on reducing the risks involved with water resource decision making.

While all of these aims have been addressed as part of the project, it was inevitable that a project of this type would raise almost as many additional questions as it would answer those that were posed as part of the project design. The main output from the project has been the development of a framework for uncertainty assessments in water resources availability analyses within South Africa. This framework has been based on international experience, the water resources analysis methods that are commonly applied within South Africa, the data constraints that exist within the country as well as the requirements for water resources management decision making. The framework has been supported by the development of some new approaches to applying existing hydrological models and illustrated by examples of their application. The framework development has certainly contributed to an understanding of uncertainty (Aim 1), is focused on the main areas of uncertainty that have been identified (Aim 2) and is supported by techniques that can be applied in practice (Aim 3). There remain some questions about how best to communicate uncertainty to different stakeholder groups (Aim 5) and consequently how uncertainty effects management, what level of uncertainty is acceptable and how uncertainty affects decision making risk (Aims 4, 5 and 6). The project has identified the main sources of uncertainty and offers some recommendations on approaches to reduce the level of uncertainty. Some of these are achievable in the short-term through changes in technical practices (such as hydrological model parameter estimation), while others require closer engagement in the future between scientists, water resources engineers and policy makers at governmental level (such as improvements in the national rainfall monitoring network).

The framework is discussed in detail in the first three chapters of this report and is largely based on the concept of generating ensemble outputs from hydrological models rather than the traditional approach of a single output. The range of differences between the ensembles represents the degree of uncertainty in our understanding of the hydrological response of a catchment as well as in the climate data used to force the hydrological response. In practice the input uncertainty is represented by using probability distributions (rather than single values) of the model parameters as well as variations in the rainfall and evaporation demand data used to drive the model. The variability in the parameters and the forcing climate data will depend on our existing knowledge about the catchment and the amount and quality of data that are available to inform that knowledge. The framework includes a method of assessing the ensemble outputs to try and distinguish between those that are not realistic representations and those that can be considered 'behavioural'. This assessment uses regional and local knowledge of hydrological response and is largely based on the integrated use of observations (measured stream flow data, for example) and prior knowledge (previous studies of groundwater recharge, for example). Where high confidence can be expressed in this knowledge, the range of behavioural outputs will be small (low uncertainty), while in other situations a high degree of uncertainty will remain. The concepts are very similar to the traditional approaches to the use of hydrological models involving calibration and validation of a result before being used for decision making. However, the traditional approach could not be applied satisfactorily in ungauged catchments where there are no data to calibrate against, and did not include any explicit quantitative uncertainty information. The new framework is far more flexible and can be applied under all conditions regardless of the quantity and quality of the available data. The report provides the details of the different parts of the framework as well as a number of examples of its application in various regions of South Africa.

It is a strong recommendation of this project that the issue of improving and sustaining the collection of rainfall data within South Africa be discussed in the very near future by all the organisations either responsible for data collection or that use the data. This could be achieved through a highly focused workshop (organized perhaps by the Water Research Commission) that has a mandate to report to the relevant Ministers and the outcomes of which will be used to guide future policy. It is important that at least the Water Research Commission, the Department of Water Affairs, the Department of Agriculture, the SA Weather Service, water resources engineering consultants as well as research organizations are represented at the workshop. It is also important that the individuals representing the government organisations have sufficient authority to influence policy directions. One of the outcomes of the workshop should be a succinct report on the state of rainfall data collection, the implications of not improving the situation and recommendations for future action.

One of the most important considerations from a practical point of view was that the project should not recommend approaches that are completely different, and that would generate completely different results, compared with existing methods used by a large number of water resources practitioners in South Africa. The intention was to recommend enhancements to existing methods such that uncertainty assessments could be explicitly included without the need for completely replacing methods that have been used with reasonable confidence for many years. Specifically, this point relates to the links between hydrological models (used to generate time series of likely natural hydrology) and water resources systems yield models that are used to assess water availability, design storage and abstractions systems and assess future scenarios so that management decisions can be made (see Chapter 4). Some inclusion of uncertainty has always been part of standard practice for yield analyses in South Africa through the use of a stochastic model component in yield models that generate multiple stream flow sequences. However, this approach represents only a form of uncertainty. The project investigated the integration of stochastic uncertainty with hydrological uncertainty (related to climate inputs and model parameter quantification) through the use of a stochastic rainfall model to provide inputs into uncertain hydrological models. The assumption was that this could replace the traditional use of a stochastic stream flow generator within the yield model. While the report presents examples and evidence to suggest that the new approach has many potential advantages, there remain some practical considerations as well as some issues related to the interpretation of the results for decision-making purposes. These will be addressed as part of a future partnership between key groups involved in both research and practice including the Department of Water Affairs. One of the recommendations of this project is that future updates to the water resources of South Africa studies (WR2020 perhaps?) should be based on improved methods of parameter estimation in ungauged catchments and should include parameter uncertainty.

One of the potential sources of uncertainty in water resources assessments is related to the available information about present day water use. This source of uncertainty also impacts on the interpretation of observed stream flows records and the process of naturalization. The uncertainty in present day flows can be dealt with in either hydrological models or within yield models. Several examples, including uncertainties in groundwater abstraction impacts, afforestation impacts and the effects of small farm dams are presented in the report. It is quite clear that the uncertainties in these components of the water balance of catchments should not be neglected and also that the available information is less than adequate in many situations.

Chapter 5 of the report refers to the analysis and software tools that have been developed during the project. Many of these are associated with the SPATSIM software package that is under common ownership by the IWR, UKZN, the WRC and DWA. Many of these have been developed for a research environment and from a practical point of view it will be necessary to translate some of the software for use with other software that is currently being used by practitioners. This issue will be addressed in the near future.

Being uncertain about the outcome of a scientific or technical analysis should not be seen in a negative light and the explicit inclusion of quantitative expressions of uncertainty should allow improve future decision-making. First of all, realistic expressions of uncertainty will help to identify the gaps and weaknesses in our knowledge and understanding and therefore promote interventions to close those gaps. Secondly, uncertainty should be part of the whole adaptive approach to managing water resources that is advocated by many leading scientists and practitioners worldwide.

Throughout this project attempts have been made to achieve a balance between the development of new approaches based on sound hydrological principles and international experience with the practical considerations associated with the use of models for water resources assessments, planning and management. The degree to which these overall objectives have been achieved can only really be measured by the impact of the project outcomes on the approaches applied in the future. Many of the techniques that have been developed during this project are already being successfully applied by Rhodes University research students in studies as diverse as large scale modelling of the Congo River basin through much smaller scale evaluations of surface-groundwater interactions in South African catchments to various climate change impact assessments. The value of the project results to future hydrological research within South Africa has therefore already been demonstrated. Many of the principles and some of the results of the project have already been internationally peer reviewed through the publication of papers in scientific journals and presentation at international conferences. This process will continue through 2011 as additional material is submitted.

Some of the follow up activities will have to be focused on ‘selling’ the concepts, the proposed techniques and the recommendations to the broader community of hydrological and water resource engineering practitioners. The project team recognizes that this will never be a simple task and practitioners are often justifiably reluctant to adopt new approaches without a very clear demonstration of the advantages. The authors believe that they have presented a strong argument for including uncertainty in standard practices for water resources estimation in South Africa but it remains to be seen whether these arguments are strong enough to encourage the paradigm shift that will be required.

Table of Contents

List of Figures

List of Tables

ACKNOWLEDGEMENTS

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A very important part of this project was the participation of various individuals in the three workshops that were held to present some of the research findings, discuss options for including uncertainty in water resources management practice and to guide some of the activities of the project. The following table lists the names of the individuals and their organizations who attended the workshops and therefore made significant contributions to the success of this project:

Name	Organisation
Alan Bailey	Stewart Scott
Richard Bugan	CSIR
Siphesihle Bukhosini	Umgeni Water (formerly part of the project team)
Renias Dube	WRC (formerly)
Mehari Frezghi	BEEH, UKZN (formerly part of the project team)
Bennie Haasbroek	Hydrosol
Brian Jackson	Incomati CMA
Paul Kagoda	Civil Engineering, Wits University
Rikard Liden	SWECO
John Ndiritu	Civil Engineering, Wits University
Elias Nel	DWA
Wandile Nomquphu	WRC (Project Manager)
Washington Nyabeze	Nyabeze and Associates
Tendai Sawunyama	IWR Water Resources (formerly part of project team)
Anton Sparks	Aurecon
Susan Swart	WRP
Isa Thompson	DWA
Estelle van Niekerk	BKS
Peter van Niekerk	DWA
Pieter van Rooyen	WRP
Niel van Wyk	DWA
Owen Wilson	Arcus Gibb

Water for Africa, WRP and BKS are thanked for hosting the three workshops.

In addition to their contributions to the workshop, Tendai Sawunyama and Mehari Frezghi contributed some research content as part of their PhD studies which overlapped with the earlier part of the project. Bennie Haasbroek and Geoff Pegram contributed to the uncertain yield analyses through the provision of the stochastic rainfall sequences.

During the course of the project we had a number of discussions with other organizations that are involved in hydrological modelling uncertainty research. We would particularly like to thank Prof Allen Hope and his group at San Diego State University and Prof Muñoz-Carpena, Dr Greg Kiker and Anna Cathay of the University of Florida, Gainsville for useful discussions about various approaches to uncertainty analysis.

CAPACITY BUILDING

At the start of the project two Rhodes University post-graduate students were already working on uncertainty issues in hydrological modelling and both have made significant contributions to the outcomes of this project. The first of these students, Dr Tendai Sawunyama (2008), was awarded his PhD degree in 2009 and took up employment with Water for Africa consulting engineers (now IWR Water Resources and headed up by Mr Stephen Mallory) as a hydrologist. Mr Evison Kapangaziwiri was awarded his MSc degree (Kapangaziwiri, 2007) with distinction in 2008 and continued with a PhD which he completed during 2010 (Kapangaziwiri, 2010) and the degree will be awarded in 2011. While the original plan was for Mr Kapangaziwiri to remain within the Institute for Water Research as a staff member, for family reasons it was necessary for him to move to a larger urban centre. He has therefore taken up a post with the CSIR in Pretoria, but is still expected to contribute to further research into uncertainty issues. During 2009, Mr Kapangaziwiri was hosted by Dr Thorsten Wagener at Pennsylvania State University for a month. Both Dr Sawunyama and Mr Kapangaziwiri attended and presented papers at international conferences during the period of this project and have become recognized members of the international hydrological community.

Mr Mehari Frezghi was a PhD student in the School for Bioresource Engineering and Environmental Hydrology at the University of KwaZulu-Natal, Pietermaritzburg under the supervision of Prof. Jeffrey Smithers. Although his involvement in the project was limited, he made some contributions to the project through the use of uncertainty assessments within the ACRU model. Unfortunately, he left UKZN before it was possible to properly integrate this work with the development of the uncertainty framework.

Ms Siphesihle Bukhosini joined the project as an external MSc student at Rhodes University with the intention of contributing to the development of the regional constraints. She was formerly with Umgeni Water and is now with the University of Zululand. It was very unfortunate that it was necessary to terminate her registration at the end of 2010 due to a complete lack of any progress. It is possible that moving to a new job did not allow time to pursue her research interests.

Apart from the students who were directly associated with the project, there are several other post-graduate students at Rhodes University who have directly benefited from this project. At the start of 2009 the Institute for Water Research began a new programme (SSAWRN) supported by the Carnegie Foundation of New York. The Sub-Saharan Africa Water

Resources Network (SSAWRN) is part of the Regional Initiative for Science Education (RISE) project managed by the Science Initiative Group (SIG) of Princeton University and is designed to build academic capacity in Africa. Four of the SSAWRN students are working on projects related to hydrological modelling and uncertainty. Mr Raphael Tshimanga (PhD candidate) is working on hydrological modelling issues in the Congo River basin, while Ms Sithabile Tirivarombo (PhD candidate) and Mr Agostinho Vilanculos (PhD candidate based at Eduardo Mondlane University in Mozambique) are working in the Zambezi River basin. Ms Jane Tanner (MSc candidate, upgrading to PhD in 2011) is working on surface-groundwater interactions and uncertainty. While Prof. Hughes is the formal supervisor of these students, Mr Kapangaziwiri has made substantial contributions to their training by passing on many of the techniques that he developed during this project.

The workshops that were held during the project have almost certainly created better awareness of the issues associated with estimation uncertainty in water resources estimation and management. It was encouraging to note that the workshops were attended by researchers, consulting engineers and water resources managers. While there will inevitably be barriers to the practical application of some of the research results contained in this report, the scene has been set and there appears to be a consensus that uncertainty assessments should be part of future standard practice.

1. INTRODUCTION

This document represents the final report for the Water Research Commission project on 'Identification, estimation, quantification and incorporation of risk and uncertainty in water resources management tools in South Africa' (K5/1838). The project duration was three years (April 2008 to March 2010) and the participants were the Institute for Water Research at Rhodes University, IWR Water Resources (a private consultancy company) and the School of Bioresources Engineering and Environmental Hydrology at the University of KwaZulu-Natal. There were 11 deliverable reports generated during the project and these can all be found on the IWR website (http://www.ru.ac.za/static/institutes/iwr/uncertainty/).

While uncertainty is a feature of everyday life, its meaning and consequences are not always apparent. Many experienced scientists will remember physics or physical sciences classes at school where we were taught that all measurements are made with certain levels of accuracy that depend on the instrument being used. Within laboratory situations observations can be made with very high levels of accuracy and there is little uncertainty. However, when the laboratory becomes the natural world and there are many complex interactions, measurement becomes much less accurate and understanding much more uncertain. It is obvious that we are not able to measure all the things that we wish to know about and understand and therefore a wide range of estimation methods have evolved over the years to try and fill the gaps. This is particularly true of the fields of hydrology and water resources engineering, in which many different estimation tools and models have been developed over many decades, to the extent that models are often considered replacements for real data (Silberstein, 2006). However, while it cannot be denied that models have proved to be valuable assets to water resources management, it should also be recognized that they are highly simplified representations of a very complex reality and can therefore never be expected to generate totally accurate results – they are therefore uncertain. The critical issues in terms of the practical (rather than scientific research) application of models are how uncertain are the results in any specific situation and how does this uncertainty affect the decision making process (Felix, 1994; Davis and Hall, 1998)?

It has always been recognized that models will never be able to give perfect answers (Beven, 1993), either because we are unable to perfectly define the inputs (Dawdy and Bergmann, 1969), or because there are errors in at least some of the data being used (Ibbit, 1972), or because the models are far from perfect representations of the real world (Naef, 1981), or because we are not able to establish model parameters for a specific site (Haan, 1972). All of these problems exist even when we have some observed information against which we can calibrate and test (validate) the results of a model. However, for many practical purposes we are more interested in making use of models to estimate water resources availability in situations where we cannot directly test the model. The ‘ungauged basins’ problem has become one of the most critical issues in hydrological sciences in recent years (Sivapalan et al., 2003) and gave rise to the PUB (Prediction in Ungauged Basins) programme of the International Association of Hydrological Sciences (IAHS). Despite the fact that the PUB programme has been operating for a number of years, the focus has almost always been on the science of applying models in ungauged basins and only very recently has attention been focused on the practical aspects. One of the dominant focus areas of PUB has been methods of estimating parameters in basin where calibration is not possible, but perhaps the real focus should be on the uncertainties involved in that process? During discussions at the IUGG General Assembly held in Perugia, Italy during 2006 it was suggested that PUB should really stand for ‘Predictive Uncertainty in Basins’.

Dealing with uncertainty is not a new problem and the links between modelling, statistical inference, uncertainty and decision making have been discussed for many years in many different disciplines (Popper, 1959). Within the science of hydrological modelling, the approaches to dealing with uncertainty developed in parallel with advancements in the power of computers (Cover and Unny, 1986) and our ability to run even complex models many times over within realistic computing times. Some of the earlier developments in automatic calibration of hydrological models, that involved searching for optimal parameter sets based on statistical comparisons with observations (Ibbit and O’Donnel, 1971; Duan et al., 1992; Ndiritu and Daniell, 1999; Madsen et al., 2002), evolved into searches of the model parameter space (Muleta and Nicklow, 2005; Vrugt et al., 2003) for outputs that could be considered realistic, acceptable or behavioural (depending on the terminology used by different groups). Determining what is realistic or behavioural may be a relatively straightforward task when some comparative observations (of stream flow, for example) are available, but is much more complex in ungauged basins (Yadav et al., 2007). There is now a vast (and ever growing) body of literature on the subject of uncertainty analysis in hydrological and water resources estimation and much of this was covered within the literature review completed for this project (Deliverable 2). This literature covers the need for uncertainty assessments (Pappenberger and Beven, 2006), sources of uncertainty, methods of model parameter estimation (Wagener and Wheater, 2006), methods of defining uncertainty (Beven and Freer, 2001; Zhang et al., 2008) and approaches that can be used to reduce uncertainty (Wagener et al., 2003). The literature review is not repeated within this final report for the reasons that it can be found on the IWR website (http://www.ru.ac.za/static/institutes/iwr/uncertainty/) and because it is expanding all of the time and any review becomes out of date very quickly. The important point is that there is a large amount of literature to choose from in the development of approaches for the practical application of uncertainty assessment. This may be a relatively daunting prospect for practitioners in the field of water resources assessment, but it also implies that the science has developed to the extent that it should be applicable in practice. Pappenberger and Beven (2006) raised a number of issues about why uncertainty analysis cannot be, or is not being, applied. The conclusions that they reached was that there is no real reason for not applying, and yet there are many very good reasons for applying, uncertainty analysis in practical water resource assessments.

From a South African perspective, the country has a long history of relying on hydrology and water resource yield models to make decisions about planning and managing water resources developments. However, while there has always been an understanding that the estimations being used are far from perfect, there have been few explicit attempts to incorporate uncertainty in the way in which the hydrological models have been used. Uncertainty has been incorporated into the applications of the water resources yield model in that the outputs are given as curves equivalent to the probability distribution of expected yields. However, this approach (in theory) only allows for one type of uncertainty in the whole estimation process (see later discussion) and therefore the risks associated with decision making are potentially ignoring other uncertainties.

The main objective of this project was to contribute to the incorporation of uncertainty assessments as part of water resources decision making in South Africa. This objective inevitable involved a number of specific aims and project tasks, which are listed below and are discussed in more detail within this final report.

i. Develop an understanding of uncertainty and associated risks in water resource management on the basis of literature and known practices, nationally and internationally. Establish how uncertainty is being addressed and identify any differences between developing and developed countries.

ii. Identify and characterise the main sources of uncertainty (focusing on current South African practice and typical situations of data availability).

iii. Develop techniques and guidelines for quantifying the uncertainty associated with different models. This will include uncertainty in all relevant areas (hydrological, climate, economic, social, etc.).

iv. Determine the effects of uncertainty on water resource management and identify what level of uncertainty is acceptable.

v. Develop guidelines for the communication of uncertainty and the impacts to various stakeholder groups involved within water resource planning and management. This aim will need to address the issue of the links between uncertainty and risk.

vi. Develop guidelines for incorporating uncertainty and the associated risk into water resource decision making processes.

vii. Identify those areas of uncertainty that can be realistically reduced and which will have the greatest impact on reducing the risks involved with water resource decision making. Part of this aim is also to specify how the uncertainties can be reduced and what resources are likely to be required to achieve this reduction.

2. A FRAMEWORK FOR UNCERTAINTY ASSESSMENTS

One of the starting points for the development of a modelling framework that includes uncertainty assessments in both gauged and ungauged basins is the identification of sources of uncertainty, how they propagate through, and how they are likely to impact on, the estimation process. Figure 2.1 illustrates the typical process associated with water resources decision making where hydrological and water resources systems models are used to provide information. The whole process is sub-divided into three main components, all of which include some aspects of uncertainty. The three main sources of uncertainty are identified as those associated with the main forcing data of the model, the model simplifications, assumptions and structure, as well as the model parameters.

2.1 Uncertainty in hydrological models

Figure 2.2 provides a detailed breakdown of the sources of uncertainty associated with the use of hydrological models to estimate natural water availability and the focus is on estimation in ungauged basins. The diagram is made more complex in the lower part because an attempt has been made to account for the different types of uncertainty that are associated with different methods of estimating the model parameter values. However, whichever method is used there are three common sources of uncertainty; the hydro-climate data used to force (and calibrate in gauged basins) the model, the structure of the model and the parameter estimates.

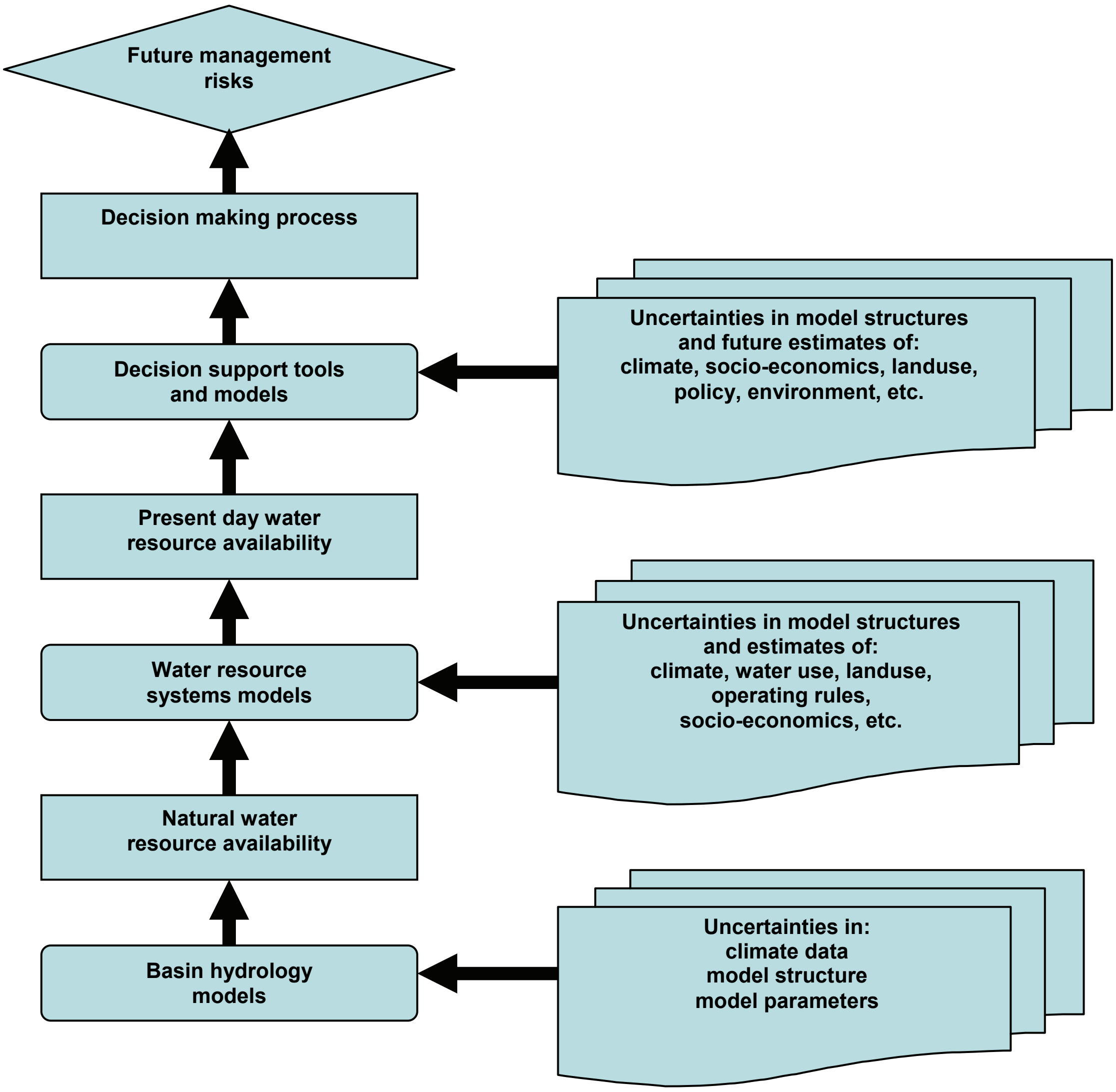


Figure 2.1 Main chart of a water resources assessment system including a hierarchy of uncertainty and risk.

2.1.1 Hydro-climate forcing data

It has long been recognized that one of the limitations to successful hydrological simulation is associated with the quality and representivity (spatial and temporal) of the input hydro-climate data (precipitation, evaporation demand and, in gauged basins, the observed flow data). They have a direct impact on the best model results that can be achieved (Dawdy and Bergmann, 1969; Beven and Hornberger, 1982; Nicks, 1982, Troutman, 1982) as well as potentially having an impact on parameter estimation (Haan, 1972; Ibbit, 1972, Troutman, 1983; Gupta and Sorooshian, 1985). One of the major causes for concern in model calibration is the fact that models can be fitted to input data that contain errors (Paturel et al., 1995; Oudin et al., 2006), which implies that the resulting parameter set cannot be considered representative of the real catchment response. This clearly has implications for the regional extrapolation of parameters based on calibrations in gauged basins.

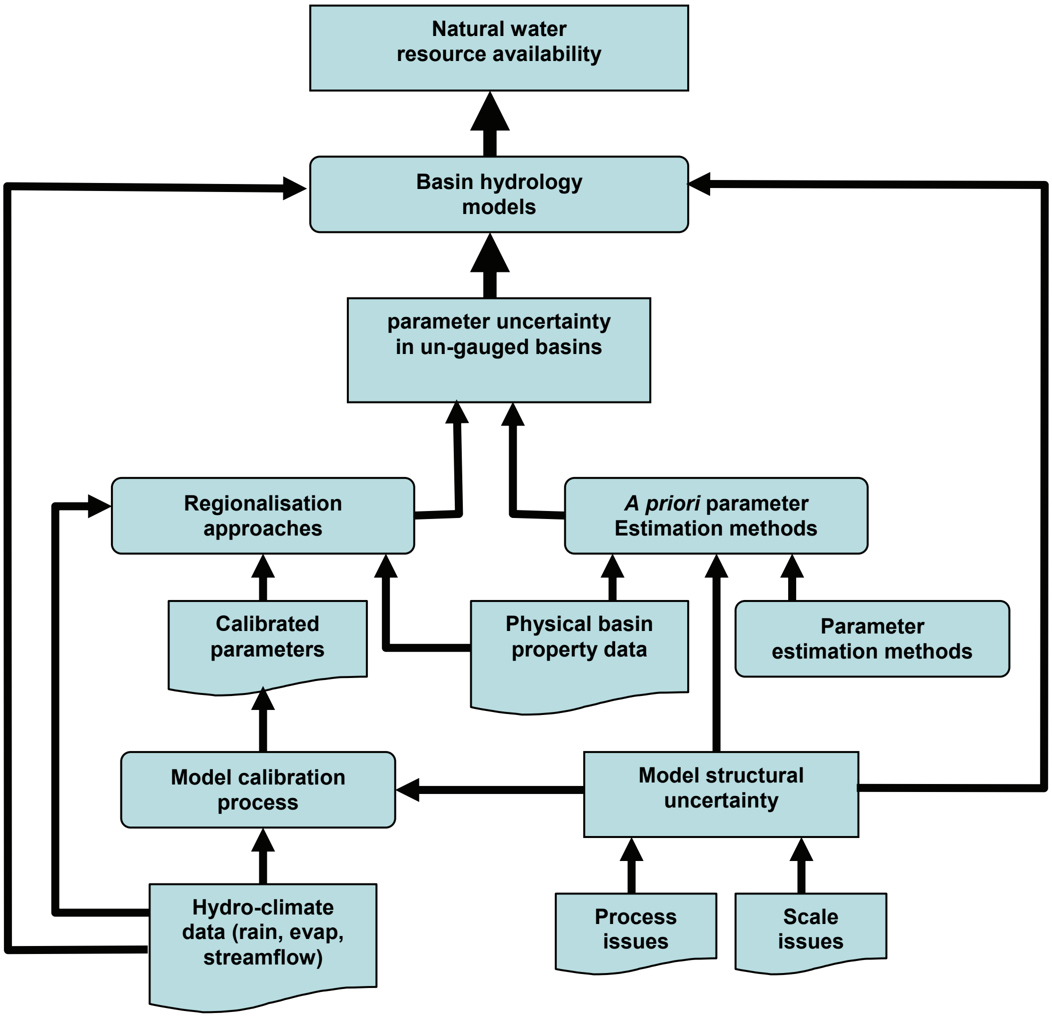


Figure 2.2 Uncertainty in the estimation of natural water availability

Both climate and hydrological data are naturally continuous and variable in space and time and this presents a major challenge in the representativeness of observed time series. The errors in the estimation of rainfall and evaporation inputs may be related to the limited density of gauge networks relative to the spatial variability of the climate and inadequacies in spatial interpolation approaches used to convert point data to a spatial time series that can be applied to a sub-basin. The accuracy in spatial rainfall estimation for rainfall-runoff modelling is a potential area for further research, especially with the continuous decrease in observation networks in developing regions such as in South Africa. Apart from errors in the input data, a further consideration is the length of the data period that is required to establish representative model parameters and Görgens (1983) found that more than 15 years of data are required to obtain acceptable calibrations in semi-arid South African situations.

Sawunyama (2009) investigated uncertainties in **precipitation estimation** over different time scales and in different geographic (and therefore climate) regions of South Africa. The geographic region determines the spatial variability of rainfall which can be highly variable depending on the time period considered, shorter time periods demonstrating greater spatial variability, especially in large parts of South Africa where convective storm activity dominates. If the critical runoff processes are also associated with short time periods, monthly scale models are rarely able to simulate patterns of runoff response very well, even if they are able to simulate longer-term averages and flow frequency distributions. This makes traditional methods of calibration quite difficult as there is a very high noise-to-signal ratio in relationship between rainfall and runoff at monthly scales. In more humid regions where runoff processes are influenced to a greater extent by storage and drainage from storage, the loss of resolution caused by the use of monthly time-step data becomes less important. Arguably, the areas that experience the greatest impacts of uncertainty in observed rainfall are those where topographic influences play a major role and where systematic variations in rainfall at all time scales are frequently in evidence (Hughes and Mantel, 2010b). Unfortunately these are also the areas where gauge networks are usually inadequate (and getting worse – Hughes and Mallory, 2008) and where alternative methods of estimating rainfall (radar and satellite) are typically less than successful.

The methods of measurement and estimation of rainfall data in South Africa have received attention in the past and are still very relevant today as the network density of ground based gauges has been dramatically reduced in recent years (Hughes and Mallory, 2008). While the type of rain gauge and its installation design can clearly affect the accuracy of point rainfall observations, this represents a minor contribution to uncertainty compared to the much more important issues of translating point observations into adequately representative spatially averaged rainfall. Similarly, the choice of method (Theissen Polygons, Kriging, Inverse Distance Squared Weighting, etc.) to convert point observations into spatial averages appear to have less impact on the final result than the representativeness of the raw station data (Schafer, 1991; Lynch, 2004). The important issue therefore appears to be related to the methods that can be used to generate spatial rainfall inputs in the future given that ground based networks are shrinking. While the future seems therefore to lie in the use of remotely sensed data products (satellite and radar – Pegram and Clothier, 2001; Hughes, 2006a&b; Sawunyama and Hughes, 2008) it is essential to understand any additional sources of uncertainty that are associated with the use of these data. There remain a number of un-answered questions:

- How do we link historical sequences of ground based observations with new data sources when there are very short overlap periods between the two sources? This is very important from a hydrological modelling perspective (Hughes, 2006a, b; Sawunyama and Hughes, 2008), given that we wish to generate long time series of flow data to better understand trends and variability. A solution proposed by Frezghi and Smithers (2008) is to develop relationships between the point rainfall measurement and the daily rainfall fields estimated using radar data calibrated to gauged rainfall data, and to use the relationships to improve the estimation of catchment rainfall using historical point rainfall data when radar data was not available.
- It is recognized that rainfall inputs to hydrological models and parameter sets are not independent (i.e. if different rainfall sources are used in a model, the appropriate parameter sets will also be different). This adds to the uncertainty associated with using mixed rainfall data sources in hydrological models.
- Many of the remotely sensed data products rely upon ground truth data to achieve effect calibration. If the ground based data are no longer available because of network density reductions, how do we calibrate the remotely sensed data?
- Global satellite data products that are readily available are often calibrated against a standard global set of ground based gauges. Is this adequate for local scale (quaternary catchment or smaller) use and, if local re-calibration is required, how can this be achieved?

With respect to estimating the future availability of water resources and the influence of future climate variations, it has become common practice in various parts of the world to make use of the outputs of climate models (downscaled outputs from Global Climate Model or Regional Climate Models – Schulze, 2000; Bàrdossy and Duckstein, 2002). If these rainfall products are to be used together with historical time series (to assess changes in the future relative to the past) we are faced with similar problems of uncertainty as in the use of satellite or rainfall data.

Evaporation and evapotranspiration losses represent the largest component of the water balance after rainfall in the vast majority of South African catchments. However, in some models and notably the conventional use of the most widely used model (the Pitman model), time series variations in evaporation demand are ignored. This is partly because long records of evaporation demand observations are few and far between and partly because the relationships between the observed information (e.g. evaporation pan measurements) and the way in which 'evaporation demand' is used in models are not all that well understood. A further reason is that in many parts of South Africa actual evapotranspiration is more dependent upon water availability than upon demand. Other models used in South Africa (e.g. ACRU) and elsewhere base their evaporation demand inputs on climate data using one of the well known estimation equations (Schulze and Kunz, 1995; Allen et al., 1998). Given the scarcity of some of the input data requirements for the more complex climate based estimations, simpler temperature based estimates have proved quite popular.

With respect to the use of the Pitman monthly model, Sawunyama (2009) found that using time series of evaporation demand had geographically variable effects on model simulations results. The time series were generated on the basis of fractional deviations of monthly temperatures from long-term mean monthly temperatures. The same fractional deviations were then applied to the mean monthly evaporation data traditionally used with the model. Sub-basins located in the Western Cape, winter rainfall region appear to be less sensitive to changes in evapotranspiration inputs, while summer rainfall regions are more sensitive to uncertainties in evapotranspiration inputs. The same conclusion was reached when the temperature based estimates (Schulze and Maharaj, 2004, 2006) of evaporation demand are used directly.

Where model parameter sets are established through some type of calibration process, regardless of whether this is a manual or automatic process, there will always be uncertainty issues associated with the quality and representativeness of the **observed flow data**. These data in South Africa are subject to the following potential problems:

- Lack of accuracy of the rating table, particularly at low flows for some of the older rectangular weirs in which stage changes are not sensitive to discharge changes. Silting in the weir pools can also have an adverse effect on the accuracy of rating tables across a range of flows.
- Rating tables that are inadequate to measure high flows, or structures that do not contain high flows. The majority of flow gauges in South Africa suffer from this problem, which means that the observed flows are not available during high flow periods. Calibrating the parameters associated with the model components that generate high flows therefore becomes a very uncertain process.
- While measurement errors should not be neglected, one of the largest sources of uncertainty in the observed flow data is what they actually represent in terms of catchment conditions. Almost all of the gauged catchments in South Africa are (or have been) impacted by some kind of upstream modification to the natural hydrological

response. These modifications can range from land use changes, through small scale abstractions from farm dams (Hughes and Mantel, 2010a), the river or boreholes, return flows from irrigation or waste water treatment works, to a wide range of impacts associated with large reservoirs. It is therefore frequently difficult to either recognize the degree to which the measurements can be considered to represent natural catchment runoff conditions or to appropriately quantify the effects so that they can be removed (naturalise the records) or included as part of the model. To further complicate the matter, the effects are rarely stationary and are typically difficult to quantify.

Given that we know the flow data are subject to error and that we are not always sure what they represent in terms of runoff response, it is hardly surprising that model calibrations that use these data are subject to substantial uncertainty. When model calibrations form the basis for developing regional parameter sets for application in un-gauged basins there is the potential for the uncertainties to be increased in an unknown manner. It would therefore seem to be important to recognize the inherent uncertainty in the use of observed streamflow data for calibration purposes and either incorporate it in the calibration parameter estimation process, or try and bypass the uncertainty by using an alternative approach for estimating parameters in un-gauged basins.

2.1.2 Model structure uncertainties

Structural uncertainties occur within all models, partly because all models are simplifications of reality and partly because we do not even have perfect knowledge of what reality is. Some of these uncertainties can be overcome to a degree through appropriate quantification of the parameter sets (i.e. parameters can, to a certain extent, be used to compensate for inadequate hydrological process representation in a model). Some of the structural uncertainties are associated with the time and space scales that used within a model. However, this does not mean that we can necessarily reduce the uncertainties by creating models with higher spatial and temporal resolutions – this may simply shift the uncertainty into the parameter estimation process (Beven, 1989, 2006). Amongst others, Beven (1989) questioned the value of physically-based modelling approaches for two reasons. The first is that the physical process understanding upon which many of the model algorithms are based were developed under very small-scale laboratory conditions which are not necessarily applicable at typical scales of modelling. The second is related to the information that is normally available to parameterize such physically-based algorithms. If this information is not directly appropriate the use of the algorithms contains as much uncertainty as would be involved in the use of simpler conceptual representations of catchment scale hydrological processes.

Some of the structural uncertainties that are linked to climate data inputs and scale associated with the Pitman monthly model are well known (the process of distributing monthly rainfall totals over the model iterations and the issue of using mean monthly evaporation demand inputs). Despite the fact that the Pitman model has been demonstrated on many occasions to have an appropriate conceptual structure for a wide range of basins within the southern Africa region, this does not mean that there are no structural uncertainties. However, it seems reasonable to suggest (without being able to adequately prove such an assumption) that the structural uncertainties are less important than the input data and parameter estimation uncertainties. In a research environment it may be possible to examine the structural uncertainties in more detail and adjust the model formulation based on the results of such a study. From a practical point of view it is probably better to ignore the structural uncertainties (or at least accept them as being present but not quantifiable) and focus on the related issue of uncertainty in parameter estimation.

The ACRU model is a physical conceptual model, i.e. it is conceptual in that it conceives of a system in which important processes and couplings are idealised, and physical to the degree that physical processes are represented explicitly (Schulze and Smithers, 2004). The model thus attempts to capture our currently imperfect understanding of the rainfall-runoff process and thus also contains inherent structural uncertainties.

2.1.3 Model parameter uncertainties

From the point of view of parameter uncertainties the critical part of the Figure 2.2 is the lower group of processes that distinguish between regionalization approaches and *a priori* estimation methods for quantifying parameter values in un-gauged basins. The sources of uncertainty and/or the way in which these contribute to model output uncertainty will be different for these two approaches.

There are a number of possible approaches to **parameter regionalization**, but most of them rely on some form of extrapolation from parameters established through calibration (manual or automatic) of the model using the available observed data. This inevitably means that the calibrated parameter sets contain uncertainty associated with the input hydro-climate data (see above) as well as the calibration process and all the attendant issues associated with equifinality (Beven, 2006). Added to these sources of uncertainty are the uncertainties associated with the regionalisation process itself, which will largely depend upon the method used, but will be related in some way to the identification of similarities between the hydrological responses of the calibration catchments and those of the un-gauged catchments. The identification of these similarities is typically based on climate and physical basin properties (topography, soils, vegetation, geology, etc.).

The ***a priori* parameter estimation** approaches typically use physical basin property data (and possibly indices of climate) to directly estimate the parameter sets in both gauged and un-gauged data. If gauged catchments are used to develop the parameter estimation equations the result (from an uncertainty point of view) will not be very different from the regionalization approach. However, if the parameter estimation equations are developed independently (based on conceptual hydrological interpretations of the model structure and the meaning of the parameters – see Kapangaziwiri and Hughes, 2008) the propagation of the hydro-climate data uncertainties through the modelling process is expected to be different. Essentially, the parameter estimation process should therefore be independent of the uncertainties in the hydro-climate data. The gauged flow data will still be used, but their use will be mainly for testing the parameter estimation equations and contributing to an evaluation of the uncertainty associated with the use of the equations.

Both methods (regionalization and *a priori* estimation) are expected to involve the use of **physical basin property** data which may be drawn from various sources, many of which were not originally developed for the specific purpose of hydrological modelling (AGIS, 2007). There are inevitably sources of uncertainty in the physical property data themselves as well as in the way these data are interpreted and used for parameter estimation. Some of these sources of uncertainty are related to spatial scale issues. While some physical property data may be available at higher spatial resolutions than used in the model (e.g. topographic data from DEMs), other data will be available at much lower resolutions (FAO soils data, for example). Both situations present potential interpretation problems and could introduce uncertainty.

If the physical property data are available at a scale which is coarser than required (e.g. ISCW or FAO soils data) the information itself is usually very generalised and difficult to interpret into parameter values and uncertainty ranges. If the physical property data are more detailed than the spatial scale of modelling (e.g. using AGIS data for modelling at the quaternary catchment scale), this presents opportunities for further analysis. Options include increasing the detail in the model (given that appropriately representative hydro-climate data can also be accessed), or developing parameter uncertainty expressions based on the variability of the physical property data within the model spatial unit.

Apart from scale considerations, it is not always straightforward to interpret the available data in a hydrological appropriate way. This applies particularly to soils data which are often compiled for agricultural purposes rather than for hydrological purposes. Soil type classifications frequently have to be interpreted into texture and structure classes and hydrological indices such as porosity, permeability, infiltration rates, etc. inferred from the secondary classifications. This will clearly introduce uncertainty into the estimation process which is difficult to quantify.

Ultimately what is required is an estimate of the properties of probability distribution functions (PDF – type, moments, etc.) that represents the estimation uncertainty of each parameter of the model. These PDFs could then be used in one or more of the methods to generate model output uncertainty based on input uncertainty. It should be recognized that the parameter uncertainty needs to be combined with the input hydro-climate data uncertainties.

2.2 Uncertainty in water resources systems models

Figure 2.3 summarises the sources of uncertainty associated with the application of water resources systems models that are typically used to simulate present day and future scenarios of water resources availability. This category of models includes the Pitman and ACRU hydrological models if their non-natural components (land use impacts, abstractions, return flows, reservoirs, etc.) are included as part of the model set-up. It also includes the full range of water resources yield models that are available internationally (Table 2.1).

As with the hydrological models, systems models are also subject to uncertainties in the climate forcing data that might be used to determine inputs (rainfall) and outputs (evaporation losses) from reservoirs or the irrigation requirements of crops under varying climatic conditions. They are also subject to similar model structural uncertainties related to both spatial and temporal scales and the way in which the water balance of the system is computed. The time scale of modelling can be an important consideration in some complex systems where storages change quite rapidly. The order in which the water balance components are calculated can make substantial differences to the results if the model time scale is quite coarse (e.g. monthly). These considerations are particularly important when storage components of the water balance are close to the extremes (full or empty) and it is often necessary to include internal model iterations. The source of uncertainty is then related to how well the automatic internal iterations represent the real time distribution of the water balance components. Other structural uncertainties may also be associated with the application of operating rules, which can be quite complex in practice but have to be simplified within the models. As with hydrological models, there are overlaps between the uncertainties associated with the model structure and those associated with the model parameters.

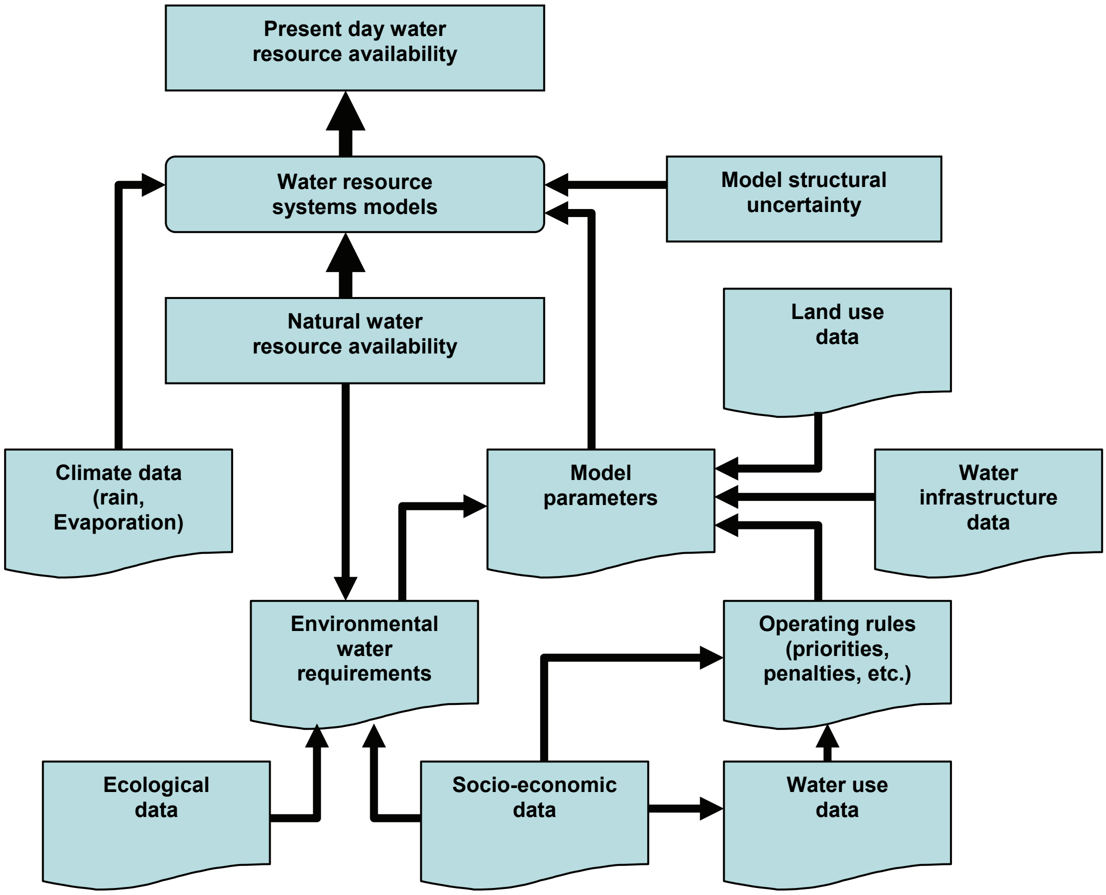


Figure 2.3 Uncertainty in the estimation of present day water availability

There is one part of a systems yield model where the time scale can make a substantial difference in the modelling results and that is where run-of-river abstractions occur (either upstream or downstream of a reservoir). Unless some approach is used to account for intra-month flow variations it is possible that monthly models can over-estimate the volume of water that can be abstracted. This specifically applies to situations where there are substantial intra-month variations (‘flashy’ catchments) and where the low flows are both a relatively small proportion of the total volume and lower than the required abstraction volume. The majority of the high flow component of the total monthly flow will not be accessible to run-of-river abstraction schemes. Hughes (2006d) attempted to overcome this problem by using only the baseflow component of the total monthly flows when assessing abstraction volumes in a simple licensing model that was designed to account for the requirements of the ecological Reserve. However, it must also be accepted that there is a great deal of uncertainty in the methods used to estimate baseflows from monthly flow time series data.

Table 2.1 Summary of water resources systems models (after Wurbs, 2005a)

Model	Descriptive Name	Reference
SSARR	Streamflow synthesis and reservoir regulation	Brooks (1975)
WRIMS (CALSIM)	Water resource integrated modelling system	Draper *et al*. (2004)
StateMOD	State of Colorado stream simulation model	Parsons and Bennett, (2006)
OASIS	Operational analysis and simulation of Integrated system	Hydrologics (2001)
ARSP	Acres reservoir simulation program	Boss International (2004)
MIKE BASIN	GIS-Based decision support for water planning and management	DHI (2000), Hallowes and Pott (2005)
RIBASIM	River basin simulation	Delft Hydraulics (2004)
WEAP	Water evaluation and planning	SEI (2001)
SUPER	SWD reservoir system model	Hula (1981)
ResSim	Reservoir system simulation	HEC (2003)
RiverWare	River and reservoir operations	Zagona *et al*., (2001)
MODISM	Generalised river basin network flow model	Labadie (2006)
WRAP	Water rights analysis package	Wurbs (2006b)
REALM	Resource allocation modelling	Perrera *et al. (2005)*
WRYM	South African water resource yield model	Basson *et al.(1994)*
WReMP	Water Resources Modelling Platform	Mallory (2005)

2.2.1 Model parameter uncertainties (water use)

Figure 2.3 illustrates that the parameters of systems models are associated with water use data (which is in turn related to socio-economic data), operating rules, water infrastructure and land use data. There is the added complexity of allowing for environmental water requirements (EWR) and while their estimation is also subject to uncertainty, this issue is not covered in detail in this report. For the purposes of this report the EWR can be considered as one of the demands on the system, the only difference being that this demand is required to remain in the channel system.

The accuracy of the available information about existing land uses, water infrastructure, water use and operating rules is highly variable across different parts of South Africa. In many cases, especially in large and well managed water development schemes, this information is readily available and generally very accurate. However, in other cases and especially where water use is distributed across many users, rather than being centrally managed, the required information is not very available and the accuracy is largely unknown (Bailey., 1993; Hughes and Mantel, 2010a & b). The problems with these data are very similar to those associated with attempts to naturalise observed flow data that have been referred to earlier.

There has always been a significant degree of uncertainty about how much water is being used in a catchment. This uncertainty is due largely to the fact that under the previous water act (Act 36 of 1956) water users had riparian rights and they were generally not required to register this water use. The exception was those areas declared as Government Water Control areas in which use was calculated or agreed upon with users and gazetted. In many cases irrigation boards where formed in which the areas and application rates were also fixed and controlled by irrigation boards. More recently, in terms of the new water act (the National Water Act of 1998), all water users must register their water use, a process that has been largely completed but the results of which are still subject to uncertainty. Some users under-registered their use so as to reduce their catchment management charge, while others over-registered in the hope of staking a claim to a greater water right than they currently had. In an evaluation of the accuracy of the registration process in the Thukela River catchment (Tylcote, 2007), it was found that approximately one third of irrigators under-estimated their water use, one third over-estimated their water use and the remaining third registered their use accurately. The net result in this test case was that the registered use was, on average, approximately correct. Within the context of uncertainty, this 'correct' estimate still contains a large degree of uncertainty. The water use by irrigators is generally estimated using models based on the evapotranspiration rates of crops and the assumptions that irrigators will irrigate to maximize the yield of their crops. The use is rarely recorded and in an assessment of irrigation requirements in the Komati River catchment, estimates of total water use varied from 439 to 716 * 10^6 m^3 depending on the approach used. The uncertainties are associated with:

- Crop area and type.
- Crop factors of the assumed crops.

- Losses due to ineffective irrigation techniques (losses range from 5 to 35%).
- Losses in the conveyance of the water from the source to the field edge.
- The effect of rainfall in the crop requirement.
- Irrigators often change the type of crop they are cultivating and hence the water demand and the monthly distribution of the water use changes.

Water services provided by the Department of Water Affairs (DWA) and their agents were often not registered. It is not clear why this is the case but it seems there is confusion as to who is responsible for registering this use. The result of this non-registration is not crucial since water use estimates for domestic use can usually be obtained from Water Services Development Plans which each municipality must submit to DWA in terms of the Water Services Act. Water use by small rural users is generally not monitored and hence unknown and the water used by afforestation (as well as other 'stream flow reduction' land use practices) cannot be monitored directly and is estimated by means of hydrology models. These estimates have a wide range of values depending on the methodologies used. The genus of tree grown also influences the water use and while afforested areas are relatively easy to ascertain using satellite imagery, the genus cannot be ascertained in this way and is hence often unknown.

2.2.2 Model parameter uncertainties (operating rules)

Operating rules play a major role in the estimation of the yield of a water resources system. However, the actual operating rules used in practice are frequently poorly defined and not always applied in a consistent manner. The operating rules relate to the specification of supply priorities, the integration of different sources of supply to users, and when, if and how restrictions are applied to users during droughts. A further source of uncertainty is related to the timing of the application of certain operating rules (e.g. when to apply restrictions). While these triggers may be relatively straightforward to include within a model, they may bear very little relationship to what actually happens in practice.

There are essentially two types of algorithms used to solve for flow in a network type model. These are rule-based algorithms and linear programming algorithms. Both algorithms have their advantages and disadvantages but both only offer a mathematical approximation of the real system. Linear programming algorithms are driven by assigning a value to water held in storage and a penalty to the non-supply of water to users. The higher the penalty assigned to a user the higher his priority of supply. The linear programming algorithm then solves the network by minimising the cost to the system. This methodology is often criticized as being subjective (Juizo and Liden, 2008). There is certainly a degree of uncertainty introduced in this modelling procedure in that it can be difficult to ascertain where water is sourced from to supply high priority users in stressed catchments. Water is essentially taken from lower priority users but the actual operational decision used is not explicit in these types of models. Rule-based models (Mike Basins, Water Resources Modelling Platform, etc.) are driven by explicit rules which make the modelling process more transparent. Nevertheless, all yield models assume the operators are always making the right decision based on a complete knowledge of the system which is never the case. Some catchments may be too complex to be modeled with rule-based models and it could be argued that in such complex catchments the operators are also operating within a range of uncertainty due to lack of a complete understanding of the system. In these complex catchments linear programming models are probably more appropriate for determining estimates of the water availability.

2.2.3 Uncertainty and risk in current yield modelling practice

While there has been little practical recognition of many of the sources of uncertainty involved in water resources assessments, the standard approach to yield modelling in South Africa has included some uncertainty through the inclusion of stochastically generated stream flow sequences that are seeded using a single estimate of the historical stream flow (typically simulated using a hydrological model). The stochastic stream flow approach is used because the single input historical hydrology cannot necessarily be considered representative of all possible sequences of flow that will determine the yield in the future, even under stable climate and land use conditions. The assumption is that there is no guarantee that the worst possible (from a yield perspective) sequence of flows has ever occurred in the historical period (derived either from observed or simulated flows). The stochastic model is therefore designed to use the statistics (general frequency characteristics such as means and standard deviations, as well as serial correlation statistics) of the historical record to generate other possible sequences of flow that will inevitably generate different yields (Basson et al., 1994). The output of such analyses is typically a yield (y-axis) versus probability (x-axis) curve (see Figure 4.1 for example). The conventional interpretation of these diagrams is based on the relationships between risk and reliability given in Basson et al. (1994) where:

$$\text{Return Period} = 1 / (1 - (1 - R_n)^{1/n})$$

where n is the period of record used for the analysis and R_n is the long term risk equivalent to the probability of at least one failure in the record. This concept of using the stochastic sequences to determine the reliability or risk of a particular yield is based on the assumption that all of the stochastic sequences are possible and will occur within a long enough period of record. Yield probability curves have been used for many years to determine the long-term yield that should be used for development planning purposes on the basis of the risks that can be considered acceptable. If designing for a highly reliable system (water supply for power generation for example) then a lower volume and higher assurance yield would be used, while irrigation systems can be designed with lower levels of reliability and higher risk.

An alternative interpretation is one based on uncertainty and operates on the assumption that we do not know which, or whether any, of the stochastically generated sequences are realistically possible or not. The concept of a return period would not be used in this approach and the probability axis would be interpreted as a measure of uncertainty of achieving a specified yield over a very long period of time. The yield that is equaled or exceeded 90% of the time (based on the ranking of the yields from say 500 stochastic sequences) would then be considered to be very reliable, while the yield corresponding to 50% exceedence would be less certain and a yield corresponding to 20% exceedence would be highly uncertain. It is not suggested that this is the 'correct' interpretation, but it is easier to combine this interpretation with other sources of uncertainty.

The type of uncertainty referred to above can be termed '**stochastic uncertainty'** (Figure 2.4) to distinguish it from '**hydrological uncertainty**' associated with our ability to define representative climate drivers (rainfall and evaporation demand) and to simulate the stream flow response to these drivers using hydrological models. The two sources of uncertainty are not independent, in as much as the stochastic sequences are dependent upon the statistical properties of the historical time series used to generate them. Different historical time series (hydrological uncertainty) can therefore be expected to generate different stochastic sequences depending on the nature and extent of the hydrological uncertainty. One of the issues raised during the various workshops held during this study was the most appropriate methods of combining these two sources of uncertainty in the most efficient way possible and without having to completely re-design the modelling tools that are currently in use in South Africa. An example of possible alternative approaches is provided later in this report.

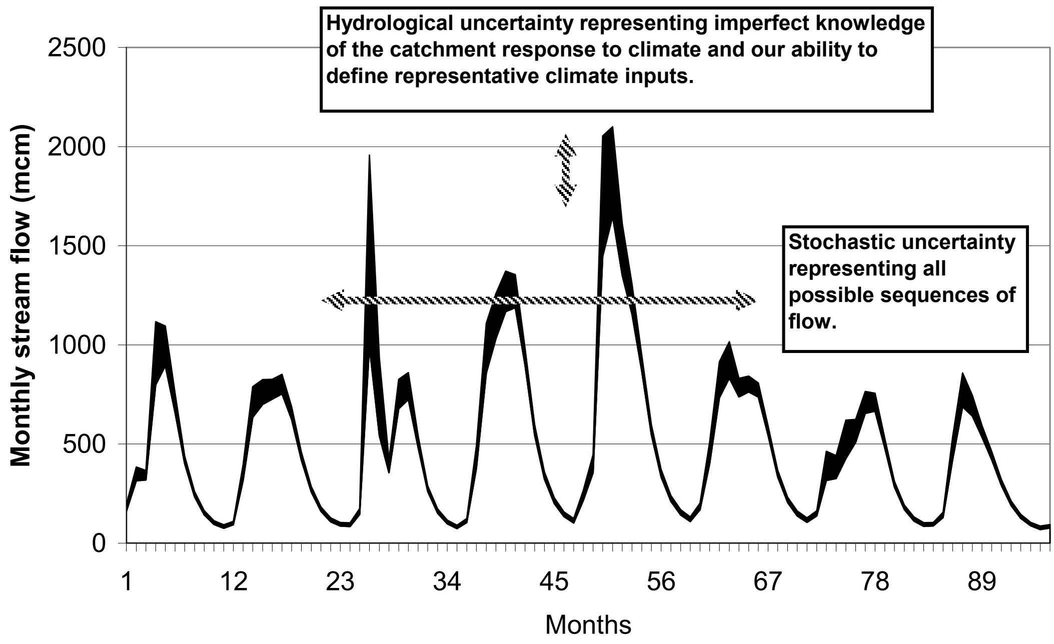


Figure 2.4 Distinction between stochastic and hydrological uncertainty.

2.3 Uncertainty and future management risks

Figure 2.5 completes the detail of the hierarchical diagram of uncertainty and risk given in Figure 2.1. The types of water resources systems models discussed in the previous section are one of the main tools used in developing future management decisions and all of the comments about the various sources of uncertainty are also applicable here. The main difference is that the estimates of future water use are subject to many additional sources of uncertainty that are related to socio-economic trends and political policy developments. While a detailed discussion of these issues is beyond the scope of this report they are acknowledged as major sources of uncertainty that contribute substantially to the risks involved in water resources decision making.

Within South Africa the development and implementation of many new policies since the end of apartheid in 1994 has enormous implications for water resources management. Some of these, such as the various provisions of the National Water Act of 1998, impact directly, while others impact indirectly through changes in the socio-economic structure of the country's population. While many of the policies are relatively clear, the pace of implementation and the impacts on society and therefore the requirements for water are not at all clear. An example is the inclusion of EWR within the water resources legislative and management framework. The law is quite clear about the legal requirement to allow for EWR, but the actual volumes and patterns of flow required to achieve the objectives of environmental sustainability are complex and have yet to be implemented in practice. The whole process of including EWR as part of future water resources assessments is also made more complex by the need for a classification system which determines the level of ecological protection (and therefore the volumetric water requirements) that is related to a number of factors, some associated with priorities for economic and social development.

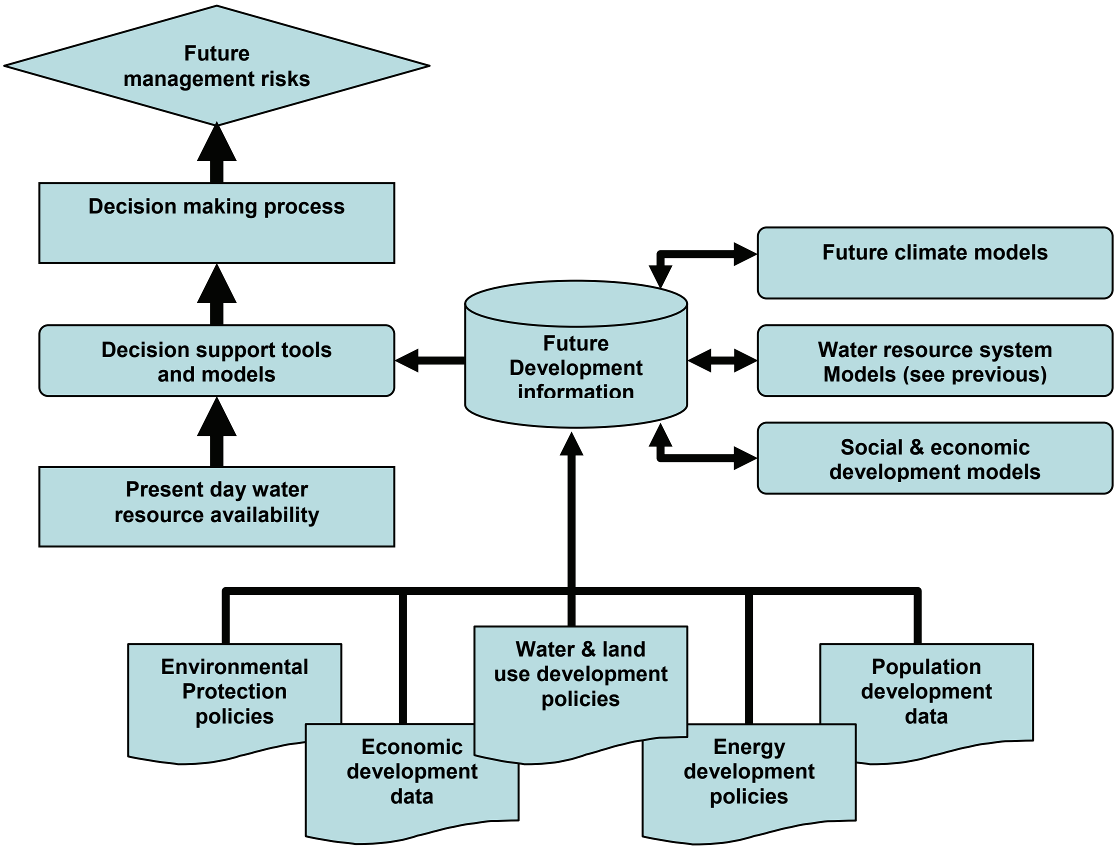


Figure 2.5 Uncertainty and future management risks

Apart from the socio-economic and political uncertainties, there are also huge uncertainties associated with the expected patterns of future climates. There are world-wide concerns about the impacts of greenhouse gasses and global climate change. However, while many popular press articles seem to be quite sure about what is going to happen, the scientific community accepts that there are many uncertainties in the outputs of the many prediction models that are currently in use and endorsed by the Inter-governmental Panel on Climate Change (IPCC) as well as how to down-scale these predictions for use in hydrological and water resources estimation models (Hewitson and Crane, 2006). Some examples of the uncertainty associated with future climate predictions are included later in this report.

The points noted under section 2.2.3 of this report are equally important for the analysis of future management as they are for the determination of present day yield assessments and the same type of analysis or assessment approaches would apply.

2.4 A generic uncertainty framework for South African water resources assessments

One of the early developments in this project was the formulation of a generic uncertainty framework (Kapangaziwiri et al., 2009) that recognizes some of the limitations of both the data and models that are available and widely used in South Africa, as well as the international developments in the science of hydrological modelling. This framework is illustrated in Figure 2.6 and is considered to be flexible enough to be applicable to a wide range of different models (both hydrological and water resources systems models). A large part of the remainder of this report is focused on illustrating the use of this framework through examples, while this section provides a brief overview of the components of the framework and its perceived advantages.

2.4.1 Prior parameter distributions

The assumption is that these distributions represent the uncertainty in the way in which a hydrological model is parameterized and can be defined in any way that is considered appropriate to the methods used for estimating parameter values. The approach is therefore compatible with parameters derived through some type of regionalization scheme where the uncertainty may be defined as prediction limits associated with regression equations used to estimate parameters from physical basin properties. It is also compatible with the direct estimation of parameters from physical basin properties, without any prior model calibration. The details of this type of approach are fully explained in Kapangaziwiri (2008 and 2010) and summarized in Kapangaziwiri and Hughes (2008 and 2009) and will be referred to in more detail within the sections of this report that illustrate the use of the framework.

The assumption is that the parameter distributions can take on any form including various shaped probability distributions such as normal and log-normal, or can be a simple uniform distribution in which all values within a range defined by maximum and minimum values are equally possible. The uncertainty distributions of the different model parameters are considered to be independent and the uncertainty in each individual parameter is also considered to be independent across all of the sub-catchments in the model spatial distribution scheme. It is therefore possible to have widely different degrees of uncertainty associated with different parameters and some may be specified with no uncertainty.

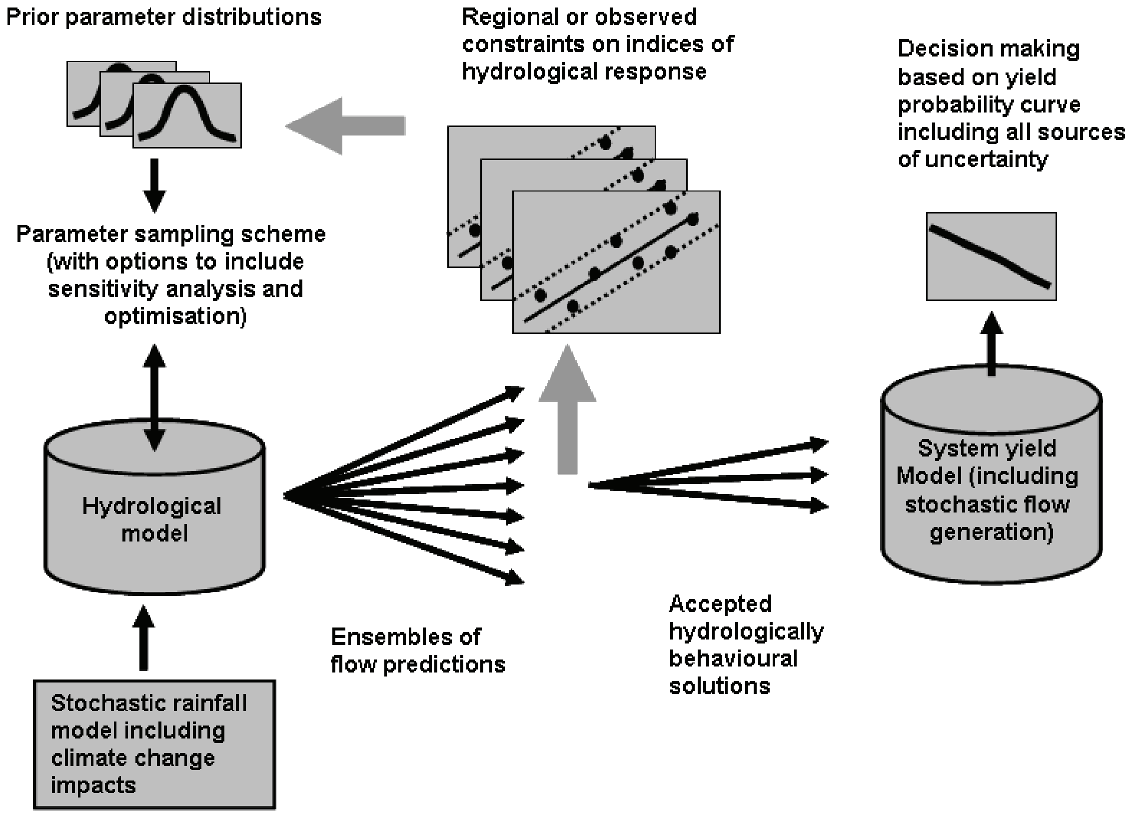


Figure 2.6 A generic framework for including uncertainty into water resources assessments.

It has already been noted that the framework is designed to be applicable to a range of different models and the implication is that the approaches used for establishing prior parameter distributions will vary with the model. While a large part of this report is focused on the application of the Pitman monthly model and the parameter estimation procedures explained in Kapangaziwiri (2010), some limited applications of uncertainty analysis using the ACRU model also formed part of the project and these are presented in Appendix A. The approaches used for prior parameter estimation and the generation of ensembles with the ACRU model are very different to those used for the Pitman model. It is not entirely clear at present how these can be integrated into the general framework and this issue requires further investigation.

2.4.2 Uncertainty in the climate inputs

The lower left part of Figure 2.6 indicates that the climate inputs to the model can also be specified as uncertain through the input of multiple time series of rainfall, for example. The assumption is that the stochastic component of uncertainty referred to in section 2.2.3 of this report could be provided for by using the outputs of a multi-site stochastic rainfall model (Srikanthan and Pegram, 2009). The uncertainty could also be represented by a set of down-scaled climate model ensembles.

2.4.3 Parameter and climate input sampling within the hydrological model

To enable existing hydrological models to be used within this framework, the main modifications required is to include a sampling scheme for the uncertain parameter and climate data inputs such that the model is run repeatedly and generates an ensemble of simulated stream flow (and other modeled variables, where appropriate) outputs. In the context of this project the Pitman model has been modified to achieve this through simple Monte Carlo sampling of the possible parameter space. The modifications that have been included cater for normal and log-normal parameter distributions (defined by means and standard deviations, with all samples constrained to lie within defined maximum and minimum parameter limits), as well as uniform distributions (defined only by the maximum and minimum parameter limits). The number of model runs (and therefore parameter samples) can be user specified (typically 1 000 to 10 000) can be specified by the user and the outputs include the time series of all the ensembles, the 95%, 50% and 5% exceeded flows for each month of the time series, the parameter values and some summary statistics (including objective function values if observed data are included) for each of the ensembles.

A separate version of the uncertainty version of the Pitman model allows for the input of different rainfall time series (outputs from a stochastic model, for example). Independent parameter samples are generated for each of these rainfall inputs such that the output ensembles include both climate and parameter uncertainty. If the inputs consist of 500 rainfall time series and 500 parameter samples are used, the result is 250 000 out put ensembles. Generating this large number of ensembles takes a lot of computer resources (time and memory) and therefore the outputs have been restricted to the final stream flow ensembles and the model does not perform any internal analyses of the simulation results.

It is acknowledged that alternative parameter sampling schemes could be incorporated into the framework and that either parameter sensitivity analyses or optimization routines (if some observed data are available) could be used to constrain the parameter sampling process. A PhD student at the University of Gainesville in Florida, USA is exploring some sophisticated sampling procedures based on parameter sensitivity analyses using the Pitman model in the Okavango River basin. The IWR members of the project team have been cooperating with the Gainesville group and more results are likely to be available after this WRC project has been completed.

2.4.4 Regional constraints on hydrological response

The traditional approach to hydrological model calibration is to make use of observed data to condition the simulated flows and determine (manually or automatically) an optimum set of parameters based on comparisons with observed data using single or multiple objective functions. This approach is clearly not possible in ungauged basins and the whole concept of attempting to determine an optimal model has been called into question (Beven and Freer, 2001; Beven, 2006). Many conceptual type models contain complex parameter interactions such that similar outputs can be achieved with several different parameter sets (the equifinality problem of Beven, 2006). It is now widely recognized that the most important part of any modelling study should be to identify those parameter sets that produce hydrologically behavioural outputs. The problem then mainly lies in defining what a behavioural output is and rejecting those outputs that can be considered non-behavioural. Yadav et al. (2007) proposed an approach that is based on a set of regionalized indices of catchment response that would be used to select from initial model ensemble outputs only those that fall within the constraints. This is an approach that is ideally suited for regional water resources assessments where there are many ungauged sub-basins.

The development of the regional constraints should be able to make use of all the available knowledge and understanding of hydrological response characteristics. The constraints should address different aspects of the simulated flow time series and may even be applied to sub-components (such as estimates of groundwater recharge) of the model, rather than to only the final output in terms of stream flow. It should be recognized that the constraints themselves will be subject to uncertainty as they will typically be based on regional relationships developed with limited data that contain errors.

Within the proposed framework (Figure 2.6) the regional constraints can be used in two different ways. They can be simply used to determine which of the initial simulation ensembles should be accepted as behavioural and therefore can be passed on to the next stage of the water resources assessment process (typically a systems yield model). This would be the appropriate method to use when there is little, or unreliable, information available that can be used to estimate the parameter uncertainty distributions. These distributions would therefore be expected to have quite large ranges and produce very different simulated flows within the full ensemble set. The alternative use of the regional constraints is to feedback information to the parameter estimation process so that the estimation equations can be improved or so that the interpretation of the physical basin property data can be checked and re-assessed. The framework is therefore applicable to practical modelling studies as well as being of value to further develop the various internal components in a research environment.

It is inevitable that the parameter estimation and modelling process will not be entirely independent of the method used to establish regional constraints as they will both share at least some common data. However, care should be taken to ensure that erroneous data (or assumptions) are not contained within both parts of the framework such that the errors are propagated through the system resulting in accepted, but not behavioural, outputs.

3. ESTABLISHING THE FRAMEWORK

This section of the report concentrates on the approaches that have been developed to estimate the parameters of the Pitman model using physical basin properties as well as the development of some initial regional constraints based on observed stream flow data and existing estimates of ground water recharge. A large part of the research work reported here was undertaken by Evison Kapangaziwiri as part of both his MSc and PhD degree programmes. Further details, particularly of the parameter estimation routines can therefore be found in the two theses (Kapangaziwiri, 2008 and 2010 accessible form the Rhodes University Library website: http://www.ru.ac.za/library/resources/theses/rutheses).

3.1 Prior parameter estimation

The approach adopted for the Pitman model (using the revised version with explicit ground water interaction routines as detailed in Hughes, 2004) is based on the physically-based parameter estimations routines that were briefly described in Kapangaziwiri and Hughes (2008) and more completely explained by Kapangaziwiri (2008). These original references explain the conceptual basis for most of the parameter estimation equations and provide examples of how they are applied. Initially they were limited to a single estimate for each parameter, but the approach has been extended to include measures of uncertainty using either Normal, log-Normal or uniform distributions (Kapangaziwiri and Hughes, 2009; Kapangaziwiri, 2010).

The basis of all the uncertainty estimation is to assume some uncertainty in the primary estimation variables (such as soil depth and texture, topographic slope, geology metrics, etc.) and to use Monte Carlo sampling of all the variables associated with the equations used for secondary variables, or the final parameter estimates, to generate ensembles of results values. A large part of the uncertainty in the primary data is related to its spatial variation within a modelling unit and how this spatial variation can be translated into a sub-basin scale estimate of the model parameters. The means and standard deviations of the results values are then used to define the uncertainty in the parameter estimates. If the skewness of the distribution of results values is greater than 2.5, the distribution is assumed to be log-Normal. A great deal of the information used to estimate the parameters is derived from the AGIS Land Type information (AGIS, 2007), particularly with respect to the main runoff generation parameters that are expected to be determined from soil and topography characteristics.

The AGIS data typically includes information for 5 dominant soil units within a land type and these will occur in different proportions across the major terrain units (hilltops, upper slopes, lower slopes and valley bottoms). The soils information includes texture and a range of depths for each soil unit. The texture type information is used to define some basic soil property values (infiltration parameters, porosity etc.), each with uncertainty (based on the literature containing typical values). The soil porosity secondary variable (right side of Figure 3.1) for the total catchment is based on sampling from all the soil types (see left side of Figure 3.1), given assumed mean and standard deviation values associated with each texture type. The number of samples taken from each soil unit depends upon its relative area over the whole catchment. If more than one land type occurs within a sub-basin, the information from all land types has to be integrated before entering the values into the table on the left side of Figure 3.1. If several land types occur within a sub-basin it is possible that the ranges of slope, soil depth and texture will be quite large and this will lead to high uncertainty in the secondary variables and eventually the parameter estimates. The only way to reduce this uncertainty would be to reduce the modelling scale so that there is less variation in the primary input data within a model spatial unit. Some examples of the effects of reducing the model scale are provided later in this section of the report.

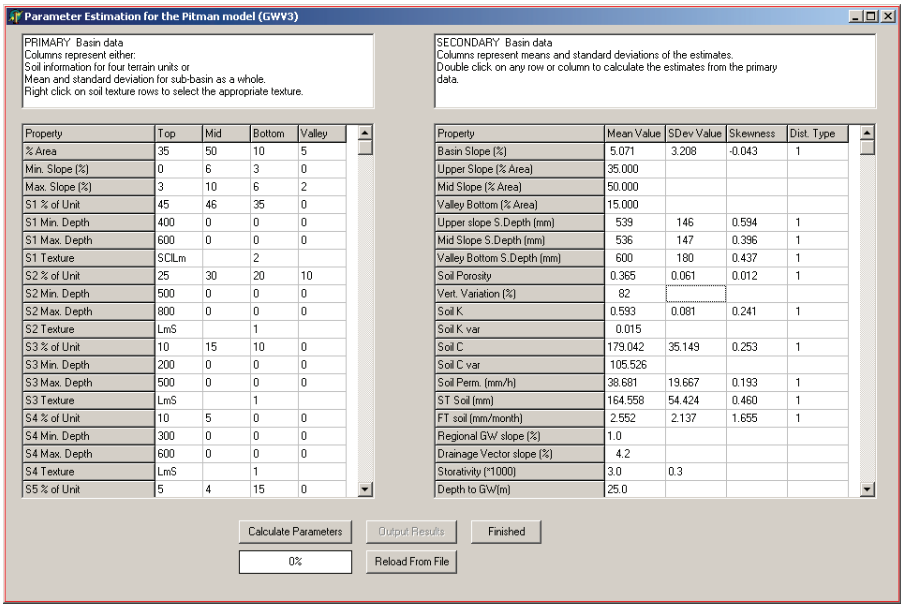


Figure 3.1 Initial screen of the Pitman model parameter estimation process.

For the basin slope estimation, the range of slopes for each terrain unit is assumed to represent the 95% limits of the distribution (Normal) of all possible slopes. If the maximum slope is greater than 40%, the distribution of slopes for that terrain unit is assumed to be log-Normal. These slope distributions are then sampled (a total of 5 000 samples with the number of samples from each terrain unit based on the % of the total catchment area) and the results used to estimate the mean and standard deviation for the basin slope (Figure 3.1, left side, 1st data row).

The same procedure is followed for all the secondary basin data variables (Figure 3.1, right side) as well as for the final parameter estimates (Figure 3.2). In some cases parameters are currently estimated without uncertainty, while in others the estimation equations involve curve fitting routines but still use the uncertainty in the input variables. Note that some of the secondary variable or parameter results end up being log-Normally distributed, despite the fact that all of the input variables are normally distributed. This is a consequence of non-linear estimation equations. The results can be output to a text file that can be imported into the SPATSIM data attribute that is used for the uncertain parameter value inputs to the Pitman model. Work is still progressing on some of the estimation equations, notably those associated with interception, evaporation losses and the groundwater recharge parameters.

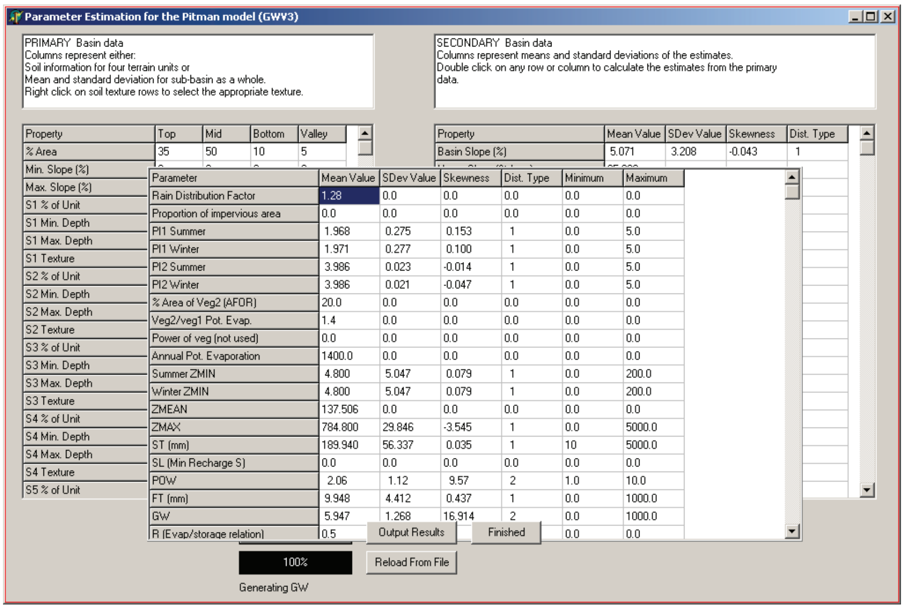


Figure 3.2 Final results screen of the Pitman model parameter estimation process.

3.2 Revised versions of the Pitman model

Three revised versions of the SPATSIM implementation of the Pitman model have been developed to deal with uncertainty analysis. The first makes use of three values in the parameter input stream; a default (or best guess value), a step size and the number of steps. If the number of steps for a specific parameter is specified as 3 then 7 values of the parameter are used in repeated model runs (the default value and 3 values either side: default ±1, 2 and 3 * step size). If 5 parameters are considered to be uncertain then the number of repeats of the model run is 7^5 or 16 807. The outputs from the model include a text file which lists all of the parameter sets plus some summary statistics of the simulation and several objective function values if observed data are available and included in the model setup. This text file can be used with Excel to analyse the parameter interactions or to identify the parameter sensitivity. While this version of the model allows for all the extremes of the parameter space to be included, the use of simple steps does not allow for a more continuous assessment of the parameter space, nor does it allow for the use of probability distributions to define the parameter uncertainty.

A second SPATSIM version of the Pitman model allows the uncertain parameter inputs to be used in a Monte-Carlo sampling framework. The input table includes for each parameter the mean value (assumed to be the 'best' estimate), standard deviation, skewness, distribution type to be used in the model (1=Normal, 2=log-Normal, 3=uniform), the minimum and maximum values. The parameters for each sub-catchment in the semi-distributed modelling scheme are sampled independently (using a sampling method appropriate to the distribution type) for each of the model run ensembles (the total number is set to 5 000 by default, but this value can be changed by the user). If the distribution type is 1, Normal distribution samples (mean = 0, standard deviation = 1) are generated and scaled using the mean and standard deviation. If the distribution type is 2, the parameter mean and standard deviations are converted to natural log values before being used to scale the Monte Carlo samples and the result calculated as the exponential of the scaled sample. For both types 1 and 2 the minimum and maximum values are used to reject any samples that are considered to be too low or high and additional samples generated. If the distribution type is 3 a uniformly distributed set of samples is generated and scaled using the minimum and maximum values. It is important to note that the minimum and maximum values are therefore used in different ways for the uniform distribution type compared to the Normal or log-Normal types.

All of the ensembles are saved within the SPATSIM database (and can be further analysed with the various utilities provided) and additional outputs are generated to two text files. The first text file (Pitmv3_{catchment ID}.un1) contains the list of sampled parameter values, the simulated mean monthly runoff volume ($m^3 * 10^6$), the simulated mean monthly recharge (mm), the slope of the flow duration curve (FDC) and the 10%, 50% and 90% points (as volumes in $m^3 * 10^6$) on the annual FDC for each of the ensembles. Additional metrics summarizing the simulated flow data can be added as the need arises. The second text file (Pitmv3_{catchment ID}.un2) contains four columns of monthly flows for each month of the simulation period. The first three columns represent the 95%, 50% (median) and 5% exceeded simulated flows for all ensembles and it should be noted that these do not represent actual simulated time series, but are the bounds within which all of the ensembles fall. The final time series is a copy of the 'observed' data passed to the model from SPATSIM for reference purposes (if included in the model setup). These 'observed' values could be real observed flows from a gauge or could be some other reference time series used to compare the simulated ensembles with (e.g. WR90 or WR2005 'conventional wisdom'). Both of the text files (un1 and un2) can be imported into Excel spreadsheets for further analysis and graphical display.

The third version of the model is very similar to the second except that it can accept multiple rainfall time series inputs (as generated by a stochastic rainfall model for example). Each of these time series is used together with the Monte Carlo parameter sampling procedure. If 500 rainfall time series are used and 500 parameter samples generated, the final output consists of 250 000 ensembles. To avoid excessive computer time and storage space the outputs are limited to the ensemble time series. It is assumed that these will be further screened for use with other models and this approach is discussed later in the report.

3.3 Developing regional constraint indices

Table 3.1 provides a list of possible indices of hydrological behaviour, together with predictor variables and sources of information that were identified early in the project. Several issues were considered in selecting appropriate indices from the list provided in Table 3.1:

- The indices must be estimated from reliable information about observed natural hydrological response. It is recognized that many of the observed stream flow records are not appropriate for this purpose without some processing. This is largely because they are affected by upstream developments (abstractions, impoundments, diversions, land use changes, etc.), are subject to measurement error and because they are not able to measure the full range of observed flows. Typically this means that the observed flows have to be naturalized. Unfortunately this process is subject to uncertainties which will affect the quality (accuracy and representativeness) and usefulness of the extracted indices.
- The indices have to be hydrologically relevant and measure some basic property of the hydrological response.
- It must be possible to calculate the indices from the simulated model ensembles so that they can be compared with the observed values of the indices.
- It must be possible to find predictor variables that can be used to estimate the indices for the whole country (at the quaternary catchment scale) with as little uncertainty as possible. If the regional constraints are estimated with a high degree of uncertainty

(defined using the confidence limits of regression relationships, for example) they will not be very useful for constraining the model output ensembles.

Table 3.1 List of possible constraint indices, predictor variable and sources of information (note that there is no intended link between the columns).

Constraints	**Predictor Variables**	**Sources of Information**
Daily & Monthly:	*Climate:*	WR90
Mean stream flow metrics	MAP	WR2005
Main slope of monthly FDC	Evaporation/MAE	SA Atlas
Some yield metrics	Temperature	DWAF GIS
Monthly or annual CV	Rainfall CV	GRAII
Measure of baseflow (FDC?)	Daily Rainfall Statistics	Smithers (Extreme rainfalls)
No. of months of zero flow	No. of Raindays	Topographic map layers
Seasonality metrics	*Topography:*	AGIS
Groundwater recharge	Slope or Relief	MODIS satellite data
	Drainage Density	NOAA rainfall satellite data
Daily only:	Basin Area	
Recession Coefficients	Basin shape	
Time-to-peak	*Vegetation:*	
Flood frequency characteristics	Indices of water use	
	Wetland area	
	Soils:	
	Infiltration properties	
	storage properties	
	Drainage properties	
	Geology:	
	Recharge	
	Storativity	
	Transmissivity	

Three of the indices referred to in the first column have been included at this stage of the development of the uncertainty framework. However, it is accepted by the authors of this report that these are not sufficient and that further work is required to refine the existing indices and include additional ones.

3.3.1 Budyko type curves for mean annual runoff volume

The first constraint has been based on the concepts developed by Budyko (1974) using a measure of aridity to predict runoff through regional P/PE versus Q/P relationships. The first step was intended to cover the whole country and therefore used the mean annual runoff (Q) from the simulated 70 year (1920 to 1990) WR90 runoff time series and the estimated mean annual rainfall (P) and potential evaporation (PE) for all 1946 quaternary catchments (Midgley et al., 1994). The runoff data used were the incremental flows, generated only within each quaternary catchment. Plotting all these data suggested a series of log-log relationships that converge at low values of both P/PE and Q/P. An iterative process was followed to define four regional relationships. The relationship for Region 1 was first established by identifying a regression equation that had a high R^2 value and for which the residuals were approximately equally divided between negative and positive values. Once the points to be included in Region 1 were finalised, the same process was followed to identify the Region 2 points and so on. All of the points and the resulting regression relationships are shown in Figure 3.3, while Table 3.2 lists the equations and R^2 values. Figure 3.4 indicates that the regions are generally spatially contiguous although there are some areas that are not clearly defined as a single region. This may be due to localised variations in runoff response, as well as artefacts related to errors in the data used.

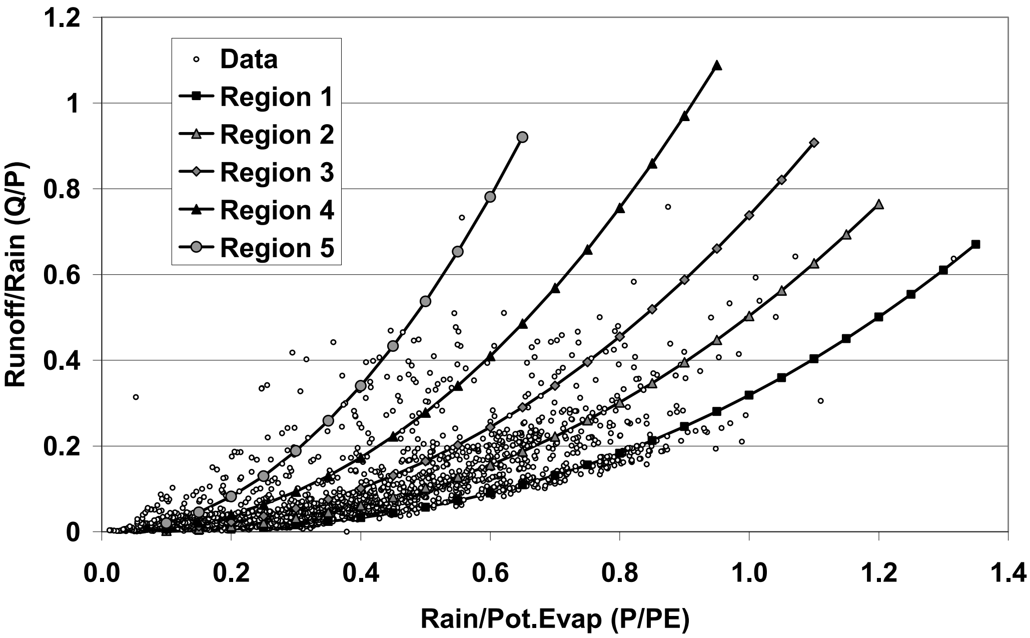


Figure 3.3 Regional Budyko type curves based on log-log relationships (see Table 3.1 for coefficients of the regression equations).

It would not be strictly good practice to develop the regional constraint relationships using simulated data, although it is considered to be acceptable to use these data to initially define the regions. These are the only data that have a reasonable national coverage and are deemed a good starting point for a first order definition of regions before these are refined using other coarser data such as observed or naturalised flows for the definition of the relationships. Therefore, the second step involved the use of the naturalised time series (also given in Midgley et al., 1994) for all available stream flow gauges. Gauges were initially rejected if they had less than 10 years of observations, if their drainage areas included quaternary catchments that fell into more than a single region or if the amount of missing (and in-filled) data was excessive. Some very small gauged sub-basins were also rejected. For each of the regions identified during the first step, Table 3.2 lists the number of gauges included in the analysis, the range of catchment areas, the coefficients of the final estimation equations and the R^2 value. It is apparent that the final equations are very similar to the initial equations (Figure 3.2 and top part of Table 3.2 based on the simulated data) for Regions 1 to 3, but that there are quite large differences for Regions 4 and 5.

Table 3.2 Regional Budyko type relationships

	Regions				
	1	2	3	4	5
Based on simulated data					
No. of Quats.	397	702	317	202	325
Area (km^2) range	59-8647	43-18108	72-10274	72-3913	89-8037
Slope (A)	2.527	2.293	2.168	2.126	1.770
Intercept (B)	-1.113	-0.687	-0.304	0.194	0.478
R^2	0.927	0.968	0.984	0.990	0.866
Based on observed flow data					
No. of gauges	40	135	45	23	27
Area (km^2) range	86-1887	81-1668	106-1691	84- 873	101-1889
Slope (A)	2.322	2.154	2.171	2.406	1.351
Intercept (B)	-1.079	-0.741	-0.338	0.475	0.173
R^2	0.932	0.905	0.890	0.917	0.820

Note: Equations are of the form ln(Q/P) = A * ln(P/PE) + B

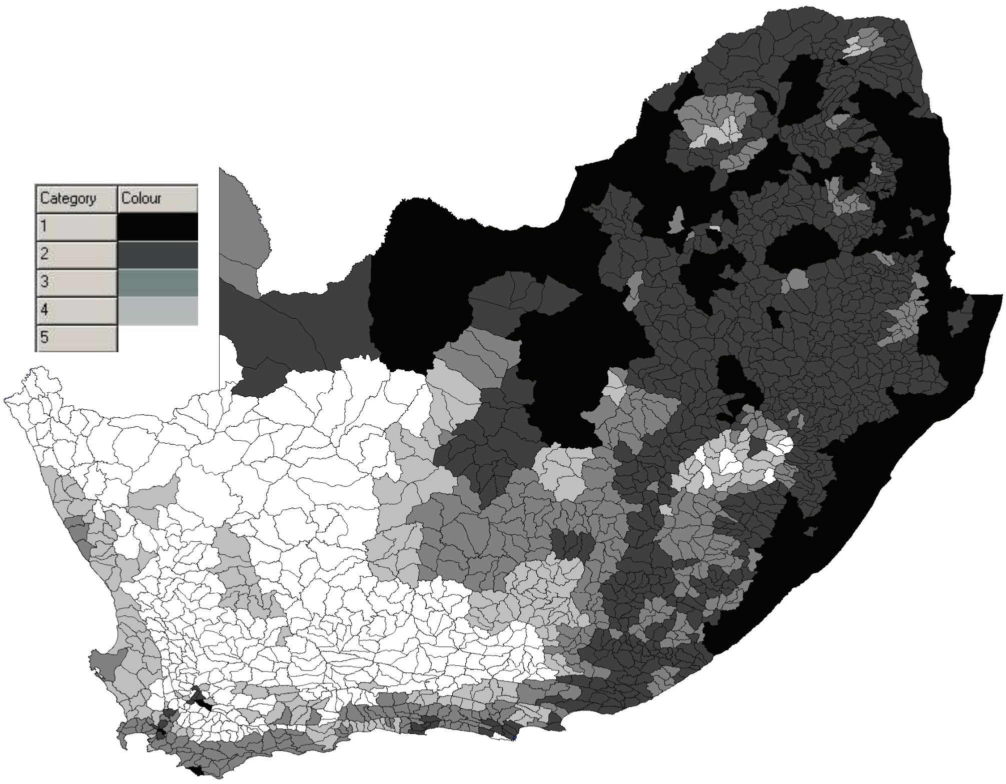


Figure 3.4 Regions based on Budyko type relationships between P/PE and Q/P

3.3.2 Slope of the annual flow duration curve for monthly stream flow volumes

In a region such as South Africa with very diverse flow regime characteristics, the shape of the flow duration curve (FDC) can be a very useful indicator of hydrological response characteristics. The shape of FDCs is also important in determining potential levels of sustainable abstraction, the need for artificial storage and is relevant to determining environmental flow requirements (Hughes and Hannart, 2003). FDC shape is therefore highly relevant to water resources management. As with the Budyko relationships the starting point for the analysis was to use the simulated flow time series for all 1946 quaternary catchments to try and identify regional relationships. For largely perennial river systems the FDC slope values were calculated as the difference between the logarithms of the Q10 and Q90 values divided by 0.8 (i.e. {90-10}/100 : dividing by 100 is simply used to avoid small numbers in the result). For those sub-basins with periods of zero flow, the Q90 value was replaced with the first non-zero FDC percentage point value and the difference in flows divided by the appropriate % differences.

Various readily available predictor variables (or combinations thereof) expected to influence FDC shapes were used to try and find suitable estimation equations, either for the whole country or for different regions. It was found to be very difficult to find suitable variables and there were no obvious regional patterns in the data. While further analyses are still being done to improve the development of a constraint relationship, Figure 3.5 illustrates the initial interim solution. The estimation equation is based on an index that combines a measure of aridity (P/PE) and a measure of sub-basin slope (relative relief). The R^2 value of the relationship is 0.63 and the equation is ln(FDC slope) = 4.0-0.6xIndex value. The relationship illustrated in Figure 3.5 excludes a number of sub-basins in the country that are strongly influenced by dolomitic geology and a region in the north-east of South Africa that appears to be anomalous based on the simulated flow data. Some of the scatter in the relationship as well as the existence of anomalies could be artefacts associated with the use of simulated data.

The regression analysis has been recently repeated with 230 naturalised observed flow records (taken from WR90) and the appropriate format of the index value was found to be closely similar to the one used for the quaternary catchment data (i.e. a scaling factor of between 0.08 and 0.06 for the log value of relative relief). The range of index values is substantially less for the observed data (reaching a minimum index value of only 2.5), the R^2 value is much lower (0.275) but the regression is very similar (ln(FDC slope) = 3.64-0.53xIndex value). The inclusion of relative relief in the analysis of the observed data does not add very much to the precision of the relationship and further work is required to assess other predictor variables that might influence the variability in slope of FDCs.

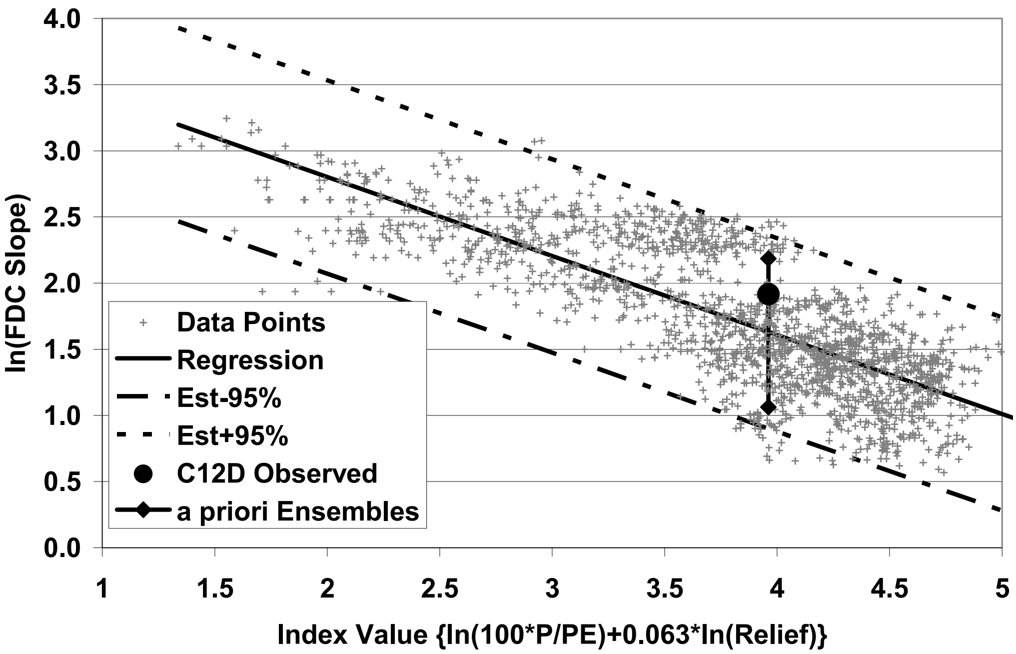


Figure 3.5 Relationships between an index of aridity (P/PE) and sub-basin slope (Relief) and the slope of flow duration curves based on simulated WR90 data.

3.3.3 Groundwater recharge

During the revision of the initial parameter estimation procedures (Kapangaziwiri and Hughes, 2008), an attempt was made to estimate the main groundwater recharge parameters (GW and GPOW) using estimates of the mean annual recharge (from the GRAII database) and an indication of average soil moisture status based on some of the other parameter estimates. While an approach has been adopted, it was not found to be very reliable during initial testing and therefore cannot be used with a great deal of confidence. In practice there are too many variables and non-linearities involved in the monthly simulation of recharge within the model to be able to reverse engineer the model output (i.e. estimate the input parameters required to achieve a defined result in terms of mean annual recharge). The alternative of using both surface and sub-surface physical catchment properties has yet to be attempted.

Given the relatively low degree of confidence in the recharge parameter estimates it was considered necessary to constrain the ensembles using the GRAII estimates of recharge. However, as Figure 3.6 indicates, this is also a highly uncertain process, particularly in those areas where recharge is expected to be high. The GRAII database contains three different recharge estimates and Figure 3.6 illustrates the range of these values for all 1946 quaternary catchments. In many cases this range can be in excess of 50mm which would translate into a very wide range of groundwater contributions to stream flow. It is worth noting that the largest range is between the middle estimates and the higher estimates, particularly at high recharge rates.

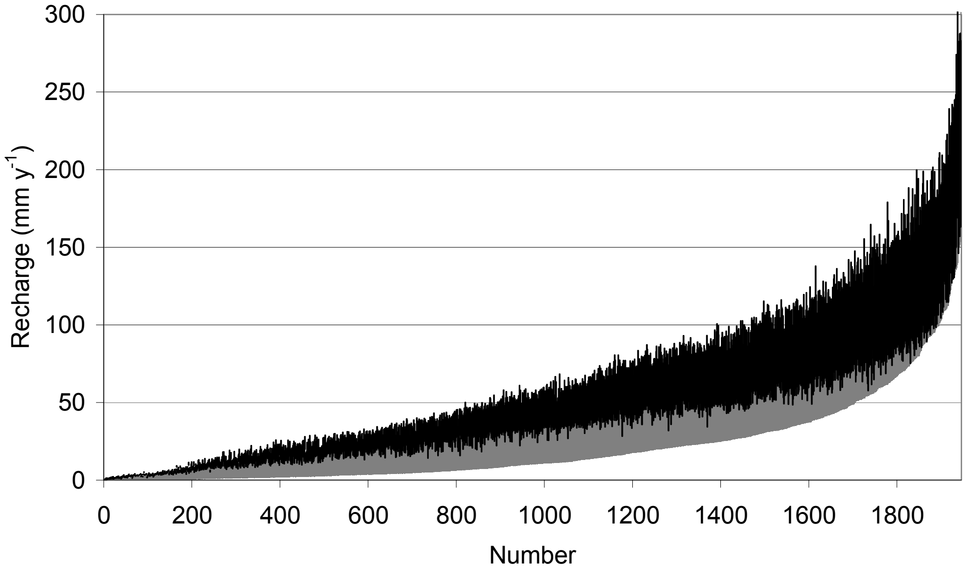


Figure 3.6 Range of mean annual recharge estimates (mm y^{-1}) extracted from the GRAII database for all 1946 quaternary catchments (the results are ranked using the lowest estimate). The grey shaded area represents the difference between the lowest and middle recharge estimates, while the black area represents the difference between the middle and highest recharge estimates.

3.4 Examples of the parameter estimation approach

Kapangaziwiri and Hughes (2008) provide some examples of the use of the parameter estimation methods and compare the values and the results with the standard regional parameter values available in WR90 (Midgley et al., 1994). One of the more noticeable features of these results is that the differences in the values generated by the estimation equations and the WR90 regional parameters are often quite large, while the differences in the simulation results are much smaller. This illustrates the concept of equifinality and the fact that multiple parameter sets can produce similar results in conceptual type models with a relatively large number of parameters. This does not necessarily mean that the model contains structural weaknesses, but does imply that it is quite important to quantify parameter values that are behavioural for the right 'hydrological' reasons (Hughes, 2010b).

Table 3.3 provides some example comparisons of the different parameter values for 5 gauged catchments. The basis for the comparisons is the use of the 'best guess' parameter values (see section 3.1 above) and two objective functions (coefficient of efficiency based on ordinary stream flow volumes and based on log-transformed values). In most of these catchments the WR90 ST parameter values are quite low, while the surface runoff routine parameters (ZMIN and ZMAX) are set at 999, which effectively turns off this part of the model. The result is that most of the wet season peak flows are generated by rainfall which exceeds the available moisture storage and therefore becomes runoff. In contrast, the physical basin property data suggest much higher storage volumes (the sum of ST_{soil} and ST_{unsat} in Table 3.3) but values for ZMIN and ZMAX that will allow surface runoff to be generated by the model. A comparison of the objective function values suggests that both sets of results provide equally good or poor simulations when compared with the observed data.

Table 3.3 WR90 and revised parameters, estimated physical properties and model results.

Basin	K4H003	V7H016	C1H004	X1H016	W5H005
MAP(mm)	702	1093	661	868	832
WR90 parameters and results					
ST	100	100	45	150	180
FT	50	50	2	24	15
POW	2.0	3.0	3.0	2.0	3.0
GW	50	20	5	18	15
ZMIN	0	999	999	999	0
ZMAX	200	999	999	999	900
CE : CE{ln}	0.66 : 0.57	0.69 : 0.79	0.61 : 0.52	0.24 : 0.61	0.62 : 0.72
Estimated physical properties, revised parameters and results					
Drain. Dens.	2.1	2.3	1.4	1.8	1.6
Soil Depth (m)	0.6	0.8	1.5	1.8	1.0
K_{soil} (m d^{-1})	1.85	0.47	0.16	0.81	0.81
Gradient	0.30	0.30	0.10	0.12	0.10
Porosity	0.41	0.35	0.35	0.35	0.35
ST_{soil}	148	224	420	378	210
FT_{soil}	41.5	15.5	2.0	18.5	8.0
GW Depth (m)	30	20	10	15	10
K_{unsat} (m d^{-1})	0.02	0.01	0.015	0.05	0.01
GW storativity	0.002	0.002	0.003	0.002	0.002
ST_{unsat}	60	40	30	34	20
FT_{unsat}	7.5	2.5	0.5	3.0	0.5
POW	2.0	2.8	5.0	3.0	3.5
GW	50	20	10	22	15
ZMIN	10	30	50	50	0
ZMAX	200	400	350	550	650
CE : CE{ln}	0.66 : 0.67	0.68 : 0.80	0.63 : 0.60	0.36 : 0.69	0.58 : 0.73

Experience, during the project, of the use of the parameter estimation routines suggests that there remains a certain degree of subjectivity in the interpretation of the available information and how it is used in the estimation process. Part of the problem lies in the fact that the AGIS (2007) data are provided at more detailed spatial scales than those typically used with the Pitman model. This means that the patterns of variation of such information as slope, soil depth and soil texture given in the AGIS data requires some interpretation before use and there is the potential for different users to interpret the data in different ways. A further problem is that not all of the information required for the parameter estimation process is directly available in the AGIS data or any other source. This is particularly the case for the groundwater components of the estimation process.

While problems of subjectivity and the additional time required to estimate the parameter values are accepted as legitimate concerns, it is necessary to view these in the context of the proposed uncertainty framework. The parameter estimation equations are designed to provide a range of possible behavioural parameter sets which will then be subjected to further scrutiny and constraint using the regional indices of catchment response (section 3.5). It is also necessary to recognize that the parameter regionalization scheme used within studies such as WR90 are based on very subjective assessments of catchment similarity. While the process that was followed to derive the parameter values in the proposed estimation process is transparent (all of the input variables can be saved for later retrieval and checking – see Figures 3.1 and 3.2), the same is not true for the procedures used to establish the WR90 regional parameter sets.

3.5 Examples of the use of the regional constraints

3.5.1 Groundwater recharge constraint

During the development phase of the parameter estimation routines the regional constraints were used quite frequently to assess the results of some of the estimation equations and revise them where necessary. A good example of this feedback process involved the groundwater recharge parameter estimation equations and the recharge constraints. Figure 3.7 shows a comparison between the constraints and the ensemble minimum and maximum recharge estimates that were generated from the original estimation equations. It is clear that the range of recharge values given by the original approach to estimating the GW parameter far exceeded the regional constraints, despite the fact that the maximum GRAII recharge estimates are considered to be very high in some catchments (see Figure 3.6).

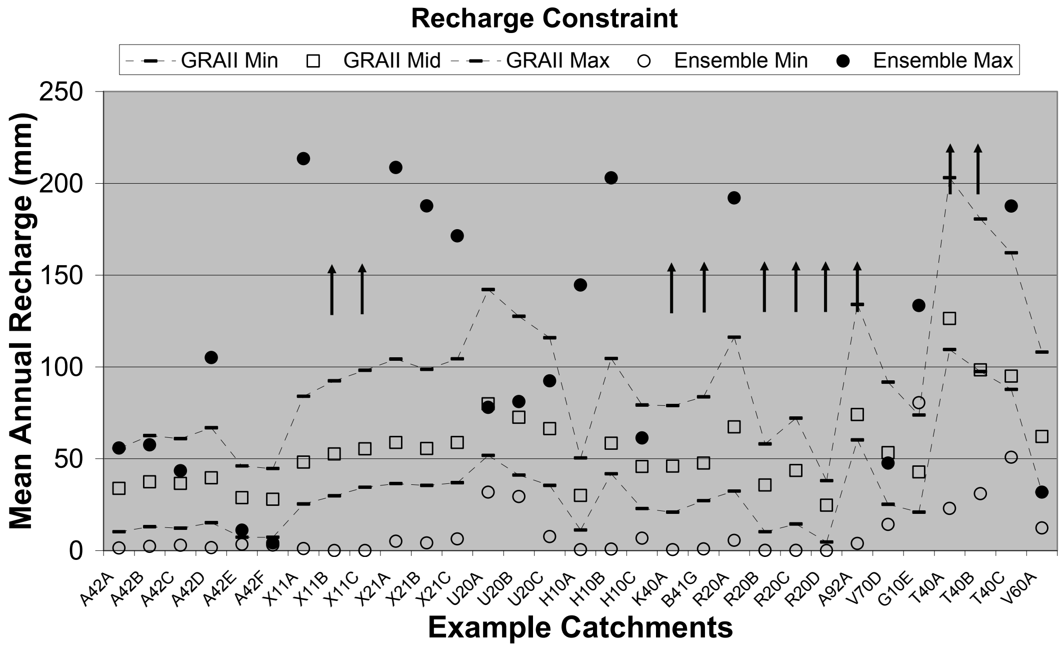
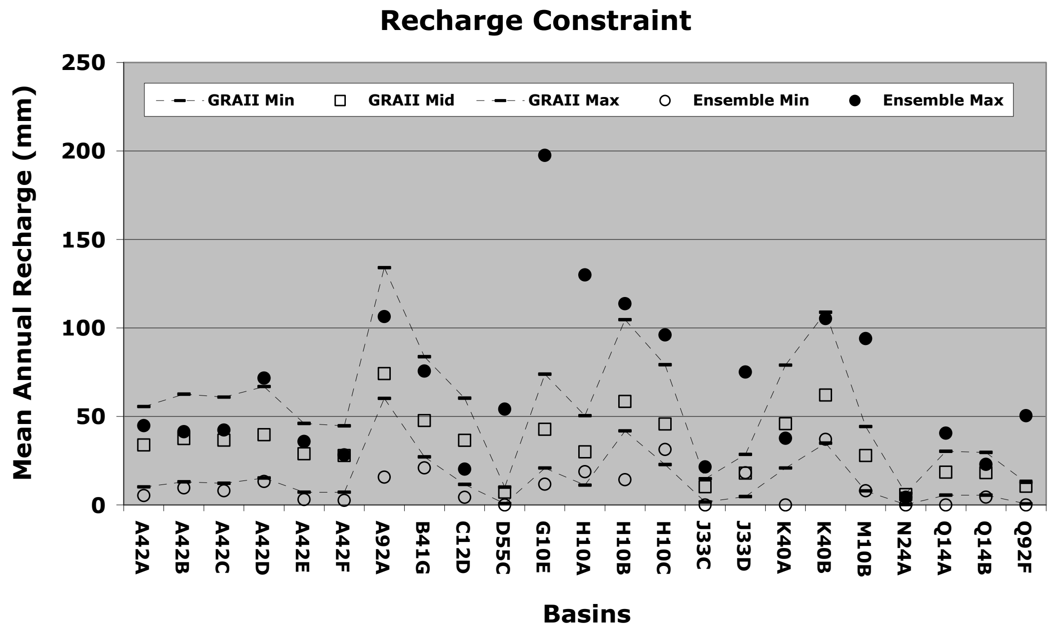


Figure 3.7 Comparisons between the three GRAII recharge estimates and the minimum and maximum recharge estimates from the 5 000 model ensembles. The maximum vertical scale has been restricted to and all those catchments with maximum ensemble recharge values above 250mm are identified with arrows.

The use of these recharge parameter values also had very large impacts on the variability of the simulated values for the other two regional constraint indices (Q/P and FDC slope). Figure 3.8 illustrates that after some modifications to the recharge parameter estimation equation many of the example catchments have recharge ensembles that lie within the bounds of the GRAII data. However, there are still some that lie beyond either the maximum or minimum GRAII values. The recommended procedure is to make initial use of the recharge parameter estimation, but then to check the range of mean annual recharge values generated by the ensembles and then adjust the mean and standard deviation of the GW parameter to constrain the simulated range if necessary. Given that many of the GRAII upper estimates of recharge might be considered excessive (Figure 3.6) a user may decide to modify the GW parameter values to constrain mean annual recharge to within the lower two GRAII estimates.



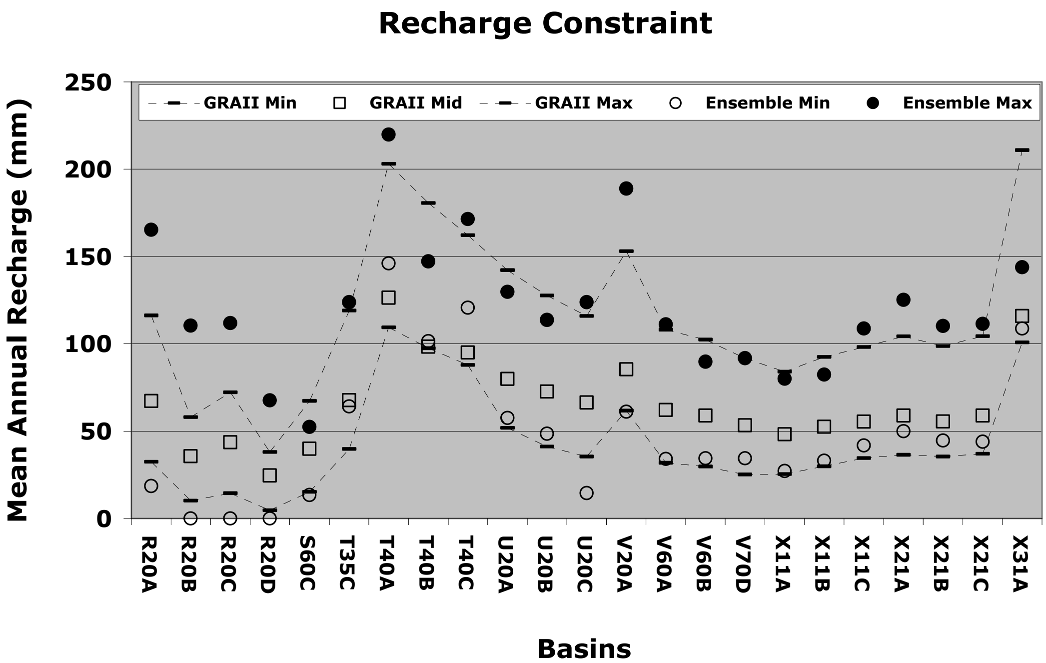


Figure 3.8 Comparisons between the three GRAII recharge estimates and the minimum and maximum recharge estimates from the revised model ensembles.

3.5.2 Mean annual runoff (Budyko type index) constraint

Figures 3.9 to 3.14 present the final results of applying the most recent versions of the parameter estimation routines to a number of quaternary catchments and comparing the range of Q/P values to the 95% prediction limits of the regional constraint regression equations (Table 3.2). The standard error of the predictions (SE_{vol}) can be estimated from the following equation (where σ_{vol} is the standard deviation of the dependent variable values used to develop the regression equations and R^2 is the regression coefficient):

$$SE_{vol} = \sigma_{vol} \,.\, \mathrm{sqrt}(1 - R^2)$$

The curves for the prediction limits are therefore given by (with R.Slope and R.Int the regression slopes and intercepts given in Table 3.2 and the ± 1.96 used to define the number of standard errors either side of the mean) the following equation over a range of different P/PE_i values.

$$Q/P_i = \mathrm{Exp}\,\{R.Slope \,.\, \ln(P/PE_i) + R.Int \pm 1.96 \,.\, SE_{vol}\}$$

The red points on all the diagrams represent the positions of the naturalized observed data for those catchments where gauges coincide with the quaternary catchment outlet. The figures for the 5 regions suggest that the parameter estimation process frequently produces a range of uncertainty that is well within the regional constraints (category A), but that there are also a number of cases where the uncertainty bounds are either large (category B) or biased to greater than (category C) or less than (category D) the regional constraints. The results for all of the regions are summarized in Table 3.4. While explanations for some of the excessive parameter uncertainty bounds can be found for some catchments (e.g. high degree of topographic and soil variation), this is not always possible. Similarly, it is not always straightforward to identify why there appears to be a substantial bias in some of the parameter ensembles. Table 3.4 indicates that this bias is nearly always toward higher flows. It should, however, be recognized that the parameter uncertainty bounds include all of the ensembles and in some cases it is a small number of extremes that cause the excessive range. Removing these from the full list of ensembles is effectively equivalent to removing a few outliers. In these cases the value of the regional constraints as part of the whole uncertainty framework has been more than adequately demonstrated.

In most cases the naturalized observed flows fall within the parameter uncertainty ranges. However, there are one or two exceptions and the parameter estimation process for these catchments requires further investigation. For X31A in Figure 3.10 the observed data point is a long way above the very narrow range of ensembles and this suggests that some errors have occurred within the parameter estimation process. There are also several examples where the observed data point is within the lower (R20D in Figure 3.10) or upper (T35C and S60C in Figure 3.12) extremes of the ensembles. Apart from checking the parameter estimation process in these cases, it is also necessary to examine the method and results of the observed data naturalization process. Reference has already been made to the uncertainties associated with this process.

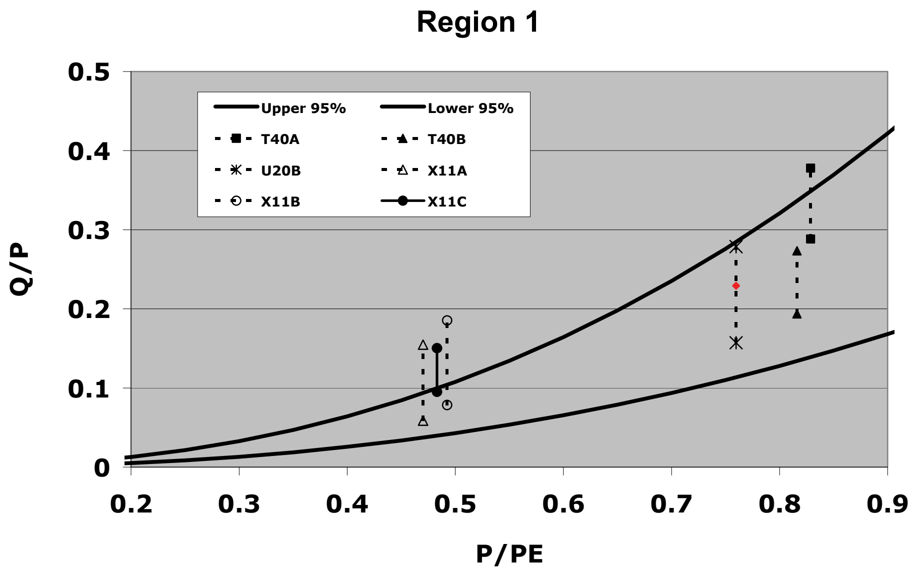


Figure 3.9 95% prediction limits for the P/PE and Q/P relationship compared with the range of ensemble outputs for example catchments within region 1.

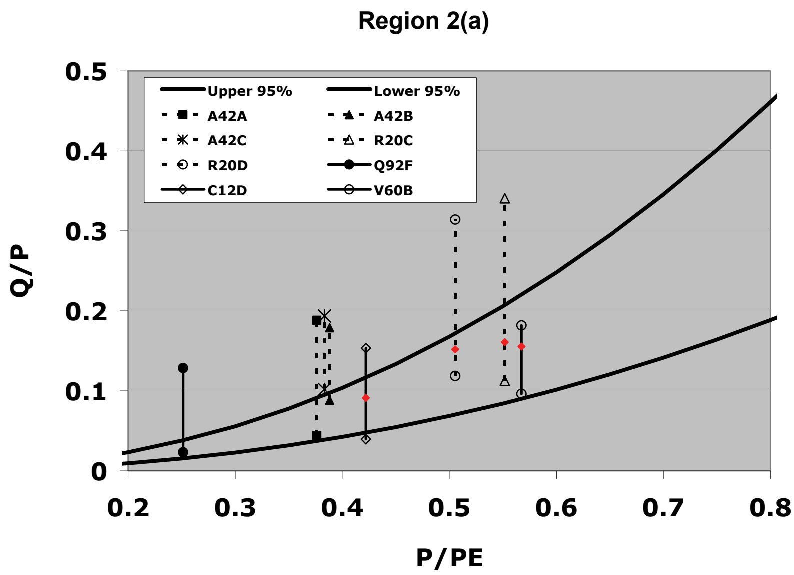


Figure 3.10 95% prediction limits for the P/PE and Q/P relationship compared with the range of ensemble outputs for example catchments within region 2 (A).

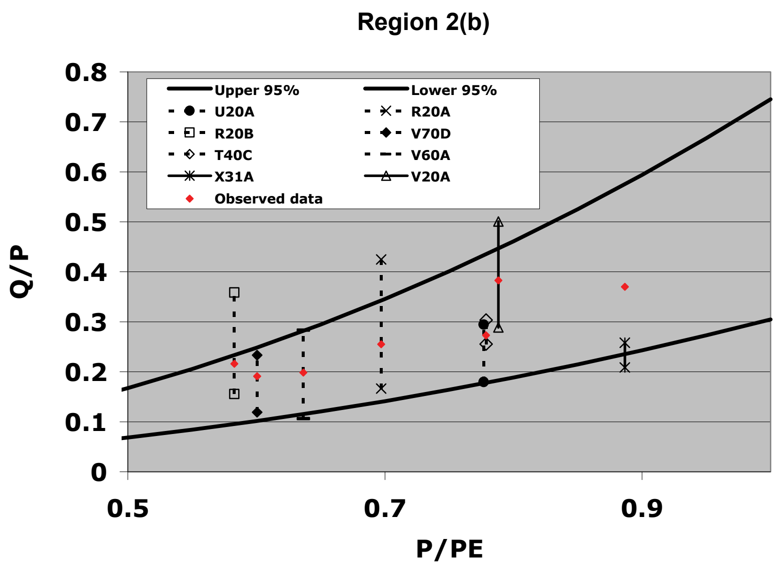


Figure 3.11 95% prediction limits for the P/PE and Q/P relationship compared with the range of ensemble outputs for example catchments within region 2 (B).

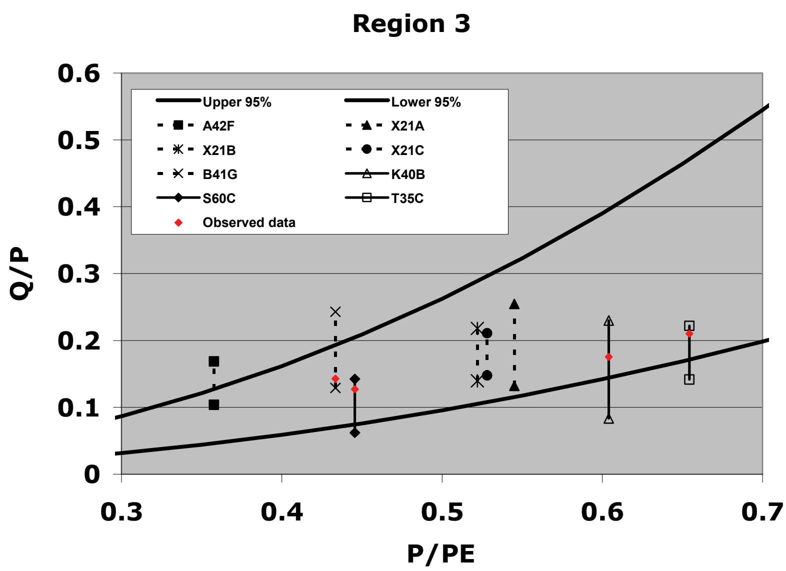


Figure 3.12 95% prediction limits for the P/PE and Q/P relationship compared with the range of ensemble outputs for example catchments within region 3.

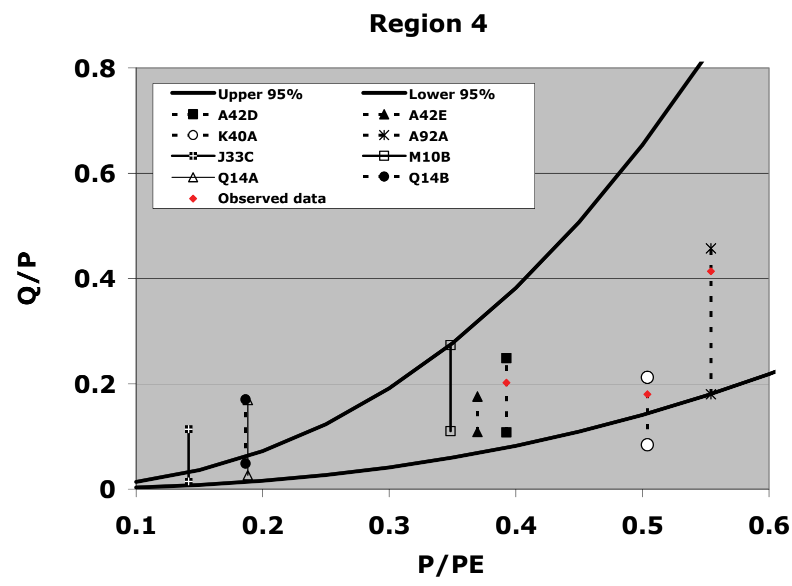


Figure 3.13 95% prediction limits for the P/PE and Q/P relationship compared with the range of ensemble outputs for example catchments within region 4.

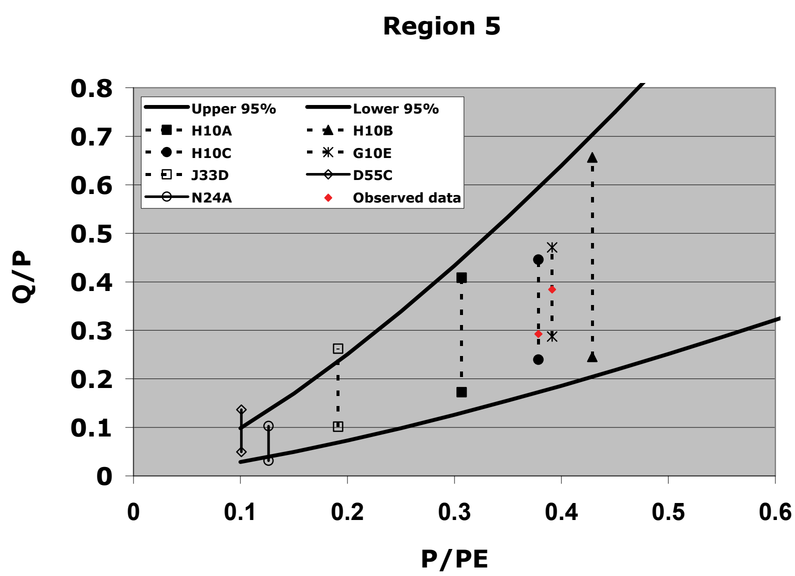


Figure 3.14 95% prediction limits for the P/PE and Q/P relationship compared with the range of ensemble outputs for example catchments within region 5.

Table 3.4 Summary of the results of the frequency of occurrence of categories A to D in the comparison of the model output ensembles with the volume and FDC slope constraints. The values are the percentage number of catchments within each region falling into the different categories.

Region	**No. in region**	**Comparison categories**			
		A	**B**	**C**	**D**
Description		Low parameter uncertainty	Excessive parameter uncertainty	Parameters giving outputs above limit	Parameters giving outputs below limit
Runoff ratio constraint					
Region 1	7	50%	25%	13%	0%
Region 2	16	44%	31%	25%	0%
Region 3	8	63%	0%	25%	13%
Region 4	8	63%	38%	0%	0%
Region 5	7	86%	14%	0%	0%
Total	**46**	**59%**	**24%**	**15%**	**2%**
FDC slope constraint					
All regions	**46**	31%	2%	2%	65%

3.5.3 Slope of the flow duration curve constraint

Table 3.4 includes summary information for comparisons of the parameter ensemble outputs with the slope of the flow duration curve (FDC) constraint, while more detail for individual catchments used in the study are given in Figures 3.15 and 3.16. For a large number of the examples the range of FDC slopes extends to well below the lower prediction limit of the regional constraint equation. While this suggests some bias and over-estimation of low flows, it is less than apparent when examining the time series of individual ensembles in more detail. The general conclusion is that, while the FDC slope constraint is potentially useful, it should be subjected to further investigation. This could involve improving the method used to calculate the slope or improving the regional estimation equation, which currently has a relatively low R^2 value and therefore a high standard error and wide prediction limits.

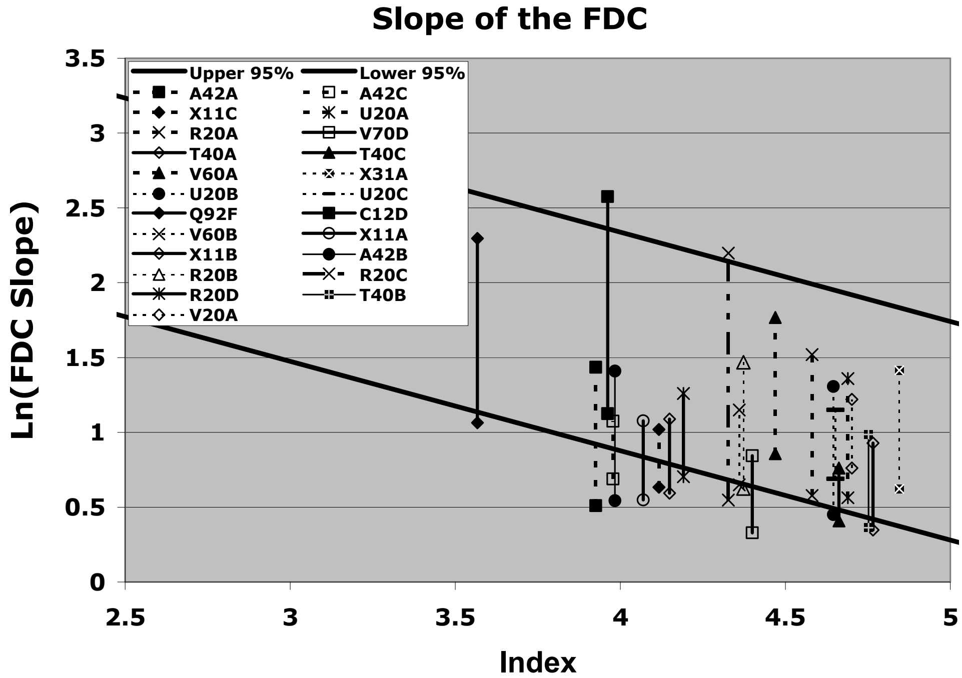


Figure 3.15 95% confidence intervals for the flow duration curve relationship compared with the range of ensemble outputs (A).

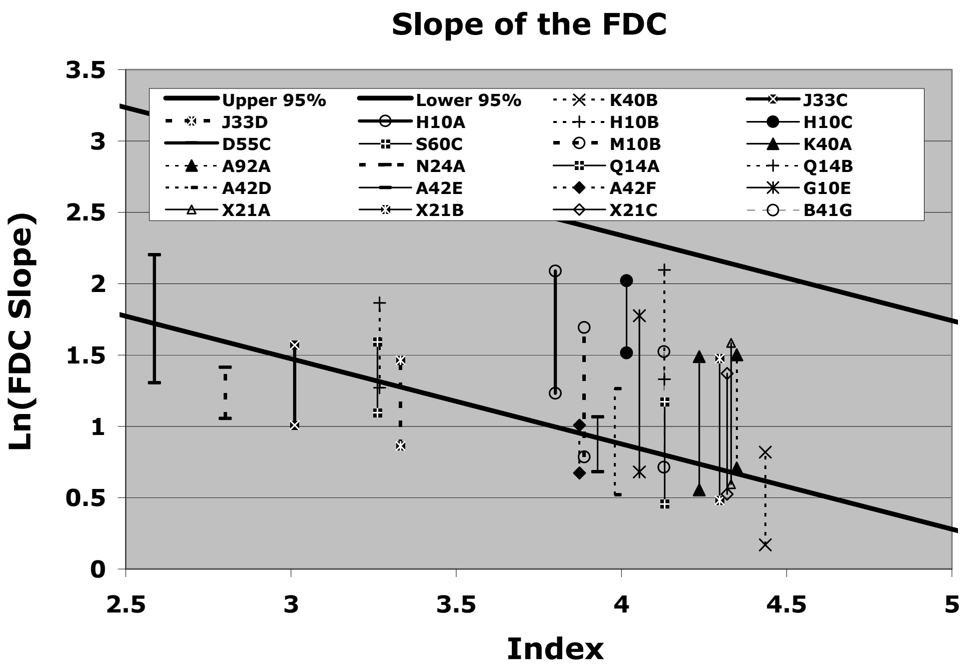


Figure 3.16 95% confidence intervals for the flow duration curve relationship compared with the range of ensemble outputs (B).

3.6 Reducing the uncertainty in the parameter ensembles

Section 2.4.4 referred to two options for the use of the regional constraints. The first is to simply remove those model output ensembles that lie outside the constraint boundaries and the second is to use the results of the comparison as the basis for a feedback loop to the parameter estimations process. Reference has already been made to one example of the latter, where the groundwater recharge constraint has been used to improve (or effectively 'calibrate') the uncertainty in the groundwater recharge parameter of the model. This process has proved to be very effective and overcomes, to a certain extent, recognized deficiencies in the recharge parameter estimation equation. The first option for using the constraints will be applicable for the category B results (Table 3.4), but will not be applicable to the category C and D results because these contain too much potential bias in the model ensembles.

The feedback process will essentially involve a re-examination of the interpretation of the available physical basin property data and particularly the AGIS land type data. This re-examination can be informed by sensitivity analyses of the ensemble results to try and identify which parameters the results are most sensitive to. While the use of a spreadsheet can provide many flexible facilities for post-processing the ensemble results and to assist in a detailed understanding of parameter interactions and their effects on the model results, an additional software tool has been developed to facilitate 'regional sensitivity analysis'. This is an approach widely used in the international literature to investigate the sensitivity of the model results to changes in groups of parameter values. Figure 3.17 illustrates the approach using a screen shot of the main program interface. The top of the screen includes a button to load a UN1 output text file, while the left hand side allows the parameters to be included in the analysis to be selected (and listed in the lower-left hand display). The sensitivity analysis can be based on either a flow metric of the simulated ensembles (e.g. mean monthly flow) or on an objective function if observed data were included in the model setup. It is also possible, for some of the flow metrics, to enter the variables used to calculate the regional constraints or signatures and distinguish between behavioural and non-behavioural ensembles.

Figures 3.18 and 3.19 provide examples of the sensitivity results. All of the ensembles are ranked (based on the sensitivity criteria selected – i.e. a flow metric or an objective function) and then divided into five groups (or seven if the behavioural analysis option is included – i.e. the top and bottom groups are those that lie outside the limits of the regional constraint estimates). The four groups are then plotted as cumulative frequency curves. If an objective function is selected as the criteria for the sensitivity analysis the frequencies are weighted by the objective function values. The interpretation of the results is based on the recognition that sensitive parameters are indicated by widely spaced cumulative frequency curves across the four groups. A low degree of over-lap in the parameter value range between the top and bottom groups suggests parameters that are identifiable (i.e. changes in the values of one parameter strongly affect model results, regardless of the other parameters). Figures 3.18 and 3.19 illustrate that many of the parameters of the Pitman model are rarely identifiable and there are many different parameter combinations that give similar results.

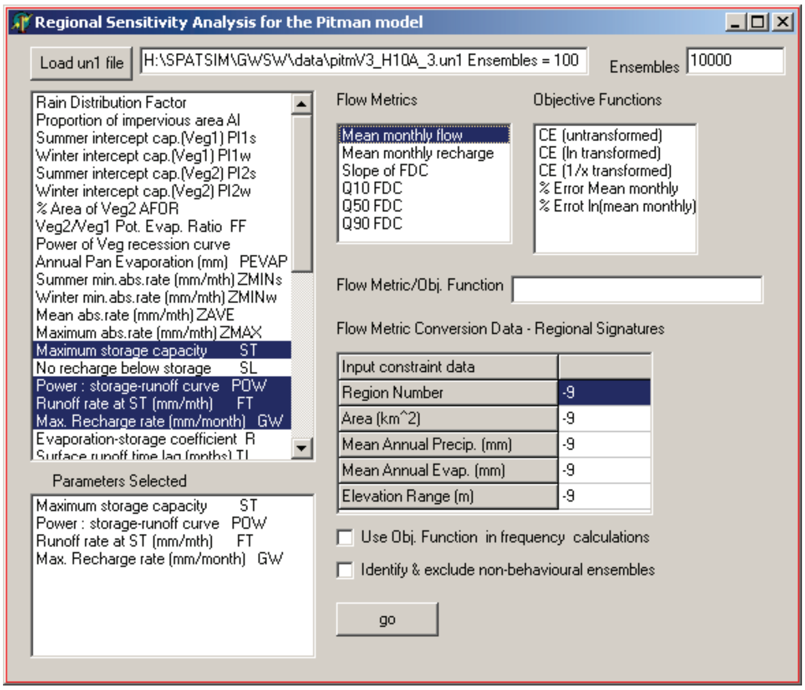


Figure 3.17 Regional sensitivity software tool – main screen

Figure 3.18 provides a relatively clear illustration of an example where too low values of the GW (groundwater recharge) parameter leads to a large number of ensembles that are below the regional constraint ('below behavioural' – also see Figure 3.12). There is also a suggestion that the extremes of the FT parameter (outflow from the main moisture storage) are also too low. However, FT and GW are highly interactive parameters, both contributing to the sustained release of low flows. For K40B adjustments to the GW parameter removed all of the non-behavioural ensembles and improved the position of the ensemble range within the regional FDC slope constraint.

Figure 3.19 shows an example of a situation where many of the ensembles are above the regional constraints (see also Figure 3.11). The sensitivity analysis clearly indicates that the main source of the problem lies with the surface runoff component of the model and specifically with parameter ZMAX. The implication is that the soil texture and surface cover properties of the catchment should be re-examined.

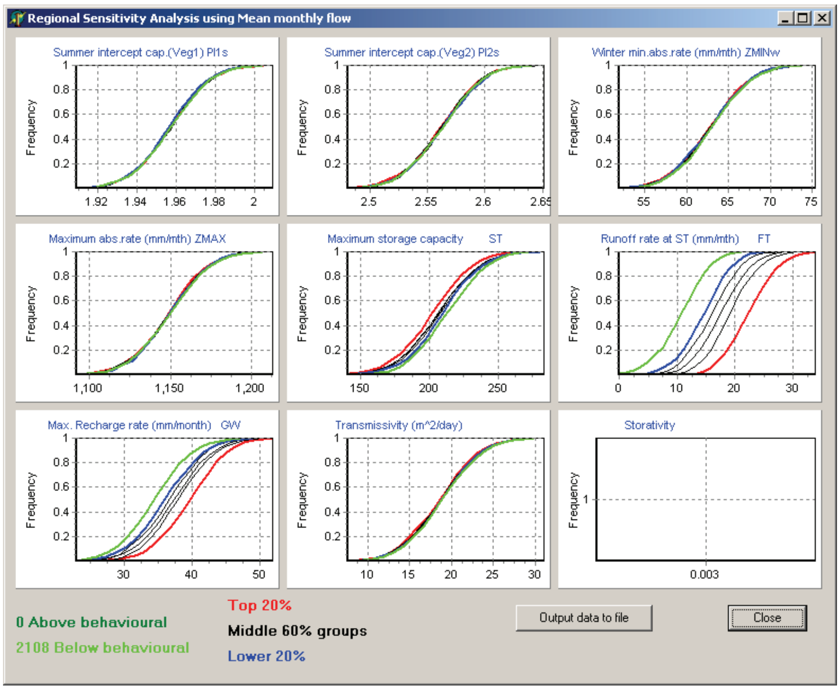


Figure 3.18 Regional sensitivity analysis of the mean monthly flow metric for K40B before the GW parameter was calibrated. After the calibration all non-behavioural outputs were eliminated.

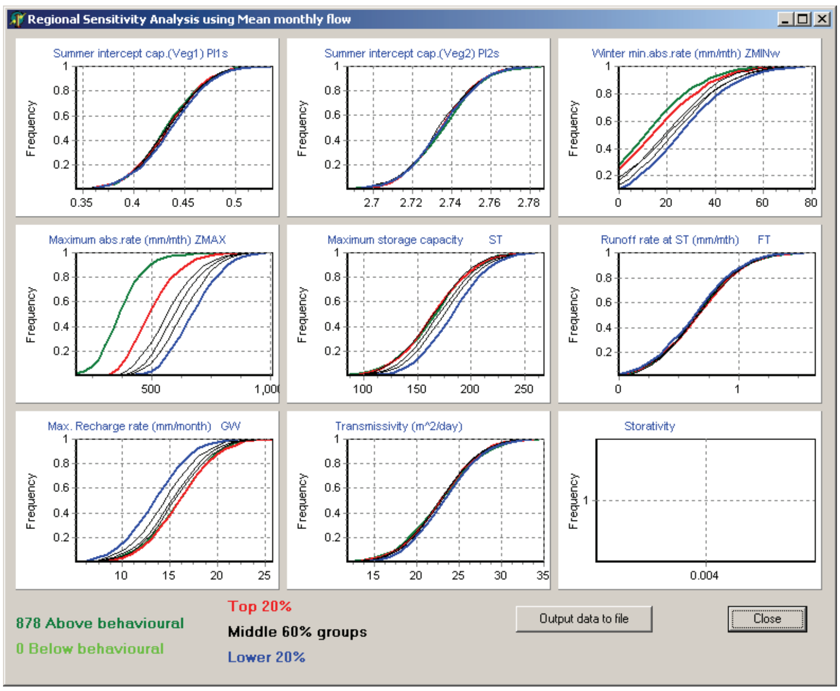


Figure 3.19 Regional sensitivity analysis of the mean monthly flow metric for R20B.

3.6.1 Feedback loops from the constraints to parameter estimation

Revisiting the parameter estimation process for X31A (headwaters of the Sabie River) revealed that:

- It had been assumed that the vegetation cover was dominated by forest, which is the developed situation rather than the un-developed situation as represented by the naturalised observed flows. Correcting this reduced the interception parameters of the model.
- The presence of dolomitic compartments had not been accounted for in the unsaturated zone storage and runoff parameters. Correcting this led to a higher storage (ST) as well as a higher runoff from storage (FT) parameter. It must be acknowledged that some of the physical basin property values used to represent these conditions are difficult to estimate. The approach followed here was to increase the fracture zone storativity and transmissivity by quite large amounts.
- The catchment slope had been slightly under-estimated, while the soils were classified as dominantly sandy clays, while it would be more accurate to classify them as sandy-clay-loams. These changes had very little effect on the results.

These changes resulted in the minimum and maximum Q/P values moving to 0.314 and 0.421, respectively. From Figure 3.11 it is apparent that the uncertainty range is wider but in the middle of the regional constraints and the observed Q/P value (0.37) falls close to the middle of the range. The FDC slope values are slightly reduced but remain in the middle of the regional constraints, while the recharge values are quite substantially increased and now fall towards the upper range of the regional constraints, rather than the lower part (Figure 3.8). The overall conclusion is that the feedback loop has resulted in more behavioural simulations, although the groundwater recharge parameter would probably benefit from some downward adjustment. The improvement has been achieved through the application of some more detailed knowledge and experience of the catchment hydrology than is available through the normal sources of information. This is an illustration of the potential inadequacies of the AGIS and GRAII data, but demonstrates that the parameter estimation routines can be successfully applied if the input information used to quantify some of the physical properties is sufficiently detailed.

Attempts to follow the same re-evaluation process for the southern Cape catchments K40A and K40B were not as successful and there were no obvious reasons why the parameter estimation process appears to have been unsuccessful. However, one observation was that the mid-slope soil depths given by the AGIS data are relatively shallow (220mm in K40A and

430mm in K40B). These are substantially lower than would be expected from personal experience of the project team. It is recognised that this will always be a difficult area to map soil variations because of the accessibility issues and extensive forest cover, but the conclusion is that the soil information has been over-generalised and that the soil depths have been under-estimated.

The most obvious problem with the simulations for R20C and B are the excessive groundwater recharge estimates that are associated with the already identified weaknesses in the estimation approach for parameter GW. Figure 3.8 illustrates that the maximum recharge values are at least 50% greater than the GRAII maximum value, while the lowest simulated recharge values are zero. The process for this feedback loop was to calibrate the GW parameter values (mean and standard deviation of the PDF) to achieve a similar range of mean annual recharge values as those given in GRAII. The result is that the upper and lower limits of Q/P for the ensembles are reduced by approximately 20% for both catchments. This mover the ensemble lines in Figures 3.10 and 3.11 down and although most of the ensembles are now within the bounds of the regional constraint there are still some that are higher. The indications are that there could be additional aspects of the parameter estimation process that should be re-visited. Both catchments are quite diverse in that they both have relatively small upland areas in the Amatole Mountains, but are dominated by lower topography and drier areas in the middle to upper reaches of the Buffalo River north of King Williams Town.

A further problem with the simulations for these catchments is the very wide range of FDC slopes that result from the model ensembles. Correcting the groundwater recharge parameters reduced both the minimum (a worse result) and the maximum (a better result). Figure 3.20 illustrates that approximately 35% of the ensembles are non-behavioural from the point of view of FDC slope (i.e. those with a ln{FDC slope} value of less than about 0.6). Further investigations would be required to determine the exact cause of this result, but initial observations suggest instability in the equation used to estimate parameter POW which is related to the unsaturated zone parameter estimation when the drainage vector slope is very close to the sub-basin slope.

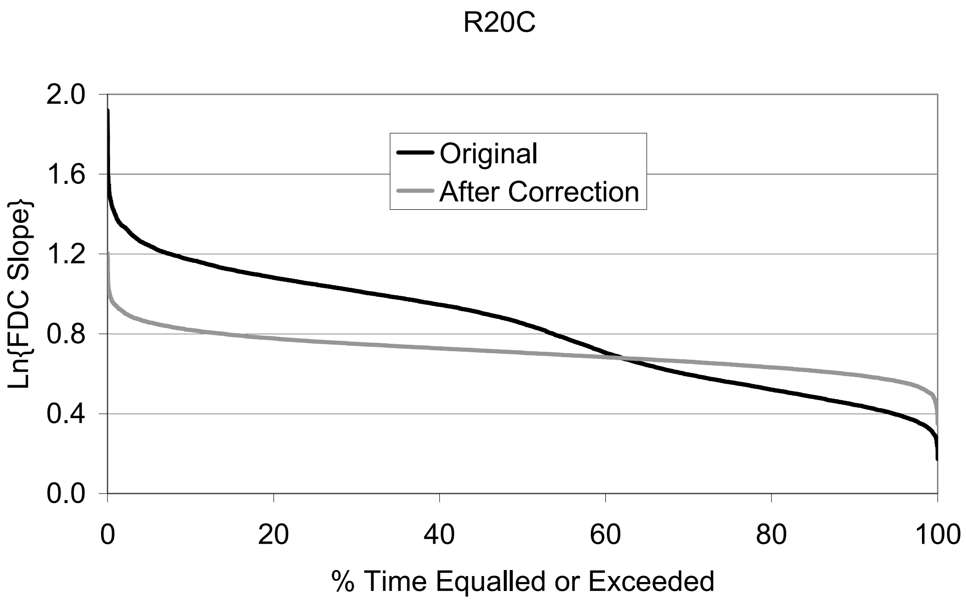


Figure 3.20 Cumulative frequency distribution of FDC slopes for R20C before and after correction of the estimation equation for the unsaturated zone storage component of ST (which also affects parameter POW)

3.6.2 Scale effects in the parameter estimation process

Hughes et al. (2010b) investigated the uncertainty in the groundwater parameters of the Pitman model and the effects on sustainable groundwater abstractions in the semi-arid catchment L21E (712 km^2), a part of the Buffalo River in the Karoo region of the Western Cape Province. The initial approach treated the catchment as a single spatial unit and uncertainty in the main groundwater parameters with a fixed recharge depth resulted in a sustainable yield range of 700 to 970 $*10^3$ m^3 y^{-1}. It is assumed that the recharge area is mostly on the higher ground where the soils are shallower, while the abstraction boreholes are expected to be in the valley bottoms where the water is needed for agricultural activities (stock watering and a limited amount of irrigation and domestic use). A second approach therefore involved dividing the area into two model spatial units, one to represent the recharge area and one to represent the abstraction zone. The main differences between the ground water parameter values that were assumed for the two zones are:

- The maximum monthly recharge parameter is assumed to be much higher for the recharge sub-catchment.
- The gradient parameter that controls downstream groundwater outflow is higher for the recharge zone.
- The drainage density parameter is lower for the recharge zone.
- The riparian loss parameter is lower for the recharge zone.

The sub-division of the total area resulted in a reduction in yield from 855 $*10^3$ m^3 y^{-1} to between 720 and 640 $*10^3$ m^3 y^{-1} for recharge zones of 30% and 70% of the total area respectively (based on parameter values giving the same input and output water balance for the catchment as a whole). Without further information about the real ground water processes that occur within this region, it is difficult to reach firm conclusions. However, the division of the total catchment into the two zones is conceptually sensible and it is encouraging that the model results are consistent with expectations associated with the effects (on sustainable abstraction volumes) of delays in recharge water reaching the sub-surface zones where abstractions are assumed to take place.

The study referred to in the previous paragraph did not involve the parameter estimation routines but throughout the duration of project, the application of the parameter estimation process was always found to be more difficult and uncertain in catchments where there are substantial spatial variations in the land type data, either because the catchments were covered by several land types, or because there is a lot of variation in topography, soil depth or soil texture within a land type. Several assessments were therefore made to determine whether reducing the scale of modelling would reduce the uncertainty in the output ensembles and ensure that they became more behavioral.

Figure 3.21 presents the results of a sub-quaternary model application on catchments H10A to H10C (headwaters of the Breede River in the Western Cape). These catchments are ringed with steep mountain topography and have relatively flat valley floors. The mountains are the higher rainfall and groundwater recharge areas and have shallow soils and steep slopes. The valley bottoms have much deeper soils and are expected to be the groundwater discharge areas. H10A was sub-divided into 3 sub-basins, while H10B and C were divided into 2 sub-basins. Figure 3.21 illustrates a substantial reduction in uncertainty, especially for H10B. The naturalized observed data suggest that the simulated outflows from H10C are all greater than observed, however, a problem with the naturalization process has been noted at this site which is heavily impacted by farm dams and has many missing peak values in the daily record.

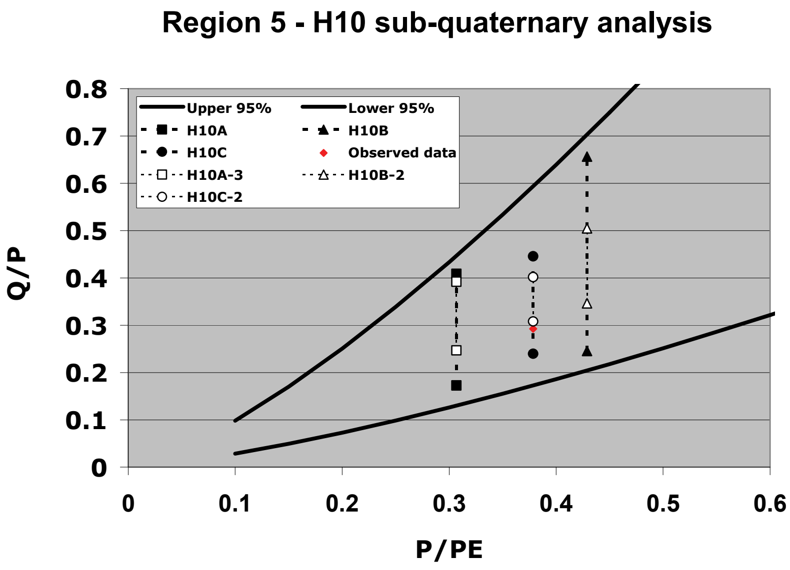


Figure 3.21 Changes in the ensemble Q/P ranges for H10A to H10C as a result of the model scale reduction.

3.6.3 Using observed data to reduce uncertainty

While, at first sight, the heading for this section of the report may seem trivial, it has to be recognized that the majority of observed stream flow data available for South Africa is uncertain. This uncertainty may be related to the accuracy and completeness of the daily flow records (i.e. missing high flows when the rating table is exceeded), or it may be related to the effects of upstream developments and the extent to which the data can be assumed to represent natural conditions. Where there are upstream developments, it has been traditional practice to remove these from the records through a process of naturalization, which is inherently uncertain given the general lack, or poor accuracy, of the available water use data.

It is therefore considered to be incorrect to consider that a single naturalized stream flow record can be used to constrain (or calibrate) the outputs from a hydrological model, unless the confidence that can be expressed in the observed record is very high. One of the approaches that could be adopted is to incorporate uncertainty into the naturalization process taking into account uncertainties in the impacts of upstream developments and adding a random error component to the measured stream flows themselves.

3.7 Uncertainty in observed rainfall data

The focus of this part of the report has been on the parameter estimation process. However, there are many mountainous areas of South Africa where the precipitation data available to force the model are very uncertain due to a lack of gauges located in elevated and remote parts of the catchments. The uncertainty is therefore derived from the assumptions made about the rainfall gradients that result from orographic effects. In two separate studies of the combined effects of uncertainty (parameters, forcing climate data and water use data) it was found that the effects of rainfall uncertainty can be very large in mountainous areas (H10C) compared to areas where orographic effects are not expected (X21F). Table 3.5 (Hughes and Mantel, 2010b) suggests that the uncertainty effects of rainfall increase with the simulation of higher flows (lower exceedence percentage points of the flow duration curve). In this example the rainfall uncertainty was defined by using monthly time series taken from both WR90 and WR2005.

Table 3.5 Comparison of uncertainty sources

Sub-basin and FDC % Point	Uncertainty source Parameters	+ Water Use	+ Rainfall
H10C: 90%	98.9 (65.4%)	113.7 (9.8%)	151.1 (24.8%)
H10C: 50%	68.1 (54.7%)	89.5 (17.2%)	124.5 (28.1%)
H10C: 10%	22.3 (26.0%)	38.4 (18.0%)	87.4 (56.0%)
X21F: 90%	124.8 (48.7%)	254.8 (50.7%)	256.5 (0.6%)
X21F: 50%	52.8 (69.7%)	70.8 (23.8%)	75.7 (6.5%)
X21F: 10%	40.9 (84.2%)	44.6 (7.6%)	48.6 (8.2%)

*The first number is based on the cumulative uncertainty within each model run (Upper prediction – Lower Prediction) * 100 / Central prediction. The second number is the % contribution to the total (all sources) uncertainty of individual sources: Water Use uncertainty for H10C: 90% is 9.8 = (113.7 – 98.9) * 100 / 151.1.*

The results from the Hughes and Mantel (2010b) study are confirmed by a study by Sawunyama et al. (in preparation) based on comparisons of the uncertainties in estimated reservoir yield (Figure 3.22). In this study, another mountainous Western Cape catchment (G10B) demonstrated the substantial effects of rainfall uncertainty (using WR90, WR2005 and independently estimated rainfall inputs), while in less mountainous areas (U20B), or areas where the orographic effects are better understood (K40A) parameter uncertainty appears to be the dominant source. These results support the frequently made calls to ensure that the national network of rainfall observations does not decline any further than it already has and in fact suggests that additional rainfall monitoring should be undertaken in key areas of the country. These mountainous areas are of great importance, either nationally or locally, for generating natural flows and therefore it is essential that we have a sound understanding of their hydrological dynamics and variability. We clearly cannot achieve this without adequate rainfall data.

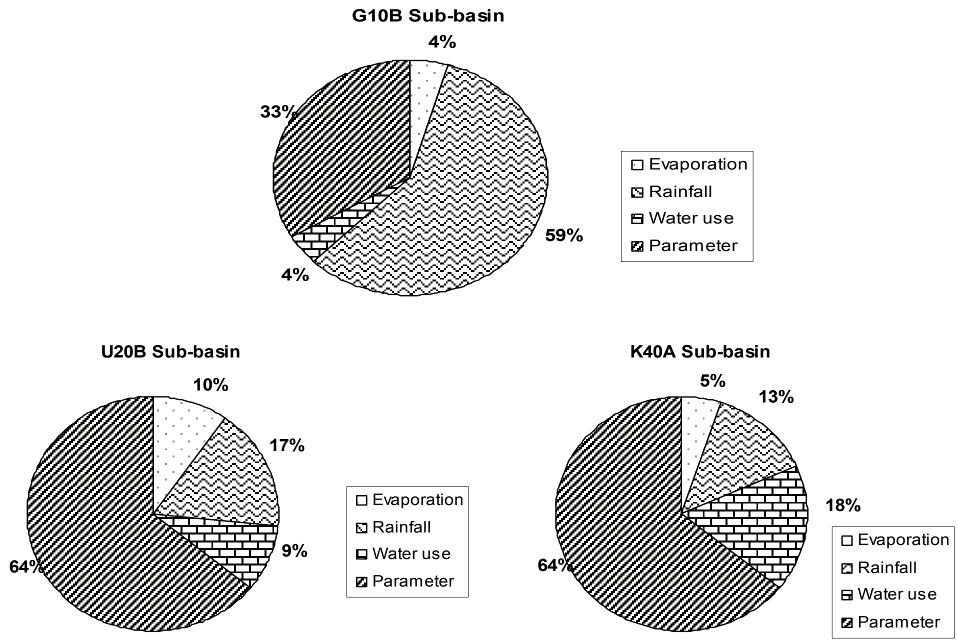


Figure 3.22 Pie charts showing the contributions of different uncertainty sources to total output uncertainty based on the % differences in achieved yield from hypothetical reservoirs.

3.8 Uncertainty related to future climates

This project has benefited from the results generated by a further WRC project started during 2010 on developing climate change adaptation strategies for local water boards in South Africa (K5/2018). Under the terms of this project, down-scaled rainfall and temperature data (using the products generated by the Climate Systems Analysis Group at the University of Cape Town – see Hewitson et al., 2005 and Hewitson and Crane, 2006) for 9 climate change models (Table 3.6) have been incorporated into a hydrological modelling study of the Buffalo River catchment in the Eastern Cape. The down-scaled products used consist of daily rainfall and temperature data for quinary catchments for a baseline period (1961 to 2000) and a near-future change period (2046-2065) using the SRES A2 emission scenario.

The approach adopted in this study has been to establish the hydrological model (Pitman) using uncertain estimates of the parameter values based on the methods explained by Kapangaziwiri and Hughes, 2009) and run the model with WR2005 rainfall data. The near-future rainfall data for each climate model was then corrected to remove any bias between the baseline period rainfall predicted by the climate models and the WR2005 data. The temperature data were used to modify the evaporative demand values used in the model for the near-future period. These calculations have been based on the widely used Hargreaves approach (Allen et al., 1998).

Figure 3.23 illustrates the results for one part of the catchment (outlet of quaternary catchment R20B) using bands of uncertainty around the simulated flow duration curves. The results clearly indicate the increased uncertainty consequent on including the simulations for all 9 GCMs, but that the signal of change is not very clear. Some models suggest increased flow, some decreased flow. Further details will be available as the use of climate change data are further processed through the uncertainty framework and the Pitman model.

Table 3.6 GCMs used in the study

GCM abbreviation	Source of GCM
CCCMA	Canadian Centre for Climate Modelling and Analysis
CNRM	France Centre National de Recherches Meteorologiques
CSIRO	Australian CSIRO Atmospheric Research
GFDL	USA NOAA Geophysical Fluid Dynamics Lab
GISS	USA Goddard Institute for Space Studies
IPSL	France Institut Pierre Simon Laplace
MIUB	Germany Meteorological Institute of the University of Bonn
MPI	Max-Planck Institute For Meteorology
MRI	Japan Meteorological Research Institute

Reference is made in Figure 2.6 and elsewhere in this report to the use a stochastic rainfall model to generate uncertainty inputs into the Pitman model. The main concept behind this approach is that both stochastic and parameter uncertainty can be incorporated in the same model. This would avoid the apparent confusion of incorporating hydrological uncertainty (parameter uncertainty) in a hydrological model and stochastic uncertainty (sequence uncertainty) into a yield model (see section 4 of this report).

A possibility for the future is that uncertainty in the magnitude of rainfall related to a lack of representative rainfall observations could be built into the stochastic generator, by sampling from uncertain values defining the statistics of the historical rainfall time series. The main components of a stochastic rainfall model are the ‘parameters’ that define the monthly means and standard deviations of rainfall, the serial correlation statistics (sequencing) and the spatial correlation statistics (spatial similarity measures). While these statistics would normally be calculated from historical data sets, there does not seem to be any reason why uncertainty could not be included. The main source of uncertainty would be in the monthly means and possibly standard deviations. This approach opens up other opportunities to incorporate climate change uncertainties into the overall uncertainty modelling framework. It seems reasonable to suggest that a stochastic rainfall generator represents a potentially very efficient method of doing this. It is likely that future rainfall regimes could be represented by changes to monthly means and standard deviations, as well as differences in the seasonal distributions of these. There may also be some changes to the serial correlation structure of the time series with potentially more persistence of certain conditions. It is proposed that these changes to the parameters of a stochastic rainfall model could be quantified through the analysis of baseline versus future down-scaled outputs from climate models. Furthermore, uncertainty could be quantified by repeating this exercise for all climate models that are considered appropriate for the region of concern. Incorporating climate change into the Pitman model (and therefore water resource assessments) would therefore involve the use of uncertain stochastic rainfall model parameters as part of the total simulation approach and they would be seamlessly integrated with the hydrological parameter uncertainty (which may also change with climate change).

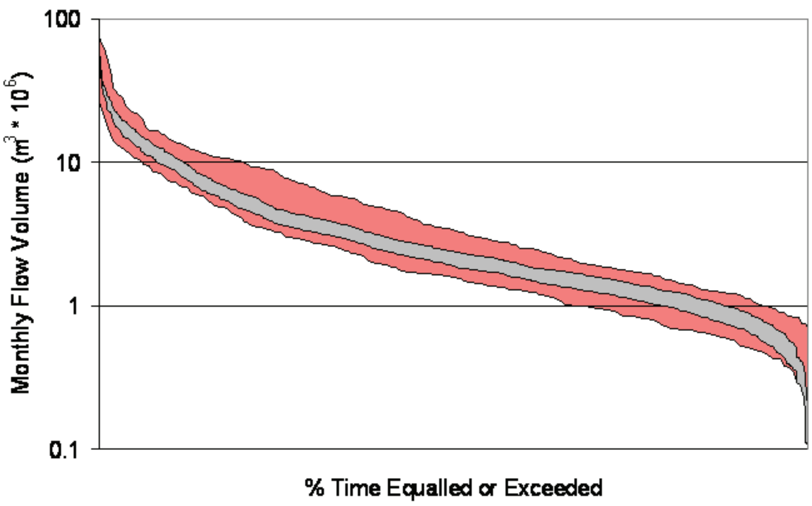


Figure 3.23 Comparison of the historical range of uncertainty (based on model parameter uncertainty) and future uncertainty (based on parameter uncertainty and future climate uncertainty across all 9 GCMs).

4. PROPAGATING UNCERTIANTY INTO YIELD MODELLING

It has already been noted that the conventional approach to water resources yield modelling within South Africa is to input a single historical time series of natural flows and to apply a multi-site stochastic stream flow model to generate a number of different time series that are used to estimate the yields. The resulting yields are ranked to generate a yield probability curve. This approach clearly ignores the parameter uncertainty and the main question that was raised during this project is related to the impacts of not allowing for parameter uncertainty.

Some of the initial investigations examined the range of yield estimates generated by a water resources yield model using the median output ensemble from the hydrological model compared to the historical firm yield generated by using the 95% and 5% exceeded simulated natural flow sequences (i.e. the extremes of the ensemble predictions). Figure 4.1 illustrates two examples of this type of comparison for the Nooitgedacht (X11C) and Kwena (X21C) dams.

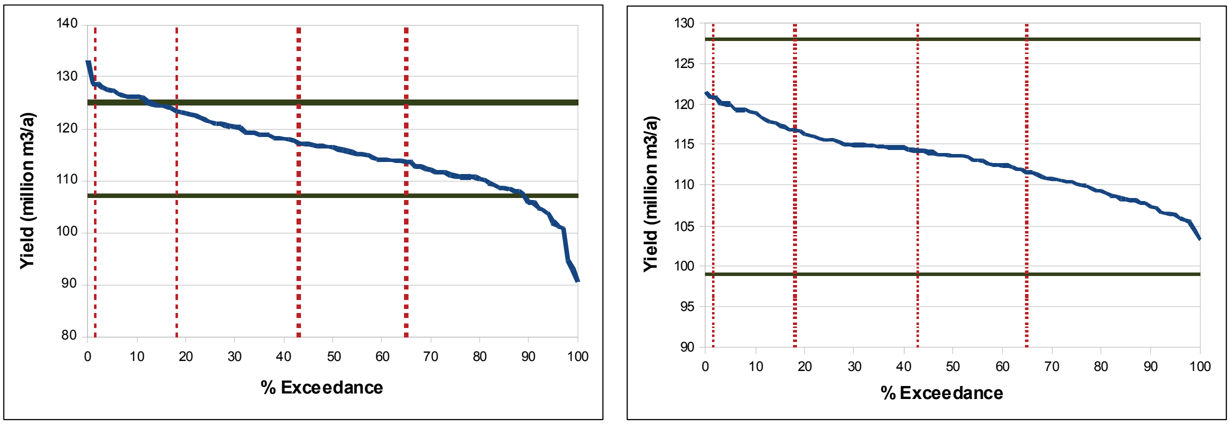


Figure 4.1 Range of possible yields using uncertainty ensembles and long-term stochastic yield analysis (Left side: Nooitgedacht Dam; Right side: Kwena Dam).

Clearly there are substantial differences between these two examples, with the parameter uncertainty impacts on the Kwena dam yield analysis being far greater that for Nooitgedacht dam. Table 4.1 summaries the comparative yield estimate analyses conducted on 5 catchments and there are no simple explanations for these differences. It is therefore essential to explore these issues further before recommendations can be made about combining the generation of uncertainty ensembles from hydrological models with the current practice of generating stochastic flow sequences within yield models. The three ensembles used in the yield analysis were selected on the basis of ranking the outputs using the simulated MAR, while the highest MAR simulations may not necessarily generate the highest yield.

Table 4.1 Summary of the results of the yield estimate comparative analysis.

Catchment		% Diff.	LTY inside Firm Yield limit	CV
Kwena	(Median – 95%)	12.3	Yes	0.42
	(5%-Median)	19.3	Yes	0.37
Midmar	(Median – 95%)	7.0	Yes	0.44
	(5%-Median)	8.0	No	0.38
Nooigedacht	(Median – 95%)	21.6	No	0.37
	(5%-Median)	15.4	No	0.38
Mokolo	(Median – 95%)	11.1	No	0.48
	(5%-Median)	11.2	Yes	0.45
H10C	(Median – 95%)	12.9	Yes	0.51
	(5%-Median)	12.5	No	0.41

Notes: The % Diff. values are the percentage differences of the MARs (from the MAR of the median ensemble) for the lower (95%) and upper (5%) hydrology ensembles relative to the median ensemble MAR and are a reflection of the uncertainty in the ensembles.
The 'LTY inside Firm Yield Limit' is a statement of whether the long term yields (based on the median hydrology) are within the limits of the firm yields at the 95% and 5% ends of the probability distributions of the long term yield..
The CV represents the coefficient of variation (standard deviation/mean) of the appropriate ensemble.

If hydrological uncertainty is to be completely combined with stochastic uncertainty using the standard approach of stream flow stochastic generation within a yield model, the process would become lengthy. If it is assumed that the hydrological uncertainty is represented by 1 000 ensemble outputs from the hydrological model and that 1 000 stochastic ensembles are generated for each hydrological model output, the result is 1 million runs of the yield model – which will generate a truly realistic yield assessment, but not within a practical computing time frame, particularly for complex systems with many nodes. The issue of combining probabilities does not come up in the example as we simply have 1 million possible yield estimates.

The question is whether a short cut can be found that involves the processing of fewer of the hydrological ensembles through the yield model. Figure 4.2 illustrates the results of a simplified hypothetical experiment to investigate this question. It has been assumed that a single representative hydrology time series would produce a range of yields between 80 and 120 * 10^6 m^3 (MCM). The dotted line ('Single') represents the cumulative probability distribution of yield based on a simple process of randomly sampling 100 yield estimates from the range (80 to 120). The second part of the process was to add an additional 10 hydrology time series, representing some uncertainty in the hydrological model outputs, and assume that each would generate a different range of yields when used as input to the stochastic model, with some giving overall higher yields and some lower yields. If the total of 1 100 (100 x 11) yield estimates are included, the frequency curve is given by the thick line ('Ensemble') in Figure 4.2.

The thin line without any symbols ('Extremes') is made up of all the yield estimates assumed to be generated from the original hydrology (yield range of 80 to 120) as well as the two hydrology groups with the highest and lowest yield estimates (a total of 300 values). This represents (in a simplified way) the result of taking the median hydrology ensemble plus two others representing the extremes and processing only these through the stochastic generator in the yield model. Figure 4.2 clearly illustrates that the yield estimates in the ends of the curves (approximately 5 to 15% and 75 to 95%) will not be very accurate representations of the real yield uncertainty based on all ensembles. This result will occur when the extremes of the hydrological ensembles are expected to be less likely than the median. This situation typically results from using Normal distribution sampling of parameter sets, while uniform distribution sampling may result in the extreme hydrological ensembles being as equally likely as the median.

The final curve in Figure 4.2 ('Extremes (corrected)') is also based on the use of the median and two extremes of the yield estimates (300 values). However, in this case the cumulative frequencies have been based on weighting the median hydrology yield estimates by 0.2 and the extreme hydrology yield estimates by 0.05. These are relatively arbitrary choices of weighting, but are related to frequency properties of a Normal distribution (approximately 0.2 or 20% of the distribution lies within 0.25 standard deviations either side of the median, while 0.05 or 5% of the distribution lies beyond approximately 1.7 standard deviations – i.e. the extremes). The result still shows some variations from the total ensemble line, but is much closer than the uncorrected 'Extremes' line.

An additional test has been added to the simple analysis to determine whether an even simpler approach can be adopted that does not add any additional stochastic analyses to the yield model. Figure 4.3 uses the same data set as used in Figure 4.2, but in this case the basic information generated by the yield model is assumed to be the historical yields based on the median and two extreme hydrology ensembles (Upper and Lower) as well as the stochastic yield analysis based only on the median hydrology ensemble ('Median Stochastic' in Figure 4.2). Two additional sets of yield estimates are added by scaling the median hydrology stochastic yield values by the ratios of the median historical yield to the upper and lower hydrology historical yields. As with the previous analysis the three sets of yield estimates are combined using probability weighting factors appropriate to the probabilities of occurrence of the three hydrology ensembles (0.2 for the median hydrology and 0.05 for the upper and lower extremes). The complete set of yield estimates is then re-sorted and the final yield frequency curve generated ('Extended Median' in Figure 9.10). The results in this simple test suggest that the differences between this curve and the one using stochastic analyses of the three hydrology ensembles are relatively minor.

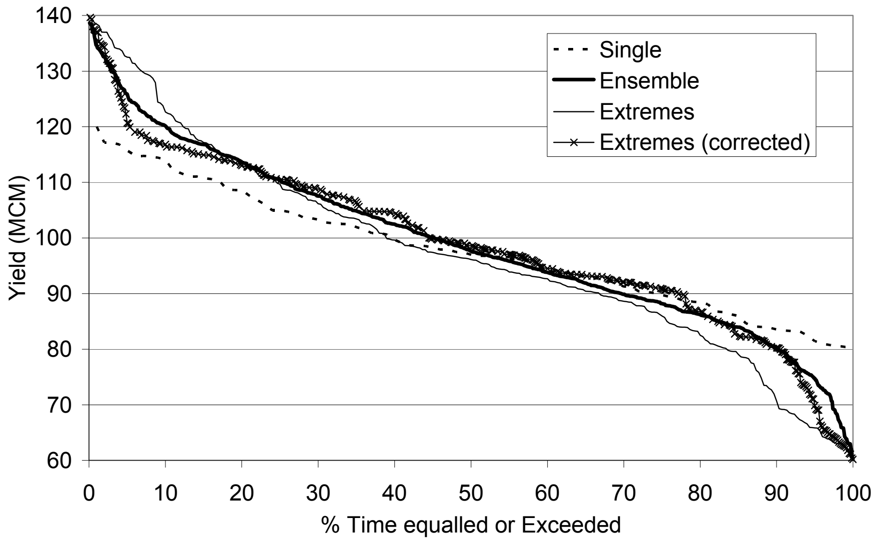


Figure 4.2 Yield frequency (probability) curves based on approaches to combining hydrological and stochastic uncertainty (A).

The simple exercise demonstrates that a relatively accurate representation of the yield probability distribution resulting from combined hydrological and stochastic uncertainty, that would normally involve an impractical number of runs of the yield model, can be obtained with a substantially reduced number. In the last experiment the only additional yield model runs required would be to determine the historical firm yields of the upper and lower hydrology ensembles.

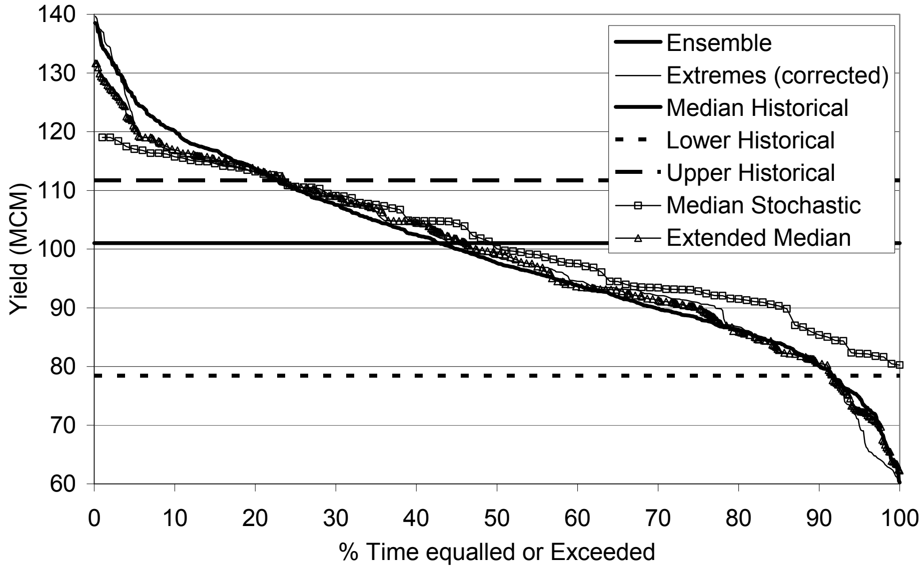


Figure 4.3 Yield frequency (probability) curves based on approaches to combining hydrological and stochastic uncertainty (B).

4.1 Stochastic rainfall versus stochastic stream flow sequences

One of the major discussion points during some of the project workshops was whether it is possible to include the stochastic component of uncertainty using a stochastic rainfall model as part of the hydrological model and run the resulting ensembles through the yield model without any stochastic stream flow generation. The other question is whether the results would be substantially different from those generated with the conventional approach. The potential advantage is that the stochastic and hydrological (i.e. parameter) uncertainty can be combined within the same model. A single test of this approach has been applied in this study using the data for the Midmar Dam catchment (U20A to U20C). The version of the Pitman model that has been created to perform this analysis has already been discussed in section 3.2.

The multisite monthly rainfall model employed in this study was based on the daily model developed by Srikanthan and Pegram (2009). The main features of this model are that it stochastically links the spatial and also the temporal dependence between the gauges using a multivariate autoregressive time series model and it post-conditions the simulations to recapture the temporal correlations and marginal statistics of the annual rainfall amounts. The first feature is fairly standard, while the second ensures that the observed fluctuations of wet and dry years is recovered, a very necessary condition for long term reservoir yield analyses. Extensive validation tests were done to ensure that the model captures the features described. Table 4.1 summarises the statistics of the forcing historical rainfall data and the range of equivalent values for 500 stochastic sequences. The sequences generally give lower rainfalls than the historical data based on annual totals (see the lower values of skewness, maximum and minimum in particular).

Table 4.2 Annual summary statistics for sub-basin U20A for the historical rainfall data and the 500 stochastic sequences.

Statistic	Historical rainfall	Stochastic rainfall sequences	
		Upper	Lower
Mean (mm)	1010.0	1010.0	1009.9
St. deviation (mm)	184.7	184.5	183.6
Skewness	0.95	0.94	0.39
Maximum (mm)	1586.8	1586.7	1527.6
Minimum (mm)	682.5	682.7	619.4

The rainfall data inputs into the **parameter uncertainty ensemble** model run were the same as those used to force the stochastic rainfall model and are recently updated sub-basin rainfalls based on available gauge information. The period of record is from October 1920 to September 2005. A total of 10 000 parameter samples were used and the results suggest a range of mean annual runoff values for U20B of 54.8 to 97.1 * 10^6 m^3, compared with the naturalized observed value of 79.8 * 10^6 m^3. Further comparisons between the time series of the ensembles and naturalized flows (and the objective functions) suggest that model has generated behavioural simulations that bracket the observed flow sequences and that the range of uncertainty is not excessive. Figure 4.4 illustrates the frequency distribution of minimum total flow volumes over all 24 month periods for all of the ensembles.

The 500 rainfall scenarios generated from the stochastic model were combined with 500 parameter samples, using the same parameter distributions as in the previous run of the model, to generate 250 000 ensembles. These were reduced to a sample of 500 ensembles for use in the yield model by simple Monte-Carlo sampling from the total of 250 000 after ranking all ensembles on the basis of the minimum 24 month reservoir inflow volumes (outlet of sub-basin U20C). This minimum inflow volume is used as a simple surrogate for the reservoir yield and the duration (24 months in this example) would be set to the critical drought period of the reservoir. Figure 4.4 illustrates that the frequency distributions of minimum flow volumes are the same for the total group of ensembles and the sample of 500. Figure 4.4 also suggests that the stochastic rainfall model has introduced some bias in the stream flow ensembles in that the median minimum volume (193 * 10^6 m^3) is substantially lower than the median given by ensembles based on only parameter uncertainty (221 * 10^6 m^3). The reasons for this are not clear at this stage but the result is consistent with the comparisons between the statistical properties of the rainfall sequences and the historical rainfall (Table 4.1).

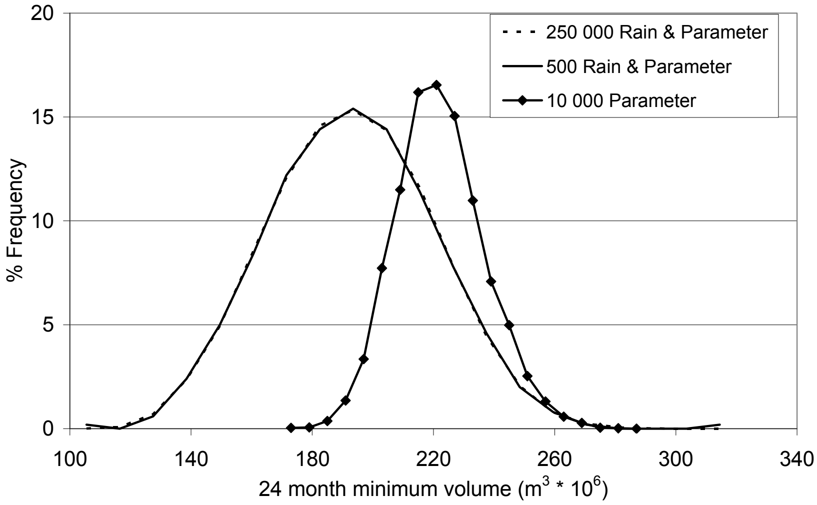


Figure 4.4 Frequency distributions of minimum 24 month flow volumes for the 10 000 parameter ensembles and the two rain and parameter ensembles (250 000 total and 500 sample).

The yield of the Midmar Dam was determined using the Water Resources Modelling Platform (Mallory et al., 2010). This is a water resources yield model which is integrated into a database of water use and hydrological information for South Africa and includes numerous utilities and algorithms for dealing with complex modelling problems, such as ecological flow requirements and reservoir operating rules. The model is able to generate a single 'historical' yield estimate based on a single inflow time series input, or the single inflow input can be used as a seed for an ARMA stochastic generator and the resulting yields ranked to produce a yield exceedence probability curve. A yield probability curve can also be generated from multiple inputs of inflow time series and is therefore ideally suited for this specific study.

Figure 4.5 shows the results of the different yield analyses. The 'stream flow stochastics' curve is based on seeding the stochastic stream flow model in the yield model with the median hydrology ensemble generated by the rainfall-runoff model using a single historical rainfall time series. The three horizontal lines represent the historical yield (i.e. no stream flow stochastic generation) based on the 5% ('max flow'), 50% ('median flow') and 95% ('min flow') exceeded flow ensembles from the rainfall-runoff model. The 'Rain stochastics &

parameters' curve represents the distribution of historical yield estimates for the 500 sample ensembles generated by combining stochastic rainfall sequences and parameter uncertainty in the rainfall-runoff model. An immediate observation is that the yields generated by the stream flow stochastic approach are biased to lower yields compared with the historical yield generated from the median hydrology (used to seed the stochastic stream flow model). This result is similar to that noted for the stochastic rainfall model and requires further investigation.

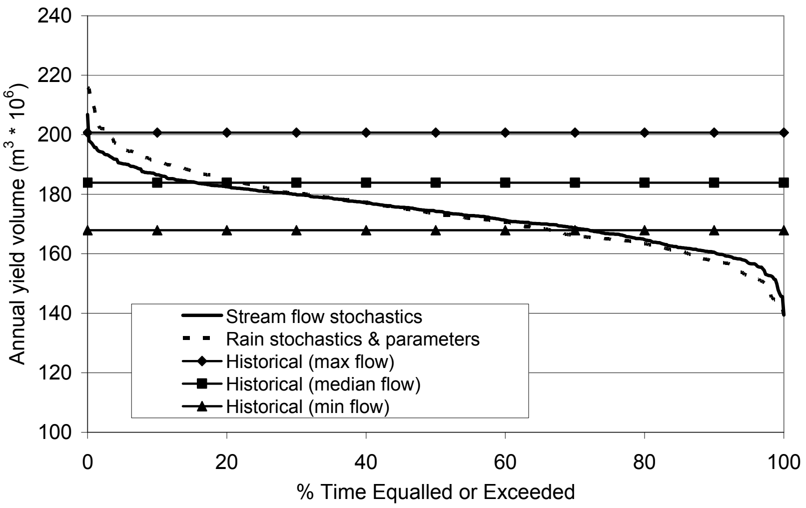


Figure 4.5 Yield exceedence (probability) curves based on different yield analyses (A).

Two additional stream flow stochastic yield analyses were based on the two extreme ensemble outputs from the rainfall-runoff model with only parameter uncertainty. These two extremes represent the 5% and 95% exceeded simulated flows generated by the uncertainty in the rainfall-runoff model for each month of the time series. The yields determined from these are therefore less likely to occur than the yields based on the median hydrology. Figure 4.6 reproduces the two yield probability curves from Figure 4.5 and adds a third line ('Resampled') to represent the effects of allowing for the parameter uncertainty, but still using the conventional stream flow stochastic model in the yield model. This curve has been produced by sampling from the three yield curves generated from seeding the stochastic stream flow model with the two extreme flow ensembles and the median ensemble. The size of the samples (500 for each of the extreme ensembles and 2 000 for the median) has been set to reflect the probability of the different flow ensembles occurring. The three samples were combined to produce the 'Resampled' yield curve which is almost identical to the curve based on combining all the uncertainties in the rainfall-runoff model. Changing the size of the samples did not make any tangible difference to the results.

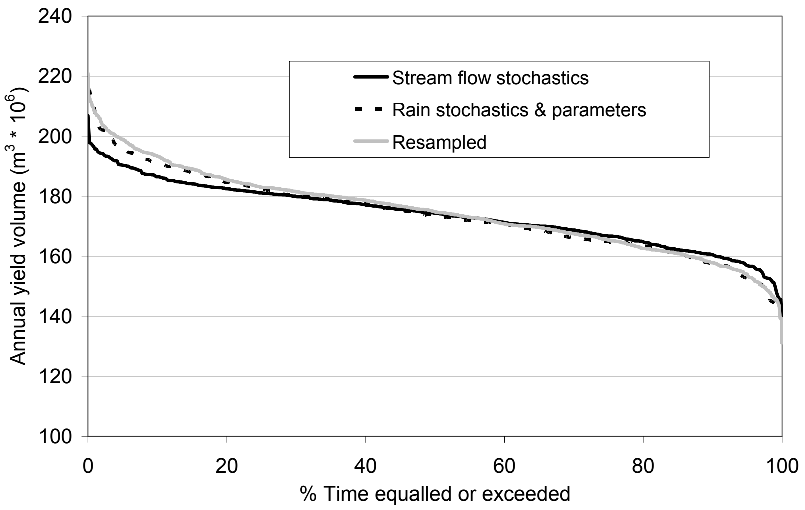


Figure 4.6 Yield exceedence (probability) curves based on different yield analyses (B).

Although the yield curves in this example are not very different (a range of 151.0 to 156.8 * 10^6 m^3 at the 95% exceedence level), this is partly a consequence of the relatively small parameter uncertainty in these sub-basins which has at least some gauged stream flow data to condition the rainfall-runoff model. The results indicate that the use of stochastic stream flow generation within the yield model has accounted for a large part of our uncertainty in water resources availability and this has been part of practical water resources management in South Africa for many years. The study has demonstrated that the explicit inclusion of parameter uncertainty is possible either through the traditional use of stream flow stochastic generation in the yield model or by including the stochastic uncertainty as part of the rainfall-runoff model. The time and computer resources required to complete a yield analysis using the two approaches are not very different now that the appropriate software is available. The effects of parameter uncertainty that have been referred to and illustrated in section 3 of this report suggest that there could be much larger differences in yield estimates in other basins. There is therefore a need to extend this type of study so that water resources managers can be made more aware of the uncertainties associated with the use of model outputs for decision making.

There are several potential advantages of using stochastic rainfall sequences in hydrological models and these are mostly related to the direct links between rainfall variability and uncertainties in other hydrological processes. It is very difficult to incorporate these links in a systems yield model when the stream flow inputs have already been calculated. An obvious example is the uncertainties in ground water recharge which would be explicitly included through the use of stochastic rainfall inputs and uncertainty in the relevant Pitman model parameters. The Pitman model is able to simulate water use and abstractions associated with afforestation, small farm dams and un-regulated abstractions. The impacts of some of these are likely to be directly linked to rainfall variations and could be usefully accounted for within the hydrological model, rather than within the systems yield model. While it is not suggested that uncertainty in these small scale water uses could not be included in future versions of yield models, it may be better to include their effects in the hydrological model. This is an issue for future research and there is a need to identify which is the most efficient and technically appropriate approach to adopt.

4.2 Uncertainty and risk: the interpretation of uncertain yield curves

If the conventional 'return period' approach (see section 2.2.3 of this report) is used to interpret the yield curves shown in Figures 4.5 and 4.6, the estimates of a 1:100 (typical design scenarios) return period yield would not be affected by the introduction of hydrological uncertainty as the two curves are very similar at the 43% exceedence probability point (the analysis used an 85-year record period). For a return period of 1:50 years (18% exceedence probability point) the yield would increase by a small amount given the inclusion of uncertainty. The implication is that if the 'return period' approach to interpretation of stochastically generated yield curves is to be retained, the analysis has to be done in a different way. Returning to the simple and hypothetical example used in Figures 4.2 and 4.3 (which based the analysis on the same approach used in Figures 4.5 and 4.6 for the Midmar dam example), Figure 4.7 offers an alternative method of analyzing the same data. In this case stochastic sequences have been generated for the median hydrology and the upper and lower bounds. Clearly, if this was based on an 85-year record a 1:100 year return period yield estimate could vary between approximately 86 and 121 * 10^6 m^3, while the yield without including any hydrological uncertainty would have been 104 * 10^6 m^3. The range of uncertainty is about 34% of the median yield value. The exact shape of these curves (and their degree of separation at different probability percentage values) will vary, in reality, from catchment to catchment with the nature of the hydrological uncertainty and how this interacts with the stochastic uncertainty.

Assuming that the upper and lower uncertainty bounds are based on the 5% and 95% exceeded ensemble outputs from the hydrological model, the interpretation is that there is a 95% probability that the 1:100 year yield will be greater than 86 * 10^6 m^3, a 50% probability that it will exceed 104 * 10^6 m^3 and a 5% probability that it will exceed 121 * 10^6 m^3. Adopting the first value would represent the low risk approach, while adopting the higher value would involve high risk. Figure 4.8 repeats the same analysis for the Midmar Dam example (see also Figures 4.5 and 4.6) where a 1:100 year event would lie between 163 and 195 * 10^6 m^3, a range of 18% relative to the mean yield value of 176 * 10^6 m^3. This provides some indication of the scale of uncertainty that is introduced for a catchment which has relatively low hydrological uncertainty. However, this result is based on running three different hydrological model outputs through the yield model using the stochastic stream flow component and does not help to inform us of the likely consequences of using the rainfall stochastic model as an alternative approach.

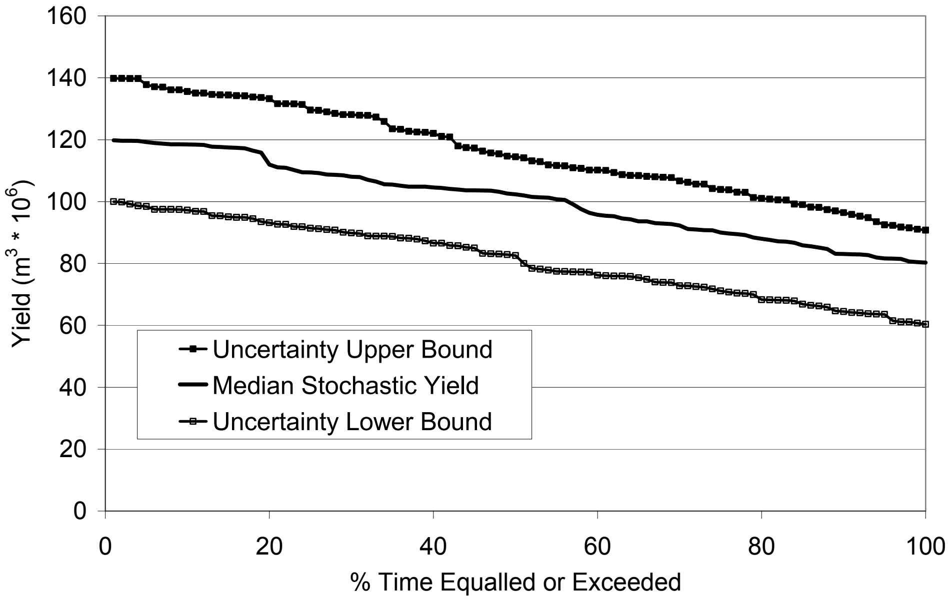


Figure 4.7 Yield probability curves with uncertainty – a hypothetical example.

Figure 4.9 is based on filtering the full 250 000 ensembles generated from the hydrological model with 500 stochastic rainfall inputs and 500 parameter samples where the filtering process is designed to extract three groups of ensembles. The ensembles are first sorted into groups of 500 such that each group has all the different stochastic rainfall sequences represented (and different parameter sets). The median value of the 24-month minimum flow volume in each group has been used to ranks the groups. The three graphs are then based on the 500 minimum flow volumes within the groups that have median minimum flows exceeded by 95% (Lower Bound), 50% (Central) and 5% (Upper Bound) across all of the groups. The ultimate intention is that these three groups would be passed to the yield model for further analysis and generation of three yield curves (without the need for stochastic stream flow generation). The median 24-month minimum flows for the three groups are 191.3, 192.8 and 202.5 * 10^6 m^3, a range of 5.8% around the central value and skewed to the lower values. It is difficult to predict how these ensembles would translate into differences in the three yield curves, but the indications are that a diagram similar to Figure 4.8 would show less variation.

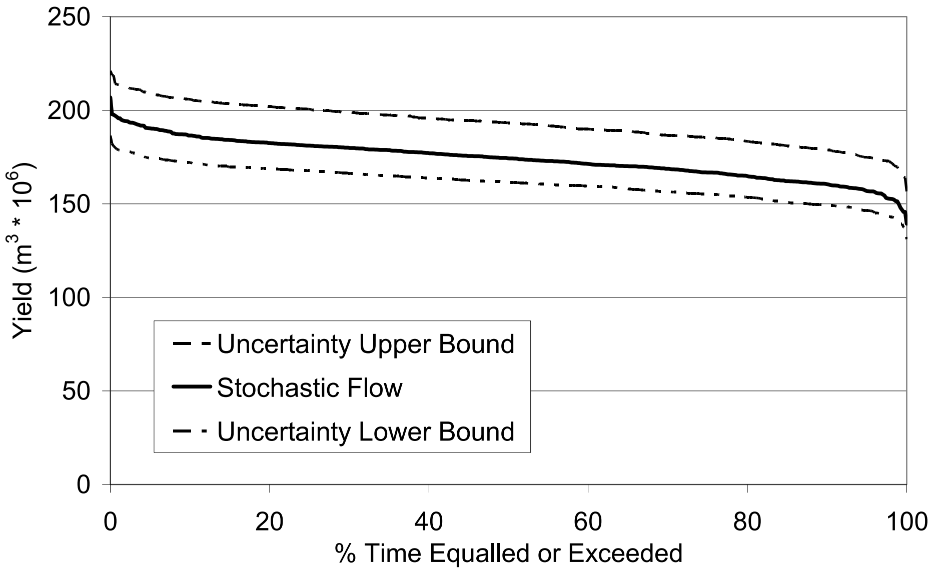


Figure 4.8 Yield probability curves with uncertainty – the Midmar Dam example.

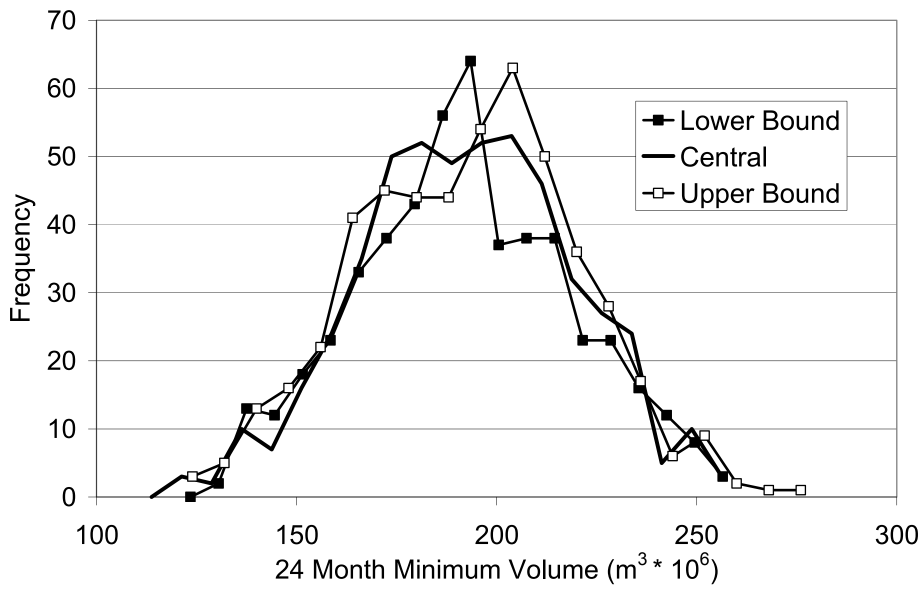


Figure 4.9 Frequency distributions of 24-month minimum flow volumes for three stochastic rainfall – parameter variation combinations – the Midmar Dam example.

Section 2.2.3 referred to different approaches to interpreting yield curves depending on what the stochastic (rainfall or stream flow) sequences are assumed to represent. However, the important issue is that recommendations for the future use of uncertainty outputs in yield and risk assessments should not require a radical re-thinking of the interpretation of yield curves. The ensemble filtering approach that was initially adopted and that produced the results given in Figures 4.5 and 4.6 is therefore not likely to be appropriate. A more appropriate approach is one that produces results similar to Figure 4.8 and the filtering approach used to generate Figure 4.9 would therefore appear to be better aligned with the conventional interpretation of yield curves.

The analyses of using stochastic rainfall versus stochastic stream flow applied within this project are simply a starting point and need to be investigated further before recommendations can be made for implementation in practice. There are, however, indications that several possible approaches could be used and the choice of which is the most appropriate will depend on their efficiency and the extent to which they can be correctly aligned with conventional practice.

4.3 Additional issues of uncertainty in simulating present day flows or yield estimates

4.3.1 Uncertainty in upstream inflows related to small farm dams

In many parts of South Africa farm dams have the potential to impact substantially on downstream resource availability either for other users or for ecological Reserve requirements. However, these impacts and their uncertainty have not been fully documented. This section summarises a separate study that investigated the uncertainty in the impact of small farm dams in three regions based on a thorough investigation of the sources of information that are available.

Arguably the largest source of ***model structural uncertainty*** lies in the aggregation of all dams into a single volume and the use of a model parameter to define the proportion of the catchment area that contributes runoff to the dams. If all the dams are situated on separate tributaries, this approach will normally produce realistic results. However, if a significant number of dams are located on the same tributaries the model may not be able to simulate the impacts correctly. If the headwater dams are the largest, overflow plus incremental flows below this dam may exceed storage in the lower dams and the model will over-estimate runoff losses. However, if the larger dams are downstream, the model will generate more realistic runoff losses. A further issue is that the approach does not account for spatial variations in runoff within the catchment relative to the location of the dams. The only way to completely resolve these uncertainties would be to use smaller catchments in the modelling system which could add other uncertainties associated with parameter estimation and simulating the natural hydrology. Additional structural uncertainties are associated with the lack of any feedbacks between the water stored in or abstracted from the dams and the natural hydrology. Examples include the lack of dam seepage and return flow routines, which could impact on soil moisture storage, ground water recharge and therefore the generation of low flows. While these are expected to have relatively minor impacts where the number of farm dams and the abstractions from them are small, there are some regions of South Africa where there are many farm dams and where abstractions are a significant component of the natural runoff volume. These structural uncertainties have not been addressed in this study, mainly because the objective was to investigate uncertainties in the outputs of an existing widely used model.

The ***full capacity surface area*** of the combined dams is not a parameter of the hydrological model, but it is used to evaluate the parameters of the area-volume relationship. The area can be calculated from maps, areal photographs or satellite information, while it is not possible to calculate the volume without field surveys. Two approaches to estimating the surface area of small dams were used in this study. The first was based on the information generated by Silberbauer (Chief Directorate of Surveys and Land Information, 1999) and contained within a GIS layer for South Africa. The polygons representing the dam areas were based on digitizing 1:50 000 scale topographic maps. The second approach was to use Google Earth images together with a set of pre-defined geometric shapes (circles, rectangles, triangles, trapezoids, etc.). The area estimation process involved selecting the most appropriate shape for an individual dam and measuring the geometric parameters (width, length, radius, etc.) required to calculate the area using the ruler tool within Google Earth. The most noticeable difference between the two estimates was that some of the dams included in Silberbauer's database were found to be dried-up or used for agriculture or forestry, while some new dams were found in Google Earth. Apart from differences in the number of dams, the accuracy of the two area estimation methods was compared using data for 14 farm dams in the Bedford area (90 km north of Grahamstown in the Eastern Cape Province) that were ground surveyed for area and volume during a previous Rhodes University project in 1989 (unpublished data) and that could be reliably located on the Silberbauer coverage. The means and standard deviations (SD) of the absolute relative errors (compared to the surveyed areas) were 65% (SD=37%) and 22% (SD=14%) for the Silberbauer and Google Earth estimates respectively. The Google Earth approach is therefore expected to generate more reliable estimates, particularly as the Silberbauer estimates were all lower than the surveyed areas.

A recent database (DWAF, 2008) includes dam area and ***full capacity volume*** for about 4500 major and minor dams in South Africa. After excluding all records with areas greater than 500 ha (not considered to be farm dams for the purposes of this study) regression relationships between area and volume were developed. It became immediately obvious that no significant regression relationships could be achieved at a national scale and regional assessments would be necessary. The parameters of the three regional regression equations (slope and constant), the sample size and the coefficients of determination (R^2) are given in Table 4.2. It has been assumed that the distribution of uncertainty in dam volume estimates for a given dam area (DA) can be given by a Normal distribution with a mean of Slope x ln(DA) + Constant and a standard deviation of the standard error of the predicted volume. For each of the study catchments 1 000 samples of volume were generated through Monte Carlo sampling for each dam and the total volume summed for each of the samples. The uncertainty is represented by the mean and standard deviation of the aggregated volumes for the 1 000 samples (assuming a Normal distribution). This process was repeated for the dam areas estimated from the Silberbauer and Google Earth approaches.

Table 4.3 Dam volume–area regression equation parameters, sample size and R^2 for the three regions included in the study.

Region	Area of region (km^2)	Slope	Constant	Sample size	R^2
H10 and H20	2879	0.715	4.137	88	0.62
D51 and D52	6088	0.884	3.549	10	0.60
X21	3091	0.796	3.453	9	0.47

Regression equations: Ln {Volume (10^3 m^3)} = Slope x ln{area (ha)} + Constant

The ***area-volume relationship*** is defined in the model using a power function and is used to determine the evaporation losses from the aggregated dam volume during any single month. It is not strictly realistic to allow the scale (A) and power (B) parameters to vary independently, nor for them to vary independently of the uncertainty variations in full supply volume. It was concluded that uncertainty in the estimation of evaporation losses would be adequately covered through the uncertainty in the full supply volume parameter (previously discussed) together with some uncertainty in the scale (A) parameter of the area-volume relationship.

There are many different approaches to estimating the ***contributing catchment areas*** of individual farm dams depending on the available time and map or GIS resources. The simplest and quickest approach would be based on a rapid visual assessment of maps, or GIS layers, of dams and river channels, with or without contour information. This approach will always be subject to quite a high degree of uncertainty. At the opposite end of the scale would be a detailed mapping exercise using maps or GIS data at the 1:50 000 scale and explicitly defining each dam's catchment area. While expected to generate the most accurate information, this approach could be very time-consuming even with digital elevation data and appropriate automated catchment area definition software. In this study an intermediate level approach was adopted that makes use of at least three GIS layers; the main sub-catchment polygons (used in the hydrological model), a river-line layer and a farm dam polygon layer. The accuracy of the process is improved if a contour layer (or an image of a 1:50 000 map which includes contour lines and channels) is also available. Clearly, it is only necessary to assess the most downstream dam on any tributary, as all the upstream dams will be included.

The information available for abstraction patterns is typically confined to an annual volume and/or area of irrigation and crop type. There is rarely any information about the way in which abstractions are managed, if at all, through operating rules. In situations where farm dams are mainly used for stock watering there is rarely any reliable information about the number of large or small stock units. Google Earth can be useful in identifying the area of irrigation and crop type, while standard tables of crop factors for different crops (Midgley et al., 1994) can be used to convert monthly potential evaporation data into estimates of water requirements.

A total of ***6 example catchments*** have been used in the study and were selected to represent catchments with a relatively large number of farm dams taken from climatically different parts of the country. All of the hydrological analyses have been based on simulated natural monthly flow data (October 1920 to September 1990) using regional model parameter values and standard rainfall time series inputs obtained from Midgley et al. (1994).

The H10A to D group of catchments are located in the headwaters of the Breede River in the winter rainfall region of the Western Cape Province. The topography is a mixture of steep mountain slopes and flat valley floors, while the dominant land use activity is deciduous fruit orchards. Mean annual rainfall is highly variable (500->1000 mm) and strongly controlled by topography, while mean annual potential evaporation is about 1600-1700 mm.

X21F is located in the headwaters of the Elands River in Mpumalanga. Mean annual rainfall is approximately 760 mm, while potential evaporation is about 1400 mm y^{-1} and the flow regime has a substantial baseflow component (Table 6.10). The main land use is large stock grazing with some game farm tourism and mining activities. Table 6.11 indicates large differences in the numbers of dams (and consequently surface area and storage capacity) between the two estimates (Table 6.11) and this could be an indication of a recent increase in farm dam development.

D52A is located in the headwaters of the Hartebeest River within the arid western Karoo region and experiences low annual rainfall (320 mm) and high evaporation (1900 mm). Topographically it has steep mountain sides and a relatively flat valley floor that supports stock grazing supported by irrigated fodder crop cultivation along the margins of the river channel. There are a relatively large number of dams for such an arid area with only limited runoff and some of them are quite large.

The uncertainties in the farm dam input data to the model are given in Tables 4.3 and 4.4. In the absence of any better approach, uncertainty in the contributing catchment areas was represented with a uniform distribution, the minimum and maximum values being set at 10% either side of the area estimated (Table 4.3). Parameter B in the area-volume relationship was assumed to be 0.8 with no uncertainty, while parameter A was initially calculated from the mean dam areas and volumes given in Table 4.3 and a uniform distribution assumed with maximum and minimum values set at ±10% of the initial value. It was difficult to estimate the water demands and Google Earth was used to determine approximate areas of irrigation. The use of a Normal distribution to represent the uncertainty is rather arbitrary, while setting the standard deviations to 20% of the mean for the H10 and D52A catchments and 30% for X21F is a reflection of the higher uncertainty expected for X21F.

The ***Results*** are based on 1 000 model runs and are summarized in Figure 4.7 using four flow regime characteristics (mean monthly flow volume, Q10, Q50 and Q90). The impacts are expressed as a % reduction from natural flow and D52A is absent from Figure 4.7D because the natural Q90 is zero. Sensitivity analyses based on simulated monthly runoff volume clearly reveal the dominance of the uncertainty in the irrigation area (i.e. water demand) parameter for most of the example catchments. The exception is D52A, where contributing catchment area plays the dominant role. The uncertainty in the dam volume estimate is usually the second most important parameter. The importance of the water demand information is problematic from a water resources assessment point of view because this is also the most difficult parameter to quantify given existing, readily available, information sources. If low flows are used in the sensitivity analyses contributing catchment area becomes the most sensitive parameter, with water demand second in importance. This is a reflection of the long durations during which the dams are using all of the upstream inflow, a situation exacerbated in the Western Cape catchments where the highest water demands are during the low-flow season (summer). For X21F, water demand remains the most sensitive parameter even when using Q90, a reflection of the much higher natural baseflows that have been simulated for this catchment, as well as lower relative water demands during the low-flow season (winter). The implication is that the dams in X21F are under-utilised relative to their capacity and inflow volumes and are therefore expected to regularly spill.

Table 4.4 Small farm dam aggregated full capacity surface areas and volumes and % catchment area contributing to dams. The values provided are the means and standard deviations of Normal distributions or the minimum and maximum of uniform distributions used to represent the uncertainty.

Catchment	Aggregated small farm dam measures (based on full capacity)							
	No. of dams	Surface area (km^2)	Volume (m^3 * 10^6)		% catchment area contributing		Parameter A	
			Mean	St.Dev	Min.	Max.	Min.	Max
Based on Google Earth area estimation								
H10A	134	3.16	15.905	1.132	72.0	88.0	4.8	5.8
H10B	61	1.95	9.000	0.936	45.1	67.4	3.8	4.6
H10C	181	5.98	23.907	1.734	45.8	68.6	6.5	7.9
H10D	0	0.00	0.000	0.000	N/A	N/A	N/A	N/A
X21F	188	1.84	6.476	0.424	62.0	76.0	6.3	7.7
D52A	49	1.98	6.163	0.434	50.0	62.0	6.1	7.5
Based on Silberbauer area estimation								
H10A	150	2.50	13.736	0.871	72.0	88.0	4.4	5.4
H10B	84	1.09	6.603	0.581	45.1	67.4	3.2	4.2
H10C	220	5.68	26.194	1.781	45.8	68.6	5.9	7.3
H10D	0	0.00	0.00	0.00	N/A	N/A	N/A	N/A
X21F	104	1.57	5.372	0.404	62.0	76.0	5.9	7.1
D52A	50	1.14	3.628	0.323	50.0	62.0	5.9	7.1

Figure 4.10 reinforces many of the conclusions reached from the regional sensitivity analyses discussed above. X21F has the greatest uncertainty range, a reflection of the higher assumed uncertainty (30% of the estimated mean, compared with 20% for the other areas) associated with the water demand parameter and the dominance of this parameter in the simulations. The % reduction is greatest for the low flows (high percentiles of the flow duration curve) as well as in the catchment with the most arid climate (D52A), although high water demands during the summer dry season in the H10 catchments also leads to

substantial reductions even in Q50. The higher % reductions for Q50 and Q90 within catchment H10A is a reflection of the large contributing catchment area (Table 4.3). Further details of the results of this study can be found in Hughes and Mantel (2010a), while comparisons with other sources of uncertainty can be found in Hughes and Mantel (2010b) and Table 3.5 of this report.

Table 4.5 Catchment area and annual water use uncertainty expressed as the mean and standard deviation of irrigation area (km^2) for a Normal distribution.

Catchment	Area (km^2)	Irrigation area (km^2)	
		Mean	St. Dev.
H10A	233.7	5.0	1.0
H10B	162.5	21.0	4.2
H10C	259.6	42.0	8.4
H10D	97.0	0.0	0.0
X21F	396.7	4.8	1.5
D52A	377.6	0.76	0.15

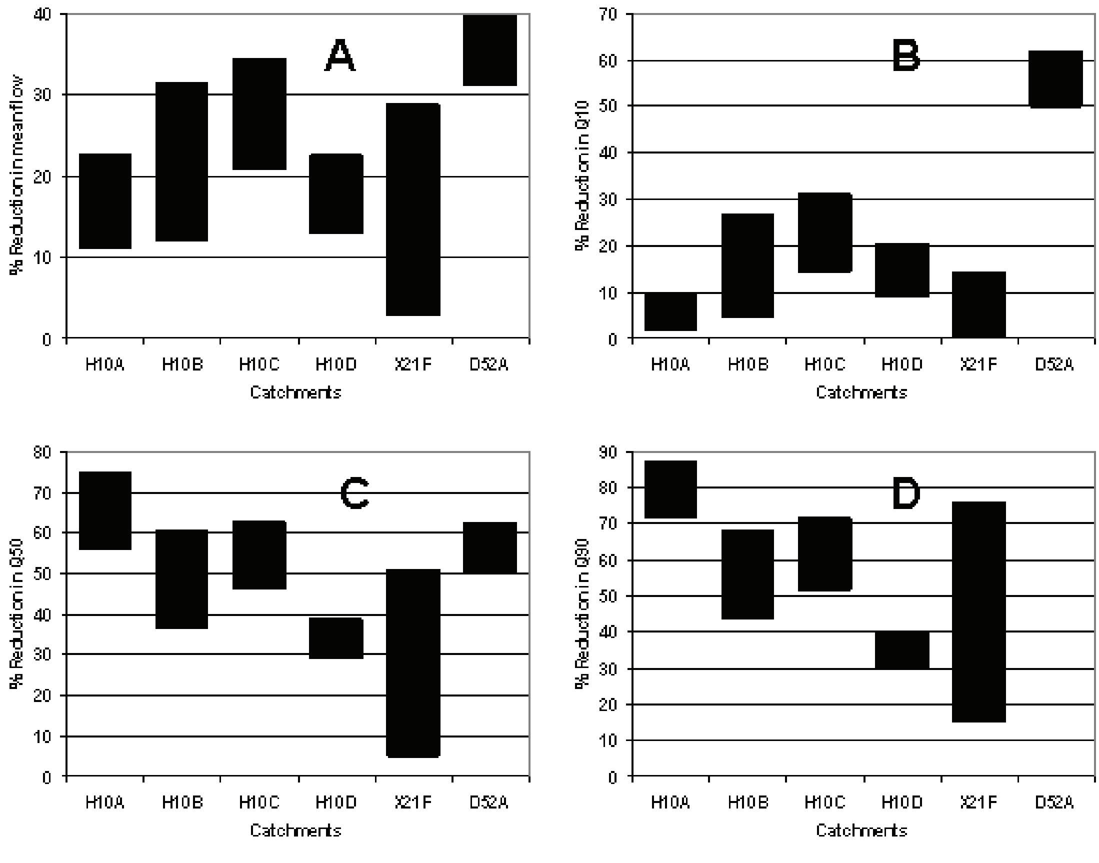


Figure 4.10 Uncertainty in the impacts of farm dams on mean flow (A) and three percentiles of the 1-month annual flow duration curve; Q10(B), Q50(C) and Q90(D). The uncertainty is represented as ranges of % reduction relative to the natural flow.

4.3.2 Uncertainty in groundwater abstraction impacts

It is not very clear at present how successfully the impacts of groundwater abstractions can be incorporated into either hydrological models or water resource systems models. The current version of the Pitman model has groundwater abstraction components (based on either the Sami version or the Hughes (2004) version). Hughes et al. (2009) report on a study designed to look at some of the uncertainties in estimating the catchment-scale groundwater yield of a semi-arid catchment (no significant groundwater contribution to streamflow), but there do not seem to be any published evaluations of the use of the groundwater components of the model for estimating the impacts of abstraction on low flows. It is also not clear to the project team how such impacts are currently managed within the yield model.

The previous section reported on the impacts of small farm dams that are used for irrigation purposes in a headwater catchment of the Breede River (H10A to C). This area is expected to receive substantial volumes of recharge on the mountain areas surrounding the flatter valley bottoms where the irrigation is practiced. The GRAII database refers to mean annual recharge values of between 11 and 50 mm for H10A (having some Bokkeveld and some Table Mountain Sandstone ridges), 42 to 105 mm for H10B (TMS) and 23 to 79 mm for H10C (mostly TMS). Even if the lower value is used for H10A this represents approximately the same volume that was used as the abstraction volume from small farm dams.

An initial assessment of groundwater abstraction impacts was based on replacing all the effects of farm dam abstractions with groundwater abstractions in H10A. This represents a total of some $3 * 10^6$ m^3, which is 17% greater than the lower estimate of mean annual recharge. The impact on the pattern of monthly flows is relatively small reducing the mean annual runoff by less than 5% and having almost no effect on low flows. The impact of the abstractions on ground water levels has been assessed using the simulated GW gradient nearest the channel (the surrogate for GW level that is used in the model). Under natural conditions it is apparent that GW only contributes to surface water (+ve gradients) during July to October, while the abstractions remove all the contributions and draw the groundwater down significantly. If the model is simulating the sources of surface runoff in this catchment realistically, the implication is that groundwater abstractions have far less impact on patterns of streamflow than abstracting similar volumes of water using small farm dams, which is a highly significant observation from a water management and especially from an environmental flow perspective. However, as already mentioned, it must be recognized that this is a model result that has yet to be assessed with field observations.

4.3.3 Uncertainty in afforestation impacts

Several approaches (including Hughes, 2006) to estimating afforestation impacts make use of the so-called Gush curves that were generated using the ACRU model (Gush et al., 2002). One version of these data provides streamflow reduction values for several percentage points on monthly and annual flow duration curves. During the Southern Africa FRIEND project (Hughes, 1997) the Pitman model was used to simulate the impacts of afforestation in a number of small experimental catchments throughout South Africa and one of the results of those assessments were that the main parameters to change were the interception (PI_{Forest}) and evaporation scale (FF) parameters. The latter represents a scaling factor to apply to the afforested part of the catchment. The guidelines were that PI_{Forest} should be set to 4.0mm and FF to 1.4. The uncertainty version of the Pitman model has been run (1000 ensembles) for quaternary catchment T35A with PI_{Forest} set to a range of 3 to 5mm and FF to a range of 1.2 to 1.5 and a forest area of 40% of total catchment area. The range of reductions in the 10, 50 and 90% points of the annual FDC are compared with the Gush database (all three forest types) in Figure 4.11. While the Gush results for the median (50%) flow are between the Pitman model ensembles, the high flow reductions (10%) for the Pitman model results are generally lower than Gush. The Pitman model tends to under-estimate the reductions (relative to Gush) for the low flows (90%). It is clear that some of these uncertainties would have to be resolved if the two methods were to be used in parallel during different studies.

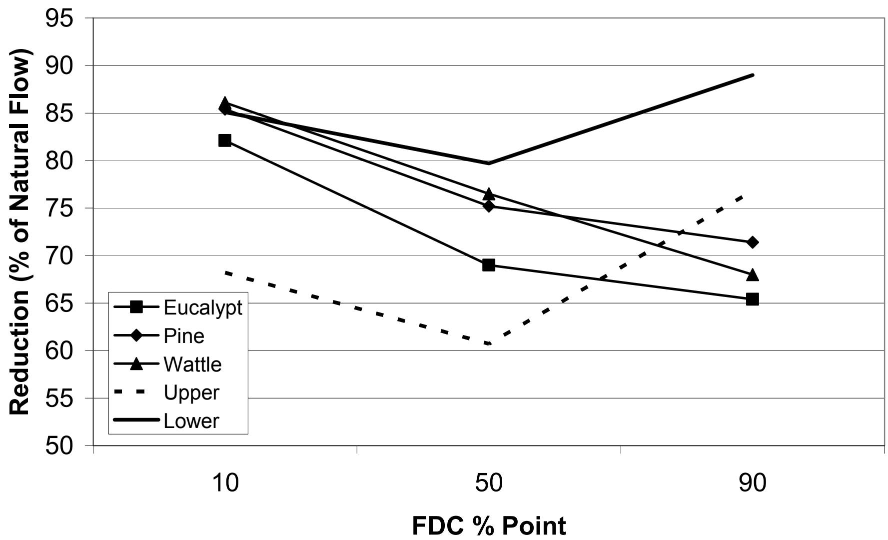


Figure 4.11 Comparison of afforestation impacts for T35A with 40% forest cover as generated by the Gush curves and by the Pitman model uncertainty ensembles.

4.3.4 Reservoir operating rules and uncertainty

The manner in which a reservoir or bulk supply system is operated appears to depend very much on the economic impact that would result from the failure of the reservoir or system to supply the desired or expected quantity of water. Very little effort goes into operating a farm dam since generally only one farmer or farming community will suffer the consequences of less than anticipated water supply, while large systems such as the Vaal and Mgeni have complex operating rules and sophisticated models with which to assist operators and decision makers to operate the system within defined levels of risk. More recently, real-time operation has been implemented in the Mhlatuze and Crocodile (east) catchments. These operational procedures provide feedback to the operator as to how much water is actually abstracted from the river as opposed to the amount released into the river from upstream dams. This feedback loop should further reduce the uncertainty as to how much water can be made available to water users in the short and long-term. Figure 4.12 provides a graphical representation of the concept of reducing uncertainty with increasing operational sophistication.

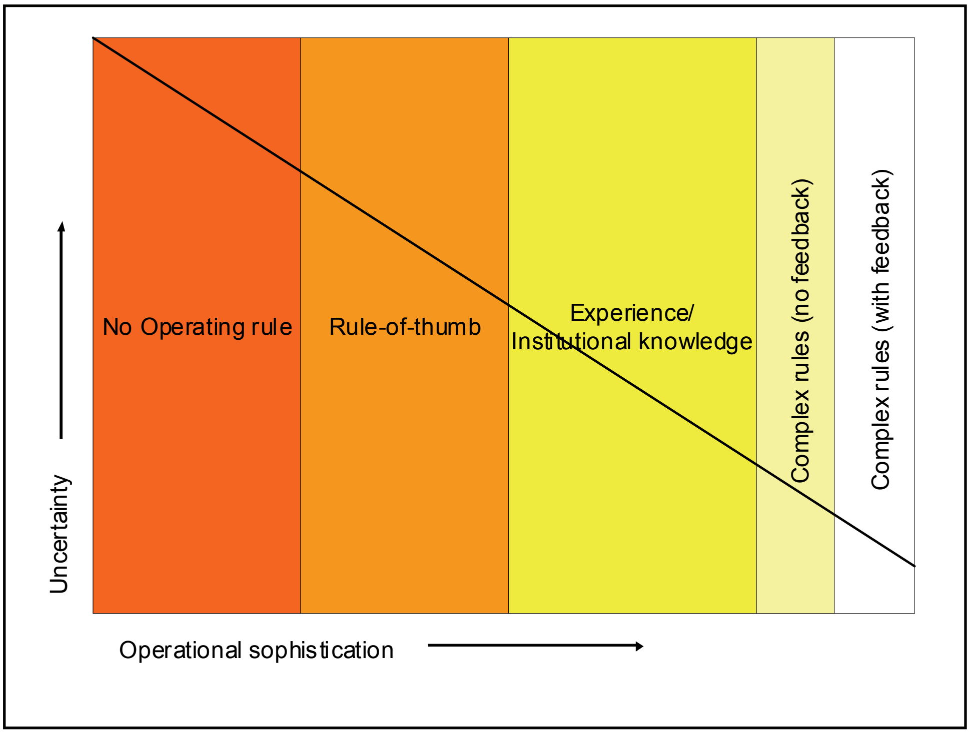


Figure 4.12 Effects of increasing operational sophistication on uncertainty.

Small farm dams generally operate, at best, on a rule-of-thumb basis and the farmer generally learns by trial and error how much water he can supply from his dam and plan accordingly. Small domestic water supply schemes are probably more problematical since the expertise is not available to develop operating rules and the institutional knowledge is often lost with staff turnover. Schemes such as these are generally operated to supply on demand and continue to supply until the reservoir is empty. Large schemes, generally operated by organizations such as the Department of Water Affairs, Water Boards and in some cases irrigation boards, experience less uncertainty due to the operating procedures that are in place and which have been developed by means of complex water resources models and applied in practice. A few examples of water supply schemes operating in South Africa and their level of uncertainty are listed in Table 4.5.

Table 4.6 Examples of water supply schemes and the associated levels of uncertainty in the present day operating rules.

Scheme	Supplying	Comment
High uncertainty		
Middle Letaba Dam	Thoyandou	Although operating rules were developed for this dam, they were never adhered to resulting in a very high level of uncertainty.
Acornhoek	Acornhoek	No operating rule or any idea of the sustainable yield of the dam
Medium uncertainty		
Sandile Dam	Irrigators and small towns downstream of the dam	The yields of the dams are known and the demand placed on the dams does not exceed this yield, but there are no restriction rules in place.
Low uncertainty		
Vaal system	Large bulk supplies.	Complex operating rules in place. Decisions made annually or bi-annually
Mgeni System		
Komati System		

While the development of complex operating rules results in a reduction in the uncertainty as to how much water can be obtained from a reservoir or bulk supply system, these rules are developed with the aid of models which attempt to mimic the real world. A crucial assumption made in models is that information is readily available in order to make the best decisions. The information required would be the flow in the river at any point in time and location and the actual water use as apposed to the water requirement. In reality, this information is often not known to a high degree of accuracy and the system operator has to make some assumptions in determining how much water to release from a dam to downstream users. These assumptions therefore introduce uncertainty into the real world.

Modelers of complex systems usually assume that water users downstream of a reservoir will make use of incremental inflows or accruals downstream of the reservoir and releases will only be made when required. The reason for this is that such an operating procedure maximizes the yield of a system. When it comes to operating the system in real-time, however, the operator does not necessarily know what the flow in the river is and merely responds to requests for releases from the users. Also, since river abstractions are seldom monitored or audited, the efficient operation of a system seems to depend on the integrity and honesty of the water users. A hypothetical modelling exercise was carried out to demonstrate the significant difference in system yield should a system be operated with a continual release from the dam to downstream users (Mode 1) assuming they are not making use of incremental inflows (i.e. a system with no knowledge of downstream conditions) on one hand and a perfect knowledge of incremetal inflows downstream of a dam coupled with abstractions by users (Mode 2). It is clear from Figure 4.13 that the release required from the dam in operational Mode 1 will be greater (and the dam will empty sooner) than for Mode 2. From a system yield perspective, the sustainable or firm yield obtainable under Mode 2 will be greater than under Mode 1. This increase in system yield is commonly referred to by water resource practioners in South Africa as the 'leverage effect'. The comparative firm yields are 31.3 $*10^6$ m^3 y^{-1} for Mode 1 and 48.0 $*10^6$ m^3 y^{-1} for Mode 2.1

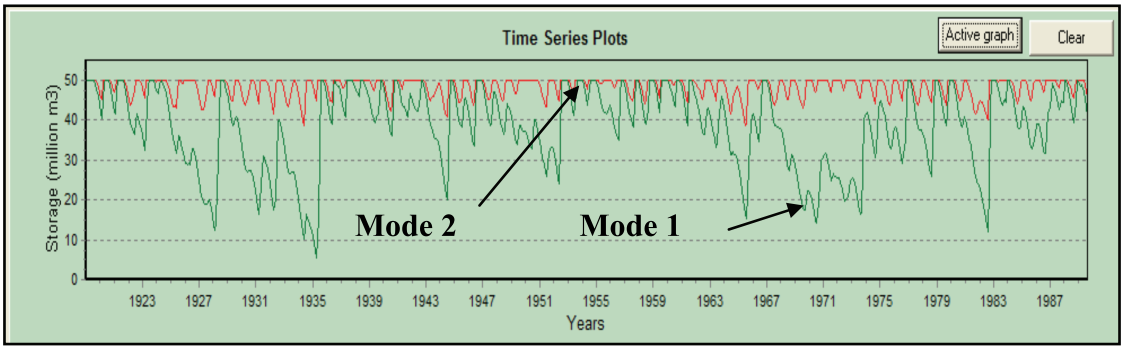


Figure 4.13 Storage trajectory of a hypothetical dam under different operation modes

The Kat River provides a practical example of how lack of knowledge of conditions in a catchment results in uncertainty about the system yield. The operation of the Kat River dam underwent a major change in 1982, from a system of constant uniform releases to that of a 'release-on-demand' system. Figure 4.14 shows the observed storage of the Kat River Dam since its construction up to the end of 1989, which was the extent of the natrual flow time series available at the time of carrying out this analysis. Plotted on this same axis are the modelled trajectories of the dam assuming the two operation modes, Mode 1 and Mode 2. It is interesting to note how closely the modelled operating modes follow the actual reservoir strorage trajectory. Up until the severe drought in the early 1980's water was released at a constant rate to irrigators downstream of the dam. This mode of operation, while requiring very limited management, was not sustainable and not surprisingly the system failed during the drought. After the drought a 'release-on-demand' mode of operation was adopted and since then the Kat River Dam has never been in danger of failing. It can be concluded from the Kat River case study that the way in which a dam is operated and the lack of information on water use and incremental inflows downstream of a dam introduces uncertainty about system yield. Methods to quantify and reduce these uncertainties need to be developed.

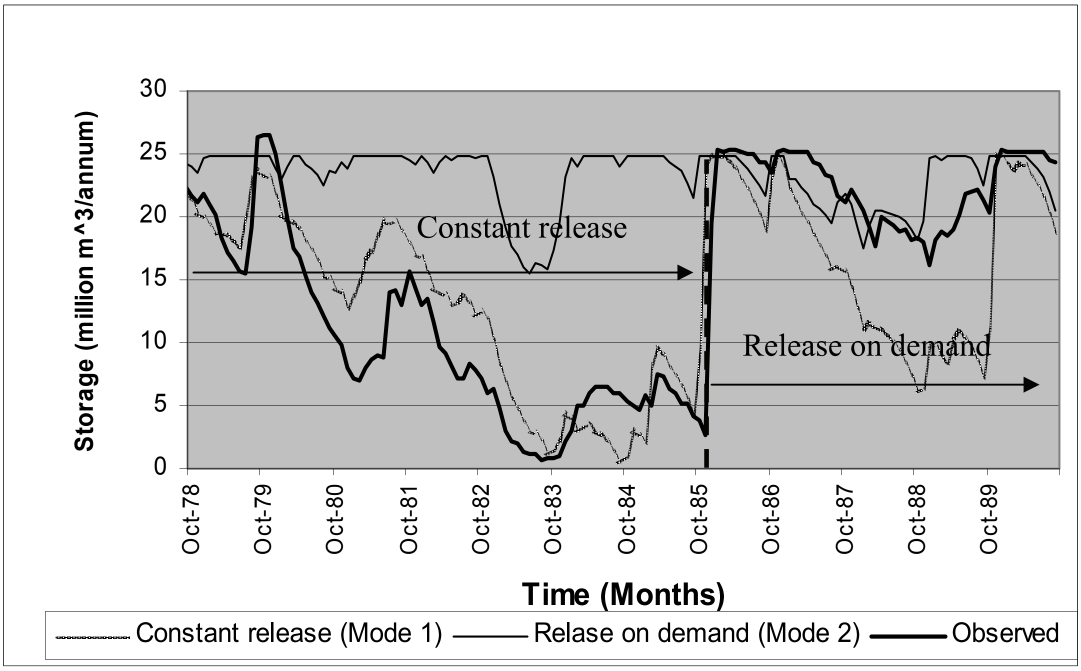


Figure 4.14 Observed and modelled storage of the Kat River Dam

5. TECHNIQUES AND TOOLS FOR QUANTIFYING UNCERTIANTY

This section of the report is designed to highlight and summarise the techniques and software tools that have been developed during the project. The majority of the software products have been either incorporated as part of the SPATSIM hydrological framework software, or are interfaced with that software in some way.

5.1 Pitman model parameter estimation procedures

These are the parameter estimation procedures that were developed by Kapangaziwiri (2008, 2010) and the software is designed to use any available physical basin property data to estimate the distribution statistics of the Pitman model parameters. While the design of the software has been largely influenced by the type of data that can be obtained from the AGIS (2007) land type database, it is flexible enough to be able to be used with any available data after some interpretation. The basis for the parameter estimation approach is the conceptual interpretation of the hydrological 'meaning' of the parameters of the Pitman model and the subsequent development of estimation equations based on information that is expected to be available (with differing degrees of accuracy and resolution) about the physical properties of a catchment (Kapangaziwiri, 2008 and Kapangaziwiri and Hughes, 2008). The initial approach did not include uncertainty, while work undertaken for this project was designed to modify the original approach to include estimates of uncertainty. The principal that was adopted for the inclusion of uncertainty was that the available physical property data would always be either less accurate than is really required or they would be available at a spatial scale (greater or lower) that is different to the scale of modelling. Within South Africa, a great deal of the required information is available from the AGIS (2007) land type data and the spatial scale of the data is more detailed than the quaternary scale of modelling. In other cases (such as large parts of southern Africa or for data inputs that are not part of the AGIS database), more generalized information is expected and the approach for incorporating uncertainty would be different.

Figure 5.1 Illustrates the data entry interface (Left side) and the calculation of the so-called 'secondary' variable distribution statistics (right side). There are a number of default settings for the data entry part of the program that can be accessed by double-clicking on the relevant rows of the left hand side. These help with establishing default values for some of the hydrogeology, soil and vegetation physical properties. The results (and the input data) can be saved to a text file for storage and later retrieval and editing.

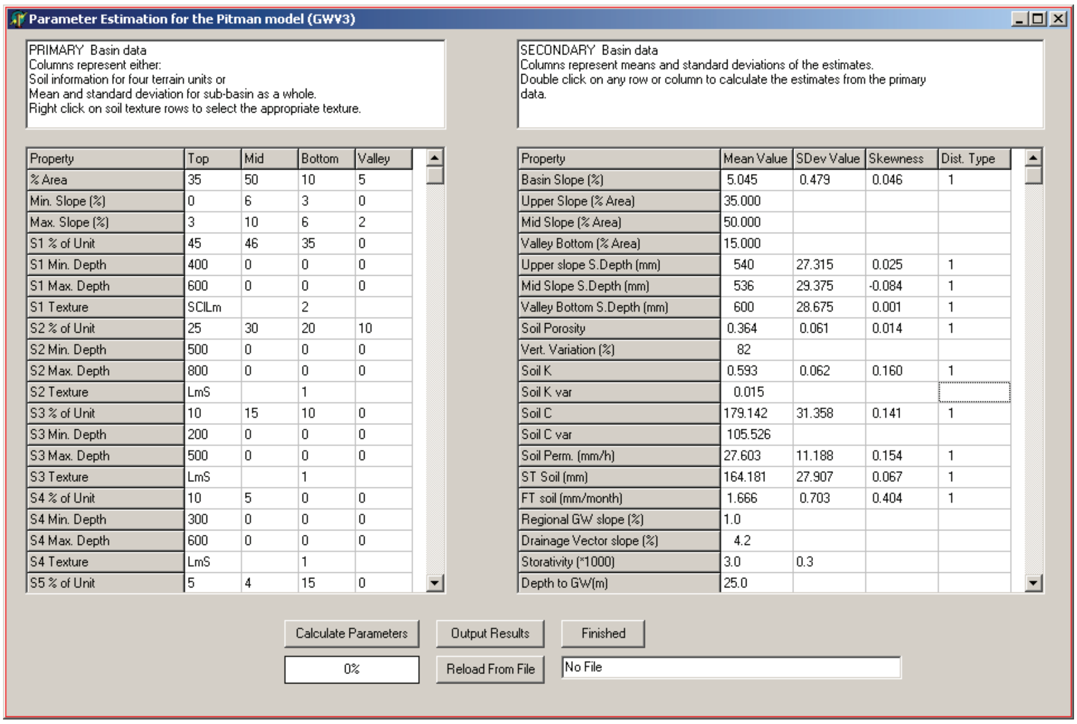


Figure 5.1 First screen and data entry window for the parameter estimation program.

The second part of the software (final parameter estimation) is activated using the 'Calculate Parameters' button and the result is the table of mean, standard deviations, skewness, distribution type, minimum and maximum values for each parameter (Figure 5.2). This table is included in the text file (generated by the 'Output Results' button) and the first two parts of that file (the raw physical property data and the secondary variables)) can be deleted from the file to leave a text file input that can be directly imported into an uncertainty parameter attribute of the SPATSIM system. This type of data attribute is required for the parameter input to the SPATSIM uncertainty version of the Pitman model.

The 'primary' physical variables are used to estimate the probability distributions of a number of 'secondary' variables (soil permeability, mean catchment slope, etc.). It is generally assumed that the primary variables are normally distributed, while the distribution properties of the secondary variables depend on the form of the estimation equations and can be either normally distributed or log-normally distributed. The only exception to this general rule is where the maximum topographic slope is very high, in which case a log-normal distribution is assumed for the primary slope input variable. The approach used is to randomly sample from the primary variable distribution functions, use the estimation equations to generate ensembles of secondary variables and then to calculate their distribution properties (mean, standard deviation and skewness). The skewness property is used to decide whether the secondary variables are normally or log-normally distributed. The results of the secondary variable estimations are listed on the screen so that the user can assess the validity of both the mean estimates and their standard deviations against their own understanding of the hydrological properties (and variability characteristics) of the catchment.

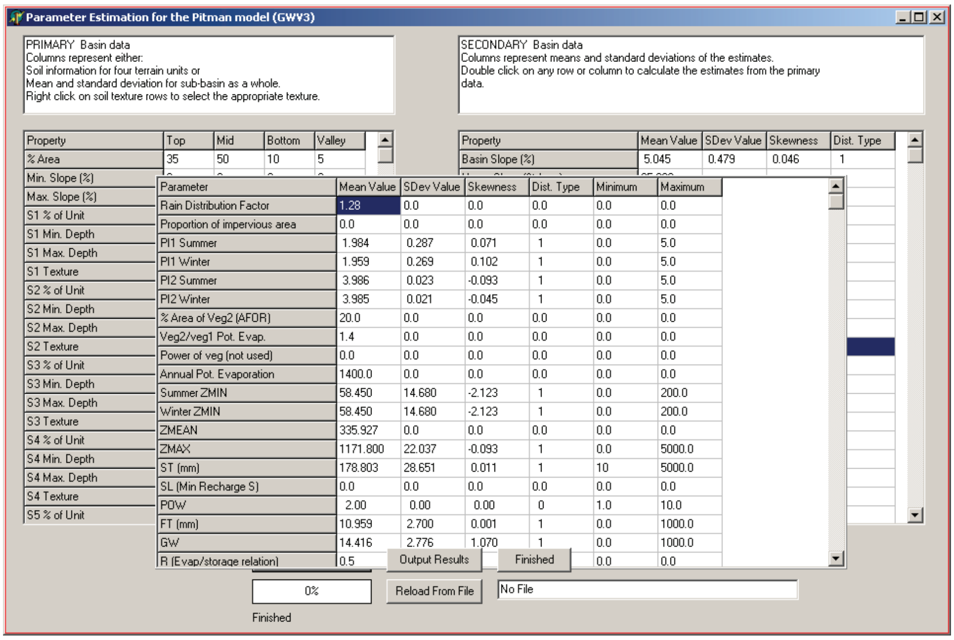


Figure 5.2 Second screen of the parameter estimation program.

The same process is used to generate the distribution properties of the parameter value estimates from a combination of the primary and secondary variables using estimation equations that thoroughly presented and discussed in Kapangaziwiri (2010). The minimum and maximum values are not calculated by the software but are required as part of the input to the uncertainty version of the Pitman model. If the distribution type is 1 or 2, the minimum and maximum values are used to constrain the parameter sampling process within the model. Some of the parameters are not included as part of the estimation process (notably the parameters associated with impacts on natural hydrology), but their values can be edited at a later stage. The third distribution type (3) has been included to allow users the flexibility to over-ride the automatic choice of either normal or log-normal distributions and represents a uniform distribution, where all parameter values between the minimum and maximum are expected to be equally likely.

While the software is simple to use (it operates much the same as a spreadsheet) the interpretation of the available physical property data requires some training and experience to ensure that sensible and realistic parameter estimates are achieved. Experience in the use of the software within the IWR (staff and post-graduate students) suggests that there remains a degree of subjectivity in the interpretation of the AGIS data and therefore the final parameter distribution properties. One of the major problems encountered with obtaining consistent estimates was in those situations catchments have highly variable soil and topography characteristics (i.e. a number of different land types within a single quaternary catchment). Some limited experiments with reducing the model scale (to sub-quaternary level), and therefore the number of land types used for a set of parameter properties, produced better results in terms of reduced uncertainty as well as more consistent estimates.

5.2 The uncertainty versions of the Pitman model

Two uncertainty versions of the Pitman model have been included as part of the SPATSIM software package; one that assumes a single rainfall input time series and an extension program that assumes the rainfall input is a set of stochastically generated sequences. The input parameter details are the same as the table referred to in the previous section (Figure 5.2) and the user specifies how many ensembles should be generated (typically between 1 000 and 10 000). The parameter sets for each ensemble are based on random sampling from the parameter distributions, with each parameter and each sub-area being sampled independently. This means that it is assumed that there are no structural relationships between the parameter sets for sub-catchments within the spatial distribution system. The random generation process has been checked to ensure that truly random parameter sets are generated and an earlier version of the software was found to fail in that respect (repeated patterns of the same parameter values were found to occur with a large number of sub-areas and ensembles). The outputs from the single rainfall time series version are:

- Time series of simulated flows for all ensembles stored within the SPATSIM database.
- A text file (for each sub-catchment) of all parameter values plus some flow statistics and objective functions calculated if observed data are included as part of the model setup (UN1 file).
- A text file of the median, 5% and 95% exceeded flows for each month of the simulation period and including observed flows if part of the model setup. The first three values are not ‘real’ time series in that they do not represent specific ensembles but rather the range (or distribution) of possible simulated flows in all the months (UN2 file).

The amount of computer time taken to run the model clearly depends upon the number of sub-areas included in the spatial distribution system and the number of ensembles (as well as type of computer hardware being used). A typical time for 3 sub-areas and 5 000 ensembles is approximately 5 minutes including the time taken to save the results. The latter can be quite time consuming and therefore almost all of the outputs have been removed from the second version of the model that included stochastic rainfall inputs. In this program it would be typical to use 500 rainfall input time series and 500 parameter samples – a total of 250 000 ensembles. In this situation the output ensembles are stored in binary files and no other outputs are included. The binary files (one for each sub-area) for an 85 year simulation period are approximately 1 Gbyte.

5.3 Post-processing the uncertainty outputs of the Pitman model

There are a range of different analyses that can be performed on the uncertain outputs, including simple visual examination of the ensembles versus other data (observed flows or previous simulations) using the TSOFT facility within SPATSIM. The TSOFT utility can also be used to compare flow duration curves and seasonal distributions (between different ensembles and between ensembles and other results) as well as calculate some comparative statistics.

The UN1 output files can be imported into a spreadsheet and the sorting and graphical analysis facilities of the spreadsheet (Excel for example) used to examine such as the interaction between parameters, the relationships between parameters and flow statistics or objective functions (Figures 5.3 and 5.4). Spreadsheet analyses of the UN1 outputs are also used to evaluate the ensembles against regional or observed constraints.

While the use of a spreadsheet can provide many flexible facilities for post-processing the ensemble results and to assist in a detailed understanding of parameter interactions and their effects on the model results, an additional software tool has been developed to facilitate ‘regional sensitivity analysis’. This is an approach widely used in the international literature to investigate the sensitivity of the model results to changes in groups of parameter values. Figure 5.5 illustrates the approach using a screen shot of the main program interface. The top of the screen includes a button to load a UN1 output file, while the left hand side allows the parameters to be included in the analysis to be selected (and listed in the lower-left hand display). The sensitivity analysis can be based on either a flow metric of the simulated ensembles (e.g. mean monthly flow) or on an objective function if observed data were included in the model setup. It is also possible for some of the flow metrics to enter the variables used to calculate the regional constraints or signatures and distinguish between behavioural and non-behavioural ensembles.

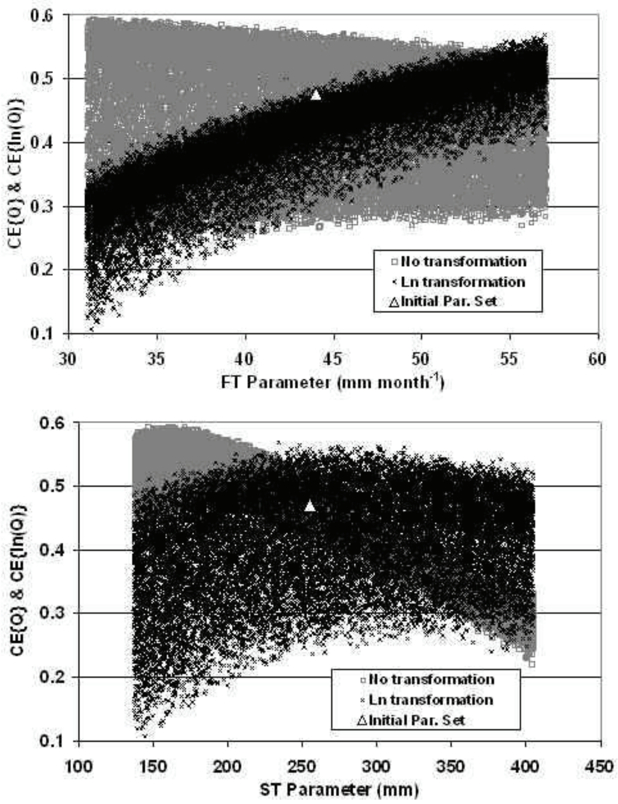


Figure 5.3 Example plot of parameters FT and ST versus two objective functions, indicating the effects of different objective functions on optimum parameter values.

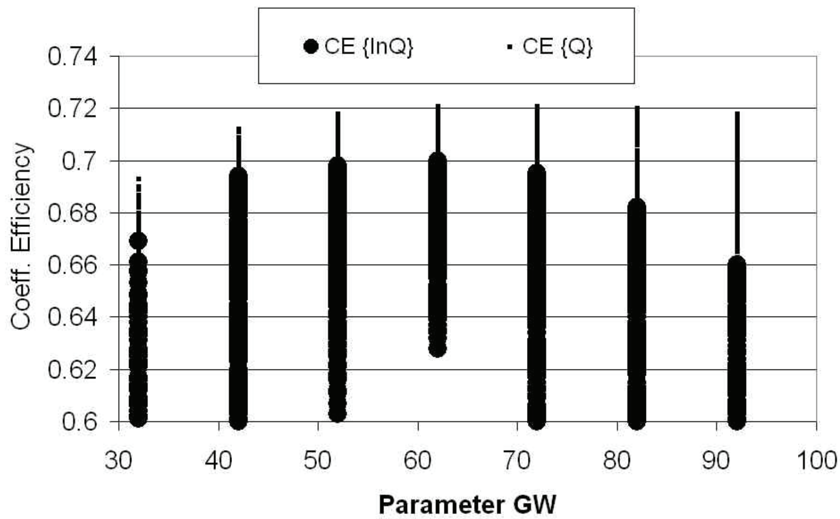


Figure 5.4 Example plot of parameter GW versus two objective functions, indicating an optimum result (given other parameter variations) at approximately 60 to 70 mm month^{-1}.

Figure 5.6 provides an example of an output. All of the ensembles are ranked (based on the sensitivity criteria selected – i.e. a flow metric or an objective function) and then divided into five groups (or seven if the behavioural analysis option is included – i.e. the top and bottom groups are those that lie outside the limits of the regional constraint estimates). The four groups are then plotted as cumulative frequency curves. If an objective function is selected as the criteria for the sensitivity analysis the frequencies are weighted by the objective function values. The interpretation of the results shown in Figure 5.6 is based on the recognition that sensitive parameters are indicated by widely spaced cumulative frequency curves across the four groups. A low degree of over-lap in the parameter value range between the top and bottom groups suggests parameters that are identifiable (i.e. changes in the values of one parameter strongly affect model results, regardless of the other parameters). Figure 5.6 illustrates that the parameter values of the Pitman model are rarely identifiable and there are many different parameter combinations that give similar results. The data used to plot the graphs in Figure 5.6 can also be output to a text file that can be imported into Excel to facilitate generating publication quality graphs of the same information.

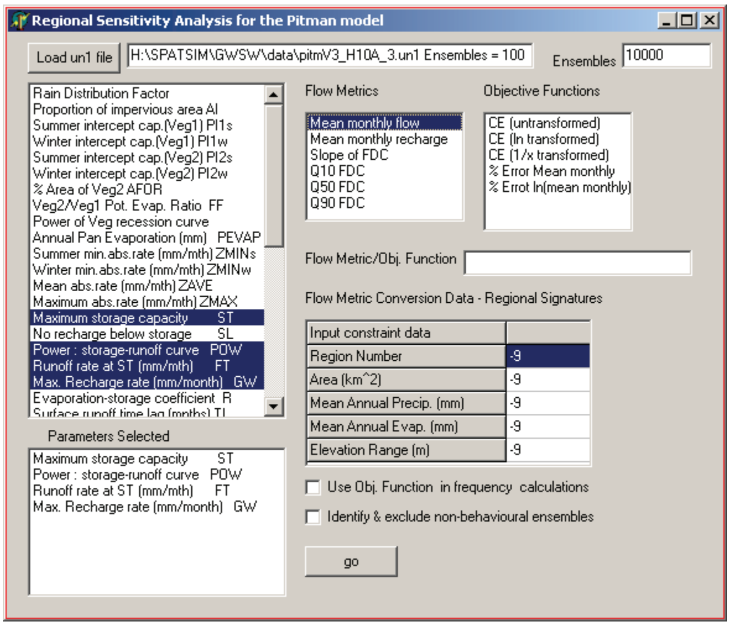


Figure 5.5 Regional sensitivity software tool – main screen

Figure 5.7 illustrates the use of the UN2 output file to generate time series plots of the upper and lower bounds of the simulations for each month of the simulation period and clearly shows the degree of uncertainty and the relationships with observed flow.

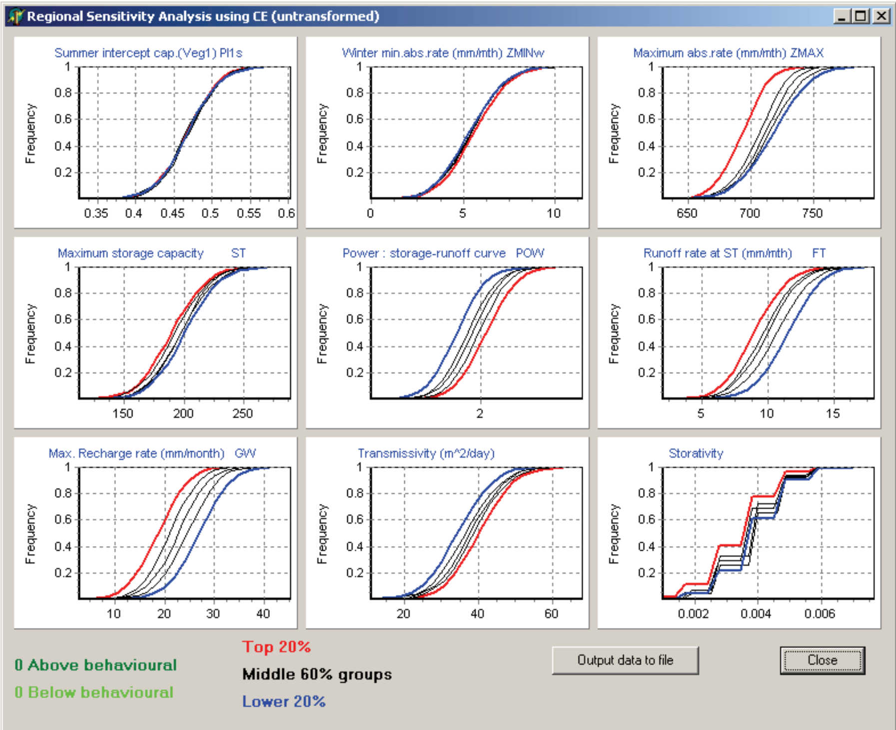


Figure 5.6 Regional sensitivity software tool – graphical results screen

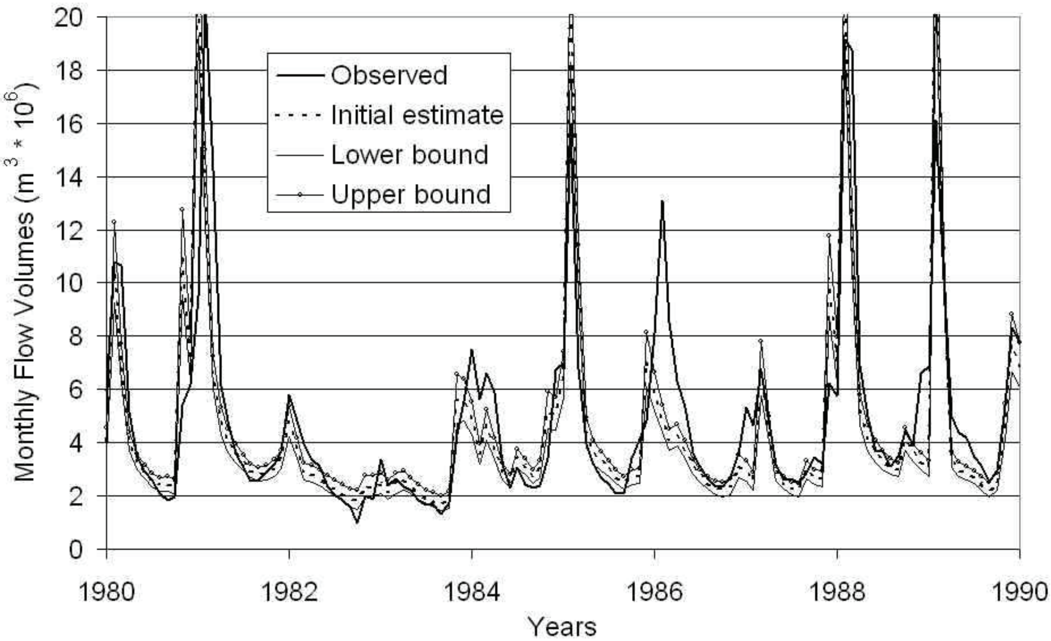


Figure 5.7 Time series plots of the upper and lower bounds of the simulation ensembles together with results based on initial parameter estimates and observed data.

The type of analyses discussed in this section are not expected to be applied during typical practical applications of the Pitman model as they may be too complex and time consuming to complete. However, they do provide a comprehensive range of tools that can be used during either scientific applications of the model or when detailed 'calibration' is required and justified to obtain the best possible results.

An additional facility has been included within SPATSIM to sort the ensemble outputs from either of the Pitman model uncertainty versions. This post-processing facility is designed to sample from a large number of ensembles and generate text file outputs for use with a yield model. The sorting and sampling process is based on the minimum volume over a user defined critical period within each ensemble. This approach is used as a rapid surrogate for a yield assessment and is considered to be a better sampling approach than one based on the mean annual runoff. Figure 5.8 provides an illustration of the approach.

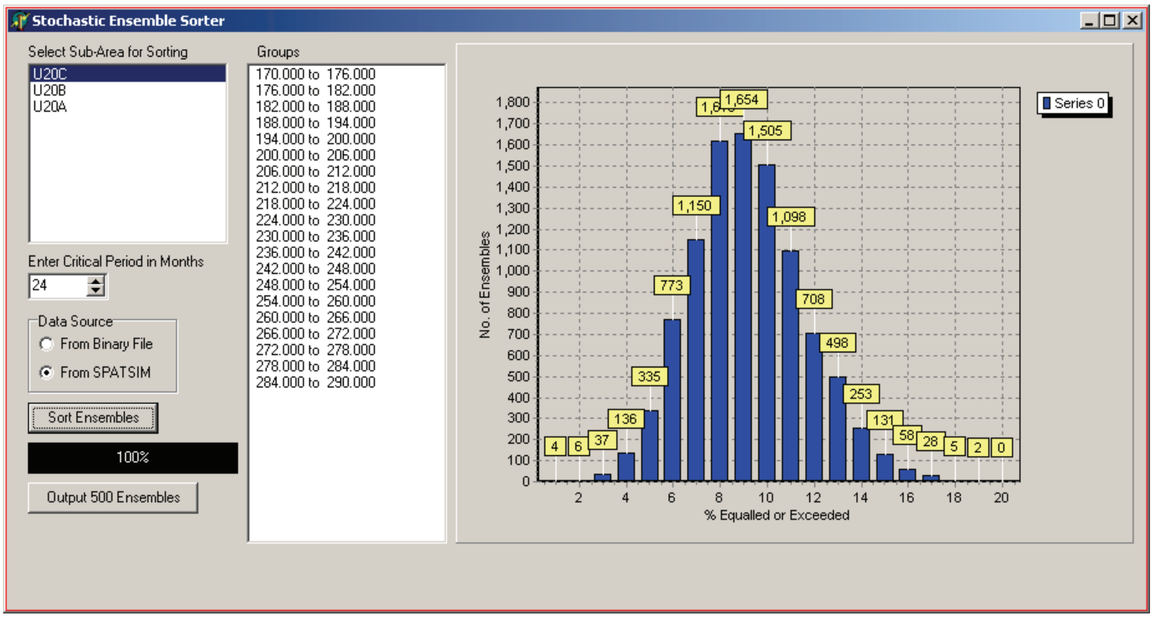


Figure 5.8 Stream flow time series ensemble sorter.

The application of the facility is set up for all the sub-areas in the spatial distribution system that was modeled and the user can decide which sub-area to focus on and can set the critical period (which is expected to depend upon the reservoir storage and the flow regime characteristics which in turn will be related to the region in which the catchment lies). The data source can be the binary files that are generated by the 2nd uncertainty version of the Pitman model, involving stochastic rainfall inputs (there is one file for each sub-area and they have the same name for all model runs – gw3_ensembles0.tmp, gw3_ensembles1.tmp, etc, where the number is the sub-area). Alternatively the data source can be a multiple time series attribute of SPATSIM that stores the output ensembles from the 1st uncertainty version of the Pitman model. The 500 sample ensembles are written to a different multiple time series attribute (which can also be used as in input to generate the distribution characteristics of the samples for comparison with the original ensemble set).

All of the software tools that have been developed during the project are designed to support both research and the practical application of uncertainty analysis. While training will be required for some of the tools to be used effectively, the amount of training should not excessive for any hydrologists or water resources engineers who are already relatively experienced in the application of hydrological models.

6. COMMUNICATION OF UNCERTAINTY TO DECISION MAKERS

The deterministic approaches applied to hydrological estimation during the 20th Century led to a culture of ignoring uncertainty in favour of the development of supposedly more exact estimates. The expectation that more complex models would reduce uncertainty has not been realized, largely because of the complexity of natural hydrological processes and the limitations of our ability to represent these in mathematical form. This means that exact estimates are rarely possible and that models can generate the same results for different reasons (Hughes, 2010b). More recently, scientific approaches to hydrological estimation have been based on explicitly recognizing uncertainty and that exact estimates are not possible in most cases. This means that it is essential to be able to identify the sources of uncertainty and quantify them so that the overall uncertainty can be managed. These approaches offer many opportunities for the development of the science and practice of modelling. Unfortunately though, water resource managers and other end-users of model results are still largely stuck in the previous paradigm that ignores uncertainty. One of the major communication challenges (Brashers, 2001) is to change that and to ensure that managers are provided the tools and knowledge to be able to deal with uncertainty.

Papenberger and Beven (2006) compiled a very thought provoking paper entitled '*Ignorance is bliss: Or seven reasons not to use uncertainty analysis*'. The objective of the paper was to identify the reasons often given for not using uncertainty in water resources analyses and to assess the validity of these reasons. In all cases they concluded that there are no valid excuses for not using uncertainty, except for the fact that decision makers do not really understand what they are dealing with. It is therefore essential that the concepts of uncertainty are communicated to the very people who need to understand them and modify their decision making processes accordingly.

It is apparent that there is very limited information available about how people interpret uncertainty (Montanari, 2007) but it is recognized that there are links between uncertainty and credibility, as well as uncertainty and trust. Effectively, all hydrological and water resource estimates are offered with uncertainty, but the way in which the estimates are provided can be very different. The following phrase contains uncertainty, but it is not explicitly stated, nor quantified:

'*Based on the model results, the estimated yield is 120 * 10^6 m^3*'

An alternative phrase explicitly includes uncertainty, but does not offer any probabilistic statements that can be used to link the uncertainty to risk:

'*The estimated yield lies between 100 and 130 * 10^6 m^3*'

The alternative might be a full statement of the probability of getting yields greater than defined amounts coupled with confidence statements to assist in the interpretation of the assumed probabilities (Table 6.1). The yield estimate that would be selected for use by a water resources manager would clearly be linked to the level of risk aversion that was considered acceptable, which in turn would be linked to the purpose of the water resources development. However, there appears to be very little information available on how to determine an appropriate level of risk aversion.

Table 6.1 Uncertain yield estimates, probabilities of exceedence and confidence statements.

Yield estimate (10^6 m^3)	Probability of exceedence	Confidence level
100	0.95	Very high
105	0.75	High
110	0.50	Moderate
115	0.25	Low
125	0.05	Very low

One interpretation of yield curves that are generated with a single hydrology and stochastic generation of many stream flow time series is that they represent the 'frequency' with which a certain yield can be abstracted from the system over an infinitely long period of time. The implication is that all of the yield values given by the curve will occur eventually. This is not a statement that is associated with uncertainty, except that we would be uncertain what the amount available for abstraction would be at any one time. The alternative is that it is accepted that, because of imperfect knowledge about the system, we do not know what the yield is. Part of that uncertainty is associated with a lack of experience of the possible sequences of low flows that will contribute to storage and therefore yield (stochastic uncertainty in Figure 2.4) and part because we have imperfect knowledge of the real flows that will occur (hydrological uncertainty in Figure 2.4). Both contribute to the overall uncertainty and represent the same thing in terms of the risks associated with designing a water resources development scheme for a certain target yield.

The main point to be made is that the two sources of uncertainty cannot and should not be separated, except from the point of view of reducing the uncertainty and therefore the risk.

The stochastic uncertainty cannot effectively be reduced as we do not have long enough records of either stream flow or rainfall (and other climate variables) to define all possible sequences of low flows. The hydrological uncertainty, however, can be reduced with improvements in such as rainfall and stream flow observations, improved parameter estimation processes and improved methods of quantifying upstream impacts and water use. Thus any attempts to reduce the risk of water resources decision making must necessarily focus on reducing the hydrological uncertainty, and given appropriate tools and methods, the main sources of uncertainty can be identified and targeted. This is particularly the case in terms of all the future uncertainties associated with possible climate change impacts on water resources availability.

A further issue is the level of risk aversion that is used by water resources managers in making decisions. Studies have been undertaken to investigate this issue as well as experiments that have clearly demonstrated that participants in decision making 'games' made better decisions when they had access to uncertainty information. Figure 6.1 illustrates the results for a game associated with making decisions about salting roads in the US on the basis of forecasts of freezing temperatures. Groups B and C both have uncertain information and maximized their 'profits' (or decision success) far better than group A.

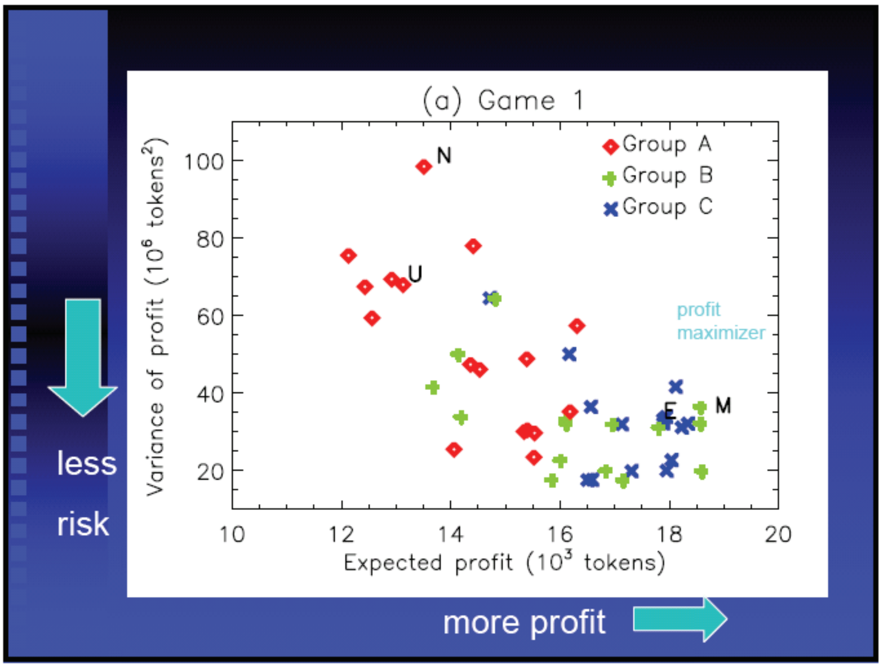


Figure 6.1 Outcomes of a decision making game based on three groups of participants – Group were given a point forecast, Group B were given a forecast with a standard error and Group C were given a standard error and probability.

While there remain some issues about the communication of uncertainty that are not very clear, what is certain is the importance of ensuring that the users of uncertain information recognize its existence. It may not be essential for the users to understand all the details of the sources of uncertainty, but they do need to be fully aware of the implications for decision making and the risks involved. In some cases it is important to emphasise the sources of uncertainty, so that there is greater motivation for implementing approaches that can contribute to a reduction in the uncertainty. An example is the contribution that poor rainfall monitoring networks make to the estimates of available water resources into the future, while the lack of available information about historical upstream landuse and water abstraction patterns can contribute to uncertainty in the naturalization of observed streamflow data. With all the speculation about future climate variability and change, it is critically important to not only maintain, but to extend and improve our ability to measure the rainfall inputs into the hydrological cycle, as well as the extent to which water resources are already developed.

One of the issues that were raised during the project workshops is the uncertainty associated with making operational decisions. This type of decision is inevitably based on short-term projections of future demand and supply and it is clear that a large degree of uncertainty will remain until improvements are made in short-term weather forecasting. These forecasts will always represent one of the major sources of uncertainty. The Water Resources Planning Model makes use of short-term stochastic projections and this appears to be the best that can be achieved in the absence of improved weather forecasts. The use of ENSO predictions and other short-term forecasting tools remain largely untested in terms of reducing the uncertainty (and therefore risk) in operational decision making and such studies are long overdue. Throughout the duration of this project it has become clear that most water resources managers in South Africa are familiar with the concepts of uncertainty. The main communication issue appears to be the need to enhance the understanding of the contributions of different sources of uncertainty as well as the need to fully appreciate the links between uncertainty and risk.

7. CONCLUSIONS AND RECOMMENDATIONS

The main objective of the project was to contribute to the incorporation of uncertainty assessments in water resource decision making in South Africa, thereby quantifying the risks associated with specific decisions about planned future water resource developments. This objective was supported by several specific aims and this section on conclusions and recommendations is focused on the extent to which the project has addressed these issues:

(i) Develop an understanding of uncertainty and associated risks in water resource management on the basis of literature and known practices, nationally and internationally.

(ii) Identify and characterise the main sources of uncertainty (focusing on current South African practice and typical situations of data availability).

(iii) Develop techniques and guidelines for quantifying the uncertainty associated with different models. This will include uncertainty in all relevant areas (hydrological, climate, economic, social, etc.).

(iv) Determine the effects of uncertainty on water resource management and identify what level of uncertainty is acceptable.

(v) Develop guidelines for the communication of uncertainty and the impacts to various stakeholder groups involved within water resource planning and management. This aim will need to address the issue of the links between uncertainty and risk.

(vi) Develop guidelines for incorporating uncertainty and the associated risk into water resource decision making processes.

(vii) Identify those areas of uncertainty that can be realistically reduced and which will have the greatest impact on reducing the risks involved with water resource decision making.

The following sections of the report present the main conclusions and recommendations of the project orientated to the seven major aims of the project listed above. The key recommendations are highlighted in the text.

7.1 Understanding uncertainty and risk

The project has certainly contributed to an improved understanding of water resources assessment uncertainty in a South African context. It was readily apparent at the start of the project that the existence of uncertainty has always been recognized but not completely understood. The long history of using a stochastic stream flow model within the standard yield simulation approaches in South Africa is a testament to the recognition of uncertainty. This approach generates a yield probability curve rather than a single yield value. However, many water resources planning reports still only refer to single yield values. Others may refer to the yield curve but tend to select a single value from it and refer to such as the 1 in 50 year yield as opposed to a yield with a certain probability of being equaled or exceeded (Table 6.1 for example). The use of the return period expression is based on some assumptions about what stochastic sequences really represent and has become part of standard practice in South Africa for assessing the risks associated with different estimated yields (see section 2.2.3). While there are potentially other interpretations that use probabilities of yield exceedence, these would not be aligned with current practice and therefore should not be encouraged at this stage. ***The implication is that if stochastic rainfall sequences input to hydrological models are to replace stochastic stream flow sequences in system yield models, the information transferred must be aligned with current practices and understanding of the links between uncertainty and risk (see section 4.2).***

7.2 Sources of uncertainty

The various sources of uncertainty that exist within water resources assessments have been extensively covered during this project. Several examples are included within this report, while additional examples have been documented in some of the publication (e.g. Hughes and Mantel, 2010a and b) outputs and the student theses (e.g. Sawunyama, 2008 and Kapangaziwiri, 2010). In summary the dominant sources of uncertainty that affect the simulation results of both hydrological and water resources yield models are:

- Historical climate input data, with uncertainties in rainfall inputs generally being more important than evaporation demand inputs. Uncertainties in rainfall inputs are apparently one of the major sources in mountainous areas where orographic gradients are important and where the small number of rainfall observation stations is inadequate to represent spatial variations in rainfall. ***As these areas are often very important water supply sources these rainfall uncertainties are critical from a water resources management perspective (see sections 7.4 and 7.7) and need to be addressed in the future.***
- Future climate data generated from downscaled global climate models (GCMs). There remain many uncertainties in the predictive ability of GCMs and the associated downscaling techniques. The uncertainties are associated with the greenhouse gas emission scenario that is assumed, as well as with the ability of the various GCMs (and downscaling methods) to translate the emission effects into information that is appropriate for use in hydrological models. The project has provided an example

(section 3.8) of the application of uncertainty analysis using climate change data in the Buffalo River catchment. The initial results presented in this report are part of an ongoing WRC project and further results will be available in the near future.

- Hydrological model parameter uncertainty. This issue has been one of the main focus areas of the project and is dealt with extensively in this report and a number of other outputs from the project.
- Present day water use uncertainty (including uncertainty in system operating rules) is important, not only from the perspective of yield modelling, but is also critical for the process of naturalizing observed flow data. The project has addressed a number of aspects associated with water use data and has identified it as a major source of uncertainty in many South African catchments.
- Uncertainty in observed stream flow data. During some of the workshops held during the project it was frequently suggested that there is little uncertainty in those catchments where observed stream flow data are available. While this may be true in some areas where there is a clear understanding of what the observed data represent, but is certainly not true in many other areas where there is a lack of information on historical water use (or land use) patterns. There are also many gaps in observed stream flow data associated with limited rating curves. These gaps have a potentially huge impact on our knowledge of the high flow responses of catchments.
- Uncertainty in model structure is an issue that is considered very important internationally. However, this project has generally concluded that this source of uncertainty is less important than many of the others and can frequently be considered part of the model parameter uncertainty. There has been a great deal of debate within South Africa in recent years about the appropriate time scale to be used for modelling water resources systems. The country has a long history of using monthly time step models and there are clearly structural uncertainties associated with the averaging that occurs within a month. From this perspective, a strong argument can therefore be presented for changing to daily time steps. However, there is little doubt that the resources required for daily modelling are greater and the availability and accuracy of daily time step data are often open to question, as are some of the results generated by available daily time step models. There is little doubt that daily time steps are warranted in some situations, but there are almost certainly many other situations where monthly time steps are still appropriate. ***One of the critical issues to consider if there is general movement towards daily time steps is that the results of any new modelling approaches should be aligned to the 'conventional wisdom' that is available from the old approaches. The use of the uncertainty framework proposed by this project should facilitate this***

process of alignment. An attractive option for a future daily model is the conversion of the Pitman model to a daily time step using the same parameter set as used in the monthly model coupled with internal parameter conversion routines. It is understood that such a development has already been started (Bailey and Pitman, Pers. Comm.).

7.3 Quantifying uncertainty

One of the main outputs of the project is the generic framework for uncertainty assessments that is discussed in sections 2, 3 and 4 of this report. This framework offers an approach for quantifying various sources of uncertainty in hydrological models and suggests approaches for constraining the uncertainty and propagating it into water resource yield estimates. A large part of the research into uncertainty quantification has focused on the use of basin physical property data to estimate the parameters of the Pitman model. This represents a complete divergence from the traditional regionalization approaches that have been used in South Africa. The regional parameter sets for the whole country that are part of the WR90 and WR2005 databases represent a major asset for water resources assessments in South Africa. However, they do not include any recognition of uncertainty and were based on very subjective regional extrapolation approaches. ***One of the recommendations of this project is that future updates to the water resources of South Africa studies (WR2020 perhaps?) should be based on improved methods of parameter estimation in ungauged catchments and should include parameter uncertainty.***

The project also addressed the issue of linking stochastic and hydrological uncertainty within water resources yield models and demonstrated an approach based on the use of a stochastic rainfall model to generate uncertain climate inputs that can be combined with parameter uncertainty to generate outputs (ensembles of natural hydrology) that can be used as inputs to yield models. While further tests of this approach are still required, the initial results suggest that it represents a practical alternative to conventional methods and, perhaps more importantly, integrates all uncertainty sources. ***It is recommended that further assessments of this approach be undertaken in collaboration with practicing water resources engineers as the next step towards modifying standard practices for yield assessments in South Africa (see also section 7.6).***

Uncertainties in existing (and historical) patterns of water use were also identified as a key source of uncertainty in many areas and it is recommended that improvements in the availability of this type of information should be identified as a priority. This recommendation is clearly aligned with the ongoing process of water use registration by the Department of Water Affairs.

7.4 Effects of uncertainty

This aim referred to determining what level of uncertainty is acceptable. However, in retrospect this was probably the wrong question to ask and is almost certainly impossible to answer. The real point is to quantify the uncertainty as realistically as possible and then to assess what the impact of that uncertainty would be on the decision making process. That is also something that is very difficult to generalize and is linked to the level of risk aversion that is considered acceptable, which in turn would be linked to the purpose of the water resources development. However, there appears to be very little information available on how to determine an appropriate level of risk aversion. There are various examples provided in this report that clearly demonstrate the effects of uncertainty, but these have not really addressed the impacts on decision making. ***It is recommended that further studies of different levels of risk aversion should be undertaken.*** Such studies need not necessarily be very complicated and could be focused on a range of typical water resources development decisions. However, they must involve individuals and organizations (DWA) who make real decisions. The uncertainty framework that has been developed as part of this project can be used to generate the information required as input to such studies.

7.5 Communicating uncertainty

The project concluded that the correct methods used to communicate uncertainty are important and that it is necessary to represent the use of uncertainty assessments as a positive development and to prevent the impression that uncertainty is a result of 'bad' models or modelers. Uncertainty is inherent in all estimations or predictions of environmental systems, largely due to their complexity and our inability to understand or measure every single component. While scientists and engineers have always recognized the limitations of the models that they use, they have not always communicated these uncertainties to the users of the model outputs. ***It is therefore necessary to change the paradigm under which the users of model results operate so that they have a better appreciation of uncertainty and its impacts.*** This can only happen if all modelers adopt uncertainty approaches. While expressions of the level of confidence in model results can go a long way to communicating uncertainty, the explicit quantification of the uncertainty will always be a better approach that should lead to improvements in the assessment of decision making risk.

A further advantage with the explicit inclusion of uncertainty is that it will improve the awareness of the problems associated with poor data and shrinking observational networks. This is a worldwide problem that is getting worse. The extent to which sophisticated modelling tools have contributed to this problem is largely unknown, but there is certainly an impression that political decision makers view models as a replacement for data collection which is expensive and resource intensive.

7.6 Incorporating uncertainty assessments in practice

Several recommendations about incorporating uncertainty assessments into standard practice have already been made under section 7.3, but are repeated here for clarity:

- ***Future updates to the water resources of South Africa studies should be based on improved methods of parameter estimation in ungauged catchments and should include parameter uncertainty.***
- ***Standard yield modelling approaches should begin incorporating both stochastic and hydrological uncertainty and this project has tentatively concluded that this can be achieved using the suggested framework and generating stochastic rainfall inputs into hydrological models.***
- ***If there is a move towards the use of daily models as part of standard water resources assessment practice, it is important that uncertainty is incorporated and that the outputs are aligned with existing estimates based on monthly models.***

Many of the techniques and tools that have been developed and used in this project have been incorporated as part of the SPATSIM hydrological modelling software system. While this system is used by some practitioners, there are other software products that are used to support modelling studies that are used by many other individuals and organizations. ***It is therefore recommended that an assessment of the feasibility of incorporating uncertainty components into these software products be investigated in the very near future.*** The methods used within the SPATSIM models are relatively straightforward and should be readily applied in the other models without too much effort. All of the software code and algorithms used by the project team can be made available to other software developers.

7.7 Reducing uncertainty

7.7.1 Hydrometeorological data

One of the most obvious ways of reducing uncertainty in hydrological modelling is to force the model with accurate and representative data including input precipitation and evapotranspiration data, as well as observed stream flow data to calibrate the model or to constrain the results. Unfortunately, it appears that the collection of hydrometeorological data is not high on the list of funding priorities in many countries of the world and in some countries the availability of such data are restricted by sharing protocols, issues of intellectual property rights and other bureaucratic obstacles.

The project has demonstrated the value of accurate and representative rainfall data in the application of any hydrological model. Unfortunately, in South Africa the national database of rainfall data appears to have been impacted in recent years to a greater extent than any of the other hydrological databases. This is occurring at a time when it is important to understand trends in rainfall patterns to assess possible climate change and when our water resources in many regions are highly stressed and where accurate assessments of natural runoff are a high priority. It is recognized that the maintenance of any national data collection system is expensive in terms of money and human resources and is very time consuming. However, the costs, in terms of increased uncertainty in such as water resources assessment, of not maintaining routine data collection will surely be greater than the costs of data collection. It is this point that needs to be communicated to decision makers. It is too easy to conclude that we have a great deal of historical data and therefore the whole data collection network can be rationalized – this ignores the existence of a spatial and temporal variability, as well as the possible existence of future non-stationarity and trends associated with climate change.

It is essential therefore that South Africa reviews the data collection policy and places greater emphasis on basic data collection using efficient and reliable collecting and data storage systems. Replacing ground-based rainfall observing systems with remote sensing platforms (radar and/or satellite) do not offer valid alternatives unless there are overlaps in the two data sets so that the remotely sensed data can be ground-truthed. The remotely sensed data can be very useful in extending the spatial coverage of rainfall data, but without the link to the long historical records of gauged rainfall data, they are of limited value.

It is a strong recommendation of this project that the issue of improving and sustaining the collection of rainfall data within South Africa be discussed in the very near future by all the organisations either responsible for data collection or that use the data. This could be achieved through a highly focused workshop (organized perhaps by the Water Research Commission) that has a mandate to report to the relevant Ministers and the outcomes of which will be used to guide future policy. It is important that at least the Water Research Commission, the Department of Water Affairs, the Department of Agriculture, the SA Weather Service, water resources engineering consultants as well as research organizations are represented at the workshop. It is also important that the individuals representing the government organisations have sufficient authority to influence policy directions. One of the outcomes of the workshop should be a succinct report on the state of rainfall data collection, the implications of not improving the situation and recommendations for future action.

It is extremely difficult to observe measures of **evaporation or evapotranspiration** that are directly appropriate for use in hydrological models and there are many uncertainties associated with the internal structure of models and the way in which actual evaporation is estimated. It could therefore be argued that accurate observations of evaporation are probably less important than an understanding of evapotranspiration processes from different vegetation types and densities. This, of course, does not mean that the relevant observations should be totally neglected. It means that perhaps the focus should be on regional and national observation networks of some of the basic driving variables (at least temperature) and a better understanding of the processes involved through focused, but localized, experimental observation networks.

One of the main issues associated with **stream flow data** is that, to reduce hydrological model uncertainties, attention has not only to be given to how representative the flow gauging network is, but also to the data and understanding required to accurately assess what the stream flow observations are measuring. There is little point, from a hydrological modelling perspective, of extending the stream flow gauging network (at great cost in terms of both financial and human resources) if the information required to quantify upstream development impacts is ignored.

7.7.2 Parameter estimation uncertainty

While there are potentially many areas where the uncertainty in the parameter estimation process can be improved to reduce uncertainty, the conclusions of this project focus on two main issues; improving the conceptual understanding of hydrological processes in general and improving the understanding and the availability of quantitative information about surface – groundwater interactions.

Any addition to our conceptual understanding of hydrological processes in different regions must contribute to our ability to parameterize hydrological models, or at the very least, to assess the outputs and re-calibrate parameters. The assumption is that information is available to improve our understanding and that it is in an accessible format and at appropriate spatial scales for use with models. There have been a number of detailed hydrological studies that have been conducted within South Africa over the period in which the Water Research Commission has been in existence (and even before that). These have covered forest hydrology, semi-arid area hydrological processes, evapotranspiration studies from different land types and surface-groundwater interactions. However, the outputs from these studies have often not been incorporated into standard hydrological modelling practices, and have rarely contributed to improved parameter estimations for models used in water resources assessments. Many of these detailed process study outputs may have contributed to the development of models that are used for research or very specialized purposes, but they do not seem to have contributed much to the approaches used for the Pitman model – the mostly widely used model for practical water resources assessments.

It would seem reasonable to suggest that this situation needs to change in the future if the uncertainty in water resources assessments (using the Pitman model) is to be reduced through improvements in parameter estimation methods or through improved assessments and validation of some of the model outputs. These assessments should, arguably, include not only simulated stream flow volumes, but also some of the state variables that can be validated with detailed process study outputs. Examples could include validation of interception and evapotranspiration depths across different land covers and improvements in the estimation of the associated parameters of the model. There are certainly data available from this type of study (the work of Dr Colin Everson and his associated at the CSIR over many years). ***The recommendation of this project is that the detailed process, or small scale catchment hydrology studies that have been conducted in South Africa be reviewed and assessed for their potential to contribute to the reduction of uncertainty***

in hydrological modelling. This could be achieved through a relatively short-term (say 2 year) project.

The renewed interest in surface-groundwater interactions and the encouragement of close cooperation between surface and groundwater hydrologists represents a promising development for the future. However, it is important to recognize that the objectives of understanding the processes at relatively detailed scales and the requirements for larger scale modelling are different. It is therefore important that both of these objectives are considered when designing future research programmes. Experience of applying the surface – groundwater interaction components of the Pitman model during this WRC project have identified a number of gaps in either the available data, or in our understanding of processes and addressing these gaps is a recommendation of this project:

- ***There is not enough information about recharge processes and their variability over time at the catchment scale. The GRA II estimates are very uncertain and give no information about temporal variability. Without accurate estimates of recharge patterns, the other groundwater components of the model will always be highly uncertain.***
- ***It is known that surface and groundwater catchments do not always coincide and that this issue has been neglected in surface hydrology models that have recently included groundwater components. However, there is very little direct information on the sub-surface routing of groundwater flow. Before this type of process can be satisfactorily included in models guidelines need to be developed on how the relevant parameters would be quantified.***
- ***Recharge water is generally assumed to either leave the immediate surface water (SW) catchment as sub-surface transfers to other SW catchments, contribute to stream flow within the SW catchment, be lost to evapotranspiration (in the riparian margins of the channel perhaps), or be abstracted. However, there is very little explicit information available to quantify any of these processes and therefore quantify the relevant model parameters.***
- ***More information on riparian evapotranspiration losses and the relationships with groundwater levels would be very useful.***
- ***One of the only signals that can be used to quantify the groundwater contribution to stream flow is the 'baseflow' signal in observed flow data. However, in some areas this may be confused by the presence of other 'baseflow' processes (Hughes, 2010a)***

7.7.3 Regional hydrological signatures as uncertainty constraints

One of the main conclusions of this project is that an integrated uncertainty framework can be extremely useful, not only for identifying and quantifying uncertainty, but also for reducing the uncertainty. The framework proposed by this project includes new and flexible methods of estimating parameters with uncertainty, generating uncertain model outputs (ensembles), evaluating the validity of the ensembles using regional hydrological signatures and feedback loops that contributes to improved parameter estimation and ultimately a reduction in uncertainty (Figure 2.6). **While the project has developed some useful constraint indices, it is recommended that the search for improved constraints should continue.** Ultimately, this search is related to a number of the points raised in the previous section about conceptual understanding and parameter estimation, as well as being linked to the quality of the available data that can be used to develop constraint relationships. This type of study is ideal material for post-graduate research projects because it requires to students to develop and test their understanding of catchment hydrological responses.

7.8 Final observations

Throughout this project attempts have been made to achieve a balance between the development of new approaches based on sound hydrological principles and international experience with the practical considerations associated with the use of models for water resources assessments, planning and management. The degree to which these overall objectives have been achieved can only really be measured by the impact of the project outcomes on the approaches applied in the future. Many of the techniques that have been developed during this project are already being successfully applied by Rhodes University research students in studies as diverse as large scale modelling of the Congo River basin through much smaller scale evaluations of surface-groundwater interactions in South African catchments to various climate change impact assessments. The value of the project results to future hydrological research within South Africa has therefore already been demonstrated. Many of the principles and some of the results of the project have already been internationally peer reviewed through the publication of papers in scientific journals and presentation at international conferences. This process will continue through 2011 as additional material is submitted.

Some of the follow up activities will have to be focused on 'selling' the concepts, the proposed techniques and the recommendations to the broader community of hydrological and water resource engineering practitioners. The project team recognizes that this will never be a simple task and practitioners are often justifiably reluctant to adopt new approaches without a very clear demonstration of the advantages. The authors believe that they have presented a strong argument for including uncertainty in standard practices for water resources estimation in South Africa but it remains to be seen whether these arguments are strong enough to encourage the paradigm shift that will be required.

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APPENDIX A: UNCERTAINTY ANALYSIS USING THE ACRU MODEL

Contribution from M. Frezghi (with some editorial inputs from D.A. Hughes)

A1. Introduction

The *ACRU* agrohydrological model is a physically based conceptual rainfall-runoff model and it is structured to integrate various water budgeting and runoff producing components of the terrestrial hydrological systems (Schulze, 1995). The model is a daily time step, multi-layer soil water budgeting and multi-level model. Input variables are generally estimated from physical characteristics. As with any simulation model, limitations in the model structure, in parameter estimation, and the observed input, result in uncertainty in the simulated model output. A methodology to assess the uncertainty is being developed for the *ACRU* model based on Bayesian inference. In Bayesian uncertainty analyses a prior probability distribution of parameters is deducted from experiments and previous experience in order to derive posterior parameter distributions. In the approach, a marginalized posterior probability distribution of the model parameters is used to predict the total uncertainty in the model output. A description of the process is explained in the following three subsections.

Prior *ACRU* Parameters

In the Bayesian inference methodology the amount of information and accuracy is extracted from one or more experiments or from previous experience, which is referred as prior information, and is the most important knowledge that guarantees the success of predicting uncertainty using the Bayesian process. In case of the *ACRU* model, the conceptual parameters in the model are modeled through the Bayesian uncertainty framework. The coefficients selected in this study are critical soil depth for runoff generation (SMDDEP), coefficient of initial abstraction (COIAM), base flow coefficient (COFRU), A and B horizon response (ABRESP and BFRESP) and quick flow response coefficient (QFRESP). The output simulated by *ACRU* is sensitive to these parameters (Schulze, 1995) and, most importantly, to SMDDEP. In addition, physically-based parameters also contribute to uncertainty in the model outputs. The range and a non-informative prior marginal distribution of the *ACRU* parameters are estimated from experiments and from experienced users of the model. The prior distribution of these parameters is assumed to be a uniform distribution and the range of each parameter is used as specified in the *ACRU* theory manual (Schulze, 1995). Monte Carlo simulations are used to sample prior distributions of each parameter within the estimated range.

Posterior *ACRU* parameter

According to Bayes' theorem (Gelman *et al.*, 2004), the probability density of the posterior parameter distribution, $f_{\Theta|Y}(\theta|y^{obs})$, is derived from the prior density, $f_{\Theta_{pri}}(\theta)$, the likelihood function of the model, $f_{Y^M|\Theta}(y^{obs}|\theta)$, and data, y^{obs}, according to

$$f_{\Theta|Y}(\theta|y^{obs}) = \frac{f_{Y^M|\Theta}(y^{obs}|\theta).f_{\Theta pri}(\theta)}{\int f_{Y^M|\Theta}(y^{obs}|\theta')f_{\Theta pri}(\theta')d\theta'}$$

Numerically, there are two generic Monte Carlo approaches to approximate the posterior parameter distribution (Gelman *et al.*, 2004), i.e., Markov Chain Monte Carlo (MCMC) and Importance Sampling (IS).

A Metropolis Hastings algorithm, which is a general term for a family of Markov chain simulation methods that are useful for drawing samples from Bayesian posterior distributions (Gelman *et al.*, 2004), is used to sample the posterior *ACRU* parameters. The Metropolis algorithm is an adaptation of a random walk that uses an acceptance/rejection rule to converge to a specified target distribution. The algorithm used is as follows:

(i) Draw a starting point θ^0, satisfying $f(\theta^0) > 0$

(ii) Using current θ value, sample a candidate point θ^* from some jumping distribution

(iii) Calculate the ratio of densities,

$$\alpha = \frac{f_{\Theta|Y}(\theta^* / y^{obs})}{f_{\Theta|Y}(\theta^{t-1} / y^{obs})} = \frac{f_{Y^M|\Theta}(y^{obs}|\theta^*)}{f_{Y^M|\Theta}(y^{obs}|\theta^{t-1})}$$

Normalising marginal likelihood in Bayesian Inference, which is the denominator in posterior parameter distribution, cancels out.

(iv) if $\alpha > 1$ accept the candidate point (set $\theta^t = \theta^*$) and return to Step (ii), if $\alpha < 1$ then with probability α accept the candidate point, else reject it and return to Step (ii).

In hydrology, the likelihood function is often constructed by assuming the residuals between observations, y^{obs}, and model results, y^M, are identically, independently and normally distributed. However, because of the measurement errors in the model input and response, and errors in model structure (Yang *et al.*, 2007), this assumption is usually not satisfied and residuals are often hetroscedastic and autocorrelated. Therefore, in order to correctly apply

Bayesian inference, the likelihood function must either address these errors explicitly or contain an auto-correlated component of residuals to describe their effect on model output.

Predictive *ACRU* uncertainty

The predictive uncertainty is derived using the same method used by Liu *et al*. (2005) where each parameter set relevant to a predictive uncertainty can be obtained via the Normal Quantile Transformation (NQT), initially by forming a joint probability distribution in a normal space and deriving a conditional probability density. The conditional density can then be transformed back in the original space through the inverse of the NQT. Then the predictive uncertainty can be derived by marginalising all the densities with respect to the parameters, which can be approximated by summing up the products of all the realisations of their probability density of occurrences.

A2. Assessment of ACRU uncertainty approach

The Midmar dam catchment, as shown in Figure A1, was selected as a study area. The catchment was divided into 25 sub-quaternary catchments and in this preliminary test; the same values of prior parameters were used for each catchment. In this preliminary test, observed data from gauging weir U2H007 was used to determine the errors between the *ACRU* simulated results and observed data at a point of interest. Each of the uncertain parameters is constrained within a range derived from past experiments. Their prior parameters values are assumed to be uniformly distributed within their range and in this study 10 000 random numbers are generated using Monte Carlo simulation.

An *ACRU* input menu was setup for the MIDMAR catchment in a way which enables multiple runs to be made by changing the selected *ACRU* parameters for each run. Once the required number of runs have been completed, an error is calculated for each run to determine the likelihood value for each run. Using the Metropolis Hasting Algorithm described above, 398 parameter values were accepted for each *ACRU* parameter considered from the 10 000 runs performed. The accepted parameter values are populated to produce a histogram and cumulative distribution of parameter values versus frequency as shown in Figures A2 and A3. Any number of parameter values for each parameter can be sampled from the cumulative posterior parameter distribution to perform multiple runs. In this preliminary test, the 398 parameter values accepted through the Bayesian framework were used to perform 398 runs of the *ACRU* model.

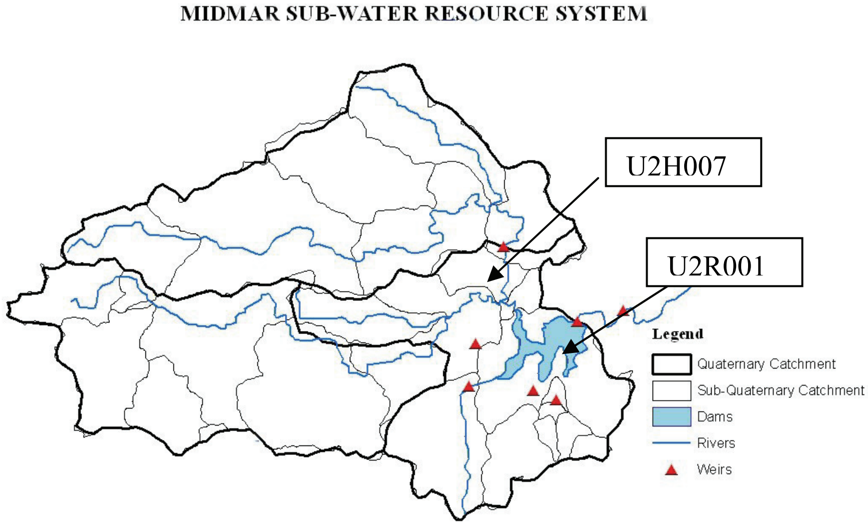

Figure A1 Midmar Dam catchment

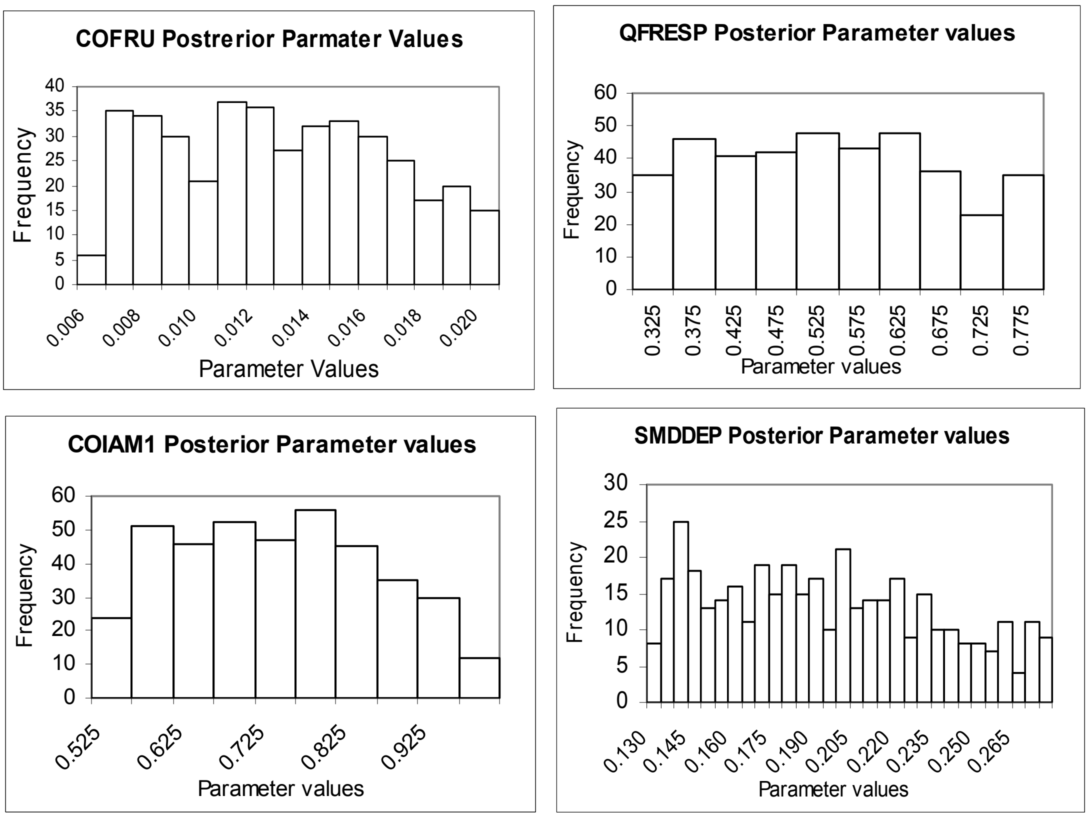

Figure A2 Posterior parameter values of *ACRU* parameters.

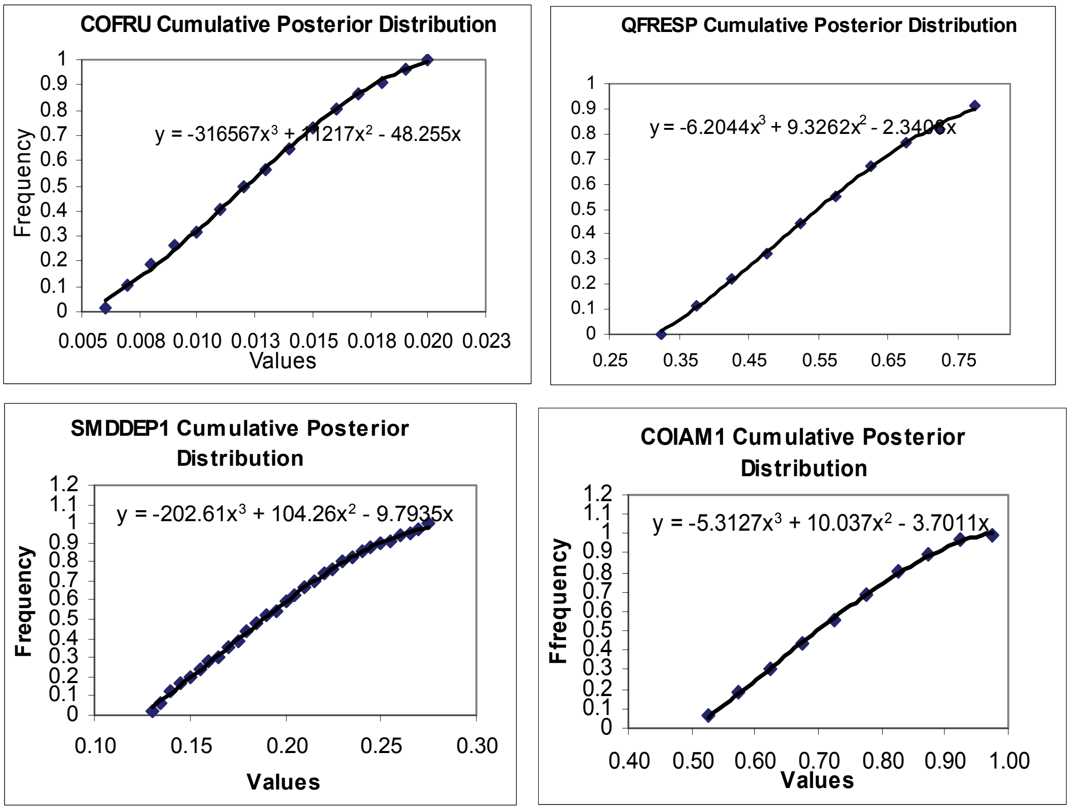

Figure A3 Cumulative Posterior distribution of *ACRU* parameters.

Figure A4 shows the frequency analysis of mean *ACRU* streamflow ensembles from posterior parameter values and Figure A5 contains the frequency analysis of maximum *ACRU* streamflow ensembles from posterior parameter values. Each box-whisker shows a frequency analysis for each month, the whisker represents a 100 and 0 percentile of mean ensembles while the box represents upper and lower quartile of the mean ensembles. A frequency analysis of the mean *ACRU* ensembles shows that *ACRU* simulates the mean monthly total of daily streamflows very well.

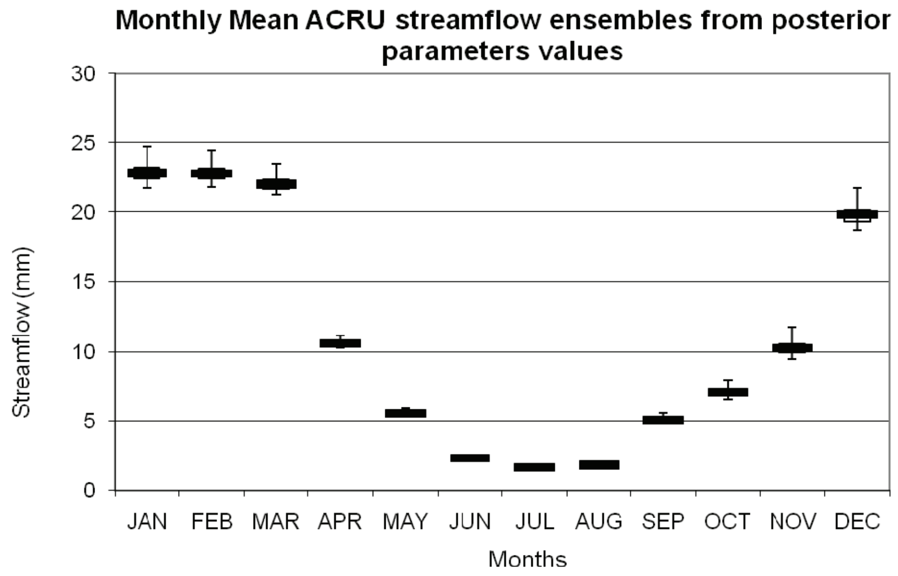

Figure A4 Monthly Mean *ACRU* streamflow ensembles for each month.

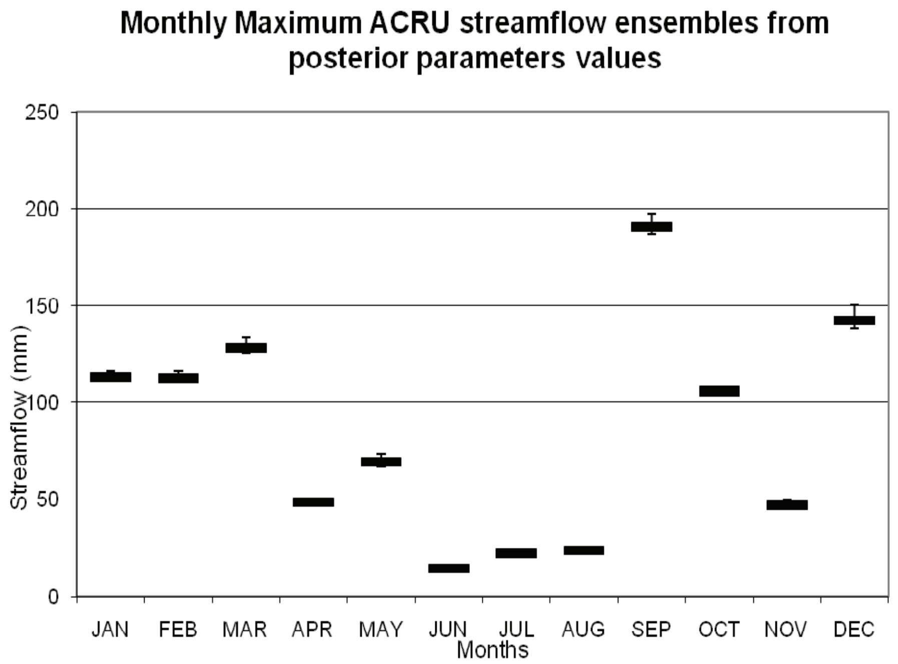

Figure A5 Monthly Maximum *ACRU* streamflow ensembles for each month.

A3. Integrating the ACRU approach with the framework

The previous section made use of observed flows to constrain the sampling from the parameter distributions, which is a different approach from that suggested for the framework and could not be applied in ungauged basins. The ACRU model has been run in an uncertainty environment for catchment C12D using the same procedures discussed in section A1 and based on Bayesian inference. In simple terms the prior parameter space is estimated from experience of the model. In contrast to the Pitman model, all of the ensembles have very similar mean flow values which are very close to the observed flow and there is no value in further evaluating the P/PE v Q/P relationships. While this is an unexpected result that was not repeated during the previous test on the Midmar catchments the ACRU Midmar results also showed a much lower range of mean flow variation than was evident for the Pitman model approach. These differences require further investigation that was not possible during the project as Mr Frezghi left the University of KwaZulu-Natal before the study could be completed.

In this brief assessment, the minimum and maximum flows for each day of the simulation (1950 to 1999) have been extracted from 532 ensembles generated by the ACRU model. These are therefore not real time series but represent the range of simulated flows for all the ensembles (the same data are used to represent the ensemble ranges for some of the analyses of the Pitman model results). Figure A6 compares the observed flow duration curve with the range of ACRU model outputs, while Figure A7 compares the results using the time series.

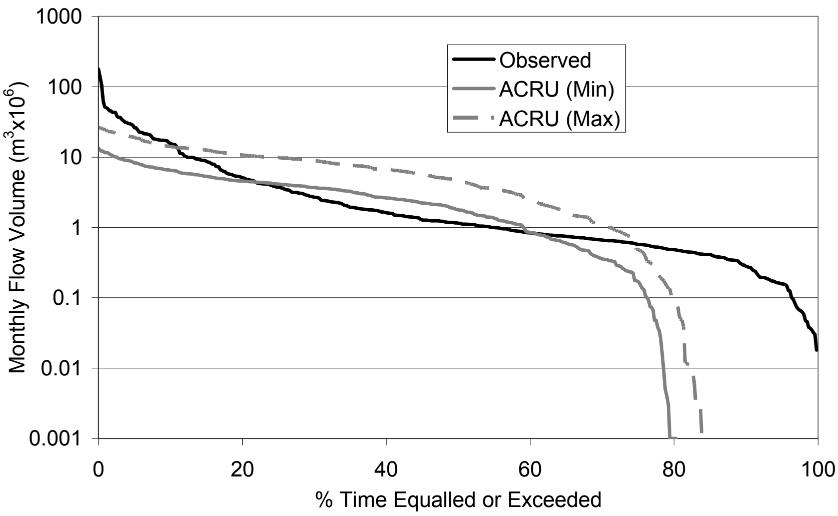

Figure A6 Observed, minimum and maximum ACRU flow duration curves for C12D (based on data for 1960 to 1999).

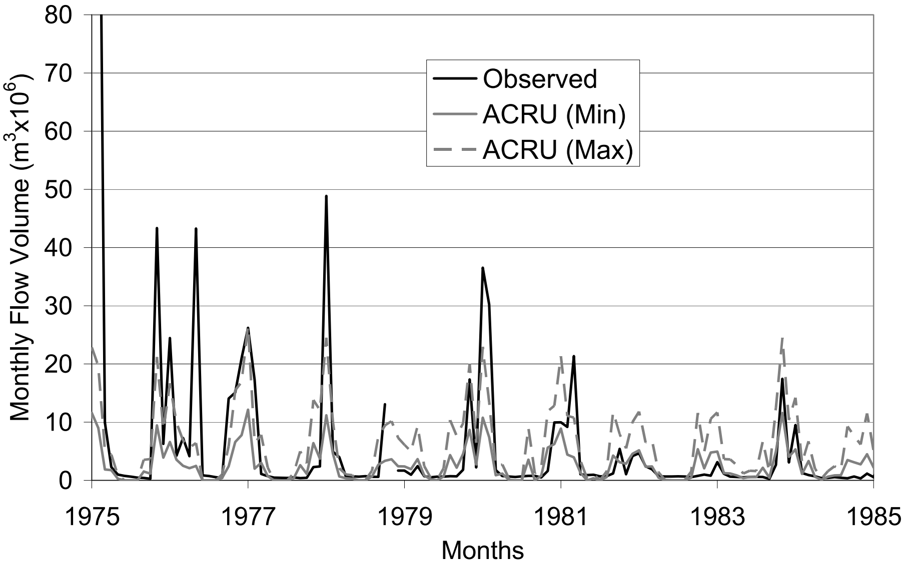

Figure A7 Observed, minimum and maximum ACRU monthly flow time series for C12D.

The first point to note is that the simulated and observed responses are very different despite the fact that the mean runoff response (and the slope of the flow duration curve) is very close to the observed data. The implication is that the constraints being used in the framework to determine whether a model is generating behavioural results are not necessarily sufficient. Figure A8 illustrates the equivalent time series results for the Pitman model (observed plus the minimum and maximum simulated monthly flows for each month of the time series across all 10 000 ensembles). While the overall uncertainty output from the Pitman model (based on the mean monthly flow metric) is far greater than for the ACRU model, the uncertainties in simulating individual monthly flows and relatively short sequences of the time series are very similar for the two models.

Visual comparison of Figures A7 and A8 suggest that the Pitman model has generated somewhat more behavioural sequences of flows than the ACRU model in this specific catchment, although both models show advantages and disadvantages in specific years. It is clear that the results for both models are impacted to a certain extent by un-representative rainfall inputs in some years (1976 being probably the best example). The ACRU model appears to be unable to reproduce the very small runoff responses in dry years (1982 and 1983, for example) and also tends to under-simulate the higher flow responses.

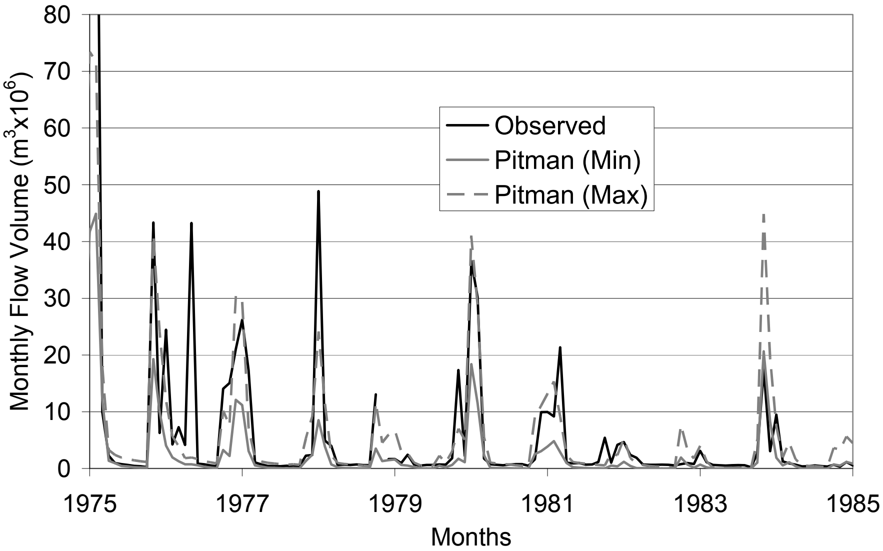

Figure A8 Observed, minimum and maximum Pitman monthly flow time series for C12D.

The purpose of these observations is not to compare the models, but to highlight the issues associated with the different approaches to establishing prior parameter sets, generating ensembles and assessing (as well as constraining) the results. The use of relatively simple summary metrics to assess and constrain the ensembles may not be sufficient in some catchment situations, regardless of the model being used. To further illustrate this point a very simple yield analysis has been performed on the minimum and maximum time series generated by the two models and assuming a dam (at the catchment outlet) of 50 m^3 x 10^6 with a seasonal distribution of demand similar to the seasonal variation in evaporation demand. The objective of this very simplified analysis was to determine a maximum annual demand that could be met without the hypothetical dam running dry for the four scenarios. The range for the ACRU model minimum and maximum time series was between 31 and 65 m^3 x 10^6, while for the Pitman model the range and the overall yield was much lower at 20 to 28 m^3 x 10^6. This is consistent with the differences between the two model results illustrated in Figures A7 and A8 and specifically that the ACRU model does not simulate low flows in dry years very well. There is no suggestion in this report that one of the models is giving a more accurate yield estimate than the other. The important issue is that they are giving very different answers, despite the fact that all of the simulations would be considered behavioural based on the regional constraints currently being used in this study.

APPENDIX B: LIST OF ABBREVIATIONS

ACRU	Agricultural Catchments Research Unit.
AGIS.	Agricultural Geo-referenced Information System.
ARMA	Auto Regressive Moving Average (a stochastic model).
BEEH	Bioresources Engineering and Environmental Hydrology, UKZN.
CE	Coefficient of Efficiency (Nash Coefficient): a statistical objective function.
CV	Coefficient of Variation (Standard Deviation / Mean).
DWA	Department of Water Affairs (formerly DWAF, Department of Water Affairs and Forestry).
EWR	Environmental Water Requirements.
FDC	Flow Duration Curve.
GCM	Global Climate Model or General Circulation Model.
GIS	Geographical Information Systems.
GRA II	Groundwater Resource Assessment.
IAHS	International Association of Hydrological Sciences.
IPCC	Inter-governmental Panel on Climate Change.
IUGG	International Union of Geophysics and Geodesy.
IWR	Institute for Water Research, Rhodes University.
KISC	Key International Science Capacity (an NRF support programme).
LTY	Long-Term Yield.
MAE	Mean Annual Evaporation or Evapotranspiration.
MAP	Mean Annual Precipitation.
MAR	Mean Annual Runoff.
MCM	Million Cubic Metres or $m^3 * 10^6$.
ML	Mega Litres or $m^3 * 10^3$.
NRF	National Research Foundation of South Africa.
P	Precipitation.
PDF	Probability Density Function.
PE	Potential Evapotranspiration.
PUB	Prediction in Ungauged Basins (an IAHS research programme).
Q	Stream Flow Discharge
Q10, Q90	10^{th} and 90^{th} percentage point on a flow duration curve.
SPATSIM	Spatial and Time Series Information Modelling.
SD	Standard Deviation.
UKZN	University of KwaZulu-Natal.
WRC	Water Research Commission of South Africa.
WR90	Water Resources of South Africa 1990.
WR2005	Water Resources of South Africa Update 2005.