IMPLEMENTING UNCERTAINTY ANALYSIS IN WATER RESOURCES ASSESSMENT AND PLANNING

Report to the
WATER RESEARCH COMMISSION

by

DA HUGHES[1], T MOHOBANE[1] and SJL MALLORY[2]

[1] Institute for Water Research, Rhodes University, Grahamstown
[2] IWR Water Resources Pty (Ltd), Pretoria

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EXECUTIVE SUMMARY

The main objective of the project was to contribute to the incorporation of uncertainty assessments in practical water resource decision-making in South Africa. There are three main components to this objective. The first is the quantification of realistic levels of uncertainty that are as low as possible given the available information (reducing uncertainty). The second is the availability of tools to implement uncertainty analysis across the broad spectrum of data analysis and modelling platforms that form part of practical water resources assessment (including hydrological and water resources yield models). The third relates to the issue of using uncertain information in the process of making decisions about the design, development or operation of water resources systems. The latter includes social, political and economic uncertainties as well as the hydrological uncertainties that are directly addressed in this report. None of these are independent and all are associated with the fundamental issue that all of the role players should understand the key concepts of uncertainty and that virtually all of the information we use to make decisions is uncertain. One of the major challenges in this project as well as the previous WRC-supported project on uncertainty methods, was the lack of understanding of some of the key issues, or a lack of appreciation of the importance of uncertainty in all water resources decision-making. This was evidenced by the lack of support by both the DWA and the WRC for a proposal to undertake a 'real' practical demonstration project that emerged from this project and which was intended as a partnership between scientific researcher groups, consulting engineering service providers and state institutions (DWA) to move ahead and identify (and resolve) any further stumbling blocks in the implementation of uncertainty principles in practice.

Internationally, the science of hydrology has embraced the concepts of uncertainty and it is almost impossible to get a hydrological modelling study published in a recognized journal unless an analysis of the uncertainties is included. This is largely because of the enormous contribution that was made by the IAHS PUB decade. These concepts, and the importance of uncertainty in both science and practice, have also been included in the new IAHS decade on change in hydrology and society (Panta Rhei). While South Africa has a long history of using models for water resources assessments, uncertainty approaches are relatively new to the country and have not been embraced by either scientists or practitioners. There has been a tendency to think of uncertainty approaches as being in the realm of academic science and that they cannot be used in practical situations. The result is that many present day water resources allocations are made using extremely approximate information and with no attempt to assess how potential errors may affect the risks of making certain decisions. The future is even more uncertain and many climate change projects conclude that adaptation of some form is necessary. However, hardly any of these take into account the huge uncertainties associated with future climate projections and therefore fail to discuss the implications of uncertainty on adaptation decision-making. This report makes yet another attempt to convince the South African community of scientists and practitioners in hydrology that uncertainty assessments are possible, that they can be implemented in practice and that it should be possible to incorporate them into decision-making.

The overall conclusion with respect to reducing uncertainty is that there is nothing better than good observed data and good understanding for reducing uncertainties. One of the important issues is that we have to acknowledge and understand the uncertainties in our observed data before we can even begin to think about reducing the uncertainty. The report includes two quite detailed studies based on a progressive reduction in uncertainty using as much information as is available, some that might be considered 'hard' data (stream flow gauging stations within the region) and some that is certainly 'soft' data (conceptual understanding and published information about expected hydrological processes from other areas). These assessments involve a considerable amount of detailed analysis of the simulation ensembles (both parameter space and output results) which is very time consuming and is not practical for normal operational model use. Performing uncertainty analyses on large basins with many sub-catchments is very difficult and confusing. There is simply such a large uncertainty space (even without uncertain climate inputs) that resolving the interactions and the inter-dependencies is almost impossible. These conclusions led to further research on the methods used for uncertainty assessments.

A revised approach to including uncertainty in the modelling of large basins with many sub-areas has been developed and it includes two steps to avoid some of the practical problems that were experienced in previous work on this project related to the interpretation and further use of uncertain ensemble outputs from the Pitman model. The first step involves the use of regional or local constraints to limit the parameter sets that can be considered behavioural in the simulation of natural (un-impacted) incremental flows for each sub-basin. These parameter sets are saved and then used with uncertain water use parameters (sampled independently) in the second step of the model when the cumulative flows at the outlet of all sub-basins are simulated. One of the advantages of the approach is that where there are high confidence gauged data, the constraints can be set with very narrow uncertainty bounds, while in ungauged areas these could be much wider. The approach therefore allows for different levels of uncertainty to be included in basins where the hydrological response in some areas is well understood and known, but where other areas have much higher uncertainty.

One of the important issues about the practical use of hydrological model uncertainty analysis, is the need to link the outputs of the uncertainty version of the Pitman model with existing approaches used for water resources yield analysis. The revised approach ensures that all of the natural incremental flows generated as part of the full set of ensembles are behavioural relative to what is known (from observed data or regional analysis) about the real catchment responses. The methods have been developed to be compatible with both the traditional approach of using stochastic stream flow sequences in the yield model and the emerging approach of using stochastic rainfall sequences within the hydrological model. The relatively simple yield analyses included in this report are designed to illustrate the differences between using stochastic stream flow analysis with uncertainty, combined stochastic rainfall and parameter uncertainty and stochastic rainfall uncertainty with separate parameter uncertainty. It is apparent that there are differences between the results obtained using stochastic stream flow and stochastic rainfall analyses that could be related to the non-linear transformation of rainfall into runoff. While the statistics of a stream flow time series will be preserved during stochastic stream flow generation methods, this may not be the case when stochastic rainfall data are used to force a hydrological model.

The overall conclusion is that the project has demonstrated that including uncertainty analysis as part of the widely used Pitman hydrological model (Hughes, 2013) is a practical proposition and that the uncertainty outputs can be successfully linked to existing water resources yield models. This statement should be qualified by the consideration that all of the research for this project has made use of the IWR's SPATSIM version of the Pitman model, while it is recognized that almost all practitioners use the WRSM2000 software in which uncertainty options have yet to be included. It is therefore up to the community of hydrological and yield model practitioners to decide how best to proceed into the future. The project team have demonstrated the potential, identified some of the likely shortcomings, and suggested some ways forward that include possible revisions to computer code and software architecture. However, it is now up to the user community to respond to these initiatives and suggestions.

The final chapter of the report offers some initial ideas about the use of uncertain information in decision-making. The Institute for Water Research at Rhodes University has initiated an MSc level study to review international approaches to decision-making in the face of uncertainty and to conduct some pilot studies in the Crocodile River basin where other IWR research activities have the potential to offer support. Some preliminary results of these studies are presented in chapter 4.

Throughout this, and the previous WRC, project, attempts have been made to achieve a balance between the development of new scientific 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. The techniques that have been developed have already been successfully applied by Rhodes University research staff and students and the results published internationally or presented at international conferences.

The report makes a single important recommendation and that is that the hydrological science and water resources practice communities within South Africa (including those organisations that fund research and practice) start to take the concepts of uncertainty far more seriously than they have in the past.

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The project team is very grateful for the financial and administrative support provided by the Water Research Commission. Some of the contributions to this project by Mr T Mohobane were funded through a PhD bursary provided by the Carnegie Foundation of New York and the SSAWRN (Sub-Saharan Africa Water Resources Network) that formed part of the RISE (Regional Initiative for Science Education) programme.

A very important part of this project was the participation of various individuals in the Reference Group meetings and a single workshop that was held to discuss some of the issues associated with the practical application of uncertainty analysis and decision-making The following table lists the names of the individuals and their organizations who attended the reference group meetings and/or the workshop and therefore made significant contributions to the success of this project:

Name	**Organisation**
Alan Bailey	Stewart Scott
André Görgens	Aurecon
Bennie Haasbroek	Hydrosol
Herman Keuris	DWA, WRIW
Tendayi Makombe	DWA, NWRP
Stephen Mallory	IWR Water Resources
Chris Moseki	WRC
John Ndiritu	Civil Engineering, Wits University
Tendani Nditwani	DWA, NWRP
Elias Nel	DWA
Wandile Nomquphu	WRC (Project Manager)
Anton Sparks	Aurecon
Sabine Stuart-Hill	CWRR, UKZN
Isa Thompson	DWA
Peter van Niekerk	DWA
Geoff Pegram	UKZN/Pegram & Associates
Kornelius Riemann	Umvoti Africa
Pieter van Rooyen	WRP
John Wise	Umvoti Africa
Niel van Wyk	DWA

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 and Prof Hughes would specifically like to thank Prof Keith Beven of Lancaster University in the UK for letting us know that we were not moving in a false direction with our rather practically orientated uncertainty research and for providing some information about decision-making and uncertainty research directions in the UK.

CAPACITY BUILDING

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. Two of these students worked directly on the project. Dr Jane Tanner (graduated in 2014) is the senior author on the companion report related to surface-groundwater interaction uncertainties, while Mr Thabiso Mohobane is an author on this report and has been focusing on the Caledon River basin. He was finalising his PhD study during 2014. Ms Madaka Tumbo, from the University of Dar es Salaam in Tanzania, is registered for a PhD at Rhodes University is funded by Danish support (as part of a the CLIVET project) and has been using some of the developing uncertainty modelling techniques on the Great Ruaha River basin. She was also finalizing her PhD during the early part of 2014. Mr Sbongiseni Mazibuko is a RISE MSc student who has been investigating the value of MODIS data products for calibrating and validating the evapotranspiration component of hydrological models. Mr Gregory Pienaar started his MSc with the Institute for Water Research (and funded by the IWR) at the start of 2014 and he will be looking at water resources decision-making with uncertain information.

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 one of the final reports for the Water Research Commission project on ‘Implementing uncertainty analysis in water resources assessment and planning’ (K5/2056). The other report volume addresses the part of the project that dealt with uncertainties in understanding and modelling surface water-groundwater interactions (Tanner and Hughes, 2014). The project duration was three years (April 2011 to March 2014) and the participants were the Institute for Water Research at Rhodes University and IWR Water Resources (a private consultancy company). There were 7 deliverable reports generated during the project and these can all be found on the website of the Institute for Water Research at Rhodes University (http://www.ru.ac.za/static/institutes/iwr/uncertainty/).

This project represented a follow-up of the successfully completed previous project (K5/1838; 2008 to 2011) that initiated uncertainty research in South Africa (Hughes et al., 2011). The first project concentrated on developing a framework for uncertainty estimation and some of the tools necessary for application of the Pitman model within this uncertainty framework. The second project concentrated on uncertainty issues in surface-groundwater interactions (Tanner and Hughes, 2014) as well uncertainty reduction and the practical application of uncertainty analysis. Both of these projects should be seen within the context of international research of the same type through the Science Decades of the International Association of Hydrological Sciences (IAHS). The PUB (Predictions in ungauged basins) decade was concluded in 2012 and had a very large component of uncertainty analysis (Hrachovitz et al., 2013; Blöschl et al., 2013) as well as addressing some aspects of uncertainty in practice (Whitfield et al., 2014). The new science decade was launched in 2013 with the theme of ‘Everything Flows (Panta Rhei)’ and is designed to address change in hydrology and society (Montanari, 2013), and inevitably retains some of the uncertainty issues that came out of the PUB programme.

Many of the PUB contributions to the issue of uncertainty, understandably, deal with the topic in a truly scientific manner, but this does not always translate into practical methods of uncertainty analysis that can be used in water resources assessments. Sometime the range of uncertainty might be set unrealistically high precluding the use of the outputs in water resources decision-making. In other cases the length of time required (and the complexity) to complete an uncertainty analysis might render it impractical for real-world applications, particularly if this analysis is to be coupled to a yield analysis that already takes a long time in many complex water resources decision-making situations. There are therefore two main focus areas of this report: how can uncertainty be reduced and how can uncertainty be included as part of practical water resources assessments (typically linked to yield analysis). These two topics are not independent of each other and arguably, practical applications of uncertainty involve the reduction of uncertainty. While always seeking to reduce uncertainty as far as possible to ensure that decisions are made on the basis of reliable information, it is important to carry realistic uncertainty estimates through to the decision-making process to avoid a false sense of confidence that could lead to poor decisions being made.

The report is divided into two main sections. The first investigates the quantification of realistic uncertainty bounds and approaches to reducing uncertainty. The second addresses a range of issues associated with the practical application of uncertainty analysis in water resources assessments that includes the framework for the application of uncertain hydrological models, the use of stochastic rainfall sequences in hydrological models as an alternative to using stochastic stream flow sequences in water resources yield models, computer run-time issues in uncertainty analysis and propagating uncertainty from hydrological models into yield models. A relatively short third section is included to initiate the debate about the use of uncertain information in decision-making approaches – a topic that the project team did not address in detail during the project, but which they consider to be of vital importance and should be more fully addressed in the near future.

A relatively complete literature review of uncertainty issues was included in the previous projects final report (Hughes et al., 2011) and is not repeated here, however, more recent contributions to the local and international literature are included in the appropriate sections of this report. Similarly, the previous report included a relatively detailed introduction to the concepts of uncertainty and that is not repeated here. Readers who are new to these concepts are directed to the previous Water Research Commission report (Hughes et al., 2011), or to many of the international or local sources of literature (see e.g. Beven, 2000; Pappenberger and Beven, 2006; Beven, 2009; Hughes et al., 2010). The earlier report presented a framework for uncertainty assessments (chapter 2 of Hughes et al., 2011) and the details of this framework are not repeated here.

2. REDUCING UNCERTAINTY

The fact that there are uncertainties within any system of water resources assessment and planning should not come as a surprise to anyone. The various models that are used (hydrology, water resources yield and various decision support tools) are all dealing with complex interactions within the natural and human environments, as well as complex interactions between these two environments. The many variables and processes (both natural and anthropogenic) that are part of these complex interactions are not all measurable at the temporal and spatial scales appropriate to developing a full understanding of their operation. The fact that the networks of measurements that exist fall very short of what it is possible to measure just adds to the problem. While the existence of uncertainty therefore should not be a surprise, it is perhaps surprising that the uncertainties have not been fully acknowledged in the past.

It has been pointed out on many occasions that there is little point in developing methods to reduce uncertainty (or in fact to quantify uncertainty) if it is not acknowledged, not understood, nor used within the decision-making process. These issues have been recognized in other disciplines as evidenced by the three paragraph quote from an article by Robert Johnson (Executive Director of the Institute for New Economic Thinking in New York) published in Time Magazine (Jan. 30, 2012). Parts of the quote have been changed (see italics), but with the original wording added in parenthesis:

> "First, ***hydrologists*** (economists) should resist overstating what they actually know. The quest for certainty, as philosopher John Dewey called it in 1929, is a dangerous temptress. In anxious times like the present, experts can gain great favor in society by offering a false resolution of uncertainty. Of course, when the falseness is later unmasked as snake oil, the heroic reputation of the expert is shattered. But that tends to happen only after the damage is done."
>
> "Second, ***hydrologists*** (economists) have to recognize the shortcomings of high-powered mathematical models, which are not substitutes for vigilant observation. Nobel Laureate Kenneth Arrow saw this danger years ago when he exclaimed 'The math takes on a life of its own because the mathematics pushed toward a tendency to prove theories of mathematical, rather than scientific interest.'"
>
> "***Hydrological*** (financial-market) models, for instance, tend to be constructed with building-blocks that assume stable and anchored expectations. But the long

> history of ***water resources*** (financial) crisis over the past 200 years belies that notion. As far back as 1921, Frank Knight of the University of Chicago made the useful distinction between measurable risk and 'unknown unknowns', which he called radical uncertainty. Knight's point was that in a period of radical uncertainty, expectations couldn't be anchored because they have nothing to latch onto. ***Hydrological*** (financial) theories and regulatory designs that hinge on the assumption of stable and anchored expectations are not resilient enough to meet the challenges presented by real ***water resources variability*** (financial markets) in radically uncertain times."

Clearly there are overlaps between the issues of uncertainty in the disciplines of economics and hydrology (or water resources science). One of the 'radical uncertainties' that face water resources management is arguably the impacts of climate change on water resources, but there are almost certainly many others related to the lack of sufficient 'vigilant observation'. While we therefore will always strive for a reduction in uncertainty in our hydrological estimates and predictions, the message from the economics parallel is that we should only do that realistically and not end up with 'false resolutions of uncertainty'. The implication is that we will always be left with some uncertainty in the decision-making process and the extent to which we have to reduce this further is dependent upon the risks involved in making decisions with such information. The very clear message is therefore that the need to reduce uncertainty, and the extent to which we have to achieve this is not independent of the way in which the information is used within a decision-making process.

Arguably, uncertainty cannot be reduced unless it is understood, both qualitatively and quantitatively. It is also true that in certain circumstances we do not fully understand the sources of uncertainty and therefore cannot properly (realistically) quantify them. Therefore it can be argued that a substantial contribution to uncertainty reduction can be made through a better quantitative understanding of different sources of uncertainty and their relative contribution to total uncertainty. This issue is partly reflected in some of the contents of this report, which do not directly address uncertainty reduction, but rather address improvements in the understanding of certain sources of uncertainty. The context of the WRC project is uncertainties in water resources assessment and planning. This means that uncertainties in both our knowledge of the past and our ability to predict the future are equally relevant.

2.1 Uncertainties in our knowledge of the past

Given perfect observed records of ‘adequate’ length to characterise temporal variability, there would be very little uncertainty in our ability to quantify historical water resources availability. However, this is almost never achieved and is arguably almost impossible to achieve given the complexity of water resources decision-making. We have many very good (but not perfect) stream flow gauging records, but even these are not always adequate for some water resources decision-making. In some cases they are impacted by poorly defined and largely un-quantified variations in upstream impacts, in other cases the gauging methods do not allow for the full range of flows to be accurately monitored. At the same time, there may be water resources decisions that require more information than can be accurately determined from only stream flow gauges. An example would be the joint development of surface and groundwater resources. There are techniques that can be used to approximate the groundwater contributions to stream flow from the flow records themselves (hydrograph or so-called ‘baseflow’ separation approaches), but all of these are subject to a great deal of uncertainty and do not explicitly allow for the complex processes associated with the interactions of rainfall, surface runoff, soil water drainage, recharge to groundwater and re-emergence of groundwater in springs and rivers. A further source of uncertainty exists if it is necessary to consider different water resources development issues in different parts of a gauged basin. Even basins with moderate catchment areas (less than 100 km^2) can have very spatially variable response characteristics and it is typically not realistic to consider that all parts of the basin will contribute equally (or be dominated by the same runoff generation processes and temporal patterns) to the runoff observed at the basin outlet. The estimation of available water resources in the basins of the country that are considered to be ‘gauged’ can therefore still be considered to be uncertain. The implication is that additional data, understanding and/or ‘modelling’ (in the broadest context of the word and including even simple data analysis and interpretation) will be required to provide the information necessary to make an informed management decisions. These additional resources will all come with some degree of uncertainty.

Hydrological scientists involved in the IAHS PUB (Prediction in Ungauged Basins) programme (Hrachovitz et al., 2013; Hughes et al., 2014b) often refer to uncertainty and prediction issues in data rich, data poor and data scarce regions (with large parts of southern Africa identified as being data scarce). However, the question of data richness depends not only on the amount of data, but also on whether or not the data are directly appropriate for the type of water resources management and planning decisions that have to be made. This is the difference between data richness from a purely hydrological perspective and from a practical water resources management perspective. While there are potential sources of uncertainty in the use of gauged data, there are clearly many more in the majority of situations where there are no gauged stream flow data and where it is necessary to rely on one or more of the many hydrological and water resources assessment modelling tools that are available within South Africa and internationally. As soon as we introduce models into the estimation approach, we introduce many more sources of uncertainty than those associated with available data. Quantifying these uncertainties as well as understanding how they interact is extremely difficult in ungauged situations where we do not have the data required to assess the results. Even understanding which sources are independent (or not) is extremely difficult, but nevertheless important from the point of view of quantifying the total uncertainty in the final result (appropriate estimates of water resources availability). These sources of uncertainty can be summarized as:

- Input climate data uncertainties (rainfall, evaporation demand, etc.), including uncertainties in the actual measured data, the degree to which the available data are spatially and temporally representative and the extent to which the available data are adequate to represent what is being simulated in the model (e.g. the use of temperature-based potential evaporation estimation equations, or such as pan data).
- Uncertainties in the climate data processing tools (and the assumptions inherent in their application) that might be used to extend, fill or spatially extrapolate from the available climate data to provide the necessary inputs to a hydrological or water resources system model.
- The structure of the model and whether it is appropriate for the basin under study. Model structural uncertainties include many issues associated with the conceptual design of the model and the way in which water fluxes and storages are represented by the mathematical formulations of the model. They also include related issues of model temporal and spatial scale. While, there are many discussions in the hydrological modeling literature that attempt to resolve these issues, the practical reality is that the choice of model to be used for specific water resources assessments is often constrained by personal preference or institutional convention. The impacts of structural uncertainty are also not entirely independent from the skill and experience of the user.
- A source of uncertainty that is arguably related to the previous point is the methods used for parameter estimation. This is a huge topic that is very complex and difficult to resolve. Parameter uncertainty and the best (or most appropriate) methods of parameter estimation have been at the forefront of discussion in the hydrological modelling literature for many years (Blöschl et al., 2013; Hrachovitz et al., 2013). However, from a practical perspective, we are not very far advanced from where we

were many years ago when hydrological models first became part of the toolbox typically used by water resources engineers. There are many issues associated with the application of uncertainty principles in model parameter estimation and this project has addressed some of them. This is also a topic where the issues of quantifying uncertainty in a realistic way versus reducing uncertainty become quite fuzzy.

- Uncertainties in the data that are used to assess modelling results are also related to the issue of parameter uncertainty. This is true whether local data are used (i.e. gauging stations within the basin being modelled), or whether regional data are used to either assess the model results or to constrain the parameter estimation process.

2.2 Uncertainties in our ability to predict the future

All of the uncertainties in our knowledge of the past are equally relevant to our ability to predict the future. However, there are many additional uncertainties that have to be included when attempting to predict the future:

- The uncertainties in the input climate data will be much greater in predicting the future. This applies to all future predictions, whether they are short-term (flood forecasts), medium term (seasonal forecasts) or much longer-term (climate change projections). The additional uncertainties exist even without assumptions about non-stationarity, but they clearly become far greater if it is assumed that future climates will be non-stationary. Many water resources management decisions (whether infrastructure planning and design, or setting operating rules) are based on the analysis of historical data and therefore include some assumptions that the patterns of the past will be somehow repeated into the future, or that future changes in pattern can be predicted. Stochastic analyses can be used to add some components of uncertainty to this type of analysis, but it remains difficult to establish whether the uncertainty added through the use of stochastic sequences is real or simply a statistical artifact.
- A specific sub-set of the above source of uncertainty is the use of GCM outputs and downscaling methods to provide inputs to hydrological models. There are many GCMs and several different types of downscaling and all of them produce different results – very different in some situations (Hughes et al., 2014a). There does not appear to be any real clarity about which results are more likely than others and therefore, from an uncertainty analysis perspective, they all have to be treated as equally likely.
- There is a strong likelihood that changes in future climates will lead to other changes in the landscape (vegetation, land cover and land use, etc.). Parameter sets (either a single set or many sets defining uncertainty) established on the basis of historical

conditions are therefore not likely to be applicable in the future. However, it will always be difficult to define what should be changed and in what direction.

2.3 Opportunities for reducing uncertainty

This section introduces some of the approaches and opportunities that may exist for reducing uncertainty, or improving the ability to quantify uncertainty, in a very general way. These approaches include the collection of new data to fill spatial or temporal gaps, the collection of data to develop understanding of processes (and therefore improve the application of a model) and the development of new analysis approaches that make better use of existing (and new) data:

- Reducing uncertainty through improvements in the national hydrometeorological data collection network and the way in which the existing data are analysed.
- Reducing uncertainty through improvements to model structures and specifically the inclusion of sub-models to deal with specific hydrological processes (e.g. wetland storages and exchanges with stream flow).
- Improving understanding of processes and their interactions through short-term focused field observations with the intention of improving model parameter estimation and for ensuring that model results are generated for the right reason. This approach overlaps with the second volume of the project final report that is focused on improved understanding and modelling of surface-groundwater interactions (Tanner and Hughes, 2014).
- Improving some of the techniques for accounting for uncertainty and propagating uncertainty through a model. The objective of these studies is not so much on uncertainty reduction, but on ensuring that uncertainty is being represented in the model in an appropriate way.
- Assessing the uncertainty introduced into models through the use of stochastic sequences of rainfall and stream flow.
- Assessments of how uncertain observed flow data can contribute to reducing uncertainty with a hydrological model – this is similar to the traditional approaches to calibration, but is also an extension of the use of various data sources to constrain model uncertainty (Kapangaziwiri et al., 2012; Westerberg et al., 2013) that formed a major component of the previous WRC project on uncertainty (Hughes et al., 2011).
- Further investigation of climate change uncertainties and how these should be incorporated into hydrological and water resources systems models.

- The use of new data products (e.g. EO data) and techniques to assimilate these data into hydrological models.

Not all of these topics are discussed in detail in the report, while some of them were already covered in the final report of the first WRC project on uncertainty (Hughes et al., 2011).

2.4 Input climate data uncertainties

Inevitably, uncertainties in the climate data that are used to force hydrological models are critical components of any output uncertainties. Unfortunately, the data that are available to quantify these uncertainties are under threat due to budget cutbacks or lack of understanding of the critical importance of data within some of the government agencies responsible for collecting the data.

2.4.1 The value of data

All scientists and engineers understand the value of data, because it affects the way in which they generate results and the confidence that they have in those results (even if they do not explicitly quantify the uncertainty). However, placing any kind of monetary value on data is a completely different matter. It is also very difficult to quantify the value of data if the uncertainty associated with not having it is never acknowledged when we make decisions.

A recent study for the Department of Water Affairs (DWA, 2012) attempted to place a value on the various monitoring programmes of the Department including the surface flow, groundwater, national chemical and the national microbial monitoring programmes. From the literature review of this type of study, it was noted that, while estimates of cost are relatively straightforward, it is much harder to quantify benefits. This is partly because they are difficult to identify, there exits co-sharing of benefits and there is a lack of standard procedures. Interestingly, no mention is made of the costs associated with making poor decisions without data or with uncertain information. Arguably, this is because there are no data available (or methods) to analyse the costs of such occurrences. The DWA (2012) report therefore focused on quantifying the benefits of data approximated by the economic value of contributions to various water use sectors. The report also details the results of a macroeconomic impact assessment. The main inputs to the benefit calculations were based on a Delphi Technique through workshops with key stakeholders in the water sectors that benefit from the monitoring programmes. The surface flow monitoring programme has the highest net present value (R12.243 million) but the lowest benefit cost ratio (6.45 versus an overall ratio of 10.77 for all programmes). Some sensitivity analyses were included that attempt to show the effects of budget changes in the monitoring programmes. Surprisingly the report suggests that all of the programmes are relatively close to the optimum budget with respect to benefit cost ratios. However, the report also clearly shows the rapid decrease in benefit cost ratios if the budget allocations are decreased. On the one hand the latter conclusion is what (as hydrologists) we might expect, but the former does not seem to agree with general consensus that we do not have enough data.

It is encouraging to note that the Department of Water Affairs is taking the role of information very seriously and that they have made efforts to evaluate the benefits of their data collection programmes. While there are some difficulties of directly linking the outputs of the DWA (2012) study to issues of making decisions with uncertain information, the report clearly identifies the economic value of data. It is unfortunate that a similar study has not been published on the value of other data used in hydrological and water resources assessment modelling that are not managed by the DWA. Specifically, this comment refers to the national network of rainfall observation stations that appears to have seriously deteriorated over the last 10 years or more.

Many previous studies have clearly demonstrated the importance of uncertainties in rainfall and evapotranspiration demand data and have attempted to improve the quantification of climate variables through analysis of the existing data (Lynch, 2004) or using satellite observations (Hughes and Mallory, 2008; Sawunyama and Hughes, 2008). However, the fact remains that it is very difficult to reduce the uncertainties without additional data and unfortunately these are simply not available.

2.4.2 Uncertainties in rainfall inputs to models

The uncertainties in rainfall inputs to models are derived from several factors, mostly associated with the available data, but some are also related to the structure of the hydrological models. The latter are associated with the spatial and temporal scales used within the model structure.

Model scale issues: One of the criticisms of coarse scale models is that they are not able to represent the spatial and/or temporal variability within the real world. This criticism is certainly valid, but we are all too frequently faced with the problem that even if we use finer spatial and temporal scales, we do not have the data to adequately quantify the variability.

There is therefore still a great deal of doubt about which is worse and generates the most output uncertainty:

- High resolution inputs, but with high uncertainty in their estimates?
- Lower resolution inputs that smooth the variability, but with unknown uncertainties?

From a ***spatial scale*** perspective, most hydrological models can be run at higher spatial resolutions if the input data and expected hydrological response characteristics can be adequately quantified (Hughes et al., 2013b). The situations where such an approach would be considered appropriate are those catchments that have steep topographic, rainfall and runoff generation gradients from mountain tops down to flatter plains areas. Unfortunately, they are also the areas where the observation data that are available to define the rainfall gradients (dominated by strong orographic effects) are simply not available. It is therefore feasible to approximately estimate the uncertainty (we expect more rainfall on the mountains than is gauged lower down in the catchment) but it is not feasible to reduce the uncertainty without some additional data to verify the assumptions that are made. A stream flow gauging station at the outlet of the total catchment (or better still, several gauges located at different places within the catchment) would possibly allow the rainfall inputs to the model to be 'calibrated' (together with the model parameters), but this type of situation is rare in the real world of practical water resources assessment.

The ***temporal scale*** used within models has always been a somewhat contentious issue and there is little doubt that monthly time scale models are unable to represent the highly variable relationships between monthly rainfall amounts and daily (or less) distributions of rainfall. This is particularly relevant to semi-arid climate zones where short time-interval variations in rainfall (and subsequent runoff) can be highly variable and associated with high degrees of spatial variability. However, we are again faced with the paradox of wishing to represent the inputs to models with high resolution, but not having sufficient data, or sufficiently reliable data, to achieve this. The overall conclusion is that while daily time-step models almost certainly represent better modelling platforms than monthly time-step models from a scientific perspective, the advantages are not always achievable because of the limitations of the available input data. Nevertheless, it is encouraging to note that the daily version of the Pitman model has been re-introduced as part of the WR2012 WRC project. Hughes et al. (2013a) were certainly able to demonstrate that a daily version of the model has a great deal of potential as a modelling tool for more than just stream flow simulations.

One of the versions of the Pitman model that has been included with SPATSIM allows for stochastic rainfall inputs together with uncertain distributions of parameters. This could also be used to examine the uncertainty effects of a number of different rainfall input time series and not just those generated by a stochastic rainfall model. For example, it would not be difficult to develop a simple 'error model' around existing WR2005 rainfall data time series and generate additional time series of rainfall that represents the uncertainties. However, we are left with not only the problem of what information to use to define the 'error model' but also how are we going to reduce that uncertainty? ***The overall conclusion is that we have the modelling tools available to explore the possible effects of uncertainties in rainfall data, but we frequently do not have the information available to define the uncertainties, nor reduce them.***

The main ***data observation issues*** are associated with obtaining data to adequately describe the spatial and temporal variability of rainfall over a catchment. The problem is what constitutes 'adequately', given that we already know that doing this 'accurately' is virtually impossible at a national scale (i.e. it is possible to achieve locally, under ideal conditions, but not for the whole country). What is 'adequate' is partly determined by the nature of the rainfall variability, the characteristics of the hydrological response and the purpose of the modelling study. There are many areas where rainfall is highly variable at short time scales, but less so at the time scales that are adequate for simulating water resources availability and therefore coarse scale data that smooth the shorter-term and finer spatial scale variations are often adequate. For flood modelling within the same region, the coarse resolution data would be totally inadequate.

It is a widely recognized fact that no system of measuring rainfall is able to accurately measure the amount of water that reaches the surface of a catchment. All the different measuring systems (rain gauges – of different types, radar, satellite imagery, etc.) measure different things. However, hydrologists have generally accepted ground-based rain gauges as the standard and typically all other measurement systems are either compared with rain gauge observations, or calibrated against them. This may not be the ideal approach because rain gauges are subject to many different catch errors (particularly in areas of steep topography where turbulence substantially affects catch) and have to be converted from point observations to areal estimates for use with catchment scale hydrological models. If we are to move away from this approach to ones that integrate several different observation platforms, then it is essential that we consider a number of uncertainty issues:

- As already noted, we do not have **ANY** observations in many topographically steep areas and therefore validation of any rainfall data product is almost impossible.
- We have many years of historical rainfall data that are of vital importance in generating long time series of stream flow data. While we accept that these are uncertain, they are

all we have and we cannot go back very far in time with alternative data products based on radar or satellite.

- The implication of the previous point is that new data products should be made compatible in some way with the historical data, or the historical data should be bias corrected to agree with the new data products. The latter is, however, not the best option as many of our water resources assessments have been made with hydrological models calibrated against the historical data and these same parameter sets are used with updated rainfall data to update the resource assessments. If the historical rainfall data are going to be changed, the hydrological models will almost certainly need to be re-calibrated.
- It should be clearly recognized that any new methods will not be likely to reduce current uncertainties, largely because the existing uncertainties are not quantified. The new methods will, however, offer many opportunities for improving the way in which we quantify uncertainty in rainfall inputs. The quantification of the uncertainties may provide greater evidence of the need for improved monitoring networks.

The project referred to as ‘Revision of the mean annual precipitation (MAP) estimates over southern Africa’ (WRC K5/2241) that started during 2013 proposes to use a number of different methods to improve the daily rainfall database of South Africa and *inter alia* generate a 1 minute grid of daily rainfall (back to 1950) with confidence limits. It is also intended to bias correct the TRMM 3B42RT satellite 3-hourly rainfall data (available since 2000) at a 0.25 degree grid. These are ambitious proposals and should benefit the hydrological modelling community when the project begins to generate outputs. Although they are unlikely to have a large impact on the reduction of our existing uncertainties in many parts of the country, they will provide a lot more information on the quantification of those uncertainties.

We are left with the major conclusion that the only way to substantially reduce uncertainty in the rainfall inputs to hydrological models is to improve the monitoring network in key locations. Given that the current trend in South Africa and many other parts of the world is completely the opposite (i.e. reductions in the number of observation stations), future hydrological simulations can be expected to get more uncertain and not less uncertain. The project team is aware of initiatives by the WRC as well as other interested parties to try and reverse this trend of reducing hydrometeorological information and these initiatives should be supported by all scientists, engineers and water resources managers who rely on such data. As we move into future uncertainties, it is imperative that observational data are available to check the trends of change suggested by climate and hydrological models.

2.4.3 Uncertainties in evapotranspiration inputs to models

The data used to estimate potential evaporation inputs into models have always been uncertain and there appear to be different opinions about the impacts of these uncertainties on total modelling uncertainty. Many of these differences could be related to the specific climate region and the extent to which the actual evapotranspiration is dependent upon water available or input energy (potential evapotranspiration - PE). Hughes et al. (2013a) recently demonstrated the benefits of including estimates of daily evaporation demands over fixed seasonal distributions in a daily version of the Pitman model applied to two sites. Figure 2.1 shows some results for the Manubi Forest (Eastern Cape coastal area) based on fixed seasonal distribution values and distributions based on daily estimates of PE using weather station data. Figure 2.2 shows a comparison of the daily estimates of PE for a small study catchment in Grahamstown using fixed seasonal distributions (based on WR90) and values for ET_0 derived from weather station data. The differences are very clear at the daily scale, but it is also apparent that some monthly mean values would be very different (see days 500 to 600) and therefore would also affect the results of a monthly time-scale model. Certainly, within the daily model used in the Hughes et al. (2013a) study, the simulation results for soil moisture (Manubi Forest) and stream flow (Grahamstown site) were greatly improved when the more detailed potential evapotranspiration data were used. The conclusion is that providing more detail in the input evapotranspiration data should improve the outputs of a model and reduce the uncertainties. However, any reduction in uncertainty must be measured against some validation data. While this could be done in a catchment with gauged stream flows (as in the Grahamstown study), it would be better to have a more direct method of assessing whether the actual evapotranspiration simulations obtained from a model are sufficiently representative of reality. Such information is almost totally lacking from ground based observation networks (except in a few small scale research studies such as the Manubi Forest) and therefore remote sensing products (Mu et al., 2011) offer an opportunity in this regard.

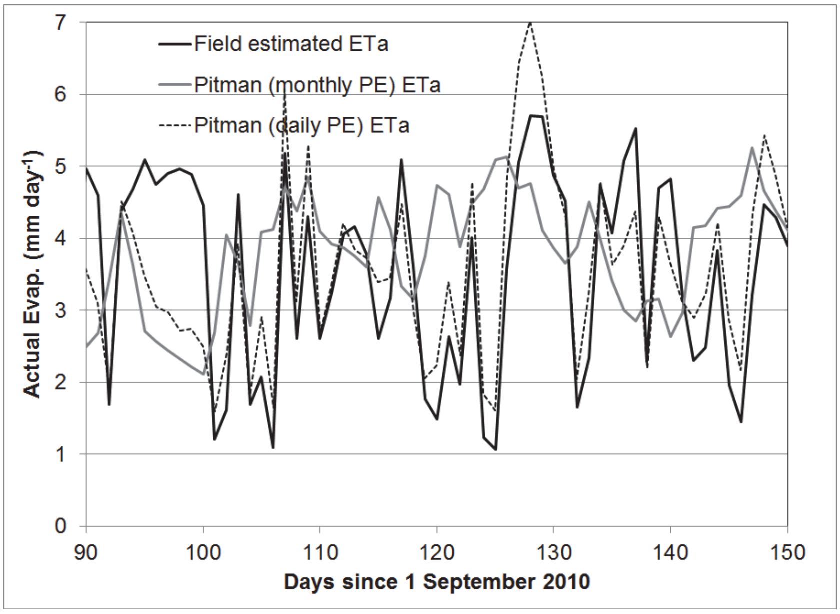


Figure 2.1 Manubi Forest simulated actual evapotranspiration (with fixed seasonal distribution and distributed using daily PE estimates) compared with field estimated values.

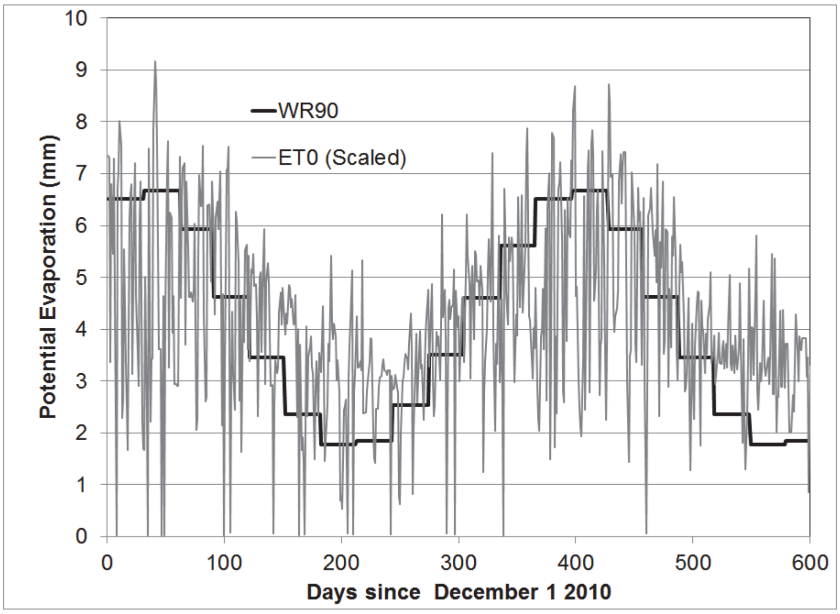


Figure 2.2 Grahamstown site: daily PE using fixed seasonal distributions based on WR90 compared with scaled ET_0 values derived from weather station data (both use the same mean annual value of PE).

MODIS evaporation products: One possible area of research that has been explored internationally, but less so in South Africa, is the use of Earth Observation data (satellite imagery, such as MODIS) to provide additional information about spatial and temporal patterns of evaporative loss and soil moisture. In a study in the Western Cape, Műnch et al. (2013) concluded that it was very useful to have some MODIS data to improve the simulations of evaporative losses from the coastal Sandveld area, where there are no stream flow data available for calibration purposes.

Figure 2.3 illustrates MOD16 actual evapotranspiration time series for a 6 grid (1 * 1 km) transect across the headwaters of quaternary catchment K40B and a 16 grid transect from the headwaters to the coast (north-south), while Figure 2.5 provides an integrated view of all the data compared to Pitman simulated ET_a. It is immediately apparent from all three Figures that the range of estimates for individual MODIS grid squares is extremely high and that many of the estimates are significantly greater than the available input rainfall. While the latter is physically possible on a seasonal basis, it is not possible for this to happen consistently over the whole time series. Taking the average MOD16 evapotranspiration signal over the entire K40B catchment also generates results that are totally inconsistent with the rainfall data. A further issue is that the MOD16 data do not seem to reflect any time series differences in catchment wetness as reflected in the rainfall variability.

An examination of differences in the ground conditions (based on Google Earth imagery) between those grid squares that suggest either very high or very low evapotranspiration depths reveals no possible explanations for these differences. The overall conclusion is that, within this specific geographical region of the country (southern parts of the coastal region between the Outeniqua Mountains and the sea) there is far more uncertainty within the MODIS data products than within the ability of the Pitman model to realistically simulate actual evapotranspiration. The MODIS data are therefore of no use in constraining model outputs. The implication is that if the MODIS data are to be used in other parts of the country additional checks on the validity of the data are certainly required. However, it is not clear what information could be used for such checks.

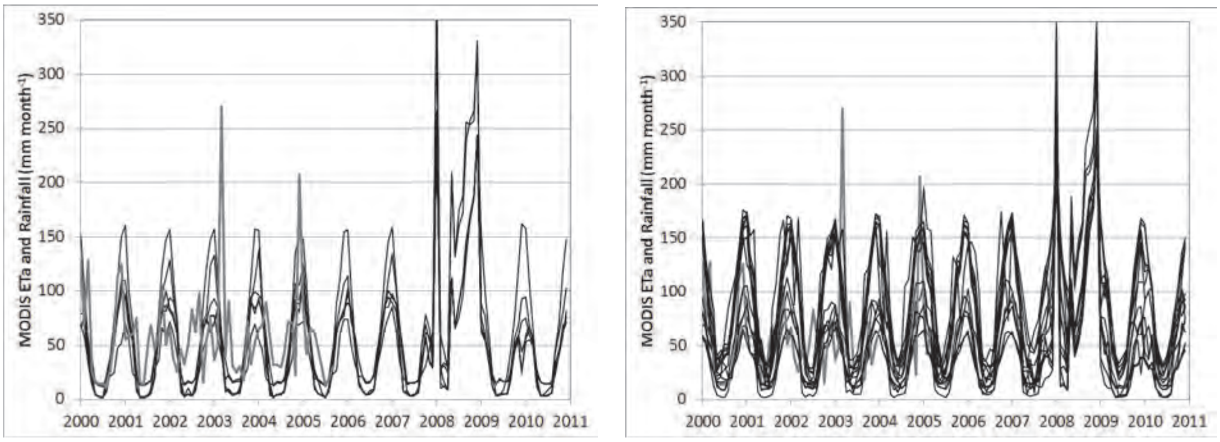


Figure 2.3 K40B: Monthly MOD16 ET_a data for 6 grids (left side: East-West) across the headwaters and for 16 grids (right side: North-South) from the headwaters to the catchment outlet (the grey lines represents the WR2005 monthly rainfall data).

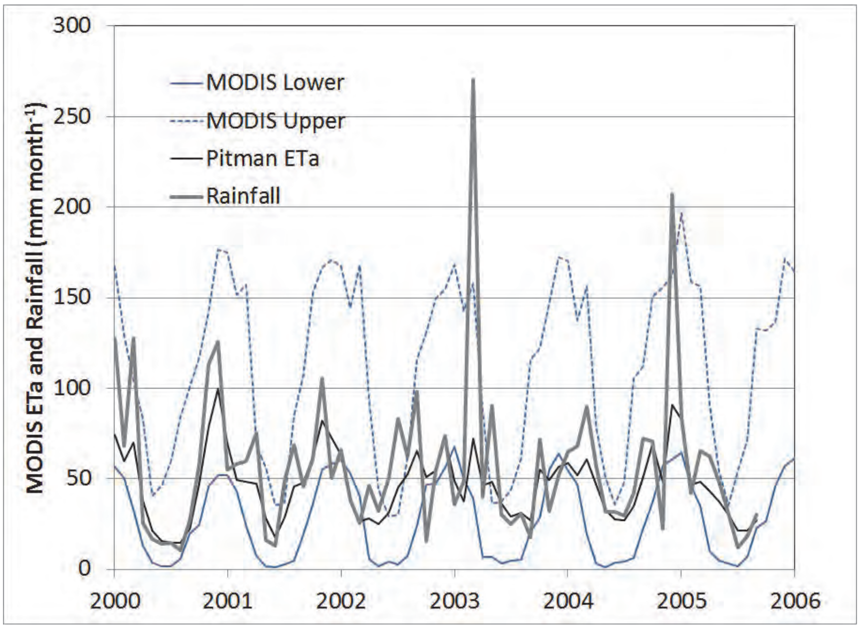


Figure 2.4 K40B: Range of monthly MOD16 ETa data for the 22 grids used in Figures 6.4 and 6.5, ET_a simulated by the Pitman model and the WR2005 rainfall data.

Figure 2.5 compares the MOD16 ET_a data averaged over 4 grids to the south of Grahamstown that represents the same area used in the Hughes et al. (2013a) study. The MODIS data are compared with ET_0 estimates from a local weather station (based on Penman Monteith estimates) and the actual evapotranspiration simulated using a daily version of the Pitman model. The start of the modelling period (early December 2010) was particularly dry and that is reflected in the large difference between the ET_0 and simulated ET_a values. However, the MODIS data suggest actual evapotranspiration values that are very similar to the weather station ET_0 data. The converse is true for the wet winter of 2011 when the simulated ET_a data are much closer to the potential evaporation estimates, while the MODIS data are much lower. However, there is one short period where the MODIS data do increase in response to rainfall. While this report does not suggest that the simulated ET_a data are accurate, they do at least follow the known patterns of moisture availability, while this is not the case with some of the MODIS data.

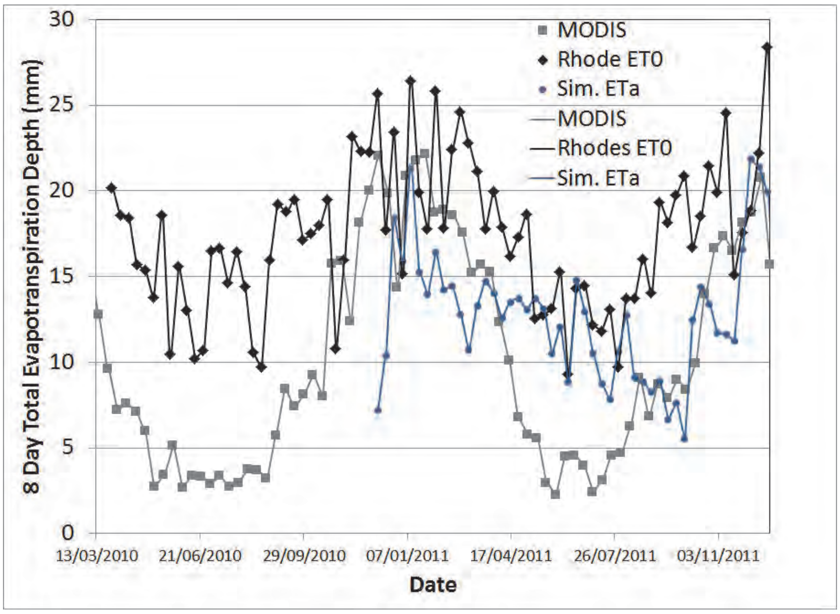


Figure 2.5 Grahamstown: MOD16 ETa data for 4 grids, compared with ET_0 data from the Rhodes University weather station and a simulation of ET_a using a daily version of the Pitman model.

Figure 2.6 presents perhaps the most rigorous assessment of the MODIS data using field estimated ET_a data for the Manubi Forest (Hughes et al., 2013a). The figure illustrates the 8 day MOD16 totals for closely adjacent forest and grassland areas and for the field estimated forest data based on calibrations against Eddy Covariance observations. During the period at the end of summer and through most of winter, the field estimates and MOD16 data are very well matched. However, this is not the case for the spring and early summer months at the start and end of the field observation period. A more encouraging result is the consistently large difference between the MOD16 forest and grassland ET_a estimates, the forest being almost twice the grassland on average. This scale of increased evapotranspiration is, however, somewhat higher than is conventionally considered acceptable and suggests that the relationships between evapotranspiration losses between different vegetation types should be re-investigated.

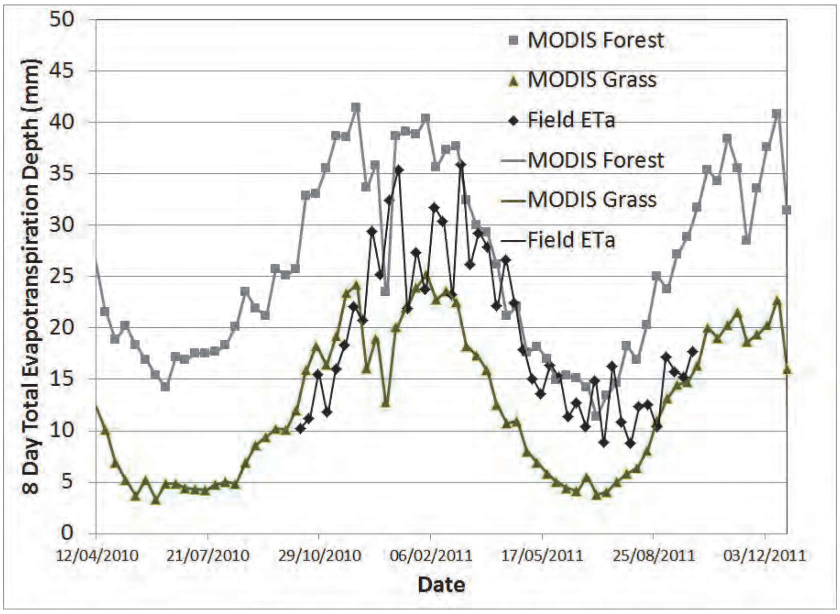


Figure 2.6 Manubi Forest: MOD16 ETa data for 4 grids within the forest and 2 grids in a grassland area to the south, compared with field estimated ET_a data using local weather station data.

While the potential for using MODIS data to constrain the actual evapotranspiration outputs of hydrological models and to improve our understanding of land cover-evapotranspiration relationships has been recognized by a number of authors (see additional references in Műnch et al., 2013), the assessments carried out as part of this project suggest that care must be taken in the use of the MODIS data. The southern Cape (K40B) example suggests that there are large differences between individual MODIS grids that cannot be readily accounted for or explained by other information, making the value of the MODIS data extremely suspect in this region. The Grahamstown example indicates that the variation in MOD16 estimates do not fit very well with the expected patterns of evapotranspiration based on quite good local knowledge of the water balance of the area, supported by Pitman model simulations. While it is possible that the patterns of simulated ETa shown in Figure 2.2 are ignoring some additional losses to evapotranspiration, it is unlikely that the low MODIS estimates during the wet winter of 2011 can be considered realistic. The Manubi Forest data, based on accurate local ground observations, confirm that there are potential problems with some of the MOD16 data.

2.5 Reducing the uncertainty in the parameter ensembles

The issues of parameter uncertainty were discussed at length within the previous project report (Hughes et al., 2011). However, a scheme that allows for parameter uncertainty to be reduced in a systematic way in all situations remains elusive. This may not be achievable given the large diversity in available data and catchment complexities, not to mention the large degree of equifinality that is known to exist in the structure of the Pitman model. The latter refers to the high level of interaction between the model parameters and the fact that it is easily possible to get very similar solutions from many different combinations of parameter values. During the course of this project the whole issue of constraining parameter values with very little information was re-visited. The purpose of this was to contribute to reducing uncertainty and to determine if there are better and more practical approaches to parameter estimation. The first of these is discussed in the section of the report, while the latter forms part of Chapter 3.

Figure 2.7 illustrates the generic uncertainty framework suggested by Kapangaziwiri et al., (2012). Part of the process involves parameter estimation procedures based on physical basin properties proposed by Kapangaziwiri (2008 and 2010), which may be affected by the spatial of modelling. These issues are discussed in the next sub-section. However, it was also decided to assess an alternative approach that starts with quite large ranges for the parameters and then uses some constraints on the output ensembles to progressively reduce the parameter ranges and (hopefully) the output uncertainty. These approaches were applied to a single catchment in the southern Cape and then to the Caledon River basin consisting of 31 quaternary catchments.

2.5.1 Scale effects in the parameter estimation process

Hughes et al. (2010a) 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.

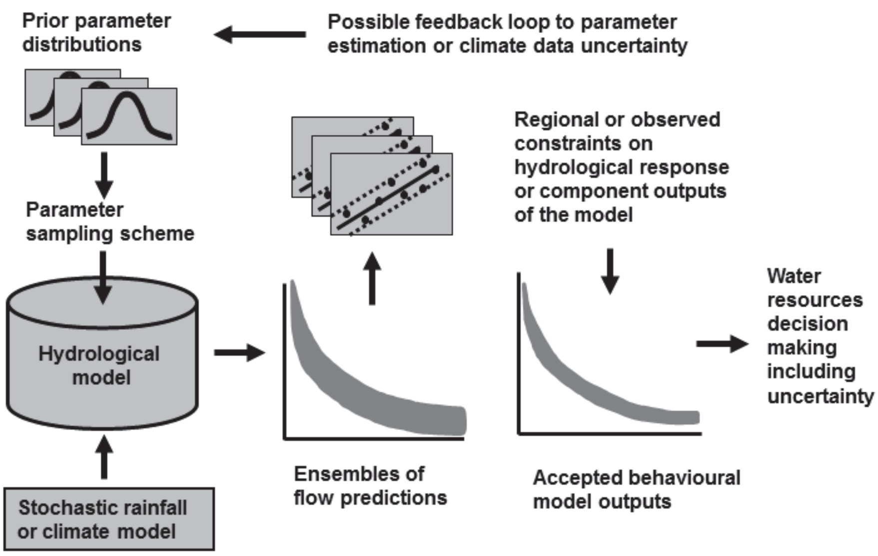


Figure 2.7 A generic framework for uncertainty analysis (based on Kapangaziwiri et al., 2012)

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 behavioural (Hughes et al., 2013b).

Figure 2.8 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 2.8 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. Further details of the process followed are provided in the published paper (Hughes et al., 2013b).

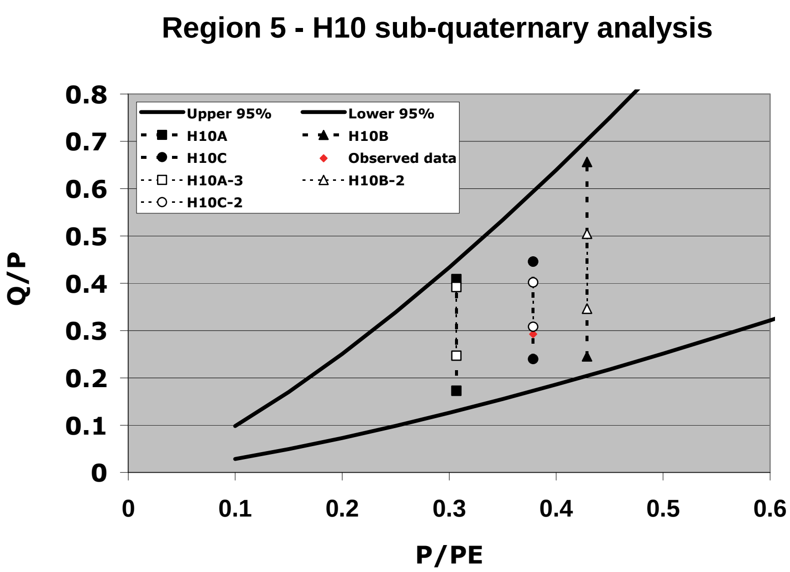


Figure 2.8 Changes in the ensemble Q/P ranges for H10A to H10C as a result of the model scale reduction.

The brief example provided in this section, as well as later sections that refer to southern Cape and Caledon River catchments, suggest that at least some of the 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.

2.5.2 Constraining uncertainty: Southern Cape example (Quaternary catchment K40A)

The South African Department of Water Affairs (DWA) gauging station K3H003 lies on the Diep River at the outlet of a 72 km^2 topographically steep catchment (mean slope of 28%) in the area of the southern Cape between the Outeniqua Mountains and the coast. The geology consists of fractured quartzites of the Table Mountain Sandstone Series. The natural vegetation consists of scrub bush (fynbos) on the steep slopes and mountain tops, with dense deciduous forest in the lower parts of the catchment and the river valleys. Much of the indigenous forest was replaced before stream flow gauging began with managed pine and eucalypt plantations covering approximately 40% of the catchment. The soils are shallow, stony and sandy in the mountain areas, but can be much deeper with a high organic content in the foothills and valleys. The gauged catchment is part of catchment K40A (87 km^2). The climate inputs to the model are relatively uncertain, largely due to the steep topography and the lack of records for the mountain areas. However, Table 2.1 suggests that most estimates of mean annual rainfall are relatively similar (700 to 750mm), while mean annual potential evapotranspiration has been estimated to be 1 400mm.

Table 2.1 lists the parameter values and some objective functions that have been used in five previous Pitman modelling studies (Pitman et al., 1981; Hughes, 1985; Midgley et al., 1994; Bailey and Pitman, 2005; Kapangaziwiri, 2010). Only the last two studies included the groundwater routines of the model and the 2010 study was based on uncertain parameters estimated using physical basin properties derived mostly from AGIS (2007). The 1981, 1994 and 2005 results are based on the regional parameter values generated by these national assessments, the 1985 results are based on local calibration, while no calibrations were used for the 2010 ensemble results. Some of the groundwater parameters used for the 2005 and 2010 studies are not shown, but are referred to in the next paragraph.

Table 2.2 itemises the steps followed in a simplified revised uncertainty assessment using uniform distributions for all parameters (Table 2.3, column 2). The period simulated was for Oct. 1960 to Sept. 2005, while the observed flow data covers the period Oct. 1961 to the present day (the additional year of simulation was to ensure a model warm up period). The objective of the revised assessment was to begin with relatively large uncertainty (covering all possible parameter values based on many years of model experience) and attempt to identify additional information that could be used to constrain the uncertainty in some parameters. The observed data are not used in the first 4 steps of the analysis (Table 2.2) except to evaluate the results in terms of the three objective functions listed in Tables 2.1 and 2.3. Some parameter values have been fixed at the same values used in the 2010 study: SL and SLG = 0 mm, TL = 0.25 months, drainage density = 0.2, transmissivity = 20 m^2 d^{-1} and storativity = 0.001. While these will have an impact on the time distribution of low flows, it will be smaller than many of the other parameters and will not affect the overall simulated flow volume. In a similar way the uncertainties in the rainfall inputs, potential evapotranspiration and coverage of commercial afforestation have also been ignored. The focus is therefore on the main runoff generating parameters. The final step (5) used the observed data to identify the ensembles that met certain criteria associated with 5 objective functions (Table 2.2). Three of these are those used to evaluate the outputs from all steps, but step 5 also included the Nash-Sutcliffe coefficient based on the inverse of the data values (CE(Inv) – strong emphasis on low flows) and the % bias based on natural log transformed flows.

Table 2.2 refers to some constraints that were used in steps 1 to 4 to identify which of the total of 10 000 ensembles could be considered behavioural. The unit runoff and flow duration curve (FDC) constraints were based on records from 10 stream flow gauging stations located in the same region between the Outeniqua Mountains and the coast. As all of the upstream catchments have varying areas of commercial afforestation and this effect was included in the Diep River simulations (assumed to be 40% coverage), the constraints were adjusted to account for afforestation based on the recommended regional adjustments to natural flows provided in Gush et al. (2002). An additional constraint was based on the expected range of mean annual recharge depth using regional data (DWAF, 2005).

Table 2.1 Previous applications of the Pitman model to the Diep River catchment

Model Attempts	1981	1985	1994	2005	2010
Rainfall (mm y^{-1})	750	750	706	706	706
Parameters					
PI1 (mm)	1.5	1.5	2.1	1.5	2.0±0.1
PI2 (mm)	n/a	10.0	4.0	4.0	2.6±0.1
% Veg2	n/a	54.3	66.7	5.0	40.0
FF	n/a	1.1	1.1	1.1	1.3
PEVAP (mm y^{-1})	1400	1400	1400	1400	1400
ZMIN (mm $mnth^{-1}$)	0	0	0	50	50±5
ZAVE (mm $mnth^{-1}$)	200	125	100	142	235
ZMAX (mm $mnth^{-1}$)	400	250	200	235	1160±20
ST (mm)	250	100	100	120	100±5.0
FT (mm $mnth^{-1}$)	40	38	50	25	35±2.5
POW	2.0	1.7	2.0	2.0	2.0±0.05
GW (mm $mnth^{-1}$)	n/a	n/a	n/a	2.0	16.0±2.8
GPOW	n/a	n/a	n/a	2.0	3.0
R	0.0	0.17	0.0	0.0	0.0 : 0.2
TL (mnth)	0.0	0.0	0.25	0.0	0.25
Riparian %	n/a	n/a	n/a	0.2	0.2
Objective Functions					
CE	0.67	0.68	0.65	0.61	0.50 : 0.62
CE(ln)	0.59	0.61	0.48	0.59	0.39 : 0.63
%Bias	5.6	-16.3	23.3	8.0	-40.7 : 1.2

Notes: PI1 and PI2 refer to the interception parameter for Fynbos bush and plantation forest, respectively, while FF refers to the factor by which PEVAP is increased over the forested area (% Veg2). For the 2010 study, *Mean±St.Dev* is used to denote a normal distribution of uncertainty while *Min : Max* is used for a uniform distribution. CE and CE(ln) are the Nash and Sutcliffe (1970) coefficients of efficiency based on ordinary and natural log transformed flows, while % Bias refers to the % bias in the simulated mean monthly flow relative to the observed value.

Table 2.2 Sequence of steps in constraining parameter values ranges

Step	Information source	Constraints	Results summary
1	10 stream flow gauges in the same physiographic region and GRAII (DWAF, 2005).	Estimates of mean monthly unit runoff (m^3 km^2 $mnth^{-1}$) and non-dimensional FDC percentage points at Q10, Q50 & Q90 (relative to mean monthly flow). Groundwater recharge limited to between 15 and 30 mm y^{-1}.	Limits ST to < 300 mm and ZMAX to < 280 mm. Suggests limits to behavioural ratios of FT/POW and GW/GPOW.
2	Results from step 1.	Same as in step 1. Limits to maximum values of ST and ZMAX. POW and GPOW fixed.	No extra information provided about how parameter ranges can be reduced.
3	Some additional assumptions about interception and evapotranspiration.	Same as in step 2. Range of PI1, PI2, FF and Riparian % parameter values reduced.	Greater frequency of some parameter values in behavioural ensembles.
4	Step 3 constraints plus additional information based on the frequency of behavioural values for parameters ZMIN, ST, FT, GW and R (see Table 3).		Behavioural range not changed but many more behavioural ensembles.
5	Observed data at K4H003.	Combination of 5 Objective functions: CE>0.6, CE(ln)>0.65, CE(Inv)>0.5, %Bias and %Bias(ln)<±10%.	Reduces the range of some parameters, but there remains substantial equifinality even in 11 ensembles.

Tables 2.2 and 2.3 indicate that, while only 74 out of 10 000 ensembles were accepted as behavioural after step 1, there were relatively few differences in the parameter value ranges of the behavioural and non-behavioural ensembles. Apart from some constraints on the ranges of ST and ZMAX, the only other clear results were that only certain ranges of FT/POW and GW/GPOW could be considered behavioural. Step 2 therefore involved fixing POW and GPOW and limiting the range of ST, ZMAX and GW. This resulted in somewhat more behavioural simulations (419) and slight improvements in the worse values of the objective functions. However, the behavioural and non-behavioural parameter ranges remained similar. Step 3 involved applying some literature data (Dye and Versfeld, 1992; Everson et al., 2011) to reduce the range of the interception and evapotranspiration parameters. While this resulted in more behavioural parameters (803), it had a slightly negative impact on some of the objective functions (Table 2.3). It was originally intended to make use of the MOD16 actual evapotranspiration (ET_a) data product (Mu et al. 2011) to further constrain some of the model outputs. However, the MOD16 data for this region show very large variations between adjacent MODIS pixels that do not make any sense and also

suggest ET_a values that are often much higher than the monthly rainfalls. Step 4 was based on a more detailed analysis of the behavioural and non-behavioural parameter sets than simply their ranges and reduced the ranges using the more frequently occurring parameter values within the 803 behavioural ensembles at the end of step 3.

Table 2.3 Parameter ranges and objective functions for some of the steps listed in Table 2.2

Model Runs	Step 1	Step 2	Step 3	Step 4	Step 5
PI1 (mm)	1.5 : 2.5	1.5 : 2.5	1.4 : 1.6	1.4 : 1.6	1.7 : 2.4
PI2 (mm)	3.0 : 5.0	3.0 : 5.0	2.8 : 3.2	2.8 : 3.2	3.0 : 5.0
% Veg2	40.0	40.0	40.0	40.0	40
FF	1.2 : 1.5	1.2 : 1.5	1.2 : 1.3	1.2 : 1.3	1.2 : 1.5
PEVAP (mm y^{-1})	1400	1400	1400	1400	1400
ZMIN (mm $mnth^{-1}$)	0 : 100	0 : 100	0 : 100	20 : 80	11 : 78
ZAVE (mm $mnth^{-1}$)	0.5 * (ZMIN+ZMAX)				
ZMAX (mm $mnth^{-1}$)	150 : 500	150 : 280	150 : 280	150 : 280	176 : 268
ST (mm)	100 : 500	100 : 300	100 : 300	120 : 200	165 : 470
FT (mm $mnth^{-1}$)	20 : 100	20 : 100	20 : 100	25 : 55	21 : 71
POW	1.8 : 3.0	3.0	3.0	3.0	1.9 : 2.8
GW (mm $mnth^{-1}$)	20 : 100	25 : 50	25 : 50	40 : 50	26 : 100
GPOW	2.0 : 5.0	4.0	4.0	4.0	2.0 : 4.3
R	0 : 0.5	0 : 0.5	0 : 0.5	0.25 : 0.5	0.0 : 0.15
Riparian %	0.1 : 0.5	0.1 : 0.5	0.2 : 0.4	0.2 : 0.4	0.15 : 0.49
Objective functions after application of MMQ, FDC & GW recharge constraints.					
No. of ensembles	74	419	803	3644	11
CE	0.47 : 0.63	0.47 : 0.64	0.41 : 0.64	0.41 : 0.63	0.6 : 0.63
CE(ln)	0.07 : 0.68	0.24 : 0.64	0.11 : 0.64	0.12 : 0.61	0.65 : 0.71
%Bias	-15.5 : 48.2	-15.5 : 55.5	-15.5 : 66.7	-13.9 : 67.3	-9.7 : -1.0

Figure 2.9 illustrates the differences in the range of simulated flows for the un-constrained ('Total') and constrained results for a 10-year period after step 3, while Figure 2.10 illustrates the same results using flow duration curves based on the total simulated data record and including the behavioural outputs from step 4 ('Final constrained'). Figure 2.11 illustrates the

results for the 11 'best' results after step 5 that are effectively calibrated based on multiple (5) objective functions. Perhaps the most obvious result is the fact that a large amount of equifinality remains within the parameter sets even when the observed data are used to constrain the 10 000 ensembles to the best 11 (Table 2.3, column 6). There is very little change in the behavioural results between steps 3 and 4, but there are far more behavioural ensembles (803 to 3644). The unit runoff constraint was the least effective, while the recharge constraint was the most effective in reducing the number of behavioural ensembles. Figure 2.10 illustrates that the observed data tends toward the lower limits of the ensembles for moderate to all but the highest flows and this is confirmed by the high positive values of the % bias values (Table 2.2). One possible explanation is that the correction of the observed data from the 10 local gauging stations for the effects of commercial forestry using data from Gush et al. (2002) has not accounted for enough runoff reduction at moderate to high flows (affecting the unit runoff and FDC 50% and 90% constraints). The implications are that a more localised assessment of afforestation impacts on flow would be required to develop more appropriate constraint boundaries.

The overall conclusion of this, admittedly, limited uncertainty exercise is that the uncertainty can be reduced in an ungauged catchment using regional information together with a detailed assessment of the parameter space, but that there are limitations to this reduction as demonstrated by Figures 2.9 and 2.10. It is also important to recognise that any observed data used to develop regional constraints must be representative of the conditions being simulated in the ungauged catchment. It is pertinent to note that the final ranges of parameter values, determined after steps 1 to 4, are quite different from those obtained in the earlier 2010 study (Table 2.1) that used physical basin properties (Kapangaziwiri, 2010) to estimate parameter uncertainty, while the results are relatively similar. Which are the more physically appropriate parameter sets remains unclear and would involve either more information than is currently available, or a more detailed examination of the parameter space coupled with conceptual reasoning that was beyond the scope of this relatively brief example. It is also possible that these differences are not able to be resolved and that they are a reflection of the real uncertainties in the nature of the runoff response of this catchment coupled with the equifinality of the model structure and parameter set.

The important message revealed by this analysis is the extent of the model parameter equifinality in this catchment, a situation that could quite easily have been predicted given the nature of the catchment and the complexities of the runoff generation processes. This effectively means that a further reduction of the parameter uncertainty will only be able to be achieved by an improved understanding of the runoff dynamics of the catchment (quantitative estimates of the different sources of runoff), such that these could be translated into additional constraints on some parameters.

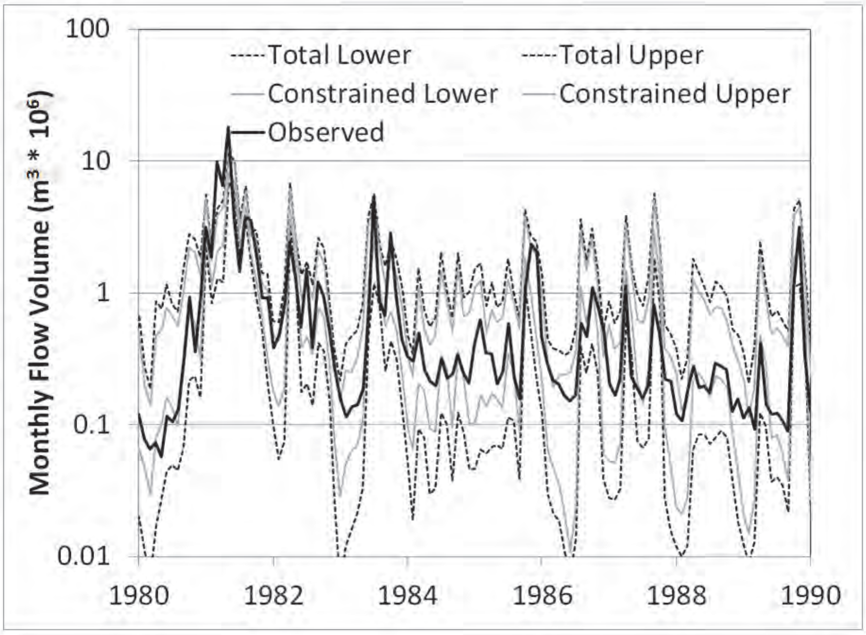


Figure 2.9 Diep River (K4H003): Time series of observed (black line) and the range of ensembles before (black dotted) and after (grey) applying constraints to step 3 (Table 2.2).

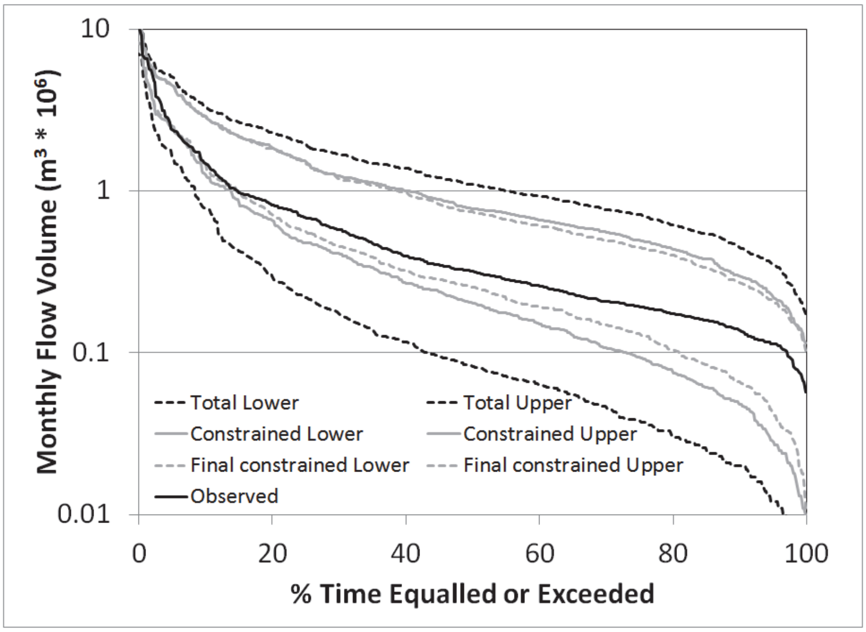


Figure 2.10 Diep River (K4H003): Flow duration curves of observed (black line), range of ensembles before (black dotted) and after (grey) applying constraints to step 3 and final range after step 4 (grey dotted).

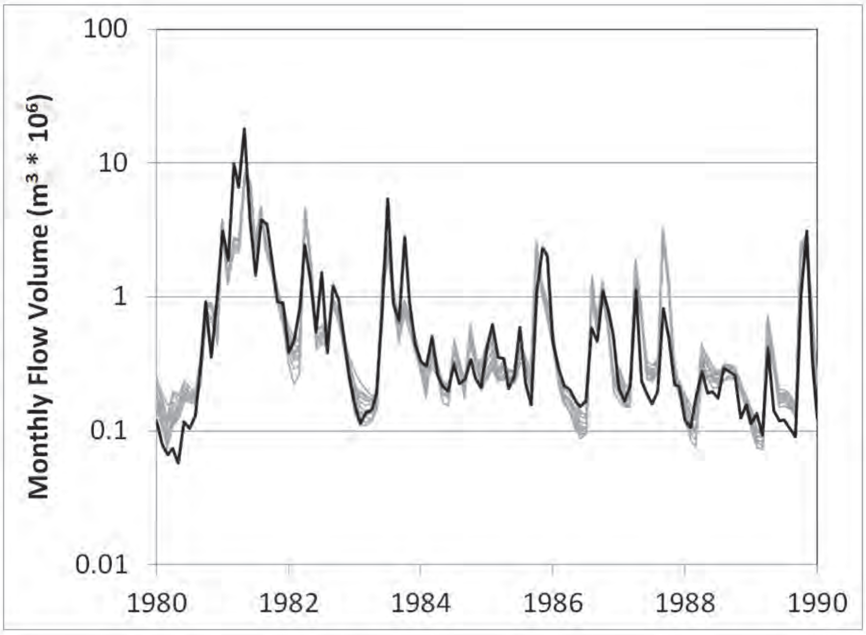


Figure 2.11 Diep River (K4H003): Time series of observed (black line) and the 11 'best' simulations selected from 10 000 ensembles (grey band) based on 5 objective functions (see text for details).

2.5.3 Caledon River Basin: Constraining natural flow simulations.

The Caledon River represents a much more complex example of uncertainty analysis for several reasons. The first reason is that there is a great deal of distributed water use (irrigation from farm dams and from the river, coupled with some municipal supplies) within the catchment that impacts on the interpretation of the observed stream flow data. These data are also very limited and there are no gauges to represent the steep mountain sub-catchments that drain the Lesotho parts of the basin (Figure 2.12). A further reason is that the whole uncertainty analysis becomes complicated by the differential effects of upstream sub-catchment uncertainty on the uncertainty outputs of downstream sub-catchments. The same type of constraint analysis used in the K40A analysis can therefore only be applied to headwater sub-catchments (i.e. no inflows from upstream areas that will have different parameters for any given member of the output ensemble).

One of the important issues is the grouping of the 31 quaternary catchments into groups that are assumed to have similar directions of uncertainty. This is important if the range of output uncertainty at the catchment outlet is to be reasonably consistent with the ranges of uncertainty in the upstream areas. This concept and the way in which the structured uncertainty version of the Pitman model has been coded were discussed in previous project report (Hughes et al., 2011). Table 2.4 lists the quaternary catchments, their groupings and some of the characteristics that have been used to determine the groupings. Table 2.5 lists the gauging stations that are available in the area, some of which were used to develop the regional constraints. As with the southern Cape example it was decided to use uniform distributions to represent the parameter uncertainty, thus avoiding the need for any assumptions about mean values, the shapes of the distributions (normal or log-normal) and the extent of any outliers.

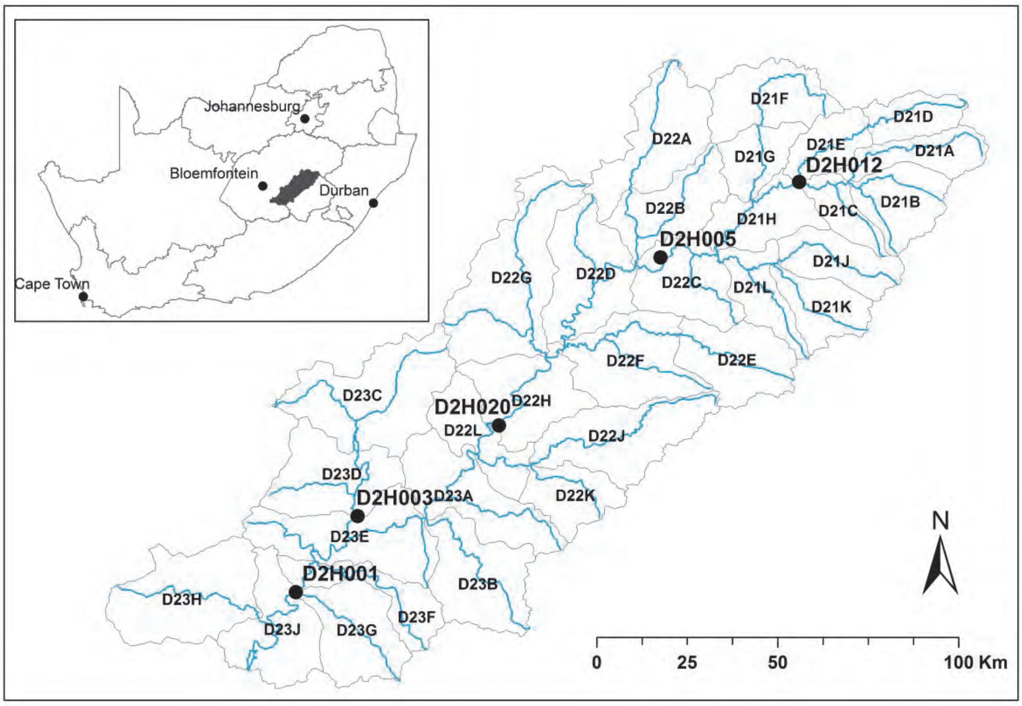


Figure 2.12 The Caledon River basin showing modelled sub-basins and some of the stream flow gauging stations.

Establishing the constraints: The same constraints were used as in K40A. The groundwater recharge data were obtained from DWAF (2005) and the range of uncertainty was based on the lowest recharge estimates of the three that are available in the GRAII (DWAF, 2005) database for the quaternary catchments falling into each group (Table 2.6, columns 4 and 5). The constraints given in Table 2.6 are in % rainfall and are dimensionalised for use with individual quaternary catchment by the mean monthly rainfalls used in the simulations (WR2005 data).

Table 2.5 provides information on most of the gauging stations that could be useful for setting the mean monthly flow and flow duration curve constraints. However, all of them have their limitations and some are of little value. Gauge D2H012 has a relatively long record, but is affected to some extent by poor high flow measurements and abstraction impacts on low to moderate flows. It also covers two of the quaternary groups. The observed (after some corrections to the high flows) mean monthly flow depth (5.4 mm) is expected to be under-estimated but not to the same extent that is reported in either WR90 (9.3 mm) or WR2005 (5.9 mm). The under-estimation is expected to effect the Q90 estimates the most.

Table 2.4 Uncertainty groups for the Caledon basin.

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

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

Table 2.5 Stream flow gauging stations

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

Gauge D2H003 represents group 3, the driest parts of the catchment, and has a record that pre-dates any of the large dams within this area. However, it is assumed that some distributed agricultural water use was occurring even before 1934 and therefore the observed data are expected to under-estimate flows, particularly low to moderate flows. The mean monthly observed flows of 1.6 mm are substantially lower than the values given in either

WR90 (3.8 mm) or WR2005 (3.1 mm) and it is difficult to justify an almost doubling in mean volume on the basis of the likely agricultural water use in the 1940's and 1950's.

Gauge D2H034 (representing group 2) will be heavily impacted by distributed agricultural water use and therefore the 2.9 mm mean monthly flow will definitely be an under-estimate. WR90 and WR2005 both suggest that the values should be in the region of 4.6 to 6 mm month^{-1}.

Gauges D1H006 and D1H032 both drain the eastern slopes of the Lesotho mountains and have very large mean monthly runoff values of 16.8 mm and 29.6 mm, respectively. Both of these catchments have more consistently steep and mountainous terrain than the Group 1 Caledon catchments and even more so for the Group 4 catchments. WR90 and WR2005 suggest mean monthly flows of between 13 mm and 22 mm for D1H006 and D1H032, respectively. Developing constraints for Groups 1 and 4 is therefore difficult because of the high variability.

The flow duration curve (FDC) constraints were based on the same gauges (with the same problems of interpretation) and all of the constraints are given in Table 2.6 (as unit runoff values or non-dimensional values). While it is accepted that some of the constraint boundaries are subjective, attempts have been made to ensure that they are at least realistic. Group 5 is made up of catchments in the lower parts of the catchment through which the main Caledon River flows. They have been allocated runoff and FDC constraints that are the same as Group 3 on the basis of the much lower rainfall in this area.

Table 2.6 Constraints developed for the quaternary catchment groups of the Caledon River basin.

	Mean monthly flow (mm)		Mean monthly recharge (% Rainfall)		Flow duration curve constraints (values are factors * mean monthly flow)					
					Q10		Q50		Q90	
Group	Min.	Max.	Min.	Max.	Min.	Max.	Min.	Max.	Min.	Max.
1	10.0	17.0	4.7	8.3	2.5	3.0	0.35	0.55	0.04	0.08
2	2.8	6.0	2.5	3.7	2.0	2.7	0.15	0.25	0.02	0.05
3	1.2	3.2	0.8	2.5	2.0	2.5	0.15	0.25	0.02	0.05
4	6.0	10.0	1.2	7.2	2.5	3.0	0.35	0.55	0.04	0.08
5	1.2	3.2	1.0	4.2	2.0	2.5	0.15	0.25	0.02	0.05

Stage 1 of the uncertainty analysis: Table 2.7 lists the parameter value ranges that have been used at the start of the first stage of the uncertainty analysis. The assumption is that these cover the range of likely values for all of the quaternaries and that some parameters (e.g. the interception parameter {PI}, routing parameter {TL} and the drainage density {DDENS}) can remain fixed as they are expected to have little influence on the ensemble outflows if their values are restricted to sensible ranges based on previous experience and the information on the physical basin properties. Most of the ranges have been set the same for all groups, while some are slightly different based on known physical catchment characteristics. POW has been fixed at a value of 3.0 to avoid the well-known interactions between POW and FT and because a value of 3.0 represents a relatively high degree of non-linearity in the relationship between soil moisture and interflow.

Table 2.7 Initial parameter ranges for all groups

Group	1		2		3		4		5	
Parameter	Min.	Max.	Min.	Max.	Min.	Max.	Min.	Max.	Min.	Max.
PI	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5
ZMIN	10	100	10	100	10	100	10	100	10	100
ZMEAN	Set at 0.5 * (ZMIN + ZMAX) for all Groups									
ZMAX	200	1000	200	1000	200	1000	200	1000	200	1000
ST	60	500	60	500	60	500	60	500	60	500
POW	3	3	3	3	3	3	3	3	3	3
FT	0	20	0	20	0	20	0	20	0	20
GW	5	50	5	50	5	50	5	50	5	50
R	0	1	0	1	0	1	0	1	0	1
TL	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
GPOW	3	6	3	6	3	6	3	6	3	6
DDENS	0.2	0.2	0.4	0.4	0.4	0.4	0.3	0.3	0.4	0.4
Trans	10	50	10	50	10	50	10	50	10	50
S	0.001	0.004	0.001	0.004	0.001	0.004	0.001	0.004	0.001	0.004
Slope	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011
Depth	25	25	25	25	25	25	25	25	25	25
Riparian	0.2	0.6	0.2	0.8	0.2	0.8	0.2	0.6	0.2	1.2

The first stage in the uncertainty analysis is to run 10 000 ensembles with the parameter ranges given in Table 2.7 and identify narrower parameter ranges for sample catchments in each group based upon the five output constraints listed in Table 2.6. This process is illustrated below using several representative catchments. The term ‘behavioural’ is used to distinguish those ensembles falling within the constraints.

Stage 1 constraint results for D23C (Group 3):

- The number of behavioural ensembles was reduced to 28 and most of the reductions resulted from the Q50 and Q90 constraints.
- Few of the individual parameter ranges were reduced (see Table 2.7 for the original ranges):
  - ZMIN range reduced to 30 → 100.
  - ZMAX range reduced to 400 → 994.
  - FT range reduced to 0.8 → 8.4.
  - R range reduced to 0 → 0.67.
- However, the range of some parameter combinations were substantially reduced:
  - The range of the ratio of GW/GPOW was reduced from 0.8 → 16.7 to 1.1 → 9.5.
  - The relationships between R (evapotranspiration parameter) and ST and FT suggested that only certain combinations of these parameters are behavioural (Figure 2.13). These suggest that if R is fixed to a specific value the range of other parameters can be further constrained. It was eventually decided to constrain R to between 0.4 and 0.6 and fix GPOW at 5, which allowed FT, GW and ST to be further constrained.
- The ranges that have been determined for stage 2 of the analysis are given in Table 2.8.
- As Group 5 has no sub-catchments that are not on the main Caledon River (and therefore the output flow metrics include upstream flows and cannot be compared to the constraints), the revised ranges for most parameters were set the same as for Group 3. The range for GW was increased to allow for the higher range of the recharge constraint.

Stage 1 constraint results for D22A (Group 2):

- The number of behavioural ensembles was reduced to 767 after applying the first three constraints, but only 3 and 2 ensembles remained after using the Q50 and Q90 constraints, respectively. There is a possibility that the constraints for this region are miss-matched and the Q50 upper constraint was relaxed to 0.35 (from 0.25 given in Table 2.6). This extended the number of final ensembles to 10.

- Similar effects were found for Group 2 as listed above for Group 3, including relationships between R and other parameters (see Figure 2.13). These allowed some parameters to be highly constrained.
- The revised parameter ranges for Group 2 are given in Table 2.8.

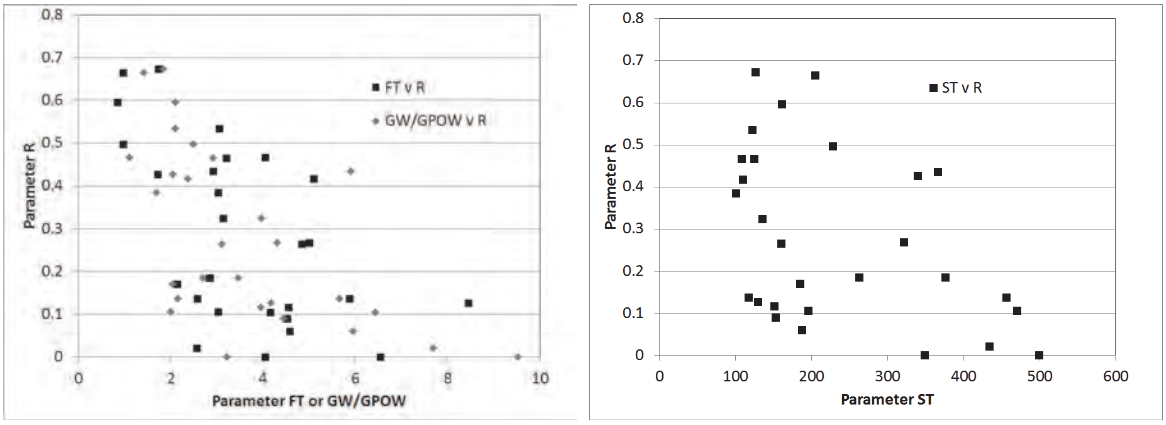


Figure 2.13 Behavioural relationships between parameter R and FT, GW/GPOW and ST for catchment D23C.

Stage 1 constraint results for D22J (Group 4):

- The number of behavioural ensembles was reduced to 233 after applying all five constraints with the FDC constraints having the biggest effect.
- There were very few reductions in the range of individual parameters (rather than relationships between parameters) and only the minimum value of ZMAX was increased (to 320).
- There are, however, some relationships between R values and other parameters as with the previous groups. It was again decided to fix the range of R to 0.4 to 0.6 and GPOW to 5, which helps to constrain some of the other parameters (Table 6.8).
- Although there is a weak relationship between R and ST, the biggest cluster of ST values (given 0.4≤R≤0.6) lies in the range of 100 to 250. Similar analyses of the results suggest constraints for GW and FT (Table 2.8).

Stage 1 constraint results for D21A (Group 1):

- The number of behavioural ensembles was reduced to 14, although the Q90 maximum constraint had to be increased to 0.15 to achieve this, implying some inconsistencies in the constraints affecting low flows (i.e. Q90 and recharge).
- There were very several reductions in the range of individual parameters (rather than relationships between parameters), including ZMAX, FT, GW, R, GPOW.
- There are some relationships between R values and other parameters as with the previous groups. It was decided to fix the range of R to 0.3 to 0.5 and fix GPOW at 5, which helps to constrain some of the other parameters (Table 2.8).

There are no headwater catchments that fall into group 5 and therefore the constraint analysis is more difficult. It was therefore decided to use the group 3 parameter ranges for group 5 with the exception of the Riparian parameter, which is expected to be higher in the main Caledon channel area.

The individual sub-catchment constraints were combined to assess the results at D23F (the location of D2H001). The mean monthly flow constraints were summed for all catchments, while the FDC constraints were calculated as relative area weighted sums. The recharge constraint is always a local constraint to the specific sub-catchment and does not need to be changed. The constraint analysis results for D23F resulted in 1 417 behavioural ensembles after the use of the first two constraints and 216 after applying the Q10 constraint. As might be expected, there were no ensembles that were also within the final two constraints (Q50 and Q90). The reason for this is that there are very few ensembles where individual sub-catchments fall within the local (i.e. specific sub-catchment) Q50 and Q90 constraints and therefore it is unlikely that these behavioural ensembles will be grouped together at the outlet of D23F. Thus there will always be combinations of upstream behavioural and non-behavioural results, leading to no downstream behavioural results. The objective of stage 2 is therefore mainly to increase the sample size of behavioural ensembles in the expectation that these will be combined to generate at least some downstream behavioural results.

Stage 2 of the uncertainty analysis: On the basis of the stage 1 results, which found that most of the reductions in ensemble numbers were associated with the Q50 and Q90 constraints, it is clear that the main focus of the stage 2 assessment should be on low flows. This is supported by the fact that no low flow behavioural ensembles are found in the downstream areas (D23F).

Stage 2 constraint results for D23C (Group 3):

- The number of behavioural ensembles was increased to 1560 and as with stage 1 most of the reductions resulted from the Q50 and Q90 constraints.
- None of the individual parameter ranges were reduced but there were clear indications of more frequent parameter values within the behavioural ensembles and there were more frequent combinations of certain variables than other combinations.
- It was also noted that there are more ensembles greater than the maximum Q90 constraint than there are below the minimum Q90 constraint and therefore the minimum value (1.0) of FT may be too high and the range has been shifted downwards.
- The revised parameter ranges are given in Table 2.9.
- As group 5 parameter ranges and constraints are the same it was decided to eliminate group and make all of those catchments behave in the same direction as group 3, except for the Riparian parameter which remains as group 5 with generally higher values.

Stage 2 constraint results for D22A (Group 2):

- The number of behavioural ensembles was 339 and as with stage 1 most of the reductions resulted from the Q50 and Q90 constraints. The maximum Q50 constraint was increased during stage 1 and this clearly has affected stage 2 in that most of the ensembles did not reach as low as the minimum constraint values for Q10 to Q50. This result was borne out by checking D21F, which also falls within group 2. In this catchment only 10 ensembles were behavioural and the parameter ranges suggest lower values of FT and GW than the minimums given in Table 2.8.
- The revised parameter ranges for group 2 are given in Table 2.9.

Stage 2 constraint results for D22J (Group 4):

- The number of behavioural ensembles was 1256.
- The revised parameter ranges for group 2 are given in Table 2.9.

Stage 2 constraint results for D21A (Group 1):

- The number of behavioural ensembles was reduced to 6 and this is partly a consequence of allowing the Q90 maximum to be increased to 0.15 in stage 1.
- There were very several reductions in the range of individual parameters including ZMIN, ZMAX, FT, GW, R, S and T.

- The FT and GW lower limits were reduced to below the minimum values of stage 1 to try and extend the number of low flow ensembles (Table 2.9).

Table 2.8 Parameter ranges for all groups after stage 1.

Group	1		2		3		4		5	
Parameter	Min.	Max.	Min.	Max.	Min.	Max.	Min.	Max.	Min.	Max.
PI	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5
ZMIN	10	100	35	90	30	100	10	100	30	100
ZMEAN	Set at 0.5 * (ZMIN + ZMAX) for all Groups									
ZMAX	400	1000	400	1000	400	1000	320	1000	400	1000
ST	120	190	100	160	100	220	100	250	100	220
POW	3	3	3	3	3	3	3	3	3	3
FT	2.5	6.0	2.0	4.8	1.0	4.0	2.5	8.0	1.0	4.0
GW	16	30	16	19	5	15	8	28	5	20
R	0.3	0.5	0.4	0.6	0.4	0.6	0.4	0.6	0.4	0.6
TL	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
GPOW	5	5	5	5	5	5	5	5	5	5
DDENS	0.2	0.2	0.4	0.4	0.4	0.4	0.3	0.3	0.4	0.4
Trans	24	50	35	40	10	50	10	50	10	50
S	0.001	0.003	0.001	0.004	0.001	0.004	0.001	0.004	0.001	0.004
Slope	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011
Depth	25	25	25	25	25	25	25	25	25	25
Riparian	0.2	0.6	0.5	0.6	0.2	0.8	0.2	0.6	0.2	1.2

Table 2.9 Parameter ranges for all groups after stage 2.

Group	1		2		3		4		5	
Parameter	Min.	Max.	Min.	Max.	Min.	Max.	Min.	Max.	Min.	Max.
PI	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	n/a	n/a
ZMIN	40	80	80	90	30	80	30	80	n/a	n/a
ZMEAN	Set at 0.5 * (ZMIN + ZMAX) for all Groups									
ZMAX	470	970	470	900	650	800	450	700	n/a	n/a
ST	120	140	130	160	110	160	110	140	n/a	n/a
POW	3	3	3	3	3	3	3	3	n/a	n/a
FT	2.0	4.5	1.0	3.8	0.0	3.0	3.5	7.0	n/a	n/a
GW	12	22	12	18	5	12	12	25	n/a	n/a
R	0.3	0.45	0.4	0.5	0.4	0.5	0.4	0.6	n/a	n/a
TL	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	n/a	n/a
GPOW	5	5	5	5	5	5	5	5	n/a	n/a
DDENS	0.2	0.2	0.4	0.4	0.4	0.4	0.3	0.3	n/a	n/a
Trans	40	50	35	40	30	50	10	50	n/a	n/a
S	0.001	0.001	0.001	0.004	0.001	0.003	0.001	0.004	n/a	n/a

Group	1		2		3		4		5	
Parameter	Min.	Max.	Min.	Max.	Min.	Max.	Min.	Max.	Min.	Max.
Slope	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	n/a	n/a
Depth	25	25	25	25	25	25	25	25	n/a	n/a
Riparian	0.3	0.6	0.5	0.6	0.4	0.8	0.2	0.6	0.8	1.2

Stage 3 of the uncertainty analysis: The main objective of the stage 3 analysis is to generate a sufficiently large number of behavioural ensembles at the gauged catchment D23F (D2H001) to allow for uncertainty bands to be drawn, but within the constraints. Essentially this requires that there are a relatively large number of behavioural ensembles in each of the headwater catchments to allow for random combinations that are both behavioural and non-behavioural at the downstream assessment point.

Stage 3 constraint results for D23C (Group 3):

- The number of behavioural ensembles was increased to 4166 with most of the non-behavioural ensembles falling into the Q50<0.15 range (i.e. under-simulated in moderate flows).

Stage 3 constraint results for D22A (Group 2):

- The number of behavioural ensembles was increased to 1412 with a relatively large number under-simulating the recharge minimum constraint. Within the recharge constrained group, most of the non-behavioural simulations over-estimated Q50 and Q90. The implication is that the recharge and moderate to low flow constraints are not very compatible. This will always be a potential problem area as the two constraints are based on very different data and analyses.

Stage 3 constraint results for D22J (Group 4):

- The number of behavioural ensembles was increased to 3361. The highest possible values of the recharge, Q10 and Q50 metrics were not represented in the behavioural ensemble set.

Stage 3 constraint results for D21A (Group 1):

- The number of behavioural ensembles was increased to 2097. Within this ensemble set the highest possible recharge and Q50 values were not represented, and neither were the lowest possible Q10 and Q90 values. However, overall the behavioural ensemble set represents the range of constraints quite well.

The final step in the analysis of the stage 3 results is to compare the outputs at key gauging stations, bearing in mind that these represent developed conditions and probably non-stationary time series with respect to water use. However, before this can be achieved it is necessary to calculate appropriate constraints at the downstream sites. The mean monthly flow (MMQ) constraint can be estimated as the sum of the upstream MMQ constraints, while the recharge constraint is local to the downstream quaternary and remains the same. The FDC constraints (Q10, Q50 and Q90) could be based on catchment area weighting or on mean monthly flow weighting and it was decided to use the latter. The other issue is that behavioural downstream ensembles may be combined with non-behavioural upstream ensembles (over- or under-simulations in some upstream areas being compensated for with under- or over-simulations in other catchments). This can be resolved when only two or three sub-catchments are involved (by selecting those ensembles that are only behavioural throughout the total catchment), but is much more difficult for the total catchment when over 30 sub-catchments are involved. Strictly speaking, to achieve a totally correct result downstream it would be necessary to further constrain all of the upstream ensembles until they are all locally behavioural. Given the equifinality in the model, this is almost certainly not possible. The output results for stage 3 are compared with previous estimates of uncertainty ranges that were largely based on subjective estimations of normal distributed parameter uncertainties.

Stage 3 results at D2H012 (D21D and D21E): The use of integrated constraints for the outlet of D21E led to 4744 behavioural ensembles, while D21D had a total of 3082 behavioural ensembles. 1696 ensembles were jointly behavioural for the headwater catchment (D21D – Group 1) and the downstream catchment (D21D – Group 2) and these have been used to plot the full range of uncertainty in Figure 2.14. In this example the observed data have been approximately corrected for under-measurement of high flows and for the effects of farm dams. The old (stage 2) and new (stage 3) uncertainty ranges are not very different, although the new range is slightly wider particularly at high flows.

Stage 3 results at D2H003 (D23C and D23D): The use of integrated constraints for the outlet of D23D led to 4573 behavioural ensembles, while D23C had a total of 4166 behavioural ensembles. 2552 ensembles were jointly behavioural for both catchments (both in Group 3) and these have been used to plot the full range of uncertainty in Figure 2.15. The new bands of uncertainty appear to be similar to the old simulations, with the width of the range being somewhat higher for the high flows, which is probably a better reflection of the real uncertainty.

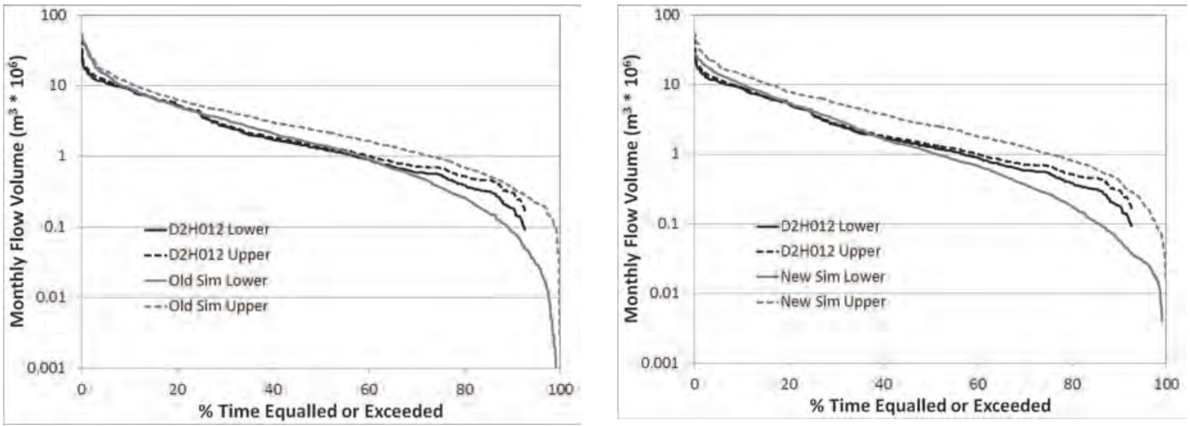


Figure 2.14 Comparison between the previous uncertainty results (Left side) and those based on the constraint analysis (Right side) with patched observed data for D2H012.

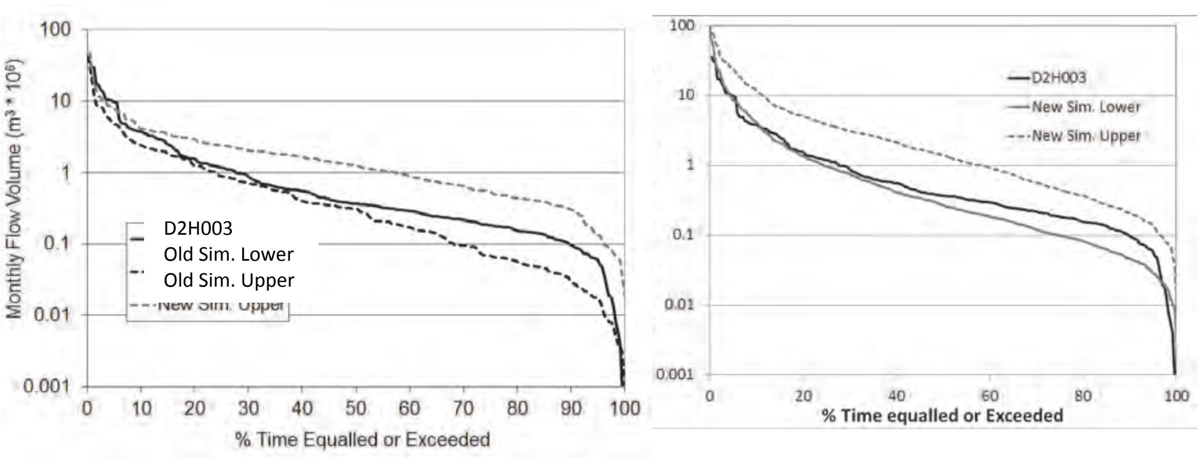


Figure 2.15 Comparison between the previous uncertainty results (Left side) and those based on the constraint analysis (Right side) with patched observed data for D2H003.

Stage 3 results at D2H001 (outlet of D23F): It is not really possible to select only those ensembles that are behavioural throughout the catchment above D23F as this would entail a great deal of ensemble matching. It would be possible to automate this, but such an approach has not been developed yet and at present most of this type of analysis relies upon the use of spreadsheets. The uncertainty bands plotted in Figure 2.16 therefore reflect the ensembles that are behavioural at D23F regardless of whether the contributing catchments are also behavioural. It is apparent that the main effect has been to reduce the moderate to high flows and to increase the range of uncertainty in most parts of the FDC.

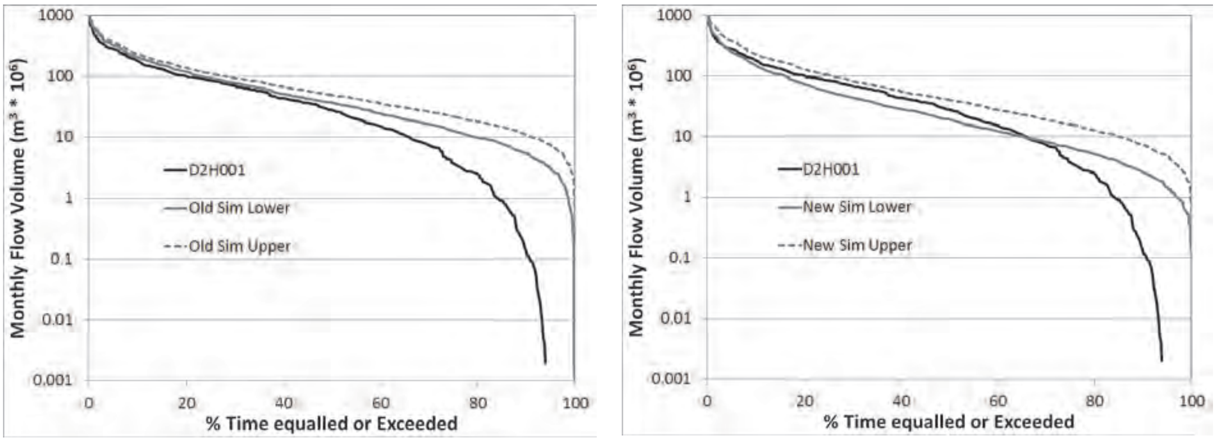


Figure 2.16 Comparison between the previous uncertainty results (Left side) and those based on the constraint analysis (Right side) with patched observed data for D2H001.

General comments: More confidence can be expressed in the revised uncertainty ranges because they are based on better defined constraints than previously. The constraints have been used to reduce the initial range of parameter values to ones that are considered behavioural for each of the sub-catchments. However, this means that only the behavioural ensembles have to be selected from the full set, a process that currently involves quite a substantial effort in the use of the sorting facilities of spreadsheets for each of the stages of the uncertainty analysis. If this type of approach is likely to be useful in practice it requires further automation through the creation of a post-processing method that allows for various methods of analyzing the full details of the output ensembles. This will be addressed for the next deliverable on practical approaches to uncertainty assessment.

2.5.4 Caledon River Basin example for developed conditions.

Previous estimates of water use for irrigation from the farm dams were largely based on the farm dam volumes. However, additional information provided from WRP Consultants suggests that the original estimates of irrigation areas could be very under-estimated. The extent to which this is likely to impact on downstream flows largely depends on whether the WRP estimates are realistic, as well as whether the estimates of farm dam volumes (as well as the simulated inflows) can support such expanded irrigation areas. This also depends to a certain extent on the seasonal distributions of water use. If the majority of the seasonal water use for irrigation is during the dry winter months, then it will largely have to be met from storage with minimal inflows. However, if part of the requirement is within months of higher flow then wet season storage will be used and more upstream inflows will be intercepted by the farm dams, causing reduced downstream flows. In revising the water use estimates a more detailed assessment of Google Earth images was employed together with a comparison between the original estimates and the WRP estimates. The overall conclusion was that there remains a large degree of uncertainty in any of the estimates as it is not always possible to distinguish between dryland farming and irrigated agriculture. It is evident, however, that the WRP estimates appear to be extremely high in many areas (Table 2.10).

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

The data provided by WRP was very useful in terms of identifying the dominant crop types and therefore improving the estimates of seasonal distribution of water use. The crops are dominated by pasture/lucerne (25%), maize (25%), maize/wheat (18%) and wheat (13%). It is very possible that many of the summer grain crops are in fact not irrigated most of the time. The seasonal distribution of irrigation requirements that was used in the present day uncertainty analysis was therefore a weighted distribution dominated by lucerne and wheat (based on WR90 data) and is given in Table 2.11. It is, however, accepted that the validity of this distribution is substantially uncertain.

In assessing the results of the present day uncertainty model runs, it must be noted that not all of the ensembles can be considered behavioural from a natural hydrology perspective. However, as the output summary statistics include the effects of variability in the natural and water use parameter sets, it is very difficult to isolate the uncertainties and only select those ensembles that are naturally behavioural. This is a serious shortcoming of the uncertainty approach and will be difficult to overcome unless natural parameter uncertainty ranges are established that result in all 10 000 ensembles being behavioural. This, however, is not straightforward to achieve as it is not only individual parameter value ranges that affect whether a result is behavioural or not, but also the combinations of parameter values. Filtering out the results (i.e. rejecting non-behavioural natural simulations) during the model run would be possible, but would be achieved at the expense of much longer model runs. This is because the natural simulations would have to be assessed first (before adding abstraction impacts) and some would be rejected and the parameter space re-sampled. Obtaining 10 000 final ensembles would therefore require many more model runs.

Table 2.10 Dam volumes ($m^3 * 10^6$) and irrigation areas (km^2) estimated by different methods (domestic direct abstractions are in $m^3 * 10^3 y^{-1}$).

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

Table 2.11 Seasonal distribution of irrigation requirements (mm)

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

The analyses presented below are based on the locations where there are some observed data. The results are presented as frequency distributions of Q10, Q50 and Q90 simulated values for natural conditions (total ensemble set and behavioural results) and present day conditions (total ensemble set). Any shifts in the distribution of the total ensemble set for present day conditions to account for behavioural natural simulations can be inferred from the two natural flow distributions.

Present day results at D2H012 (D21D and D21E): Figure 2.17 illustrates the results for the outlet of D21D. There are not large differences in the two frequency distributions for natural conditions and therefore there is no real need to consider shifts in the present day distributions. The observed data suggest values for Q10, Q50 and Q90 of 8.7, 1.1 and 0.08 $m^3 * 10^6$, respectively. The higher flows are expected to be under-represented (poor high flow gauging), while the record starts in 1966 and might represent somewhat lower water use than has been accepted for the present day. The simulation results therefore can be considered to be representative based on the available evidence. However, there are some indications that the lower estimates of water use (Table 2.10) are perhaps more appropriate than the higher values.

Present day results at D2H034 (D22A and D22B): These sub-catchments were not evaluated in detail during the natural simulation tests, but a recently built (1991) gauge is available to assess the results. Both sub-catchments have a large number of farm dams and apparently a substantial amount of irrigation. All of the water use has been assumed to be extracted from farm dams, while the % catchment areas contributing has been set to 90% and 85% for D22A and D22B. This means that despite the large volumes of water abstracted, the simulations do not show zero flows (Table 2.12), while there are zero flows for approximately 35% of the time in the observed record. It is possible that some of the irrigation requirements are satisfied by pumping direct from the river. A reservoir supplying Ficksburg has been included in the simulation at the outlet of D22B and therefore it is quite surprising that zero flows are not simulated. This issue would have to be further investigated as part of a refinement of the present day uncertainty model runs. The observed data values for Q10 and Q50 fall within the (rather large) uncertainty range.

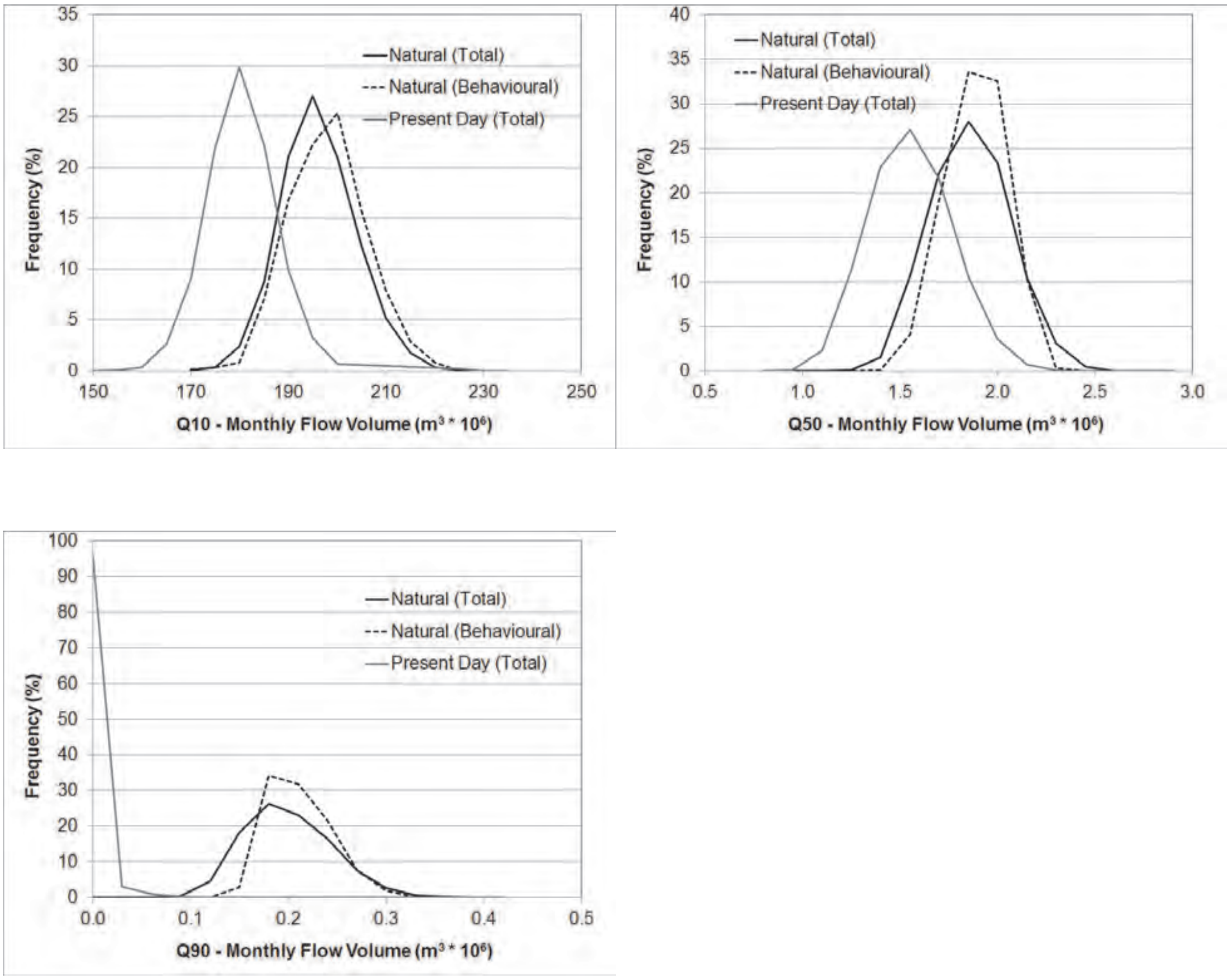


Figure 2.17 D21E (D2H012): Comparison between the frequency distributions of simulated Q10, Q50, Q90 for natural conditions (all ensembles and only behavioural ensembles) and for present day conditions (all ensembles).

Table 2.12 Simulation results compared with observed flows for D22B and D2H034 (all values given in $m^3 * 10^6 month^{-1}$).

	Simulation range	Observed
Q10	4.36 to 11.51	9.22
Q50	0.07 to 1.35	0.38
Q90	0.006 to 0.038	0.00

Present day results at D2H003 (D23C and D23D): The observed record at D2H003 is an old record and not expected to reflect present day conditions. However, a similar frequency analysis to that done for D21E has been undertaken for these sub-catchments (Figure 2.18) and the position of the observed data points has been included as arrows. As might be expected in this intensively cultivated area, the differences between natural and present day are very large even for the Q10 flows. There are a number of major reservoirs in this part of the Caledon and the agricultural water use is expected to be very high.

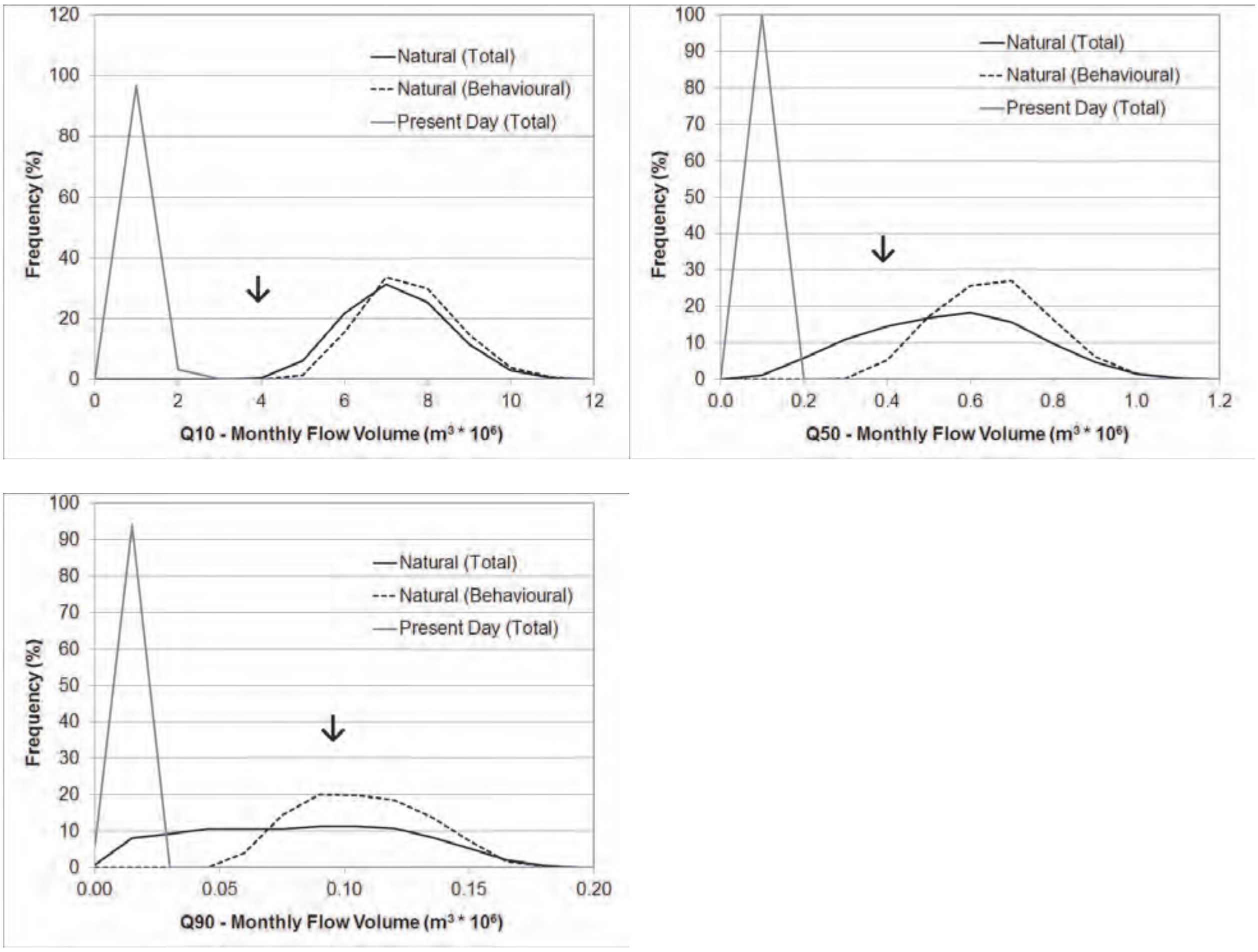


Figure 2.18 D23D (D2H003): Comparison between the frequency distributions of simulated Q10, Q50, Q90 for natural conditions (all ensembles and only behavioural ensembles) and for present day conditions (all ensembles).

With respect to comparisons between the simulated and observed data, it is more difficult to be conclusive as the records are from 1935 to 1954 when there would have been some water use but much less than today. It is also unlikely that high flows have been measured with a great deal of accuracy leading to under-representation of flow volumes at Q10 and Q50 (as illustrated in Figure 2.18). As with D21E, there is unfortunately not enough information to adequately validate the model results, nor to reduce the uncertainty any further. It is interesting to note that there is much more agreement between the different sources of information about irrigations areas for these catchments than in most of the other parts of the basin.

Present day results at D2H001 (Outlet of D23F): Figure 2.19 presents the frequency results for D23F and as might be expected the difference between the total and behavioural distributions for natural conditions are quite large. This is related to the 'mixing' of all simulations from upstream catchments. The arrows on the figures indicate the positions of the observed values for Q10, Q50 and Q90, the first two being quite uncertain due to the need to correct the high flow observations at the gauging station.

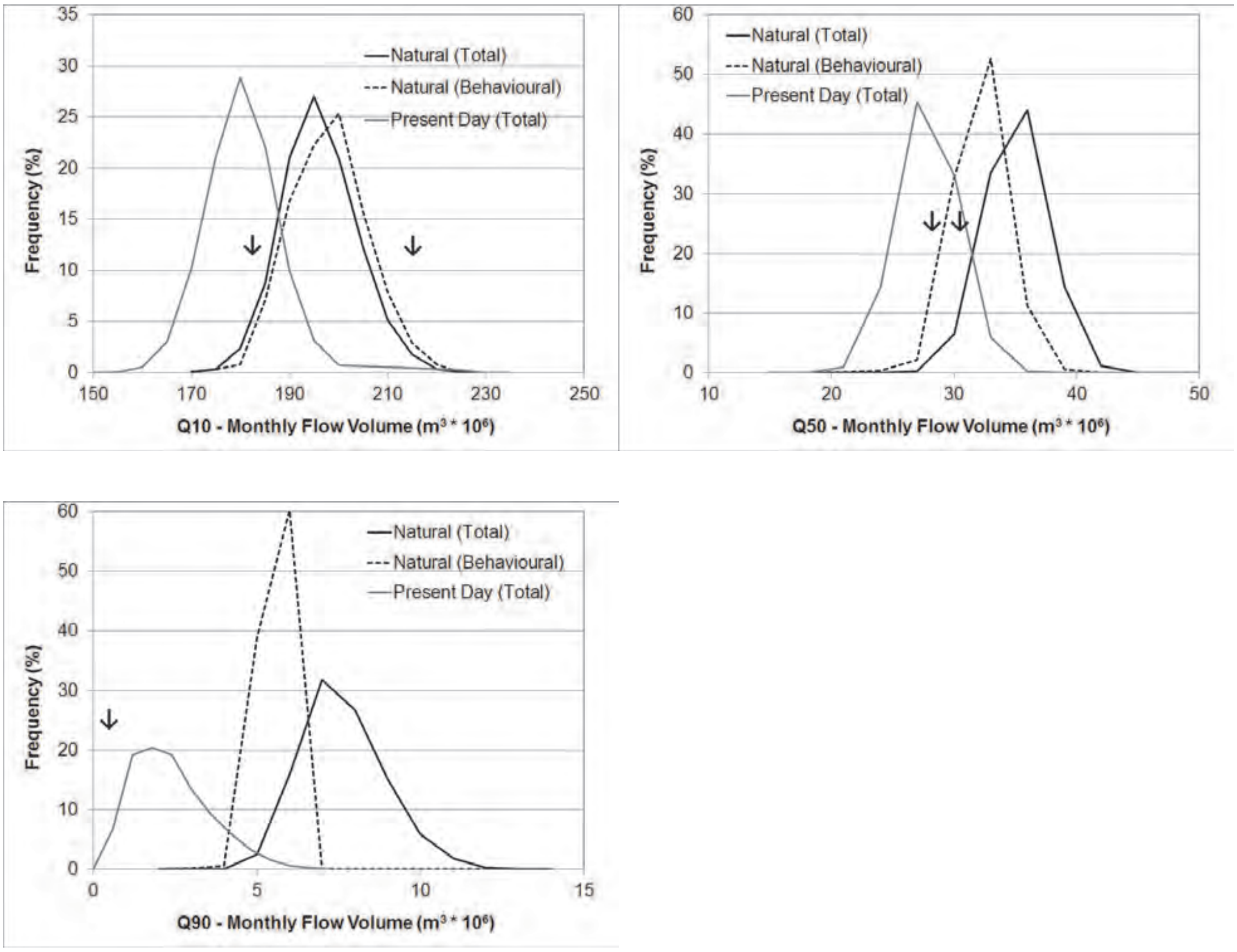


Figure 2.19 D23F (D2H001): Comparison between the frequency distributions of simulated Q10, Q50, Q90 for natural conditions (all ensembles and only behavioural ensembles) and for present day conditions (all ensembles).

There is very little shift in the behavioural Q10 simulations (from the total ensemble set), but surprisingly the present day simulations show quite a large impact. This result may be somewhat counter-intuitive given that the main abstractions are based on relatively small farm dam storage or direct abstractions (rather than large impoundments which might be expected to attenuate high flows). However, this result was carefully checked and does appear to be realistic, given that the model includes quite a large amount of irrigation even during the wet season. There is a substantial downward shift in the natural behavioural simulations relative to the total and therefore the fully behavioural present day simulations would be expected to similarly shifted to the left. This is reasonably consistent with the observed data (1927 to 1973) which would, arguably, be expected to over-represent moderate to low flows under more intensive water use in present day conditions. Similarly, the present day low flow (Q90) distribution is expected to be shifted to the left if non-behavioural natural flows were excluded and this would introduce a much higher frequency of very low flows that would be similar to (or even less than) the observed Q90 value (0.12 $m^3 * 10^6$).

Despite the assumed limitations of the observed data in terms of representing present day conditions it is nevertheless useful to look at the range of objective functions of the full ensemble set (Table 2.13). The results are surprisingly good given the very large uncertainties that have been included as part of the model and the fact that the level of development in the observed sequence is non-stationary and increases over time. The time series for the best overall ensemble member are shown in Figure 2.20.

Table 2.13 Objective functions measuring the goodness of fit between the simulated present day ensembles and observed data at D2H001 (Coeff. Eff. is the Nash-Sutcliffe coefficient).

Objective Function	Range for all ensembles	Best overall	No. ensembles better or equal to	
Coeff. Eff.	0.668 to 0.742	0.715	0.7	7391
Coeff. Eff. (ln values)	0.179 to 0.469	0.469	0.4	626
% Monthly bias	-28.7 to 7.8	-14.1	± 10.0	2537
% Monthly bias (ln values	-9.9 to 20.0	8.2	± 10.0	6551

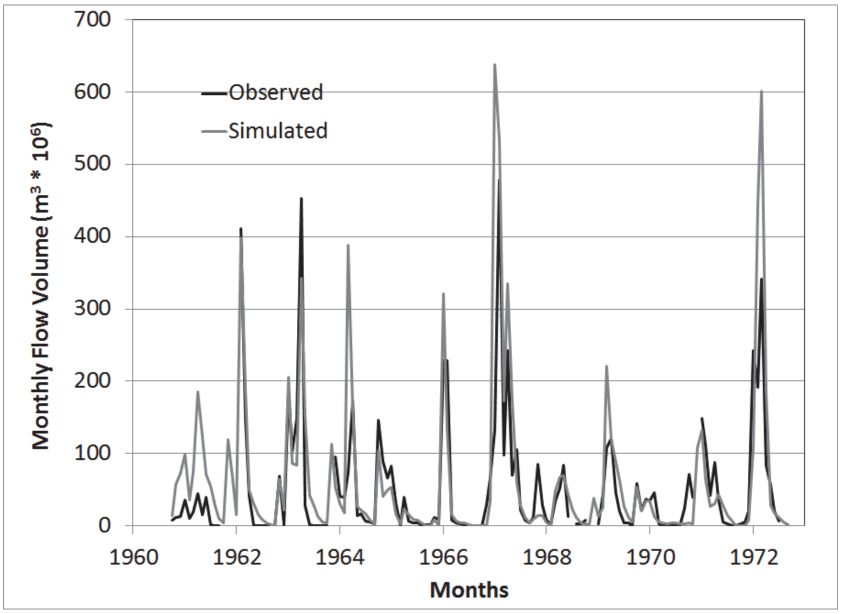


Figure 2.20 Observed versus simulated flow for the ensemble member with the best overall values for the objective functions (see Table 2.13, column 3).

Caledon River Basin – summary of uncertainty sources and reduction: The Caledon River basin represents a very good practical example of uncertainty analysis in hydrology as there are so many sources of uncertainty and very little observed data to resolve the uncertainties. The sub-sections below summarise the main uncertainties as well as the attempts that have been made in this study to reduce them.

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

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

Natural hydrology parameter values: The report has detailed a 3-stage process that involved the use of four constraints on the model outputs and a detailed examination of the parameter space for behavioural and non-behavioural ensembles. As with the Southern Cape example, it was found that the initial parameter ranges could be quite significantly reduced and the number of behavioural ensembles increased. The process is much more complex in the Caledon because of the number of sub-catchments and the interactions between them when examining the outputs at downstream sub-catchments. This process was, however, made slightly easier by grouping the sub-basins on the basis of their expected physical properties.

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

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

2.6 SUMMARY OF UNCERTAINTY REDUCTION

The final part of this chapter concentrated on two quite detailed uncertainty reduction attempts in the Diep River (single sub-catchment) and Caledon River (31 sub-catchments) basins. It is essential to note that these assessments resulted in some reduction in uncertainty but involved a considerable amount of detailed analysis of the simulation ensembles (both parameter space and output results) that was mostly carried out using spreadsheets. This is very time consuming and is not practical for normal operational model use. One of the options is to develop software that can be used to post-process the ensemble data and automatically perform the type of analyses that have been done for this study. It can also be noted that performing uncertainty analyses on large basins with many sub-catchments is very difficult and confusing. There is simply such a large uncertainty space (even without uncertain climate inputs) that resolving the interactions and the inter-dependencies is almost impossible. One of the main conclusions is that while there are approaches that can be used to reduce uncertainty, they can become quite time-consuming and are therefore unlikely to be adopted in practice unless they are supported by efficient and effective means of implementing them. This is always a major problem when it comes to applying uncertainty principles in practice – adopting new approaches to either the application of models or the use of model outputs (in decision-making) is always constrained by the traditional practices of the user group and reluctance to adopt new methods unless they are fully supported by efficient and reliable software. The next chapter is related to the use of uncertainty methods in practice and will address some of these issues in more detail and describe some of the software enhancements that have been developed to try and resolve some of the practical concerns.

3. PRACTICAL ISSUES OF UNCERTAINTY ANALYSIS

Introducing uncertainty analyses into standard modelling practice will never be achieved if the efforts and computer run-time required to obtain a result are excessive. It is therefore essential that these problems are addressed. The previous chapter outlined a process of uncertainty analysis that involves the use of local or regional constraints on hydrological behavior, but the analysis was performed manually once the ensembles had been generated. This is clearly not a practical approach and led to the development of an alternative two-step approach.

3.1 Revised approach to uncertainty analysis for the pitman model

The structured uncertainty approach that was used for the Caledon River example discussed in Chapter 2 (and for previous uncertainty assessments in this project) works very well for single or headwater catchments and is relatively practical to implement. The output ensemble time series results are written to the SPATSIM database, while summary data (including the values of the constraints referred to above) and all parameter values are written to a text file. It is relatively straightforward to sort the output file using constraint values and identify those ensembles that can be considered behavioural based on whether the results fall within the bounds of the regional constraints. However, this process is not straightforward for basins with many sub-catchments. The previous project identified the problem of uncertainty being largely cancelled out if simple independent random sampling is used across all sub-basins. The uncertainty in the headwater catchments is adequately defined by the input parameter ranges, but the downstream uncertainty is substantially reduced as both generally higher and lower flow simulations from the sub-basins are mixed to generate the downstream ensembles (Figure 3.1). This approach was later replaced with a structured sampling method that uses sub-basin groups within which the uncertainty always moves in the same direction for a specific parameter (i.e. increasing a parameter in one sub-basin of the group will be associated with similar increases in the same parameter for the other groups). The method also involved a prior estimate of what would be expected in the downstream uncertainty and rejected some samples to ensure that these expectations were met. The details of this structured sampling approach are not provided here, largely because a new approach has now been adopted. Figure 3.2 provides an example to compare with Figure 3.1 and it is clear that the uncertainty is better preserved with the structured approach.

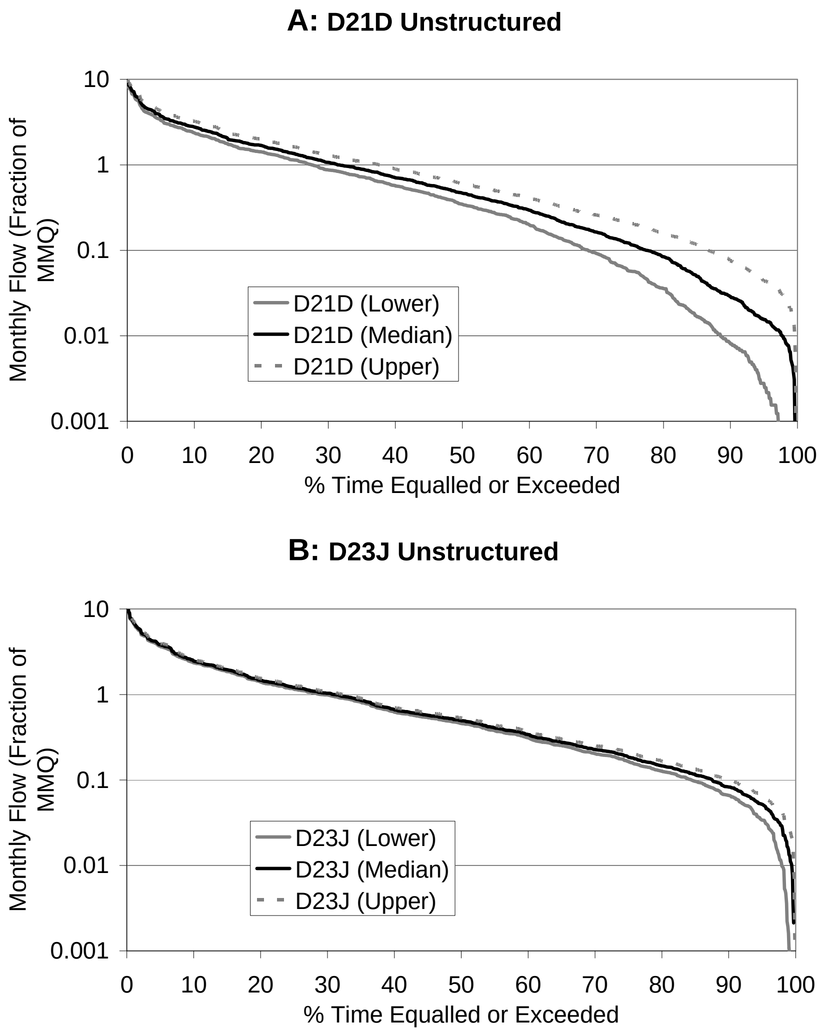
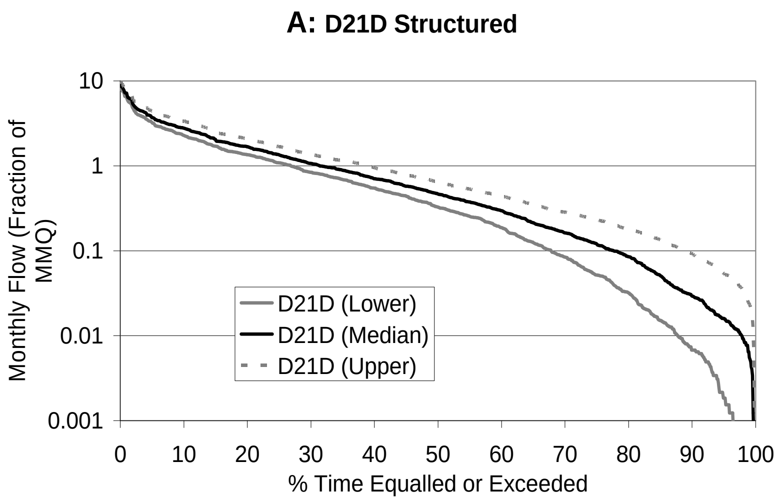


Figure 3.1 Unstructured sampling: Upstream (A) and downstream (B) uncertain flow duration curves for the Caledon River with 31 sub-basins (based on 90% of all output ensembles from a model run using 10 000 samples).

While the structured approach to sampling largely preserves the uncertainty, a problem exists with the post-modelling analysis of the results with respect to regional constraints and the selection of ensemble time series to carry forward into further analysis using a yield model or any other kind of water resources assessment. The essence of the problem is that we can select downstream ensembles that lie within some behavioural criteria (regional constraints or uncertain bounds around observed flow data), but it is quite difficult and time consuming to identify those ensembles that are behavioural for all sub-basins within the basin as a whole. Thus, we can find behavioural downstream ensembles that can be made up of complex mixtures of behavioural and non-behavioural upstream inputs. It is therefore quite likely that out of 10 000 ensembles a very small number (if any) are made up of behavioural ensembles everywhere and the identification of which these are is very time consuming. This problem prompted a different approach that involves 2 steps and which is explained in the following sections of the report.



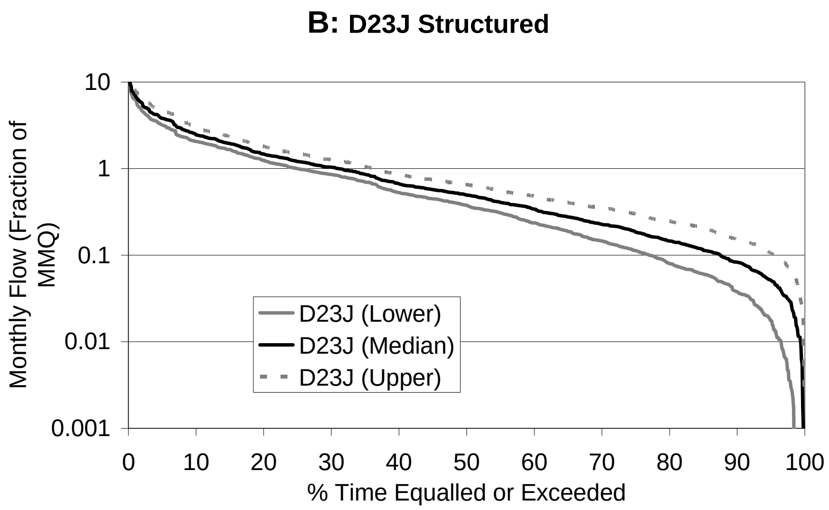


Figure 3.2 Structured sampling: Upstream (A) and downstream (B) uncertain flow duration curves for the Caledon River with 31 sub-basins (based on 90% of all output ensembles from a model run using 10 000 samples).

3.1.1 Step 1 in the revised approach for simulating uncertainty ensembles

Step 1 involves reading in regional constraint bounds as an additional input to the model. These constraint bounds may be obtained by different methods, some of which were discussed in Chapter 2 and were largely based on observed flow data within the region. It is also possible that the constraint bounds could be very small if observed data are available for a specific sub-basin. Effectively, the width of these bounds represents the uncertainty in our knowledge of the hydrological response of the each sub-basin given the climate inputs used with the model. Setting these bounds is therefore a critical component in terms of representing realistic uncertainty in the output ensembles.

The first step of the new model approach is designed to have uncertainty only applied to the natural runoff parameters of the model and therefore the constraints are associated with natural runoff characteristics. Uncertainty in the water, or land use, parameters are included as part of step 2. Step 1 only simulates incremental flows in each sub-basin and makes no attempt to route or sum flows in a downstream direction. The model is run repeatedly for up to a maximum of 100 000 times on each sub-basin and for each ensemble the simulated values of 5 constraints are calculated and compared with the input regional/observed constraints. If the simulations fall within the regional constraint bounds then the full parameter set and the constraint values are saved back to the SPATSIM database. This process is repeated until 2 000 parameter sets have been saved or until the limit of 100 000 model runs has been reached for that sub-basin. The process is based on simple random sampling of all the input parameter ranges (either normally or uniformally distributed probability density functions) and no attempt is made to search the parameter space to optimize the parameters that generate results to find outputs within the regional constraint bounds. The five constraints used in the current version of the software are MMQ (mean monthly runoff in $m^3 * 10^6$), MMR (mean monthly groundwater recharge in mm), Q10, Q50, Q90 (percentage points of the flow duration curve expressed as a fraction of MMQ) and %Zero (% number of months of zero flows).

Figure 3.3 illustrates the approach used in Step 1 and three possible extremes of outcome. In Figure 3.3A the parameter bounds and constraint bounds are compatible, and the constraint bounds are compatible with each other. The outcome is that the required 2 000 parameter sets are found quite quickly and it is likely that far less than 100 000 test runs of the model would be needed. Figure 3.3B illustrates a situation where the constraint bounds are not compatible with each other and therefore no ensembles are found that meet all of the behavioural requirements. This situation could arise, for example, if the mean monthly recharge constraint is inconsistent with the Q90 and % zero flow constraints. Figure 3.3C illustrates a situation where the 'cloud' of test model results is largely inconsistent with the constraints. This situation could occur if the parameter bounds reflect sub-humid runoff characteristics (relatively high baseflows), while the constraints are based on assumptions of arid conditions (low baseflows and some zero flows).

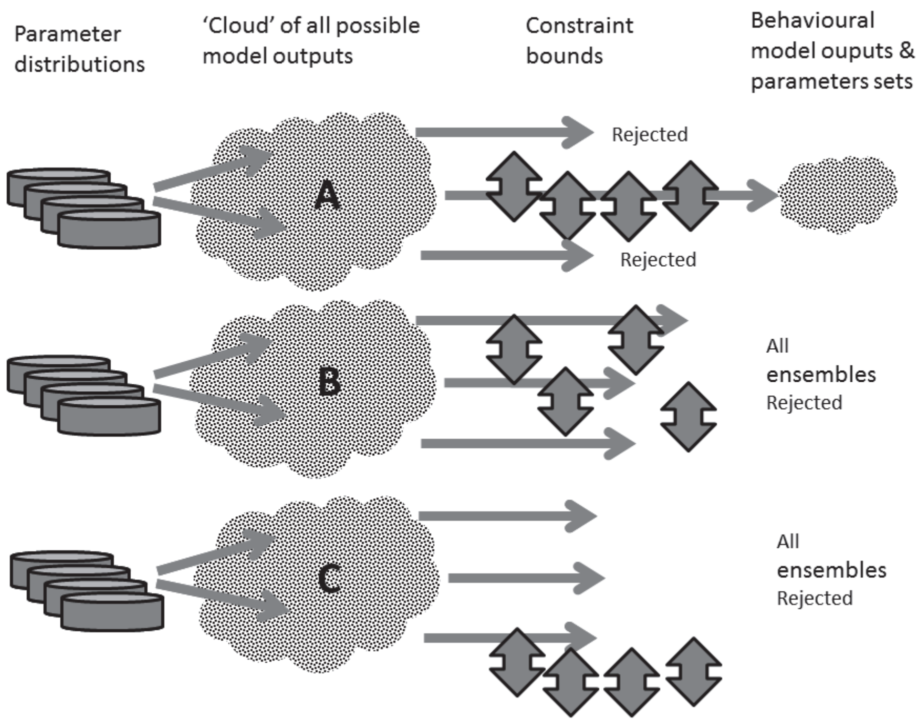


Figure 3.3 Step 1 in the revised approach to uncertainty estimation with the Pitman model.

It is therefore important that both the input parameter bounds (defining the uncertainty distribution functions - pdfs) and the constraints are appropriately quantified. If the parameter bounds are too large it is possible that the 100 000 runs will not be enough to identify 2 000 behavioural results, while too narrow ranges might not be adequate to represent the real uncertainty. The parameter bounds may also be biased towards generating too much or too little runoff or groundwater recharge relative to the constraints. There is therefore an element of 'calibration' involved in suitably matching the parameter ranges or pdfs with the constraint bounds and additional software has been developed to assist in this process.

Figure 3.4 illustrates the new component of the model that allows the parameter space within the saved ensembles to be explored, as well as the range of the 5 constraints:

- The second column lists the sub-basin names that were included in the model run and one can be selected for analysis.
- The left hand column lists all of the parameter values and up to 5 can be selected for plotting in the graphs on the right side of the screen.
- The lower text box lists the selected parameters and their ranges (at present the software is designed to be used with uniformly distributed parameter uncertainties).
- The frequency of saved parameters falling into 10 evenly spaced groups between the minimum and maximum parameter values are plotted on the five graphs.
- The values of the constraints for the saved parameter sets are used to plot the frequencies within 5 groups in the top left hand graph.

Figure 3.4 Illustration of the new tool designed to help with determining appropriate parameter bounds in step 1 of the revised uncertainty modelling approach. This is an example of a successful sub-basin where 2 000 behavioural ensembles were found.

Figure 3.4 illustrates that the 2 000 saved results for 5 constraints (excluding % zero flows which is always 0 in this example) are relatively evenly distributed within the input constrain ranges. It is also evident that at least some of the parameter values are evenly distributed over their input uncertainty range. The conclusion is that the parameter uncertainty ranges and the constraint ranges are consistent with each other and that this sub-basin is properly 'calibrated'.

Figure 3.5 shows a sub-basin where only 388 ensembles were saved and therefore where further parameter adjustment is needed (or where the constraint ranges should be checked and re-evaluated). Figure 3.5 illustrates that while the simulated FDC90 (low flows) values are reasonably well distributed throughout the constraint range, the others are all grouped at the lower ends of the constraint bounds and that further adjustment of the parameter ranges would be required to achieve 2 000 ensembles, given the climate inputs (rainfall and potential evaporation demand) that were used as inputs to the model. This last point should be emphasized as these inputs could also be uncertain. Examination of the parameter graphs in Figure 3.5 suggests that the main problem lies with the range of the ZMIN and ZMAX values as the behavioural parameter sets all tend towards the lower values of the ranges (notably ZMAX) and that these parameter values should be reduced. One of the advantages of the approach based on simulating sub-basins without downstream linkages is that the whole model would not have to be run to re-calibrate a few sub-basins. This could save a great deal of time as the model run for the 31 sub-basin Caledon River takes approximately 5 hours.

Figure 3.5 Illustration of a sub-basin that requires further 'calibration' of the parameter bounds to achieve 2 000 behavioural ensembles.

3.1.2 Step 2 in the revised approach for simulating uncertainty ensembles

Figure 3.6 illustrates the process used during step 2 of the revised approach. At the start of the model run the saved parameter sets (noting the assumption that these are designed to represent natural conditions) are sorted on the basis of the 6 simulated constraint values from generally wetter to drier. As with the previous approach to structured sampling, the sub-basins are grouped and random samples are drawn from the saved parameter sets using the groups. A random number between 0 and 1 is generated for each group (RND_i), while an additional random number between 0 and 0.1 is generated for each sub-basin (RND_j). The latter is used to introduce some within-group variation. These are combined and scaled to a number between 1 and the number of saved parameter sets for the specific sub-basin (2 000) and this number is used to seek within the ranked parameter sets to retrieve the parameter values.

The program also reads the table of values used to set the parameter pdf's in step 1 but after it has been modified to include uncertainty in some of the water use and downstream routing parameters. Random samples for these parameters are then generated independently of the samples taken from the saved parameters (but also used a structured sampling approach based on the sub-basin groups). The full set of parameter samples are then used to run the total model for all sub-basins and generate the cumulative flows at all sub-basin outlets.

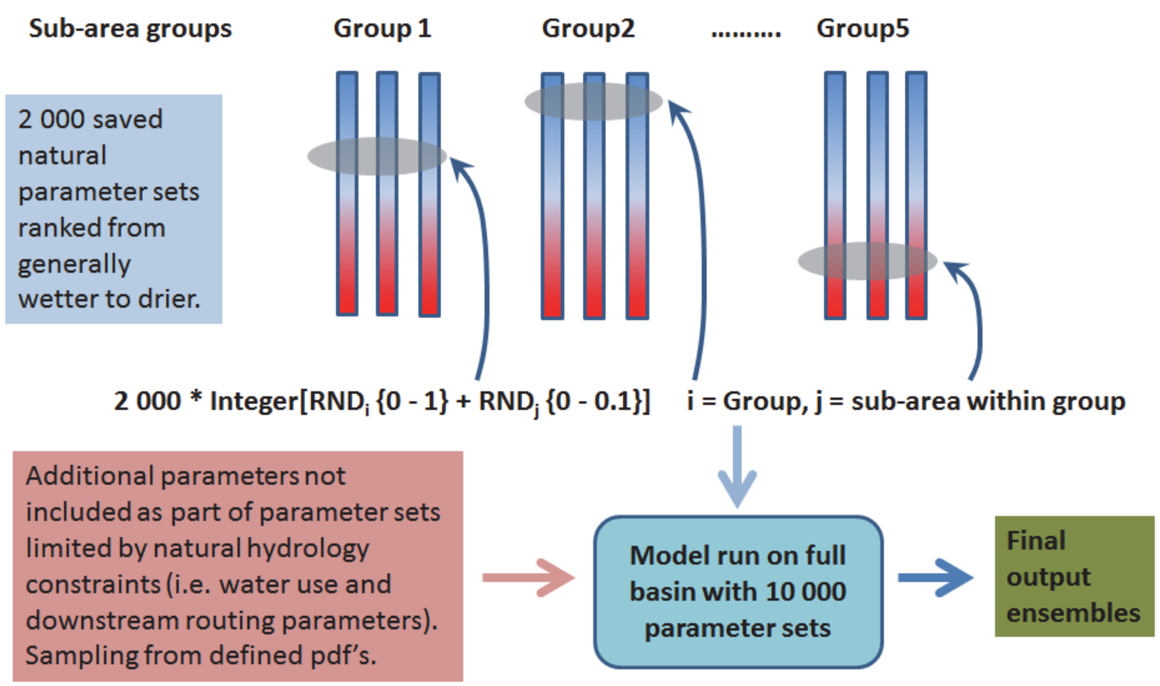


Figure 3.6 Illustration of the process used in step 2 of the revised uncertainty model.

Figures 3.7 to 3.9 illustrate some of the outputs of the model for the Caledon River basin using frequency distributions of standardized indices of three of the constraints (MMQ, Q10 and Q90). The standardized indices on the horizontal axes are based on the fractional deviations of the simulated values for all of the 10 000 ensembles from the ensemble mean for the natural flow simulations for that sub-basin. This allows the upstream and downstream frequency distributions to be directly compared. The graphs include the simulations of natural conditions as well as present day conditions which are largely based on uncertainty in the volume and abstractions from farm dams. The observed values are also indicated on the graphs.

As with the previous approach to structured sampling (Figure 3.2) there has been some loss of uncertainty (narrower frequency distributions) in a downstream direction, but a large proportion of the uncertainty has been retained. While the observed values for the constraints do not always fall within the simulated present day frequency distributions, this is not really surprising given the large uncertainty in the observed data and the fact that the time periods of the observed and simulated data are different. It is also possible that the ranges of some of the water use parameters could be re-examined.

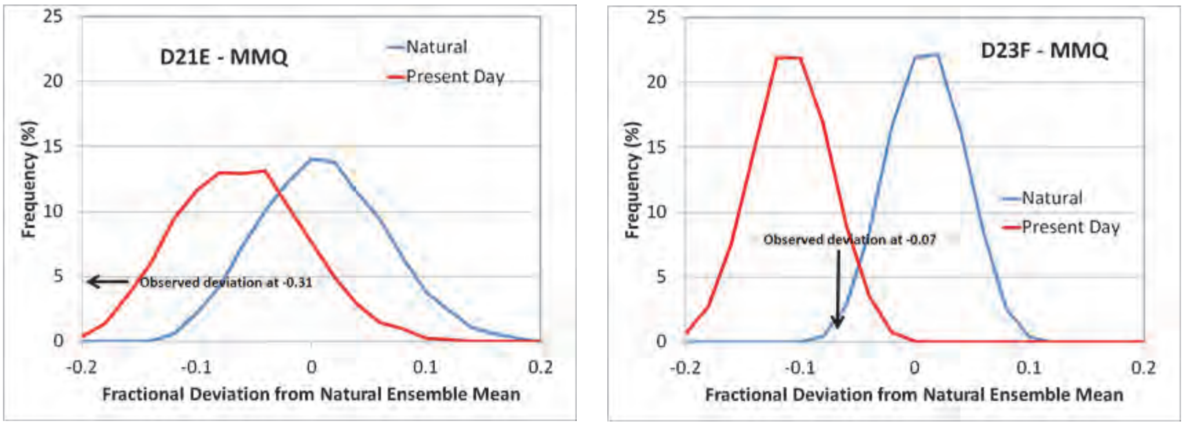


Figure 3.7 Example outputs using standardized flow indices for MMQ at an upstream (D21E) and downstream (D23F) sub-basin.

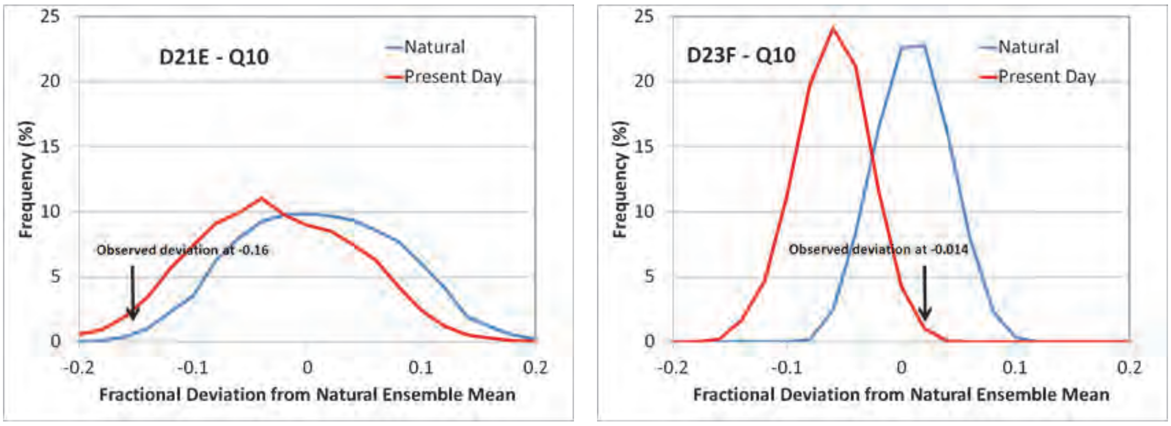


Figure 3.8 Example outputs using standardized flow indices for Q10 (high flows) at an upstream (D21E) and downstream (D23F) sub-basin.

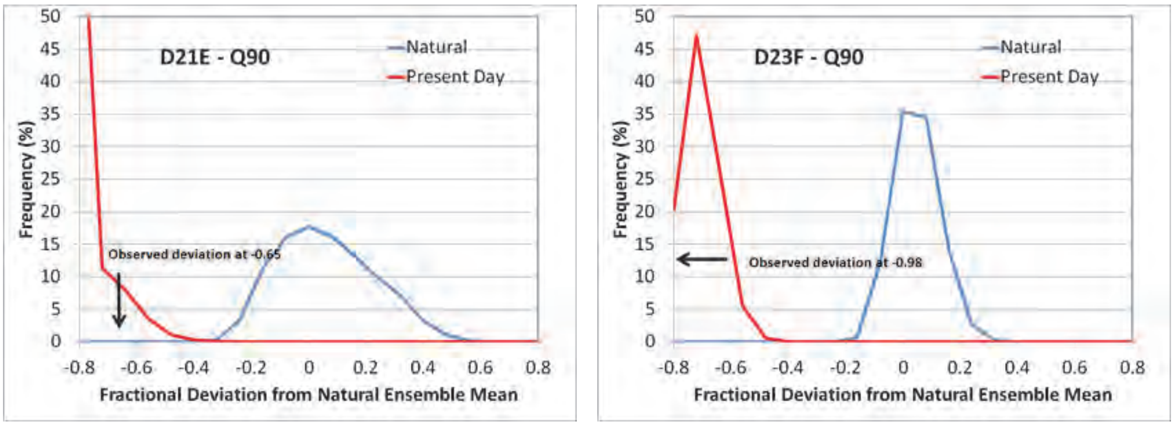


Figure 3.9 Example outputs using standardized flow indices for Q90 (low flows) at an upstream (D21E) and downstream (D23F) sub-basin.

The overall conclusion of the Caledon River test case is that the revised 2-step approach achieves most of the objectives, in that:

- All downstream ensembles are made up of behavioural (based on constraint ranges) upstream contributions.
- Uncertainty is 'largely' preserved, certainly better than the original independent (unstructured: Figure 3.1) sampling and as well as the structured sampling (Figure 3.2).
- The method is a useful approach for combining constrained uncertainty in natural hydrological responses with relatively un-constrained uncertainty in water use impacts.

- The method generates ‘realistic’ uncertainty bounds in an approach that is practical to apply.

One of the outcomes of the trial run on the Caledon River is that this would seem to be a plausible approach that could be applied to the whole country to generate sets of uncertain parameter values to represent natural flow conditions for all 1 946 quaternary catchments in the country (including Lesotho and Swaziland). The process would initially involve establishing regional constraint ranges that can also be locally modified to account for those quaternary catchments where observed data exist. Existing simulations (WR90, WR2005 and WR2012), as well as observed data and indices of physical basin properties, could be used to guide the process of both setting the constraints and establishing initial parameter ranges.

The approach has also being applied to the Great Ruaha River basin in Tanzania through the PhD programme of a student from the University of Dar es Salaam (Ms Madaka Tumbo). The constraint bounds for all of the sub-basins were initially based on an analysis of 24 observed flow records, of which 15 are located on headwater rivers that correspond to modelled sub-basins. The initial parameter bounds were largely based on some manual calibration test runs of the model. While it was found that it was quite quick to identify appropriate parameter bounds in some sub-basins, there were others where Step 1 of the revised approach had to be run several times (with adjustments to both the constraint and parameter bounds) before 2 000 behavioural outputs could be generated. Further investigation of this problem identified several of the stream flow records that had periods where the data could not be relied upon and which had quite large effects on the estimated constraints. It was also found to be difficult to establish suitable constraints and parameter bounds for some of the incremental downstream sub-basins where there were few or no clues contained in the observed data about their response characteristics. One of the conclusions from this study of the Great Ruaha River basin is that the revised uncertainty approach allows a great deal of information to be integrated at the basin level which allows for a better understanding of the available data as well as the uncertainties. It was also noted that the application of the 2 step approach should probably be iterative and that a relatively coarse scale (i.e. quite large constraint and parameter bounds) first attempt should be followed by revisions that focus on reducing the uncertainty in areas where the available data are considered to be more reliable. In the case of the Great Ruaha River basin this would almost certainly result in reduced upstream uncertainty (in those areas that have quite good flow data and where there are a number of rainfall stations), but may not have an appreciable effect on the downstream uncertainties because of the other parts of the basin that are not gauged and where the climate inputs are also very uncertain and because of a major wetland area in the centre of the basin that will always be difficult to model.

3.2 Model efficiency and software considerations

Mr Dale Tristram of the Rhodes University Computer Science Department has been investigating the problem of excessive computer run time and the software architecture of the existing versions of the Pitman model. The current versions of the uncertainty models being used at Rhodes are all written in Delphi and are attached to the SPATSIM software framework, accessing the data from the SPATSIM database tables. For the Caledon River example with 31 sub-catchments and 10 000 ensembles the structured sampling version of the model (without stochastic inputs) takes about 2.5 hours to complete, while the stochastic rainfall version, that generates 250 000 ensembles, takes 45 hours. These are generally unacceptable run times for practical purposes.

Mr Tristram's work has been based on using different software languages as well as the possibility of using Graphical Processing Units (GPUs) as cost effective accelerators. The basis for these different tests is that GPUs can very effectively deal with problems that map well to a Single Instruction Multiple Data (SIMD) architecture. In hydrological terms this is equivalent to running the same model many times with different inputs, which is the very essence of uncertainty models. The description of the computer science details and some preliminary results have been published (Tristram et al., 2014) and Table 3.1 summarises a typical example using the structured uncertainty version of the model for a test area of 3 sub-catchments and 50 000 ensembles. Table 3.1 clearly indicates that up to 14 times improvements in run time can be achieved on ordinary CPUs by using a different software language and that this improvement can be greatly extended by using GPU architecture. However, one of the issues is that almost all of the really significant improvements would not be easily achieved by typical scientific programmers and would require specialist computer scientists to make the necessary changes. The benefits are very clear and if these performance measures can be considered applicable to the stochastic uncertainty version then the Caledon run time would reduce from 45 hours to just over 3 hours for the best CPU option, to less than 1 hour for the simplest GPU option and to no more than 15 minutes for the option with 2 GPUs.

While there are cost considerations in terms of installing GPUs into computers, the benefits will far outweigh the costs if uncertainty runs of hydrological models are likely to become standard practice. The project team is currently engaged with integrating more efficient versions of the uncertainty models into SPATSIM.

Table 3.1 Model performance for different software architecture implementations.

Model implementation	Time (secs)	Performance measure
Delphi	2933.7	1.0
C# (single-threaded)	1691.1	1.7
C# (multi-threaded)	335.3	8.7
OpenCL (CPU)	204.8	14.3
OpenGL (GPU – not optimized)	58.8	49.8
OpenGL (GPU)	28.9	101.3
OpenCL (2 * GPUs)	14.5	202.3

3.3 Including stochastic rainfall uncertainty in hydrological models

This section of the report investigates the use of stochastic rainfall generation methods within hydrological models as an alternative to using stochastically generated stream flows within a yield model. The latter has been the traditional approach in South Africa for many years and is based on the generation of a single historical hydrological time series (for each input node of the yield model) from a hydrological model, together with stochastic stream flow generation within the yield model. The result is a number of different stream flow sequences used to determine yield estimates, from which a yield probability curve can be derived.

It is useful to re-examine some of the basic concepts that underlie the conventional approach to yield analysis (Basson et al., 1994) in the light of recent approaches to uncertainty analysis in hydrological modeling. Chapter 2 of Basson et al. (1994) refer to two types of generated sequences used in yield analyses. The first are deterministic sequences '…used mainly to fill in and extend incomplete streamflow sequences via rainfall runoff models' (Basson et al., 1994). They continue by suggesting that 'stochastic streamflow sequences purport to offer alternatives to the historic sequence of what might have been in the past, or what might plausibly be in the future'. Figure 3.10 attempts to summarise these concepts within a more general uncertainty framework.

In Figure 3.10 ‘hydrological uncertainty’ is designed to represent the degree of confidence in our knowledge of the historical patterns of stream flow. No distinction is made in this report between knowledge based on measured stream flows or simulated (by a hydrological or rainfall runoff model) stream flows. The reason for this is that many of the available stream flow gauging records are either incomplete, subject to unknown inaccuracies or have measured stream flows that are affected by poorly quantified upstream impacts. It is typically assumed that the historical hydrology inputs to a yield model represent the ‘natural’ situation and that the yield model will simulate the development effects (storage, abstractions, return flows, land use effects on stream flow reduction, etc.). Even where stream flow gauges are assumed to measure flows accurately across a wide range of possible flows, the records still have to be ‘naturalized’ to remove the historical development effects. Many of the effects are far from being stationary and are typically not very well documented. There is therefore a large degree of uncertainty in the process of naturalizing any observed stream flow record. Most of the stream flow gauging stations in South Africa do not, however, measure flows accurately across a wide range of possible discharges. Many of the older designs of weirs have long thin plate crests such that small variations in low flows cannot be accurately determined and are subject to temporary interference from in-channel vegetation detritus and sedimentation of the weir pools. The accuracy of the low flow records are therefore open to question and highly dependent on regular maintenance of the gauging station. At the other extreme, many gauges have a very low limit to the stage-discharge rating curve and any estimates of larger flows (if they exist at all) are based on surveyed flood levels and hydraulic estimation equations. The result is that observed stream flow data frequently contain long gaps that have to be in-filled and that the measurements themselves are subject to indeterminate inaccuracies.

There are many different approaches to filling in gaps and correcting stream flow records to account for gauge inaccuracies. All of them, together with the methods used for naturalization, are effectively models that contain assumptions and are all subject to uncertainty. Where gauges do not exist (or are considered inappropriate for use), rainfall-runoff models are frequently used to simulate the historical hydrology from historical records of rainfall and other climate variables. The catchment-specific response to the climate forcing data is represented by the parameters of the rainfall-runoff model and appropriate values for these may be determined in several different ways including calibration against some observed data, regionalization from parameter sets calibrated in adjacent (or similar) catchments, or through direct estimation from physical catchment properties.

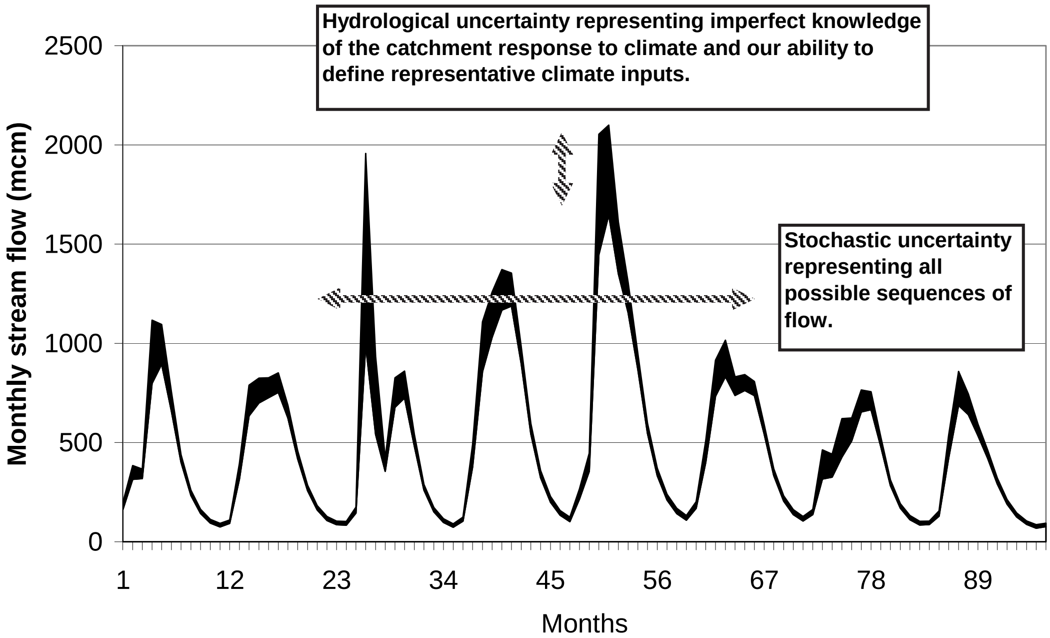


Figure 3.10 Distinction between stochastic and hydrological uncertainty based on a short period of simulated flows.

The width of the hydrological uncertainty band illustrated in Figure 3.10 will therefore be dependent on the amount and perceived quality of any observed data (stream flow and climate data) that are available and the techniques (patching, naturalization, hydrological modeling, etc.) used to generate representative historical time series of natural flow data.

Figure 3.10 refers to the stochastic uncertainty as representing all possible sequences of flow and this is what has been traditionally included as ‘uncertainty’ in the yield analyses. This definition is approximately similar to that used in Basson et al. (1994) and is associated with the fact that relatively short periods of historical time series (measured or simulated) may not adequately represent all possible sequences of stream flow, even under stationary conditions. This is an important consideration, given that the yield of a system involving storage is very dependent upon the most critical sequence of flows, rather than the lowest possible flows over a relatively short period of time. The length of that critical sequence is partly dependent upon the volume of storage and partly on the sequence characteristics of the natural flow. The stochastic stream flow sequences used within the yield model are considered to originate from the same population (and have the same statistical behaviour) as the historical time series. The approaches that have been used within South Africa are based on multi-site stream flow modelling to preserve spatial correlations and are documented in chapter 4 of Basson et al. (1994).

In considering the two sources of uncertainty identified in Figure 3.10, it is immediately apparent that they are not independent. The statistical properties of the individual uncertainty ensemble members of historical stream flow time series could be very different from each other and therefore stochastic sequences generated from them could similarly have different properties. There are additional complications if the hydrological uncertainty across the many different sub-basins (or incremental natural hydrology nodes) in a complex implementation of a yield model are considered to be independent. The sampling space required to represent the uncertainty becomes huge and intractable from a practical point of view. Within each node of the yield model the use of 500 hydrological uncertainty ensembles together with the generation of 500 stochastic stream flow sequences results in 250 000 possible combinations. The number of possible combinations across a total catchment with (say) 100 nodes becomes a number which is too large to even contemplate from a practical computing point of view. ***The issue of adequately representing the uncertainty sources and their independence in a manner which is also practical is therefore a critical issue.*** One of the questions that was raised in the previous project is whether a stochastic rainfall model can be used with the hydrological models to combine all the uncertainty elements within a single model and whether this will make the uncertainty sampling problem easier to manage in a practical way.

3.3.1 Probability issues in yield modelling

Before discussing the issue of uncertainty sampling and the most practically appropriate approaches to combining uncertainty sources, it is important to discuss some of the issues related to the interpretation of probability in yield modelling. It became apparent during the previous project that there existed some differences of interpretation between individuals and groups with different backgrounds and experience. Basson et al. (1994) define ‘Base Yield’ as ‘*the lowest yield level recorded when a reservoir/system of a given configuration is fed by a given inflow sequence of a fixed length while attempting to satisfy a given target draft associated with a specified temporal (monthly) demand pattern (for water) under a specific operating policy*’. ‘Firm Yield’ is ‘*the maximum base yield that can be abstracted from a reservoir/system of unique configuration for a given inflow sequence, temporal demand pattern and operating policy*’. It follows that abstractions that are greater than the firm yield will be subject to periodic failure and using a single historic sequence it would possible to determine the reliability of a specific abstraction on the basis of the number of failures. This could be expressed as a probability of failure or as an annual return period of failure.

When stochastic sequences are used to generate measures of reliability for base or firm yield, Basson et al. (1994) plot the curve as the exceedence probability of a range of base yields (i.e. each stochastic sequence will generate a different base yield), but they also attach recurrence intervals to the probabilities (see Figure 2.12 in Basson et al., 1994, page 41). Given the standard interpretation of recurrence intervals (similar to an annual flood peak analysis) this suggests that the different base yields resulting from the stochastic analysis **WILL** occur over an extended period of time. However, this assumes that all of the stochastic sequences will occur, while the alternative interpretation is that these stochastic sequences represent uncertainty in the expected occurrence of the volume of inflows over the critical period for the reservoir/system configuration. The implication is that some critical period volumes contained within the full suite of stochastic sequences may **NOT** occur. This makes no difference whatsoever to the yield probability diagrams as long as the horizontal axis is not re-defined as a recurrence interval (or return period). The uncertainty interpretation of these diagrams is therefore that there is only a single firm yield for the reservoir/system configuration (including the temporal demand pattern and operating policy) and that this is determined by the real inflow sequence (assumed to be stationary) over a long period of time. However, as we are not able to quantify what the real long-term inflow sequence will be, the stochastic analysis based on a relatively short period of historical observations (or simulations) allows us to quantify the uncertainty (as probabilities of exceedence) in the firm yield.

While this may all seem like a rather pedantic approach to interpreting the yield probability curves it becomes very important if additional sources of uncertainty are added to the analysis. Adding hydrological uncertainty to the conventional interpretation (that includes the concept of recurrence interval) involves a different process than if the stochastic and hydrological uncertainties are combined into a single expression of uncertainty. In the former case an ensemble of historical flow sequences would be generated by a hydrological model and each one treated to stochastic analysis within a yield model, generating multiple firm yield lines. The approach of identifying yields with different recurrence intervals (RI) could still be applied, but now the firm yield associated with (say) a 1:50 year RI would not be a single value but a frequency distribution of values determined by the hydrological uncertainty. This is illustrated in Figure 3.11 where the red lines represent stochastic yield analysis results using a wide range of historical hydrology uncertainty ensembles. The frequency distribution shown at the 42% exceedence probability is designed to illustrate that the hydrology ensembles (and therefore the estimated yields) are not all considered equally probable. This type of situation would result where uncertain parameter inputs into a rainfall-runoff model are based on normal distributions. However, if the parameter inputs are based on uniform distributions it is possible that all of the hydrology ensembles could be considered equally likely.

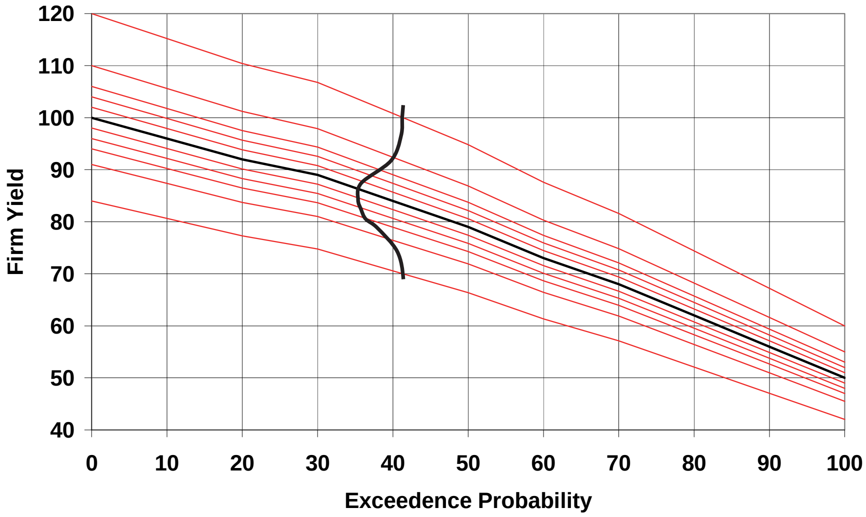


Figure 3.11 Adding hydrological uncertainty to conventional stochastic yield analysis (black line represents the yield analysis based on the median hydrological ensemble, while the red lines represent yield analyses using other ensembles).

Figure 3.11 is the type of diagram that would be produced if many hydrological ensembles were all subject to stochastic analysis in the yield model – a process that would be very time consuming in all but simple systems. Fortunately, there is a possible alternative based on pre-processing the hydrology ensembles and only passing 3 to the yield model for stochastic analysis. The pre-processing would be based on ranking the hydrology ensembles on the basis of the minimum flow volume over the critical duration for the system. Identifying the characteristics of the minimum flow frequency distribution and deciding on appropriate uncertainty probabilities (the median plus the ensembles equalled or exceeded 90% and 10% of the time for example) would allow three flow ensembles to be selected for stochastic yield analysis.

Adding hydrological uncertainty based on the second (uncertainty) interpretation of the stochastic model results would have to be dealt with in a different way. In this case all of the yield estimates from all of the stochastic sequences run with each hydrological ensemble would be treated as uncertainty estimates of the 'real' yield and the yield probability curve would look something like that shown in Figure 3.12. Note that it is now no longer appropriate to associate the exceedence probabilities with recurrence intervals. The part of the curve in Figure 3.12 that lies between approximately 75% and 25% probability is very similar to the yield curve based on stochastic sequences using the median hydrology ensemble. While the parts of the two curves that correspond with each other will clearly depend on the degree of uncertainty in the hydrology ensembles and this example has used hypothetical data, the result should be very similar for all situations. The conclusion is therefore that yield assessments based on a probabilities of exceedence of between about 75% and 25% would not be affected by including hydrological uncertainty.

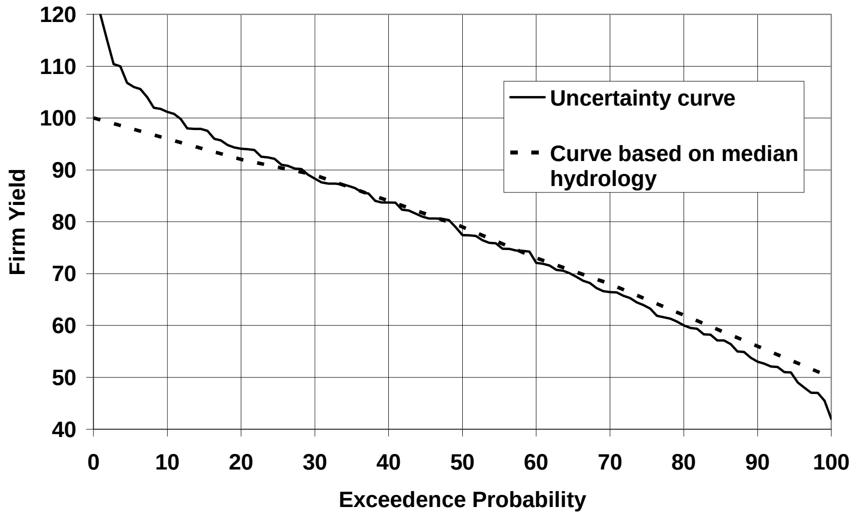


Figure 3.12 Adding hydrological uncertainty to stochastic yield analyses that are also treated as uncertainty estimates of the real yield (the same data are used as in Figure 3.11).

Differences in interpretation: Considering the hypothetical results shown in Figure 3.11 (and assuming an 85 year length of record for the historical flow ensembles) the 1:100 year yield would be estimated as approximately 83 * 10^6 m^3 if the hydrological uncertainty is ignored. Including the hydrological uncertainty would suggest that there is a 90% probability that the 1:100 yield would be greater than about 75 * 10^6 m^3, while there is a 5% probability that the 1:100 year yield would be greater than about 92 * 10^6 m^3. As pointed out by at least one participant in the workshops held as part of the previous WRC uncertainty project these expressions of reliability are compound statements of probability. However, the use of the recurrence interval expression for the stochastic component means that the two probabilities can be separated.

The interpretation of the results presented in Figure 3.12 cannot be expressed using a recurrence interval approach and all that can be said is that the 'real' firm yield will be greater than 60 * 10^6 m^3 with 80% confidence and greater than about 94 * 10^6 m^3 with 20% confidence.

The differences in interpretation of essentially the same data arise as a direct result of the differences in interpretation of the stochastic sequences. As already noted, the first interpretation relies on the assumption that all of the sequences will occur over a long enough time period and therefore they can be used to express the ranking and the exceedence probabilities of the outcomes in terms of recurrence intervals. This is not true of the second interpretation in which it is assumed that the stochastic sequences represent the uncertainty in the ability of an historical sample of flows to represent all possible sequences within a much longer, stationary period.

Implications of interpretation differences: One of the proposed approaches to incorporating both sources of uncertainty (hydrological and stochastic) is to substitute the stream flow stochastic model in the yield model with a rainfall stochastic model in the hydrological model. From a modeling perspective, this is potentially very attractive as it allows both sources of uncertainty to be combined in a single model. It is also attractive from the perspective of adding observational uncertainty into the rainfall inputs to the hydrological model, through some additional error terms added to the parameters of the stochastic rainfall model. However, this type of approach would generate a single ensemble of flow time series which would be equivalent to the second interpretation discussed in the previous section. It would be possible, but much more difficult, to isolate the stochastic uncertainty components from the other uncertainties so that these could be treated differently when the ensemble members are processed through the yield model (i.e. the equivalent of the first type of interpretation discussed above).

This report has made no firm conclusions about the correctness of either the first or second interpretation options. It is suspected that the majority of the water resource engineering community in South Africa will agree with the first interpretation option, largely because this is the approach that is aligned with the conventional approach to yield analysis without any hydrological uncertainty. However, that does not mean that it is the most statistically correct approach.

3.4 Examples of stochastic yield analysis with uncertainty

During the course of the project, several trials of stochastic rainfall analysis were carried out, but the one that has been included in the final report is based on the use of the most up-to-date versions of the uncertainty models. To assess the effects of different types of uncertainty on reservoir yield analyses, the example of Nyaka Dam and the outlet of quaternary catchment X31E have been used. Three different types of analysis have been used and all are based on WR2005 rainfall data and existing simulations of the hydrological regime as background. The uncertainty ranges of the model parameters are all based on the approach discussed in section 3.1 of this report. The flow constraints (Table 3.2) were based on the assumption that the existing natural hydrological simulations (obtained from Mr Stephen Mallory) are realistic, but with some uncertainty. The groundwater recharge constraints were based on the low to moderate estimates available from the GRAII database. Figures 3.13 and 3.14 illustrate the parameter bounds that have been used as well as the results of the parameter constraining analysis. All of the other parameter values were fixed at appropriate values based on past experience. The top left graph in both diagrams illustrate that the results for the saved parameter sets tend to favour the lower range of the MMQ and Q10 constraints, are fairly well distributed for the recharge constraint, tend to have a quite low range for the Q50 constraint and favour the lower range of the Q90 constraint. The diagrams also illustrate that there is no obvious bias in the range of accepted parameter values relative to the original input uncertainty bounds (lower left table of values in Figures 3.13 and 3.14).

Table 3.2 Constraints used in establishing parameter uncertainty bounds for natural flow (no afforestation) simulations.

Constraint	Lower bound	Upper bound
Mean monthly flow ($m^3 * 10^6$) - MMQ	7.5	10.5
Mean monthly GW recharge (mm)	4.5	8.0
Q10 (fraction of MMQ)	2.0	2.2
Q50 (fraction of MMQ)	0.5	0.7
Q90 (fraction of MMQ)	0.20	0.25
% Zero flows	0	0

Figure 3.13 Outputs of the parameter constraining analysis for ZMIN, ZMAX, ST, POW and FT.

Figure 3.14 Outputs of the parameter constraining analysis for GW, R, GPOW and Riparian strip %.

The following text explains the approaches that have been used to assess various methods of stochastic analysis.

Step 1 using stochastic stream flow analyses (traditional approach)

1A. Step 1A involves the use of the existing hydrological input data coupled with the existing conventional yield analysis.

1B. Step 1B involves generating uncertainty ensembles based on parameters that more or less bracket the existing input data. Three ensembles representing wet, moderate and dry situations are extracted and used as inputs to the yield model with stochastic stream flow included. The forestry is taken out of the yield model and included as part of the uncertain parameter sets used with the Pitman model. The parameter uncertainty method is unconstrained but uses the same parameter ranges given in Figures 3.13 and 3.14 with additional uncertainty (using uniform distributions) added for the % area of afforestation (55-70%) and the FF parameter (1.2 to 1.4) used to scale up potential evaporation for the forest areas. The main difference between the unconstrained parameter uncertainty method and the new approach, adopted in Step 2, is the fact that parameter combinations are possible that result in ensemble outputs that will be beyond the range of the constraints provided in Table 3.2 and therefore higher overall parameter uncertainty.

Step 1 therefore represents 4 stochastic stream flow runs of the yield model.

Step 2 using stochastic rainfall data provided by Mr Bennie Haasbroek.

Use the stochastic rainfall data and the new approach to setting uncertainty bounds using constraints (Table 3.2) to generate 250 000 mixed (rain and parameter) ensembles and extract a sample of 500 ensembles based on an appropriate critical period for the dam for processing through the yield model. The parameter uncertainties are made up of a combination of sampling from the constrained saved parameter sets plus random sampling from the uniform distributions of the % area of afforestation and FF parameter.

An additional assessment is made using the old version of the Pitman model with stochastic rainfall inputs (i.e. not using the constrained natural parameter sets). However, to avoid an excessive number of yield model runs, this assessment is only based on the critical period frequency analysis of the Pitman model outputs.

This will mean 1 run of the yield model (without stochastic stream flow) with 500 sets of input flow data.

Step 3 Stochastic rainfall analysis based on separating stochastic and parameter uncertainty

During earlier discussions it was noted that it might be important to distinguish between stochastic uncertainty (where traditionally probabilities are converted to return periods) and hydrological uncertainty due to varying model parameter values. Step 2 does not make this distinction and all of the sources of uncertainty are lumped together in a single set of ensembles. Step 3 therefore involves extracting the minimum and maximum parameter uncertainty ensembles for each stochastic rainfall input. Thus two sets of 500 ensembles are generated and each set subjected to yield analysis to generate two yield probability curves representing the upper and lower bounds of hydrological uncertainty. The minimum and maximum ensembles could be based on mean annual runoff or minimum flow over a defined critical period and the latter has been used in this project so that the Step 2 and Step 3 results are more compatible.

3.4.1 New software to facilitate analysis of the output ensembles

A facility to sort and analyse the ensemble outputs from the Pitman model was added to SPATSIM some years ago when the uncertainty versions of the model were created. However, it was not comprehensive enough for the analyses that are proposed above and therefore was modified during this phase of the project. Table 3.3 lists the input/output requirements of the ‘model’ that is referred to as the ‘Stochastic Ensemble Sorter’, while Figure 3.15 provides an example screen shot of the computer program. The notes below explain more about the use and operation of the program.

Table 3.3 Input/output requirements (links to SPATSIM attribute data) for the Stochastic Ensemble Sorter program.

Number	Attribute	Description
1	Catchment ID	Sub-catchment names.
2	Rainfall Input Ensembles (T/S)	Stochastic rainfall ensembles used as input to the Pitman model.
3	Flow Ensembles (T/S)	Output stream flow ensembles generated by any of the uncertainty versions of the model and stored within a SPATSIM attribute.
4	Output Sample Ensembles (T/S)	An output generated by the sorter program representing a 500 sample of the total ensemble set.
5	Output Rainfall Min. Ensembles (T/S)	Outputs generated by the sorter program representing 500 samples of the total ensemble set but based on the minimum and maximum for each rainfall group used as input to the Pitman model.
6	Output Rainfall Max. Ensembles (T/S)	

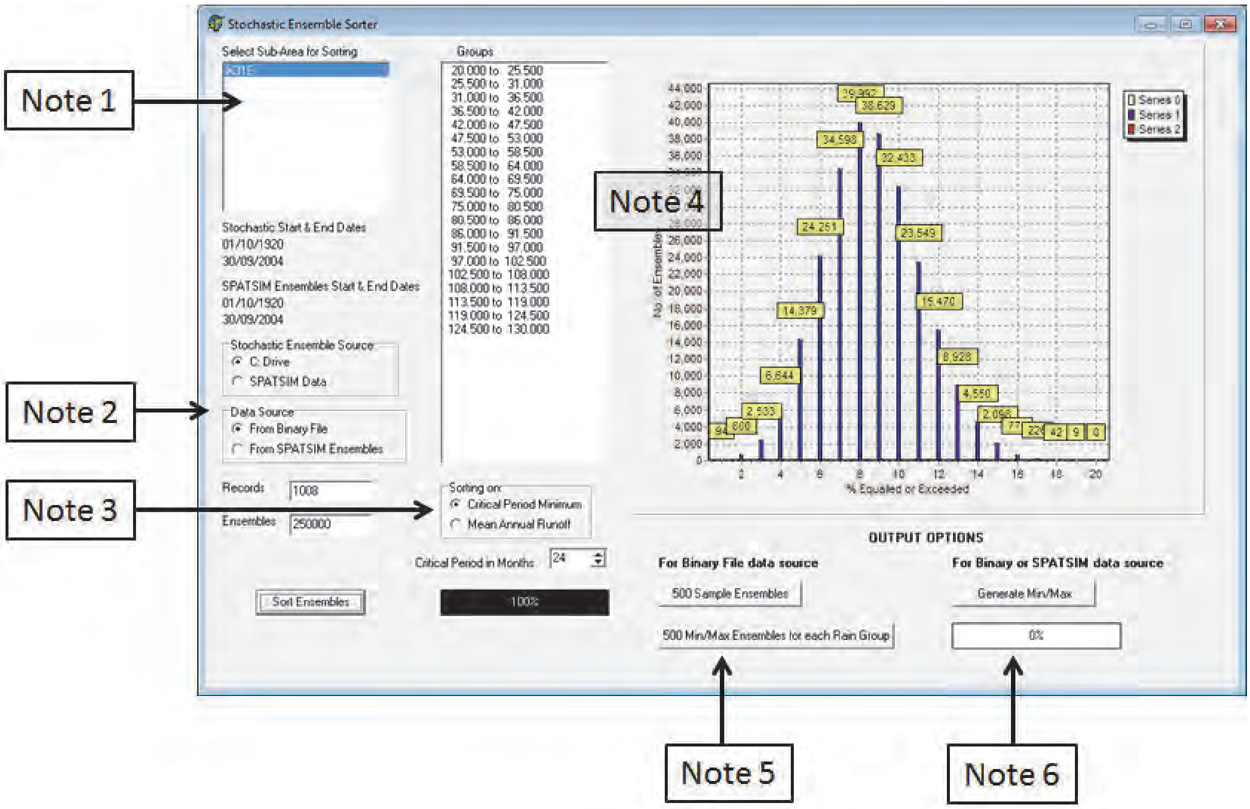


Figure 3.15 Example screen shot of the Stochastic Ensemble Sorter program

Note 1: The list of sub-catchments is provided so that any part of the total basin can be analysed separately.

Note 2: If the stochastic rainfall uncertainty version of the Pitman model is used then 250 000 output ensembles are typically generated (assuming 500 input rainfall sequences and 500 parameter samples). This represents too much data to save to SPATSIM and instead the outputs are stored in binary files. The options under Note 2 therefore allow the user to decide which type of ensemble set is to be analysed. If the binary file option is selected then this file can be sourced from C drive or from the default SPATSIM data folder used for the specific SPATSIM application. If the 'From SPATSIM Ensembles' option is chosen then the data stored in SPATSIM attribute requirement 3 (Table 3.3) are used in the analysis. The SPATSIM stored data can be a full ensemble set (e.g. 10 000 generated by the normal, non-stochastic, version of the uncertainty Pitman model, or can be one of the 500 sample sets generated by this program (see Step 5). The latter can then be used to test that the 500 samples generated are a realistic sample of the full ensemble set by examining the shape and range of the frequency distributions.

Note 3: The ensemble frequency analysis can be based two main methods of classifying the ensembles; mean annual runoff or a critical period minimum flow. If the latter is selected the user can specify the length of the critical period. The mean annual runoff analysis is simply based on the annual flows for each year of the record. If the critical period analysis method is selected then, for each ensemble, the total flow over all possible durations of the period are calculated and the minimum value is determined and used in the frequency analysis.

Note 4: The ensembles are sorted using either the mean annual runoff or critical period criteria and the frequencies of ensembles calculated for 20 evenly spaced groups between the minimum and maximum values. The list box gives the group boundaries, while the histogram plot provides the frequencies and a visual impression of the frequency distribution. The boundary values and frequencies can be copied into an excel spreadsheet for further analysis and plotting.

Note 5: The two buttons under this note allow for an unstructured sample of 500 ensembles to be generated and saved to SPATSIM (500 Sample Ensembles), as well as two sets of ensembles structured according to the stochastic rainfall sequences (500 Min/Max ensembles for each rain group). The latter is used to generate the outputs required for Step 3 of the stochastic yield analysis referred to above and in section 3.4.4 below. The parameter uncertainty ensembles that form part of each set of stochastic rainfall inputs are sorted (see

Note 3) and the minimum and maximum found for each rainfall input. These are then saved back to SPATSIM and can be used as inputs (item 3 in Table 3.3) in a separate run of the ensemble sorter program (see also Figure 7.18 which illustrates the sort results for a full set of 250 000 stochastic rainfall/parameter uncertainty ensembles as well as the sets of 500 minimum and maximum rainfall group samples).

Note 6: The final output option allows for the minimum and maximum monthly time series to be generated to a text file for a set of ensembles. This process is based on searching through each month of all ensembles and identifying the minimum and maximum monthly flows. These two output time series can then be used to plot either two time series or flow durations that represent the full band of uncertainty across all ensembles (using the ensemble data stored in attribute 3 of Table 7.3).

At this stage of the development of the SPATSIM uncertainty modelling software, this ensemble sorting facility has provided all of the tools necessary to analyse the ensembles and generate outputs that can be passed on to the yield model. However, if additional facilities are required in the future it will be relatively straightforward to add to the program.

3.4.2 Step 1 Results: Traditional stochastic stream flow analysis with uncertain parameters

Figure 3.16 illustrates the results for Step 1. The yield results for the median ensemble are very similar to the IWAAS (existing yield analysis), given the fact that the IWAAS Pitman model calibrations would be different to the ensemble results used in this study and the fact that the afforestation effects were added as a demand in the yield model for the IWAAS results, while they are included as part of the Pitman model simulations in this study. The parameter uncertainty bounds have had an approximately ±10% impact on the yield for all of the exceedence percentages.

3.4.3 Step 2 Results: Stochastic rainfall analysis combined with uncertain parameters

The main Pitman approach used in Step 2 was to generate 250 000 ensembles based on the 500 stochastic rainfall inputs combined with 500 parameter samples accessed from the saved natural parameter sets coupled with random sampling of the afforestation parameters. Figures 3.17 and 3.18 show the frequency distributions of the ensemble outputs based on all ensembles for the 60 month minimum flow (assumed to represent the critical period for storage of Nyaka Dam) and the mean annual flow. These are referred to as 'New Stochastic Analysis' in Figures 3.17 and 3.18. The 'New Parameters' line in Figure 3.17 represents the frequency distribution of minimum flows for the 10 000 ensembles using only the WR2005 rainfall data (no stochastics). The 'Old Stochastic Analysis' refers to the results based on no constraints on the parameter sampling (i.e. not using the saved natural parameter sets, but simply sampling from the full range of possible parameter values).

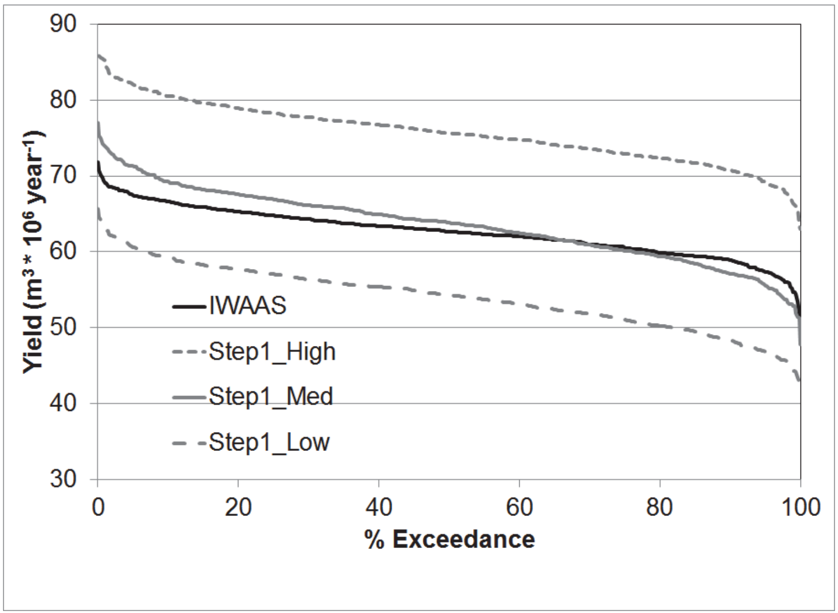


Figure 3.16 Comparison of yield results for Step 1 (IWAAS represents the existing yield analysis).

As might be expected the width of the frequency distribution for no stochastics in Figure 3.17 is much less than either of the results using stochastic rainfall. In addition the maximum frequency of the mean annual flow distribution is higher for the new analysis compared to the old. These are both expected results. The former is based on the additional uncertainty added by the use of stochastic rainfall sequences, while the latter is a reflection of the narrower band of parameter uncertainty in the new approach and associated with the constrained parameter samples. What is less easy to understand is why the latter result is not reflected in the comparison between the old and new approaches when the 60 month minimum flow is used, nor why the 'Old Stochastic' analysis results are both biased towards lower flows. One possible answer to this is related to the link between the parameter ranges used in the new version of the Pitman model and the constraints listed in Table 3.2. Figure 3.13 suggests that there is a potential bias towards lower MMQ vales relative to the full range used for that constraint and this could point to the fact that there other parameter combinations that did not meet the constraint range would be generally lower (rather than higher than the constraint range). Hence, unconstrained parameter sampling would result in generally lower flows rather than both lower and higher. Figure 3.19 illustrates the combined uncertainty (stochastic and parameter) yield results and, not unexpectedly, the range of possible yields has increased. Interestingly, the effect is greater at high yields and low frequencies of exceedence and this is not straightforward to explain.

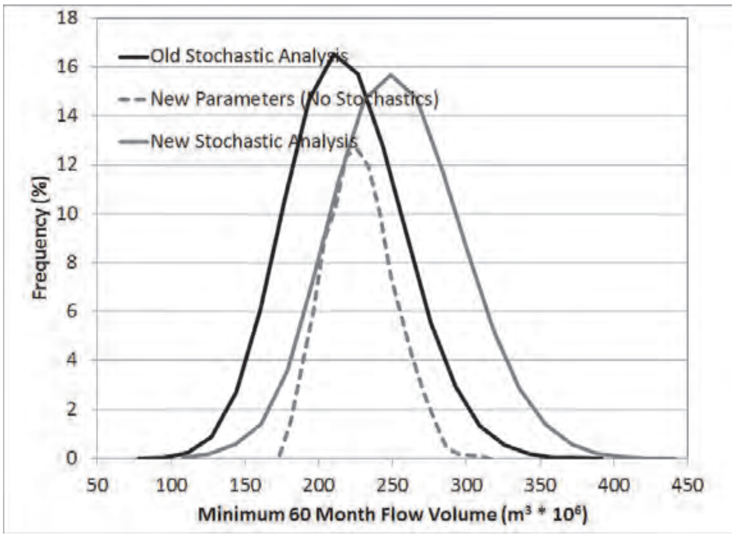


Figure 3.17 Comparison of frequency distributions of 60 month minimum flow.

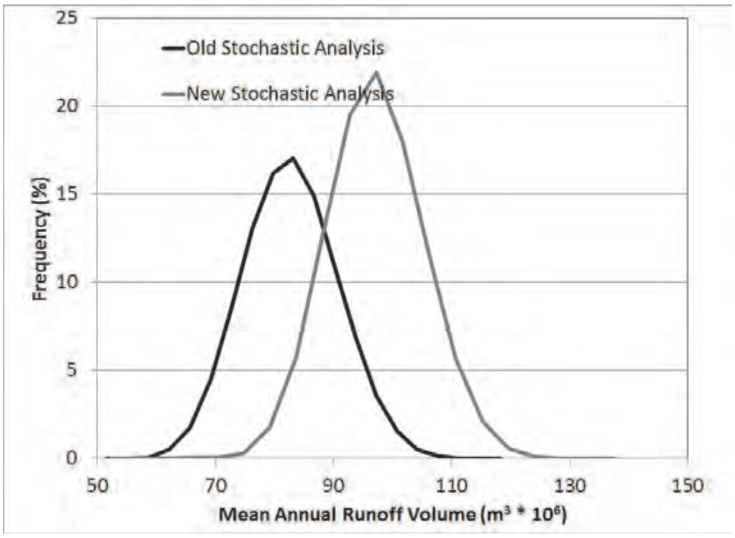


Figure 3.18 Comparisons of frequency distributions of mean annual flow.

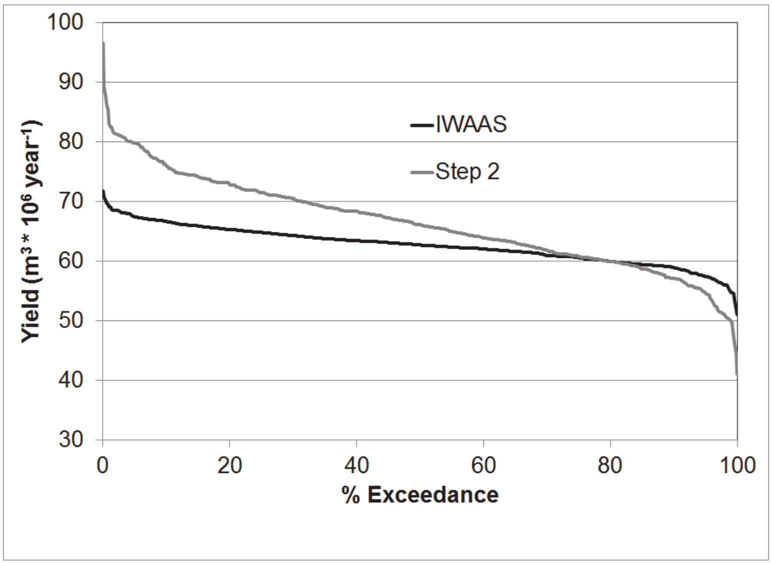


Figure 3.19 Comparison of yield results for Step 2 (IWAAS represents the existing yield analysis).

3.4.4 Step 3 Results: Stochastic rainfall analysis based on separating stochastic and parameter uncertainty

Figure 3.20 illustrates the results based on the frequency analysis of the minimum 60 month flow volume for the total 250 000 ensembles compared with the minimum and maximum parameter uncertainty ensembles (500 each) for each stochastic rainfall group. Figure 3.21 illustrates the yield results for Step 3. The shapes of the frequency distributions of minimum 60 month flow volumes shown in Figure 3.20 conform to what might be expected, as do the shapes of the resulting yield curves to a certain extent (Figure 3.21). Comparing this result with the previous one in Step 2, it is apparent that the maximum and minimum yields are more or less identical for the full set of ensembles. However, the results are quite different to the Step 1 results Figure 3.16) using stream flow stochastic analysis and the same parameter uncertainties. These differences are mostly evident at low exceedence percentages (i.e. low return periods) while the differences are quite small for the 1:100 year yield (approximately 55 to 77 $m^3 * 10^6$ for the stochastic stream flow sequences and 58 to 80 $m^3 * 10^6$ for the rainfall stochastic analysis).

Providing an explanation for these differences is not straightforward without a great deal of further analysis of the rainfall stochastic sequences and (probably) a great deal of speculation about the interaction between these and the uncertainty ranges of the parameters. However, it is likely that the increased rainfall within the wetter stochastic rainfall sequences has a marked non-linear effect on simulated runoff, regardless of the parameter sets that are used. The consequence would be higher stream flow values even when generally 'drier' (or lower runoff generation) parameter sets are used. The inevitable result is that the statistical properties of the stream flow ensembles generated through the stochastic rainfall process with any given uncertain parameter set would not be the same as the statistical properties of the historical stream flow record generated with the same parameter set. Figure 3.15 illustrates that the stream flow stochastic analysis results in almost a linear shift in the yield curves away from the curve based on simulated stream flows without parameter uncertainty. This implies that many of the statistical properties (apart from the mean) have been preserved even when uncertain parameters are used.

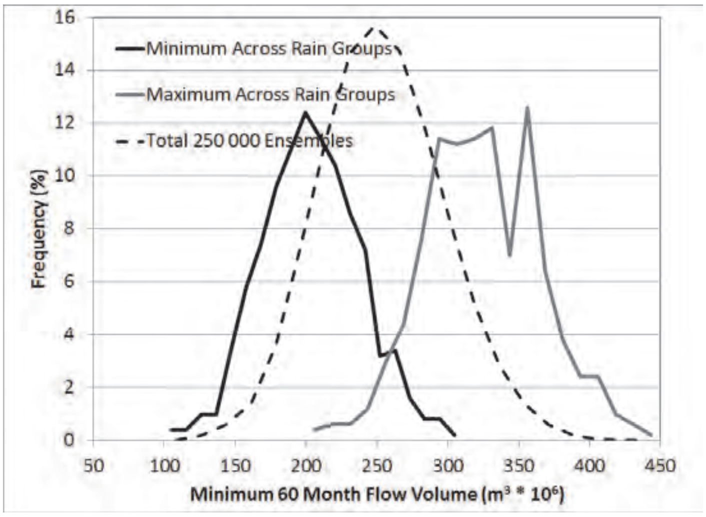


Figure 3.20 Comparison of frequency distributions of 60 month minimum flow for minimum and maximum ensemble results within each rainfall group.

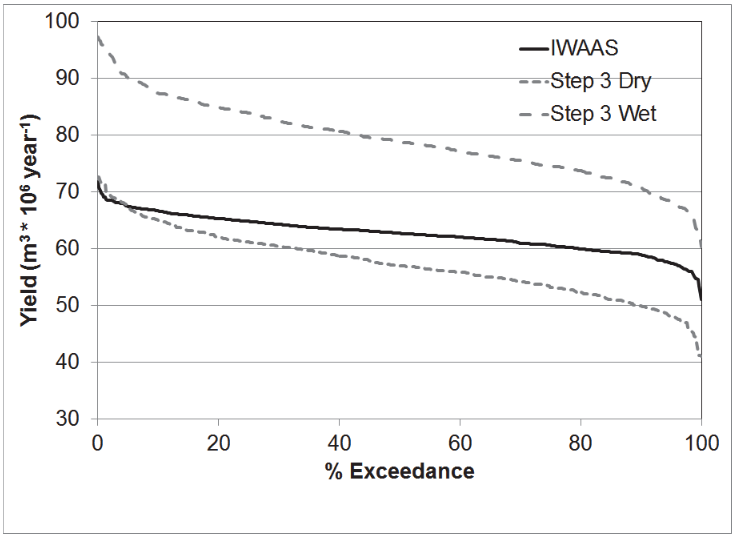


Figure 3.21 Comparison of yield results for Step 3 (IWAAS represents the existing yield analysis).

The relatively simple yield analyses included in this report are designed to illustrate the differences between using stochastic stream flow analysis with uncertainty (step 1B), combined stochastic rainfall and parameter uncertainty (step 2) and stochastic rainfall uncertainty with separate parameter uncertainty (step 3). It is apparent that there are differences between steps 1 and 3 that could be related to the non-linear transformation of rainfall into runoff. However, this requires further investigation on many more catchments and probably a deeper theoretical assessment of the differences between using stochastic stream flow and stochastic rainfall methods. This project team had neither the resources, nor time, to complete such a detailed analysis.

3.5 Using climate change data with the uncertainty models

Using the uncertainty models with future climate data obtained from downscale GCMs and RCMs is a relatively trivial issue as it is only necessary to replace the historical climate inputs with time series representing possible future conditions and changing the parameter uncertainty bounds to represent possible land cover (or other) conditions. Several climate change studies were completed during the course of the project, including one for the Caledon River basin using inputs from 9 statistically downscaled GCMs (data obtained from the Climate Systems Analysis Group at the University of Cape Town). The results indicate that the band of output uncertainty increases substantially, but there are no indications of general drying or wetting. The results are not presented in any more detail in this report as it is understood that the downscaled data have been revised and the authors are reluctant to publish results on what are out-of-date future projections. The main point is that the outputs from GCMs and RCMs are changing all the time as the climate modellers revise and improve their approaches. The majority of the effort involved in running the hydrological models for climate change scenarios is associated with pre-processing the climate data provided by the climatologists. This can be a substantial amount of work when there are a number of sub-basins involved and when several climate scenarios or several climate models are involved. By the time some of these data are released and processed through the hydrological models they are often out of date.

An alternative approach has therefore been suggested by the project team, but has not been tested because the methods and associated software have still to be developed. The basic concept behind the suggested method is that the rainfall sequences generated by climate models for a future climate are expected to have different statistical properties to the outputs from the model that relate to the past period (typically referred to as the baseline period). One additional issue is that the baseline simulations from all of the models are usually quite different and all of them are different from historical rainfall data (Hughes et al., 2014). The suggested method is therefore designed to identify the shifts in the statistical/stochastic properties of the rainfall simulations between the baseline and future for a range of different GCMs and downscaling methods. The statistical properties would be the monthly means, standard deviations and skewness, serial and spatial autocorrelation or any other properties that are used within a stochastic model.

The steps in the suggested process are outlined below:

Step 1: Historical rainfall records (HPTS) are used to generate stochastic parameters (SPH).

HPTS > SPH > Historical stochastic sequences.

Step 2: Use several downscaled GCM rainfall products consisting of baseline rainfall data (BPTS: 1960 to 2000) and a future time series (FPTS: 2030 to 2065, for example) and apply the same stochastic rainfall model to both.

$BPTS_i$ > SPB_i Baseline stochastic parameters for CC model i.

$FPTS_i$ > SPF_i Future stochastic parameters for CC model i.

Step 3: Calculate the changes between present and future in stochastic properties of rainfall for all models (i) and all appropriate stochastic parameters.

$\Delta SP_i = (SPF_i – SPB_i)$

Step 4: Run the stochastic rainfall model based on random samples from ΔSP_i to modify the stochastic parameters established from the historical rainfall data (SPH) when generating each stochastic sequence (assume that all of the GCM outputs are equally possible and therefore assume a uniform distribution of ASP_i). The resulting stochastic rainfall sequences can then be used directly with the uncertainty version of the Pitman model.

SPH + Random (ΔSP_i) > Range of possible future stochastic sequences.

The objective would be to generate future time series that are conditioned on the stochastic properties of the historical data but modified to account for the range of possible future changes. No individual GCM would be identifiable (nor do they need to be) within the final stochastic sequence. Any updates in the likely range of statistical property changes based on new climate change information can be easily applied through changes in the ASP_i arrays, thus saving a substantial amount of work in pre-processing many different rainfall time series. It is also assumed that a similar process could be applied to input evaporation demand data that will presumably change with future temperature changes.

4. DECISION-MAKING WITH UNCERTAIN INFORMATION

Within Beven's (2009) book on Environmental Modelling, chapter 6 deals with decision-making under uncertainty (see also Beven, 2000 and Beven and Alcock, 2011) and refers to one possible approach (Info-Gap Analysis) that was developed by Ben-Haim (2006) and has been applied in many different disciplines including water resources assessments (Korteling et al., 2012). A detailed explanation of the approach as well as many references on its application can be found at (http://en.wikipedia.org/wiki/Info-gap_decision_theory). In summary the approach involves the use of 3 models, each of which is linked to the previous ones:

- The first is a model of the situation around which a decision is required – such as the yield of a reservoir. As part of this model an estimate is made which is assumed to be substantially wrong. The uncertainty model determines how distant other values are from the first estimate (the best guess perhaps).
- The second model is the robustness/opportunity model. For this we require a minimal level of a desired outcome and given the uncertainties of the first model, how uncertain can we be of achieving this outcome (robustness). Conversely, given a better outcome (higher yield perhaps) than the estimates, how uncertain must we be for this outcome to be possible (opportunity or opportuneness).
- To make a decision (the third model), the robustness or the opportunities are optimized. For a minimum desired outcome, which decision is more robust (can still be achieved with the most uncertainty)? Alternatively, for a more beneficial outcome, which decision requires the least uncertainty for achieving the outcome?

Info-Gap analysis does not use probability distributions and measures the deviation of possible errors, but not the probability of different outcomes. The stated advantage is that it is not sensitive to any assumptions that are made about the probabilities of different outcomes. However, the approach does include the concepts of what are 'closer' or 'more distant' (from a first estimate) outcomes. Reading through some of the various applications of the method it is not very straightforward to understand how it can be linked to the type of hydrological and yield estimation uncertainty analyses that have formed part of this research project. Part of the problem is that the language and terminology used in many of the publications is not very familiar to hydrologists who have not been involved in the application of decision theory.

The paper by Korteling et al. (2012) provides a direct example (although focused on UK water issues, but which are not that different to some of the key water resources decision issues in South Africa) related to water resources planning. They also make use of Multi-Criteria Decision Analysis (MCDA) that has been used in the South African water resources sector previously (Joubert et al., 1997, for example). The MCDA method ‘is used to combine results for multiple criteria over multiple-steps of increasing uncertainty’. Info-Gap analysis is applied for the individual analysis of the multiple criteria. The example provided is based on a single reservoir that supplies roughly 89% of the demand (residential, commercial and agricultural), while the remainder is supplied from a regional supply scheme. The uncertainties that are accounted for in the example include climate change impacts (supply-side parameters), demand forecasts (demand-side parameters), accuracy of metering (both supply and demand) and cost. They considered 81 possible management options that included increases in reservoir volume, increases in transfers from the regional scheme, increases in water treatment, increased water use efficiency, domestic rainwater collection for different purposes, use of grey water and many combinations of these primary options. Part of the assessment (robustness) was based on a reservoir management risk metric (MMR) calculated as the product of the probability of the reservoir dropping below the drought management curve and the average deficit below this curve. The opportuneness of different management options was measured by a safety margin deficit (volume of water between the optimal management curve and the drought management curve – or the optimum and minimum acceptable reservoir volumes at different times of the year). Further details of the example are not repeated here, but it should be clear that the example includes a very comprehensive range of possible management options, as well as quite a lot of detail about the uncertainty sources.

There is little doubt that hydrologists and probably water resources engineers will require additional expertise from other disciplines if they are to confront the issues associated with making decisions with uncertain information. Whether info-gap analysis combined with some other methods are appropriate or not has yet to be determined. Durbach and Stewart (2012), as well as Hajkowicz and Higgins (2006) present a number of options, the former focusing on uncertainty and MCDA, the latter on different MCDA techniques for water resources management. Neither of them refer to info-gap analysis. Hall et al. (2012) made a comparison between Info-Gap analysis and Robust Decision-Making. It remains somewhat unclear which is the most appropriate method to use in different situations. It will therefore be necessary to establish some test cases to ensure that whatever type of decision-making tool is to be used is compatible with the types of uncertainty information that is being generated through the methods suggested by this (K5/2056) and the previous WRC uncertainty project (K5/1838).

4.1 A starting point for uncertain decision-making

This project did not spend a great deal of time on the decision-making issues linked to uncertainty, but has initiated an MSc level study that will investigate some of the questions of linking uncertainty to decision-making. The first step was to set up a trial hypothetical model of a water resources decision-making problem and look at how uncertain input information might affect the process. This initial test study that has been undertaken by Mr Gregory Pienaar is based on some of the concepts presented in Hughes and Mallory (2009) designed to integrate the effects of shortfalls in water supply across different water use sectors. The basic idea was that it should be possible to determine the approximate shape of the relationship between relative impact (0 to 100) and shortfall (0 to 100%, where 100% represents total loss of the water supply). The impact is measured on a nominal scale and could be determined using different criteria for different water sectors (i.e. financial, social, environmental or a combination). The overall impact of a shortfall in supply for a community would then be based on sector weightings that can take into account various socio-economic, strategic, political and environmental factors. With respect to uncertainty, the initial trial was designed to see how evaluations of this nature might be affected by uncertain simulations of time series of available water.

The test case was designed around quaternary catchment X22F in the headwaters of the Crocodile River and a large part of the uncertainty in the stream flow simulations was assumed to be related to the impacts of commercial afforestation. The uncertainty version of the Pitman model was run for the whole catchment (X22D, E and F – total area of 639 km^2) and the range of simulations compared with the gauged stream flow records at X2H005 to ensure that the simulations were representative. Figure 4.1 shows the uncertainty results based on the mean annual runoff that varies between about 70 and 120 * 10^6 m^3.

The median ensemble was used to generate ‘B’ and ‘D’ category ecological Reserve requirement using the revised desktop model (Hughes et al., 2012) and the low flow Reserve requirements at various FDC % points were expressed as a fraction of the equivalent baseflows separated from the total flows of the median simulation ensemble. The Reserve is therefore considered as the first user in the system and the required water use is defined as a fraction of the monthly natural baseflow, but with the fractions varying depending on the position of the natural baseflow on the FDC. An additional three users are defined to represent a rural community water supply, commercial cash crop irrigation and irrigation of pastureland. All of the users in this first example are assumed to abstract water direct from the river without any form of reservoir storage. The users therefore are assumed to only have access to the baseflow component of the stream flow and therefore the analysis is based on separated baseflows and the high flow components assumed to be inaccessible for use.

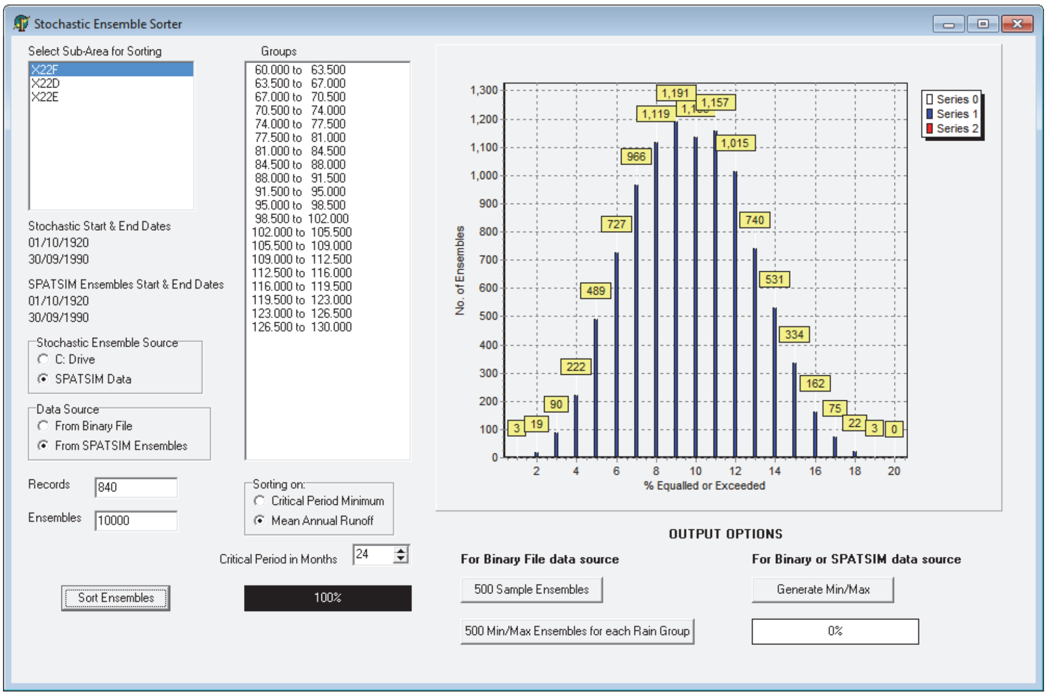


Figure 4.1 Screen shot of the ensemble sorter program for X22F to illustrate the simulated uncertainty for 10 000 ensembles.

Figure 4.2 provides an example screen shot of the new program that has been developed to analyse the impacts of various decisions and the uncertainties associated with the input data. **Note 1** refers to the table of user information that includes an impact index (see also Note 2) a community weight factor and an annual demand. The latter is supported by a table of seasonal distribution fractions for users 1 to 4. **Note 2** shows the deficit versus impact curves for the different users based on the impact index given in the table above. In this example the community water supply has been assumed to have the lowest use but the biggest impact of shortages. **Note 3** illustrates that although 10 000 ensembles of stream flow are available the user can take a sample of any size (in Figure 3.23 this is 500). **Notes 4 and 5** refer to the various decision options that have been included. The first level of decision refers to the way in which the ecological Reserve is treated; either being always met at the B level of protection, always met at the D level or treated as a user and therefore competes in the same way for water as other users. Note 5 offers several possible second level decision options:

- Equal allocation refers to providing the same amount of water to each user until either their requirements are met or the available water runs out. Clearly this option will favour users with the lower requirements.
- Proportional allocation refers to allocating the available water on the basis of the proportion of their individual requirements relative to the total requirement for all users.
- Proportional allocation with community weighting is the same as the previous on but with an allowance for the assumed community importance of each user.
- Equal individual sector impacts refers to an allocation approach that tries to equalize the relative impacts across all users (given the first decision level the affects the Reserve allocation).

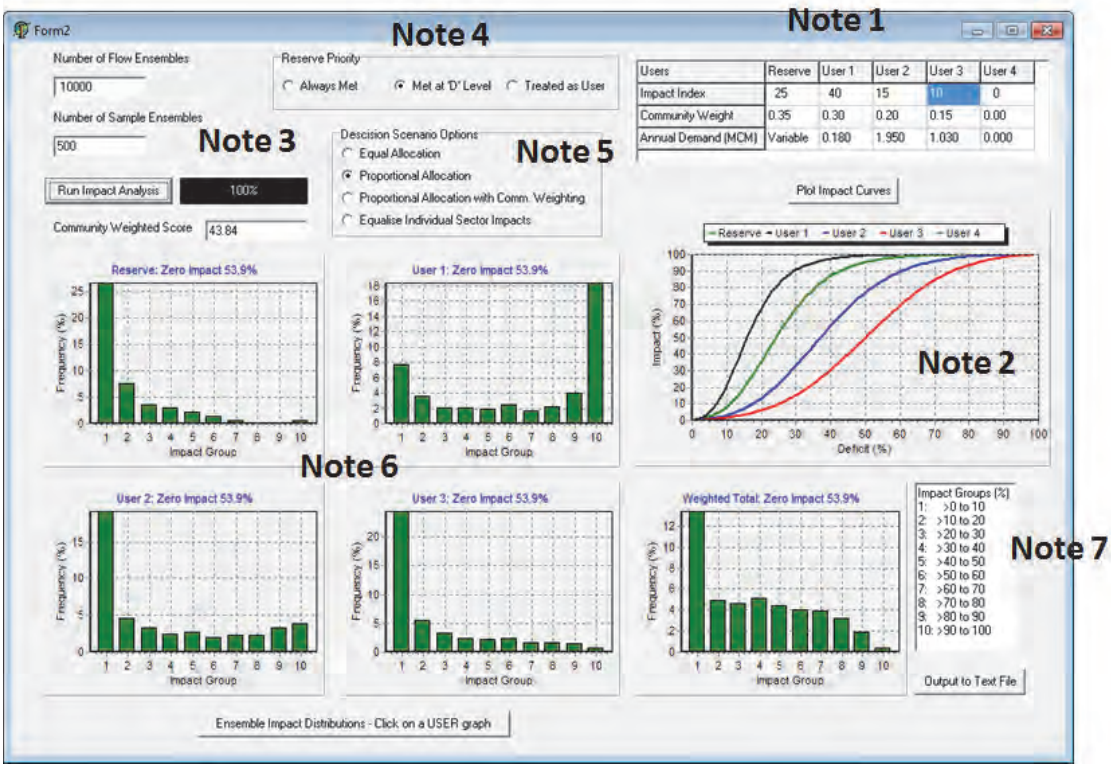


Figure 4.2 Screen shot of the water use uncertainty program for X22F.

Note 6 provides the graphs of frequency distributions of the impacts for each user and the total weighted impact for the community as a whole. **Note 7** is simply a key to the impact groups plotted in the graphs. The impact frequency values are calculated from the maximum impacts in all years of all ensembles and therefore integrate inter-annual variations with uncertainties across all of the ensembles used in the sample. The frequency of zero impacts is given in the title of each graph.

Figure 4.2 does not allow for the uncertainties related to the simulated stream flows to be resolved and therefore an additional level of analysis is provided through clicking on the button at the bottom of the screen (Figure 4.3). This analysis looks at the impacts within all of the months of the uncertain simulations. The user first selects which water user to deal with and up to four impact groups (middle top). The horizontal axes of the bar graphs refer to the number of months where the selected impacts occur within individual uncertainty ensembles. The number of months are counted within 10 groups (top right list). Thus, for the >70 to 80% impact group (bottom left graph), for 10% of the ensembles there is only 1 month with such an impact, 15% of the ensembles have 2 months, 45% have >2 to 5 months and 20% have >5 to 10 months of such impact. The uncertainty in the very high impact group (>90 to 100%) is very large with ensembles showing almost no months of impact, while others (16%) have >50 to 100 months of high impact.

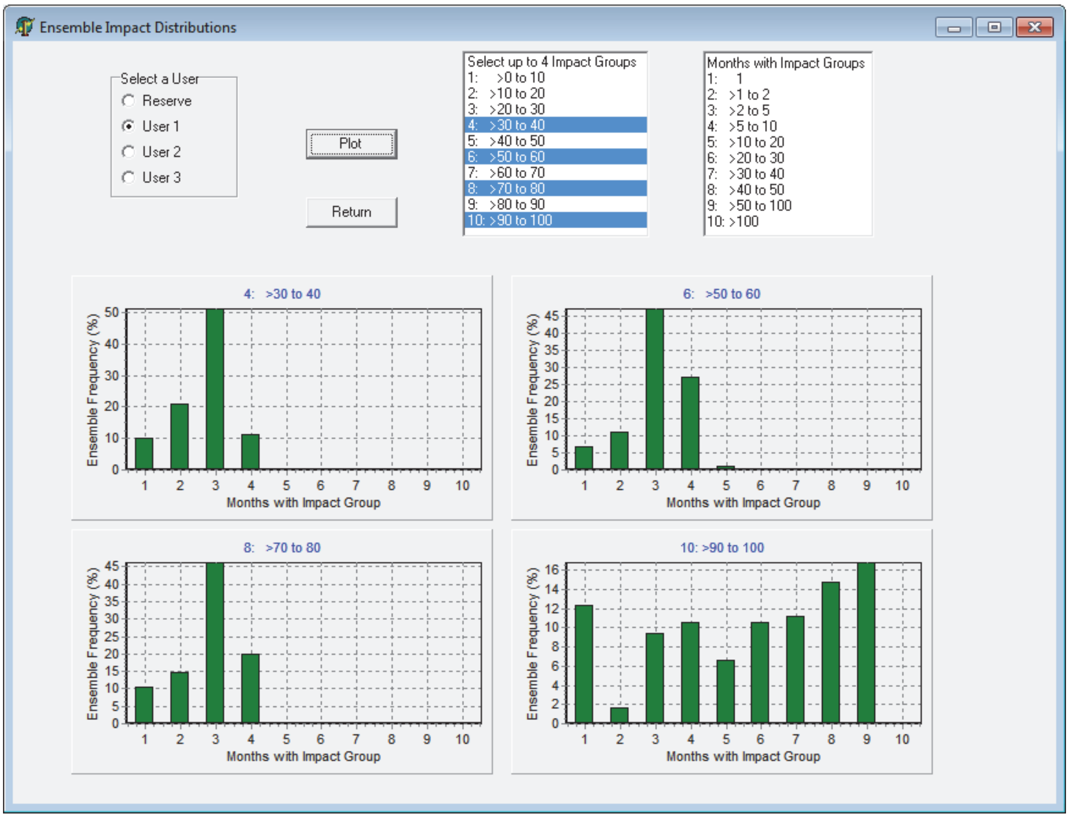


Figure 4.3 Screen shot of the sector impacts due to input stream flow uncertainty.

While some of the impacts appear to be very high, it should be remembered that this simple hypothetical example is based on quite substantial uncertainty in low flows consequent upon different assumptions about the impact of afforestation and that all of the users are abstracting directly from the river without storage – a high risk water supply option.

The nest step in the development of this approach is to include a simple reservoir water balance component within the new program so that allocation from storage (and reservoir operating rules) can be included in the analysis. The objective of developing these models is not necessarily to create final tools for water resource allocation decision-making, but to use them to demonstrate the approach (proof of concept) to using uncertain input information in decision-making tools. Ideally, these concepts will then be adopted (and probably adapted) for use in existing water resources allocation decision-making methods.

5. CONCLUSIONS AND RECOMMENDATIONS

The main objective of the project was to contribute to the incorporation of uncertainty assessments in practical water resource decision-making in South Africa. There are three main components to this objective. The first is the quantification of realistic levels of uncertainty that are as low as possible given the available information (reducing uncertainty). The second is the availability of tools to implement uncertainty analysis across the broad spectrum of data analysis and modelling platforms that form part of practical water resources assessment (including hydrological and water resources yield models). The third relates to the issue of using uncertain information in the process of making decisions about the design, development or operation of water resources systems. None of these are independent and all are associated with the fundamental issue that all of the role players should understand the key concepts of uncertainty and that it is a simple fact of life that virtually all of the information that we use to make decisions is uncertain, some more than others. One of the major challenges in this project as well as the previous WRC supported project on uncertainty methods (Hughes et al., 2011), was the lack of understanding of some of the key issues, or a lack of appreciation of the importance of uncertainty in all water resources decision-making. This was evidenced by the lack of support by both the DWA and the WRC for a proposal to undertake a ‘real’ practical demonstration project that emerged from this project and which was intended as a partnership between scientific researcher groups, consulting engineering service providers and state institutions (DWA) to move ahead and identify (and resolve) any further stumbling blocks in the implementation of uncertainty principles in practice. Towards the end of this project it was also proposed to launch a technology transfer project that would add quantitative uncertainty analysis to the ongoing updates to the national water resources assessment projects (WR90, WR2005, WR2012, etc., etc.). The proposed cost of this project was a minor fraction of the current and likely future costs of keeping the knowledge of available water resources updated at the national scale and yet it was not accepted. Clearly there is a long way to go before the concepts of incorporating uncertainty into water resources assessments are accepted as being important.

Internationally, the science of hydrology has completely embraced the concepts of uncertainty and it is almost impossible to get a hydrological modelling study published in a recognized journal unless an analysis of the uncertainties is included. This is largely because of the enormous contribution that was made by the IAHS PUB decade (Hrachovitz et al., 2013; Blöschl et al., 2013; Whitfield et al., 2014). These concepts, and the importance of uncertainty in both science and practice, have also been included in the new IAHS decade on change in hydrology and society (Panta Rhei: Montanari et al., 2013). While South Africa has a long history of using models for water resources assessments, uncertainty approaches are relatively new to the country (Hughes, 2013) and have not been embraced by either scientists or practitioners. Pappenberger and Beven (2006) asked many questions about why uncertainty approaches were not considered practical, but it would seem that at least in South Africa these questions remain unanswered. There has been a tendency to think of uncertainty approaches as being in the realm of academic scientists and that they cannot be used in practical situations. The result is that many present day water resources allocations are made using extremely approximate information and with no attempt to assess how potential errors may affect the risks of making certain decisions. The future is even more uncertain and many climate change projects conclude that adaptation of some form is necessary (Beven, 2011). However, hardly any of these take into account the huge uncertainties associated with future climate projections and therefore fail to discuss the implications of uncertainty on adaptation decision-making.

This report makes yet another attempt to convince the South African community of scientists and practitioners in hydrology that uncertainty assessments are possible, that they can be implemented in practice and that it should be possible to incorporate them into decision-making.

5.1 Reducing uncertainty

The overall conclusion with respect to reducing uncertainty is that there is nothing better than good observed data and good understanding for reducing uncertainties. One of the important issues is that we have to acknowledge and understand the uncertainties in our observed data before we can even begin to think about reducing the uncertainty. Observed data are hardly ever perfect and it will always be difficult to quantify climate inputs to models. Even if the data are collected accurately they typically refer to a specific point or small area and the uncertainty is associated with extrapolation to other areas. Some new work on quantifying rainfall variations (with uncertainty) for the whole of South Africa is being undertaken on behalf of the WRC and we look forward to some of these results with great anticipation. Even if the rainfall estimates are likely to be only small improvements on our existing data, the explicit inclusion of uncertainty is certainly a step in the right direction. This section of the report also looked at using MODIS data for constraining the actual evapotranspiration outputs (and associated parameter values) of models. While there have been very positive reports in some of the literature on the use of the EO data, some of the limited assessments reviewed did not return very favourable results and it is clear that MODIS data, while potentially useful, should be treated with caution.

The final part of the chapter on uncertainty reduction concentrated on two quite detailed studies in the Diep River (single sub-catchment) and Caledon River (31 sub-catchments) basins. The approach was based on a progressive reduction in uncertainty using as much information as is available, some that might be considered 'hard' data (stream flow gauging stations within the region) and some that is certainly 'soft' data (conceptual understanding and published information about expected hydrological processes from other areas). Further assessments of uncertainty and attempts to reduce it within surface water-groundwater interaction studies are included in the companion report on this project (Tanner and Hughes, 2014). It is important to note that these assessments involve a considerable amount of detailed analysis of the simulation ensembles (both parameter space and output results) that was mostly carried out using spreadsheets. This is very time consuming and is not practical for normal operational model use. One of the options is to develop software that can be used to post-process the ensemble data and automatically perform the type of analyses that have been done for this study. It can also be noted that performing uncertainty analyses on large basins with many sub-catchments is very difficult and confusing. There is simply such a large uncertainty space (even without uncertain climate inputs) that resolving the interactions and the inter-dependencies is almost impossible. This was identified as a critical area of research that needed further investigation for practical uncertainty analyses and the outcomes of that research are covered in chapter 3 of the report.

5.2 Uncertainty analysis in practice

A revised approach to including uncertainty in the modelling of large basins with many sub-areas has been developed and it includes two steps to avoid some of the practical problems that were experienced in previous work on this project related to the interpretation and further use of uncertain ensemble outputs from the Pitman model. The first step involves the use of regional or local (based on observed stream flow data) constraints to limit the parameter sets that can be considered behavioural in the simulation of natural (un-impacted) incremental flows for each sub-basin. These parameter sets are saved and then used with uncertain water use parameters (sampled independently) in the second step of the model when the cumulative flows at the outlet of all sub-basins are simulated. As with previous versions of the uncertainty model, sub-basins can be grouped and both the natural parameter sets and the individual water use parameters structured in a way that allows groups of sub-basins to follow patterns of uncertainty that are similar.

One of the advantages of the approach is that where there are high confidence gauged data, the constraints can be set with very narrow uncertainty bounds, while in ungauged areas these could be much wider. The approach therefore allows for different levels of uncertainty to be included in basins where the hydrological response in some areas is well understood and known, but where other areas have much higher uncertainty.

Some additional software has been developed to facilitate the process of matching the uncertainty ranges of the natural model parameters to the constraints used in step 1. Experience of using this approach thus far suggests that a great deal of care is needed to ensure that the constraint bounds are compatible with each other and with the parameter bounds. The new software can help to identify the potential problems when less than 2 000 behavioural ensembles are generated from step 1 for some sub-catchments and this speeds up the process of achieving a final result for a whole basin. This approach is also currently being applied and further tested in the Great Ruaha River basin in Tanzania by a PhD student from the University of Dar es Salaam. Part of this study is looking at the impacts of observed stream flow data uncertainties on establishing the constraints used for step 1 of the revised approach.

One of the important issues about the practical use of hydrological model uncertainty analysis, is the need to link the outputs of the uncertainty version of the Pitman model with existing approaches used for water resources yield analysis. The revised approach and some new software tools have improved the practical value of the uncertainty assessments in the following way:

- The revised approach ensures that all of the natural incremental flows generated as part of the full set of ensembles are behavioural relative to what is known (from observed data or regional analysis) about the real catchment responses.
- The methods have been developed to be compatible with both the traditional approach of using stochastic stream flow sequences in the yield model and the emerging approach of using stochastic rainfall sequences within the hydrological model.
- The hydrological model generates many more simulated stream flow ensembles than can be typically used within the yield model. A new, fairly comprehensive, model utility has been developed that can be used to extract appropriate information from a full set of ensembles for use with a water resources system yield model. One of the options in this utility program is to be able to generate outputs that either combine parameter and stochastic uncertainty or separate them out when stochastic rainfall inputs are combined with parameter uncertainty. This was previously identified as a very important practical issue by members of the project Reference Group.

The introduction to the sections of the report on the combination of hydrological model parameter uncertainty and stochastic analysis raises some issues about the interpretation of probability information in yield analyses when different forms of uncertainty are combined. The report does not make any firm conclusions about these interpretations and it is necessary for these to be resolved through discussions amongst the community of practitioners.

The relatively simple yield analyses included in this report are designed to illustrate the differences between using stochastic stream flow analysis with uncertainty, combined stochastic rainfall and parameter uncertainty and stochastic rainfall uncertainty with separate parameter uncertainty. It is apparent that there are differences between the results obtained using stochastic stream flow and stochastic rainfall analyses that could be related to the non-linear transformation of rainfall into runoff. While the statistics of a stream flow time series will be preserved during stochastic stream flow generation methods, this may not be the case when stochastic rainfall data are used to force a hydrological model. However, this requires further investigation on many more catchments and probably a deeper theoretical assessment of the differences between using stochastic stream flow and stochastic rainfall methods. This project team had neither the resources, nor time, to complete such a detailed analysis.

The overall conclusion is that the project has demonstrated that including uncertainty analysis as part of the widely used Pitman hydrological model (Hughes, 2013) is a practical proposition and that the uncertainty outputs can be successfully linked to existing water resources yield models. This statement should be qualified by the consideration that all of the research for this project has made use of the IWR's SPATSIM version of the Pitman model, while it is recognized that almost all practitioners use the WRSM2000 software in which uncertainty options have yet to be included. It is therefore up to the community of hydrological and yield model practitioners to decide how best to proceed into the future. The project team have demonstrated the potential, identified some of the likely shortcomings, and suggested some ways forward that include possible revisions to computer code and software architecture (Tristam et al., 2013). However, it is now up to the user community to respond to these initiatives and suggestions.

5.3 Decision-making and uncertainty

The final chapter of the report offers some initial ideas about the use of uncertain information in decision-making. While this was meant to be a quite important part of the project, the project team could not make a great deal of progress because of the lack of interest and engagement with key decision makers. However, the Institute for Water Research at Rhodes University has initiated an MSc level study at its own cost to review international approaches to decision-making in the face of uncertainty and to conduct some pilot studies in the Crocodile River basin where other IWR research activities have the potential to offer support. Some preliminary results of these studies are presented in chapter 4.

5.4 Final observations and recommendations

Throughout this, and the previous WRC, project attempts have been made to achieve a balance between the development of new scientific 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. The techniques that have been developed have already been successfully applied by Rhodes University research staff and students in studies as diverse as large scale modelling of some southern African river basins to smaller scale evaluations of surface-groundwater interactions, climate change and development 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 results of the project have already been published internationally or presented at international conferences.

The report makes a single important recommendation and that is that the hydrological science and water resources practice communities within South Africa (including those organisations that fund research and practice) start to take the concepts of uncertainty far more seriously than they have in the past.

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APPENDIX A: LIST OF ABBREVIATIONS

AGIS.	Agricultural Geo-referenced Information System.
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).
EO	Earth Observation data (Satellite Imagery, for example).
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.
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 $m^3 * 10^3$.
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.
RCM	Regional Climate Model
SPATSIM	Spatial and Time Series Information Modelling.
SD	Standard Deviation.
WRC	Water Research Commission of South Africa.
WR90	Water Resources of South Africa 1990.
WR2005	Water Resources of South Africa Update 2005.