Quantitative modelling for assessing system trade-offs in environmental flow management

by

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Candidate's Declaration

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university. To the best of the author's knowledge, it contains no material previously published or written by another person, except where due reference is made in the text.

Emily Jane Barbour   Date: 21 August 2016

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Abstract

This research aims to better enable the management of environmental flows through exploring the opportunities and challenges in using quantitative models for decision making. It examines the development and application of ecological response models, river system models, and multi-objective optimisation for improved ecological outcomes and the identification of trade-offs. In doing so, the thesis endeavours to capture a deeper and more holistic understanding of uncertainty in the application of quantitative models, to assist in making more informed decisions in water resource management.

The thesis includes three main components. Firstly, an ecological response model is developed to advance previous methods by: (1) adopting a systems approach to representing water availability for floodplain vegetation, considering rainfall and groundwater in addition to riverine flooding; (2) including antecedent conditions in estimating current ecological condition; and (3) including uncertainty in modelling ecological response through the use of upper and lower prediction bounds and multiple conceptual models derived through expert elicitation.

Secondly, the ecological response model is evaluated using sensitivity and uncertainty analysis. Global sensitivity analysis was used to identify model components that are both uncertain and have critical impact on results, and demonstrated that conceptualisation of ecological response had the greatest impact on predicted ecological condition. A novel application of Bayesian analysis was then used to evaluate different expert derived models against observed data, considering multiple sources of uncertainty. The analysis demonstrates a number of remaining challenges in modelling ecological systems, where model performance depends upon assumptions that are highly uncertain.

The third and final component evaluates opportunities and challenges in using multi-objective optimisation, to assist in water resource management and the improvement of ecological outcomes. This component begins with a synthesis of previous studies drawing upon literature from hydrology, ecology, optimisation and decision science, and identifies a number of strategies for improvement. The synthesis is followed by a case study on the Lachlan catchment of the Murray-Darling Basin, Australia. The case study uses multi-objective optimisation to explore different environmental flow rules using a river system model combined with the expert-based ecological models. In doing so, it addresses the challenges of objective setting and problem framing in the context of significant uncertainty. The case study evaluates results generated using the optimisation framework in terms of likely actual decision outcomes.

The research identifies a need to revisit fundamental questions regarding system understanding and objective framing in the light of rapidly improving computational capacity and sophistication. This is particularly relevant in the case of ecological management, where objectives form an interplay between ecological science and social values. Modelling tools

provide valuable pathways to system learning and communication, yet a deeper understanding and evaluation of model behaviour in the context of actual decisions is needed.

The methods presented in this thesis aim to provide a step toward addressing the challenges of working with uncertain information, incomplete knowledge, and integration across multiple disciplines within a decision-making environment. Through the methods developed here, the research seeks to advance the science of model development and application.

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Glossary and Terms

Allocation	The amount of water which can be taken from a river system based on the current available water in the system
Environmental flows	Surface water in a regulated river system that is intended for sustaining instream, wetland and/or floodplain ecosystems
Model elements/components	Constituents which produce a particular set of model outcomes, and include input data, model formulation, model structure, parameters
Natural flow regime	Characteristics of river flow based on conditions prior to any development, and consider the magnitude, frequency, duration, timing and rate of change of flow
Translucency	Dam operational rules which allow for dam releases to meet environmental flow requirements, and are based on the inflow to the dam, water availability, and system constraints

Part A

Chapter 1: Introduction

Water is a critical resource for human wellbeing, and river systems have been altered globally to meet human water needs. Many anthropogenic benefits derived through river regulation and water extraction have played a fundamental role in development, and in transition out of poverty (Smith, 1972; Grey and Sadoff, 2006; Grey and Sadof, 2007). These benefits include improved water security for towns and agriculture, flood mitigation, and hydropower with reduced reliance on alternative energy sources such as fossil fuels. Other benefits include aquaculture, improved transportation routes and promotion of trade.

However, many of these benefits come at great environmental and social cost, with the potential to result in long term economic impacts. Previous river management practices have caused significant changes in the structure and functioning of rivers and floodplains, as well as changes to flow patterns, water quality and ecology (Poff *et al*., 1997; Bunn and Arthington, 2002; Poff *et al*., 2010). In response to the severe degradation of many of the world's rivers, there has been a growing recognition of the importance of maintaining river systems and the incorporation of ecological objectives in river system management (Richter *et al.*, 2006; Arthington *et al.*, 2006; Acreman *et al.*, 2014b; Poff and Matthews, 2013). This is reflected in the substantial financial investment in river restoration globally. For example, over US $1 billion has been committed to addressing pollution in the Ganga river basin in India (World Bank, 2010); US $3.2 billion has been invested in re-connecting wetlands with the Yangtze River (WWF, 2011); whilst an average of >US $1 billion is estimated to be spent each year on river restoration projects in the United States (Bernhardt *et al.*, 2005).

In the late 1940's, the new scientific field of environmental flows was formalised with the goal of identifying the flow characteristics (such as magnitude and timing) required to sustain instream and floodplain ecosystems; assessing the impact of hydrologic alteration (river regulation and water extractions); and developing strategies for minimising these impacts (Tharme, 2003; Arthington *et al.*, 2006). Over the last 75 years, the environmental flows field has evolved from focusing primarily on minimum flows for sustaining fish populations of economic value, to understanding the dynamic nature of river systems in a wider management context (Poff and Matthews, 2013).

The complex nature of river management calls for a variety of approaches to meet multiple and often conflicting objectives. It requires an understanding of both biophysical and social systems, including societal values. Described as a 'wicked problem', there is no right or wrong solution, and the system is sufficiently complex, dynamic and uncertain that it cannot be fully understood using current knowledge and information (Churchman, 1967; Rittel and Webber, 1973; Reed and Kasprzyk, 2009; Game *et al.*, 2014). As such, one of the biggest challenges currently being faced in river management is the identification of how rivers and their ecosystems are valued, and how they should be managed in the broader socio-political context given the significant uncertainty in understanding and predicting ecological response (Pahl-Wostl *et al.*, 2013).

Quantitative models are one of a number of tools which can aid decision making in river management for improved ecological outcomes. They have been effectively applied in many river basins world-wide, such as the Murray Darling Basin (Australia), the Colorado (USA), and the Thames (UK) (Jamieson, 1986; Hameed and Podger, 2001; Zagona *et al.*, 2001). Models can assist in understanding system processes; identifying gaps in data and knowledge; integrating and building upon multiple sources of information; facilitating communication between modellers, researchers, decision makers, and the community; as well as estimating future change and evaluating alternative management options (Loucks and van Beek, 2005). However, the uncertainties involved in modelling any complex system require a deep understanding of model assumptions and the impact on results, as well as effective integration with other sources of information and influences in the decision making process (Beven and Alcock, 2012).

Pahl-Wostl *et al*. (2013) propose that the primary limitation in environmental flow management results from social factors including governance, institutional capacity, and stakeholder engagement and support, rather than lack of ecological understanding. Whilst this thesis argues that lack of adequate ecological knowledge remains a key challenge, there is a clear need to bridge the gap between science and the wider decision making context. The research presented here aims to close this gap for the application of quantitative models for environmental flow management.

This is addressed through three major components: improving system representation and consideration of uncertainty in ecological response modelling; investigation of model behaviour and impacts on decision outcomes; and exploration of the opportunities and challenges in using multi-objective optimisation to aid in environmental flow management. Throughout these three components, problem framing and consideration of uncertainty play a central theme.

Figure 1 shows the conceptual framework applied in the current research. The framework was informed by the Sustainable Management of Hydrological Alterations (SUMHA) framework developed by Pahl-Wostl *et al*. (2013), with the integration of hydrology, ecology and social science for the management of environmental flows. The conceptual framework demonstrates that whilst the research presented here focuses on the advancement of environmental flow science, this is viewed as a single influence in a much wider decision making context. Social values, culture, and norms interwoven with politics and governance can be both a great enabler for and hindrance to change (Bakker and Morinville, 2013; Lebel *et al.*, 2005). Additionally, public knowledge and experience can play a significant role in the progression and adoption of scientific finding and vice versa (Lebel *et al.*, 2010). Although direct consideration of these factors is outside the scope of the current work, the research endeavours to contribute to the wider decision making process.

The current research advances previous work through integrating hydrology, ecology, sensitivity and uncertainty analysis, optimisation and decision science, thereby providing additional insight and methodologies for environmental flow management. Using the Lachlan catchment in the Murray-Darling Basin as a case study, the research explores the challenges of representing ecological objectives in a modelling framework, and in evaluating trade-offs with non-ecological objectives which may be more easily defined and quantified. Recommendations and strategies are then provided to enable more informed application of quantitative modelling tools.

A summary of originality and contribution is provided in Section 1.1, followed by an outline of specific aims, objectives and hypotheses (Section 1.2), and an overview of the thesis structure (Section 1.3). More detailed reference to relevant literature is included at the beginning of each subsequent chapter.

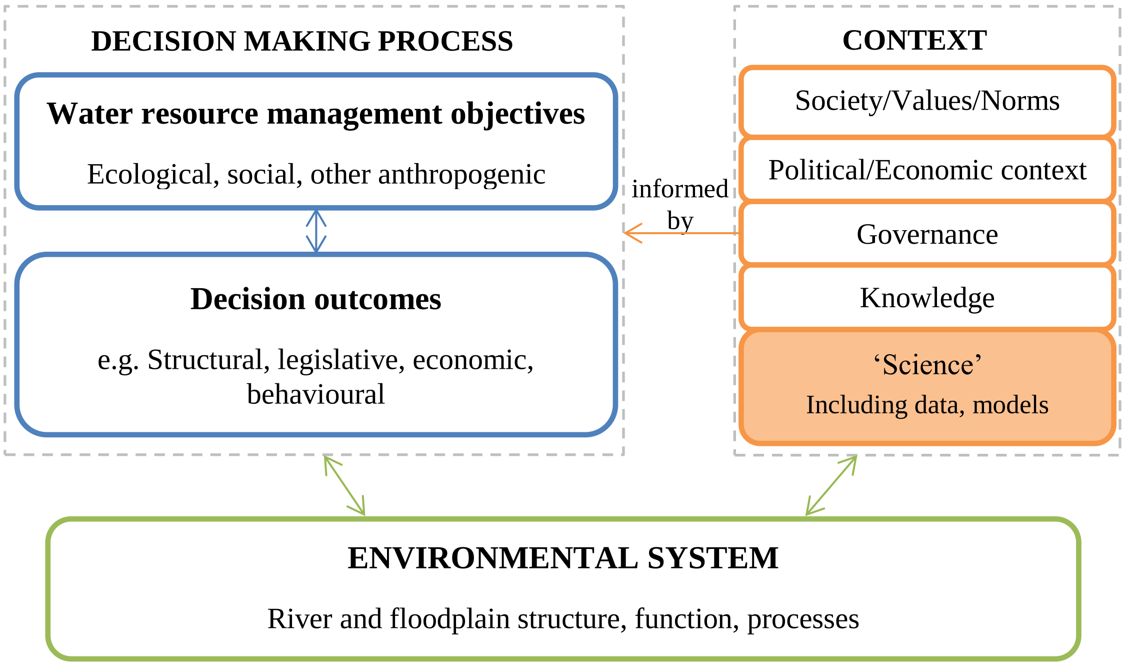


Figure 1. Environmental flow science within a broader decision making context. Decision outcomes are influenced by management objectives and knowledge of the river system, and are informed by social values and norms, political and governance context, community knowledge as well as science.

1.1 Originality and contribution

Environmental flow science has advanced significantly in the last 40 years, progressing from the determination of minimum instream flow requirements to the identification of key elements of the natural flow regime required to support ecosystems (Poff *et al.*, 1997). Multiple approaches for investigating environmental flow requirements have been developed, including models to assess habitat suitability for specific species (e.g. Waters, 1976; Bovee, 1982; and Young *et al*., 2003); flow based metrics to assess the impacts of changes to natural flow variability (Richter *et al*., 1996; 1997), and frameworks which provide strategies for combining field based methods, modelling and stakeholder engagement (e.g. Bovee, 1982; Tharme and King, 1998; Poff *et al*., 2010; and Pahl-Wostl *et al*., 2013).

Despite these advances, there remains significant uncertainty in our ability to predict ecological response, and a greater need to apply environmental flow science in a wider decision making context such as that shown in Figure 1. As identified in reviews by Poff and Matthews (2013) and Pahl-Wostl *et al*. (2013), until recently research has focused on the biophysical elements of estimating ecological response, whereas it is now recognised that environmental flow management requires greater consideration of society, politics and governance. Consequently, there is now increased focus on objective setting and the consideration of trade-offs between ecological and non-ecological objectives (Poff and Matthews, 2013; Acreman *et al.*, 2014b).

This research addresses the challenges identified above through advancing the prediction of ecological response using a systems approach to assessing water availability and changes in ecological condition, and applying this approach in the examination of trade-offs between ecological and agricultural objectives. Through both model development and application, multiple sources of uncertainty are considered, and their impacts on decision making assessed. Specific limitations which are addressed in the current research are as follows:

1. *Advancing the estimation of ecological response*

Existing methods for assessing environmental water requirements can be described using two main categories: species preference curves and the natural flow approach. Species preference curves were initially developed in the late 1970's and early 1980's through the weighted usable area (WUA) method of habitat suitability (Waters, 1976) and the Physical Habitat Simulation (PHABSIM) model (Bovee, 1982). These focused on instream habitat, whilst more recent methods such as the Murray Flow Assessment Tool (MFAT) (Young *et al.*, 2003) and Exploring Climate Impacts on Management (EXCLAIM) (Fu *et al.*, 2015) consider the water requirements of wetland and floodplain species in addition to instream requirements.

The importance of the natural flow regime was brought to wider attention in the mid to late 1990's through the work of Richter *et al*. (1996; 1997) and Poff *et al*. (1997). Poff *et al*. (1997) identified and discussed five key elements of the natural flow regime which define ecosystems and their habitat: magnitude; frequency; duration; timing; and rate of change (Figure 2). These flow characteristics were used to develop metrics for comparing natural and altered flow patterns in the Indicators of Hydrologic Alteration (IHA) (Richter *et al.*, 1996), and estimating an acceptable level of hydrological alteration in the Range of Variability Approach (RVA) (Richter *et al.*, 1997).

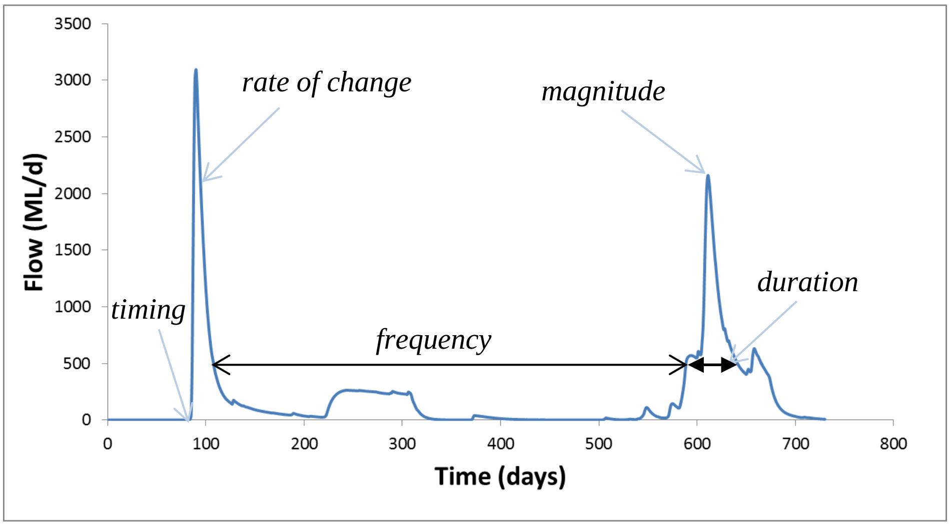


Figure 2. Five ecologically significant characteristics of the natural flow regime as defined in Poff *et al*. (1997).

Building upon both the natural flow and species preference approaches, a number of assessment frameworks have been developed. These include the Instream Flow Incremental Method (IFIM) (Bovee, 1982), the Building Block Methodology (BBM) (Tharme and King, 1998), and the Ecological Limits of Hydrological Alteration (ELOHA) (Poff *et al.*, 2010). These frameworks use a combination of field based assessment, modelling, and expert input to develop relationships between flow alteration and ecological response. Following ELOHA was the development of the Sustainable Management of Hydrological Alterations (SUMHA) framework by Pahl-Wostl *et al*. (2013), to incorporate the wider social, political and governance context in the assessment of environmental flows.

These methods and frameworks have enabled environmental flow requirements to be more easily evaluated and incorporated into river system management. They can increase transparency, and can be used in consultation with stakeholders to identify and assess different management alternatives. However, a number of limitations remain which restrict the acceptance and applicability of ecological response models. The limitations which are addressed through the current research are as follows:

- **Rainfall and groundwater:** Few models exist which consider wetland and floodplain ecosystems in addition to instream habitat. Those which do, such as MFAT, generally do not consider multiple water sources in the estimation of ecological condition, instead focusing only on river flows. However, studies have shown that rainfall and groundwater can play an important role in sustaining floodplain vegetation (e.g. Mensforth *et al.*, 1994; Thorburn and Walker, 1994). The model developed here incorporates both rainfall and groundwater in the estimation of ecological response, and also investigates the relative importance of these sources of water in survival during drought.

- **Antecedent conditions:** Existing models include minimal consideration of antecedent conditions, both in terms of preceding hydrological conditions and ecological condition. This research endeavours to address this through altering floodplain inundation patterns based on the extent of the preceding dry period, as well as modifying the ecological response curves based on the ecological condition at the start of each wet and dry event.
- **Uncertainty in ecological response models:** There is limited representation of uncertainty in existing ecological response models. With the exception of work by Fu and Guillaume (2014), there has been no explicit representation of uncertainty in the estimation of habitat suitability or ecological condition of the models reviewed here. Given existing models have been criticised for their limited capacity to predict ecological response (e.g. Tharme, 2003; Acreman and Dunbar, 2004), the consideration of uncertainty is essential. This work uses upper and lower uncertainty bounds developed through expert elicitation to explore the impact of model uncertainty on decision making.

2. Assessing uncertainty in the estimation of ecological response

The importance of assessing the impact of different uncertainties and assumptions on model results is well recognised (Jakeman *et al.*, 2006; Matott *et al.*, 2009; Walker *et al.*, 2003; Refsgaard *et al.*, 2007). Two types of approaches for investigating model behaviour are sensitivity analysis and uncertainty analysis. Both have been widely applied in hydrology and ecology (e.g. Beven and Binley, 1992; Tang *et al*., 2007; Cressie *et al*., 2009 Kasprzyk *et al*., 2012; Perz *et al*., 2013), yet there has been minimal application in environmental flow assessment. Consequently, this work addresses limitations in assessing uncertainties for environmental flows as follows:

- **Sensitivity Analysis:** Previous applications of sensitivity analysis have primarily focused on the impacts of different parameter values for the purpose of model calibration. However, there has been little investigation into the impact of different conceptualisations of ecological response on results. The current research evaluates sensitivity to different conceptualisations based on expert elicitation, and compares this with hydrological and ecological parameter values.
- **Model evaluation:** Many different approaches exist for evaluating model behaviour, such as the Generalised Likelihood Uncertainty Estimation (GLUE) method (Beven and Binley, 1992), the Model-Independent Parameter Estimation and Uncertainty Analysis (Doherty, 2015), and the Bayesian Total Error Analysis (Kavetski *et al.*,

2006). However, as with sensitivity analysis, few studies consider the impact of multiple sources of uncertainty including system conceptualisation (Butts *et al.*, 2004; Clark *et al.*, 2011). This work uses Bayesian analysis to compare the different expert defined conceptualisations of ecological response, considering multiple sources of uncertainty.

3. Environmental flows: opportunities and trade-offs in a decision making context

There are an increasing number of studies examining alternative environmental flow strategies and trade-offs between ecological and non-ecological objectives. Optimisation provides one approach for efficiently exploring multiple alternative management strategies, and explicitly evaluating trade-offs. It has now been widely applied for assessing ecological objectives in river systems (e.g. Suen and Eheart, 2006; Dittmann *et al*., 2009; Yin *et al*., 2012; and Szemis *et al*., 2014). The application of optimisation for environmental flow assessment has been facilitated by advances in optimisation algorithms which place fewer restrictions on problem formulation.

Until recently, previous optimisation research has focused on the development and application of different types of algorithms, with limited consideration of objective setting and problem formulation (Maier *et al.*, 2014). As identified in the 1960's and 70's, the identification of objectives and the representation of complex systems in a modelling framework is both essential for informing decision making, as well as being extremely challenging (Hitch, 1960; Churchman, 1967; Liebman, 1976; Rittel and Webber, 1973). For these reasons, the current research addresses limitations in evaluating environmental flows through the following:

- **Synthesis of current challenges:** Undertaking an in-depth analysis of existing applications of optimisation for environmental flows to identify current challenges.
- **New approach for addressing uncertainty:** Proposing a new strategy for addressing these challenges with greater consideration of the impact of uncertainties in objective setting and problem formulation on environmental flow management
- **Impact of objectives and problem formulation**: Evaluating the impact of different objectives and model assumptions on environmental flow alternatives using a case study.

Through the novel contributions outlined above, it is aimed to improve the evaluation of different environmental flow alternatives, thereby facilitating more informed decisions, and enabling better outcomes for both the environment and for people. To address the challenges identified, the following aims, objectives and hypotheses were adopted.

1.2 Aims, Objectives and Hypotheses

The primary objective of the research was to investigate the use of quantitative modelling in environmental flow management, examining different sources of uncertainty and the likely impact on decision making. Specific objectives for each of the three major components include:

1. *Objectives: Understanding Ecological Response through Model Development*

1. To investigate the importance of river flows, rainfall and groundwater for the prediction of ecological response, using a systems approach to explore water use by floodplain vegetation.
2. To develop an ecological response model for water management that incorporates the influence of groundwater and rainfall, as well as the impact of previous hydrological and ecological conditions on response.
3. To investigate uncertainty in ecological response modelling through the development of multiple conceptualisations of ecological response using expert elicitation, and the incorporation of uncertainty bounds.

2. *Objectives: Investigating Model Behaviour using Sensitivity Analysis and Bayesian Analysis*

4. To investigate the impact of uncertain model inputs on estimated ecological response using global sensitivity analysis.
5. To identify the relative impact of uncertainty in the hydrological and ecological components of the ecological response model.
6. To explore the impact of different conceptualisations of ecological response derived through expert elicitation.
7. To assess the credibility of different conceptualisations of ecological response using Bayes Theorem to compare model outputs with observed data.
8. To explore the trade-off between the incorporation of uncertainty within a modelling framework and loss of precision and predictive capacity.

3. *Objectives: Exploring Opportunities and Trade-offs using Optimisation*

9. To examine the opportunities and challenges in using multi-objective optimisation for identifying and meeting ecological objectives through a synthesis of previous literature.
10. To develop an alternative approach for using optimisation in environmental flow management, which incorporates greater consideration of objective setting and problem formulation compared with previous work.

11. To test the proposed approach using a case study in the Lachlan catchment, Murray Darling Basin, Australia.
12. To explore different environmental flow rules and trade-offs between ecological and non-ecological objectives for the Lachlan catchment.

Through these twelve objectives, the thesis aims to take a more holistic view of environmental flow management, and address previous limitations to improve the link between quantitative modelling and decision making. Hypotheses associated with these objectives are as follows:

1. Hypotheses: Understanding Ecological Response through Model Development

a) Rainfall and groundwater (where accessible and of adequate quality) play an important role in sustaining floodplain vegetation during periods of low surface water availability.

2. Hypotheses: Investigating Model Behaviour using Sensitivity Analysis and Bayesian Analysis

b) Conceptualisation of ecological response has a significant impact on model results, and is as important if not more so than identifying adequate parameter values.
c) Bayes' Theorem can assist in critically evaluating model performance, leading to new insight about model behaviour and what constitutes a 'better' model.

3. Hypotheses: Exploring Opportunities and Trade-offs using Optimisation

d) The primary challenge of using optimisation for environmental flow management lies in the conceptualisation of the problem rather than the performance of the optimisation algorithm.
e) Through considering the assumptions and uncertainty in problem formulation, multi-objective optimisation can assist in identifying alternative environmental flow rules, and trade-offs between objectives.
f) Conceptualisation of ecological response, as well as uncertainty in hydrological assumptions, can influence the resulting management solutions identified using optimisation.
g) Similarly, the formulation of objective functions and decision variables can influence what management solutions are seen to perform 'best'.

1.3 Thesis structure

This thesis develops and applies a coupled river system model and ecological response model for analysing system trade-offs for environmental flow management. It is structured as a set of distinct but connected components of work with four separate parts (Figure 3): the current part (Part A) introduces the thesis objectives and case study area; Part B focuses on the development and evaluation of an ecological response model; Part C explores the use of multi-objective optimisation in developing environmental flow rules and meeting ecological objectives; and Part D provides a summary discussion of the research, as well as recommendations for future work. Specific literature, methodology and results of relevance are provided within each component chapter.

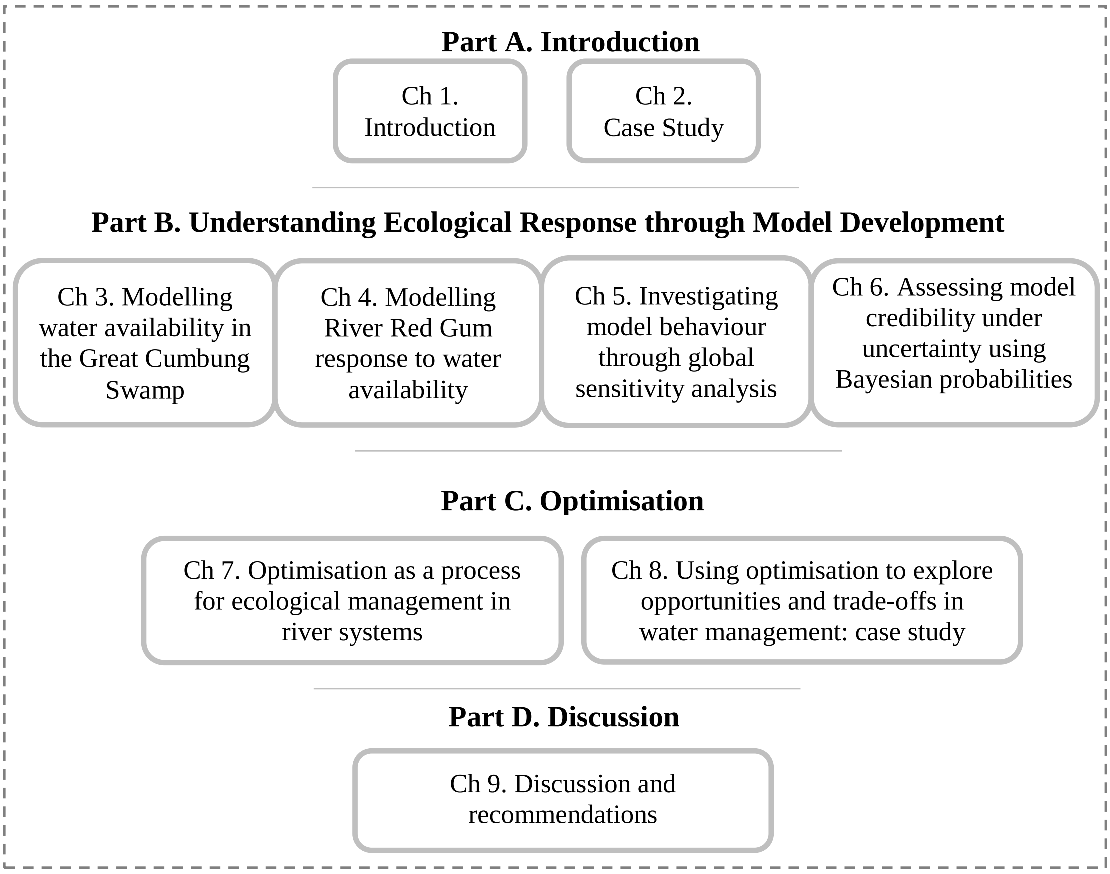


Figure 3. Thesis structure consisting of four main parts and nine chapters.

Chapter 2: Case Study

Managing water resources and ecosystems at multiple scales:

The Murray-Darling Basin & Lachlan Catchment

The Lachlan catchment is one of 20 river valleys within Australia's Murray-Darling Basin (MDB), and was selected as a case study as it is representative of the biophysical and regulatory complexity across the MDB as well as other basins globally (Figure 4). It contains iconic wetlands of ecological significance as well as large scale agriculture, and hence can be used to examine environmental flow management in the context of competing water use objectives. Particular focus is given to the River Red Gum (*Eucalyptus camaldulensis*) community in the Lachlan's terminal wetland, the Great Cumbung Swamp. The Great Cumbung Swamp is listed as having ecological value both at a regional and national level, and supports a diversity of wetland and floodplain species. River Red Gum is the dominant tree species within the Great Cumbung Swamp as well as being an iconic species throughout the MDB. Decline in River Red Gum condition in the Great Cumbung Swamp due to river regulation is considered symptomatic of wider ecological impacts (Kingsford, 2000; Catelotti *et al.*, 2015).

The current research commenced just prior to the end of one of the most severe droughts in the MDB, lasting approximately ten years from the year 2000 to 2010 (the 'Millennium drought'). This timing provided a unique opportunity to observe the impact of drought and recovery within the Lachlan and Great Cumbung Swamp. In addition, the research developed alongside a number of major reforms in the management of the MDB. These physical and regulatory changes provided insight into the impacts of severe water scarcity on both ecosystems and communities, as well as the need for greater understanding of environmental water requirements and system trade-offs.

A brief overview of the biophysical and regulatory setting of the Murray-Darling Basin and Lachlan catchment is provided below in Sections 2.1 and 2.2 respectively. This is followed by a description of the Great Cumbung Swamp and River Red Gum in Sections 2.3 and 2.4. Further detail on the case study area is also provided in subsequent chapters: hydrology of the Great Cumbung Swamp (Chapter 3), River Red Gum (Chapter 4), and hydrology of the Lachlan catchment (Chapter 8).

Figure 4. The Murray-Darling Basin and Lachlan catchment, Australia (source: MDBA, 2010)

2.1 The Murray-Darling Basin

The Murray-Darling Basin covers an area of over 1 million km^2, approximately 14% of the total landmass of Australia and crossing five states and territories (Jolly *et al.*, 2001; Quiggin, 2001). The combined Murray-Darling River is the longest river in Australia, and one of the longest in the world (Jolly *et al.*, 2001). It is also one of the driest river basins, with over 90% of rainfall returning to the atmosphere through evapotranspiration (Crabb, 1997; MDBA website, accessed 2015). Rainfall is highly variable both spatially and temporally, ranging from 2000 mm/y in the north east of the basin to 200 mm/y in the south west (Jeffrey *et al.*, 2001; MDBA, 2010).

The MDB is both ecologically and economically significant, presenting a complex biophysical and socio-economic context for water management. Irrigated agriculture in the MDB produces approximately 30% of Australia's food as well as food for export (MDBA, 2015). However, high levels of river regulation and water extraction have been required to sustain agriculture, as well as providing water for urban, industrial and recreational purposes (Leblanc *et al.*, 2012). Consequently, the MDB has been classed as one of the most highly altered basins due to river regulation globally (Döll *et al.*, 2009).

Following significant environmental degradation, the MDB has undergone a series of reforms to better balance both environmental and human water needs, and to better understand the trade-offs between often competing objectives (Kingsford, 2000; Connell and Grafton, 2011). The first of these reforms was implemented in 1995 with a capping of total water extractions to reduce over-use (MDBMC, 1995). Whilst this was found to be effective in reducing environmental decline, additional measures were deemed necessary (Connell and Grafton, 2011).

Further reform was precipitated by the beginning of the 'Millennium drought' (van Dijk *et al.*, 2013). Existing basin management was ill-equipped to respond to the unprecedented levels of water scarcity, and the exacerbated tension between providing water for environmental outcomes and for human water use. A number of institutional and legislative changes occurred in response, with a transition from a primarily state controlled system to the establishment of national level institutions, policy and legislation. These changes were facilitated by the commitment of up to AUD $12.9 billion over a ten year period to restore parts of the MDB (Connell and Grafton, 2011).

Changes included the establishment of the National Water Initiative and National Water Commission in 2004, followed by the legislation of a new *Water Act 2007*. The *Water Act 2007* was a significant departure from previous legislation in that it provided greater emphasis and legality to environmental water requirements. It also formalised the transition to basin scale management through the establishment of the Murray-Darling Basin Authority, which was tasked with developing a Basin Plan for the whole basin in consultation with the states and stakeholders. In addition, a Commonwealth Environmental Water Holder was established with the purpose of buying water licences on the water market specifically for environmental water requirements.

The combination of a severe drought and greater focus on returning water to the environment resulted in renewed tension between stakeholders and government institutions over the sharing of water resources. This was further exacerbated by the difficulty in defining environmental water requirements and measuring environmental outcomes. The resulting Basin Plan was adopted in 2012, and aimed at providing a compromise between the multiple and conflicting objectives with a view to long term sustainability. However, a number of challenges remain, particularly in the integration of social and economic components (Baldwin *et al.*, 2009), as well as understanding ecological objectives and response.

2.2 The Lachlan Catchment

The Lachlan catchment (Figure 5) covers an area of approximately 85,000 km^2, stretching 1450 km from undulating tablelands in the east to wide expanses of alluvial floodplain in the west, where it the Lachlan River terminates except for during extremely large floods (Driver *et al.*, 2010; CSIRO, 2008). It encompasses significant diversity in terms of rainfall, land use, geography and ecology. The catchment is highly regulated with two headwater dams and two major re-regulating storages, which has facilitated the development of large-scale agriculture throughout the region covering approximately 80% of the total catchment area (CSIRO, 2008).

Currently less than 20% of native vegetation remains, most of which is concentrated in the mid and lower Lachlan (CSIRO, 2008; Green *et al.*, 2011). Changes in land use and flow regime have resulted in insufficient water to meet both ecological and human water requirements, leading to significant degradation of instream, wetland and floodplain ecosystems (Podger and Hameed, 2000; DPI, 2006; Chessman *et al.*, 2006). Based on a 2008-2010 assessment of fish, macro-invertebrates, floodplain vegetation, flow alteration and geomorphology, the Lachlan catchment was ranked as one of the four ecologically poorest of all 21 MDB catchments (MDBA, 2012b).

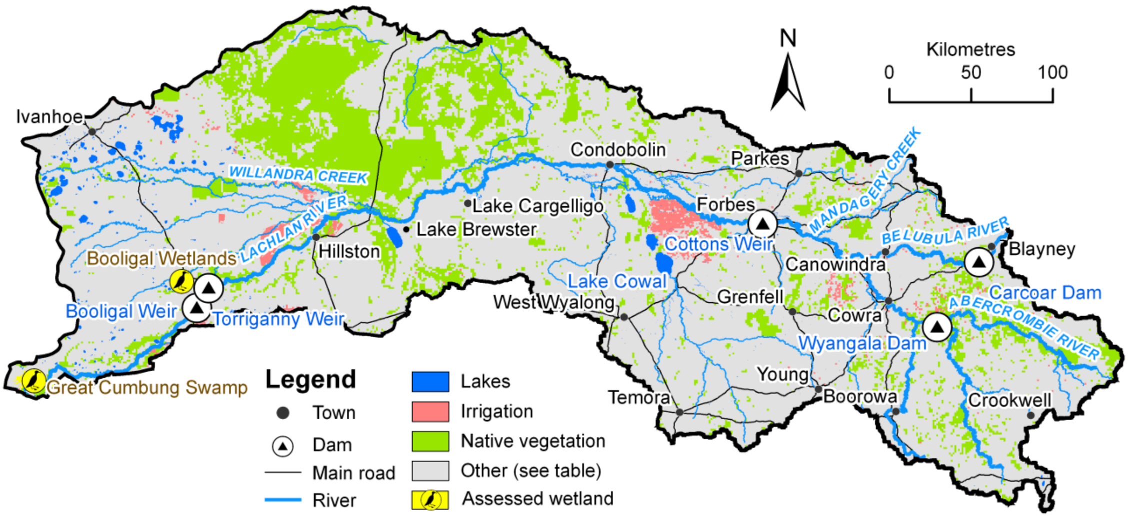


Figure 5. The Lachlan catchment, Murray Darling Basin, south-eastern Australia (source: CSIRO, 2008)

2.2.1 Biophysical setting

Whilst the Lachlan forms part of the wider MDB, it is largely a self-contained system except during large floods (O'Brien and Burne, 1994). Rainfall varies from summer dominant in the eastern catchment with an annual average of 1000 mm, to winter dominant rainfall with an annual average of 200 mm in the west (CSIRO, 2008). Relatively little rainfall ends up as runoff, with an estimated annual average of only 23 mm based on modelled outputs (CSIRO, 2008). Flows are also highly variable inter- and intra-annually, although river regulation has reduced some of this variability to provide water for agriculture during the summer months.

The high degree of regulation and development in the catchment means that much of the system is influenced by decisions involving the storage, release, extraction, and in-situ use of water. There is one main headwater dam (Wyangala), a smaller second headwater dam (Carcoar), two major re-regulating storages (Lake Cargelligo and Lake Brewster), as well as a number of smaller weirs and regulators (Figure 6). Wyangala Dam has an active capacity of 1216 GL, and regulates approximately 68% of annual inflows (CSIRO, 2008). Water use includes town water supply, agriculture, hydropower, flood storage, recreation, and mining. Irrigation uses the largest percentage of surface water, followed by local water utilities, water for livestock and domestic purposes, and mining (CSIRO, 2008; Green *et al.*, 2011).

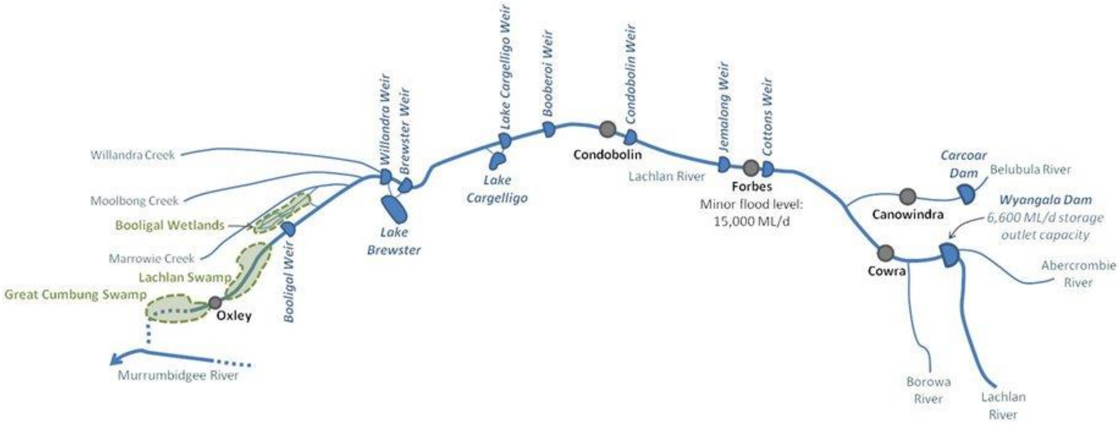


Figure 6. River regulation infrastructure and key wetland regions for the Lachlan catchment (source: MDBA, 2013).

Groundwater provides on average 45% of total water use, which can increase to 90% of water use during years of low surface water availability (CSIRO, 2008). In areas of high groundwater extraction there have been corresponding declines in observed groundwater levels CSIRO (2008). The majority of groundwater extraction is from the alluvial aquifer in the west of the catchment, where there is also significant recharge from surface water (Green *et al.*, 2011; CSIRO, 2008). The high level of surface water – groundwater connectivity in the lower catchment emphasizes the importance of considering both surface and groundwater in assessing water availability. More detail on groundwater in the lower part of the catchment covering the Great Cumbung Swamp is provided in Section 2.3.

Despite substantial development in the catchment, nine wetlands of national environmental significance remain, as well as a further nine wetlands of regional significance (BWR *et al*., 2011). The majority of these are in the lower Lachlan, and form part of three key areas considered explicitly by the Basin Plan: Booligal Wetlands, the Lachlan Swamps, and the Great Cumbung Swamp (Figure 6). As a result of flow regulation, land development and the introduction of non-native species, 21 species and communities are listed as endangered under the New South Wales *Threatened Species Conservation Act 1995* and *Fisheries Management Act 1994*, as well as the Commonwealth *Environmental Protection and Biodiversity Conservation Act 1999* (MDBA, 2010). These include the entire aquatic ecological community downstream of Wyangala Dam, a number of fish, frog species, waterbirds, and vegetation communities (BWR *et al*., 2011).

2.2.2 Regulation: sharing water in the Lachlan

Decisions made regarding the long term sharing of water resources in the Lachlan are guided by the *Water Act 2007* and the *Basin Plan*, as well as ten year Water Sharing Plans developed in consultation with stakeholders. However, short term decisions involving the release of environmental water are influenced by a number of government and stakeholder groups. Actual dam releases for all water users are managed at the state level.

As with other MDB catchments, management of the Lachlan involves national level institutions, the Murray-Darling Basin Authority and the Commonwealth Environmental Water Office, and state government departments including the New South Wales (NSW) Department of Primary Industries (DPI) Water (formerly NSW Office of Water, NOW) and Office of Environment and Heritage. The organisation responsible for river operations is Water NSW (formerly State Water), which operates under a licence administered by DPI Water and a Water Sharing Plan. There is also coordination with the Murray-Darling Basin Authority and Commonwealth government, with additional input from different stakeholder groups including the Customer Service Committee (representing irrigators), and the Lachlan Riverine Working Group (representing environmental water) (P. Driver, pers. comm., 2015).

Use of water in the Lachlan is regulated through a system of licences and allocations. A Water Access Licence is required to extract water from a specified water source, and determines the share of water a user is entitled to. There are currently eleven types of licences operating in NSW, which influence the specific terms of water extraction and use including the priority of extraction when there is limited water available (DPI Water webpage, 2015). Licence types include general and high security, groundwater, utility, and stock and domestic access licences (DIPNR, 2004; DPI Water webpage, 2015). General security licences are typically used for the irrigation of annual crops, where the crop type and area can be decided each year based on available water. In comparison, high security licences are used for town water supply and perennial crops. In addition to access licences, there are three types of basic water rights: native title rights, floodplain harvesting rights, and specific stock and domestic rights where a property is adjacent to a water body or overlaying an aquifer (DPI Water webpage, 2015).

The actual volume of water which can be extracted is dependent upon the total water available in the system, and is announced at the start of the water year (1 July). Initial allocations are deliberately conservative, such that they can increase during the year, but will not decrease. This provides improved security to water users, who can plan based on the minimum available water. However, during the Millennium drought, water levels dropped below forecast values and allocations were reduced during the water year (Leblanc *et al.*, 2009). The actual volume of water used is monitored in a water account, and any unused allocation can be partially carried over into the next water year.

Both access licences and allocations can be traded either temporarily or permanently, which can allow for more efficient water use. The trading of access licences depends on the type of licence or water right, as set out by the NSW *Water Management Act 2000*. More information on trading can be found in Hamstead (2004) and NWC (2011).

Provision of environmental water in the Lachlan currently occurs through three means – firstly through the purchase of licences specifically for achieving environmental outcomes; secondly through the allocation of environmental water to be used annually as specified in the Lachlan Water Sharing Plan (DIPNR, 2004); and thirdly through dam operational rules (Podger and Hameed, 2000).

Licences for environmental water can be purchased on the water market and are primarily managed at a national level by the Commonwealth Environmental Water Office to ensure coordination in meeting environmental requirements (CEWO website, accessed 2015). The way in which environmental water licences are used is guided by an Environmental Water Plan within the Basin Plan (MDBA, 2012c). As the licences are market based, the volume of water available for environmental use is influenced by the number of licences currently held and the current allocation.

In comparison, the environmental water allocations set out in the Lachlan Water Sharing Plan provide fixed volumes of water (if there is sufficient water in the system based on other water demands) for purposes such as extending a waterbird breeding event or encouraging fish breeding, providing increased flow variability, inundate wetland areas, or reduce salinity levels or algal blooms (DIPNR, 2004). Both licences and allocations used for the provision of environmental water are based on current priorities in the context of longer term environmental objectives. They therefore provide some flexibility for decision makers to respond to the current state of the system, with decisions typically involving stakeholder engagement.

The third type of environmental water delivery operates as part of a longer term strategy to restore part of the natural flow variability. Referred to as 'translucency rules', a proportion of the inflow to Wyangala is released between May and November (Podger and Hameed, 2000). It is these translucent rules which are used in the current research to investigate different environmental flow rules for meeting management objectives (described further in Chapter 8). More information on translucency in the Lachlan can also be found in Podger and Hameed (2000).

Daily operation of the Lachlan regulated river involves a system of water ordering and release decisions made by river operators (Water NSW). All water licence holders request a specific volume of water in accordance with their licence conditions by placing a water order. In many cases, these orders are placed by irrigation groups rather than individuals. Based on the total number of orders provided, river operators assess what can be released within the bounds of operational rules and other constraints.

2.3 Great Cumbung Swamp and 'end of system'

The Great Cumbung Swamp comprises a complex system of interconnected wetlands at the most downstream end of the Lachlan, covering a total area of approximately 15,000 ha

(Figure 7). The total area varies over time in response to flood and climatic conditions, and can cover over 21,000 ha (Sims, 1996). The Lachlan River maintains a distinct channel through the Swamp until terminating at the western edge of the Swamp in an expanse of *Phragmites australis* marshland (O'Brien and Burne, 1994). Very low gradients within the swamp (as low as 0.00003, Kemp and Rhodes, 2010) mean that estimating overbank flows are incredibly challenging. This is further compounded by land management practices within the Great Cumbung Swamp, where the addition of fences, new channels, embankments or fallen trees can significantly change the pattern of flow.

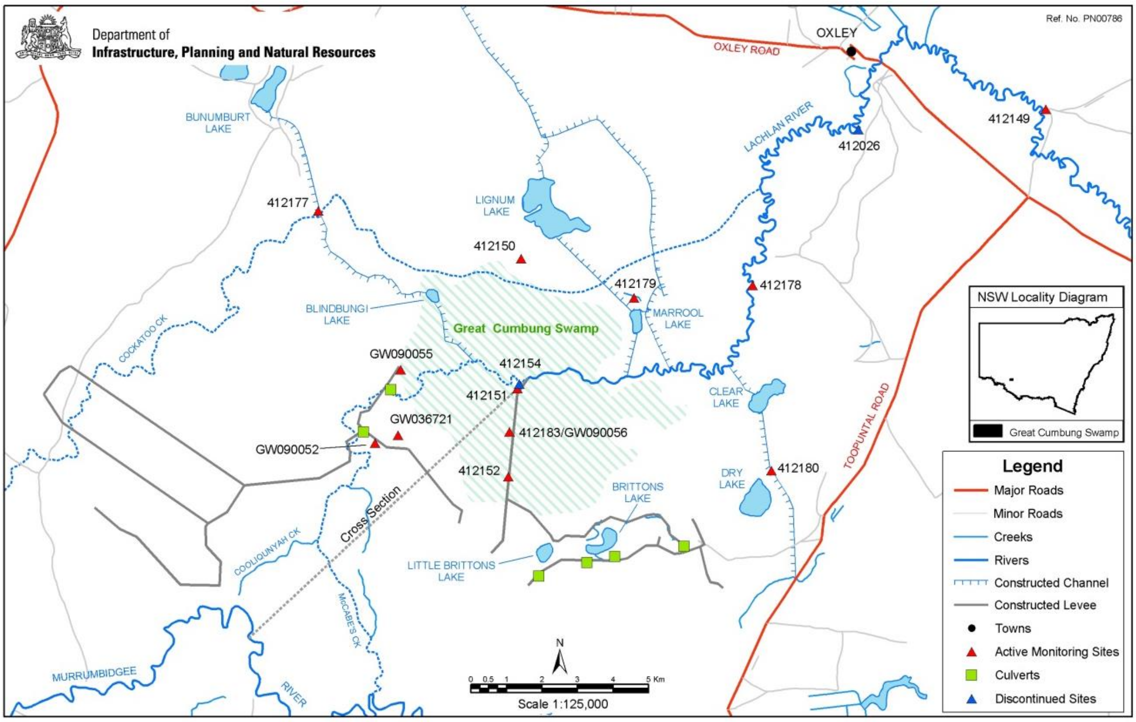


Figure 7. Great Cumbung Swamp in the lower Lachlan (source: Driver *et al*., 2004)

High connectivity with underlying aquifers result in significant infiltration of surface water (O'Brien and Burne, 1994; Brady *et al.*, 1998). There are four main geological formations underlying the Great Cumbung Swamp: Coonambidgil Formation (approximately 0 to 14.5 m based on borehole GW036721); Shepparton Formation (14.5 to 46 m); Calivil Formation (46 to 78 m); and the Onley Formation, Renmark Group (78 to 431.5 m) (Driver *et al.*, 2004; Kellett, 1989). Both the Coonambidgil and Shepparton are predominantly comprised of unconsolidated clays, with some sands, silts, gravel and palaeo-soils (Driver *et al.*, 2004). Groundwater underlying the Lachlan region generally flows from east to west, but in the Great Cumbung Swamp is impeded by north-south running ridges in the bedrock (Kellett, 1989). It has therefore been hypothesised that there is resulting groundwater flow south toward the Murrumbidgee (Driver *et al*., 2004; P. Driver, pers. comm., 2015).

A network of palaeochannels formed by earlier paths of the Lachlan River also plays an important role in distribution of water through the Great Cumbung Swamp (O'Brien and Burne, 1994; Driver *et al.*, 2004). Given the low conductivity of surrounding clay soils, palaeochannels containing higher proportions of sands and silts are believed to facilitate the distribution of shallow sub-surface flow and support isolated areas of vegetation (P. Packard, pers. comm., 2013). However, there have been no detailed studies of palaeochannels and their influence on vegetation within the Great Cumbung Swamp that the author is aware of.

The Great Cumbung Swamp is dominated by common reed (*Phragmites australis*), cumbungi (*Typha orientalis*) and lignum shrubland (*Muehlenbeckia florulenta*) in the lower depressions, transitioning to River Red Gum (*Eucalyptus camaldulensis*) communities on the floodplain. Additional floodplain species include bushy groundsel (*Senecio cunninghamii*), River Cooba (*Acacia stenophylla*) and at higher elevations, Black Box (*Eucalyptus largiflorens*) (Pressey, 1984; Pahlow, 1994). The Great Cumbung Swamp provides an important habitat for bird breeding, including species such as great egret (*Ardea alba*), glossy ibis (*Plegadis falcinellus*), freckled duck (*Stictonetta naevosa*) and Australasian bittern (*Botaurus poiciloptilis*) (Riverine Landscapes Laboratory, 2008).

Both the Great Cumbung Swamp and River Red Gum hold cultural significance for Aboriginal people (Lachlan CMA, 2006). The Lachlan Catchment Management Authority has established an Aboriginal Cultural Heritage program to assist in engaging with Aboriginal communities in the Lachlan, and identifying water requirements to sustain areas of cultural significance (Lachlan CMA, 2006). In addition, DPI Water has a program for cultural flows as part of a NSW Aboriginal Water Initiative, with further initiatives under the Basin Plan and Commonwealth (P. Driver, pers. comm., 2015).

The whole of the Great Cumbung Swamp is privately owned or managed for grazing as shown in Figure 8. As such, land management practices have the potential to significantly impact upon ecological condition within the Great Cumbung Swamp. For example, the constructed levee bank crossing the properties of Juanbung and Boyong (Figure 8) creates a barrier for floodplain inundation. Properties adjacent to the Lachlan River also have riparian stock and domestic rights, as described in Section 2.2.2. Some land managers within the Great Cumbung Swamp have played a key role in decisions regarding environmental flow delivery for the Lachlan through the Lachlan Riverine Working Group, and have also invested in strategies to minimise environmental impact resulting from agricultural practices.

The complexity and diversity of hydrology, ecology, land use and values makes the Great Cumbung Swamp an interesting case study for exploring environmental flow management in the context of competing water requirements and significant uncertainty. The existence of previous studies also facilitates working in this area by providing key background information and datasets, yet it is an area far less studied than other wetlands such as Macquarie Marshes or Booligal Wetlands, hence providing complementary knowledge to previous work.

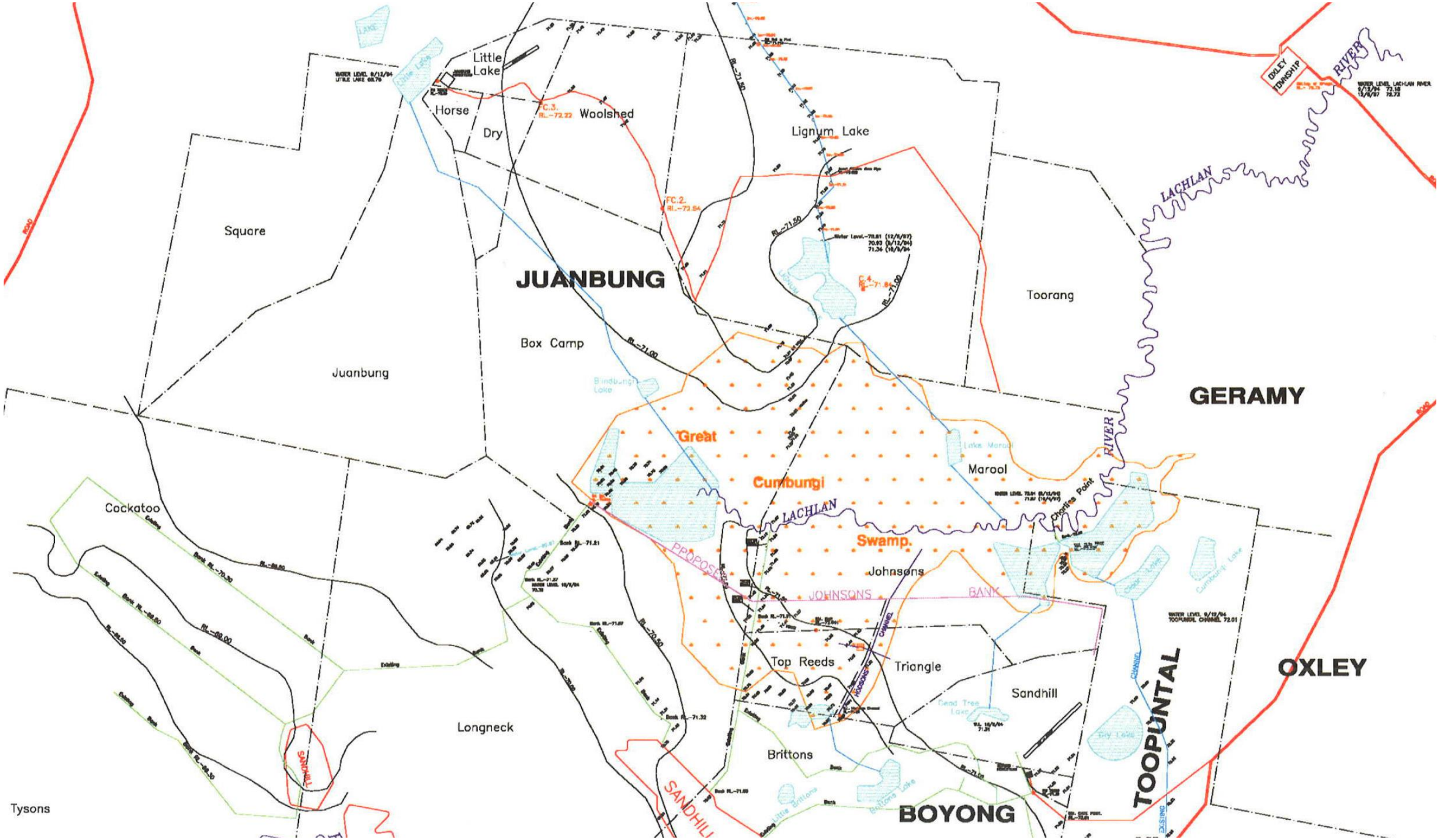


Figure 8. Land ownership in the Great Cumbung Swamp (source: Rich River Irrigation Developments, 1997)

2.4 River Red Gum – connecting people and landscapes

The ecological response model developed as part of this thesis is based on the River Red Gum community within the Great Cumbung Swamp. River Red Gums are the dominant floodplain tree species within the Great Cumbung Swamp as well as across much of the MDB. They provide habitat for birds, terrestrial and aquatic fauna, as well as other vegetation (Roberts and Marston, 2011). River Red Gum is also an important food source for a number of species both directly through leaves (insects), flowers (e.g. birds) and seeds (e.g. ants) (Roberts and Marston, 2011; Stone and Bacon, 1994); and indirectly through decomposition of leaf material and provision of carbon and other nutrients (Baldwin, 1999; Briggs and Maher, 1983). Additional ecological functions include moderation of water temperature through shading (Roberts and Marston, 2011).

For these reasons, River Red Gum is often seen as an umbrella species in the context of providing environmental flows (Overton *et al.*, 2014). Although there are variations in water requirements between species within the Great Cumbung Swamp, it is generally acknowledged that loss of River Red Gum would result in a complete change in the Great Cumbung Swamp landscape and ecosystem. Similarly, expert interviews with ecologists described in Chapter 4 indicated that meeting the water requirements of River Red Gum will largely create sufficient habitat to support other species.

As well as being viewed as a representative species, the River Red Gum is of particular relevance to the current research, being long lived and able to utilise both surface water and groundwater (Mensforth *et al.*, 1994; Thorburn and Walker, 1994). It is thought that River Red Gum can survive for up to 950 years with adequate water (Ogden, 1978; Colloff, 2014), and hence changes in condition can be more easily examined compared with species exhibiting shorter lifespans and greater seasonal variation.

Because River Red Gum is a key species throughout the MDB, it has been relatively well studied compared with many other floodplain species. Of particular note are Overton *et al*. (2014), Roberts and Marston (2011), and Rogers and Ralph (2010), who have reviewed and assessed existing information on the water requirements of River Red Gum (and other wetland and floodplain species). This information was instrumental in the development of the River Red Gum ecological response model described in Chapters 3 and 4. River Red Gum characteristics of particular relevance to the current research are described in greater detail in Chapter 4.

Part B

Understanding Ecological Response

Through Model Development

Understanding Ecological Response Through Model Development

Part B explores ecological response to water availability through the development and analysis of an ecological response model for River Red Gum in the Great Cumbung Swamp, Lachlan Catchment, Australia. Part B is divided into four chapters:

- **Chapter 3**: Modelling water availability in the Great Cumbung Swamp
- **Chapter 4**: Modelling River Red Gum response to water availability
- **Chapter 5**: Investigating model behaviour through global sensitivity analysis
- **Chapter 6**: Assessing model credibility under uncertainty using Bayesian probabilities

The primary aim of this part was to develop an ecological response model for the purpose of: (1) estimating ecological condition under different scenarios of water availability; (2) comparing different water management options to obtain improved outcomes for all water users including the environment; and (3) evaluating trade-offs between different water user objectives. In doing so, it also aims to improve current understanding of River Red Gum response in the Great Cumbung Swamp; to explore the challenges in modelling ecological response; and to address some of the limitations in existing ecological response models. The part identifies significant uncertainty in understanding both hydrologic and ecological processes in the Great Cumbung Swamp, which are critical to consider when evaluating management interventions and trade-offs.

The ecological response model (ERM) consists of two sub-components: a hydrological component to estimate water availability; and an ecological component estimating change in River Red Gum condition (Figures 9 and 10). Chapter 3 describes the development of the hydrological component, which adopts a systems approach to water availability as shown in Figure 9. It incorporates both flow and rainfall based inundation as well as groundwater availability. Chapter 4 describes the development of five ecological response models though expert elicitation, which estimate an upper and lower bound of possible River Red Gum condition using the water availability estimated in the hydrological component (Figure 10). The ecological model is evaluated in Chapters 5 and 6 using global sensitivity analysis (Chapter 5) and Bayesian analysis (Chapter 6). The ecological response model is then applied to the Lachlan catchment case study in Part C.

An early version of the ecological response model was described in the conference papers Barbour *et al*. (2011) and Driver *et al*. (2011). However, the model presented in the following chapters has significantly advanced since these papers were published.

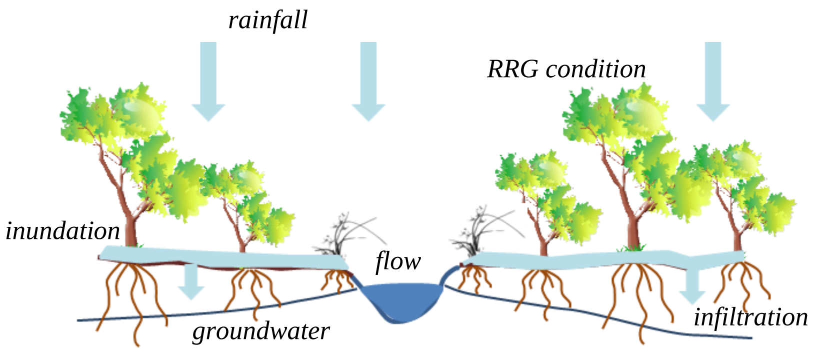


Figure 9. Conceptual model of key hydrological processes considered in evaluating River Red Gum response

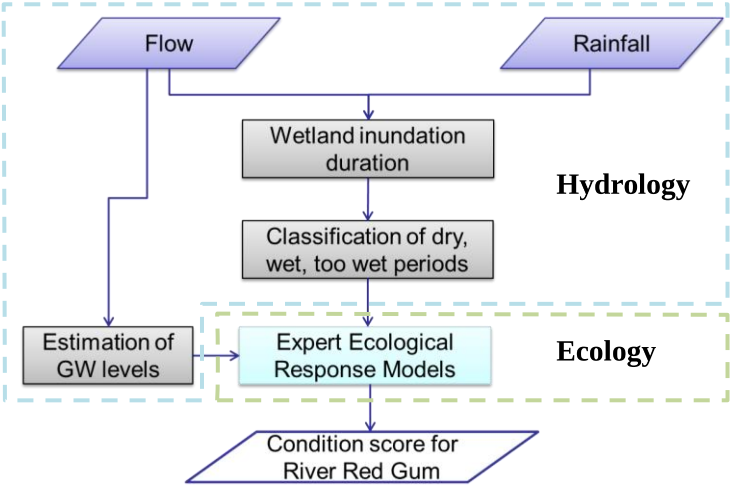


Figure 10. Ecological Response Model for River Red Gum in the Great Cumbung Swamp

Chapter 3: Modelling water availability in the Great Cumbung Swamp

3.1 Aim and overview

The aim of this chapter is to develop a water availability model of the Great Cumbung Swamp, for the purpose of estimating changes in River Red Gum condition, and subsequently for evaluating different water resource management alternatives. A new model was developed given there were no existing models suitable for the intended purpose. Model development facilitated an improved understanding of hydrological processes within the Great Cumbung Swamp, and the challenges in representing water availability using limited data.

The main contribution of this chapter is the development of a systems approach to estimating water availability considering rainfall, flow and groundwater where there is limited existing information. The chapter describes the methodology adopted as well as preliminary model evaluation results. A brief introduction summarising existing information on wetland inundation modelling is provided below.

3.2 Introduction

Wetland and floodplain inundation is challenging to model given the typically flat and complex topography, where flow paths can be dynamic and difficult to detect as floodplain features change over time. Added to this is the general lack of data by which to develop and evaluate predictive models. The two main approaches used to represent wetland inundation are: (1) physically based models; and (2) flow-inundation relationships based on satellite imagery (or a combination of the two). Physically based models vary in complexity from two/ three-dimensional hydrodynamic models to more simple storage based water balance models.

Hydrodynamic models can provide detailed physical representation of wetland inundation through the spatially explicit representation of overland and channel flow, as well as saturated and unsaturated subsurface flows (Thompson *et al.*, 2004; Wilson *et al.*, 2007). However, they require grid resolutions which are sufficiently fine to capture the complex topographic features; have significant data requirements (such as a Digital Elevation Model, DEM); and are computationally intensive which restricts their use to a single or limited number of inundation events (Overton, 2005; Powell *et al.*, 2008; Whigham and Young, 2001).

To reduce computational requirements, hydrodynamic models have been used to inform the development of simpler approaches including grid-based cells models and storage models. For example, Mackay *et al.* (2011) used a grid based approach where flow between grid cells was calculated using water-level discharge relationships derived from a MIKE21 model. Wen *et al.* (2013) used a set of interconnected storages to represent a complex wetland system, and derived flow relationships using a 1D/2D MIKE FLOOD model.

As an alternative to physically based models, remote sensing has also been used to estimate wetland inundation and flow patterns. For example, Overton (2005) used Landsat satellite imagery to estimate inundation for sections of the river Murray floodplain (Australia) based on river height at different locations. Ordoyne and Friedl (2008) evaluated multiple statistical relationships to estimate inundation within the Florida Everglades (USA) using MODIS data. Powell *et al.* (2008) used AVHRR data to examine inundation in the Gwydir wetlands (Australia).

Whilst remote sensing has reduced data and computational requirements compared with complex hydrodynamic models, it is often limited by the availability of adequate spatial and temporal resolution to represent inundation patterns (Prigent *et al.*, 2007). This limitation can be reduced through the use of multiple satellites, as demonstrated by Prigent *et al.* (2007).

For the purpose of the current research, the primary aim was to develop a system based representation of water availability for the estimation of River Red Gum response. Given the focus on estimating ecological response in a wider context of river basin management, the development of a water availability model was primarily concerned with producing an adequate system conceptualisation using available information, rather than undertaking new hydrodynamic modelling or remote sensing analysis.

A summary and evaluation of existing models for the Great Cumbung Swamp is provided in Section 3.3. This is followed by a description of the model developed for the current research, divided into two main sections: (1) Floodplain inundation: riverine driven (Section 3.4.1) and rainfall driven (Section 3.4.2); and (2) Groundwater elevation model (Section 3.5). The chapter finished with a brief conclusion.

3.3 Evaluation of existing inundation models

A handful of previous studies have examined different elements of water availability in the Great Cumbung Swamp. Sims (1996) and Shaikh *et al*. (1998) developed relationships between flow and inundation in the Great Cumbung Swamp using remote sensing. Sims (1996) used linear regression to estimate open water area based on flow at Booligal gauge, as part of a wider investigation of vegetation response in the Great Cumbung Swamp. The study identified a significant correlation between the area of open water and flow in the preceding 28 days, indicating the importance of antecedent conditions. Shaikh *et al*. (1998) developed an alternative relationship which incorporated flow from the Murrumbidgee as well as rainfall and evaporation. However, it is noted in Smith and Barr (2002) that Murrumbidgee flows are now considered unlikely to have a significant impact on inundation in the Great Cumbung Swamp, except during large floods.

Estimated inundation areas provided by both Sims (1996) and Shaikh *et al*. (1998) have been used in the current research to compare outputs from the hydrological model developed here (Section 3.4.3). However, the relationships were not adopted given neither consider the duration of inundation, or the required flow duration required to inundate the Great Cumbung Swamp.

In addition to surface water, there has been some investigation into the hydrogeology of the Great Cumbung Swamp. Of particular relevance to the current research are studies by Brady *et al*. (1998) and Driver *et al*. (2004). A more complete review of current available information on the Great Cumbung Swamp hydrogeology can be found in Driver *et al*. (2004).

Brady *et al*. (1998) examined groundwater levels in six locations within the Great Cumbung Swamp from May 1995 until December 1996, with further data collected by M. Mallick and D. Woods at DPI Water until March 1997. Data available for two boreholes (4 and 6) show that the pattern of change in groundwater levels closely matches that of change in river levels at Booligal and at Corrong (Figure 11, Figure 12). Based on the assumed high level of connectivity between shallow unconfined aquifers and surface water, Brady *et al*. (1998) hypothesize that flood waters are not stored within these shallow aquifers during periods of low surface water flow, but instead recede as flows decline. However, as discussed further in Section 3.5, this does not necessarily apply to deeper aquifers in the Coonambidgil and Shepparton formations.

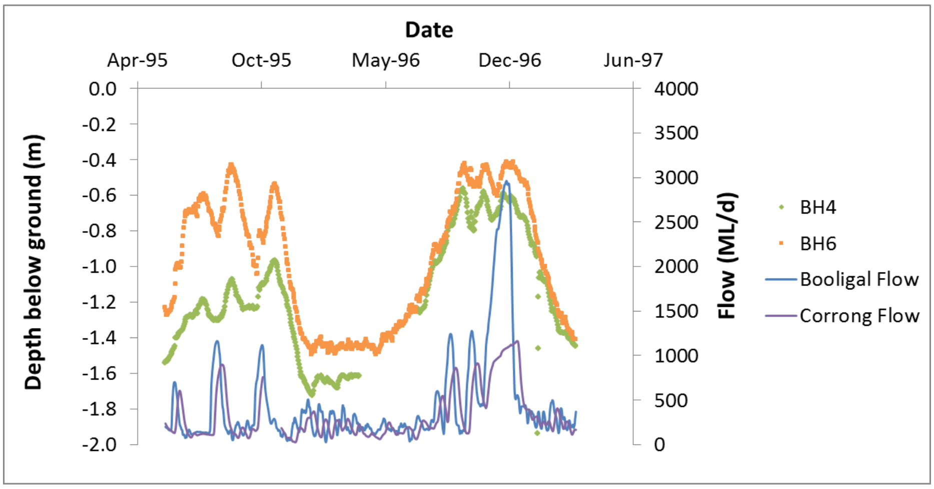


Figure 11. Groundwater depths in two locations within the Great Cumbung Swamp, compared with surface water flow at Booligal and Corrong gauges.

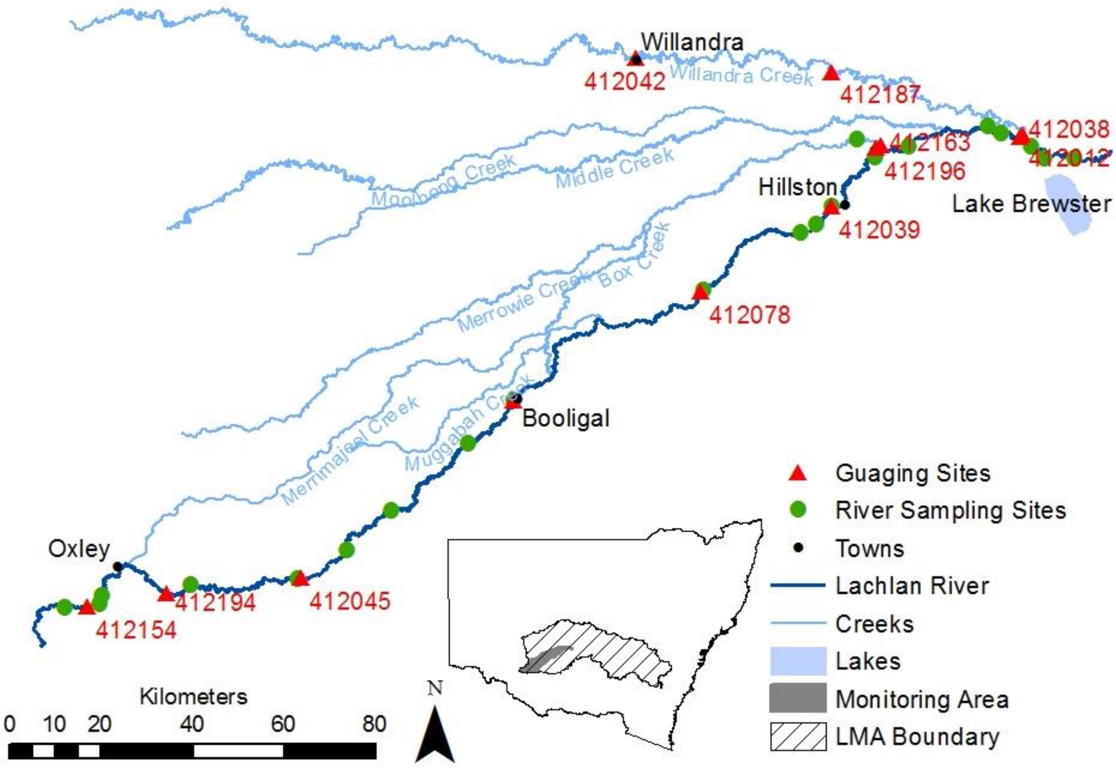


Figure 12. Location of surface water gauging stations in the lower Lachlan, including Booligal gauge and Corrong gauge 412045 (source: UC, 2015)

Driver *et al*. (2004) investigated surface water-groundwater interactions within the Great Cumbung Swamp in conjunction with a water balance assessment conducted by Smith and Barr (2002). The study involved drilling six boreholes in addition to the Brady bores, as well as installation of ultrasonic water level sensors on the floodplain, and flow meters in the channels. The data collected was made available for the current research, with more information provided in Section 3.5.

The groundwater data were used as an input to a water balance model of the Great Cumbung Swamp developed by Smith and Barr (2002). The model estimates monthly inundation area, depth, total water volume, as well as solute concentration from 1971 to 1998. Inputs include Lachlan river flow, rainfall, evaporation, and infiltration on a monthly time step. The model focuses on the more frequently inundated, low lying areas of the Great Cumbung Swamp covering the river channel, lakes and reed bed. The study identified groundwater as being a significant component of the Great Cumbung Swamp water balance, with approximately 66% of outflows occurring through infiltration.

The Smith and Barr (2002) water balance model was applied by Driver *et al* (2005b) to investigate ecological change within the Great Cumbung Swamp. The study assessed the impact of different water sharing rules and levels of development, focusing on *Phragmites australis* in the Great Cumbung Swamp reed bed. Ecological impact was estimated by identifying inundation events which met the required duration and area for *Phragmites*. The model was also applied by Driver *et al* (2010) to compare different climate change scenarios.

The water balance model could not be directly adopted for the current research as it is currently unpublished in the public domain. Additional limitations include: the model focuses on the lake and channel areas, rather than the wider floodplain which is important for assessing River Red Gum condition; the model operates on a monthly rather than daily time step (which has been adopted in the current work); and the impact of antecedent conditions on inundation is not considered. Based on personal communication with P. Driver from DPI Water (15/9/2015), the water balance model performed well prior to the Millennium drought, but once the drought had commenced the lack of modelled antecedent conditions impacted on the ability to predict hydrological and ecological outcomes (both in terms of short-term operational and long-term planning horizons). Similar water balance modelling undertaken by Barma *et al*. (2010) for other wetlands in the Lachlan (not including the Great Cumbung Swamp) also did not include antecedent conditions or rainfall, and note that in some cases these may have a significant impact on inundation.

A more detailed investigation of inundation patterns is being conducted by consulting firm Parsons Brinckerhoff, who are developing a hydrodynamic model of the Great Cumbung Swamp. However, the model has not yet been completed.

Whilst none of the studies described above provided a model suitable for the current research, they were instrumental in providing information which was used in developing and evaluating the hydrological component of the ERM (Section 3.4.3).

Similar to Smith and Barr (2002), the model developed here considers rainfall, riverine flow and groundwater, both in terms of infiltration of surface water and change in groundwater levels. However, in the current work, groundwater levels were estimated for the purpose of identifying possible uptake by River Red Gum. The model was developed based on a review of existing information in combination with expert elicitation (described in Chapter 4), consultation with government staff, water managers, modellers and scientists, as well as observations during four field trips.

Inundation of the Great Cumbung Swamp was calculated for two areas roughly coinciding with differences in elevation, and consequently differences in flow inundation patterns. The first of these areas incorporates the lakes up to the River Red Gum fringe, similar to that modelled by Smith and Barr (2002). The second covers the entire floodplain and River Red Gum area of the Great Cumbung Swamp (including the lakes), and hence is inundated less frequently. The different areas were represented in the model using different inundation thresholds (described in Section 3.4.1). Whilst the smaller lakes area consists primarily of common reed, cumbungi, lignum and aquatic plants, some River Red Gum grow on the periphery and experience more frequent inundation. The division therefore represented different levels of water availability, and hence different survival patterns.

3.4 Floodplain inundation model

The floodplain inundation model was developed to estimate the inundation of the Great Cumbung Swamp based on flow data at Booligal gauge and rainfall data at Oxley gauge, and to generate a time series of either wet or dry condition at the Great Cumbung Swamp. Booligal gauge is approximately 100 km upstream of the Great Cumbung Swamp, and provides the longest and most reliable record of daily flow data close to the Great Cumbung Swamp. Sixty years of flow data from 1/7/1953 to 30/6/2013 were used to develop and evaluate model performance. Data gaps were filled by using an average of the flow either side of the gap where flows were of similar magnitude. Where flow magnitudes differed, a linear relationship using flows either side of the gap was used.

A conceptual diagram of the inundation model is shown in Figure 13. The model assumes that riverine driven inundation dominates any rainfall based inundation, hence rainfall is only considered when there is insufficient river flow. Further description of the riverine and rainfall components are provided below.

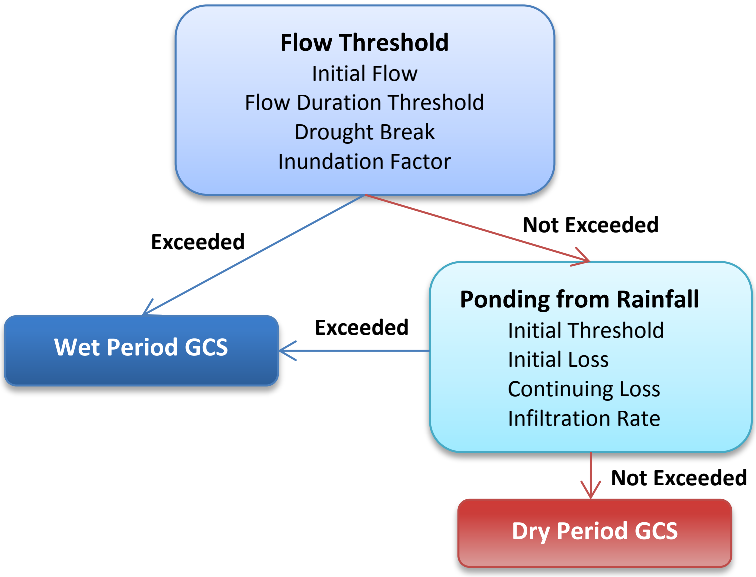


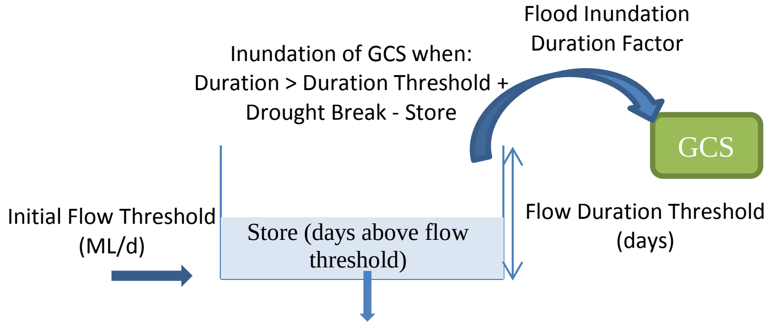
Figure 13. Floodplain Inundation Model of the ERM (GCS – Great Cumbung Swamp).

3.4.1 Riverine based inundation

The riverine based inundation model uses a bucket style approach (Figure 14), where inundation of the Great Cumbung Swamp depends on the filling of a conceptual store of water, and the length of the preceding dry period. Filling of the store is initiated once the flow at Booligal reaches an initial flow threshold, and continues to fill until the duration threshold has been reached. Should the flow fall below the initial flow threshold, the store begins to drop by one day at a time. Once the store reaches zero, it stays empty until the flow exceeds the threshold again. This approach was adopted based on available information, which consisted of an observed flow rate and duration for triggering inundation (see for example Driver *et al*., 2003 and Driver *et al*., 2004).

The conceptual store was used to represent the impact of antecedent conditions on flow, which can be particularly significant in semi-arid catchments (e.g. Mein and Larson, 1973; Karnieli and Ben-Asher, 1993; Powell *et al.*, 2008; Chiew *et al.*, 2011), and is likely to influence inundation in the Lachlan (Driver *et al.*, 2003; DWE, 2007). The reason for using time (days in this case) for measuring water in the store was due to insufficient information to develop a volumetric driven approach. The store is used as a proxy to represent the reduced duration of above threshold flow needed to inundate the Swamp if another inundation event has recently occurred. In reality, both the initial duration threshold and conceptual store should account for the variable flow rate and hence actual volume of water, as well as the non-linear process of wetting and drying (e.g. Green and Ampt, 1911; Haines, 1930; Horton, 1940). It is also likely that the initial flow threshold (as opposed to the initial duration threshold) varies depending on antecedent conditions (Sims, 1996; Driver *et al.*, 2000; Driver *et al.*, 2010), yet there was insufficient information to warrant including this within the current model.

Once inundation commences within the Great Cumbung Swamp, the duration of the inundation event is assumed to be longer than the period of above threshold flow at Booligal, due to surface storage (such as lakes) within the Great Cumbung Swamp. A summary of the main calculations used to estimate flow based inundation in the Great Cumbung Swamp is provided below.



$$Store = \begin{cases} \min(Store + 1, Flow\ Duration\ Threshold) & if\ Flow \geq Initial\ Flow\ Threshold \\ \max(Store - 1, 0) & if\ Flow < Initial\ Flow\ Threshold \end{cases}$$

Figure 14. Conceptual model of the relationship between flow at Booligal gauge and inundation of the Great Cumbung Swamp (GCS)

Model Calculations

The riverine based inundation component of the model consists of two parts: firstly, calculation of 'wet' and 'dry' events at Booligal gauge using defined thresholds; and secondly, calculation of 'wet' and 'dry' events at the Great Cumbung Swamp. In this case, wet and dry events at Booligal refer to thresholds for Great Cumbung Swamp inundation, and do not refer to any observable event at Booligal itself. The distinction between events at Booligal and the Great Cumbung Swamp is only to account for inundation of the Great Cumbung Swamp lasting longer due to surface storage. This can be seen from Figure 15, where above threshold flow at Booligal begins on 16 July 1959, but does not begin to inundate the Great Cumbung Swamp until a flow duration threshold has been reached (in this example 90 days). Inundation of the Great Cumbung Swamp then continues after Booligal flow has fallen below the initial flow threshold.

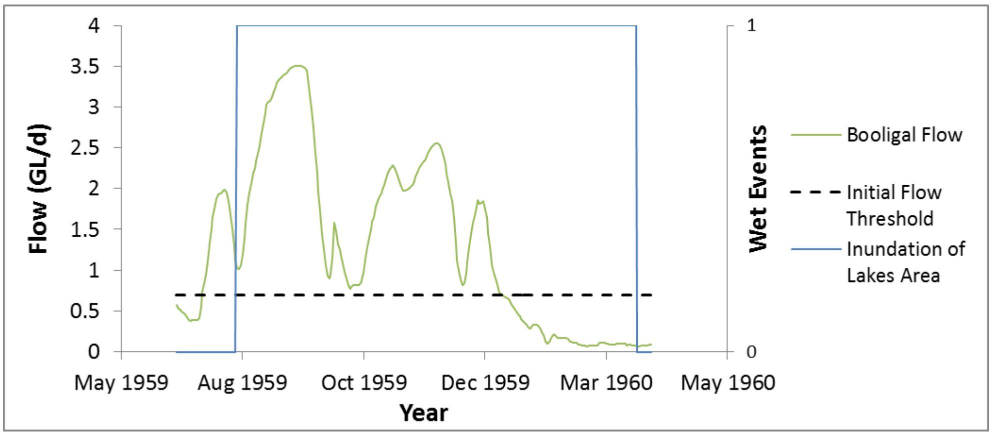


Figure 15. Comparison of above threshold flow at Booligal and inundation of the Great Cumbung Swamp

Booligal Gauge Events

1. A wet event at Booligal is triggered when flow (Q_B) exceeds the *initial flow* threshold (T_Q). At this point, the store begins to fill, and an inundation threshold (T_I) is calculated based on the flow *duration* threshold (T_{QD}), and length of the preceding dry period:

$$T_I = T_{QD} + T_{DB}(t_{sw}) - S(t_{sw}) \tag{1}$$

$$T_{DB}(t_{sw}) = \frac{Dd_C}{y} \tag{2}$$

$$S_t = \begin{cases} \max\left(S_{t-1} + 1, T_{QD}\right) \text{where } Q_B > T_Q \\ \max(S_{t-1} - 1, 0) \end{cases} \tag{3}$$

where:

T_I	=	Inundation Threshold (days)
T_{QD}	=	Flow Duration Threshold (days)
T_{DB}	=	Drought Break Threshold (days)
t_{sw}	=	Time step at which Q_B first exceeds T_Q for each new event
S_t	=	Store at time *t* (days)
Dd_C	=	Duration of the preceding dry event at the Great Cumbung Swamp (days)
y	=	constant
Q_B	=	Flow at Booligal (ML/d)
T_Q	=	Initial Flow Threshold (ML/d)

The inundation threshold defined in Equation 1 determines the time at which the Great Cumbung Swamp begins to flood, and is dependent on the flow at Booligal exceeding a threshold magnitude for a threshold duration, dependent upon the length of the preceding drought and the amount of water in the store. The inundation threshold is intended to represent the initial wetting of depressions and soil stores in the system, and the filling of lakes immediately upstream of the Great Cumbung Swamp. It was identified by Brady *et al*. (1998) that flow thresholds alone were not a reliable determinate of inundation.

It is assumed that 'wetting' the system is influenced by both short and long term processes. The short term process is represented by the store, where a minimum volume of water is required for inundation to commence. If the flow at Booligal falls below T_Q before T_{QD} is reached, the system is already partially wet and hence does not become 'reset' immediately. This accounts for variability in flow around T_Q, providing a 'fuzzy' rather than hard distinction between wet and not wet.

The influence of long term antecedent conditions are also incorporated by considering the duration of the preceding dry period, with longer durations requiring more water to inundate the Great Cumbung Swamp. The effect of the preceding dry period is considered using a 'drought break threshold' (T_{DB}), such that the duration of flow above T_Q required to inundate the Great Cumbung Swamp is increased by the length of the dry period preceding it (DD_C) divided by a constant y.

2. As long as Booligal flow (Q_B) continues to exceed flow threshold T_Q, the store will continue to fill until the flow *duration* threshold is reached. At the same time, the duration of above threshold flow d_B increments until it reaches the inundation

threshold T_I. Once $d_{B,t} > T_I$, inundation of the Great Cumbung Swamp commences, and Booligal is classed as being in a wet event (W_B):

$$d_{B,t} = \begin{cases} (d_{B,t-1} + 1) \text{ where } Q_B > T_Q \\ 0 \end{cases}$$

$$Wd_{B,t} = \left(Wd_{B,t-1} + 1\right) \text{ where } d_{B,t} > T_I$$

where:

$d_{B,t}$ = duration of flow exceeding threshold at Booligal at time *t*

$Wd_{B,t}$= duration of wet event at Booligal at time *t*

3. When Q_B falls below T_Q, a 'dry' event at Booligal (D_B) begins and the store decreases as shown in Equation 1 (Booligal itself is not dry, but flow has fallen below the threshold required to inundate the Great Cumbung Swamp). With Booligal classed as being in a 'dry' event, the duration of this dry event increments each time step until the inundation threshold (T_I) is again exceeded by $d_{B,t}$, when a wet event begins.

$$Dd_{B,t} = \left(Dd_{B,t-1} + 1\right) \text{ where } d_{B,t} < T_I$$

where:

$Dd_{B,t}$ = duration of dry event at Booligal at time *t*

4. The classification of each time step as being 'wet' or 'dry' at Booligal (i.e. surface water flow above or below inundation threshold) produces two matrices of wet and dry events of particular duration, indicating the time at which the event starts, and the duration of the event:

$$W_B = \begin{Bmatrix} m & Wd_B \\ 1 & t_{wb,\dots,}\, T_{wb} \\ . & . \\ . & . \\ . & . \\ M & t_{wb,\dots,}\, T_{wb} \end{Bmatrix} \qquad D_B = \begin{Bmatrix} n & Dd_B \\ 1 & t_{db,\dots,}\, T_{db} \\ . & . \\ . & . \\ . & . \\ N & t_{db,\dots,}\, T_{db} \end{Bmatrix}$$

where:

t_{wb} = start of wet event at Booligal

T_{wb} = end of wet event at Booligal

m = wet event with a total of M events

t_{db} = start of dry event at Booligal

T_{db} = end of dry event at Booligal

n = dry event with a total of N events

Great Cumbung Swamp Events

5. Once $d_{B,t} > T_I$, the Great Cumbung Swamp begins to inundate. Given the inundation duration in the Great Cumbung Swamp is longer than the period for which the flow at Booligal exceeds the threshold, the duration is calculated as:

$$Wd_C = FIDF \times Wd_B$$

where:

Wd_C	=	duration of inundation (wet) event at Great Cumbung Swamp
FIDF	=	Flow Inundation Duration Factor (constant)

6. The time at which the wet event ends at the Great Cumbung Swamp is then calculated as $t_{wb} + Wd_C$, with a corresponding reduction in the duration of the following dry event:

$$Dd_C(e) = \max\left[Dd_B(e) - \left(Wd_C(e-1) - Wd_B(e-1)\right), 0\right]$$

where:

e	=	current event (either wet or dry)

Where a dry event is reduced to 5 days or less, it is assumed that the wet event is continuous, and $W_B(m) = W_B(m) + W_B(m-1)$, whilst $D_B(n) = 0$. Similarly, two dry events are also aggregated if a wet event is 5 days or less. The resulting wet and dry events in the Great Cumbung Swamp are also described using matrices containing the start of each event and the total duration:

$$W_C = \begin{Bmatrix} k & Wd_C \\ 1 & t_{wc,\ldots,} T_{wc} \\ . & . \\ . & . \\ . & . \\ K & t_{wc,\ldots,} T_{wc} \end{Bmatrix} \qquad D_C = \begin{Bmatrix} l & Dd_C \\ 1 & t_{dc,\ldots,} T_{dc} \\ . & . \\ . & . \\ . & . \\ L & t_{dc,\ldots,} T_{dc} \end{Bmatrix}$$

where:

t_{wc}	=	start of wet event at Great Cumbung Swamp
T_{wc}	=	end of wet event at Great Cumbung Swamp
k	=	wet event with a total of K events
t_{dc}	=	start of dry event at Great Cumbung Swamp
T_{dc}	=	end of dry event at Great Cumbung Swamp
l	=	dry event with a total of L events

Parameter Values

There are four parameters for which values need to be assigned (Figure 14): the Initial Flow Threshold (T_Q) (ML/d); the Flow Duration Threshold (T_{QD}) (days); the Drought Break constant (y); and the Flow Inundation Duration Factor (FIDF). The Initial Flow and Flow Duration thresholds were selected to represent the two different areas within the Great Cumbung Swamp being considered for the current model: the lakes and River Red Gum fringe area; and the entire Great Cumbung Swamp River Red Gum floodplain including the lakes area (Table 1). These values were based on application of the River Analysis Package (eWater, 2012), as well as information from Brady *et al*. (1998), MDBA (2012a), Sims (1996), Smith and Barr (2002), Driver *et al*. (2003), Driver *et al*. (2004), and Driver *et al*. (2010).

Table 1. Flow thresholds for inundation of two areas in the Great Cumbung Swamp

Area Inundated	Initial Flow Threshold (ML/d)	Duration Threshold (days)
Lakes and River Red Gum fringe 4,000 ha	700	90
Whole River Red Gum area in the Great Cumbung Swamp 15,000 ha	2700	30

The magnitude of these thresholds relative to flow at Booligal is shown in Figure 16, whilst the resulting patterns of wet and dry periods are shown in Figure 17. It can be seen that despite significant variation in initial flow threshold, the total number of wet events is similar for both the lakes area and whole River Red Gum area, although there is some increase in wet event duration for the lakes area. The minimal impact is due to the greater duration threshold required for the River Red Gum fringe area. The longer threshold results in some occasions where the 2700ML/d 30d threshold is exceeded before the 700ML/d 90d threshold, in which case the lakes area is assumed to be inundated as well.

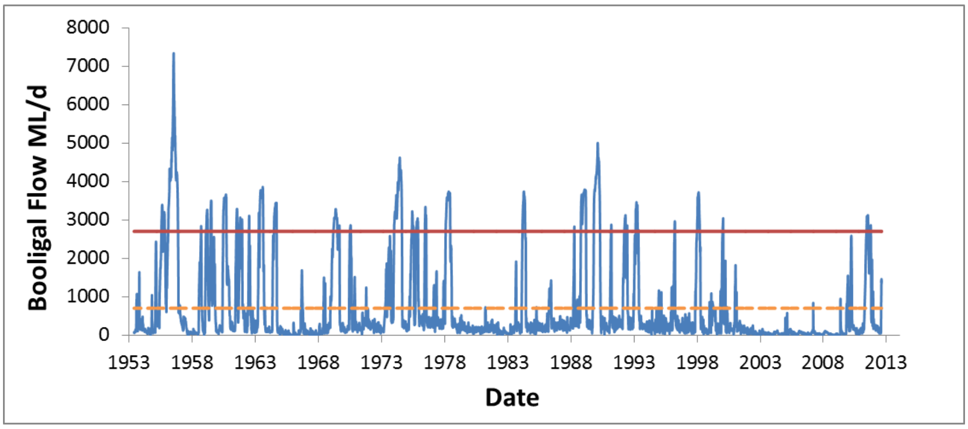
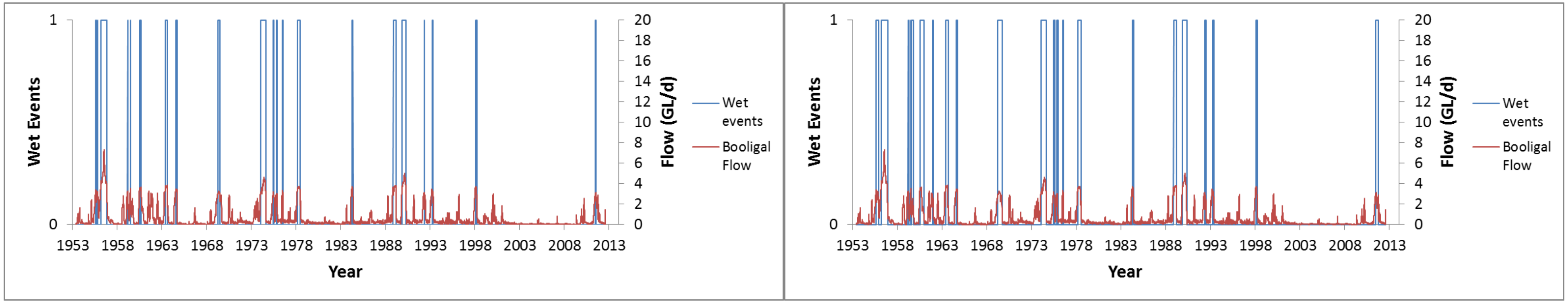
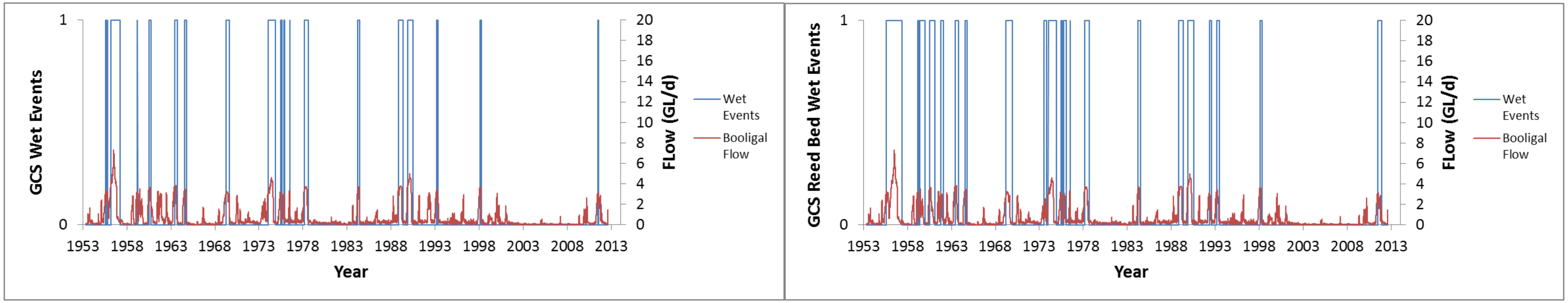


Figure 16. Flow at Booligal gauge from 1/7/1953 to 20/6/2013, showing 2700ML/d (solid red line) and 700ML/d (dashed orange line) initial flow thresholds.



(a) (b)

Figure 17. Sequence of wet and dry events at Booligal based on (a) the 2700ML/d 30d threshold, and (b) the combined 700ML/d 90d and 2700ML/d 30d thresholds, where 1 = wet and 0 = dry.



(a) (b)

Figure 18. Sequence of wet and dry events at the Great Cumbung Swamp based on (a) the 2700ML/d 30d threshold (entire River Red Gum area), and (b) the combined 700ML/d 90d and 2700ML/d 30d thresholds (Reed Bed area), where 1 = wet and 0 = dry.

The third parameter value needing to be defined is the constant in Equation 2 for the drought break threshold. Due to lack of information and the simplistic nature of the model, a linear relationship was used between drought length and the number of additional days of flow required above T_Q (Figure 19). The slope (value of y) was set at 730, such that one additional day of above threshold flow is required for every two years of preceding drought. This value can be easily modified, as can the relationship should further information become available.

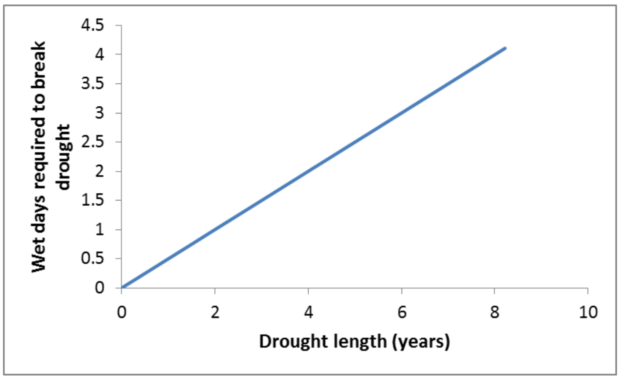


Figure 19. Additional above threshold wet days required to inundate the Great Cumbung Swamp following a drought

The last parameter value to be defined is the FIDF, relating the duration of above threshold flow at Booligal to the inundation duration at the Great Cumbung Swamp. The FIDF was used as a simple proxy of actual hydrological processes within the Swamp including storage and infiltration, given there was insufficient information to estimate actual depth of inundation based on flow thresholds alone. The FIDF is therefore used as a calibration factor to account for the inundation duration which exceeds the duration at which above threshold flow occurs at Booligal gauge.

Given a lack of existing information upon which to define this relationship (see discussion in Section 3.2, Introduction), different FIDF relationships and factors were tested. As for the drought break threshold, the simplest approach was adopted due to a lack of information, with a single multiplicative factor (FIDF) between flow at Booligal and inundation at Great Cumbung Swamp. An FIDF value of 1.5 appeared to result in patterns which were considered to be most realistic.

The impact of the drought break threshold and FIDF on inundation events can be seen by comparing the sequence of events at Booligal based on the initial flow and duration thresholds alone (Figure 17), and that of the Great Cumbung Swamp (Figure 18). The increased duration at the Great Cumbung Swamp is particularly noticeable in late 1955 to mid-1957, where two events at Booligal combine into one for the Great Cumbung Swamp.

A key outcome of the modelled sequence of wet and dry events shown in Figure 17 and 18, is the length of the Millennium Drought which extends from 23/12/1998 until 21/5/2012 for the whole River Red Gum area, a period of over thirteen years. Prior to the Millennium drought, it was estimated that inundation would be required every three years for River Red Gum forests, and every five to seven years for River Red Gum woodlands to maintain vigour (Roberts and Marston, 2011). This has since been revised to estimates that River Red Gum can survive without water for approximately four to thirteen years, depending on other factors such as initial River Red Gum condition (Overton *et al.*, 2014; Souter *et al.*, 2014). Given a dry period of over thirteen years, one would expect that no River Red Gum would have survived the Millennium drought based on flow alone. Instead, the majority of the River Red Gum community did survive despite the loss of individual trees. It can therefore be concluded that:

1. The flow threshold used is too high and more regular inundation occurred; and/or
2. River Red Gum can survive for more than 13 years without water, which contradicts current published information; and/or
3. River Red Gum is accessing other sources of water, such as groundwater or soil moisture through rainfall. Accessing water from the Murrumbidgee during the millennium drought is unlikely, as the drought affected the entire MDB.

The third of these conclusions is consistent with information provided by experts, who identified rainfall and groundwater as playing a role in sustaining River Red Gum, although the relative importance of these alternative water sources varied between experts. The outcome of the expert elicitation combined with the flow analysis above supports the inclusion of rainfall based inundation (Section 3.4.2) and groundwater access (Section 3.5).

3.4.2 Rainfall based inundation

Rainfall based inundation is represented using a simple water balance model considering rainfall intensity, initial and continuing losses, and infiltration (Figure 20). As with the flow based inundation model, further complexity was not seen to be warranted given the lack of data, significant uncertainties in other modelling components, as well as the purpose of the current study being the investigation of modelling tools for decision making rather than producing the best possible model.

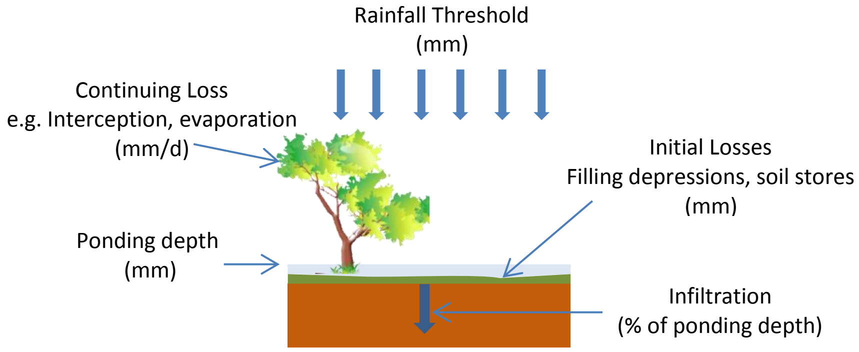


Figure 20. Water balance model for rainfall based inundation in the Great Cumbung Swamp

The water balance model was derived from the initial-continuing loss model which is widely used across Australia to estimate runoff (Pilgrim, 1987; Hill *et al*,, 1998; Rahman *et al.*, 2002). The initial loss component of the model accounts for losses prior to surface runoff and includes interception by vegetation, filling of depressions, and infiltration prior to soil saturation. The continuing loss component accounts for average losses once runoff has commenced (Hill *et al.*, 1998; Phillips *et al.*, 2014). In some models, the average continuing loss is replaced by a proportional loss based on rainfall intensity (Hill *et al*., 1998). For the purpose of this study, an average continuing loss was used to account for ongoing losses such as interceptions, evaporation and any other surface losses, whilst a separate infiltration loss was used to capture variable loss based on the ponding depth. A fourth parameter, the rainfall threshold, was used in addition to the initial loss given the large magnitude of losses within the system such that rainfall induced ponding only occurs once a sufficient rainfall intensity is exceeded.

Daily rainfall data were available from the Australian Bureau of Meteorology (2013). The closest continuous rainfall gauge to the Great Cumbung Swamp is Oxley (Walmer Downs), gauge 49055 (Figure 21), which opened in 1922. Daily rainfall and a 12 month moving total are shown in Figures 22 and 23 for 1 July 1953 to 30 June 2013. Some pre-processing of the data was required to disaggregate rainfall totals which covered more than one day. Where this occurred, the total volume was averaged across the number of missing days in the absence of further information. The limitation of this approach is that aggregated values can occur after heavy rainfall, and averaging the data fails to miss peak rainfall. However, for the purpose of this study, this is considered to have minimal impact relative to other uncertainties. Other gaps in the rainfall data were taken to be zero rainfall.

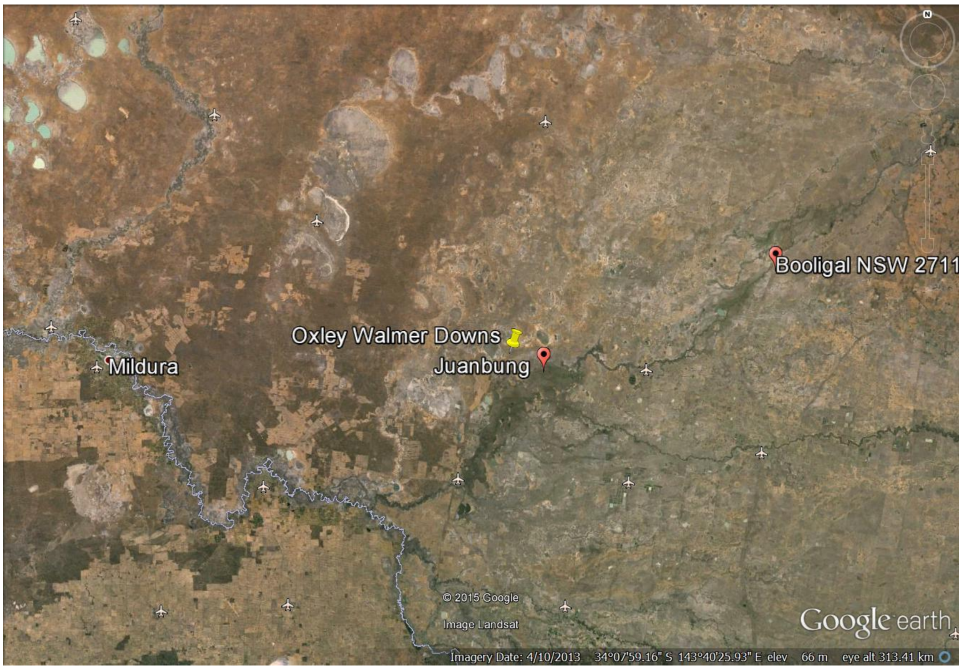


Figure 21. Location of rainfall gauge Oxley (Walmer Downs), gauge 49055 (source: Google Earth, 2013)

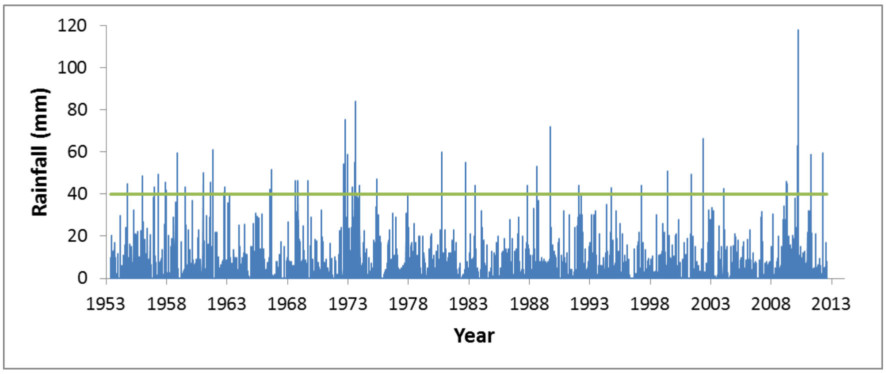


Figure 22. Daily rainfall from Oxley (Walmer Downs) from 1 July 1953 to 30 June 2013, with a 40mm/d threshold rainfall intensity.

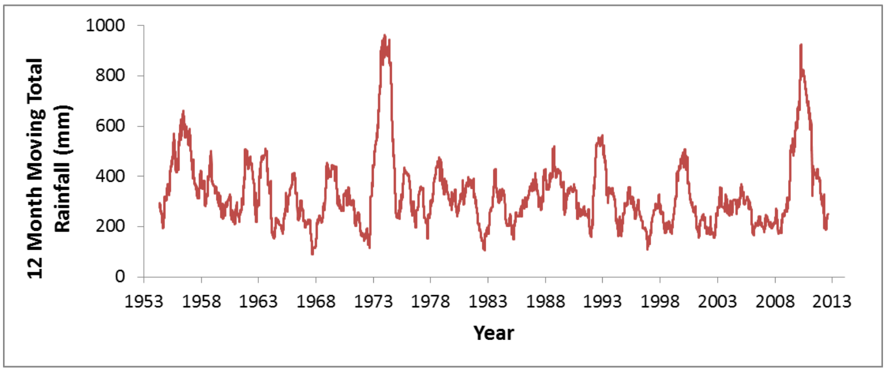


Figure 23. 12 month moving total rainfall from Oxley (Walmer Downs).

It can be seen from Figures 22 and 23 that there is significant intra- and inter-annual variation in rainfall, with less distinct periods of below average rainfall. Unlike the flow records at Booligal, the Millennium drought is less obvious from the rainfall data, although the duration of below average annual rainfall is greater during this period.

The incorporation of rainfall based inundation into the flood inundation model is described below:

Model Calculations

Once rainfall intensity exceeds the threshold value (T_R), effective rainfall is calculated as follows:

$$R_E(t) = \begin{cases} R(t) - L_I & t = 1 \\ R(t) - L_C & t > 1 \end{cases}$$

where:

$R_E(t) =$ Effective rainfall at time *t* (mm)

$R(t) =$ Recorded rainfall at time *t* (mm)

$L_I =$ Initial loss (mm)

$L_C =$ Continuing loss (mm)

1. Ponding depth (P) and infiltration (I) are then calculated based on the effective rainfall. Where there is no rainfall for the current time step but P $>$ 1.0 mm, infiltration continues to occur and ponding depth is updated.

$$I(t) = IR\left[P(t-1) + R_E(t)\right]$$

$$P(t) = P(t-1) + R_E(t) - I(t)$$

where:

IR = Infiltration rate (%)

2. Having calculated the ponding depth at time *t*, rainfall based inundation of the Great Cumbung Swamp occurs where there is insufficient flow for flow based inundation, and where P $>$ 1.0 mm. The rainfall event continues until P $\leq$ 1.0, or when flow based inundation begins. The combination of both flow and rainfall based inundation are defined as a wet event in the Great Cumbung Swamp.

Parameter Values

Parameter values for the rainfall inundation model are provided in Table 2. The threshold rainfall intensity of 40 mm/d was selected based on identifying rainfall events of sufficient magnitude to result in ponding, and resulting in a ponding depth considered likely to penetrate the clayey soils of the Great Cumbung Swamp and reach River Red Gum roots. Interviews with experts indicated that rainfall is only effective in supporting River Red Gum when there is a substantive ponding depth. J. Roberts (pers. comm., 2013) also indicated that light rainfall would benefit River Red Gum through lowering temperatures and raising humidity, but would be insufficient to infiltrate through the clayey soils of the Great Cumbung Swamp and improve River Red Gum condition. Lower thresholds of 10-30mm were also tested, but were observed to result in too many inundation events.

Table 2. Parameter values for the rainfall based inundation model

Parameter	Symbol	Value
Threshold Rainfall (mm)	T_R	40
Initial Loss (mm)	L_I	10
Continuing Loss (mm)	L_C	5
Infiltration (%)	IR	20

The initial and continuing losses were estimated to be relatively small given the topography of the Great Cumbung Swamp is very flat with minimal interception, and the majority of rainfall will pond after the initial rainfall threshold is reached. The infiltration rate was based on the percentage of ponding depth, to account for higher infiltration with increasing head. Larger values were considered unrealistic due to the clayey soils. A smaller value of 2% was also tested, but resulted in the Great Cumbung Swamp being wet for exceptionally long periods. Given the parameters here are assumed and aggregate a number of physical processes, the combination of continuing loss and infiltration rate also account for losses such as evapotranspiration which is not directly included. Further testing of the rainfall inundation parameter values is conducted in Chapters 5 and 6 using sensitivity analysis and Bayesian probabilities.

A comparison between inundation events with and without rainfall based inundation is shown in Figure 24. It can be seen that the inclusion of rainfall based inundation significantly increases the total number of wet events in the Great Cumbung Swamp, including during the Millennium drought. These shorter but more frequent events may be critical for River Red Gum survival during drought conditions. However, based on limited information, it is difficult to derive appropriate rainfall model parameters, and hence the duration and timing of these events is uncertain. It has also been indicated that a number of rainfall events in the Great Cumbung Swamp result from thunderstorms, which can deliver localised rainfall to only small areas, and may not cover the full extent of the Great Cumbung Swamp (P. Driver, pers. comm., 2013).

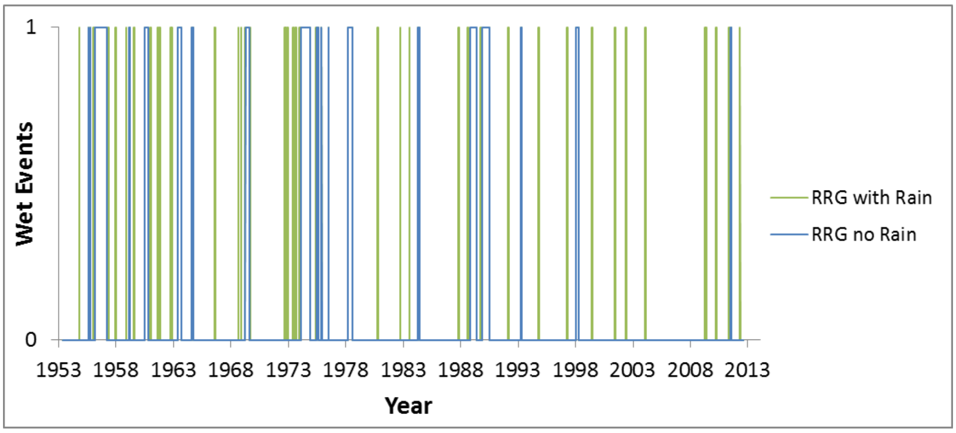


Figure 24. Comparison in wet and dry events in the Great Cumbung Swamp River Red Gum area with and without rainfall inundation.

3.4.3 Evaluation of the Floodplain Inundation Model

In the absence of continuous observed inundation data, three different information sources were used to undertake preliminary evaluation of the floodplain inundation model: anecdotal observations from two landholders and an environmental water manager from NSW Office of Environment and Heritage (P. Packard, pers. comm., 2013); the independently derived water balance model of the Great Cumbung Swamp described earlier (Smith and Barr, 2002; Driver *et al.*, 2004); and observed inundation patterns from satellite imagery from Sims (1996) and

Shaikh *et al*. (1998). As previously mentioned, further evaluation of the combined inundation and ecological response model is described in later chapters.

A full comparison between modelled results and anecdotal observations is provided in Appendix B1, whilst a summary is shown in Table 3. It can be seen that the model generally agreed with observations, although there is considerable subjectivity given the primarily qualitative nature of the observations. There were some differences between the model without and with inclusion of rainfall based inundation for the observed events, although there is no clear improvement when rainfall is considered.

Table 3. Comparison of modelled results with observations provided by two landholders and an environmental water manager.

Year	Landholder/ environmental water manager observations	Modelled Inundation	
		Without rain	With rain
1967	The reed bed was dry but the river still had some water	Yes	Yes
1968	The reed bed filled	No	Yes
1989	1989 was a bigger event than 1990	Wet but not bigger than 1990	Wet but not bigger than 1990
1990	Didn't flood.*	No	No
1996	Stayed within the main channel	Yes	Yes
1998	Everywhere got wet, including the floodplain. Stayed wet for approximately 6 months.	Yes but duration too short	Yes but duration too short
2000	Similar water levels as now (i.e. just extending onto floodplain – March 2013)	Possibly	Yes although possibly too wet
2001	Drought started end 2001	No, drought starts 1999	Similar
2002	2002 still water in the lakes but no rainfall	Yes	No – it rained
2005	2005 the Lachlan within channel was completely dry	Yes	Yes
2006	Early 2006 some water in the Lachlan channel.	Yes	Yes
2009	Some rain in 2009, but the Lachlan had dried up again	Yes	No
	At the end of 2009, the system was incredibly dry, with sparse vegetation coverage	Yes	Yes
2010	Approximately 300 ml rain. Inundation from flows also occurred, but stayed within channels and lakes	Yes	Yes
2011	The 2011 event was primarily rainfall driven, again no flooding.	Yes	Yes
2010/ 2011 and 2012	Events didn't extend as far as expected, largely due to the dryness of the system prior to 2010 event, and in particular to re-filling of the GW stores.	Possibly	Possibly
2010/ 2011	The reed bed was wet, and some River Red Gum areas also got wet for a few months. Most places dried out between the 2010 and 2011 event, only the channel stayed wet although the flows were very low.	No	Yes
2012	The 2012 event was preceded by large rainfall which had already started to fill areas. Some black box was inundated for a couple of months as a result of both rainfall and flow. After the inundation, was incredibly dry with only 50% of average rainfall, hence the inundation didn't last as long. The reed bed was wet from about end March until sometime between Nov and Feb.	Yes – although duration possibly too short	Yes – although April not wet in model, and finished before Nov

*Consultation with P. Driver (pers. comm., 2015) indicated that there was a large flood in 1990, suggesting some discrepancy in stakeholder views as to the nature of previous flood events.

The monthly water balance model (WBM) of the Great Cumbung Swamp lakes and river channels developed by Smith and Barr (2002) with groundwater inputs from Driver *et al*. (2004), estimates inundation events as well as ponded depth and total water volume from January 1971 to August 1998. Calculations are based on an assumed flat conical basin geometry and static measures for bed slope, pan coefficient, infiltration rate and river solute concentration. The model is based on pre-drought flow data from Booligal, and hence does not capture current hydrological conditions due to drought impacts (P. Driver, pers. comm., 2015).

Comparison between inundation events for the WBM model and the hydrological component of the ERM developed here is shown in Figure 25a and b. Results from the ERM only show the lakes area rather than the full River Red Gum floodplain, for consistency of comparison with the WBM. It can be seen that the WBM estimates almost continuous inundation between 1971 and 1998, whereas the ERM both with and without rain estimates a series of shorter events. To better understand the behaviour of the WBM, the ERM events were plotted against the WBM estimated ponding depth, as shown in Figure 25c and d. It can be seen that there is a reasonable match between ponding depths in the WBM and wet events in the ERM, although there is some discrepancy in timing, with the current model estimating inundation after the WBM.

The third set of observations used for comparison were the analyses of satellite imagery of the Great Cumbung Swamp by Sims (1996) and Shaikh *et al*. (1998) (Table 4). One of the first things to note from Table 4 is that there is considerable discrepancy in the estimated inundated area between Sims and Shaikh *et al*. Both studies used Landsat images, with Sims using an unsupervised maximum likelihood classification to categorise pixels into five categories: open water; active vegetation; hot vegetation; outer vegetation; and bright return (see Sims 1996 for definitions). Shaikh *et al*. used both a visual assessment of images as well as a density slicing technique to distinguish between inundated and non-inundated areas. In addition, linear regression of NDVI values were used to identify areas of open water, however it is not clear what the relationship between open water and area inundated was.

Comparing the ERM inundation model with the results from Sims (1996), there appears to be some similarity if it is assumed that a minimum of ≥ 888 ha of open water in the remotely sensed images is equivalent to full inundation of the lakes area in the ERM. An exception to this is the October 1991 event, where Sims calculates an open water area of 1403 ha but the ERM does not identify a wet event.

A poorer match can be observed with the Shaikh *et al*. (1998) data. However, it should be noted that the ERM only classifies an event as being wet if the full lakes area (or full River Red Gum area) is inundated, and does not calculate partial inundation as detected by the satellite images. In addition, there is some subjectivity involved in processing and interpretation of remotely sensed images, as demonstrated by the discrepancy between Sims and Shaikh *et al*.

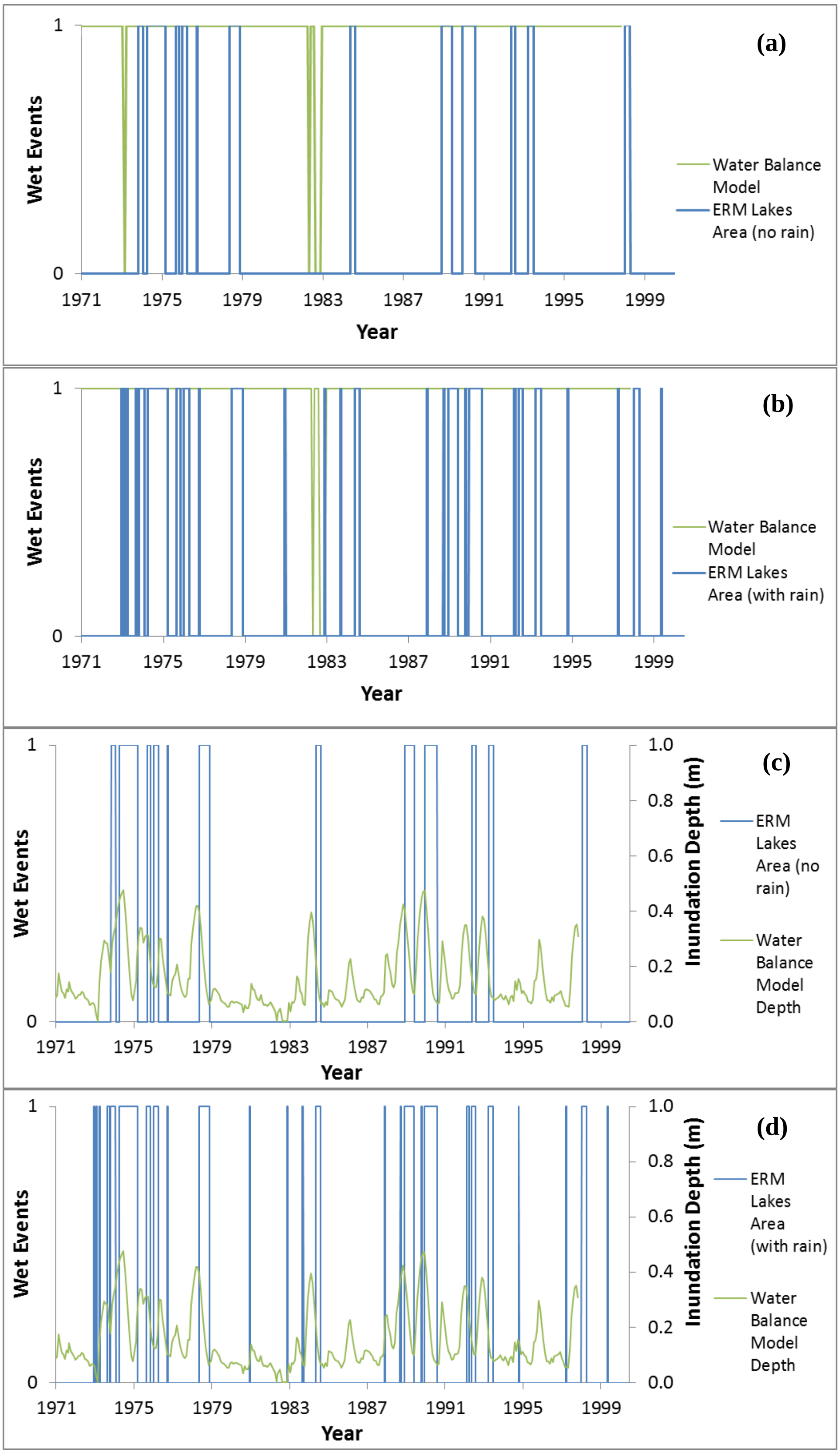


Figure 25. Comparison of the ERM hydrological model for the Lakes Area and the Smith and Barr (2002) WBM showing (a) sequence of wet and dry events assuming no rain in the ERM; (b) as for (a) but with rain in the ERM; (c) sequence of events for the ERM assuming no rain and estimated surface water depths from the WBM; and (d) as for (c) but with rain in the ERM.

Table 4. Comparison between the ERM hydrology model results and remotely sensed image analysis by Sims (1996) and Shaikh *et al*. (1998).

Image Date	ERM hydrology model (Lakes Area with rain)	Area open water/inundated area (ha)	Duration (days)	Reference
16/12/1983	Dry	Dry		Sims
16/5/1984	Dry	Dry		Sims
28/2/1985	Wet 1/10/1984 – 1/1/1985	1150		Sims
26/10/1985	Dry	622		Sims
13/12/1985	Dry	735		Sims
3/3/1986	Dry	547		Sims
29/10/1986	Dry	3560	120	Shaikh *et al.*
1/1/1987	Dry	6320	64	Shaikh *et al.*
5/10/1989	Wet 11/6/1989 – 11/12/1989 (184 days)	1611		Sims
		4240	1008	Shaikh *et al.*
14/3/1990	Wet 21/4/1990 – 8/5/1990	888		Sims
22/9/1990	Wet 26/6/1990 – 20/2/1991 (240 days)	Swamp fully inundated		Sims
		13100	352	Shaikh *et al.*
27/12/1990	Wet	1175		Sims
13/2/1991	Wet	990		Sims
11/10/1991	Dry	1403		Sims
		4400	384	Shaikh *et al.*
16/2/1992	Dry	653		Sims
30/11/1992	Wet 25/9/1992 – 28/10/1992) (34 days)	1436		Sims
		2800	416	Shaikh *et al.*
2/2/1993	Wet 24/12/1992 – 8/3/1993 (75 days)	1075		Sims
		3790	64	Shaikh *et al.*
17/11/1993	Wet 3/11/1993 – 9/2/1994 (99 days)	4160	288	Shaikh *et al.*
5/2/1994	Wet	1786		Sims

The above comparison of the ERM hydrological model against different sources of observed and modelled data highlights the uncertainty of estimating inundation patterns in the Great Cumbung Swamp. Given that water availability is assumed to be the major driver of River Red Gum condition, this uncertainty has implications for estimation of condition scores described in subsequent chapters. Consequently, the impact of different parameter values on results is investigated further in Chapters 5 and 6.

Preliminary evaluation of model performance both with and without rainfall suggests that rainfall is likely to have played a role in River Red Gum survival during the Millennium drought. The occurrence of rainfall driven inundation events is supported by observations during a field trip in 2013 based on the species distribution in the Great Cumbung Swamp (Driver *et al.*, 2013). In addition, Thorburn and Walker (1994) and Mensforth *et al*. (1994) identified rainfall as being an important water source for River Red Gum on the River Murray floodplain, where trees reliant on intermittent rainfall had a greater water use efficiency than those with access to more continuous sources such as groundwater or river water.

The estimation of rainfall based inundation could be improved through consideration of additional rainfall gauges near the Great Cumbung Swamp, or use of gridded rainfall data from products such as SILO (Scientific Information for Land Owners) (Jeffrey *et al.*, 2001) to account for variability across the swamp. Further recommendations include: calculating the number of days to break the drought using total flow rather than the preceding length of the dry period in the Great Cumbung Swamp; improvement in the flow/inundation relationship; explicit inclusion of evapotranspiration in the continuing loss parameter; and increased resolution for representing different spatial areas within the Great Cumbung Swamp, such that percentage of area inundated can be estimated.

3.5 Groundwater model

Having estimated Great Cumbung Swamp inundation events due to flow and rainfall, the second component of the hydrological model was to estimate groundwater levels. As for the inundation model, the focus of the groundwater model was to develop a simple representation of groundwater levels as proof of concept in combining both surface water and groundwater in estimating ecological response. With this focus along with insufficient data to justify development of a detailed groundwater model, a simple relationship between groundwater level and flow was derived. Estimated levels were then directly used in the ecological response model to influence River Red Gum condition, based on the depth of River Red Gum roots (described in the following chapter).

The complex surface stratigraphy and geomorphology of the Great Cumbung Swamp (described in Chapter 2) means that groundwater recharge can occur through a variety of mechanisms: direct infiltration of local rainfall; streamwater infiltration either through lateral subsurface flow or floodplain inundation; or through the network of palaeochannels throughout the Great Cumbung Swamp. As flow was considered to dominate local rainfall, groundwater level estimates were based on surface water flow only.

Shallow groundwater monitoring bores located within the Great Cumbung Swamp are shown in Figure 26. The sampling frequency and duration varies substantially between bores, with GW036721 having the longest record and the two Brady bores having the greatest number of observations and highest sample frequency (Table 5 and Figure 27). It can be seen from Figure 27 that there is significant variation in the depth of bores, which in the case of the Brady bores and GW036721, is predominantly due to different borehole screen depths. Differences in the remaining bores are representative of heterogeneity in the geology as well as distance from the river. Given the purpose of this analysis is to examine long term changes in groundwater level, GW036721 was the only bore used for deriving the groundwater level-flow relationship. The bore was constructed in 1987 to a depth of 454m (bedrock) as part of a Murray Basin Groundwater investigation (Driver *et al.*, 2004).

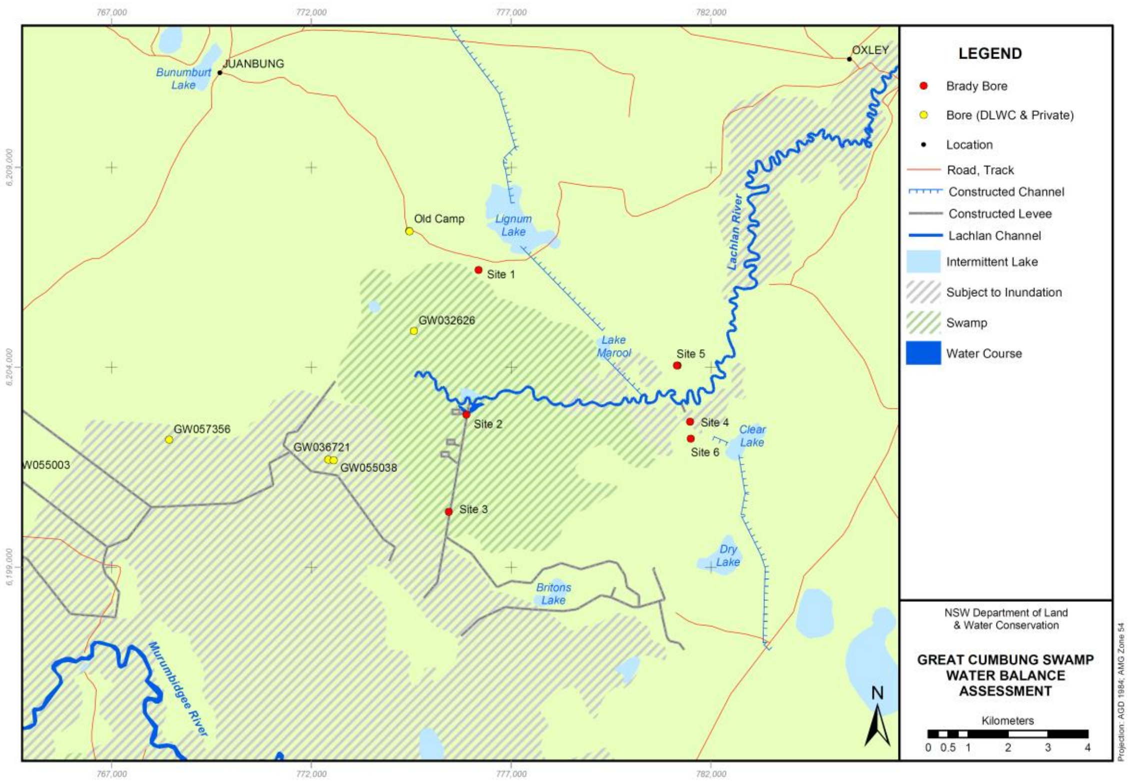


Figure 26. Location of groundwater boreholes within the Great Cumbung Swamp (source: Driver *et al*., 2004)

Table 5. Available groundwater data for the Great Cumbung Swamp.

Bore Name	Date range of data	Sampling frequency	No. data points	Comments
GW036721	22/10/1987 – 25/3/2010	Between 1 to 4 times per year	47	Three pipes at different depths. Only the shallowest (Pipe 1) was used. Site flooded during 14 observations.
GW090053	17/10/2002 – 25/3/2010	Mostly once per year, twice in 2002	5	Two pipes. Dry in 2006 and 2010.
GW090052	5/12/2002 – 25/3/2010	Between 1 to 5 years	4	Two pipes. Dry in 2010.
GW090054	30/4/2002 – 25/3/2010	Between 3 times a year to 3 years between readings	7	Two pipes. Dry in 2010
GW090055	30/4/2002 – 25/3/2010	Only one observation of being dry in 2010	1	Dry in 2010
GW090056	17/10/2002 – 25/3/2010	Every 1 to 3 years.	7	Two pipes.
Brady BH4 412156	26/5/1995 – 18/3/1997	Daily	663	Average depth of 1.36m below ground.
Brady BH6 412158	26/5/1995 – 18/3/1997	Daily	663	Average depth of 1.00m below ground

**data obtained from DPI Water

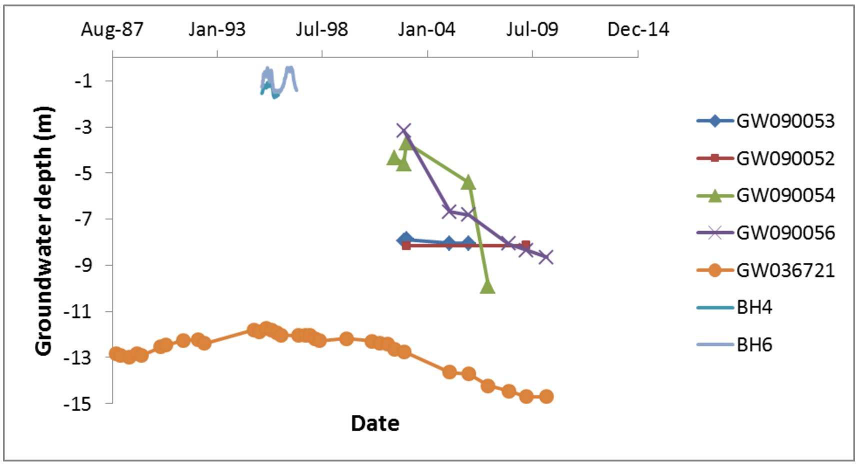


Figure 27. Available groundwater data. Depths vary from within 2m of the surface to 15m.

3.5.1 Connecting flow and groundwater level

The daily and 24 month moving average flow at Booligal gauge were plotted against groundwater data at GW036721 to identify whether a relationship could be observed (Figure 28). It can be seen that groundwater levels generally follow a similar pattern of change to Booligal flow, which is more obvious from the smoothed 24 month moving average. Groundwater levels increase with flood events, and gradually decrease as flow also decreases. The relationship between flow and groundwater displays delay and attenuation, as surface water flow infiltrates to fill shallow groundwater stores. This process is similar to that of calculating runoff from rainfall, and flow routing within channels. The clayey soils of the Great Cumbung Swamp act in a similar manner as catchment storage, where the time to infiltrate causes a reduction and delay in flows reaching the groundwater.

The observed delay between surface water peaks and groundwater peaks suggest that there is some capacity for deeper aquifers within the Coonambidgil formation to store water during periods of lower surface water availability, unlike the shallow aquifer of <5m depth investigated by Brady *et al*. (1998) shown earlier in Figure 11. However, the decline in groundwater levels during the Millennium drought suggests reasonable connectivity with surface water such that storage is limited compared with the deeper, confined aquifers. As discussed in Chapter 4, the extent of this decline in groundwater may have significant implications for River Red Gum survival.

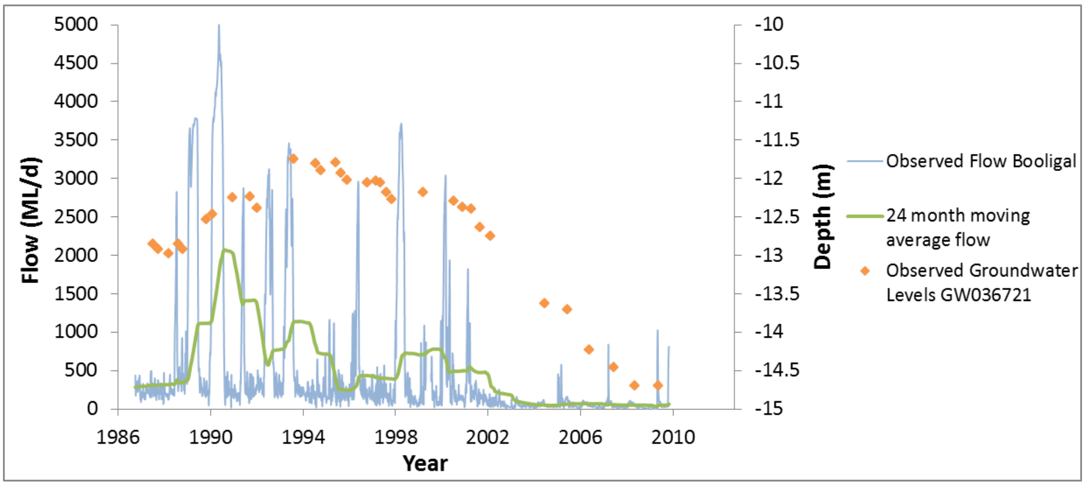


Figure 28. Comparison between flow at Booligal and groundwater levels in the Great Cumbung Swamp.

Given the behaviour of groundwater observations shown in Figure 28 and the hydrogeology of the Great Cumbung Swamp, a Nash cascade of storages (Nash, 1958) was used to relate surface water flow and groundwater level. Figure 29 shows an example of delay and attenuation using between one and three stores, for a unit impulse of one and a delay parameter of 1950. It can be seen that the more stores used, the greater the delay and attenuation of the impulse. The Nash method of representing flow by applying the unit hydrograph with a cascade of storages has been widely applied for representing rainfall-runoff models (Todini, 1988). The approach has also been previously adopted to represent SW-GW interactions in the unsaturated zone by Korkmaz *et al* (2009), but was linked to a more detailed two dimensional groundwater model. In Driver *et al*. (2011), the application of a Nash cascade of storages was investigated for relating flow at Booligal gauge and vegetation biomass within the Great Cumbung Swamp, demonstrating reasonable relationship during periods of low water availability.

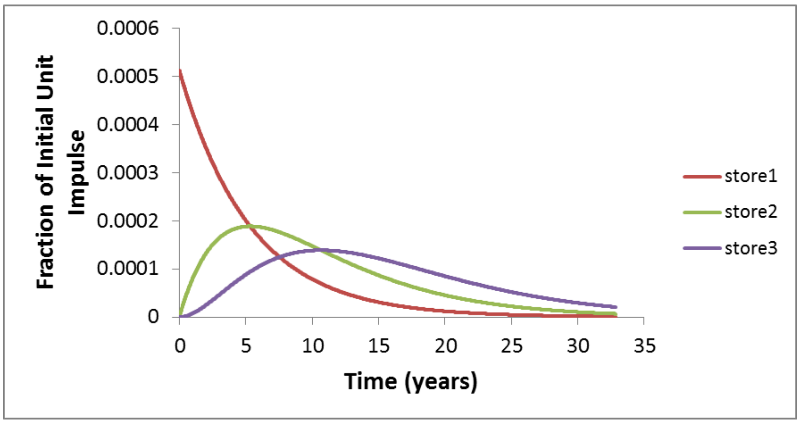


Figure 29. Nash cascade of three storages for a unit impulse and delay parameter (τ) of 1950.

In this study, a single store was initially used (Barbour *et al.*, 2011), but further analysis identified an improved fit between flow and groundwater levels using two stores. The two-storage Nash model which was applied is defined as:

$$GW = m\left[2a\tilde{Q}_{t-1} - a^2\tilde{Q}_{t-2} + (1-a)^2 Q_t\right] + c$$

where:

GW	=	Groundwater level (m)
Q	=	Flow (ML/d)
$\tilde{Q}$	=	Output flow from the second storage (ML/d)
a	=	$e^{\frac{-1}{\tau}}$
τ	=	storage delay constant
m, c	=	constants to convert values from ML/d to level (m)

The storage delay constant, τ, dictates the number of time steps from the peak of the inflow to peak for the outflow (in this case, the time taken for the peak surface flow to peak in groundwater level). Different values of τ were tested to find the best fit between modelled and observed groundwater levels (based on the maximum R^2), with a value of $\tau = 1950$ being adopted. As shown in Figure 29, a two-storage model using a τ of 1950 results in delaying the peak of the impulse by approximately 5 years. This delay approximately corresponds to the delay in observed peak flow in September 1990 with peak observed groundwater levels which occurred from January 1994 – November 1995 (a difference of between just over three years to just over five years) (Figure 28). A comparison between the storage outflow $\tilde{Q}$ and observed groundwater levels is shown in Figure 30. To correct the $\tilde{Q}$ from ML/d to a groundwater depth, a linear relationship between $\tilde{Q}$ and observed groundwater levels was used to derive the constants *m* and *c*, using the maximum R^2 value (Figure 31). This resulted in *m=0.0075*, and *c=-17.857*.

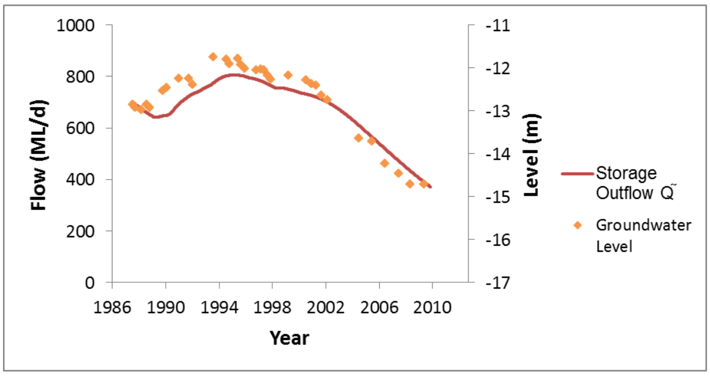


Figure 30. Comparison between flow from the Nash storages and groundwater level.

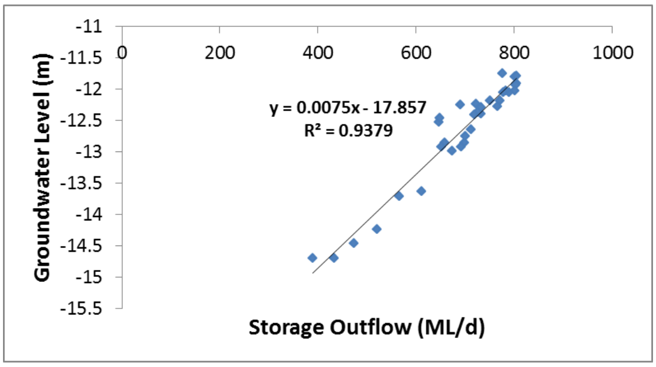


Figure 31. Identification of constants *m* and *c* relating groundwater levels (m) with Nash storage outflow (ML/d).

The resulting groundwater model compared with observed data is shown in Figure 32. The model provides a reasonable fit given the simplicity of the model and the limited information available. A better approximation can be seen during the decline in groundwater levels from 1994 onwards, suggesting that the model better represents drying processes compared with infiltration and saturation. It is acknowledged that a number of assumptions have been made, including: levels from GW036721 are representative of the entire Great Cumbung Swamp, where in reality there is significant spatial variation as previously shown; groundwater levels have been estimated using a data driven approach using flow data alone, without consideration of other physical characteristics and processes influencing groundwater recharge and flow; the limited data available meant that the model was derived using all data points, potentially leading to overfitting. Whilst these assumptions need to be considered in interpretation of results, the model is considered to provide an adequate representation of groundwater levels for the purpose of this study.

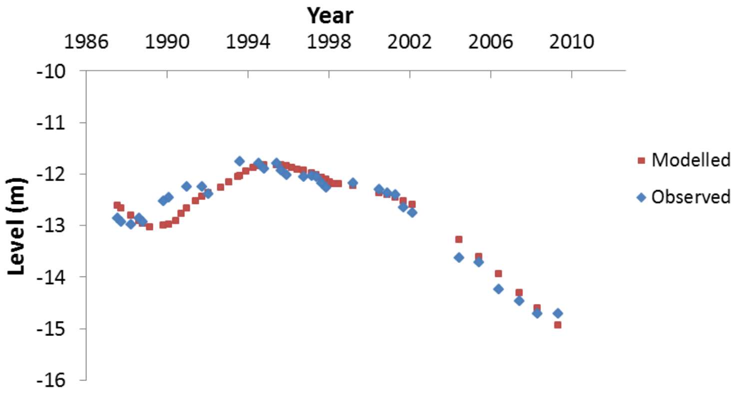


Figure 32. Comparison between modelled and observed groundwater levels.

As the groundwater levels are not used in the hydrological model to directly influence inundation patterns, the way in which groundwater influences ecological response is described in the following chapter.

3.6 Conclusions

This chapter presents the hydrological component of the ERM for the Great Cumbung Swamp, to enable the estimation of River Red Gum response. Despite the simple nature of the model, it captures the key hydrological elements influencing River Red Gum condition – flow and rainfall driven inundation, and groundwater availability. Given the motivation of the thesis is to examine the role of quantitative modelling in decision making for water resources, the development of the hydrological model was not intended to advance science in the domain of inundation, rainfall-runoff or groundwater modelling. Instead, the work demonstrates the development of a model which is fit for purpose, and which enables the exploration of key hydrological processes within the Great Cumbung Swamp using available information.

A lack of temporal and spatially distributed observed inundation and groundwater data limited the capacity to verify model behaviour, however comparison with the data available (including information from stakeholders and an independently derived water balance model) indicate that the model performs sufficiently well for the intended purpose (large scale events and patterns of change). The model is also sufficiently flexible such that components can be easily improved or substituted for more accurate approaches should they become available.

Model improvements could be obtained through: expanding the work of Sims (1996) and Shaikh *et al*. (1998) using satellite imagery to improve the inundation model; use of the hydrodynamic model being developed for the Great Cumbung Swamp when it is finalised; and application of more advanced rainfall-runoff and groundwater modelling methods. However, these would require additional data to warrant the increased complexity, and are not the focus of the current research. In addition, more complex models are unlikely to address the significant uncertainties affecting water availability in the Great Cumbung Swamp, such as changes in climate, antecedent conditions, vegetation growth, geomorphology, and land use. For example, one landholder reported that inundation patterns varied between floods due to vegetation growth, where growth would accelerate post flooding and create a barrier to floodwaters during the next event.

To explore the impact of uncertainty in the hydrological model, the sensitivity of model results to model components is explored in Chapter 5, whilst a comparison between modelled and observed River Red Gum condition is conducted for the combined hydrological – ecological model in Chapter 6. Different models are then used in optimisation in Chapter 8, to identify the impact of different model assumptions on decisions regarding environmental flows.

The following chapter builds on the hydrological model by estimating ecological response to water availability.

Chapter 4: Modelling River Red Gum response to water availability

River Red Gum in the Great Cumbung Swamp, Lachlan, 2011.

4.1 Aim and Overview

The previous chapter developed a hydrologic model of the Great Cumbung Swamp using a systems approach for estimating water availability for River Red Gum. The model considers riverine inundation and rainfall to produce a time series of wet and dry events in the Great Cumbung Swamp, as well as an estimate of groundwater levels.

The primary aim of this chapter is to describe the ecological model developed to estimate River Red Gum condition in the Great Cumbung Swamp based on available water. The model addresses a number of the limitations of previous ecological response models by explicitly incorporating uncertainty; considering different sources of water; and considering the sequence of past events in estimating condition.

Together with the hydrologic component described in the previous chapter, the ecological model presented here forms the ecological response model (ERM) which is evaluated and applied in subsequent chapters.

4.2 Introduction

The consideration of ecological objectives in river basin management has significantly increased in recent years (Pahl-Wostl *et al.*, 2013; Acreman *et al.*, 2014b). This has given rise to the development of ecological response models specifically aimed at river basin management, enabling the assessment of flow alteration impacts; the evaluation of different management interventions; and the examination of trade-offs between ecological and human water objectives (Acreman *et al.*, 2014b; Poff and Matthews, 2013; Maier *et al.*, 2014). However, few river basin models explicitly incorporate ecological models, instead focusing on human water uses such as agricultural requirements, town water supply or hydropower. Given the overall aim of this thesis is to explore effective management strategies for floodplain ecosystems and evaluate trade-offs between ecological and human water objectives, the use of an appropriate ecological response model is essential.

Ecological response models for river basin management can be categorised into two main types: (1) the natural flow approach; and (2) the species preference approach. The natural flow approach examines ecologically significant characteristics of the natural flow regime, to enable management interventions to minimise the impact of hydrologic alterations on water dependent ecosystems (see Richter *et al*., 1996 and 1997 for further information). This approach provides a holistic strategy for examining ecological impacts, but also involves a number of challenges in identifying appropriate flow metrics, and guiding priorities for management (see Chapter 7 for further discussion on advantages and disadvantages). The species preference approach aims to identify the water requirements of species and/or communities in particular locations, hence can be effective at managing ecosystems in specific areas (Arthington *et al.*, 2006; Overton *et al.*, 2014; Young *et al.*, 2003). The challenge of this approach is in identifying the water requirements of particular species, and in the management of competing water requirements between species and locations.

A species preference approach was adopted for this thesis as it can be used to directly estimate change in ecological condition and evaluate spatial trade-offs. The approach has particular relevance to the case study being considered, as the Murray-Darling Basin Plan (MDBA, 2012c) requires the use of species preference curves in the assessment of sustainable extractions (Overton *et al.*, 2014). In addition, the current study focuses on wetland and floodplain ecosystems, rather than instream ecology which forms the basis of most natural flow indices. Use of the species preference approach was facilitated by previous research having already investigated the water requirements of key wetland species in the case study area (Rogers and Ralph, 2010; Roberts and Marston, 2011).

A summary of existing models relevant to the current research is provided below, followed by an analysis of limitations and an introduction to the model developed here.

4.2.1 Existing Ecological Response Models

Existing ecological response models which adopt a species preference approach and are of relevance to the current work include: the Physical Habitat Simulation (PHABSIM) model (Bovee, 1982) and related derivatives; the Murray Flow Assessment Tool (MFAT) (Young *et al.*, 2003); the Exploring Climate Impact on Management (EXCLAIM) decision support system (Fu *et al.*, 2015); and EXCLAIM's successor the IBIS decision support system (Fu *et al.*, 2011).

PHABSIM is one of the earliest ecological response models which went beyond a purely hydrological approach to consider habitat suitability, primarily for fish species. Together with other hydraulic based habitat models, PHABSIM forms part of the Instream Flow Incremental Method (IFIM) (Bovee, 1982), and is one of the most widely applied frameworks for instream flow management (Tharme, 2003; Acreman and Dunbar, 2004). PHABSIM was developed by the U.S. Fish and Wildlife Service (Bovee, 1982) to evaluate the impact of changes to flow and channel structure on instream habitat. Building on the work of Waters (1976), PHABSIM uses hydraulic models to estimate instream flow velocity and depth, and combines these with field data on river substrate and cover to calculate a weighted usable area (WUA) of habitat (Bovee, 1982; Acreman and Dunbar, 2004). The WUA is determined for each selected indicator species at each life stage, based on habitat preference curves developed using field studies or expert opinion.

MFAT, EXCLAIM and IBIS are decision support tools developed in Australia, primarily for application in the Murray-Darling Basin although the methodologies are also applicable elsewhere. All three models evaluate ecological response by defining a sequence of wet and dry events using a flow time series for a particular location, and assessing this sequence of events using species preference curves (Young *et al.*, 2003; Fu *et al.*, 2015; Fu *et al.*, 2011). Unlike PHABSIM, MFAT, EXCLAIM and IBIS consider a combination of instream, wetland and floodplain species rather than just instream species.

MFAT has been widely applied within Australia to assist in evaluating different environmental flow strategies as well as structural interventions such as wetland regulators (e.g. Watts, 2010; Higgins *et al*., 2011; Szemis *et al*., 2012; and Szemis *et al*., 2014). The model evaluates the habitat condition for fish, waterbirds and vegetation, as well as assessing the tolerance of ecosystems to algal blooms. A river system model is used to generate a time series of instream flows, whilst an in-built floodplain model is used to estimate wetland and floodplain inundation. Annual preference curves were developed for each species based primarily on expert judgement combined with data where available (Young *et al.*, 2003). Separate curves are used to consider ecologically relevant flow components such as flood timing, inundation duration, inundation depth, and drying period. Each preference curve is based on the 'best' wet or dry event for each year (with best being defined according to the preference curves). Figure 33 shows an example of two MFAT preference curves for River Red Gum, where a score between 0 (poor habitat conditions) and 1 (optimal habitat conditions) is assigned for each curve.

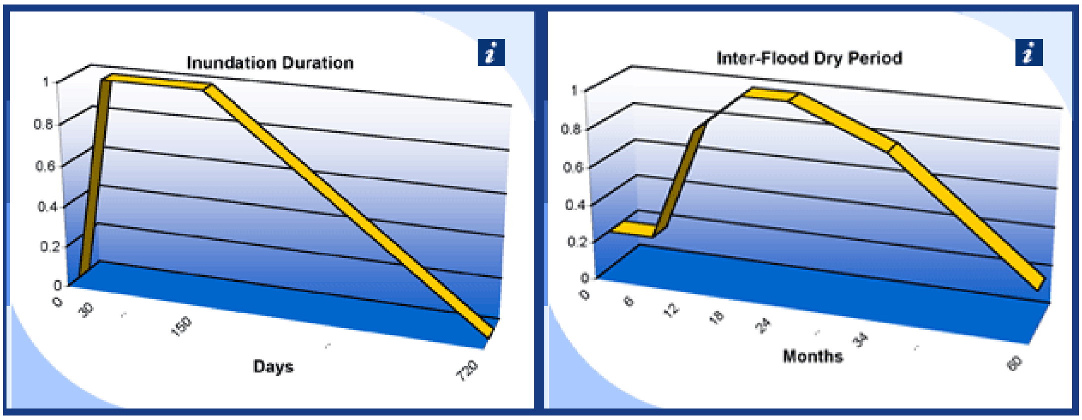


Figure 33. Murray Flow Assessment Tool – example of species preference curves for River Red Gum woodland inundation and inter-flood dry period for the Murray River (source: MDBC website, 2015).

MFAT has since been updated to estimate sustainable diversion limits (SDLs) across the Murray-Darling Basin, as part of the Murray-Darling Basin Plan (Overton *et al.*, 2014). The new model, referred to as the Ecological Elements Method (EEM), has a similar approach to MFAT in the use of annual based preference curves which are combined using weights. However, the method is fundamentally different in that it estimates the condition of particular species rather than the habitat suitability. In addition, there have been some significant advances including the consideration of ecological starting condition on response; a greater focus on the pattern of change in condition over time; and an improvement in the aggregation and weighting of individual preference curves.

EXCLAIM and IBIS adopt a similar approach to MFAT and EEM in terms of specifying species preferences for different flow components, including flood timing, duration, area, inter-flood dry period and rate of change in water levels. They also use inputs from river model simulations to generate flows, and a simple water balance model to estimate floodplain inundation. However, EXCLAIM and IBIS make a substantial departure from MFAT and EEM in the use of probabilistic Bayesian networks to estimate whether a particular flow scenario is likely to provide a poor, moderate, or good habitat condition (Figure 34).

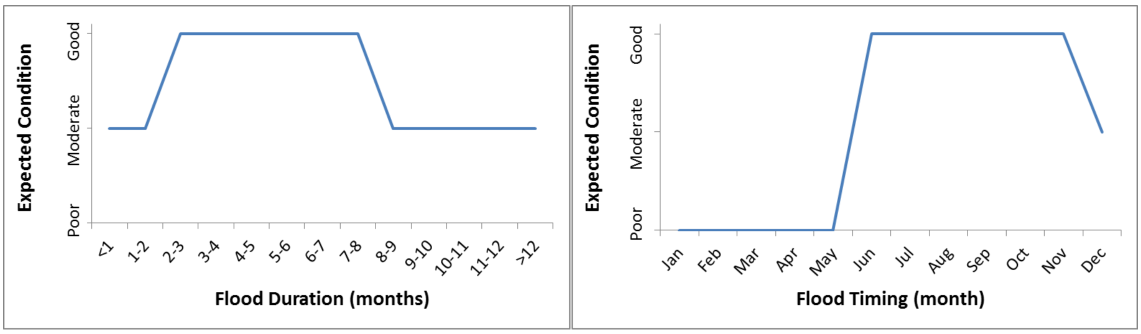


Figure 34. IBIS Ecological Response Model - example of species preference curves for River Red Gum maintenance and survival inundation and flood timing for the Macquarie Marshes (source: adapted from Fu *et al.*, 2011)

An additional ecological response model of relevance to the current work is the wetland response model for the Great Cumbung Swamp developed by Driver *et al*. (2005b) (also discussed in Chapter 3). Whilst it does not use species specific preference curves, the model estimates the suitability of inundation patterns for vegetation species in the Great Cumbung Swamp, focusing on River Red Gum, Lignum (*Muehlenbeckia florulenta*) and Common Reed (*Phragmites australis*). Inundation patterns are estimated using the water balance model developed by Smith and Davies (2002) and Driver *et al*. (2004), and are used to calculate metrics such as dry period duration and the number of inundation events exceeding a minimum threshold.

4.2.2 Current challenges and limitations

The methods and models described above have been instrumental in enabling ecological objectives to be incorporated into river basin modelling and management. However, there also remain a number of limitations regarding the consideration of uncertainty, water availability, and the formulation of preference curves, each of which are discussed below.

1. Uncertainty

There has been minimal consideration of uncertainty in the majority of current ecological response models. In addition, there has often been limited model evaluation to assess model performance and suitability for a particular application. Given the majority of riverine and floodplain ecosystems are highly complex and poorly understood, identifying model assumptions and limitations is critical in a decision making context. Whilst EXCLAIM and IBIS use Bayesian networks to consider the likelihood of an outcome being poor, moderate or good, the uncertainty in the preference curves has not been captured. Fu and Guillaume (2014) present one approach to considering uncertainty in ecological response models by comparing pre- and post-regulation scenarios, and estimating if differences lie within a bound of uncertainty in ecological response or whether they are considered significant.

2. Consideration of water availability

As discussed in Chapter 3, the majority of existing models do not consider multiple sources of water, instead focusing only on riverine flows and inundation. Exceptions include the Great Cumbung Swamp water balance model (Smith and Barr, 2002) which considers rainfall in estimating inundation, and Fu and Guillaume (2014) who consider access to groundwater in the their uncertainty assessment.

There is also a lack of consideration of how antecedent conditions impact upon inundation patterns and hence ecological response. Although models such as MFAT, EXCLAIM and IBIS consider the influence of factors such as the inter-flood dry period, these are used directly in calculating ecological scores rather than altering hydrological conditions. Following an extended dry event, a greater volume of water is required to fill surface and groundwater stores, and for inundation to commence.

In addition, most models do not consider spatial differences in inundation patterns, which can be significant in estimating response even in low gradient areas such as the Great Cumbung Swamp. Thorburn and Walker (1994) have shown that water use patterns in River Red Gum vary depending on proximity to the river channel or lakes where there is a more regular supply of water. Whilst Smith and Barr (2002) estimate the area inundated for the Great Cumbung Swamp, this has not currently been applied to the ecological response model (Driver *et al.*, 2005b).

3. Formulation of preference curves

Four main limitations regarding the current formulation of preference curves have been identified: the calculation of habitat suitability rather than ecological condition; lack of consideration of antecedent ecological condition; the use of linear response curves; and in the case of MFAT and EEM, the use of an annual time step.

The majority of current models estimate habitat suitability rather than ecological condition. This approach has the advantage of reducing complexity and uncertainty given factors other than hydrologic conditions can influence ecological outcome. However, habitat estimates provide less direct information to decision makers regarding ecological response – suitable habitat conditions may be restored before an ecosystem is able to recover from a previous decline (CRCFE, 2003; Watts, 2010). As such, the models discussed above assume that once there are a sufficient number of 'good' hydrological events, the ecosystem will respond positively.

In reality, response is highly dependent upon the current state of the ecosystem, with species in poor condition responding differently to those in good condition. This is considered to some extent in EEM, which estimates condition rather than habitat and provides different preference curves for different ecological starting conditions. However, the model assumes that a species is able to recover from any event, and subsequently never collapses (or transitions into a new state – see Briske *et al*., 2003; Bestelmeyer, 2006; and Lester and Fairweather, 2011).

The use of single linear transition curves to describe recovery, decline, and optimal condition in models such as MFAT, EXCLAIM and IBIS (Figures 33 and 34) do not allow the consideration of complex patterns of change, and can therefore have a significant impact on results. Whilst EEM also uses piecewise linear response curves, the transition phases are step-based and more complex.

The use of an annual time step for MFAT and EEM does not capture intra-annual variability which can be critical at times of low surface water availability. For example, a small inundation event may enable an ecosystem to survive up to the point where a bigger event occurs. A sub-annual time step also allows for the consideration of alternative environmental flow release impacts, and greater ability to respond to current condition. For example, whilst not applied in this research, dam releases could be triggered when condition meets specified threshold criteria.

4. Aggregation of preference curves

The last set of challenges encountered in current ecological models is the method of aggregation across multiple preference curves. MFAT, EEM, EXCLAIM and IBIS all use weights to combine different preference curves, thereby requiring user specification of the relative importance of different curves. In addition, the method used within the model to combine different curves can also influence the overall habitat condition score. Lester *et al*. (2011) found MFAT scores to be highly sensitive to different aggregation methods, calling into question the complexity and variability of methods used within the model. Conversely, they found weightings to have minimal impact, with randomly selected weights resulting in slight improvements in scores in some cases. Aggregation methods used in MFAT were similarly identified as a limitation by Louis and Read (2003) and Norton and Andrews (2006). According to Overton *et al*. (2014), EEM provides an improved aggregation method. No evaluation of sensitivity to aggregation and weights has been conducted for EXCLAIM and IBIS.

4.2.3 Addressing limitations in ecological response modelling

The ecological response model developed here addresses a number of the above challenges. Uncertainty is considered through the development and application of five ecological response models representing different conceptual views based on expert elicitation. In addition, the uncertainty in estimating preference curves is recognised in the development of upper and lower response curves rather than the use of a single condition estimate. Thorough evaluation of the model is conducted to assess the impact of assumptions on results. Both model development and evaluation draw upon mixed data sources including current literature, expert knowledge and photographic records given the limited availability of field based data.

The hydrological component of the ERM discussed in the previous chapter considers riverine and rainfall based inundation, as well as estimating potential uptake of groundwater by River Red Gum. It incorporates antecedent conditions through increasing the duration of above threshold flow required for inundation to occur, hence altering the pattern of wet and dry events. Spatial variation is considered by using two areas within the Great Cumbung Swamp – the smaller lakes area and the larger River Red Gum floodplain area (incorporating the lakes).

Limitations in preference curves have been addressed through the use of ecological condition scores rather than habitat suitability, and the consideration of starting ecological condition on both the pattern and magnitude of response. It is assumed that there is a high level of uncertainty regarding the pattern of change, hence non-linear preference curves are used with an upper and lower bound. In addition, a daily time step is used to enable the calculation of sub-annual condition scores.

The following section provides an overview of the model development process, whilst Sections 4.4 to 4.6 give a detailed description of each step in the development process. Section 4.7 presents a preliminary evaluation of the model whilst further model analysis using sensitivity analysis and comparison with observed data is presented in the following two chapters (Chapters 5 and 6).

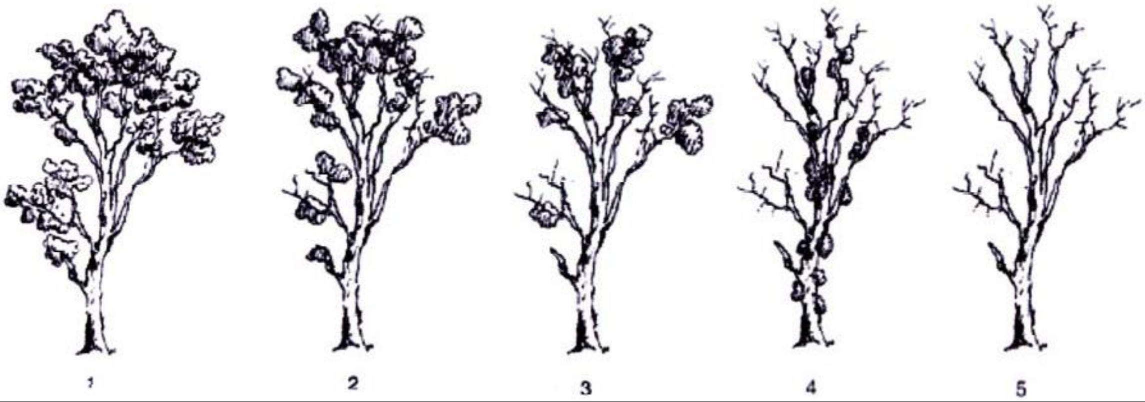
4.3 Methodology

The ecological component of the ERM (hereafter 'ecological model') calculates River Red Gum condition based on: (1) the sequence of wet and dry events from the hydrology component; and (2) the estimated groundwater level (as shown in Figure 10 at the start of Part B). As discussed in Chapter 2 - Case Study, River Red Gum is considered to be an umbrella species which defines much of the vegetation community within the Great Cumbung Swamp (Overton *et al.*, 2014), and plays an important role in ecological function such as nutrient cycling (Briggs and Maher, 1983). Whilst there are recognised limitations in the use of surrogate species (e.g. Simberloff, 1998; Caro and O'Doherty, 1999; Rogers *et al*., 2012), maintenance of River Red Gum is considered essential for the survival of the current ecosystem of the Great Cumbung Swamp.

Given the spatial scale considered in this thesis is the Great Cumbung Swamp lakes area and floodplain, River Red Gum condition was assessed at a community level rather than an individual tree level, and focused on maintenance of long term condition rather than germination and regeneration. This was considered appropriate given River Red Gum does not have a persistent seed bank, but instead relies on seeds from living trees (Roberts and Marston, 2011).

In this thesis, condition is defined as canopy condition, which provides an observable and measurable entity (Grimes, 1987; Stone and Haywood, 2006). Canopy condition (or vigour) has been used to assess River Red Gum condition by a number of previous studies, including Cunningham *et al*. (2007), Holland et. al. (2009), and Souter *et al*. (2010) . The use of canopy condition has the advantage of enabling management decisions to be tied to specific outcomes, as opposed to value laden concepts such as ecosystem 'health'. This is discussed further in Chapter 7.

Condition scores range from 0 (dead) to 1 (optimal condition), noting that condition naturally fluctuates intra- and inter-annually. Condition is taken to be an average over the area modelled, which in this case is either the smaller lakes area, or the entire Great Cumbung Swamp floodplain. Canopy condition scores were based on the Seddon scale (Seddon *et al.*, 2002) as shown in Figure 35. Given the Seddon scale ranges from 1 (vigorous) to 5 (leafless), Seddon scores were translated to equivalent scores for the ecological model (Table 6).



Vigorous	Incipient Stress	Stressed	Very Stressed	Leafless
Foliage abundant, not thinning	Foliage beginning to die from tips OR canopy is thinning	Canopy showing thinning throughout and/or foliage is 50% or less than expected	Foliage is 10% or less OR epicormics re-growth has mostly died	No canopy foliage
A few dead twigs or branches may be present	Some partly dead branches	Some completely dead branches	Many dead branches	Some or none fine twigs or branchlets

Figure 35. Seddon scale for assessing canopy condition (adapted from Seddon *et al*, 2002, based on Heatwole and Lowman, 1986).

Table 6. ERM condition scores compared with Seddon scores

ERM Score	Condition	Seddon score
0.8-1.0	Vigorous, abundant foliage	1
0.6-0.8	Foliage beginning to die from tips, partially dead branches	2
0.4-0.6	Thin canopy, some completely dead branches	3
0.2-0.4	Many dead branches	4
0-0.2	Leafless	5

One of the limitations of the Seddon scale is that is does not distinguish between decline and recovery phases. Changes in River Red Gum crown extent and density differ depending on whether the tree is in decline or recovery, and also vary depending on the starting condition (Souter *et al.*, 2010). Variations in decline and recovery trajectories were accounted for in the ecological model by using different response curves. This was facilitated by the use of photographs from Souter *et al*. (2009) and Roberts and Marston (2011) depicting different trajectories during the expert interviews.

The ecological model was developed in three main stages (Figure 36), and involved a number of iterations and improvements. In Stage 1, the initial conceptual model was developed using available literature and knowledge of River Red Gum response to water availability. The aim of this stage was to formulate an alternative model of ecological response which incorporated the key processes important for River Red Gum condition, as well as the significant uncertainty associated with estimating response. The initial conceptual model is presented here for two reasons: firstly, it demonstrates the model developed independently of the experts; and secondly, it provides context for the expert elicitation process and derivation of the final model, which follows the same overall approach to representing River Red Gum response as the initial model.

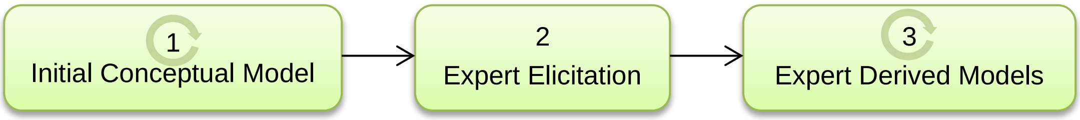


Figure 36. Three key stages used to iteratively develop the ecological model.

Stage 2 involved semi-formal interviews with six experts, who answered targeted questions drawing upon the initial conceptual model. Stage 3 then used information from experts to modify the initial conceptual model and develop separate ecological models, each representing different expert conceptualisation of River Red Gum response. This approach of using expert elicitation to inform model development has been widely applied in conservation science and environmental modelling more broadly (see for example Krueger *et al*., 2012 and Martin *et al*., 2012 for reviews). The three stages of model development are described in greater detail in the following sections.

4.4 Initial Conceptual Model

The initial conceptual ecological model aimed to address a number of limitations of previous models by considering the following:

(1) Ecological response to water availability is highly uncertain, hence the best we can currently do is provide an approximate upper and lower limit of condition scores rather than estimating a single value.

(2) Ecological response to a wet or dry event is dependent upon the condition of the ecosystem at the start of the event, i.e., it is essential to consider the pattern of previous events as well as the current event in estimating condition.

(3) Groundwater can provide an important source of water during periods of low surface water availability, hence it is critical to consider in areas where vegetation can access groundwater.

(4) Once the condition score reaches zero, the ecosystem is assumed dead, with recovery (such as through seed dispersal) taking longer than the model simulation period.

As discussed in Chapter 2, there has been extensive research on River Red Gum response to water availability compared with many other wetland species. Syntheses of current information have been provided in Rogers and Ralph (2010), Roberts and Marston (2011), and Overton *et al*. (2014). The main source of information on critical response thresholds for wet and dry conditions was provided by Roberts and Marston (2011) (Table 7).

Table 7. Hydrological characteristics identified as being optimal for River Red Gum maintenance and survival (from Roberts and Marston, 2011)

Hydrology	Preferred Outcome*
Dry Period duration	Forests: 3 years Woodlands: 5-7 years
Wet Period duration	Forests: 5-7 months Woodlands: 2-4 months
Frequency of flooding	Forests: 1-2 years Woodlands: 2-4 years
Depth of flooding	Not critical
Timing of flooding	Not critical, more growth during spring-summer

*See Roberts and Marston (2011) for full explanations

As shown in Table 7, Roberts and Marston (2011) identified that depth and timing of flooding are not considered critical for River Red Gum. The ecological model developed here therefore focused on the duration and frequency of wet and dry events in deriving response curves. Five separate response curves were developed as shown in Figure 37: (1) Initial dry period following an extended wet period; (2) Extended dry period; (3) Wet period (preferred); (4) Extended wet period; and (5) Dry period response with access to groundwater. Uncertainty in estimating the changes in condition was incorporated through the use of upper and lower bounds for each response curve.

The response curves shown in Figure 37 all used a power function of the form shown in Equation 4, thereby differing from the piecewise-linear equations used in MFAT, EEM, EXCLAIM and IBIS. This form of equation was selected based on the hypothesis that the actual response curve is unknown given the significant uncertainty associated with estimating ecological response. Instead, it takes a novel approach which attempts to identify the upper and lower limit of possible responses. These limits were included in the power function which incorporated a minimum and maximum threshold, rate of change, and the initial condition score.

$$C^t = \left(\frac{d^t - d^{\min}}{d^{\max} - d^{\min}} \right)^{\alpha} (1 - C^s) + C^s \tag{4}$$

where:

C^t	=	condition score at time *t*
C^s	=	condition score at the start of the *event* (wet or dry)
d^t	=	duration of the *event* at current time step *t*
d^{min}	=	minimum threshold duration
d^{max}	=	maximum threshold duration
α	=	fixed constant defining the slope of the response curve

Using Equation 4, changing the initial condition has the effect of 'shifting' the response curves temporally.

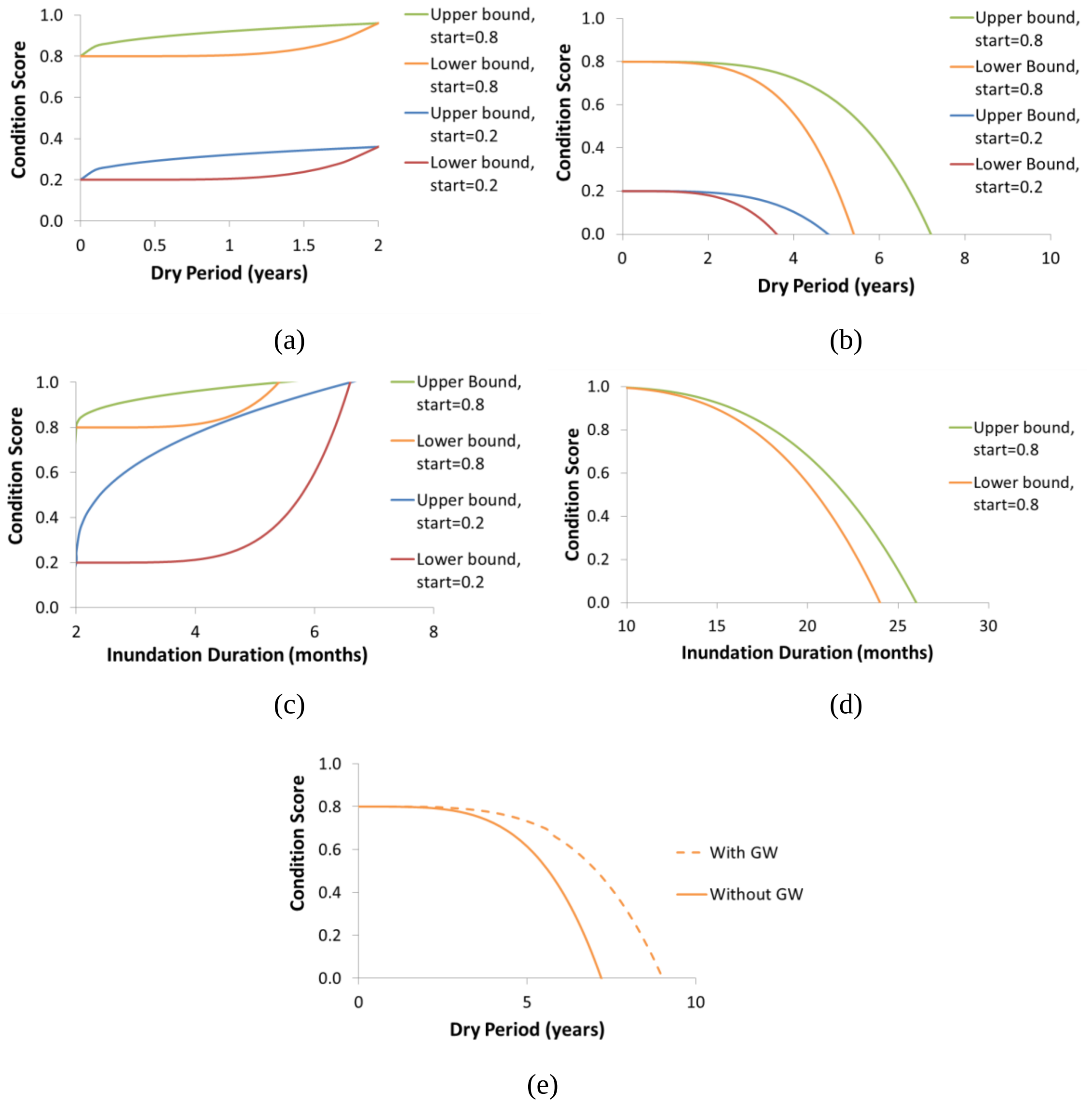


Figure 37. Initial conceptual model for River Red Gum response to water availability in the Great Cumbung Swamp: (a) improvement in condition during a dry period immediately following an extended wet period; (b) decline in condition during a longer dry period; (c) change in condition during a wet period with an initial improvement after two months; (d) decline during an extended wet period; and (e) a reduced decline with access to groundwater during a dry period.

The way in which the five response curves are applied is shown in Figure 38. During a dry period event, curve (b) from Figure 37 is adopted following a wet event which was not an extended wet period. If the preceding event was an extended wet period, initially curve (a) is adopted until two years has concluded, after which curve (b) commences. Should groundwater be available during the dry event, curve (a) is adjusted with a reduced decline as shown in curve (e). During a wet event, initially curve (c) is adopted until the 'too wet threshold' is met, after which curve (d) is used. A brief description and justification for each of the five response curves is given below.

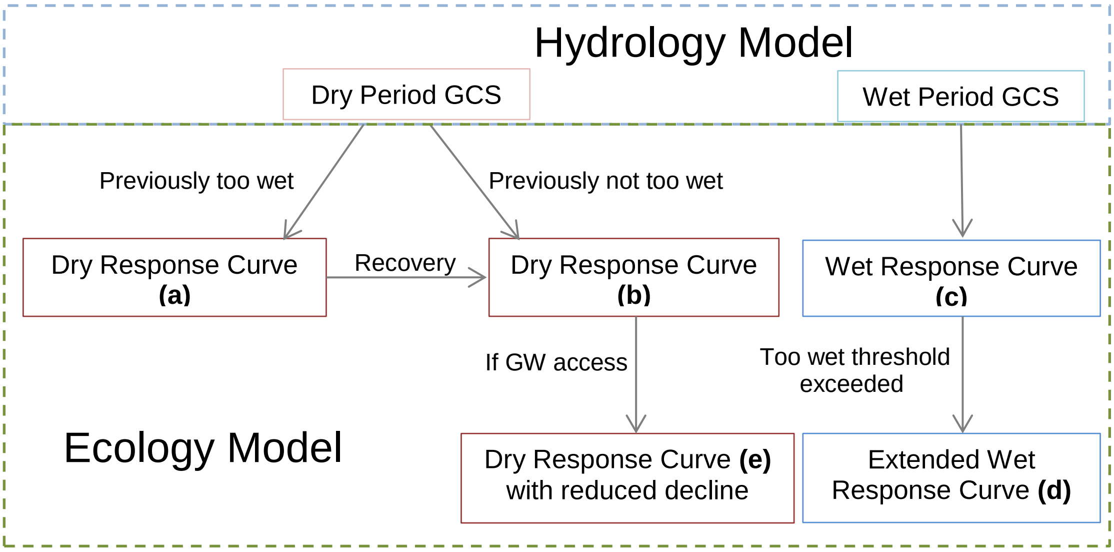


Figure 38. Model calculations for the initial conceptual model of the ERM.

Initial Dry Period

Should a dry period follow an *extended* wet period, it was hypothesised that River Red Gum condition would initially improve for approximately two years. This was based on discussions with P. Driver (pers. comm., 2013) as well as published information on preferred dry event duration. However, no previous studies were found which examined River Red Gum response following an extended wet period.

Roberts and Marston (2000) identified that River Red Gum could survive dry periods of approximately 18 months, although did not refer to the pattern of change during this period, or the effect of a preceding extended wet event. The MFAT model assumed that there would be an increase in River Red Gum habitat suitability during the first 18 months of a dry period (as shown in Figure 33), although again this was irrespective of the preceding wet event (Young *et al*., 2003; MDBA website, 2015). Roberts and Marston (2011) recommended an optimal flood frequency of one to three years for forests and two to four years for woodlands, which consequently suggests an optimal dry period of between one and four years.

Given the pattern of change is not known, the upper and lower bounds of the initial dry period curve in Figure 37a reflect two possible types of response – either a fast initial improvement which gradually reduces (upper bound, Equation 5), or a gradual initial improvement followed by fast recovery toward the end of the two years (lower bound, Equation 6). Using these bounds also captures other possible assumptions, such as a linear improvement in condition over time.

$$C_U^t = \left(\frac{d^t - 0}{2 - 0}\right)^{0.4} \left(C_U^T - C^s\right) + C^s \tag{5}$$

$$C_L^t = \left(\frac{d^t - 0}{2 - 0}\right)^{5} \left(C_L^T - C^s\right) + C^s \tag{6}$$

where:

C_U^t	=	upper bound condition score at time *t*
C_L^t	=	lower bound condition score at time *t*

In this case (due to the lack of further information), it was assumed that the *pattern* of change is insensitive to the starting condition (although the starting point along the response curve was still varied based on the starting condition).

Extended Dry Period

Should a dry period follow a wet period which is not an extended wet period, it is assumed that condition does not increase but remains the same for a minimum of two years before gradually declining. Where the dry period does follow an extended wet, the extended dry response curve will be followed *after* the two years of initial improvement described by Equations 7 and 8. The pattern of decline in condition assumes initial reduction will be gradual, given a degree of internal resilience. As the dry event continues, the tree's resilience mechanisms will become less effective, and the tree will decline at a faster rate. As for the initial dry period described above, the pattern of change was largely assumed based on informal discussions and information from Roberts and Marston (2000, 2011). The decline to zero condition was based on Roberts and Marston (2011), which described a critical dry period of three to seven years for River Red Gum forests and woodlands.

It was assumed that the rate of decline is dependent upon the starting condition, hence the maximum dry duration (when condition reaches zero) is calculated as a function of the starting condition. These equations were derived such that a River Red Gum community starting with a condition score of 1.0 would take eight years to reach zero (upper bound), whilst a community starting with a score of 0.2 would reach zero in only five years.

$$C_U^t = \left(\frac{d^t - 0}{d_U^{\max} - 0}\right)^{4} \left(0 - C^s\right) + C^s \tag{7}$$

$$C_L^t = \left(\frac{d^t - 0}{d_L^{\max} - 0}\right)^4 \left(0 - C^s\right) + C^s \qquad (8)$$

where:

d_U^{max} = maximum threshold duration for the upper bound $= 8 * \left(\frac{1-C^s}{2} + C^{t=1}\right)$

d_L^{max} = maximum threshold duration for the lower bound $= 6 * \left(\frac{1-C^s}{2} + C^{t=1}\right)$

Wet Period

During a wet event, it is assumed that condition will begin to improve after two months of inundation up until a maximum of between five and seven months duration depending on the starting condition (Table 7, Roberts and Marston, 2011). Similar to the initial dry period curve, there is currently insufficient information available to determine the pattern of change. Consequently, the upper and lower bounds again reflect two possible strategies – an initial rapid improvement which then decreases over time (upper bound), or a slow initial improvement which increases in rate over time (lower bound).

Similar to the dry period, the wet period response curve assumes that the rate of increase in condition is dependent upon the starting condition, as described by Equations 9 and 10.

$$C_U^t = \left(\frac{d^t - 2}{d^{\max} - 2}\right)^{0.4} \left(1 - C^s\right) + C^s \qquad (9)$$

$$C_L^t = \left(\frac{d^t - 2}{d^{\max} - 2}\right)^{5} \left(1 - C^s\right) + C^s \qquad (10)$$

where:

$$d^{\max} = 7 - \left[\left(7 - 5\right) \times C^s\right]$$

Extended Wet Period

The extended wet period curve assumes that inundation durations of ten months and over (depending on the starting condition) result in a gradual decline in River Red Gum condition. This assumption was based on the preferred wet period being up to seven months according to Roberts and Marston (2011), with some variability and uncertainty around this estimate. It was assumed that it would take between 24 and 26 months for the condition to reach zero, based on an estimated maximum inundation time of between two and three years from Roberts and Marston (2011) (the duration used here is conservative).

$$C_U^t = \left(\frac{d^t - 7}{26 - 7}\right)^3 \left(0 - C^s\right) + C^s \tag{11}$$

$$C_L^t = \left(\frac{d^t - 7}{24 - 7}\right)^3 \left(0 - C^s\right) + C^s \tag{12}$$

Access to Groundwater

The final response curve was used to modify the dry period curve if River Red Gum has access to groundwater, by reducing the rate of decline (Figure 37e). The degree to which the decline in condition is reduced is dependent upon the amount of groundwater which can be accessed, calculated as a function of groundwater level and maximum River Red Gum root depth. There is considerable uncertainty regarding River Red Gum rooting depths, as well as significant variation between locations depending on factors such as water availability and soil type. Studies by Canadell *et al*. (1996) and Cunningham *et al*. (2011) suggest that River Red Gum can access groundwater up to 10-15m. Figure 39 shows the degree to which the dry period curve is adjusted for root depths of both 10m and 15m. Where the groundwater depth is less than the rooting depth, it is assumed that River Red Gum has 100% access, and hence there is no decline in condition. As the groundwater level falls, there is a reduction in the amount of water which can be accessed and a corresponding increase in River Red Gum decline (to the extent where it follows the original dry period curve at zero access).

The level of access shown in Figure 39 was developed as part of the current ecological model, based on the assumption that there would be an initial rapid decline in access once the groundwater level falls below the rooting depth, yet some water could be accessed by capillary forces. Access then reduces to zero, when the groundwater level is approximately 5m below the rooting depth (Equation 13).

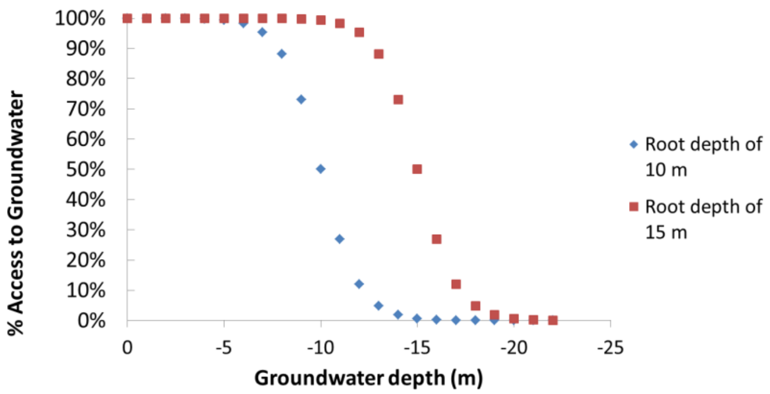


Figure 39. Access to groundwater based on groundwater depth and River Red Gum roots, showing two possible River Red Gum rooting depths: 10m and 15m.

$$GW_{scale} = \frac{1}{1+e^{-\left(GW_{depth}+x0\right)}} \qquad (13)$$

where:

x0 = approximate rooting depth

The response curves described above were presented to experts during the interviews, following preliminary questions without reference to the initial conceptual model. This was done to minimise biasing expert response to the preliminary questions. The expert elicitation process is outlined in Section 4.5 below.

4.5 Expert Interviews

The development of the initial River Red Gum response model highlighted a number of uncertainties regarding both threshold timing for different conditions and the shape of the response curves. Expert elicitation was therefore used to provide:

1. Information on flood inundation patterns for the Great Cumbung Swamp;
2. Information on River Red Gum response either generally or specifically for the Great Cumbung Swamp; and
3. Direct feedback on the initial River Red Gum response model.

The information obtained was used to update the River Red Gum response model, as well as further explore the uncertainties within the model by examining the possible effect of different model conceptualisations.

Interviews followed a semi-formal format such that there was some consistency in the questions asked, yet sufficient flexibility to modify the questions and interview style to best suit each individual. A brief summary of the experts consulted and the interview questions are provided below. This is followed by a discussion of the key outcomes from the interview process, which informed the development of the final ecological response models described in Section 4.6.

4.5.1 Experts

One-on-one interviews were conducted with six experts with different expertise, to obtain varied perspectives on River Red Gum response (Raymond *et al.*, 2010). Individual interviews were used to minimise biases arising from a group setting, particularly given the different types of knowledge provided by the experts (Martin *et al.*, 2012). This format also enabled interviews to be conducted at a location most suitable for each expert. The six experts comprised two land managers who either currently or previously lived within the Great Cumbung Swamp; a NSW government senior wetlands and rivers conservation officer with knowledge of the Great

Cumbung Swamp; an independent consultant with expertise in wetland and floodplain vegetation, with specific knowledge of River Red Gum response, the Lachlan catchment, and the Great Cumbung Swamp; a CSIRO senior research scientist in floodplain ecosystem function and expert on River Red Gum response across Australia; and a CSIRO spatial eco-hydrologist specialising in river red gum sapwood research and use of remote sensing.

Consultation with the two land managers provided observations of River Red Gum change in response to different levels of water availability within the Great Cumbung Swamp. This information was particularly valuable in testing model behaviour with observations (see Table 3 in Chapter 3). The NSW government officer also had observed River Red Gum response within the Great Cumbung Swamp under different levels of water availability, as well as having a broad perspective on delivery of environmental water and monitoring ecological response throughout the Lachlan region. The three scientists contributed to the understanding of physiological changes within the River Red Gum in response to water, and were able to provide perspectives at different scales based on their research. Two were more focused on the community scale response, whilst the third focused on individual tree response.

4.5.2 Interview Questions

Interview questions were designed specifically to provide quantitative information to inform the development of the River Red Gum ecological model. There were three components to the interview, the first being a series of questions on the flooding patterns and River Red Gum response to wet/dry periods within the Great Cumbung Swamp; the second being the production of response curves by experts; and the third being direct feedback on the initial ecological model. A summary of questions asked as part of the first component is provided in Table 8, whilst full interview questionnaires are included in Appendix B2. In the second component, experts where given blank graphs relating time to different River Red Gum canopy conditions for both wet and dry periods, as shown in Figure 40. During this exercise, experts were *not* explicitly asked to identify their level of uncertainty regarding River Red Gum response, to identify to what degree they expressed uncertainty in their estimates. In most cases, experts did provide a range of values rather than a single estimate.

Direct feedback on the initial conceptual model for the third component was only asked of the scientists and wetland managers, and was not requested of the two landholders who were less familiar with such conceptualisations. Supporting material for the second and third components is also included in Appendix B2.

The use of both the template shown in Figure 40 and the initial conceptual model (where applicable) meant that the overall approach to representing ecological response was largely consistent between experts. This was done to ensure all experts captured the key response phases identified during the development of the initial conceptual model. Despite this common framework, the expert derived models are considered in this context to represent different ‘conceptualisations’ of ecological response, given the pattern of response during wet and dry periods varied, as did the impact of initial condition and groundwater availability. Providing experts with a template to derive their own response curves prior to seeing the initial conceptual model assisted in reducing pre-framing the pattern of change (Tversky and Kahneman, 1981; Burgman, 2005). This is considered subtly different from variations in parameterisations alone, where experts may have been only presented with a pre-formulated response curve (such as the initial conceptual model) and asked to estimate condition scores for different time periods. However, it is acknowledged that the difference between conceptualisation and parameterisation is somewhat ambiguous.

Table 8. Summary of expert elicitation interview questions

Topic	**Question**	**Application***
Influence of flooding	Influence of wet and dry cycles	All
	Influence of rainfall	All
	Rainfall variability within the Swamp	Local only
Flooding patterns	Flood extent	Local only
	Flood duration in key locations	Local only
	Flow threshold for inundation	Local only
	Impact of antecedent conditions	Local only
Ecological response	Initial ecological condition at the start of drought events	All
	Impact of initial condition	All
	Change in condition during drought	All
	Change in condition during inundation	All
	Impact of extended inundation	All
	Variability in response across the Swamp	Local only
Groundwater	Impact of access to groundwater	Ecologists
	Spatial variation in condition across the Swamp	Local only

* ‘All’ refers to all experts; ‘Local only’ to only experts with local knowledge of the Great Cumbung Swamp; and ‘Ecologists’ to scientists and wetland managers.

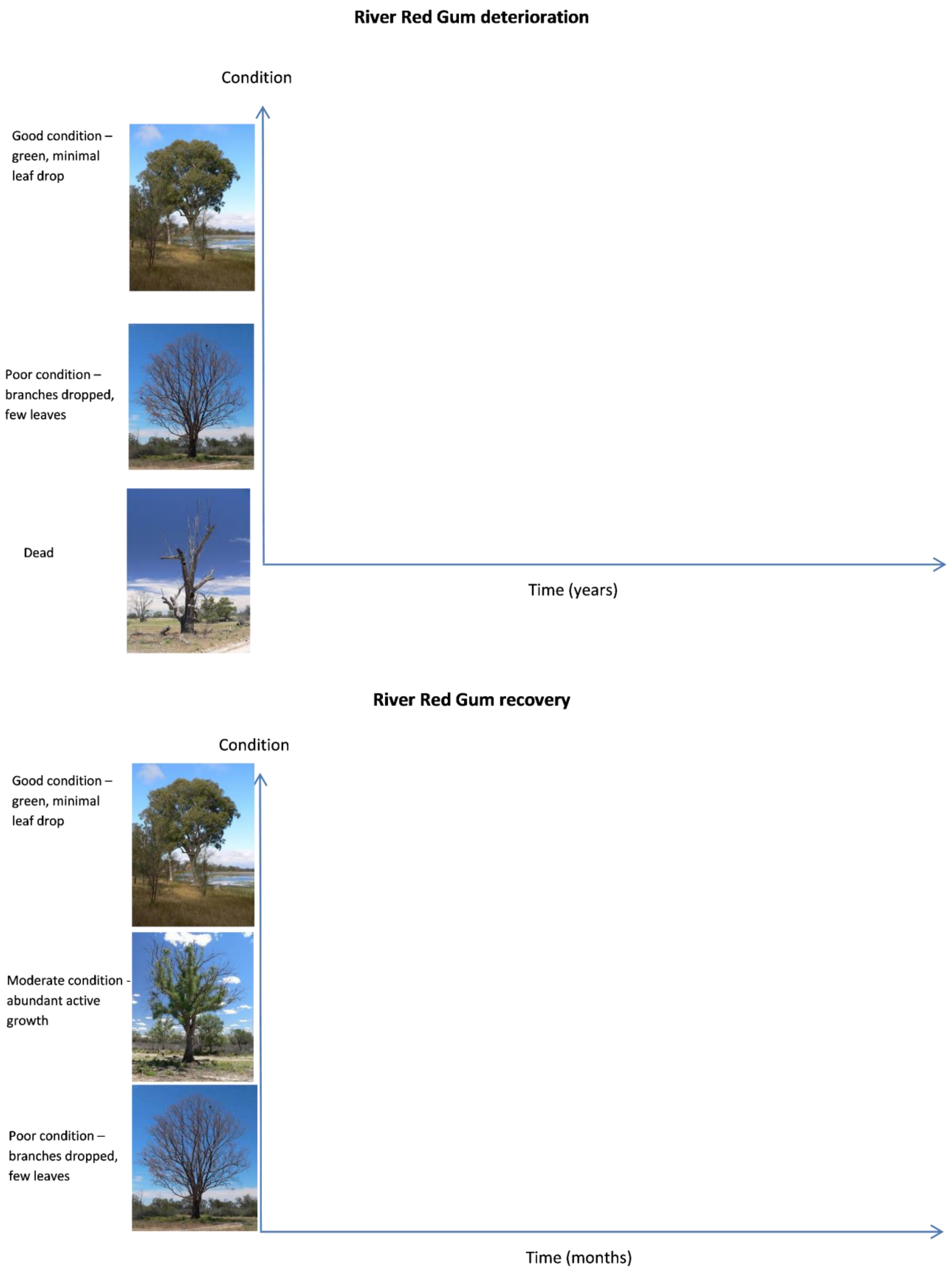


Figure 40. Template for elicitation of ecological response curves

Questions were reviewed by colleagues in hydrology and ecology as well as the ANU Ethics Committee. In this case training questions were not included given the nature of the questions, the length of the interview, the types of experts consulted, and the manner of consultation (varying between office locations and on-farm discussions). However, this could be considered for future work.

4.5.3 Interview Results and Outcomes

Three key outcomes were identified from the expert interviews:

1. Despite considerable research and knowledge regarding River Red Gum response relative to other wetland species, respondents identified significant gaps. In particular: the effect of spatial location on River Red Gum response; how previous events affect resilience; the role of groundwater vs surface water; the impact of initial condition on response; and the pattern of change under different levels of water availability.
2. A number of respondents identified that the questions asked had facilitated thinking about River Red Gum response in new ways, particularly when required to identify specific durations at key stages of change.
3. Whilst there was consistency across experts regarding the general patterns of change, the specific thresholds, durations, and specific pattern of change varied significantly between experts. This finding also supports the suggestion that there is still significant uncertainty in trying to estimate and model River Red Gum response.

The process of expert elicitation to inform model development was invaluable in the current research, improving the understanding of River Red Gum response; enabling the representation of different conceptualisations of response; and expressing different levels of uncertainty communicated by experts. In particular, talking with experts with different perspectives of River Red Gum response was critical, with landholders providing actual observations of change within the Great Cumbung Swamp, and ecologists providing physiological information more generally applicable to River Red Gum.

Responses to questions regarding spatial variability and the importance of riverine flooding, rainfall and groundwater are summarised below, whilst specific results from the interviews are discussed in the context of revised ecological response curves in the following Section 4.6. Whilst six experts were interviewed, only five expert based ecological response models were developed, given there was insufficient information in one interview for model development. However, the sixth expert provided invaluable historical information on River Red Gum response which enabled model components to be checked against this information.

Influence of wet and dry cycles on River Red Gum condition

All six respondents identified water availability as being the most important factor influencing River Red Gum condition, when referring to mature trees at a community/landscape scale. Other factors identified as having secondary importance included temperature, mistletoe, insect herbivory, domestic animals/ grazing, land and clearing. Some respondents suggested that flow alteration made River Red Gum more vulnerable to insect attack and weed infestation given they are already stressed. The relative importance of these different factors was discussed by some experts in the context of age and scale.

Influence of rainfall on River Red Gum condition

Five of the six respondents identified that rainfall had a minor influence on River Red Gum condition relative to riverine inundation, largely due to less total water available. However, they all thought that rainfall was an important component of River Red Gum survival, through providing a critical water source during periods of low flow, or through triggering a growth response. Three of the experts emphasised the importance of soil type, with the clayey soils in the Great Cumbung Swamp limiting infiltration if there is insufficient ponding depth from a rainfall event. Another expert thought that light rainfall would have a benefit through lowering temperatures and raising humidity, but did not think there would be sufficient infiltration in the Great Cumbung Swamp due to the clayey soils to improve condition.

Influence of groundwater on River Red Gum survival

The four ecologists asked about the influence of groundwater on survival all believed that River Red Gum could survive in excess of 50-100 years with adequate access to non-saline groundwater, even in the absence of inundation. However, one respondent highlighted that maintaining groundwater levels in the Great Cumbung Swamp was dependent upon surface water inundation, to provide adequate hydraulic head for infiltration (although this could occur upstream of the Great Cumbung Swamp).

Despite the resilience of River Red Gum to lack of inundation given sufficient groundwater, respondents indicated that understorey vegetation is only likely to survive for three to eight years without inundation.

When asked whether there were any areas within the Great Cumbung Swamp where River Red Gum appeared to survive longer due to groundwater access, two had not observed any such areas, whilst one had identified areas which had stayed greener, possibly due to groundwater.

Influence of proximity to the river on drought tolerance

Experts had varied views regarding the influence of proximity to the main river channel on drought tolerance. Three thought that trees further from the river would have greater drought tolerance, due to deeper roots and greater groundwater availability. They hypothesized that trees closer to the river may have less resilience to drought as they are reliant on a continuous water source, and are likely to have higher water needs due to larger canopies and denser stands of trees. They also would not have grown deeper roots, having less reliance on groundwater.

Another respondent presented an alternative viewpoint, hypothesizing that trees further from the river would not last as long, being more stressed, and with less access to water due to lower groundwater levels. The fifth respondent thought that initially those further from the river may have greater drought tolerance, but over time the response would be similar.

One respondent also thought that trees located in any local depressions would survive longer, due to ponding of rainfall or smaller flows. It was also noted that survival of trees reliant on groundwater was dependent upon low salinity concentrations.

4.6 Expert derived ERMs

The five River Red Gum response curves developed in the initial conceptual model (Figure 37) were re-defined based on the expert interviews. As indicated earlier, separate models were developed for five of the experts, with information from the sixth expert being used to check different model components (due to insufficient information to derive a full model). The revised response curves are presented below, followed by a summary of model calculations and boundary conditions.

4.6.1 Revised response curves

Similar to the initial conceptual model, five response curves were used to describe the expert ecological models: initial dry period; extended dry period; wet period; extended wet period; and groundwater access. The extended dry period and wet period curves were formulated using the expert-drawn response curves based on the template shown in Figure 40, combined with information from the interview questions and direct feedback on the initial conceptual model. An example of the collated response curves for the extended dry period is shown in Figure 41. The initial dry period, extended wet period and effect of groundwater access were either explicitly drawn by experts, were described quantitatively using thresholds, or were drawn as modifications to the initial conceptual model when presented to experts. Depending on the level of detail provided during interviews, some interpretation was required to translate the elicited information into the ecological response models.

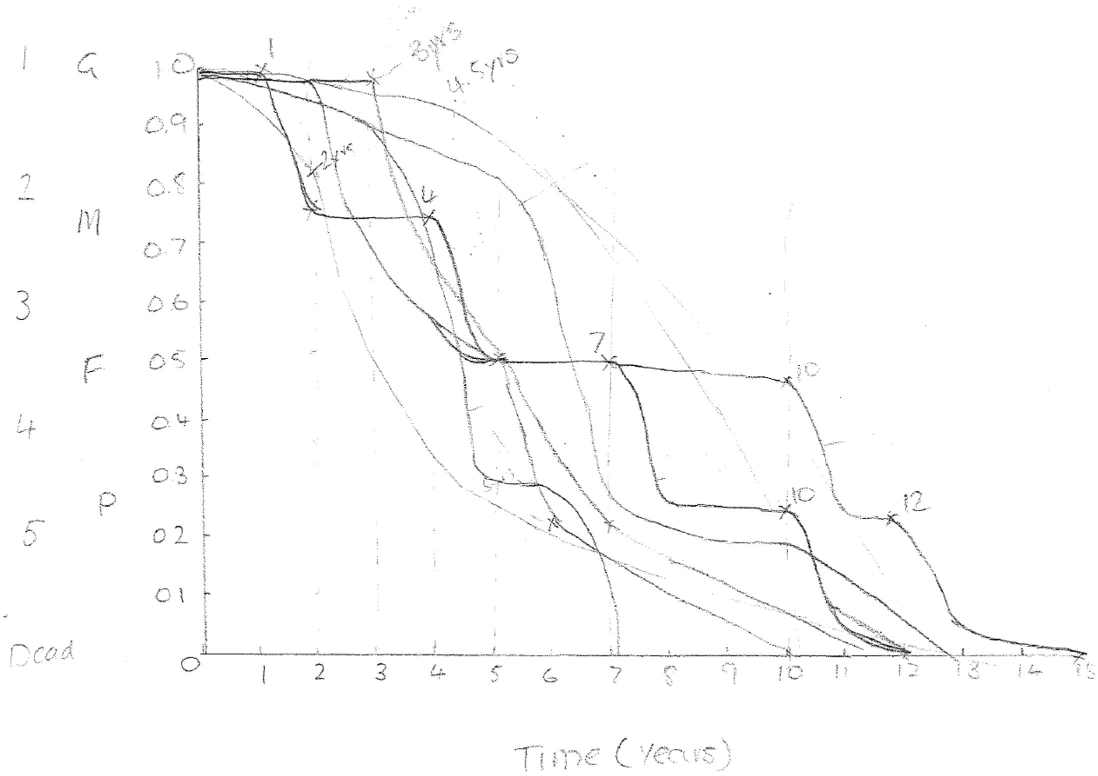


Figure 41. Example of collated response curves from experts for the extended dry period.

Due to the complexity and variation in response curves provided by experts, piecewise-linear relationships were used instead of the exponential functions adopted in the initial conceptual model. An additional variation in the expert derived models compared with the initial conceptual model is in the representation of uncertainty. Whilst the initial conceptual model used uncertainty bounds to capture the range of possible ecological response without focusing primarily on the pattern of response, the expert derived curves were focused on the pattern of response with uncertainty depending on the degree of confidence experts expressed in their assumptions. The initial intention was to use the spread of expert derived curves to define an overall upper and lower bound, yet this may not provide internal consistency where different expert assumptions are merged. It was therefore decided to apply each model independently to assess the range of estimated ecological response conditions.

The resulting expert derived response curves for the dry and wet periods are shown in Figures 42 to 45, with the main differences between experts summarised in Table 9. Access to groundwater is discussed separately in Section 4.6.2.

Table 9. Differences in conceptualisation of ecological response between experts (where E1 to E5 refer to Expert Models 1 to 5)

		E1	E2	E3	E4	E5
Influence of initial condition		Important	Important	Important	Important	Important
Initial Dry Period	*Duration of improvement*	Initial improvement but unsure how long	2-3 years	3-5 years (1-2 years in addition to following a normal wet period)	2 years	Not asked
Dry Period	*Pattern of Change*	Multi-stage	Multi-stage	Multi-stage	Multi-stage	Smooth transition
	Time to death (starting at 1.0)	12 years	12-15 years	10 years	7-13 years	10-12 years
Wet Period	*Pattern of Change*	Smooth transition	Multi-stage	Multi-stage	Multi-stage	Smooth transition
	Time to recover (starting 0.25)	7.3 years	5 years	5 years	10 years	3 years
Extended Wet Period	*Time for decline to begin*	7-10 months	24 months	3-6 months	24 months	Not asked
	Time to death	18-24 months	36 months	12 months	56 months	Not asked

As shown in Table 9, all five experts thought that the River Red Gum condition at the start of either a wet or dry event would impact upon the response. During a dry event, two experts thought that a faster decline would occur with a poor starting condition compared with a good starting condition. Other experts indicated that they thought initial condition was important, but thought there was insufficient knowledge to specify how the response would change. There were also some different views as to whether the *pattern* of response would change, or whether the same trajectory would be followed but with a different starting point.

The pattern of change also varied between experts for both dry and wet periods, with most assuming a multi-stage or step response. A step response is consistent with state-transition theory where a series of physiological changes occur to adapt to water availability. For example, the loss of leaves lowers water requirements, allowing a tree to continue in the current condition for a period of time.

There was considerable variation in thresholds for both the dry and wet curves, with time to death from a condition score of 1.0 varying from 7 to 15 years, and time to recover from 0.25 to 1.0 varying from 3 years to 10 years. There was some discussion regarding when River Red Gum is actually dead, as a number of trees looked dead during the Millennium drought, but then regenerated when the drought broke. This resilience makes it difficult to estimate River Red Gum survival based on visual observation alone.

As previously identified, whilst experts were not explicitly asked to define upper and lower bounds or level of uncertainty, in most cases experts provided ranges rather than single threshold values. However, there was substantial variability between experts in the level of uncertainty expressed.

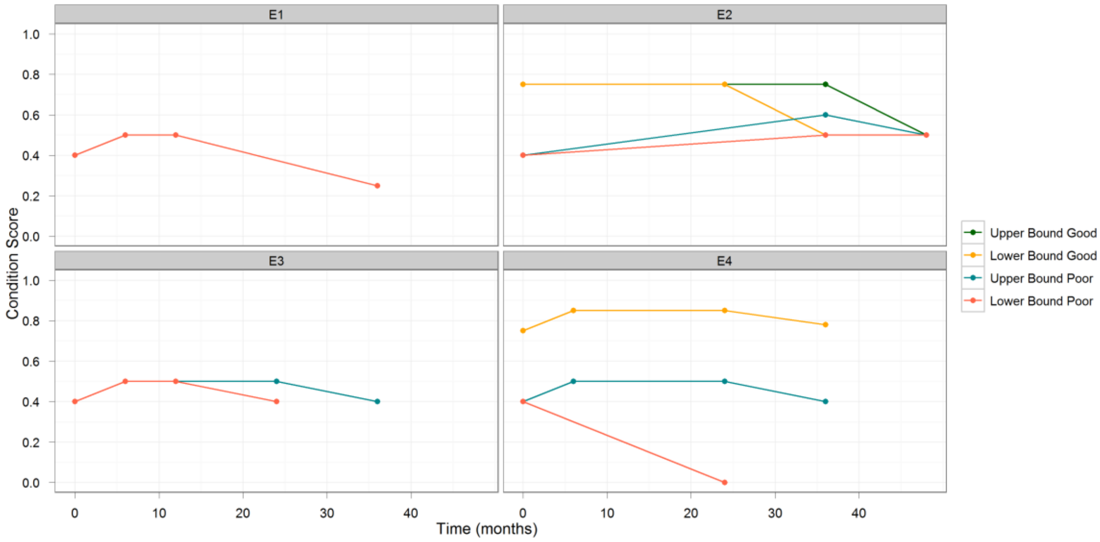


Figure 42 Initial dry period following an extended wet period for experts E1-E4 (with a normal dry curve used for E5). E1 and E3 used the same *pattern* of change irrespective of starting condition, whilst E2 and E4 defined different response curves for a good starting condition (green and yellow) and a poor starting condition (turquoise and red).

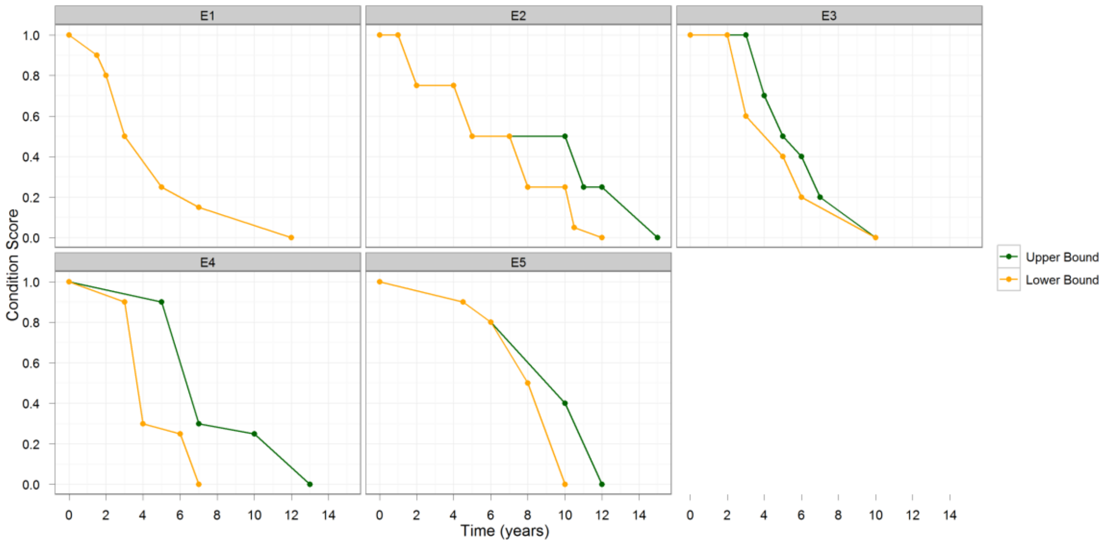


Figure 43. Extended dry period response curves for the five experts.

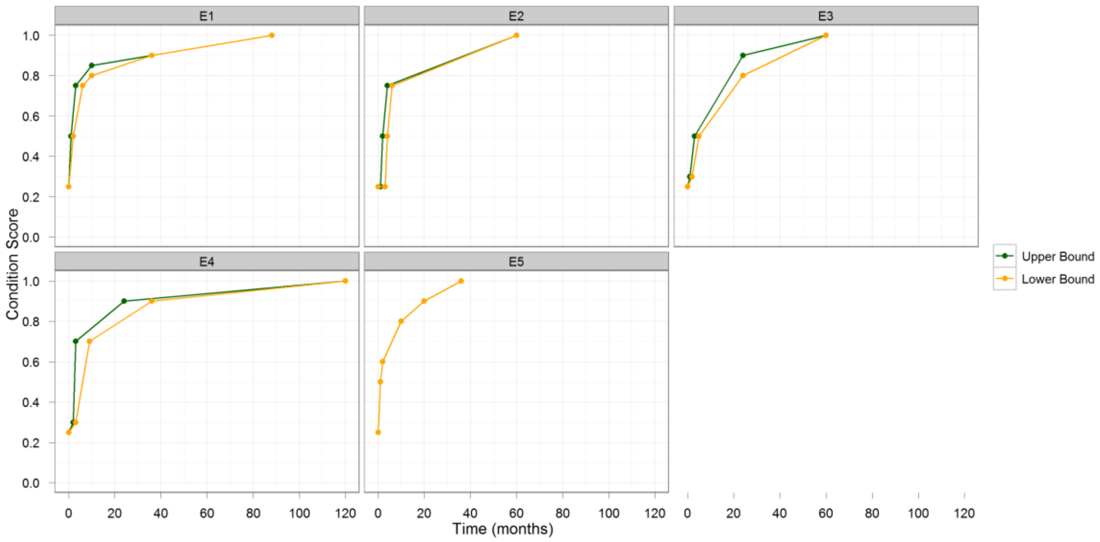


Figure 44. Wet period response curves for the five experts.

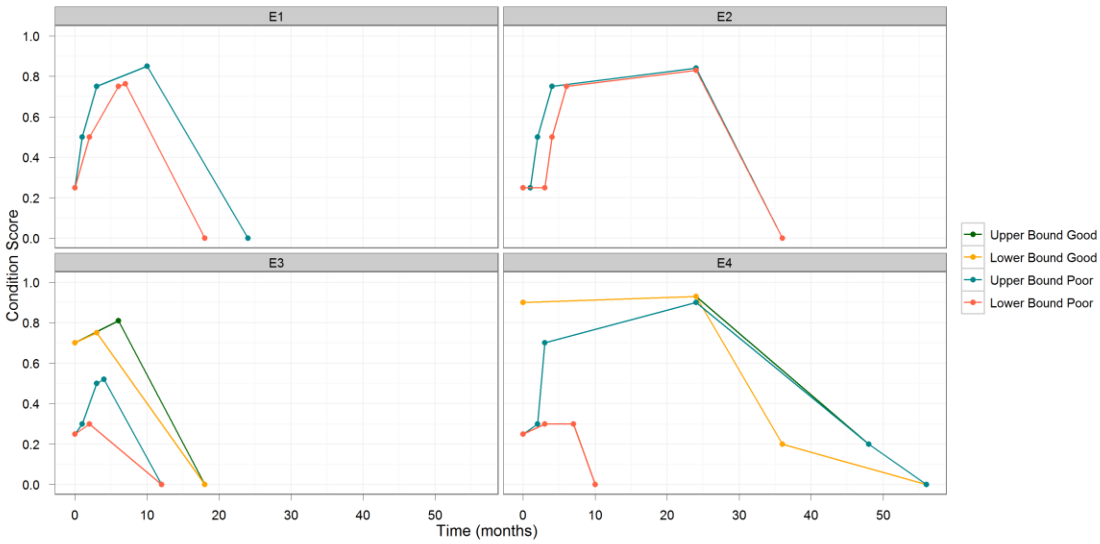


Figure 45. Extended wet period response curves for E1-E4 (with a normal wet curve used for E5). E3 and E4 assume different response curves for a good compared with poor starting condition.

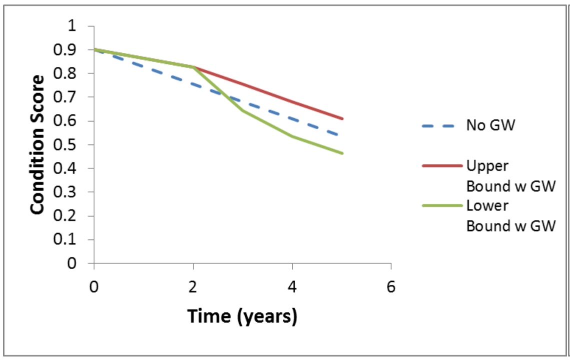
4.6.2 Impact of groundwater on River Red Gum condition

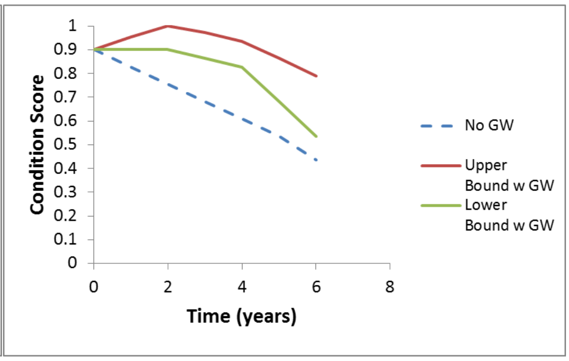
Whilst all experts were asked about the influence of groundwater on River Red Gum condition, there was insufficient quantitative information to derive separate groundwater response curves for each expert model. Consequently, a single model was developed which drew upon information from all of the interviews.

Given the majority of experts indicated that River Red Gum could survive almost indefinitely with adequate water, it was assumed that the upper bound response curve would follow the wet period response curve (Figure 44) if groundwater access was >90%, even in the absence of riverine or rainfall based inundation. If access is <90%, the rate of decline in condition is reduced in proportion to the percentage access. For the lower bound, the rate of decline is also reduced in proportion to the percentage access.

It was less clear from the interviews how a tree would respond if it initially had access to groundwater, but then groundwater levels dropped, and how this would compare with a tree which had adapted to no groundwater access. One expert felt that having access to groundwater initially would enable the tree to last longer, as it is starting in a better condition and the lack of water is for a shorter period. Another expert felt that the tree would decline more quickly, as it has adapted to relying on groundwater, and once this access has gone, it would become more stressed and less able to cope. To capture both of these possibilities, once groundwater access falls below 1%, the dry period curve is followed for the upper bound but with an overall improvement in condition, whilst the lower bound initially declined at a faster rate once access to groundwater dropped until it has adapted to the lack of water.

To demonstrate the effect of the groundwater model component, two examples are shown in Figure 46.





(a) (b)

Figure 46. Impact of groundwater access on upper and lower response curves, with (a) 50% groundwater access for two years, followed by a no groundwater access for a further three years; and (b) 100% groundwater access for two years, followed by 50% groundwater access for a further two years, followed by no groundwater access for a final two years.

In Figure 46a, the upper and lower bound dry period response curves show a reduced decline for the first two years, based on the 50% access to groundwater. Once groundwater levels drop to zero, the upper bound starts to follow the decline rate of the original dry period curve. The lower bound initially decreases at a faster rate than the original dry period curve, based on the assumption that the tree has become partially reliant on groundwater access. However, the increased rate of decline is also relative to the level of access, where a previous access at 100% results in a faster decline compared with a 50% access. After four years have passed, it is assumed that the tree has re-adapted to no groundwater access, and the decline follows the original dry period curve.

Figure 46b considers two years of 100% groundwater access, followed by two years with 50% access, and a further two years with no access. Whilst there is 100% access, the upper and lower bounds follow the wet period response curves, hence resulting in an improvement in condition. Once access reduces to 50%, the same pattern shown in Figure 46a is followed, where the upper and lower bounds begin to decline but at a reduced rate relative to the dry period curve. When access declines to 0%, the upper bound follows the dry period curve, whilst the lower bound initially declines more rapidly. In reality (and in the hydrological model), groundwater levels change gradually each time step rather than the step changes shown here for demonstration.

4.6.3 Model calculations

A summary of model calculations is provided below, with the main purpose of providing sufficient context for the remaining sections of the thesis.

Figure 47 shows the key steps within the revised ecological model. As with the initial model, the time series of wet and dry events calculated in the hydrological component (described in Chapter 3) is firstly used to identify which set of response curves are used. During a dry event, the response depends on the availability of groundwater, as well as whether it follows an extended wet event. During a wet event, initially the wet response curve is followed, and transitions into an extended wet if the duration continues.

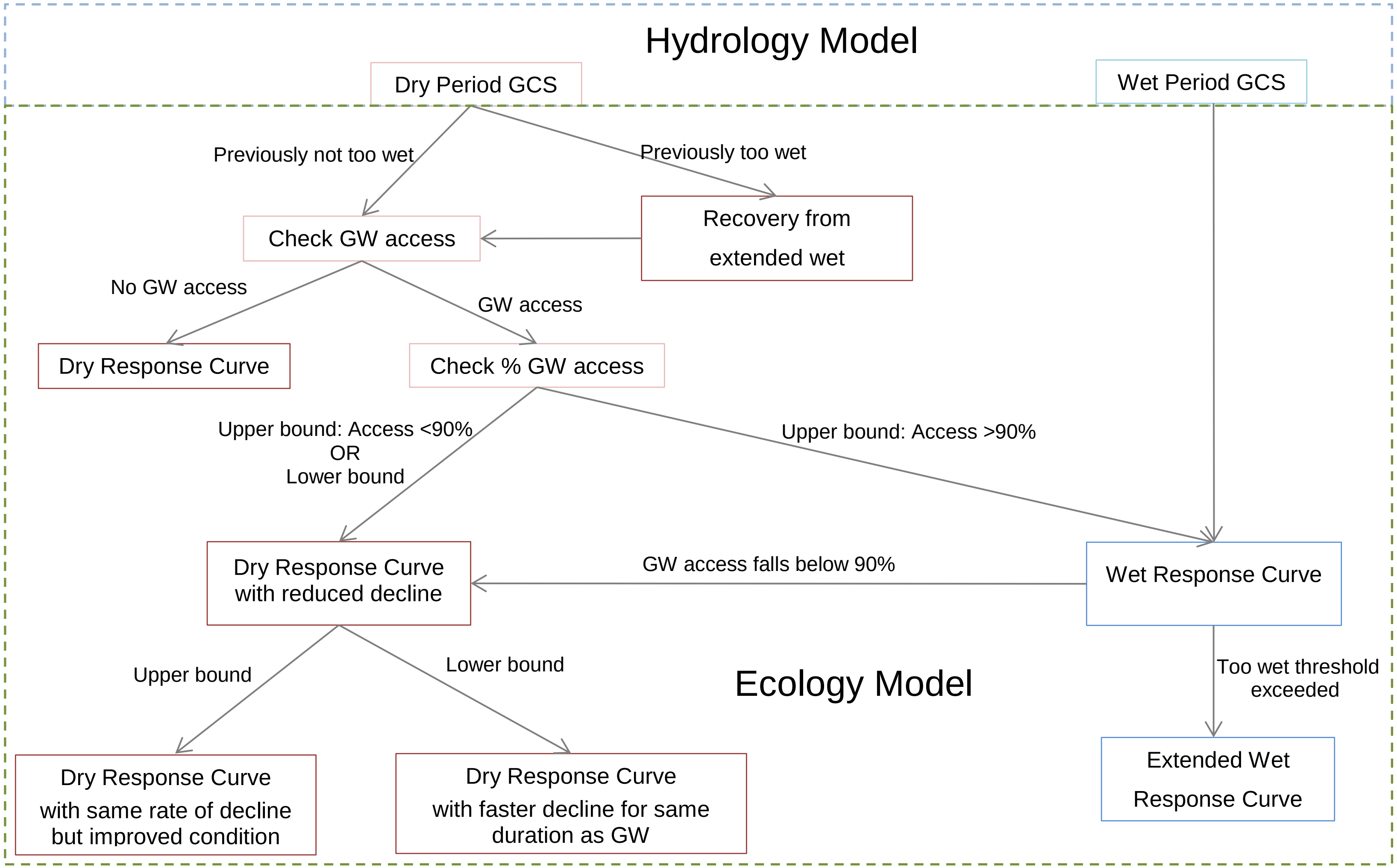
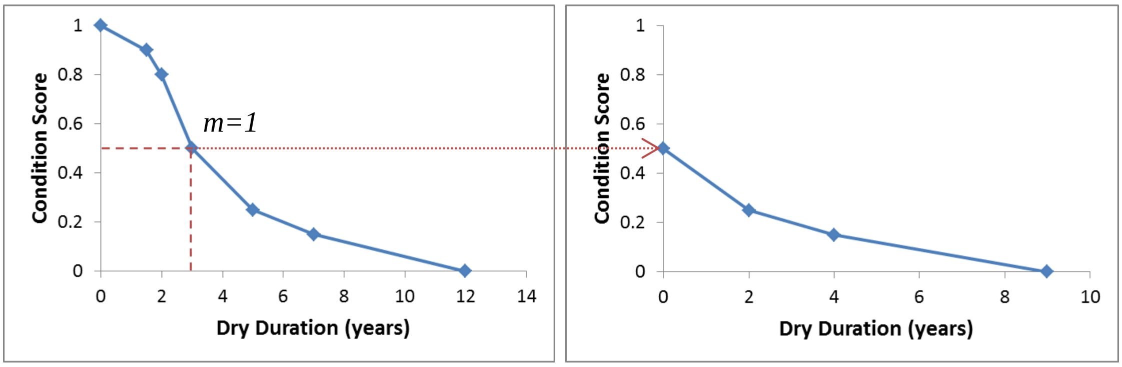


Figure 47. Revised model calculations for the ecological component of the ERM (GCS – Great Cumbung Swamp).

Dry Event

1. Calculate % access to groundwater using Equation 13
2. At the start of each dry event, use the condition score from the previous time step to identify the start point on the response curve. This is demonstrated in Figure 48 for a condition score of 0.5 at the start of the dry event, where the response curve is adjusted by three years, such that 0.5 becomes the starting condition. This process is performed for each expert and for both upper and lower bounds.



(a) (b)

Figure 48. Adjusting the start of a response curve to account for the current River Red Gum condition, where (a) is the base dry response curve for E1, and (b) is the time adjusted dry response curve for E1.

3. Divide into upper and lower bound calculations for each expert.

Upper Bound

a) Identify whether the previous wet event was an extended wet event, or a normal wet event. If previously in an extended wet event, an initial improvement in condition is calculated based on each expert's upper bound response curves shown in Figure 42.

b) Access to groundwater is then checked. As described above, if access is >90%, the wet period curve is followed. In this case, the time adjustment described in step 2 is undertaken for the wet period curve.

c) Where groundwater access is >1% but <90%, a dry period event starts but with a reduced rate of decline. This is calculated by adding the percentage groundwater access (as a factor) to the start time, which has the effect of delaying the decline:

$$t_a = t_a + GW_{scale}$$

where:

t_a	=	time adjustment
GW_{scale}	=	GW scale factor

The time adjustment is then used to linearly interpolate the response curve's piecewise linear relationship to calculate the new condition score:

$$C(t) = C_{low} + (m - t_{low}) \times \frac{C_{up} - C_{low}}{t_{up} - t_{low}}$$

where:

C(t) = condition at current time step

CLow = condition score in piecewise linear relationship below the current condition

CUp = condition score in piecewise linear relationship above the current condition

tLow = time in piecewise linear relationship below the current time step

tUp = time in piecewise linear relationship above the current time step

m = current time step for the dry *event* (as opposed to for the entire simulation)

d) If the groundwater access is less than 1%, the dry curve is followed.

Lower Bound

a) Identify whether the previous wet event was an extended wet event, or a normal wet event. If previously in an extended wet event, an initial improvement in condition is calculated based on each expert's lower bound response curves.
b) Dry period begins.
c) If access to groundwater is >1%, a reduced decline is calculated.
d) If previously had access to groundwater but does not currently, an increased decline is calculated for the same duration for which there was access to groundwater.

Wet Event: Upper and Lower Bounds

1. Adjust wet period response curve based on condition at the start of the wet event, using the same process used at the start of a dry event.
2. Check whether in an extended wet event. If not, then apply the wet period response curves for upper and lower bounds; if yes, apply the extended wet response curves for upper and lower bounds.

4.6.4 Boundary Conditions

The three boundary conditions considered here are the starting River Red Gum condition scores, and the minimum and maximum condition scores. An initial starting condition of 0.7 was used for both the upper and lower bounds, based on analysis of Booligal flow for the five years prior to 1953 (insufficient flow data were available prior to 1948). Using a flow duration curve to assess the sequence of wet, medium and dry years, the years from 1948 to 1952 were identified as being a combination of wet and moderate. Consequently, a moderate-good condition score was adopted. As described earlier, subsequent condition scores at the start of each wet or dry event was based on the score from the previous time step.

If the condition score becomes <0.00001, it is assumed that the community has died. It is also assumed that recovery does not occur within the time scale of the simulation period. It is assumed that re-establishment only occurs through transfer of new seeds via dispersal mechanisms, followed by favourable conditions. The maximum condition score is 1.0.

4.7 Preliminary Model Evaluation

Given the following two chapters undertake a detailed evaluation of the combined hydrological and ecological components which make up the ecological response model (ERM), only a brief analysis is presented here. Figure 49 shows the five expert models for the whole Great Cumbung Swamp (using a flow threshold of 2700ML/d for 30 days), incorporating both rainfall and groundwater access in addition to riverine inundation. It is assumed that River Red Gum roots can access groundwater up to 12m. As for the hydrological component of the ERM, the complete ERM is run using observed Booligal flow data and observed Oxley rainfall data from 1 July 1953 to 30 June 2013 with a daily time step.

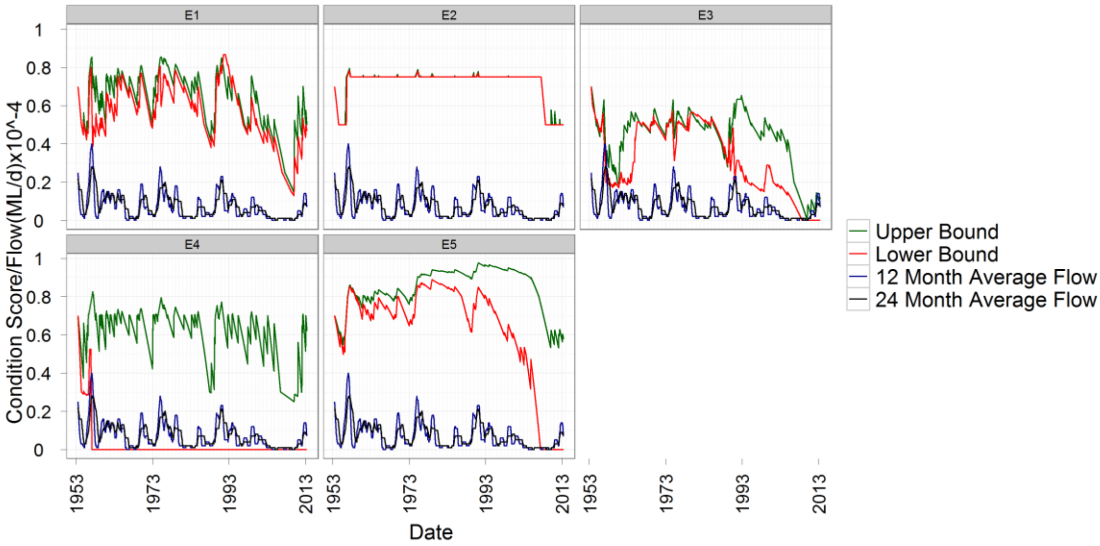


Figure 49. River Red Gum condition scores from 1953 to 2013 for the five expert ecological models for the entire Great Cumbung Swamp, assuming riverine and rainfall inundation, and groundwater access up to 12m. Also shown is the 12 and 24 month moving average flow for Booligal Gauge.

It can be seen from Figure 49 that the expert ecological models produce significantly different estimations of River Red Gum response in the Great Cumbung Swamp. Expert Model

1 (E1) is a relatively precise model, and follows a similar pattern of change as the observed flow data. Importantly, the Millennium drought is represented through a decline and recovery in condition. Expert Model 2 (E2) is the most precise of all the five models, and shows little sensitivity to changes in flow. This would suggest that River Red Gum is incredibly resilient. Whilst there is some decline in condition at the start of the Millennium drought, the condition does not fall below 0.5. The recovery in condition after the drought is not captured.

Expert Model 3 (E3) on average estimates lower condition scores relative to E1 and E2. It is also a less precise model during periods of recovery and decline. There is some observable relationship between flow patterns and change in condition. Some recovery post Millennium drought occurs in the upper bound, whilst the lower bound reaches zero during the drought. E3 is particularly sensitive to extended wet periods, which is the cause of the sudden decline in condition during 1956/1957, 1974/1975, and 1990 (lower bound).

Expert Model 4 (E4) shows a similar pattern of change to that of E1 for the upper bound, although the lower bound declines to zero within the first four years due to an extended wet event. As a result of this decline, the model shows the least precision of all five models, however this is caused by the drop to zero for the lower bound. Expert Model 5 (E5) is the most variable of the models, with the upper bound reaching condition scores of 0.98, whilst the lower bound drops to zero during the Millennium drought. It appears to be more sensitive to large changes in flow, but less sensitive to small changes. Neither the upper nor lower bounds capture the recovery after the drought, and the model becomes less precise during the simulation period.

It can be seen that for some expert models, the lower bound can exceed the upper bound for some periods. This is due to different degrees of uncertainty communicated by experts during model development. For example, the dry period response curve for E3 is shown in Figure 50, where the expert gave different time ranges for the decline of River Red Gum, but only a single duration for when River Red Gum reaches zero. Consequently, the rate of decline for the lower bound between six and ten years is more gradual than the rate of decline for the upper bound. Whilst this discrepancy was not resolved as part of the current work, future work would benefit from a second round of interviews to address such issues.

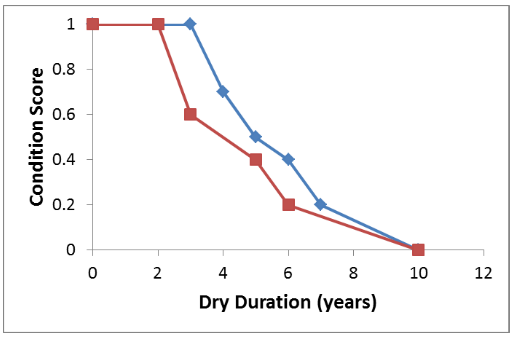


Figure 50. Dry period response curve for E3

4.8 Conclusions

This chapter describes the ecological component of the ERM, which was developed to estimate changes in River Red Gum condition within the Great Cumbung Swamp under different levels of water availability. It addresses a number of limitations of previous models, by considering uncertainty in the conceptualisation of ecological response through expert elicitation, as well as incorporating uncertainty explicitly stated by experts through upper and lower bounds. In addition, River Red Gum response is based on a systems approach to understanding water availability, considering riverine inundation, rainfall and groundwater. A further advance is that estimation of condition is based on the condition at the start of a wet or dry event, hence capturing the sequence of wet and dry periods which previously occurred. The model also calculates condition scores on a daily time step rather than only at the end of an event, which allows tighter coupling with decision models with some further model development.

Despite these advances, it is acknowledged that there is significant scope for further advances in understanding and representation of River Red Gum and ecological response more broadly within a modelling framework, particularly given the focus of the current work is on the exploration of different water resource management strategies rather than ERM development. The advantage of the model presented here is that individual components can be updated as new information becomes available, or alternatively additional ecological models can be included and compared.

The large discrepancy between expert models shown in Figure 49 leads to further questions regarding the degree of uncertainty involved in estimating ecological response. For example:

- Which model performs best compared with observed data, and should be used when assessing different environmental flow rules?
- What is the impact of the vertices used in defining the ecological models, given there was a degree of interpretation required when translating expert interviews into quantitative models?
- What is the impact of different hydrologic assumptions on results?
- What is the trade-off between model precision/utility compared with incorporation of greater uncertainty at the expense of being less informative?

Based on preliminary results from the ERM and the questions raised, an in-depth analysis of model behaviour was warranted. This is conducted in the following two chapters, by firstly undertaking a global sensitivity analysis to examine which model components have the greatest impact on River Red Gum condition scores; and secondly, an evaluation of model performance under different model assumptions using observed data. The model evaluation is conducted using Bayesian probabilities, to explicitly incorporate different sources of uncertainty.

In addition to having developed an ERM for use in subsequent chapters, one of the key outcomes of the two model development chapters (Chapter 3- hydrology and Chapter 4 - ecology) is the knowledge gained through the model development process. The quantification required in model development as well as the representation of physical processes using different assumptions, resulted in a journey of exploration in understanding River Red Gum physiology, the complexity of estimating available water and ecological response, the value of consulting with a range of people with different knowledge of River Red Gum response, and the challenge of managing such a complex and value-laden system.

Chapter 5: Investigating model behaviour through global sensitivity analysis

5.1 Aim and overview

A global sensitivity analysis was used to investigate the behaviour of the ecological response model (ERM) presented in Chapters 3 and 4, thereby providing insight into the impact of uncertainty in model components on results. This type of investigation is valuable in improving understanding of the system and how well it is represented by the modelling framework. It provides context for interpreting model results and identifying management strategies, and it can guide future research to address the most influential knowledge and data gaps.

Initial testing of the ERM using different parameters and expert models suggested that the results are sensitive to both hydrological and ecological components. Whilst hydrological parameters were determined using an understanding of wetland processes and available information, data are limited and hence there is a high degree of uncertainty around these assumptions. Similarly, the derivation of ecological response based on expert elicitation involved a number of uncertainties, with experts indicating that for a number of elements they were providing an educated guess because insufficient data were available.

The analysis described in this chapter addresses current research gaps by exploring the sensitivity of the ERM results to different expert derived models, and by comparing and ranking the sensitivity of hydrological and ecological parameter values. This allows the results to be interpreted in the context of uncertainty in model conceptualisation and parameter values, particularly where the model is highly sensitive to uncertainty in the components. It also identifies which components are more important to estimate as accurately as possible (or should be the focus of future data collection), and which should be used to estimate uncertainty bounds.

This chapter makes four main contributions. The first is demonstration that model results can be highly sensitive to different model conceptualisations, and the impact of different conceptualisations can be greater than that of different parameter values. The second is that ecological condition scores can be highly sensitive to hydrological parameters, indicating that uncertainty in flow and inundation assumptions can lead to erroneous results in ecological response, irrespective of how well this response is modelled. The third contribution demonstrates the importance of considering groundwater access in supporting vegetation, which is often neglected in ecological response models derived for basin management. The fourth supports previous research, demonstrating the role of sensitivity analysis as a valuable tool for model investigation, particularly for complex systems with high input uncertainty. However, given such analysis is influenced by factors such as parameter ranges, comparison metrics and simulation length (Shin *et al.*, 2013), the focus should be on improving system and model *understanding* rather than providing definitive and comprehensive statements regarding sensitivity. Future work also needs greater focus on the implications of sensitivity analysis outcomes for management decisions.

5.2 Introduction

Sensitivity analyses can assist in understanding model behaviour and the influence of different parameters and inputs on model results, and is considered to be a key component of model development (e.g. Saltelli *et al*., 2000; Jakeman and Letcher, 2003; Norton, 2015). Sensitivity analysis can be used to better understand the impact of uncertain inputs on model outputs; to understand model structure through identifying which parameters (and hence processes) most influence results; and to identify highly influential inputs whose values must be estimated most accurately (Homma and Saltelli, 1996; Saltelli *et al.*, 2000; Jakeman and Letcher, 2003; Shin *et al.*, 2013).

The use of sensitivity analysis can therefore assist in the evaluation of model performance, and identifying whether the model adequately represents key processes. Should components *representing* key processes have minimal impact on results, modification of the model may be required (Saltelli *et al.*, 2000; Shin *et al.*, 2013). Similarly, data collection can be focused on elements (including model input and formulation) that are both uncertain and have high sensitivity indices. Sensitivity analysis can also enable model simplification, and can improve calibration by identifying and fixing insensitive parameters (or removing them completely where they do not represent key processes) (Homma and Saltelli, 1996; Saltelli *et al.*, 2000; Shin *et al.*, 2013; Norton, 2015).

The evaluation of different management options can also be aided by sensitivity analysis, by identifying which decision elements (decision variables) have the most impact on results (objectives) (Figure 51). For example, Kasprzyk *et al*. (2012) compared the sensitivity of a water distribution model to changes in decision elements such as the proportion of initial water rights, and the growth of water demand into the future. Some decision elements had a significantly greater impact on the model outcomes than others. Understanding which decision-relevant model components have the largest impact can allow decision analysis to place greater focus on varying these elements, with non-sensitive components being kept fixed. Varying non-sensitive components through scenario analysis or optimisation will often yield little return compared with varying components with high sensitivity indices. Kasprzyk *et al*. (2012) found that computational efficiency could be improved whilst having minimal impact on model outcomes by fixing some of the low sensitivity elements. However, it was also found that the inclusion of some decision elements with low sensitivity improved results by enabling more complex management rules to be defined.

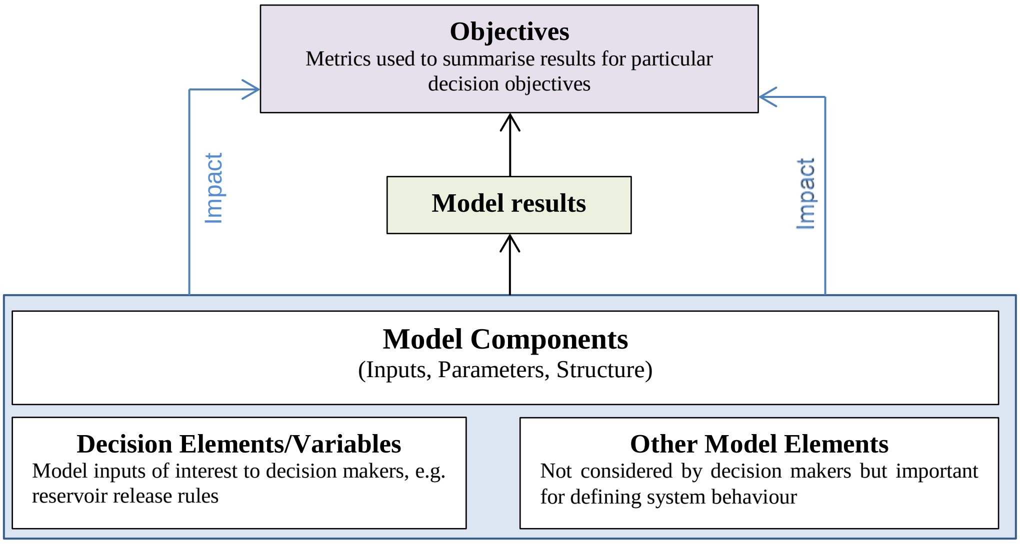


Figure 51. Using sensitivity analysis to explore the impact of decision elements and other model elements on model results and decision objectives.

Whilst sensitivity analysis has been widely identified as a key component of model development, in practice its application has been limited until recently (Saltelli and Annoni, 2010; Norton, 2015). Where it is applied, the most commonly used approach is the one factor at a time (OAT) method. This involves changing one parameter independently to examine the effect on solutions, whilst other parameters remain fixed (Saltelli *et al.*, 2000; Saltelli and Annoni, 2010). The disadvantage of both OAT and other local methods is that they rely on models being linear and additive (i.e. parameters do not interact), and only consider changes in one location in the parameter space (Saltelli *et al.*, 2000; Saltelli and Annoni, 2010).

As an alternative to OAT methods, global sensitivity analysis has the advantage of calculating sensitivity by sampling all parameters each time across the full range of parameter values; incorporating parameter interactions; and not being limited to models which are linear and additive (Saltelli *et al.*, 2000). Global methods include the Fourier Amplitude Sensitivity Test (FAST) (see Saltelli *et al.*, 1999 for extended FAST), Sobol' (1990; 1993), and Morris (1991). Despite the advantages of these methods they are less frequently used due to greater complexity and computational time (Saltelli and Annoni, 2010; Helton and Davis, 2003; Shin *et al.*, 2013). Rakovec *et al* (2014) have developed a hybrid global-local method (DELSA) to address this issue, thereby improving computational time as well as enabling the exploration of different parts of the parameter space. Whilst not discussed here, other types of sensitivity analysis that are less commonly used in environmental modelling to date include algebraic approaches, regionalised sensitivity analysis, and density based methods. A summary of algebraic and regionalised methods can be found in Norton (2008) and Norton (2015); and of density based methods and developments in Pianosi and Wagener (2015).

One of the primary elements of the current work is the investigation of uncertainty in model conceptualisation, and the impact of this uncertainty on resulting management alternatives. As described in Chapter 4, model conceptualisation is defined here as the representation of system processes based on different expert response curves, where each expert model uses a different conceptual understanding of the relationship between water availability and River Red Gum condition. In comparison, model parameters are used to define the specific *values* attached to these processes. It is recognised that the distinction between conceptualisation of processes and parameter values is somewhat grey, where a different parameter value can also be argued to change the representation of system processes. However, the distinction is used here to emphasize the importance of representing key processes, rather than variation in model elements that may be less significant.

Although sensitivity analysis has been identified as a way to investigate the impact of model conceptualisation (e.g. Saltelli *et al*., 2000; Jakeman and Letcher 2003; Perz *et al*, 2013), most applications have instead focused on variation in parameter values. This is seen to be a key shortcoming, given that uncertainty in model conceptualisation and structure can be far greater than uncertainty in parameter values. The impact of different model conceptualisations is demonstrated by Saltelli *et al*. (2000), who used an environmental model to examine decisions regarding solid waste disposal. Using the extended FAST sensitivity analysis, they found that using different sets of environmental indicators had the greatest impact on model outcomes, and the impact was significantly greater than that of other input data. Other components tested include: a factor to select whether target values or expert judgement are used to evaluate environmental objectives; which set of stakeholders are considered; and the use of different data sets. However, the effect of these was much less than that of which indicator set was used.

In another study, Muñoz-Carpena and Muller (2009) compared three models of increasing complexity for estimating surface water phosphorous concentration. Whilst a separate sensitivity analysis was undertaken for each model (rather than using model selection as an input to the sensitivity analysis), the results demonstrated significant differences in model behaviour (also summarised in Perz *et al*., 2013).

The current analysis uses the Sobol' method to explore the effect of uncertainty in model conceptualisation on model output, as well as to better understand model behaviour through the variation of key parameters. Sobol' has been demonstrated to be an effective and robust method of identifying global sensitivity indices (e.g. Tang *et al*., 2007; Kasprzyk *et al*., 2012; Chu-Agor *et al*., 2012; DeJonge *et al*., 2012; Shin *et al*., 2013; Perz *et al*., 2013). It is a variance based method, where the variance resulting from changes in a subset of model elements is divided by the total variance (Sobol, 2001; Homma and Saltelli, 1996). Both first order and total sensitivities are calculated, with total sensitivities incorporating parameter interactions. A summary of the process used in applying the Sobol' sensitivity analysis is provided below. This is followed by a description of the components tested in the sensitivity analysis; definition of the metrics used to evaluate changes in model outputs; a summary of results in terms of impacts of parameter values and model conceptualisation; and lastly a discussion of key findings and next steps.

5.3 Methodology

5.3.1 Sensitivity Analysis of the ERM using Sobol'

There are three main considerations when applying sensitivity analysis: (1) which model components should be included in the analysis and what their parameter range should be; (2) what summary metrics should be used to compare the results from different parameter sets; and (3) what boundary conditions should be used, such as the simulation length and input data, and spatial scale. These elements can all significantly impact on the sensitivity of model results to variations in model components (e.g. Shin *et al*., 2013; Song *et al*., 2015). A summary of the process adopted in applying Sobol' sensitivity analysis to the ERM is provided below:

1. Select model components (different conceptualisations, model structures or parameters) for analysis.
2. Identify upper and lower bounds for each model component based on feasible ranges, and the number of samples (N) required to ensure adequate Monte Carlo sampling.
3. Sampling of parameters to generate a total number of parameter sets (TN), where TN= N(P+2) and P is the total number of model components (details contained in Pujol *et al*., 2012). This results in each model component being combined with different combinations of values for all other model components.
4. Identify summary metrics to enable comparison between model outputs for each set of model component values.
5. The ERM is run TN times and summary metrics are calculated for each set of model component values.
6. Summary metrics are used to calculate both the variance for each individual model component independently (first order sensitivity, S_i); and the model component's total sensitivity (S_{Ti}) considering interactions with other model components.
7. Bias, standard error, and the minimum and maximum confidence intervals can also be calculated for each S_i and S_{Ti} to ensure sufficient samples were taken. 95% confidence intervals are estimated using the bootstrap method implemented in R.

Calculation of first order and total sensitivity is shown below (Saltelli and Annoni, 2010; Homma and Saltelli, 1996):

$$S_i = \frac{V_{x_i}[E_{x_{\sim i}}(Y \mid X_i)]}{V(Y)} \tag{14}$$

$$S_{Ti} = \frac{E_{x_{\sim i}}[V_{x_i}(Y \mid X_{x_{\sim i}})]}{V(Y)} \tag{15}$$

$$S_{Ti} \equiv S_i + S_{i,x_{\sim i}} = 1 - S_{x_{\sim i}} \tag{16}$$

where:

X_i	= model component *i*
$X_{x_{\sim i}}$	= all model components except X_i
Y	= model output
$V_{x_i}[E_{x_{\sim i}}(Y \mid X_i)]$	= expected reduction in variance if X_i were fixed
$E_{x_{\sim i}}[V_{x_i}(Y \mid X_{x_{\sim i}})]$	= expected variance if all input factors except X_i were fixed
$V(Y)$	= total variance
$S_{i,x_{\sim i}}$	= interaction between factor X_i and all other factors
$S_{x_{\sim i}}$	= sensitivity of all terms excluding factor X_i

First order sensitivity values of all model components (Equation 17) sum to one in an additive model where there are no parameter interactions (Saltelli, 2002). However, where interactions exist as is the case in this study, the sum of all first order *and* higher order interactions add to one (Equation 18). The sum of all total sensitivity indices is greater than one as each interaction is repeated between parameters (Equations 19 and 20). For example, for a three parameter model S_i and S_{Ti} are calculated as follows (Homma and Saltelli, 1996; Saltelli, 2002):

$$\sum_{i=1}^{3} S_i = S_1 + S_2 + S_3 \tag{17}$$

$$\sum_{i=1}^{3} S_i + \sum_{i<j}^{3} S_{ij} + S_{123} = S_1 + S_2 + S_3 + S_{12} + S_{13} + S_{23} + S_{123} = 1 \tag{18}$$

$$S_{T1} = S_1 + S_{12} + S_{13} + S_{123} \tag{19}$$

$$\sum_{i=1}^{3} S_{Ti} = (S_1 + S_2 + S_3) + 2(S_{12} + S_{13} + S_{23}) + 3(S_{123}) > 1 \tag{20}$$

Sobol’ was implemented using the enhancements developed by Saltelli (2002) with reduced computational cost, as applied in the “Sensitivity” package in R (Pujol *et al.*, 2012). For details on the Sobol’ method and various extensions refer to Sobol’ (1993), Homma and Saltelli (1996), and Saltelli (2002).

The ERM was run for same period as the preliminary analysis described in Chapter 4, covering a total of 60 years from 1/7/1953 to 30/6/2013 and hence including a combination of wet, dry and moderate climatic periods. The Sobol’ sensitivity analysis was initially tested using N=1x10^3 parameter sets, however this resulted in negative values for some of the sensitivity indices. This was corrected using N=1x10^4 parameter sets. Whilst some negative sensitivity values still resulted suggesting additional samples could be used, the majority of these were less than -0.01 with the maximum of -0.02 (4% of the maximum index value for that scenario). Additional samples significantly increased the computational time, hence 1x10^4 parameter sets was considered adequate for the purpose of this analysis. In all cases, samples are generated assuming a uniform distribution. A description of the model components and metrics used is provided in the following sections.

5.3.2 Model Components and Value Ranges Analysed

To examine the influence of both model parameters and different expert model conceptualisations, two separate sensitivity analyses were conducted. The first (Case 1) compared the effect of hydrological parameters with ecological parameters for a single expert model, whilst the second (Case 2) compared the influence of the five different expert defined ecological models with the same hydrological model parameters used in Case 1.

The hydrological parameter set used in both Case 1 and Case 2 examined eight different variables: three were used to define the relationship between flow upstream of the Great Cumbung Swamp and inundation within the Great Cumbung Swamp; four defined rainfall based inundation; and the remaining variable specified the maximum depth to which River Red Gum can access groundwater (Table 10). These were considered to be the key parameters that define inundation patterns within the Great Cumbung Swamp, and all are highly uncertain. Further information on these parameters is provided in Chapters 3 and 4.

Value ranges for each of the selected parameters are shown in Table 10, and define the bounds of values to be sampled from. Value ranges were selected based on available information and knowledge of the system, with the assumption that they represent feasible values. However, a disadvantage of the ranges selected is that they vary with respect to the percent change of the original value, and hence some ranges are larger than others. In addition, whilst individual parameter ranges may be plausible, it is possible that some combinations of parameter values may not be. In the case of the flow threshold and duration threshold, the ranges reflect an aggregate of two components: firstly, uncertainty in the threshold required to inundate the Great Cumbung Swamp; and secondly, uncertainty in the area of inundation. Referring back to Chapter 3, two main areas within the Swamp are considered, the smaller lakes area (c. 4000 ha), and the entire River Red Gum area (c. 15000 ha). The range of 500 - 3500 ML/d encompasses the 700 ML/d threshold used for the lakes area, and 2700 ML/d used for the whole Swamp area, whilst the duration range of 30 – 90 days spans the range of the two areas (90 for the lakes, 30 for the whole Swamp).

Base case values were also selected for calculation of comparison metrics. For this study, summary metrics (see definitions in Section 5.3.4) were used to evaluate changes in ecological condition between a base case simulation and each new parameter set. Base case values are also shown in Table 10, whilst Chapter 3 provides further details on how these were derived.

Table 10. Hydrological parameter values for base case and sensitivity analysis bounds

Model Component	Parameter(s)	Short Name	Base Case	Lower	Upper
Flow Inundation	Flow threshold (ML/d)	FlowTrsh	2700	500	3500
	Duration threshold (days)	DuraTrsh	30	30	90
	Flow-inundation duration factor (multiplier)	FIDF	1.5	1	10
Rain Inundation	Rain threshold (mm)	RainTrsh	40	10	80
	Initial Loss (mm)	InitLoss	10	2	40
	Continuing Loss (mm)	ContiLoss	5	1	40
	Infiltration rate (%)	InfiltRate	20	1	80
Groundwater	Access depth (m)	GWAcc	-10	0	-15

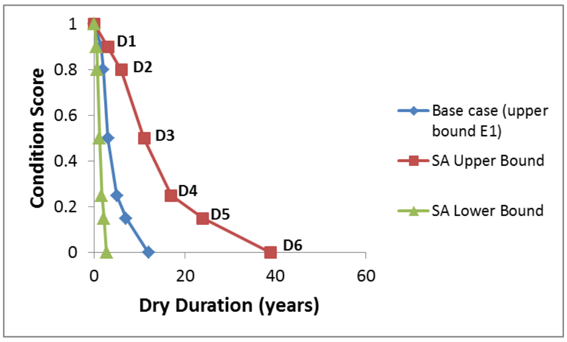
In addition to hydrological parameters, specific ecological parameters and model components were examined in Cases 1 and 2 as described below.

Case 1: Comparing hydrological and ecological parameters

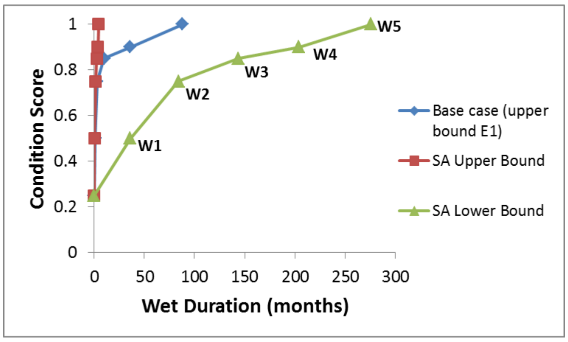
Case 1 compared the hydrological parameters described above with thirteen ecological parameters defining the expert models, giving a total of 21 parameters and TN=$2.3\text{x}10^5$ parameter combinations, where TN is defined in Section 5.3.1. The ecological parameters consisted of different vertices of the upper bound of Expert Model 1 (E1), with the condition scores of the base case version of E1 being used for comparison. The vertices describe the change in condition under dry, wet, and too wet conditions, and are defined as (time t, condition C). As the condition scores are serially correlated (e.g. for the dry period curve, the score at time (t) is relative to the score at time (t-1)), they could not be directly varied. Hence t was varied to influence the time at which a particular condition score was reached based on available water. As time must also be monotonic for each vertex, Δt was used as the parameter for testing sensitivity, and was added as an increment to the previous vertex.

Selection of parameter ranges provided a bound around the base case scenario, as shown in Figure 52. These ranges represent uncertainty in the expert's assumptions, in addition to the uncertainty explicitly stated by experts in deriving the upper and lower bound response curves described in Chapter 4. However, the ranges around the expert's response curves were estimated, as it was not feasible to quantify how large they were. The ranges aimed at providing a similar shaped response curve to that derived by the expert, although were constrained by the y-axis in the case of the lower bound for dry and too wet durations ((a) and (c)) and upper bound (b) in Figure 52.

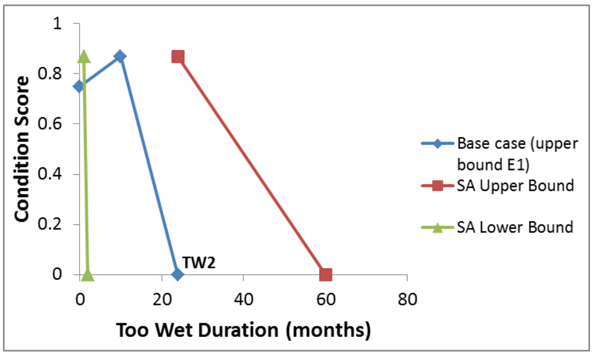
Whilst sensitivity to parameters was not examined for the other four expert models in the current analysis, this could be explored in future work.



(a)



(b)



(c)

Figure 52. Parameter ranges for Expert Model 1 (E1) upper bound response curves for (a) dry, (b) wet and (c) too wet conditions. SA Upper and Lower Bound refers to sensitivity analysis parameter upper and lower bounds.

Case 2: Testing different ecological model conceptualisations

Case 2 examined the impact of model conceptualisation on model outputs relative to changes in hydrological parameters. Instead of considering only a single expert model as in Case 1, Case 2 uses a parameter that acts like a switch to select one of the five discrete ecological response models for each set of hydrological parameters. Comparison metrics therefore compare the effect of different ecological models as well as different hydrological parameter values.

As for Case 1, hydrological parameters are sampled from a continuous set of values within the defined parameter ranges. This means that whilst there are N=1x10^4 different values used for the hydrological parameters, there are only five different model conceptualisations. The expert models are selected by randomly generating a value from 1 to 5.999999, which is converted to the nearest integer between 1 and 5 to represent each of the five models. All eight hydrological parameters were included, giving a total of nine different model components analysed, and TN=1.1×10^5 different parameter combinations. E1 was again used as a base case, meaning that iterations that also select the E1 model only vary in their hydrological parameters relative to the base case. If a separate base case had been used, sensitivity to the expert model is likely to be even greater.

5.3.3 Testing the impact of different parameter bounds

Shin *et al* (2013) and Wang *et al*. (2013) demonstrated that sensitivity to model components can vary depending on the parameter bounds chosen. Different parameter bounds were therefore also tested for both Case 1 and 2. Initial results indicated that both FIDF and FlowTrsh were two of the most sensitive parameters (excluding sensitivity to different expert models), and hence were used to modify the bounds as follows:

Table 11. Parameter bounds tested for Case 1 and 2

	Case 1	**Case 2**	
	FIDF	FIDF	FlowTrsh
Scenario 1 (Base Case)	(1, 10)	(1, 10)	(500, 3500)
Scenario 2	(1, 5)	(1, 5)	(500, 3500)
Scenario 3	-	(1, 5)	(700, 2700)

5.3.4 Comparison metrics

Four different metrics were used to compare the base case scenario with results from each new parameter set:

a) Nash-Sutcliffe Efficiency (NSE)
b) Log_{10} NSE
c) 0.3xNSE + 0.3xNSC + 0.4xRBias where NSC is number of sign changes and RBias is the relative bias
d) Low flows (F_{20}: 20 percentile of base case)

These metrics were selected to investigate a range of characteristics of the ecological condition time series. As demonstrated by Shin *et al*. (2013), the choice of comparison metric can also influence the outcomes of the sensitivity analysis, hence using a range of relevant metrics is recommended (Bennett *et al.*, 2013). A summary of the above four metrics is provided below, as well as a discussion of what information they provide from an ecological perspective. A fifth objective function (0.5 x NSE + 0.5 x logNSE) was also tested, but given that it provides an average of the first (NSE) and second (logNSE) functions it is not discussed further.

a) Nash-Sutcliffe Efficiency

The Nash-Sutcliffe Efficiency (NSE) is often used to compare model performance against observed data, but in this case is used to examine variation from a base case model scenario using different parameter sets. NSE is defined as:

$$NSE = 1 - \frac{\sum_{t=1}^{T}(C_b^t - C_s^t)^2}{\sum_{t=1}^{T}(C_b^t - \overline{C_b})^2}$$

where:

t	=	time step from 1 to T
C_b^t	=	ecological condition score for base case scenario
C_s^t	=	ecological condition score for each parameter scenario
$\overline{C_b}$	=	mean condition score for base case scenario

Efficiency values can vary from -∞ to 1, where a value of 1 represents an exact match between the scenario and base case ($C_s^t = C_b^t$); a value of 0 means that model performance is equivalent to having a constant value equal to the mean of the base case; and a negative value indicates that the mean of the base case has better predictions than the scenario. This is demonstrated in Figure 53, where scenarios 1 (S1) and 2 (S2) provide a better approximation to the base case model compared with the mean of the base case (with NSE values of 0.8 and 0.2 respectively). However, scenario 3 (S3) is sufficiently different from the base case to have a negative NSE (-0.8), and hence is considered to be a worse approximation than the mean of the base case (note that the models shown in Figure 53 are for demonstration only and do not represent the actual ERM).

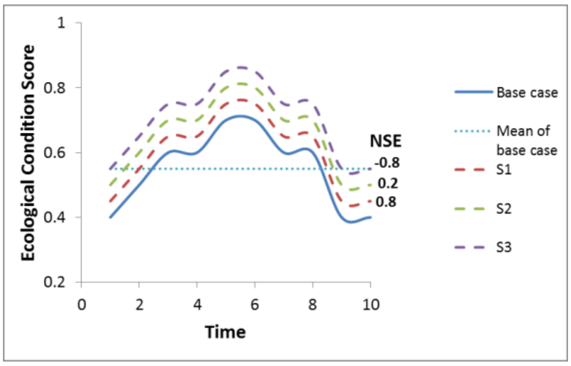
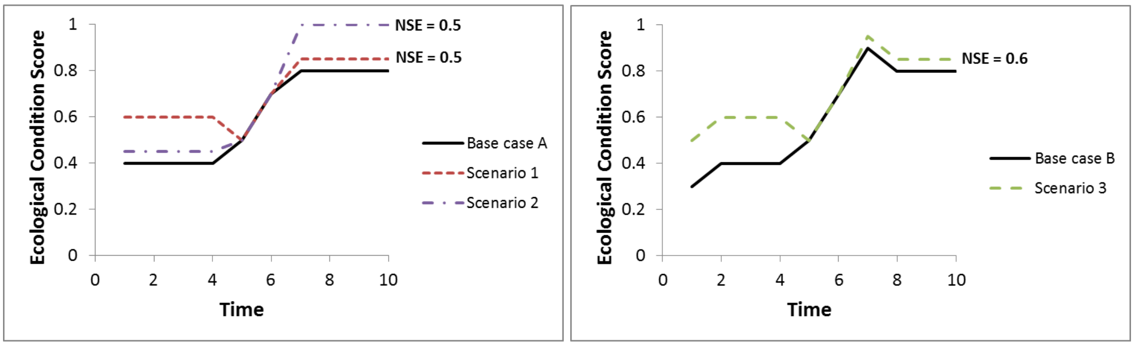


Figure 53. Variation in NSE with different arbitrary models (S1 to S3) relative to the mean of the base case, with calculated NSE values shown next to each model .

NSE is influenced by the difference between the scenario and base case (numerator), and the degree of variability of the base case (denominator). For an identical base case, NSE is therefore influenced by the magnitude of the difference between the base case and scenario, and is insensitive to the raw values of both the base case and scenario. This is demonstrated in Figure 54a, where NSE is calculated using the same base case (Base Case A) and two different scenarios. Both scenarios 1 and 2 have the same NSE value irrespective of whether the deviation from the base case is greater for smaller or larger condition values, as the total difference is the same.

Where there is greater variation within the base case, NSE is lower for the same difference between the base case and scenario. This is because the denominator calculates the difference between the base case values and the mean, producing larger differences for greater variation for an identical mean. Figure 54b shows Base Case B, which has the same mean as Base Case A, and the same numerator value (i.e. the magnitude of difference between base case and scenarios are the same as Figure 54a. However, the NSE for Scenario 3 is greater due to the increased variability of Base Case B, and hence a larger denominator. As the same base case is used for all analyses in this case study, this does not affect the comparison between scenarios.



(a) (b)

Figure 54. Effect of different (a) scenario values and (b) base case variability on NSE, using arbitrary models.

As differences between a base case and scenario become larger, they are magnified due to the squared term in the NSE. This can be seen from Figure 55, where a consistent increment of 0.025 added to each score in the base case results initially in an NSE of 0.95, followed by NSE values of 0.8, 0.55 and so on for additional increments of 0.025. Hence the reduction in NSE increases at a greater rate than the difference between the base case and scenario. The magnification of large differences is why NSE often emphasizes differences in peak flows compared to low flows when applied to comparing hydrographs. This is not due to the larger raw flow values, but the fact that the differences are generally greater for peak flows. As this study examines ecological condition scores from 0 to 1, there is no emphasis on high scores.

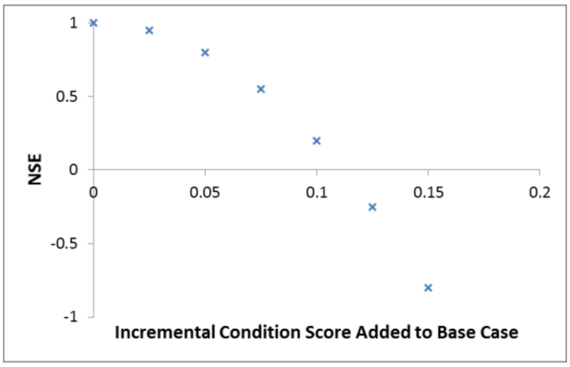


Figure 55. NSE relative to consistent increments in modelled condition score for an arbitrary base case model.

b) Log$_{10}$NSE

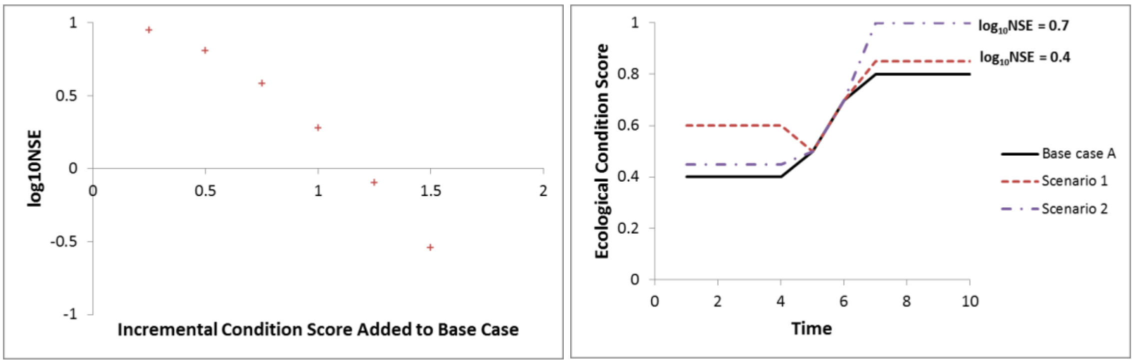
Calculation of log$_{10}$NSE is as follows:

$$\log_{10} NSE = 1 - \frac{\sum_{t=1}^{T}\left[\log(C_b^t + \varepsilon) - \log(C_s^t + \varepsilon)\right]^2}{\sum_{t=1}^{T}\left[\log(C_b^t + \varepsilon) - \log\overline{(C_b^t + \varepsilon)}\right]^2}$$

where:

ε = the lowest 10 percentile condition score for the base case

Log$_{10}$NSE places less emphasis on larger differences between a base case and a scenario compared with NSE, although it still decreases at an increasing rate (Figure 56a). Unlike NSE, the actual value of C_s^t influences log$_{10}$NSE, such that the same difference between a base case and a scenario at low scores results in a larger log$_{10}$NSE than at high scores (Figure 56b). In sensitivity analysis, any deviation of the scenario from low scores in the base case will produce a greater variance than from high scores.



(a) (b)

Figure 56. (a) Variation in log$_{10}$NSE with increasing difference between a base case and a scenario; (b) small deviations in low scores result in a larger log$_{10}$NSE than deviations in high scores.

c) Combined NSE, number of sign changes and relative bias

The third comparison metric uses a weighted combination of NSE, number of sign changes (NSC) and relative bias (RBias):

$$\text{combined metric} = 0.3\text{NSE} + 0.3\text{NSC} + 0.4\text{RBias}$$

NSC counts the number of times the base case changes from being higher than the scenario to lower than the scenario, or vice versa. It demonstrates whether there are consistent differences between the base case and scenario (e.g. with one always being higher), or whether the pattern also changes. This is particularly relevant when comparing observed and modelled data, but is still useful in comparing a base and scenario to emphasize differences in raw values as well as the magnitude of differences (e.g. the scenario may oscillate around the base case showing greater variability in scores). NSC is calculated as follows:

1. Assign index value:
   a. $\mathrm{C_b^t} < \mathrm{C_s^t}$, Index=1
   b. $\mathrm{C_b^t} > \mathrm{C_s^t}$, Index=2
2. Count number of times Index(t) ≠ Index(t-1)

RBias only considers differences between the base case and scenario, and hence is insensitive to whether the scores are high or low for the same base case. However, for different base case time series, RBias is higher where the base case is dominated by low rather than high values. This does not affect the current analysis in the comparison of scenarios, as the same base case is used. RBias is calculated as:

$$\text{RBias} = \left|\frac{\overline{\mathrm{D}}}{\overline{\mathrm{C_b}}}\right|$$

where:

$\overline{\mathrm{D}}$	=	Mean difference between base case and parameter scenario
	=	$\dfrac{\sum_{t=1}^{T}(C_b^t - C_s^t)}{T}$
$\overline{\mathrm{C_b}}$	=	Mean condition score for base case scenario

The combined effect of NSE, NSC and RBias reduces the magnification effect of NSE for larger differences, whilst also emphasizing greater oscillation in values around the base case.

d) Low ecological condition

To examine the impact of different assumptions on poor ecological condition, a threshold is defined using the 20th percentile condition score (F_{20}) of the base case scenario. The number of times the parameter scenario falls below this threshold is counted and divided by the total number of time steps:

$$F_{20} = \frac{\text{Count}\ (C_s^t < C_{b20}^t)}{T}$$

where:

C_{b20}^t = 20th percentile value of the base case

If F_{20} is greater than 0.2, there are a greater number of low condition scores in the parameter scenario compared with the base case. It is therefore used to identify a greater proportion of the time in low ecological condition, without taking into consideration high condition scores. The F_{20} metric results in greater variance and hence higher sensitivity with increasing deviation of the scenario from the base case for low condition scores.

5.4 Results

Results for the two cases are summarised below. Across all analyses, the standard error was less than 0.04 for the total sensitivity index. The 95% confidence intervals were within 0.09 either side of the S_{Ti}. This indicates that the number of samples used to calculate the sensitivity analysis is reasonable.

Case 1: Comparing hydrological and ecological parameters for Expert 1

The ERM for Expert 1 was found to be most sensitive to the flood inundation duration factor (FIDF) (Figure 57). The next most sensitive parameters with $S_{Ti} \geq 0.1$ include flow threshold (FlowTrsh) and groundwater access (GWAcc) for the hydrological parameters, and the two vertices defining the ‘too wet’ period in the expert model. The GWAcc parameter had a higher sensitivity index for the F_{20} objective (which focuses on low ecological condition), followed by the combined NSE+NSC+RBias metric.

The majority of rainfall parameters were relatively insensitive (rain threshold, initial and continuing loss), although sensitivity to rain threshold is higher for the combined metric and F_{20}. Many of the expert model parameters were also relatively insensitive, including most of the dry and wet parameters, although W1, W2, D3 and D4 (Figure 52) had some sensitivity. The less sensitive parameters generally had more sensitivity using the combined metric, where the oscillations around the base case are emphasized rather than larger absolute differences as for NSE and logNSE.

Comparing S_i and S_{Ti} shows a significant increase in sensitivity for S_{Ti}, indicating significant interaction between parameters. In the case of FIDF, it can be seen that S_i is also significant irrespective of other parameter values. The type of comparison metric used influenced the degree of interaction shown, particularly for FIDF where there is a larger difference between S_i and S_{Ti} for the combined objective function and F_{20}. The sum of all first order indices varied between 0.38 and 0.58 depending on the comparison metric, indicating the parameters chosen for analysis account for a significant percentage of the total sensitivity excluding interactions.

Reducing the FIDF range from (1 to 10) to (1 to 5) in Figure 58 resulted in a reduction in sensitivity to FIDF as expected, as well as an increase in sensitivity of the other significant parameters. However, it did not change the pattern of which parameters were most significant, with FIDF still being the most significant in all cases except for F_{20}, where GWAcc became more significant.

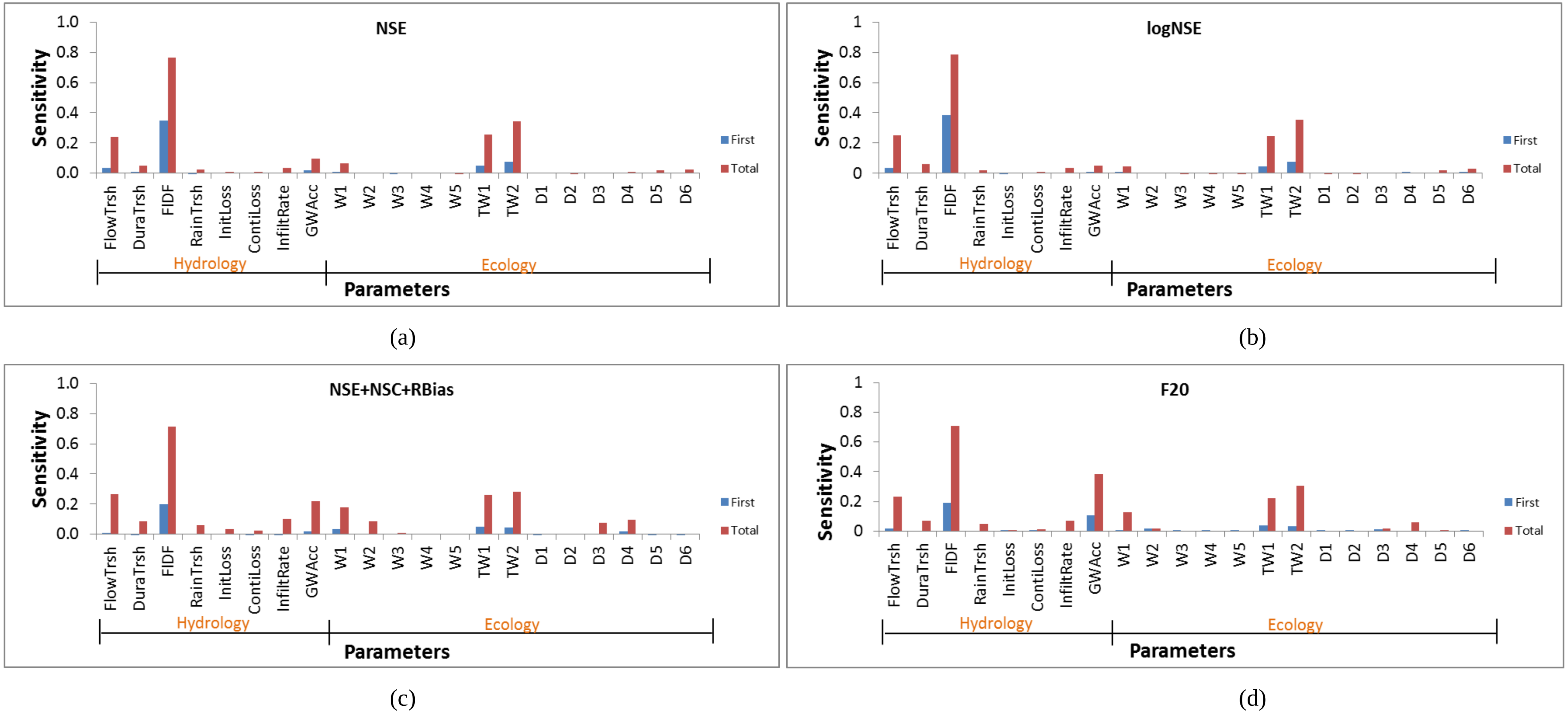


Figure 57. Case 1 Scenario 1: First order and total sensitivity values for hydrological and ecological parameters using an FIDF range of 1 to 10, showing the four comparison metrics used (a) NSE; (b) logNSE; (c) NSE+NSC+RBias; (d) F_{20}.

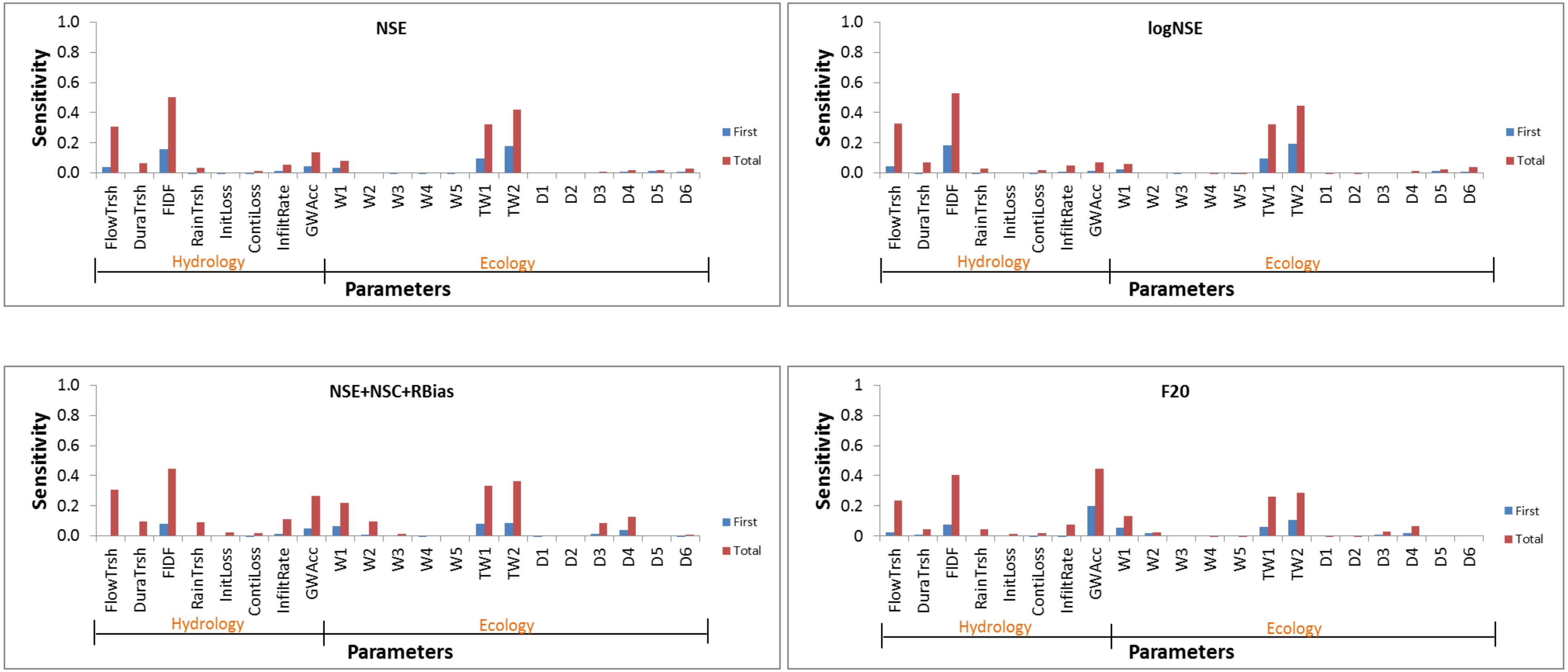


Figure 58. Case 1 Scenario 2: First order and total sensitivity values for hydrological and ecological parameters using an FIDF range of 1 to 5, showing the four comparison metrics used (a) NSE; (b) logNSE; (c) NSE+NSC+RBias; (d) F_{20}.

Case 2: Testing different ecological model conceptualisations

The analysis for Case 2 identified that model outputs were more sensitive to ecological model conceptualisation than hydrological parameters in the majority of cases (using different metrics and parameter ranges). Of the hydrological parameters, FIDF followed by FlowTrsh and GWAcc had the greatest sensitivity (Figures 59, 60 and 61), consistent with the results from Case 1. Results for Scenario 1 using an FIDF range of (1, 10) and FlowTrsh range of (500, 3500) ML/d are described below, followed by a discussion on the impacts of different parameter ranges (Scenarios 2 and 3).

Scenario 1

The expert model conceptualisation had the greatest sensitivity in all but three cases – NSE lower model bound; NSE upper model bound; and NSE+NSC+RBias upper bound (Figure 61 Scenario 1). An example of the first and total sensitivity index values for all model components is shown in Figure 59 using the logNSE objective function for the lower bound ecological model. Each model component/parameter was also ranked from highest to lowest in terms of S_{Ti} value for both upper and lower model bounds using each comparison metric (Figure 60). For example, in Figure 60a, three of the comparison metrics ranked the expert model as having the highest sensitivity of all components tested, with the fourth metric ranking the expert model as having the second highest sensitivity. Both Figures 59 and 60 show the higher sensitivity of the expert model followed by flow and groundwater parameters, with rainfall parameters having the lowest sensitivity. Expert model and FIDF are the only components having an S_i >0.1 across all metrics (upper and lower bounds), whilst expert model, FIDF and FlowTrsh are the only components with an $S_{Ti} > 0.1$ across all metrics (upper and lower bounds).

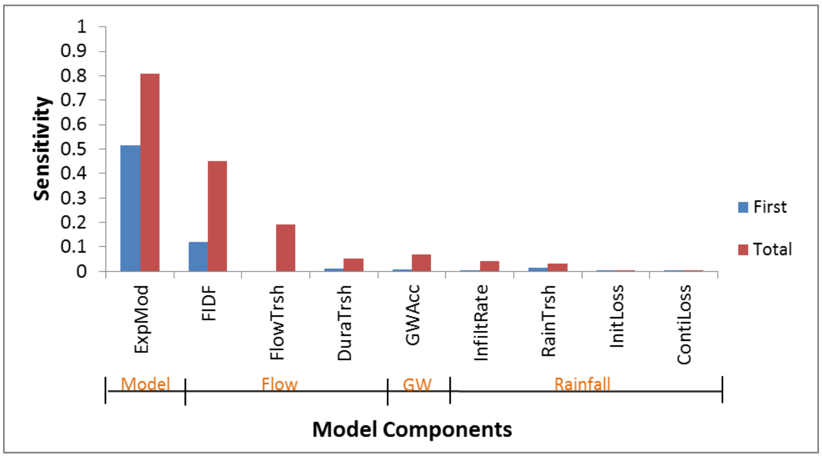
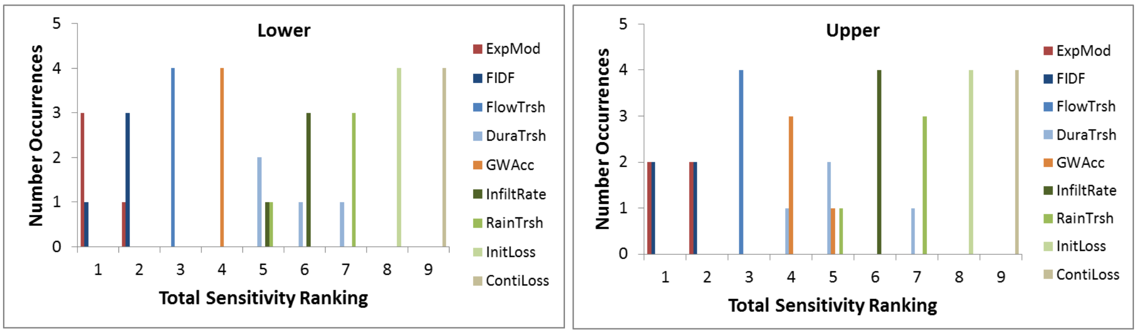


Figure 59. First order and total sensitivity index values for Scenario 1, logNSE, lower bound, showing differences between the conceptual model (Model), flow, groundwater (GW) and rainfall parameters.



(a) (b)

Figure 60. Ranking of each model component across all four comparison metrics for (a) lower ecological model bound and (b) upper bound; with 1 being the highest total sensitivity and 9 being the lowest.

The total sensitivity of the four model components with the highest sensitivities are shown in Figure 61 (Scenario 1) using each of the four comparison metrics. It can be seen that sensitivity varies depending on the metric used, with the expert model having the highest sensitivity when the F_{20} metric is used, whilst FIDF, Flow Threshold and GW Access have the highest sensitivity score when NSE and combined NSE+NSC+RBias are used. Model component sensitivity and the effect of different metrics also vary between the lower and upper bounds of the ecological response model. For example, the effect of the expert model selection has a greater impact on the lower bound compared with the upper bound.

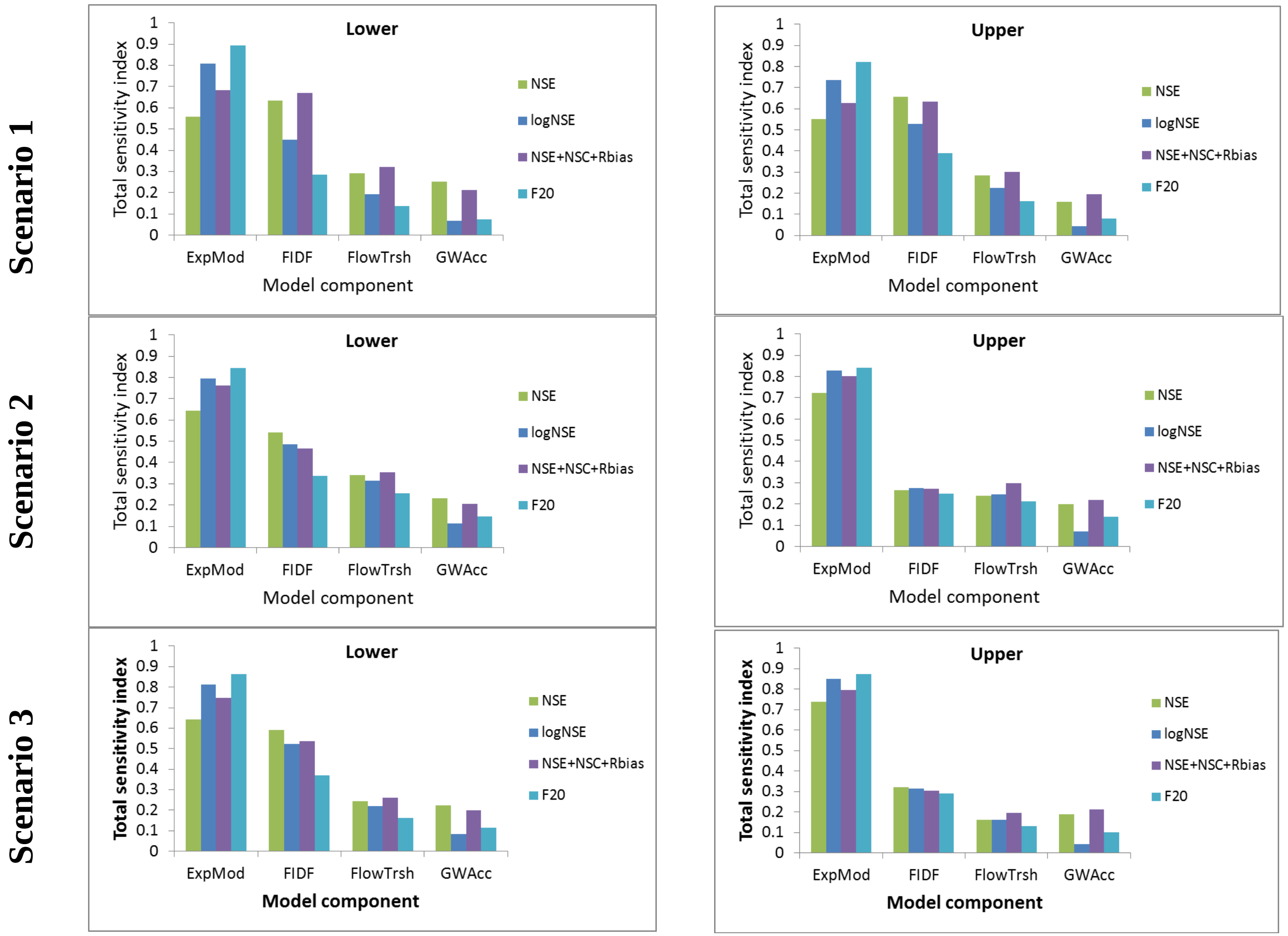


Figure 61. Total sensitivity for model components with the highest sensitivity for different comparison metrics, parameter ranges (scenarios), and upper and lower expert model bounds. Scenario 1: FIDF (1,10), FlowTrsh (500,3500); Scenario 2: FIDF (1,5), FlowTrsh (500,3500); Scenario 3: FIDF (1,5), FlowTrsh (700,2700).

As was found in Case 1, there is a high degree of interaction between the parameters in Case 2. Figure 62 shows the difference between S_{Ti} and S_i for the lower and upper bounds. The interaction is generally greatest using the combined metric, and is highest for the FIDF parameter and expert model (of the four most sensitive components). Interactions are also higher in the FIDF factor for the upper bound compared with the lower, but less for the FlowTrsh and GWAcc parameters.

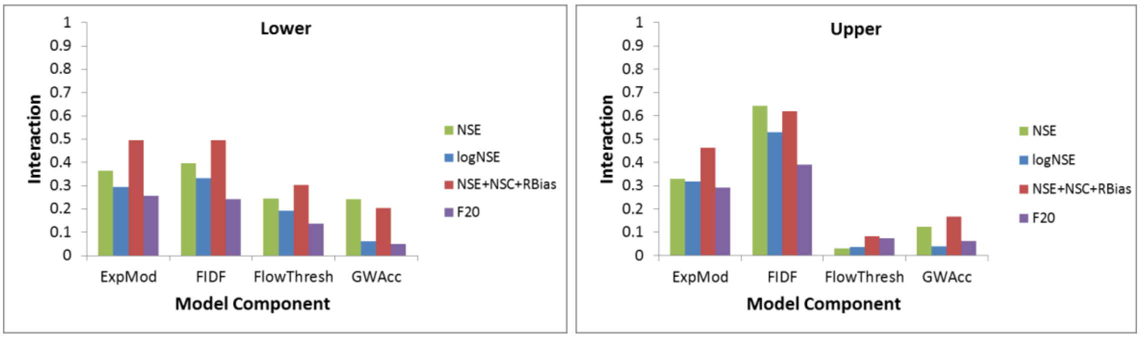


Figure 62. Interaction (S_{Ti}-S_i) for the four most sensitive model components for each objective function.

Impact of parameter ranges (Scenarios 2 and 3)

Scenarios 2 and 3 modified the FIDF and Flow Threshold parameter ranges as described in Table 11. Reduction of the FIDF range in Scenario 2 generally increased the sensitivity of the expert model and decreased the sensitivity of FIDF, although this varied between comparison metrics and upper and lower bounds (Figure 61). Subsequently decreasing the Flow Threshold range in Scenario 3 reduced its sensitivity, and resulted in some increase in FIDF sensitivity.

Whilst it is evident that parameter ranges have an impact on sensitivity, they did not change the overall pattern of which parameters were most sensitive, based on the metrics and ranges tested here.

5.5 Discussion

The sensitivity of model outcomes to model conceptualisation clearly demonstrates the importance of understanding key processes that influence ecological response, as well as understanding the consequences of model conceptualisation on predicted outcomes. Sensitivity analysis can help identify system processes that are not adequately represented within the model, or processes that may not be as important as originally expected.

The challenge of conceptualising complex systems is well recognised (Rittel and Webber, 1973; Game *et al.*, 2014; Hirsch *et al.*, 2011) and is by no means new. However, few studies in the fields of water management and ecology have examined the implications of problem conceptualisation. Refsgaard *et al*. (2007), Saltelli and Annoni (2010), Shin *et al* (2013), Uusitalo *et al*. (2015) identified a lack of studies that undertake a rigorous uncertainty and sensitivity analyses, and those which do primarily focus on parameters and data inputs which can be much less significant depending on the inputs considered. This study endeavours to address this gap for the case of ecological models. However, the results presented here on the use of sensitivity analysis to explore model behaviour have significant implications not just for ecological models, but for environmental modelling generally.

Given that many of the uncertainties associated with modelling complex systems cannot be fully understood and represented, it is recommended that modelling such systems consider different plausible model conceptualisations in interpreting any results. As part of this study, the five expert models have been utilised in the analysis of different management options (as described in Part C, Chapter 8) to explore the impact of uncertain conceptualisations on management strategies. This work could be extended to investigate the impacts of different types of ecological response models such as the Murray Flow Assessment Tool (Young *et al.*, 2003), which is likely to result in larger variations still.

Whilst the expert model conceptualisation had the greatest impact on outcomes across the majority of comparison metrics and parameter ranges, a number of parameter inputs were also found to have a significant impact on results based on Expert Model 1. The most sensitive parameters were the flow inundation duration factor, flow threshold and groundwater access for the hydrological component, and the 'too wet' factors for the ecological component.

The flow inundation duration factor is a multiplication factor to convert flow duration at Booligal gauge to an inundation duration within the Great Cumbung Swamp. The sensitivity of the model to this parameter is expected given that inundation is the driving factor that determines River Red Gum condition within the model. Similarly, it is expected that sensitivity to the flow threshold would occur, and in this case is at least partly desirable as it is used to define two different areas within the Swamp for the purpose of estimating inundation.

However, these sensitivities also highlight the importance of understanding flow and inundation patterns in estimating the impact of environmental flow releases on wetland vegetation. In many wetland systems this can be incredibly challenging given the flat topography and complex network of interconnected channels and water bodies. Small changes in landscape such as build-up of vegetation or artificial construction of barriers on farmland can have significant impact on the distribution of flood waters.

In addition, the duration of any flood event is highly dependent upon factors such as previous flood events, rainfall and groundwater levels (influencing soil moisture); temperature and evapotranspiration; as well as land management and water extractions such as diversions between the Booligal gauge and the Great Cumbung Swamp. Of these, the ERM model presented here considers the influence of rainfall on inundation, and the effect of previous flood events on inundation by adjusting the threshold required to trigger an inundation event.

Access to groundwater was also found to have a significant impact on results. The model assumes that access to groundwater will reduce or delay the decline in condition during periods of no surface water availability, and hence it can be critical for survival during droughts. Whilst there have been a number of studies examining uptake of groundwater by vegetation (e.g. Greenwood *et al*., 1992; Robinson *et al*., 2006; and Jobbágy and Jackson, 2007) as well as those specifically looking at River Red Gum (Thorburn and Walker, 1994; Mensforth *et al.*, 1994; Cunningham *et al*., 2011), there is limited understanding of the interaction between surface and groundwater availability on plant condition, and few ecological response models used in basin management that have incorporated such interactions. There is often also limited data available to estimate groundwater levels across a wetland to an accuracy that can be used to estimate likely access by vegetation. Given that results suggest that groundwater can have a significant impact on modelled condition, further research into surface water/groundwater dynamics in sustaining wetland vegetation is needed.

The higher sensitivities of flow based inundation parameters compared with those of rainfall indicates that riverine based inundation has a greater impact across all expert models compared with rainfall based inundation. This is not surprising given flow based inundation is given precedence in the model (if flow exceeds the threshold, rainfall is not considered as the inundation is considered to dominate). However, the dominance of the FIDF parameter in particular may be partially due to its parameter range, where small changes in the FIDF can have a significant impact on the River Red Gum condition score due to the multiplication effect of flow duration at the upstream Booligal gauge (where Great Cumbung Swamp inundation duration = FIDF x Booligal duration). Despite the comparatively low sensitivity of rainfall parameters, preliminary testing of the model with and without rainfall in Chapter 4 demonstrated the importance of considering rainfall in the calculation of River Red Gum condition.

Case 1 demonstrated that the parameters defining the 'too wet' period of the ecological model also had a significant impact on results. Whilst the sensitivity of the TW1 and TW2 parameters were not as great as FIDF, Case 1 further highlights that defining appropriate ecological parameters is essential, in addition to model conceptualisation. In this case, the high sensitivity of the 'too wet' parameters is likely to be caused by the fast decline in River Red Gum condition to zero compared with the dry period (the lower sensitivity bound results in a decline to zero condition (dead) after two months inundation). Whilst smaller parameter bounds reduce the sensitivity to this parameter, the too wet curve for the base case also reduces condition far more quickly than the dry period curve for River Red Gum starting in good condition (approximately 14 months compared with 10 years). Based on the expert interviews, response of River Red Gum to extended inundation periods is not well understood, and there was substantial variation in views between the five experts. As with inundation patterns, the change in condition is highly dependent on preceding events. If River Red Gum has already sustained extended wet periods, or is in poor condition due to a long drought, a new extended inundation can have a greater impact compared with a healthy individual (P. Packard, pers. comm., 2013).

The large interactions between parameters when comparing first and total sensitivities is not surprising given the parameters chosen. Expert Model and FIDF have the highest interactions, with Expert Model being dependent on all the other model parameters, and FIDF being closely linked with both the Expert Model and parameters defining inundation (such as flow threshold and duration threshold). Ideally, the exact interaction effects would be calculated to provide further information about model behaviour, but these cannot be determined by the Saltelli (2002) implementation of Sobol' (which calculates a reduced set of interactions). Calculating each order of interactions is computationally prohibitive, requiring up to $N x 2^P$ evaluations (Homma and Saltelli, 1996; Saltelli, 2002).

Variation in sensitivity for different parameter ranges for FIDF and flow threshold in both Case 1 and Case 2 demonstrated that the results of sensitivity analyses need to be considered as indicative only. Similarly, the comparison metrics also varied the sensitivity of model components, and in some cases changed the order of the most sensitive parameters (for example, FIDF had a larger S_{Ti} than Expert Model for NSE in scenario 1, but a lower S_{Ti} for the other three metrics). Similar impacts of parameter ranges and metrics have been shown by Shin *et al* (2013).

Comparison metrics are a means of summarising the results and can emphasize some differences more than others. They should also be carefully selected based on the intended use of the model, with the impact of different functions being investigated. There has been much discussion in the literature regarding the use of metrics such as NSE in hydrology, and the need to understand the physical meaning of metrics rather than applying them blindly to compare simulated and observed outputs (e.g Gupta *et al*., 2009; van Werkhoven *et al*., 2009; and Clark *et al*., 2011). In this case, metrics were selected to compare a base case model with variations in model conceptualisation and parameter values. Four different metrics were compared to examine different types of deviations from the base case. However, this work could be improved by using metrics which have greater ecological significance, or which are more relevant to the management options being investigated. For example, the objective functions used in multi-objective optimisation in Chapter 8 could be used as metrics, as demonstrated by Kasprzyk *et al*. (2012). Further discussion on the impact of metrics is provided in the following chapters (Chapters 6, 7 and 8).

Given the impact of parameter ranges and metrics on sensitivity, insensitive parameters should not necessarily be discounted. Insensitivity within the model also does not mean the processes they represent are insensitive in reality, and may still have important impacts on the conclusions being made in a management strategy (Shin *et al* 2013). In this case, whilst parameter ranges and metrics varied the sensitivity of model components, the results showed similar patterns of sensitivity with FIDF, FlowTrsh, GWAcc, Expert Model and the too wet parameters having the highest sensitivity.

5.6 Conclusions

The above analysis demonstrates the importance of undertaking a sensitivity analysis to better understand model behaviour, and facilitate exploration of why certain model components and parameters have a greater impact than others. This type of investigation is particularly important in complex models where inputs and model structure are highly uncertain.

The current work provides four main contributions:

(1) Demonstration that different ecological model conceptualisations can have a significant impact on model results, and the impact can be much greater than that caused by variation in parameter values;

(2) Sensitivity to hydrological parameters indicates that the ability to estimate ecological response is highly dependent on the capacity to represent hydrological processes which are often uncertain;

(3) Results suggest that further investigation into the role of groundwater in supporting wetland vegetation is warranted, given few existing ERMs take it into consideration; and

(4) Demonstration of the importance of using methods such as sensitivity analysis to improve model and system understanding, with careful consideration of the assumptions applied in the analysis, such as the comparison metrics used.

This work also identified the need for greater consideration of how the outcomes of sensitivity analyses impact on management options in future research. For example, given the sensitivity of model outcomes to the expert model, what would be the impact of different types of environmental flow approaches? How would the natural flow approach compare with the species preference approach in terms of recommended management? How would the same management strategy perform using these different environmental flow approaches?

Chapter 6: Assessing model credibility under uncertainty using Bayesian probabilities

6.1 Aim and overview

Chapters 3 to 5 explored some of the significant challenges in understanding and modelling ecological response to changes in water availability, using the case study of the Great Cumbung Swamp, Lachlan catchment. Development of the ecological response model in Chapters 3 and 4 identified multiple sources of uncertainty, with preliminary analysis indicating these have potential to significantly impact on results. Sensitivity analysis was then undertaken in Chapter 5 to explore the impact on ecological condition scores of both expert conceptualisation of ecological response, as well as ecological and hydrological parameters. It was identified that different expert models generally had the largest impact, followed by hydrological assumptions including flow threshold, groundwater access, and to a lesser extent rainfall. Both the system conceptualisation and parameters are highly uncertain, and hence have significant implications for management decisions.

Given these uncertainties and the range of 'plausible' models for representing ecological condition, the question remains which model(s) (if any) is most likely to represent *actual* ecological response. The purpose of this chapter is therefore to evaluate model performance to identify whether any of the expert models and set of assumptions provide a credible estimate of condition based on observed data. In doing so, a novel approach for assessing uncertainty for environmental flow management is developed.

The approach draws upon Bayes Theorem and considers both model and observational uncertainty. The three main contributions of this chapter are:

(1) Development of an approach for comparing different model assumptions with observed data, considering multiple sources of uncertainty in both hydrological and ecological components;

(2) Undertaking a comprehensive evaluation of model behaviour to improve system understanding, and to further explore existing uncertainties in ecological response modelling; and

(3) Examining the implications of these uncertainties in applying ecological response models to support decision making for environmental flows.

6.2 Introduction

The effective use of models to aid in decision making lies in an understanding of the system being represented, of how well it is represented by the modelling framework, and an awareness of the limitations and uncertainty around this understanding. Developing this understanding is fundamental to any model evaluation exercise, especially for complex systems where uncertainties are significant. Given the complexity entailed in environmental flow management, there has been remarkably little assessment of uncertainty. As discussed in Chapter 4, a study by Fu and Guillaume (2014) is one of the few which evaluates uncertainty in ecological response modelling.

In comparison, there has been a large volume of research devoted to model assessment in the fields of hydrology and ecology. Previous research has explored and developed methods, metrics and frameworks for model comparison and selection, model averaging, and model evaluation. Examples of these are provided below.

Model comparison

A number of generalised frameworks have been developed to aid in model comparison, including both Bayesian and non-Bayesian approaches. Approaches include the Generalised Likelihood Uncertainty Estimation (GLUE) (Beven and Binley, 1992); the Bayesian total error analysis (BATEA) method (Kavetski *et al.*, 2006); the differential evolution adaptive Metropolis (DREAM) method which builds on BATEA (Vrugt *et al.*, 2008); and the Model-Independent Parameter Estimation and Uncertainty Analysis (PEST) (Doherty, 2015). These were developed primarily for parameter estimation and uncertainty analysis in environmental models (predominantly hydrological models), thereby providing a method for comparison of different parameter sets. Whilst the focus of these methods is on calibration, they also provide a mechanism for comparing multiple model structures and conceptualisations (Krueger *et al.*, 2010; Clark *et al.*, 2011).

Alternative selection methods include the Framework for Understanding Structural Errors (FUSE) developed by Clark *et al*. (2008), which considers differences in conceptualisation and parameterisation of individual model elements. Kampf and Burges (2007) also developed a framework for considering differences in represented processes, flow equations, model coupling, solution techniques, and spatial and temporal resolution. Both frameworks were developed for hydrological modelling.

In ecological modelling (primarily for conservation planning), two commonly used methods are the Akaike's Information Criterion (AIC) and Bayesian Information

Criterion (BIC), which calculate the maximum likelihood over the parameter space rather than integrating the likelihood function (Ward, 2008).

Model averaging

A number of Bayesian based methods have also been developed specifically for model averaging. For example, Bayesian model averaging (BMA) (Madigan *et al*., 1996; Duan *et al*., 2007) and hierarchical mixtures of experts (HME) (Jordan and Jacobs, 1994; Marshall *et al*., 2007) combine models using a weighted average calculated using the Bayes factor (the ratio of the posterior probability for different models, i.e. the probability of observing the data set given Model A compared with Model B). The Bayesian HME method developed by Marshall *et al*. (2007) is an extension to BMA in that weights are varied during the simulation to draw upon different model strengths, such as representation of high or low flows. A similar method is also applied by Hsu *et al*. (2009) to update model weights at each time step based on available information.

Most studies using multiple models have found an improvement in outcome and understanding of model behaviour compared with using a single model (Butts *et al.*, 2004; Marshall *et al.*, 2007; Buytaert and Beven, 2011; Gudmundsson *et al.*, 2012; Foglia *et al.*, 2013; Pande, 2013; Duan *et al.*, 2007), although the magnitude of the improvement varied. However, other studies report relatively little variation in results (see Clark *et al*., 2011 for summary).

Model evaluation metrics

In addition to model comparison and averaging methods, statistical metrics have been developed for evaluating model performance against observed data, and have primarily been applied in hydrological modelling. These include the Nash Sutcliffe Efficiency (NSE) index (e.g. Marshall *et al*., 2007; Hsu *et al*., 2009; and Krueger *et al*., 2010); Root Mean Square Error (RMSE), bias, correlation coefficient and mean absolute error (e.g. Hsu *et al*., 2009); and deviation between observed and modelled (e.g. Krueger *et al*., 2010). The capacity of these metrics to provide meaningful comparison is the subject of considerable scrutiny (e.g. Węglarczyk, 1998; Criss and Winston, 2008; Jain and Sudheer, 2008; Gupta *et al*., 2009).

Despite the substantial increase in model comparison and multiple model use, many studies in hydrology and ecology lack a comprehensive exploration of model performance and the impact of key uncertainties on decision outcomes (Butts *et al.*, 2004; Clark *et al.*, 2011; Regan *et al.*, 2002). A number of remaining gaps and challenges have been identified, and include: the majority of modelling studies still apply only a single model, even if multiple models are considered during the development phase (Clark *et al.*, 2011; Foglia *et al.*, 2013); few studies consider differences in processes and model structure, with the majority focusing on variations in parameter values (Butts *et al.*, 2004); limited studies consider (and distinguish between) the full range of uncertainty in input data, conceptualisation, and model representation (Clark *et al.*, 2011; Regan *et al.*, 2002); there is a need for indices which better reflect physically meaningful processes, as current metrics may provide poor indication of difference in model performance (Clark *et al.*, 2011; Foglia *et al.*, 2013).

Given the limitations described above, this chapter has three main aims: to address existing limitations by developing an approach for investigating model behaviour and evaluating performance in the context of limited data and significant uncertainty; to provide a methodology which can be applied specifically for environmental flow management; and to apply this methodology to the Great Cumbung Swamp case study. Limitations which are addressed include: the application of multiple models to aid decision making; the consideration of multiple sources of uncertainty including different model conceptualisations informed through stakeholder engagement; and the development of metrics which incorporate different uncertainties.

Using formal Bayesian statistics, the expert based ecological response models (ERMs) developed in Chapters 3 and 4 are assessed considering five types of uncertainty: (1) uncertainty in the conceptualisation of ecological response to water availability; (2) uncertainty defined by each expert's upper and lower ecological bounds; (3) uncertainty within these upper and lower bounds; (4) uncertainty in hydrological assumptions; and (5) uncertainty in the observed data.

A description of the methodology developed is provided below, followed by a discussion of results and implications for environmental flow management.

6.3 Methodology

Bayesian analysis was applied to investigate the five sources of uncertainty described above. A description of the general approach developed is provided below, followed by application to the current case study. The methodology is therefore divided into the following subsections: (1) Application of Bayes Theorem for model evaluation; (2) Derivation of likelihood functions for the expert models; (3) Calculation of marginal probabilities; (4) Development of software code for evaluation of model performance; and (5) Application to the Great Cumbung Swamp case study.

6.3.1 Application of Bayes Theorem for model evaluation

The five types of uncertainty considered in the current analysis are shown in Figure 63, where (e_i) is the expert conceptualisation of ecological response; (L_{ij}, U_{ij}) is the degree of confidence in modelling ecological response as stated by experts; (Δ_k) is the uncertainty in expert defined upper and lower ecological bounds relative to observations; (q_j) is the set of hydrological model assumptions; and (b_n) is the bias in observed data. The uncertainties e_i, Δ_k, q_j, and b_n can be described as a set of discrete values which represent plausible assumptions, as shown in Equations 21 to 24. (L_{ij}, U_{ij}) in Equation 25 represents the discrete set of model predictions as a set of lower and upper possible ecological condition scores.

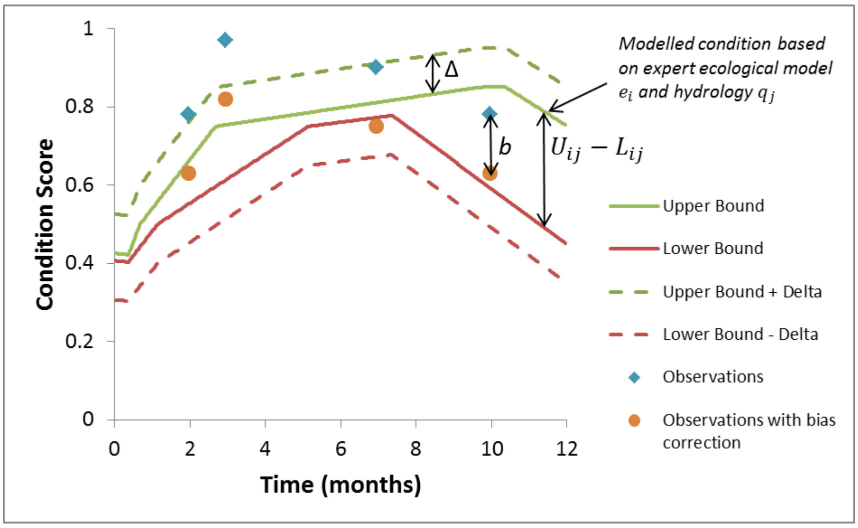


Figure 63. Five sources of uncertainty considered: conceptualisation of ecological response (e_i); upper and lower ecological bounds (U_{ij}, L_{ij}); uncertainty in these bounds (Δ); uncertainty in hydrology (q_i); uncertainty in observations (b).

$$e_i = \{i, \quad i = 1, \ldots, nE\} \tag{21}$$

$$q_j = \{j, \quad \mathrm{j} = 1, \ldots, nQ\} \tag{22}$$

$$\Delta_k = \{k, \quad \mathrm{k} = 1, \ldots, nD\} \tag{23}$$

$$b_n = \{n, \quad \mathrm{n} = 1, \ldots, nB\} \tag{24}$$

$$x_m = \left(L_{ij}, U_{ij}\right);\ x_m = \{x_{mt}, \quad t = 1, \ldots, nT\} \tag{25}$$

where:

e_i = ecological response model for expert i and a total of nE expert models

q_j = hydrological assumption set j, based on assumptions for Great Cumbung Swamp inundation, rainfall and groundwater, with a total of nQ sets of assumptions

Δ_k = the uncertainty k in the modelled upper and lower condition scores *relative* to the observed scores, with nD different possible values for Δ. This captures uncertainty in both the modelled and observed ecological condition.

b_n = bias of value n to adjust the observed data set, with nB possible values.

x_m = uncertainty in estimated ecological response explicitly defined by experts, represented through lower (L_{ij}) and upper (U_{ij}) estimates of ecological response using expert model e_i and hydrological assumptions q_j, with a total of nT modelled scores.

The uncertainties e_i, x_m, and q_j relate specifically to the expert based ERM, consisting of combined ecological and hydrological components. The first of these involves the comparison of different expert models, recognising the uncertainty in representing ecological response to water availability, and that different sources of knowledge can lead to different insights and understanding about ecological response. Secondly, experts identified uncertainty in their estimates of ecological response, hence provided ranges of possible condition scores rather than estimating a precise outcome. As described in earlier chapters, the ERM is unique in that it does not calculate an exact value for ecological condition, but instead assumes that there is sufficient uncertainty such that only an upper and lower bound of possible condition scores is feasible to model. The model is therefore indifferent to the actual ecological condition as long as it falls within the uncertainty bounds. The degree of stated uncertainty varies between experts, influencing the precision of the modelled condition scores. The third component considers the uncertainty in the hydrological model through exploring different hydrological assumptions. These three components have all been introduced in preceding chapters.

The fourth (Δ) and fifth (b) components consider uncertainty in both the model predictions and observations, and are introduced in this chapter for the specific purpose of evaluating model performance relative to observed data using likelihood functions. Whilst the experts define upper and lower bounds for estimating condition scores, it is assumed that there is also uncertainty associated with these bounds. In addition, there is uncertainty associated with the observed data, hence a discrepancy between observed and modelled condition scores may be a combination of uncertainty in both. Δ is therefore used to avoid discounting models which are close to the observations but do not encompass them. A larger value of Δ provides greater leniency toward differences in modelled and observed values, at the cost of reduced model precision.

Bias (b) accounts for uncertainty in modelled and observed values through a systematic shift of all observations. Systematic differences may occur due to the observations not being representative of ecological condition throughout the entire case study area, or a consistent under or over estimation of condition in either the observations or expert models. In this case study, a bias is applied to account for a difference in resolution between modelled and observed condition scores, where observations are at a coarser resolution and hence there is uncertainty in what the equivalent value is at a finer resolution. This is explained in greater detail in Section 6.3.5.3.

It is recognised that the total uncertainty is not fully described by these components. However, this analysis enables the consideration of multiple sources of uncertainty derived from model components shown to have a significant impact on results in the sensitivity analysis, as well as knowledge of uncertainty in observations. It also acknowledges that the magnitude of uncertainty is unknown, hence different combinations of expert models, hydrological assumptions, Δ values and bias are explored.

Taking a given set of upper and lower modelled ecological condition scores (x_m), the posterior probability of a particular set of assumptions $\{e_i, q_j, \Delta_k, b_n\}$ given a set of observed ecological condition using historical data can be described as:

$$P\left(\theta_{ijkn} \middle| x_o H\right) \tag{26}$$

where:

$\theta_{ijkn} = \{e_i, q_j, \Delta_k, b_n\}$

x_o = observed data, $x_o = \{x_{ot}, \quad t = 1,...,nT\}$

H = additional model assumptions not explicitly explored (hereafter assumed to be implicit in $P\left(\theta_{ijkn} \middle| x_o\right)$)

Given a systematic bias b_n is used to adjust the observed data by a specified value to account for differences in resolution between modelled and observed condition scores, Equation 26 is rewritten as:

$$P\left(\theta_{ijkn} \middle| x_o\right) = P\left(\theta_{ijkn} \middle| z_n\right) \tag{27}$$

where:

$$z_n = x_o + b_n$$

Bayes Theorem can be used to evaluate different sets of assumptions using Equation 28, to identify which set of assumptions has the highest probability of matching the observed data. Drawing upon conditional probability, Bayes Theorem states:

$$P\left(\theta_{ijkn} \middle| z_n\right) = \frac{p\left(z_n \middle| \theta_{ijkn}\right) P\left(\theta_{ijkn}\right)}{p\left(z_n\right)} \qquad (28)$$

$P\left(\theta_{ijkn} \middle| z_n\right)$ is the posterior distribution or conditional probability of the model and uncertainty assumptions (θ_{ijkn}**)**, given the set of adjusted observations (z_n); $p\left(z_n \middle| \theta_{ijkn}\right)$ is the likelihood function which defines the probability distribution used to sample the bias-corrected observations given a particular set of model assumptions; $P(\theta_{ijkn})$ is the prior probability representing existing assumptions/knowledge regarding model performance; and $p(z_n)$ is the marginal probability density of the bias-corrected observed data.

Given that $p(z_n)$ is independent of $P(\theta_{ijkn})$, Equation 28 can be rewritten as:

$$P\left(\theta_{ijkn} \middle| z_n\right) \propto p\left(z_n \middle| \theta_{ijkn}\right) P\left(\theta_{ijkn}\right) \qquad (29)$$

The likelihood function can be simplified if it is assumed each observation is statistically independent of other observations:

$$\begin{aligned} p\left(z_n \middle| \theta_{ijkn}\right) &= p\left(z_{n1}, ..., z_{nT} \middle| \theta_{ijkn}\right) \\ &= p\left(z_{n1} \middle| z_{n1:nT-1}, \theta_{ijkn}\right) p\left(z_{n1:nT-1} \middle| \theta_{ijkn}\right) \\ &= p\left(z_{nT} \middle| \theta_{ijkn}\right) p\left(z_{nT-1} \middle| \theta_{ijkn}\right) ... p\left(z_{n1} \middle| \theta_{ijkn}\right) \end{aligned}$$

hence:

$$P\left(\theta_{ijkn} \middle| z_n\right) \propto \prod_{t=1}^{n_T} p\left(z_{nt} \middle| \theta_{ijkn}\right) P\left(\theta_{ijkn}\right) \qquad (30)$$

Equation 30 assumes the difference between modelled and observed values at time *t* is independent from that at time *t-1*. This assumption is considered reasonable on practical grounds. First, each set of (observed, modelled) points are a minimum of 29 days apart. Second, there is insufficient data to guide the development of a more complex dependence model. Third, it is believed that the improvement introduced by a dependence model would be small compared with the uncertainties associated with observed and modelled ecological response.

It therefore remains to calculate the likelihood $p\left(z_{nt}\left|\theta_{ijknt}\right.\right)$ for individual instances of *i, j, k* and *b*, and prior probabilities $P\left(\theta_{ijknt}\right)$.

6.3.2 Derivation of likelihood functions

The marginal probability $p(z_{nt}|\theta_{ijkn})$ of a single observed condition value given a model and set of assumptions can be described using a likelihood function such as that shown in Figure 64. Given the majority of models developed in both hydrology and ecology predict a single outcome rather than a set of possible outcomes, likelihood functions which have been previously applied also adopt a single 'best' outcome, and typically take the form of a Gaussian or similar distribution (Beven and Binley, 1992; Kavetski *et al.*, 2006b; Duan *et al.*, 2007; Ajami *et al.*, 2007; Vrugt *et al.*, 2008; Vrugt *et al.*, 2009). As shown in Figure 64, 'X' represents the single point with the highest probability in the likelihood function.

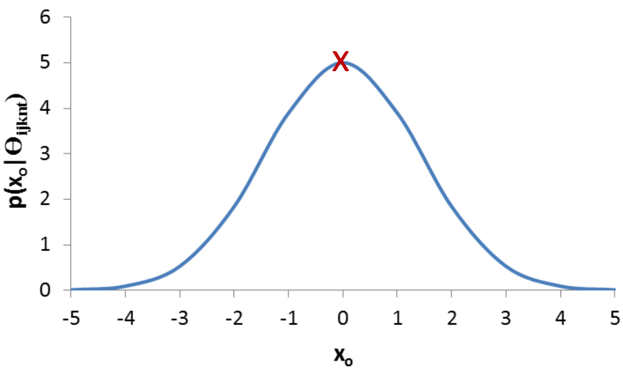


Figure 64. Example of a Gaussian likelihood function assuming a single predicted model outcome

The ERM developed here deviates significantly from previous models of ecological response in the use of upper and lower uncertainty bounds. To account for the explicit representation of uncertainty in estimating ecological response, a new likelihood function was derived to assign equal weight to observations falling between modelled bounds, and decreasing weight to observations outside these bounds. The general form of the likelihood function applied is shown in Figure 65. An exponential decay is used either side of the model bounds to account for uncertainty in the model bounds and in observed data, such that the model is not disregarded if observations fall just outside the modelled range defined by the lower and upper limits (Equation 31).

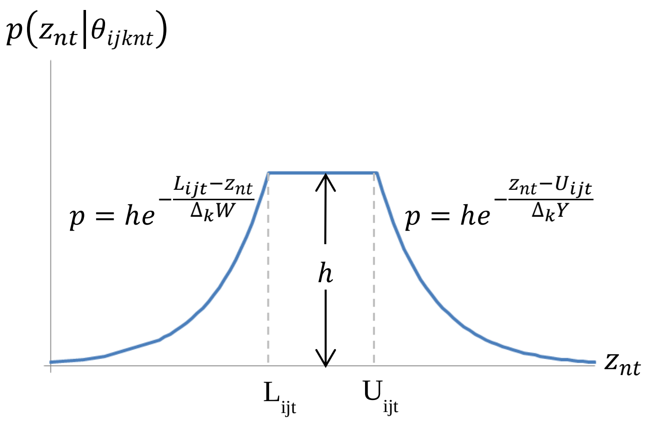


Figure 65. Likelihood function for a model with lower and upper uncertainty bounds where L_{ijt} is the lower ecological model bound at time *t*; U_{ijt} is the upper ecological model bound at time *t*; z_{nt} is the observed ecological score + bias b_n; and h is the likelihood of observing any given value of z_{nt}.

The general form of the likelihood function is

$$p\left(z_{nt}\middle|\theta_{ijkn}\right) = \begin{cases} he^{-\frac{L_{ijt}-z_{nt}}{\Delta_k W}} & if\,(z_{nt}) < L_{ijt} \\ he^{-\frac{z_{nt}-U_{ijt}}{\Delta_k Y}} & if\,(z_{nt}) > \mathrm{U}_{ijt} \\ h & otherwise \end{cases} \tag{31}$$

where:

h = likelihood of observing z_{nt}

W, Y = factors used to adjust Equation 31 for testing different variations of the likelihood function

The rate of decay is controlled by the variable Δ_k, where larger values of Δ result in slower rates of decay and hence greater tolerance of differences between observed and modelled data (Figure 66). This increased tolerance has the effect of reducing the predictive capacity of the model even when observed values fall between upper and lower bounds, as shown by lower likelihoods for Δ = 0.2 compared with 0.1 in Figure 66. Different values of Δ are compared to determine which value results in the highest likelihood score for different expert models.

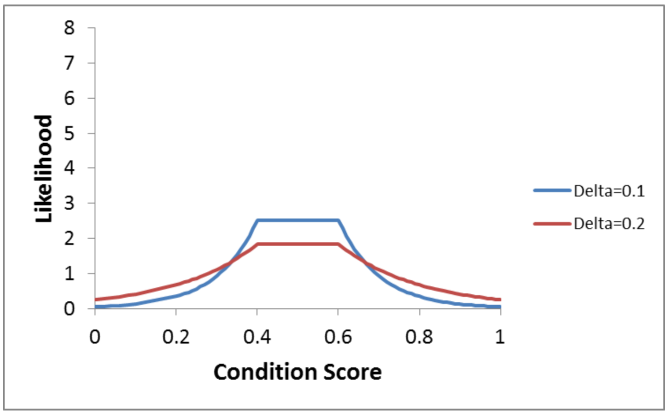


Figure 66. Higher values of Delta result in a more gradual reduction in likelihood either side of the expert model bounds.

The predictive capacity of the model is also influenced by the width of the model bounds defined by the experts, describing varying levels of uncertainty in ecological response. Wide model bounds capture a greater level of uncertainty, which is likely to be realistic in many cases given the complexity of the system. However, whilst wider model bounds have a greater likelihood of capturing the actual, observed ecological response, the model has less predictive capacity. This is demonstrated in Figure 67, where three models with different uncertainty bounds are shown, reflecting different predictive capacity. It can be seen that the wider uncertainty bounds in Model C produce a lower likelihood at any single point, reflecting the less informative nature of the model. In comparison, Model B is more precise and hence can be more informative, and therefore receives a higher likelihood score. However, if the observations fall outside its prediction, the probability score rapidly declines below that of models A and C.

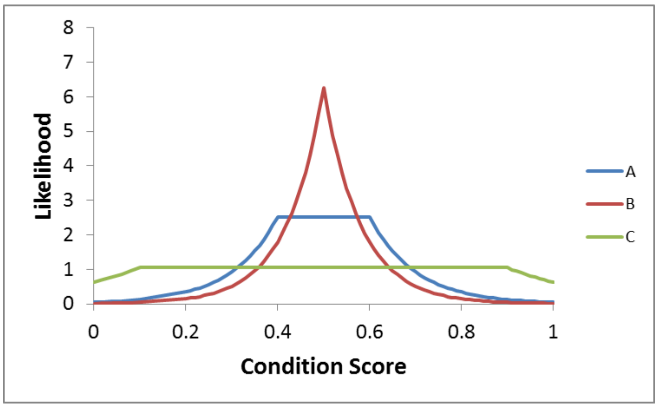


Figure 67 Examples of likelihood functions for three different ecological models with varying precision, all centred at a condition score of 0.5.

Given that the modelled condition scores are bounded by the values [0,1], and the area under the likelihood function must equal one, the shape of the likelihood functions are strongly influenced by the actual value of observed and modelled data. For this reason, three variations of the likelihood functions were compared, with slight differences in the way the likelihood $p(z_{nt}|\theta_{ijkn})$ is calculated.

Likelihood Function 1: Value Based

The Value Based likelihood function considers the actual *value* of the modelled and observed scores to be important, along with the magnitude of the *difference* between modelled and observed data points, irrespective of whether the observation is above or below the modelled point. This is demonstrated using Figure 68, where the Value Based likelihood function is shown for three different ecological condition scores (using an arbitrary model where $L_{ijt} = U_{ijt}$ for demonstration purposes).

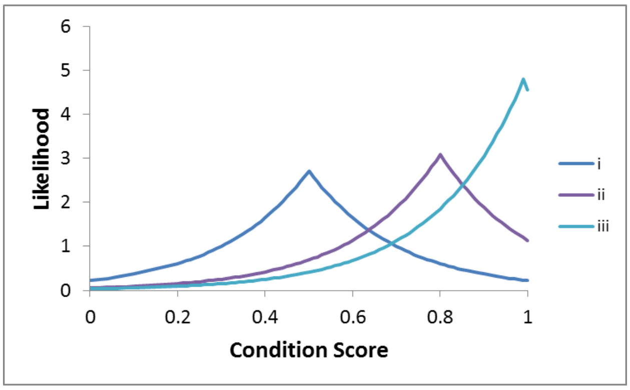


Figure 68. Value Based Likelihood functions where *h* is influenced by the value of the condition score, for an arbitrary model where $L_{ijt} = U_{ijt}$.

From Figure 68 it can be seen that higher likelihood values are obtained for higher condition scores compared with moderate condition scores. For condition scores which are either high or low, larger likelihood values are obtained given the observations can only occur on one side of the modelled values (a model with a prediction of 1 cannot have observations higher than 1). Condition scores which are either higher or lower than 0.5 have likelihood functions with a larger likelihood to accommodate the longer uncertainty tail either side of the modelled scores. In Figure 68, model *i* has two uncertainty tails either side of the modelled score of 0.5 and hence a lower value of *h*. In comparison, model *iii* which has a modelled value of 0.99, has a single long uncertainty tail and a large value of *h*.

This approach gives emphasis to matching observed and modelled data at high and low scores. The disadvantage is that it can disregard models which perform well at more moderate scores, which has implications for model comparison.

Calculation of the Value Based likelihood function is described using Equation 32, where the factors *W* and *Y* in Equation 31 are both equal to one:

$$
p\left(z_{nt}\left|\theta_{ijkn}\right.\right)=\begin{cases} he^{-\frac{L_{ijt}-z_{nt}}{\Delta_k}} & if\,(z_{nt})<L_{ijt} \\ he^{-\frac{z_{nt}-U_{ijt}}{\Delta_k}} & if\,(z_{nt})>\mathrm{U}_{ijt} \\ h & otherwise \end{cases} \tag{32}
$$

Based on Equation 32, h is calculated as follows:

$$
h\left(U_{ijt}-L_{ijt}\right)+\int_{U_{ijt}}^{1} he^{-\left(\frac{z_{nt}-U_{ijt}}{\Delta_k}\right)}dz+\int_{0}^{L_{ijt}} he^{-\left(\frac{L_{ijt}-z_{nt}}{\Delta_k}\right)}dz=1
$$

where:

$$
\int_{U_{ijt}}^{1} e^{-\left(\frac{z_{nt}-U_{ijt}}{\Delta_k}\right)}dz=\Delta\left[1-e^{1\left(\frac{1-U_{ijt}}{\Delta_k}\right)}\right]
$$

$$
\int_{0}^{L_{ijt}} e^{-\left(\frac{L_{ijt}-z_{nt}}{\Delta_k}\right)}dz=\Delta\left[1-e^{-\left(\frac{L_{ijt}}{\Delta_k}\right)}\right]
$$

hence:

$$
h=\frac{1}{U_{ijt}-L_{ijt}+\Delta_k\left[2-e^{-\left(\frac{1-U_{ijt}}{\Delta_k}\right)}-e^{-\left(\frac{L_{ijt}}{\Delta_k}\right)}\right]} \tag{33}
$$

Likelihood Function 2: Difference Based

The Difference Based likelihood function assumes that the primary goal of comparing modelled and observed data is in determining the *difference* between each set of modelled and observed data points, whilst the actual *value* of each point is unimportant. The method ensures that comparison is based only on the precision of the model (width between upper and lower bounds); and on the relative position of observed and modelled data.

This is achieved by adjusting all model upper and lower bounds so they centre at 0.5. Taking the three same arbitrary models shown in Figure 68 (i,ii,iii) at time t and model scores of (0.5,0.8,0.99) respectively, Figure 69 shows the impact on h when the models are all centred at 0.5. It can be seen that all three models now have equal values of h and are equidistant from the observed value. Observed data are also adjusted to keep the same distance between observed and modelled points.

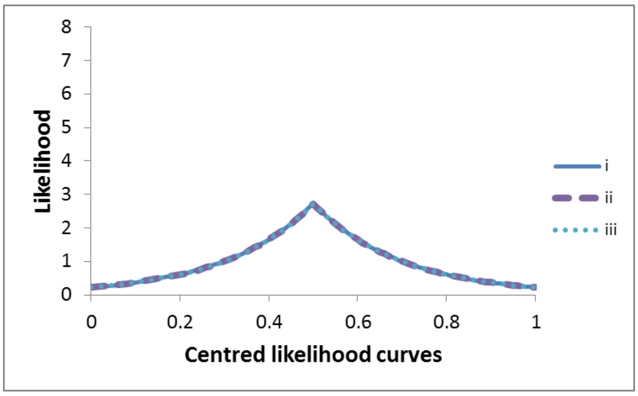


Figure 69 Difference Based Likelihood functions for an arbitrary model where L_{ijt} = U_{ijt}: differences between observed and modelled data are considered whilst the raw values are ignored.

The condition scores are centred using Equation 34, where U_{ct}, L_{ct} and z_{ct} are the adjusted condition scores for the modelled upper bound, modelled lower bound, and bias corrected observations respectively:

$$c = 0.5 - \frac{U_{ijt} + L_{ijt}}{2} \tag{34}$$

$$U_{ct} = U_{ijt} + c$$

$$L_{ct} = L_{ijt} + c$$

$$z_{ct} = z_{nt} + c$$

The modified likelihood function is described in Equation 35. In this case, factors *W* and *Y* are also both equal to one.

$$p\left(z_{nt} \middle| \theta_{ijkn}\right) = \begin{cases} he^{-\frac{L_{ct} - z_{ct}}{\Delta_k}} & if\,(z_{ct}) < L_{ct} \\ he^{-\frac{z_{ct} - U_{ct}}{\Delta_k}} & if\,(z_{ct}) > \mathrm{U}_{ct} \\ h & otherwise \end{cases} \tag{35}$$

hence:

$$h = \frac{1}{U_{ct} - L_{ct} + \Delta_k \left[2 - e^{-\left(\frac{1 - U_{ct}}{\Delta_k}\right)} - e^{-\left(\frac{L_{ct}}{\Delta_k}\right)} \right]} \tag{36}$$

Likelihood Function 3: Relative Based

The third likelihood function addresses the discrepancy in values of h for different condition scores but at the cost of different slopes either side of the upper and lower bound (Figure 70). This method assumes the actual *value* of the condition score is important (and hence does not centre values at 0.5), and preserves the same value of h irrespective of the condition score. However, it means that the value of h assigned to the model differs depending on whether the observed value falls above or below the modelled value (i.e. where the observations are *relative* to the model). This results in modelled values which fall just above observed values are rewarded over modelled values falling just below for condition scores <0.5, with the reverse true for condition scores >0.5.

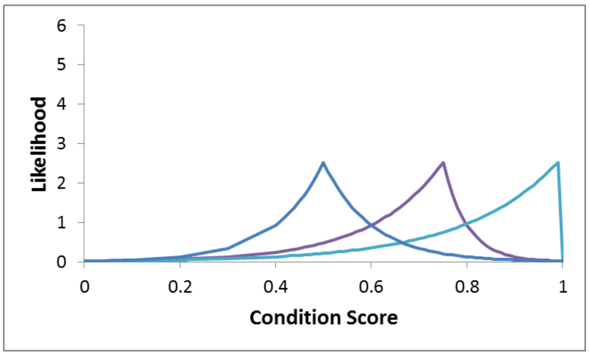


Figure 70 Relative Based Likelihood functions where the value of the condition score is considered to be important, but the position of observed data above or below modelled data influences probability.

In this case, W=L_{ijt}, and Y=(1-U_{ijt}). The Relative Based likelihood function is defined as:

$$p\left(z_{nt}\middle|\theta_{ijkn}\right)=\begin{cases} he^{-\frac{L_{ijt}-z_{nt}}{\Delta_k L_{ijt}}} & if\,(z_{nt})<L_{ijt} \\ he^{-\frac{z_{nt}-U_{ijt}}{\Delta_k(1-U_{ijt})}} & if\,(z_{nt})>\mathrm{U}_{ijt} \\ h & otherwise \end{cases} \tag{37}$$

Equation 37 results in the value of U_{ijt} and L_{ijt} being removed from the calculation of h, such that h is independent of the modelled scores:

$$h\left(U_{ijt}-L_{ijt}\right)+\int_{U_{ijt}}^{1} he^{-\left(\frac{z_{nt}-U_{ijt}}{\Delta_k(1-U_{ijt})}\right)}dz+\int_{0}^{L_{ijt}} he^{-\left(\frac{L_{ijt}-z_{nt}}{\Delta_k(L_{ijt})}\right)}dz=1$$

$$h=\frac{1}{U_{ijt}-L_{ijt}+\Delta_k\left[2-2e^{-\left(\frac{1}{\Delta_k}\right)}\right]} \tag{38}$$

Alternative likelihood functions to the three described above were also considered, and used non-exponential functions to decrease probability either side of the upper and lower ecological bounds. These were considered less suitable as they resulted in a hard boundary between observational points which were considered and those which were disregarded.

6.3.3 Calculating marginal posterior probabilities

Marginal posterior probabilities were also calculated to explore the impact of different modelling components and uncertainty assumptions on results. Two types of marginal posterior probabilities were calculated: the first examined the probability of a particular expert model given observations and the full range of possible hydrological assumptions, delta values and bias values (Equation 39). This was then repeated for a particular single set of hydrological assumptions (Equation 40), delta values (Equation 41), and bias values (Equation 42).

The second type of marginal posterior probability is for a single expert model and single set of hydrological assumptions given the full range of delta and bias values (Equation 43). This was also repeated to consider a single set of hydrological assumptions and delta values (Equation 44), and a single set of hydrological assumptions and bias values (Equation 45).

$$p\left(e_i \left| z_{nt}\right.\right) = \sum_{j=1}^{nQ}\sum_{k=1}^{nD}\sum_{n=1}^{nB} P\left(\theta_{ijkn} \left| z_n\right.\right) \tag{39}$$

$$p\left(q_j \left| z_{nt}\right.\right) = \sum_{i=1}^{nE}\sum_{k=1}^{nD}\sum_{n=1}^{nB} P\left(\theta_{ijkn} \left| z_n\right.\right) \tag{40}$$

$$p\left(\Delta_k \left| z_{nt}\right.\right) = \sum_{i=1}^{nE}\sum_{j=1}^{nQ}\sum_{n=1}^{nB} P\left(\theta_{ijkn} \left| z_n\right.\right) \tag{41}$$

$$p\left(b_k \left| z_{nt}\right.\right) = \sum_{i=1}^{nE}\sum_{j=1}^{nQ}\sum_{k=1}^{nD} P\left(\theta_{ijkn} \left| z_n\right.\right) \tag{42}$$

$$p\left(q_j e_i \left| z_{nt}\right.\right) = \sum_{k=1}^{nD}\sum_{n=1}^{nB} P\left(\theta_{ijkn} \left| z_n\right.\right) \tag{43}$$

$$p\left(q_j \Delta_k \left| z_{nt}\right.\right) = \sum_{i=1}^{nE}\sum_{n=1}^{nB} P\left(\theta_{ijkn} \left| z_n\right.\right) \tag{44}$$

$$p\left(q_j b_n \left| z_{nt}\right.\right) = \sum_{i=1}^{nE}\sum_{k=1}^{nD} P\left(\theta_{ijkn} \left| z_n\right.\right) \tag{45}$$

6.3.4 Development of software code for evaluation of model performance

The approach described above was implemented using Fortran 90 code. The code calculates total posterior probabilities and marginal probabilities using the three likelihood functions (Equations 33, 36 and 38) by iterating through each instance of $e_i, q_{j,}\Delta_k, b_n$. It was used to provide three main outputs:

1. The combined expert model, hydrological assumptions, delta and bias which produced the highest and second highest total posterior probability (i.e. performed best compared with observed data): $\max P(\theta_{ijkn}|z_n)$;
2. Marginal posterior probabilities for each expert model, hydrological assumption set, value of delta and bias: $p(e_i|z_n)$, $p\left(q_j\middle|z_n\right)$, $p(\Delta_k|z_n)$, $p(b_n|z_n)$; and
3. Marginal posterior probabilities for each hydrological assumption q_j in terms of expert model, value of delta and bias: $p(q_{j,}e_i|z_n)$, $p(q_{j,}\Delta_k|z_n)$, $p(q_{j,}b_n|z_n)$.

These are explained in further detail in Section 6.4.3.

6.3.5 Application to the Great Cumbung Swamp case study

The three likelihood functions described above were applied to the Great Cumbung Swamp case study, to investigate the performance of different combinations of model and uncertainty assumptions compared with observed data. In doing so, the objective was to identify which set of combinations (if any) best match observations, both in terms of estimated value of ecological condition, and in terms of the pattern of change. Given the focus of the current work is on analysing trade-offs for environmental flows, it is important that the models represent decline during and recovery after drought periods.

Applying Bayes Theorem to evaluate model performance for the Great Cumbung Swamp required defining four components: observed data (x_o); model assumptions (e_i and q_j); uncertainty ranges (Δ_k and b_n); and prior probabilities ($P(\theta_{ijkn})$). Observed River Red Gum condition scores derived using photographic records were provided by an environmental water manager for the Lachlan catchment (P. Driver, DPI Water). The data were evaluated using observed Booligal flow to compare patterns of decline and recovery, and were also compared with independently derived canopy cover from Armstrong *et al*. (2009). Model assumptions, uncertainty ranges and prior probabilities are based on knowledge of the Great Cumbung Swamp. A description of the four components is provided below, whilst specific detail relating to other aspects of the case study is provided in Chapters 2, 3 and 4.

6.3.5.1 Observed data

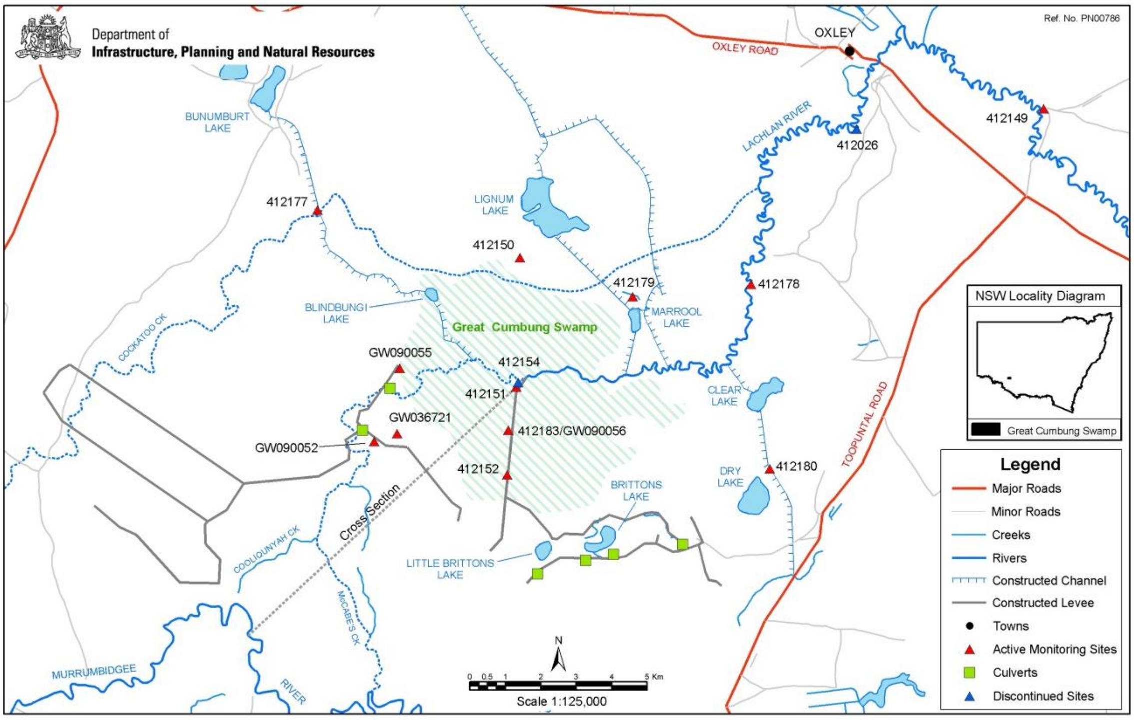
Observational field data on River Red Gum condition in the Great Cumbung Swamp as part of a targeted monitoring program did not exist at the time of analysis (a monitoring program has since begun in 2013 as part of a Commonwealth Long Term Intervention Monitoring Program, as described in Driver *et al*., 2014). However, photographic records collected as part of a wider vegetation survey through the Integrated Monitoring of Environmental Flows (IMEF) program provide a means by which River Red Gum condition can be estimated. Photographic records were collected by New South Wales Department of Primary Industries Water (DPI Water), and covered seven different locations at two main sites (Lignum Lake and Marrool Lake, Figure 71) within the Great Cumbung Swamp. The records available for the current study spanned from July 1987 to February 2013, with at most 17 observations in total for any single location during this period, and a minimum of 4 observations for location D at Marrool. This continuity over time for the same sites enabled a consistent means of estimating River Red Gum condition.

Condition scores were estimated by P. Driver (DPI Water) using the Seddon scale to provide consistency with the information provided to the five experts developing the ERMs (Chapter 4). The Seddon scale ranges from 1 to 5, where 1 is the best condition and 5 is the poorest, whilst the modelled condition scores range from 0 to 1, with 0 being dead and 1 being the best condition. Seddon scores were therefore scaled to match modelled values:

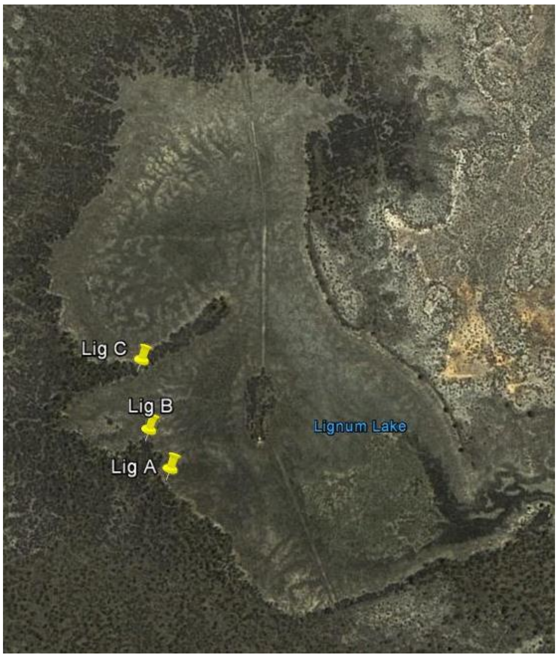
$$x_o = \left(1.1 - 0.2x_p\right) \pm 0.1$$

Where x_p = observed scores based on the Seddon scale from photographic records

The scaling of observed values from a coarse to fine scale introduces uncertainty of ± 0.1. For example, a Seddon score of 1 equates to a modelled value of 0.8 to 1.0. Scores were given an average value (in this case 0.9), with the bias parameter *b* used to account for the variation of ± 0.1 around the mean (Section 6.3.5.3). An example of condition estimates using photographic records is demonstrated using Figure 72. Figure 72 shows both seasonal and inter-annual variation in water availability, and deterioration of River Red Gum condition during the Millennium drought at locations at Lignum Lake.



(a)



(b) (c)

Figure 71. Great Cumbung Swamp showing (a) the location of the two sites (Lignum Lake and Marrool Lake) (source: Driver *et al*., 2004); (b) the three locations at Lignum Lake used for photographic analysis of River Red Gum Condition (Google Earth, 2016); and (c) the four locations used at Marrool Lake.

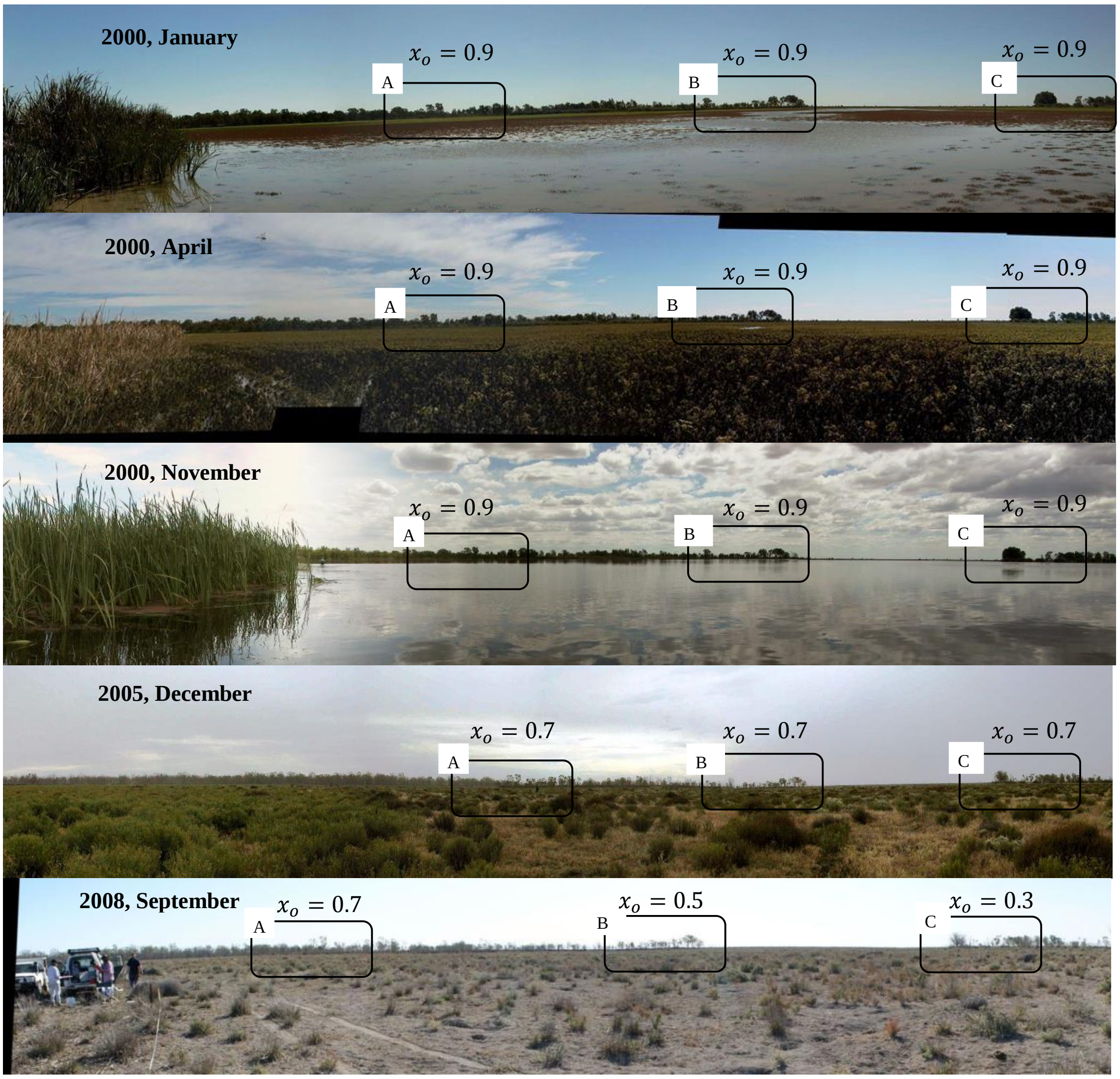


Figure 72. Changes in vegetation condition at Lignum Lake for the same three locations from 2000 (before the Millennium drought); 2005 (mid drought); and 2008 (nearing the end of the drought). Photos taken by P. Driver and P. Lloyd-Jones, DPI Water. Condition scores provided by P. Driver.

A time series of observations for all locations at Lignum Lake and Marrool are shown in Figures 73 and 74 along with a 12 month and 24 month moving average of daily flows at Booligal, upstream of the Great Cumbung Swamp. Note that linear interpolation between observed scores is shown to aid visualisation of the data. For example, the straight line between 1987 and 1997 in Figures 73 and 74 is due to a lack of data rather than a continual increase in condition during this period. The decline in River Red Gum condition during the 2001-2010 drought and following recovery can be seen across all observations. Whilst the overall pattern of change in condition is consistent between locations and sites, there is also considerable variation in individual scores. Given the lack of observed data between 1987 and 1999, it is not possible to assess how well the model performs based on a comparison with averaged flow data.

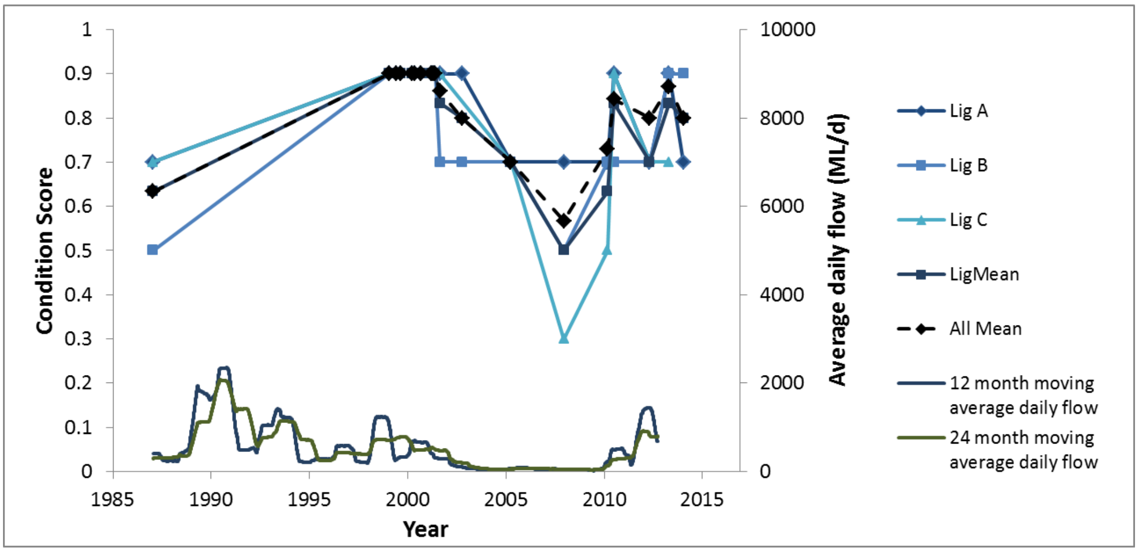


Figure 73 Observed condition scores at Lignum Lake sites A, B and C, as well as the mean across all Lignum sites, and both Lignum and Marrool sites (All Mean). Moving average daily flows are shown for comparison.

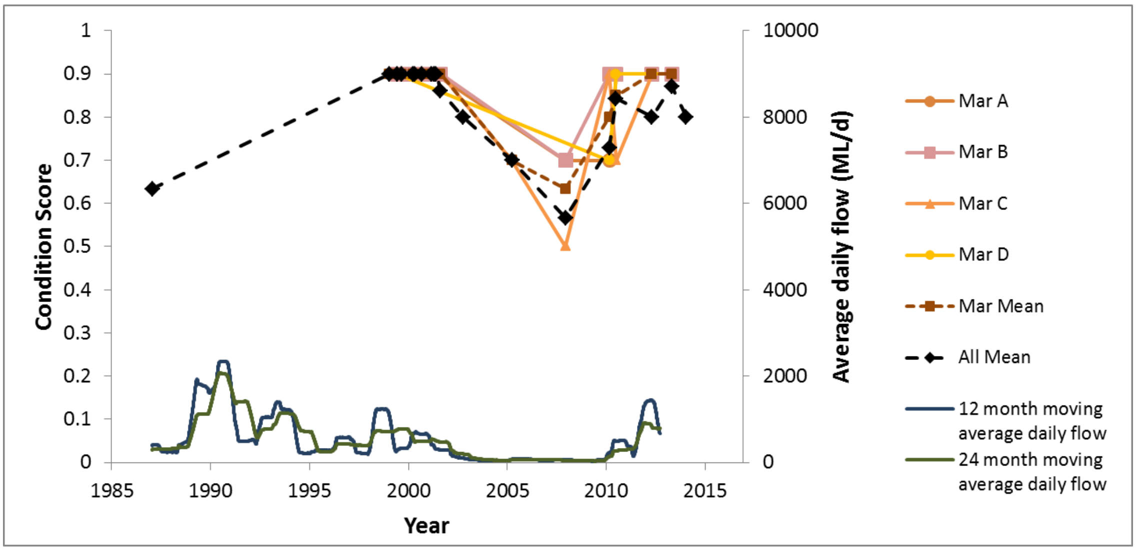


Figure 74 Observed condition scores at Marrool Lake sites A, B, C and D, as well as the mean across all Marrool sites, and both Lignum and Marrool sites (All Mean). Moving average daily flows are shown for comparison.

As an independent check of observed condition scores, River Red Gum canopy cover from a report by Armstrong *et al*. (2009) were compared with the mean observed scores obtained from the photographic analysis (Figure 75). Armstrong *et al*. (2009) estimated canopy cover using aerial photographs from 1973 to 2008 across four different sites within the Booligal Wetlands, upstream of Great Cumbung Swamp. A median canopy cover for the four sites was provided by P. Driver along with the observations from the Great Cumbung Swamp. The canopy cover scores provided were standardised to range from 0 to 1 to match the ERM developed here, although different methods used to generate these scores mean they do not exactly correspond with each other. Despite this difference, the overall similarity in pattern provides some confidence to the photographic condition scores here. Whilst the Great Cumbung Swamp scores were generally higher than those from Booligal, both show the decline in condition from the late 1990's/2000.

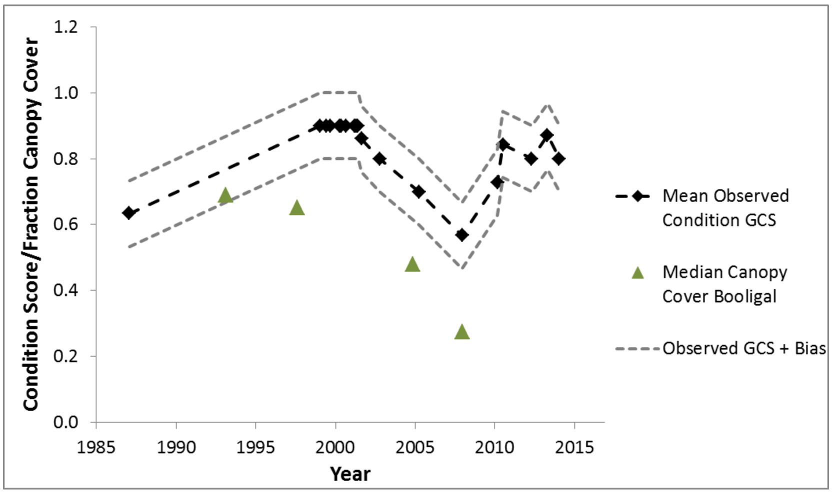


Figure 75. Comparison of observed River Red Gum condition from the Great Cumbung Swamp with canopy cover from Booligal between 1973 and 2008 (adapted from Armstrong *et al*., 2009).

6.3.5.2 Model assumptions: hydrology and ecology

Drawing upon results from the sensitivity analysis in Chapter 5, twelve sets of hydrological assumptions were explored. The primary sources of uncertainty were considered to be: (1) the flow threshold at which the Great Cumbung Swamp becomes inundated; (2) the depth at which River Red Gum can access groundwater; and (3) whether the inclusion of rainfall induced inundation is significant for River Red Gum condition. It is recognised that there are also many other sources of uncertainty, such as spatial variation in inundation patterns.

The twelve sets of hydrological assumptions are shown in Figure 76 and Table 12. The selection of the specific parameter values for flow threshold and groundwater depth is described in detail in Chapter 3. However, it is important to note that the distinction between the 2700ML/d and 700ML/d flow thresholds is the selection of either the entire River Red Gum area of the Great Cumbung Swamp (2700ML/d threshold) or the smaller lakes area where the observed River Red Gum scores have been taken. This was to test whether the observed scores did indeed reflect the more frequently inundated lakes area compared with the wider River Red Gum area.

The majority of assumption sets used the 2700ML/d 30 day threshold as this is representative of the whole Great Cumbung Swamp. Most also included rainfall, as initial comparisons between modelled and observed data indicated the inclusion of rainfall provided a better match.

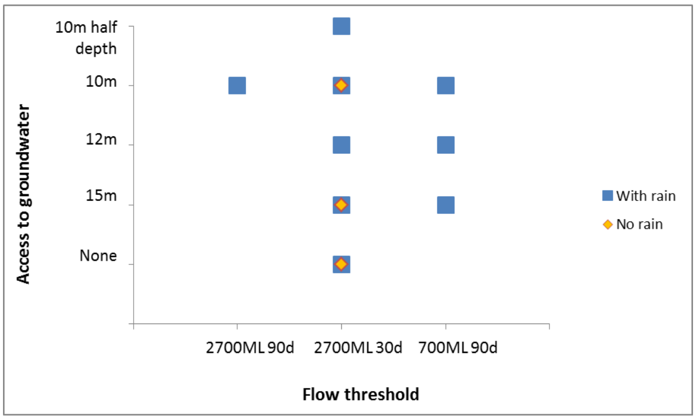


Figure 76 Twelve sets of different hydrology assumptions tested with different flow thresholds, access to groundwater, and inclusion/exclusion of rainfall.

Table 12. The twelve sets of hydrological assumptions explored

Hydrology Set	Flow threshold (ML/d)	Duration threshold (days)	Groundwater access (m)	Rainfall
1	2700	30	No access	Not included
2			10	Not included
3			No access	Included
4			10	Included
5			12	Included
6			15	Included
7			15	Not included
8			10, depths halved	Included
9		90	10	Included
10	700	90	10	Included
11			12	
12			15	

Uncertainty in ecological response was explored using the five expert ERMs, given differences between expert conceptualisations were shown to have a significant impact on condition scores based on the sensitivity analysis. Combined with the twelve hydrological assumptions, a total of 60 possible combinations of model components were evaluated.

6.3.5.3 Uncertainty ranges

The two additional parameters used to consider uncertainty for this analysis were the uncertainty in the expert estimates of upper and lower bound condition scores (Δ) and systematic bias between observed and modelled scores (b). Ten different values of Δ were examined, ranging from 0.02 to 0.2 in increments of 0.02. The effect of Δ depends greatly on the level of uncertainty expressed by each expert in the form of the lower and upper bounds (L_{ij}, U_{ij}). Higher values of Δ had the potential to improve the performance of more precise models, as a greater difference between observed and modelled data was tolerated. However, this was less effective where the ecological bounds were already wide. A maximum of 0.2 was selected because bounds wider than this would result in uninformative models.

The bias parameter *b* accounts for systematic differences in observed and modelled condition. In this case, *b* was used to account for the scaling of condition scores from the Seddon scale to the ERM as described earlier. This scaling resulted in observed values having a resolution of ± 0.1 around the mean, hence bias values of -0.1 to +0.1 were used in increments of 0.02 (11 bias values). Any greater bias would shift the observations into a new Seddon class either side of the mean, increasing the uncertainty around observations to ± 0.3 (Figure 77). For example, a score of 0.7± 0.1 can vary from 0.6 to 0.8, but larger bias values require a step to 0.7± 0.3, varying from 0.4 to 1.0. This was considered too great a range, with the uncertainty values driving the fit between modelled and observed values rather than the model itself. This assumes that there is no measurement error, i.e. the Seddon class selected is correct. Whilst this may not always be the case, the range of condition scores falling within a single Seddon class (a range of 0.2) already covers some uncertainty. Where this assumption may cause particular problems is where scores are close to the bounds between two Seddon classes. This could be further explored in future work, noting that the greater the uncertainty considered, the less informative the model and observations become.

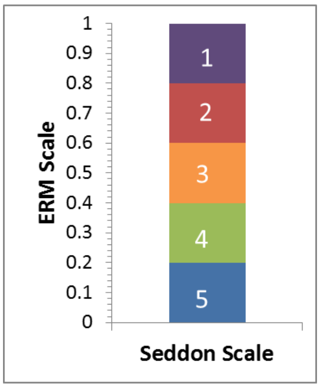


Figure 77. Mapping between the Seddon Scale and ERM model.

The same bias value is applied to all observed scores, which assumes that any variation from the mean is consistent across the whole dataset. It is recognised that this may not be the case, and improvements to the method could be obtained by allowing bias to vary for each observation. Further improvements would be through the incorporation of additional sources of uncertainty, including any discrepancies between the locations used for photographic analysis and the rest of the Great Cumbung Swamp. However, these additional sources of uncertainty were not feasible to quantify in the current analysis.

The combination of all five expert models, twelve sets of hydrological assumptions, ten values of Δ and eleven bias values gives a total of 6600 possible outcomes, making a visual comparison of all combinations prohibitive. The advantage of the method outlined above is it provides an automated way of comparing multiple sets of assumptions.

Note that for the purpose of this chapter, scenario is used to define a combination of expert model, set of hydrological assumptions, Δ and bias value. Different combinations of hydrological assumptions are referred to as a 'set', which incorporate assumptions about flow threshold, groundwater access, and rainfall.

6.3.5.4 Calculating Priors

The prior probability $P(\theta_{ijkn})$ can give preference to different expert ecological models, hydrological assumptions, or values of Δ and b, based on existing knowledge of the system and the assumptions. In this case, all models and assumptions were treated to be equally likely with no prior preference, hence $P(\theta_{ijkn}) = 1$ (where $P(e_i) = \frac{1}{n_e}$; $P(q_j) = \frac{1}{n_q}$; $P(\Delta_k) = \frac{1}{n_k}$; and $P(b_n) = \frac{1}{n_b}$). However, future work could explore variations to the prior probability, such as giving preference to different experts, flow thresholds or access to groundwater.

6.4 Results

The five expert models were run from 1953 to 2013 using observed flow and rainfall data. The combination of assumptions which performed best against observed condition scores (spanning 1987 to 2013) for each of the three likelihood functions are shown in Table 13 and Figure 78. In each case, the models were compared against the average observed condition score across all seven sites. It can be seen from Table 13 that the Difference (likelihood function 2) and Relative (likelihood function 3) likelihood functions identified the same scenario as having the highest posterior, whilst the Value likelihood function (1) identified a different scenario. It can also be seen that the posterior is only 0.13, meaning none of the scenarios performed significantly better than other scenarios.

Table 13. Scenario with the highest posterior probability (performance) for the three likelihood functions.

Likelihood Function	Expert	Hydrology Assumptions	Δ	*b*	Posterior Probability
1	5	7 2700ML/d 30d 15m GW*, no rain	0.08	0.1	0.13
2	1	6 2700ML/d 30d 15m GW, with rain	0.04	0.1	0.13
3	1	6 2700ML/d 30d 15m GW, with rain	0.04	0.1	0.13

*GW: Groundwater

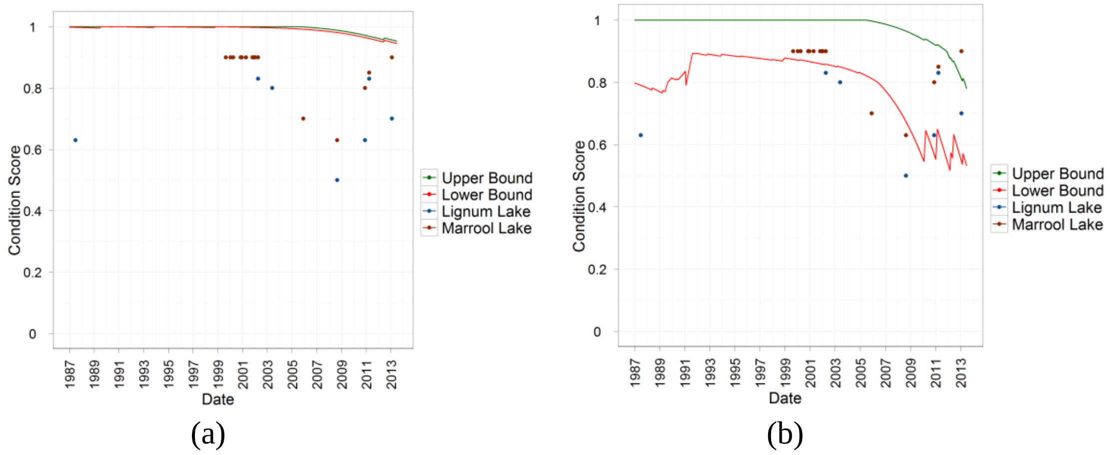


Figure 78. Observed and modelled condition scores for the expert models and hydrological assumptions with the highest posterior: (a) Expert 5 with hydrology set 7; (b) Expert 1 with hydrology set 6.

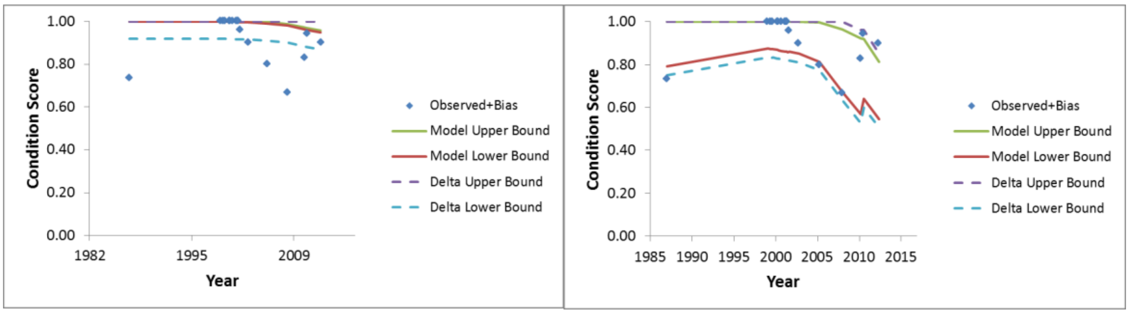
Examining Figure 78, it can be seen that neither of the two scenarios performs particularly well compared with observed data. Most importantly, they do not capture the decline and recovery of River Red Gum condition during the Millennium Drought. Figure 78a shows minimal sensitivity to any fluctuation in water availability, which can be attributed to the increased access to groundwater combined with the response strategy captured in Expert Model 5 (E5). Figure 78b shows some improvement with representation of the decline in condition, but without the recovery phase. To understand the selection of these two scenarios using the method outlined earlier, the following components are explored: (1) model precision; (2) likelihood functions; (3) marginal probabilities; (4) expert defined uncertainty bounds; and (5) observed data. Lastly, the Bayesian analysis is compared with a visual analysis of the five expert models and twelve sets of hydrologic assumptions, to assess performance of the Bayesian method developed here.

6.4.1 Model precision

Referring to Figure 78, it can be seen that two different strategies are being employed by the scenarios to obtain a better posterior probability. For E5 Hydrology 7, the model is very precise. This improves the posterior but at the expense of requiring a higher value of Δ (0.08), which subsequently decreases the posterior in order to improve the fit with the observed data. The highest value of *b* is also required to shift the observed data up by 0.1, which would suggest that the observed scores are at the higher end of the Seddon score range rather than the assumed middle. In comparison, Expert Model 1 (E1) Hydrology 6 is a less precise model, which encapsulates a number of observed data points but with a lower posterior. Given the wider bounds, a smaller Δ (0.04) can be used. A *b* value of 0.1 is again selected to shift the observed data upwards.

6.4.2 Likelihood functions

The difference in which scenario is selected for likelihood function 1 compared with 2 and 3 is a result of the ecological model bounds falling between 0 and 1. This results in an increase in the posterior for high and low scores for likelihood function 1 (as discussed in Section 6.3.2). This can be further demonstrated in Figure 79 showing the bias adjusted observed data and Δ values for the two scenarios, noting that Δ does not represent a hard bound due to the exponential decline within the likelihood functions. In Figure 79a, likelihood function 1 gives preference to the high condition scores, for which there are twelve observed data points with less than 0.05 difference compared with the modelled scores. The slightly larger Δ value has little impact in reducing the posterior probability as the upper bound is already constrained by the 1.0 condition score limit. In comparison, likelihood functions 2 and 3 are corrected to not give preference to the high condition scores, hence a better overall match between observed and modelled values produces a higher posterior probability (Figure 79b). In this case, a model with wider uncertainty bounds and a lower Δ value is selected, where thirteen observed data points fall on or within the model upper and lower bounds, and the remaining four data points are within 0.09 of the modelled scores.



(a) (b)

Figure 79 a) Expert 5, Hydrology 7 (2700ML/d 30d 15mGW no rain), bias 0.1, delta 0.08; and b) Expert 1, Hydrology 6 (2700ML/d 30d 15mGW rain), bias 0.1, delta 0.04.

The difference in likelihood functions is further demonstrated in Figure 80, where expert models are compared across all hydrological, delta and bias scenarios using Equation 39; and in Figure 81, which compares hydrological assumption sets across all experts, delta and biases using Equation 40. It can be seen that the performance of expert models is more distributed for the Difference and Relative likelihood functions, whereas only E5 performs well using the Value likelihood function (Figure 80). All three likelihood functions selected similar hydrological assumptions (Figure 81), but with the Difference and Relative likelihood functions giving a higher probability to the 2700ML/d 15mGW rain Set (6), whereas the Value likelihood function gave preference to 2700ML/d 15mGW no rain Set (7).

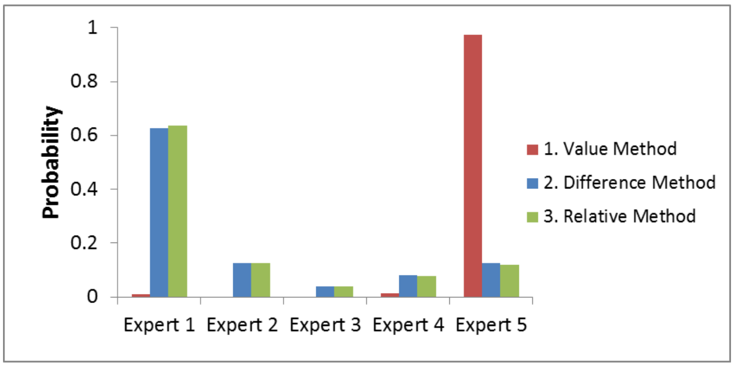


Figure 80. Comparison of the five expert models across all hydrological assumption sets, deltas and biases.

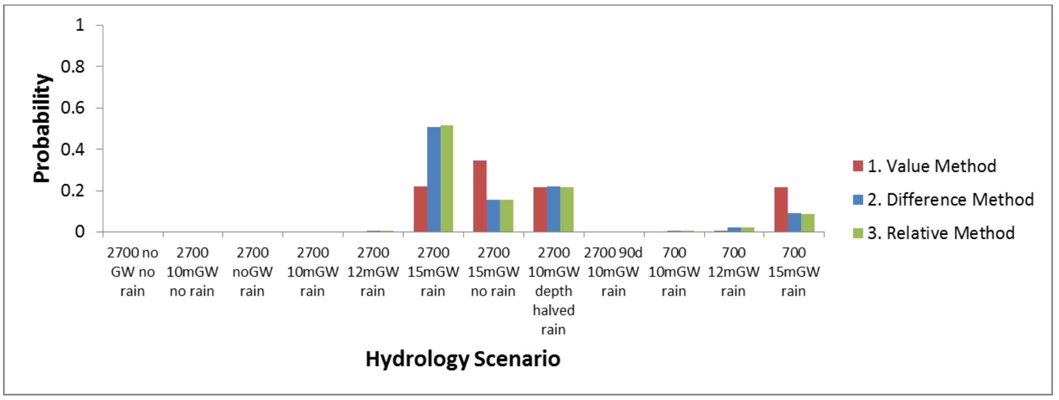
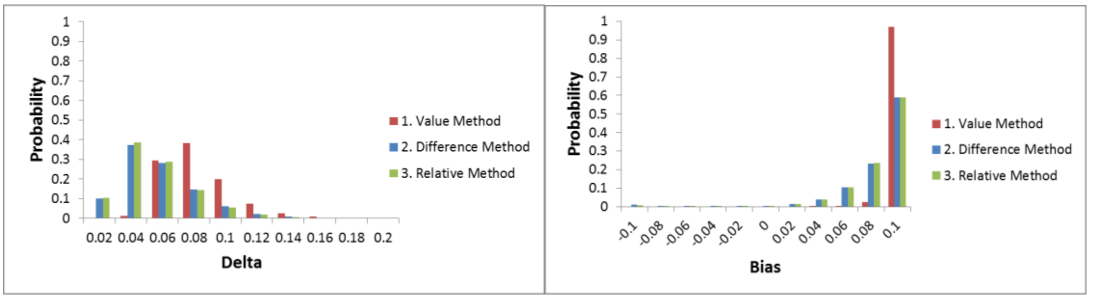


Figure 81. Comparison of hydrological assumption sets across all experts, deltas and biases.

There is some variation in which Δ values had the highest marginal probability (Figure 82), although in all cases the lower Δ values perform best as they indicate a more precise model, with a higher value of *h* and hence higher marginal probability (calculated using Equation 41). The selection of bias (Equation 42) does not influence the value of *h*, but is used to shift the observed data within ± 0.1 to better match modelled values. It can be seen here that in the majority of cases the data were shifted +0.1.



(a) (b)

Figure 82. Comparison in probability between the three likelihood functions for different (a) delta values and (b) bias values across all expert models and hydrological assumption sets.

Of the three likelihood functions, the Difference likelihood function is considered to best represent the differences between observed and modelled data as it does not bias modelled values closer to zero or one, and considers only the distance between observed and modelled values irrespective of whether the observation is above or below the modelled value. Should low or high condition scores be of particular concern, the Value method may be more appropriate. The remainder of the analysis therefore only refers to the Difference likelihood function.

6.4.3 Comparing expert models and hydrological assumptions using marginal posterior probabilities

Marginal posterior probabilities were used to further explore (1) the impact of using different expert models, and (2) the impact of different hydrological assumption sets. Marginal probabilities calculated using Equations 43 to 45 provide greater insight into the relative effect of different variables. For example, the highest performing combination is E1 and hydrological Set 6, which is a reflection of the performance of E1 across all hydrological sets, biases and deltas. It therefore does not provide complete representation of the unique combination of E1 and hydrological Set 6, being dependent on the other sets of assumptions being analysed.

The selection of expert model was shown to have a significant impact on which hydrological set resulted in a better match with observed data. Overall, the hydrological assumptions sets which performed best were: Set 6 (2700ML/d 30d 15mGW with rainfall); Set 7 (2700ML/d 30d 15mGW without rainfall); and Set 8 (2700ML/d 30d 10mGW access but groundwater levels depths halved, with rainfall) (Figure 83). In all cases, hydrological sets with a greater access to groundwater were shown to have higher probabilities. Access to groundwater appeared to be a stronger determinant of outcome compared with rainfall and flow threshold.

Comparing across hydrologic sets, E2 performed best for the majority of sets, and performs better where there is lower water availability for the 2700ML/d and 700ML/d flow thresholds (Figure 84). A mix of E1, E4 and E5 performed best for the remaining sets with higher water availability (primarily in terms of groundwater), where the probability distribution is divided amongst a greater number of expert models. E3 performed less well across all sets. Based on Figure 84 alone, one may conclude that E2 should be used given its improved performance against most hydrological assumptions, should no other prior information be provided. However, comparison with the highest performing delta values in Figure 85 indicate that higher values of delta (and hence a less precise model) are required for hydrological sets with lower water availability. The 2700 15mGW rain has the greatest proportion of low delta values, indicating improved model precision (depending on the difference in model lower and upper bounds).

The probabilities shown for different bias values in Figure 86 are closely linked to which expert model performs well for a particular hydrological assumption set, given that adjusting the observed data influences which model it matches better. This can be seen by comparing Figures 81 and 83 where bias values close to -0.1 are given preference for hydrological sets where E2 performs best under lower water availability, hence requiring a reduction in observed condition scores. Where other expert models perform better under greater water availability, bias values are closer to +0.1 to increase the observed condition scores.

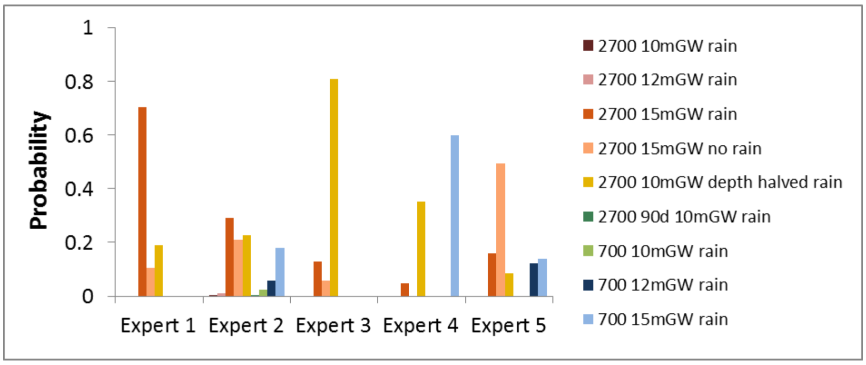


Figure 83. Performance of hydrological assumption sets for each expert model

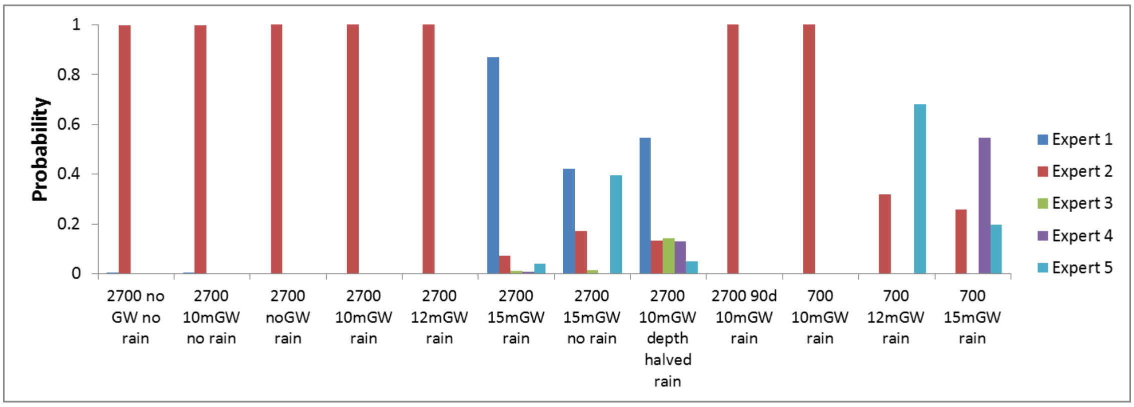


Figure 84. Performance of expert model for each hydrological assumption set.

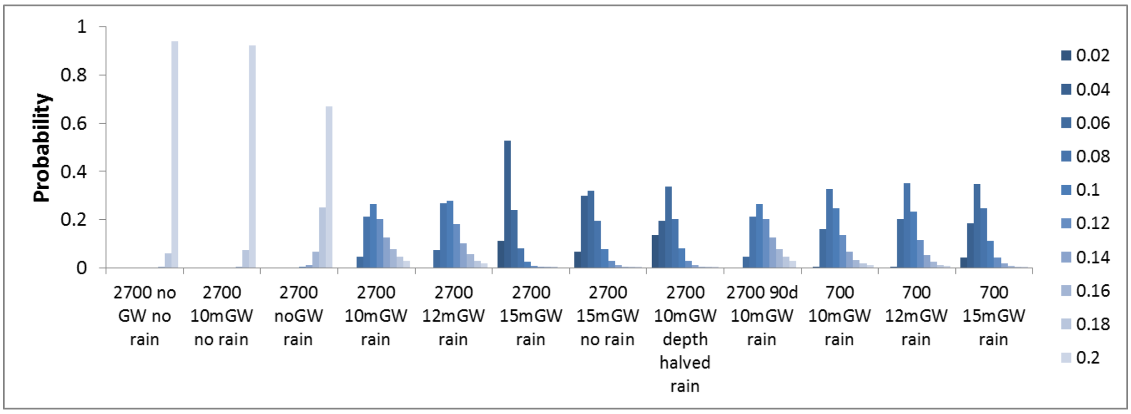


Figure 85. Marginal probabilities for each value of delta for all hydrological assumption sets.

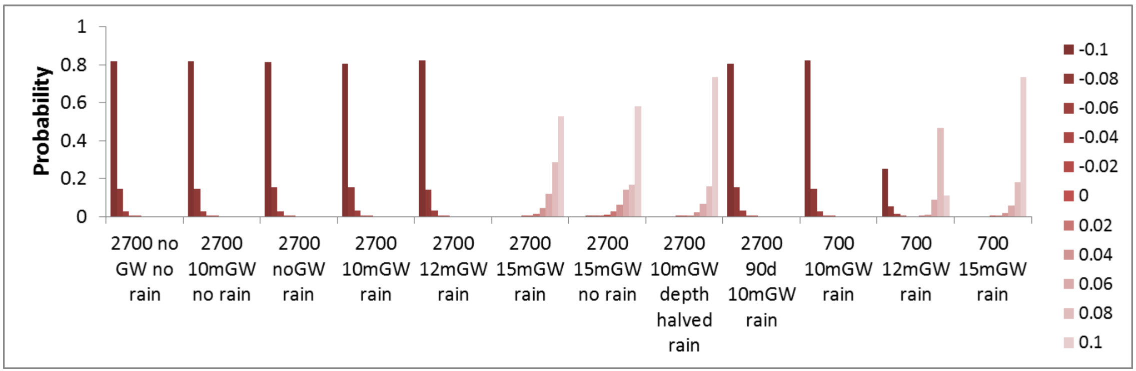


Figure 86. Marginal probabilities for each bias for all hydrological assumption sets.

6.4.4 Impact of uncertainty bounds on model performance

A number of the expert models have wide uncertainty bounds, as shown earlier in Figure 49. In some cases, the upper bound appears to match observed data better than the lower bound (Table 15), or vice versa. To examine whether experts were better able to estimate the upper bound or the lower bound, all twelve hydrological sets were re-run using the Difference likelihood function, using either just the lower bound; just the upper bound; or an average of both lower and upper bounds. These now represent precise models for all experts, of the form shown in Figure 67 curve ‘B’. Figure 87 shows a comparison in the performance of expert models across all hydrological sets, deltas and biases using either both upper and lower bounds of the expert model, just the upper or lower; or an average of the upper and lower bound which ignores uncertainty explicitly stated by the experts. This is then repeated for each hydrological set across all experts in Figure 88. Note that some expert models have upper and lower bounds which are more similar than others, in which case comparing them separately or averaging them has less impact.

It can be seen from Figure 87 that the performance of the upper and lower bounds are largely similar to the use of both bounds, with some differences such as better performance of the lower bound for E1. In contrast, the average of both bounds has a significant impact on the performance of E1 and E3, reducing the performance of E1 and improving that of E3. The improved performance of E3 is due to the wider uncertainty bounds compared with other experts for the highest performing hydrological sets (6, 7 and 8), hence an average value improves E3 relative to other models.

Comparing upper and lower bounds for different hydrological sets in Figure 88, it can be seen that the expert model bound has a significant impact on which set performs best. The use of the upper bound only gives preference to the 700ML 15mGW set, whilst the lower bound gives preference to the 2700ML 10mGW depths halved set. Both the combined use of upper and lower bounds and the average identifies the 2700ML 15mGW as performing best.

Further differences between the upper and lower bounds can be seen in Figures 89 and 90, where the performance of expert models for different hydrological sets varies depending on which bound is used. Models such as E2 which are more precise across the observed time series perform more similarly for both upper and lower bounds.

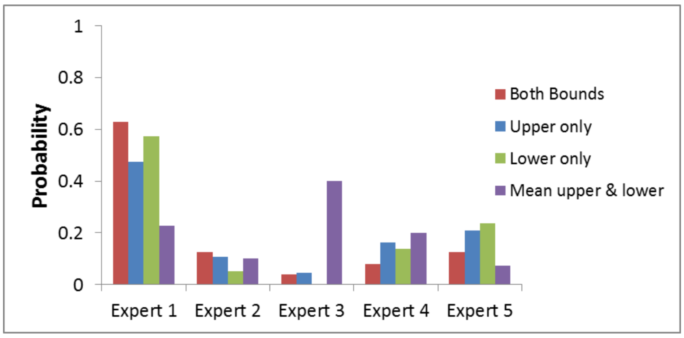


Figure 87. Comparison in expert model performance depending on whether both bounds are used, just one bound, or an average of the two.

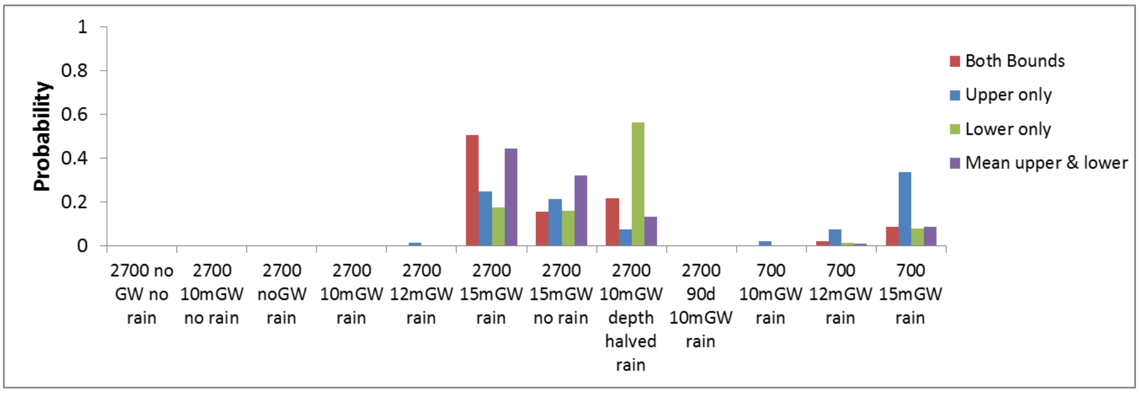


Figure 88. Comparison between hydrological sets depending on whether both bounds are used, just one bound, or an average of the two

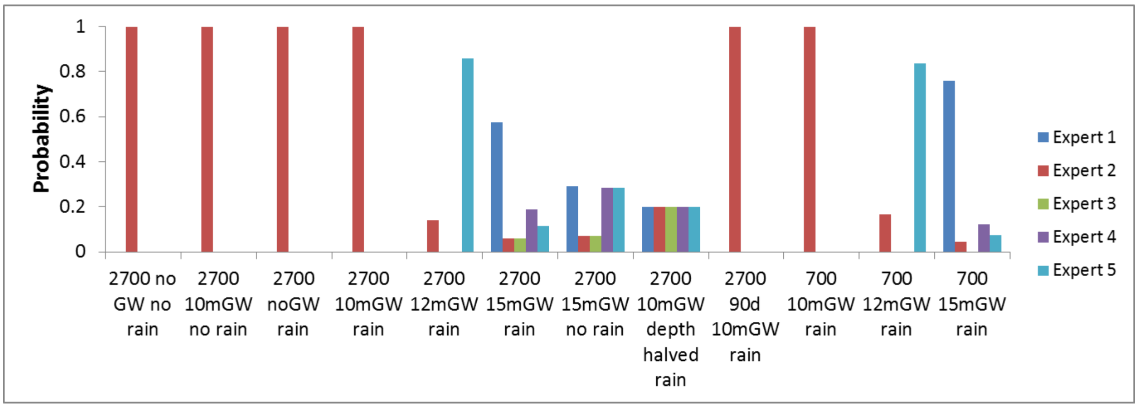


Figure 89. Comparison in hydrological sets using the upper bound only

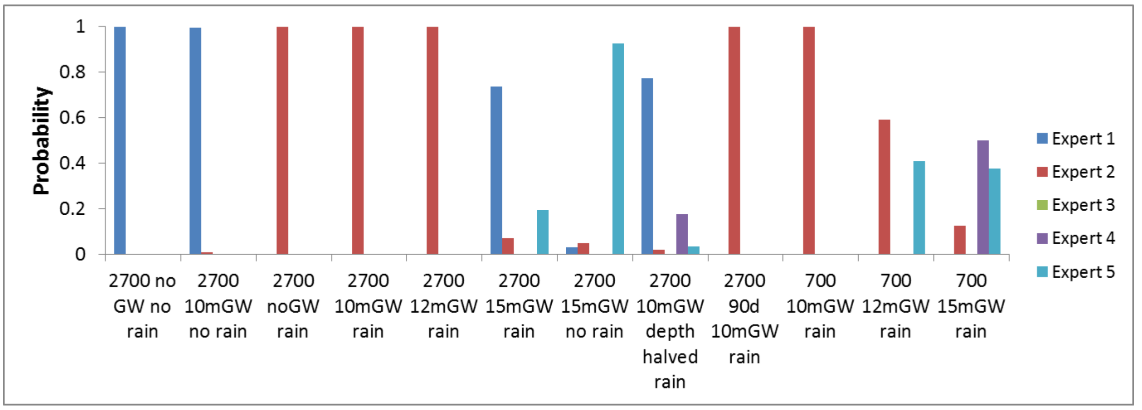


Figure 90. Comparison in hydrological sets using the lower bound only

6.4.5 Sensitivity to observed data

Given that the above analysis relies on the average observed data values across the two sites and seven locations, the sensitivity to observed data was examined for the Difference likelihood function. The model was re-run using the mean of all sites at Lignum Lake only; the mean of all sites at Marrool Lake only; and then for each location individually. The scenario with the highest likelihood for each of these data sets is shown in Table 14. Note that each location has different numbers of temporal observations, with some being more informative (17 observations) than others (minimum 4 observations). It can be seen from Table 14 that the observed data set used influenced which expert model and which hydrological assumption set performed best, indicating sensitivity to observed data. E1 performed best for the most number of different data sets, followed by E5 and E4. Hydrological set 6 (2700ML 15mGW rain) performed best most frequently (six times), with sets 7, 8 and 12 also performing well depending on the observed dataset. Despite the variation in hydrological sets, all four identified below have a greater access to groundwater.

It is possible that variations are due to heterogeneity within the Great Cumbung Swamp, with different hydrology sets and expert models better representing conditions in different areas. However, there is insufficient information to determine this.

Table 14. Influence of observed data on expert model and hydrological assumption performance

Observed data	No. observations	Expert	Hydrology sets*	Bias	Delta	Posterior Probability
Mean All	17	1	**6**	0.10	0.04	0.13
Lig Mean	17	1	**6**	0.10	0.04	0.26
Mar Mean	15	5	**7**	0.10	0.04	0.25
Lig A	17	1	**6**	0.10	0.02	0.07
Lig B	17	1	**6**	0.10	0.06	0.10
Lig C	15	4	**6**	0.04	0.02	0.08
Mar A	6	1	**6**	-0.02	0.02	0.03
Mar B	12	5	**8**	0.10	0.02	0.59
Mar C	13	5	**8**	0.10	0.06	0.07
Mar D	4	4	**12**	0.08	0.02	0.01

* 6: 2700ML/d 15mGW rain; 7: 2700ML/d 15mGW no rain; 8: 2700 10mGW depths halved rain; 12: 700 15mGW rain

6.4.6 Evaluation of the Bayesian analysis using a visual comparison

Whilst the analysis above provides greater insight into the performance of the expert models and impact of different assumptions, further exploration of the results is needed to understand the poor performance of the two models with the highest likelihood identified by the Bayesian analysis (Figure 78 in Section 6.4). A visual comparison of observed and modelled condition scores is therefore undertaken for all five expert models and twelve hydrological assumption sets. The visual comparison used two main criteria to assess model performance: first, the proximity of modelled condition scores to observed condition scores; and second, the pattern of change such that decline during drought is represented as is recovery post drought.

Based on this analysis, the two sets of hydrology assumptions considered to best match the observations were: set 5 (2700ML/d 30d); and 11 (700ML/d 90d), both with 12m groundwater access and rainfall (Table 15 and Figures 91 and 92). Across all of the hydrological assumptions, E1, E2 and E4 were considered to provide a closer match with observed data. E1 in Figure 91 represents the pattern of change in condition, particularly the upper bound, although the scores are generally lower than those of observations. Note that the sudden decline in condition for E1 in set 11 is consistent with the high sensitivity to ‘too wet’ conditions shown in the sensitivity analysis (Chapter 5). E2 better matches the observed scores, but with less representation of the pattern. The upper bound of E4 provides a reasonable match in terms of pattern, but like E1 has scores which are lower than observed.

However, none of the scenarios demonstrate an excellent fit, with differences between observed and modelled scores varying significantly between expert models and hydrological assumptions (Table 15). This is further compounded by variation and uncertainty in observations.

Table 15. Visual assessment of expert model performance for twelve hydrological assumption sets

Hydrology Set	Flow threshold (ML/d)	Duration threshold (days)	Groundwater access (m)	Rainfall	Expert model performance
1	2700	30	No access	Not included	None*
2			10	Not included	None
3			No access	Included	E1 pattern
4			10	Included	E1 pattern
5			12	Included	E1 pattern; E2; E4 upper bound only
6			15	Included	E4 but wide bounds
7			15	Not included	None
8			10, depths halved	Included	None
9		90	10	Included	E1 pattern
10	700	90	10	Included	E1 upper bound; E2
11			12		E1 upper bound; E2; E4 upper bound
12			15		None

* None indicates none of the expert models performed well for that set

From Figures 91 and 92 it can be seen that most expert models capture the decline in River Red Gum condition during the 2001-2010 drought, and the recovery after 2010. An exception is for Expert 3 in Figure 92. Here, the decline from 1956 onwards is due to conditions being too wet based on the expert model. E1, E3 and E4 generally show greater sensitivity to average flow compared with E2 and E5.

Figures 91 and 92 also show the variation in match between expert model condition scores compared with the observed data. The upper bounds of E1 and E4, and the upper and lower bounds of E2 represent the timing of the observed data reasonably well. E2 and E5 best match the actual values of the observed data, although the decline shown by the E5 model is delayed. Both E2 and E5 have very precise models compared with E1 and E4.

To compare the visual analysis with the Bayesian analysis, the time series for hydrological assumption set 6 is shown in Figure 93 (the assumption set which performed best using the Difference likelihood function, as shown in Table 13). In contrast with sets 5 and 11, set 6 results in higher modelled scores due to the increased groundwater access. Whilst E4 encompasses the majority of observed data points, none of the expert models show the pattern of decline and recovery from 2001 onwards. Plots of the remaining hydrological assumption sets are shown in Appendix B3.

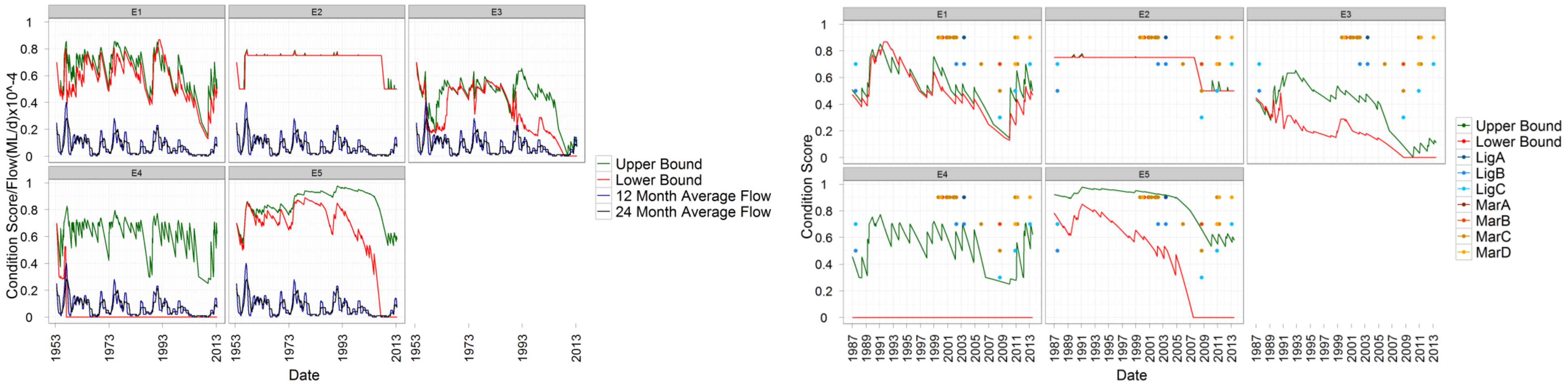


Figure 91 Hydrological Assumption Set 5: 12m GW access with rain and 2700ML/d for 30 days flow threshold

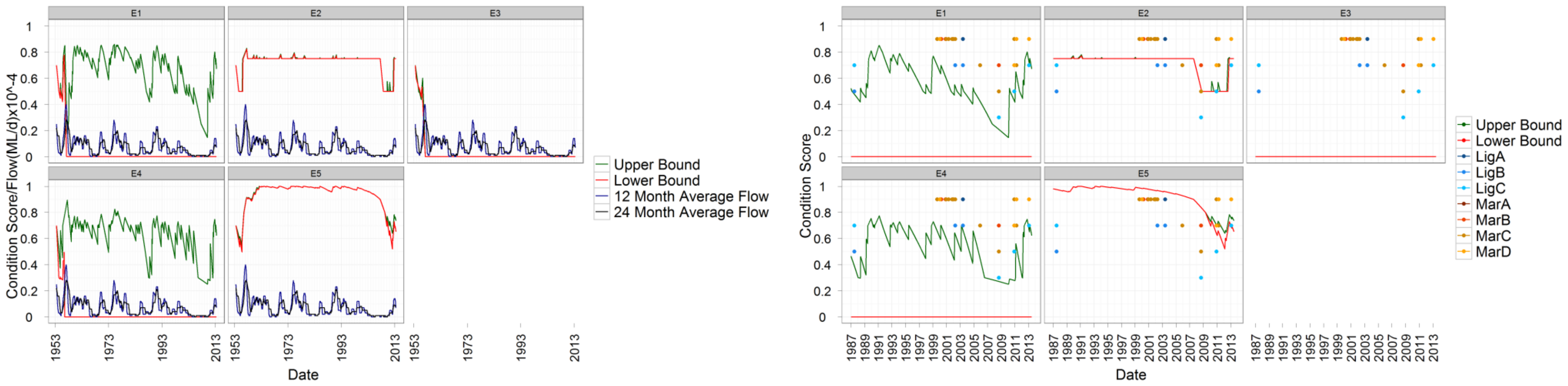


Figure 92 Hydrological Assumption Set 11: 12m GW access with rain and 700ML/d for 90 days flow threshold

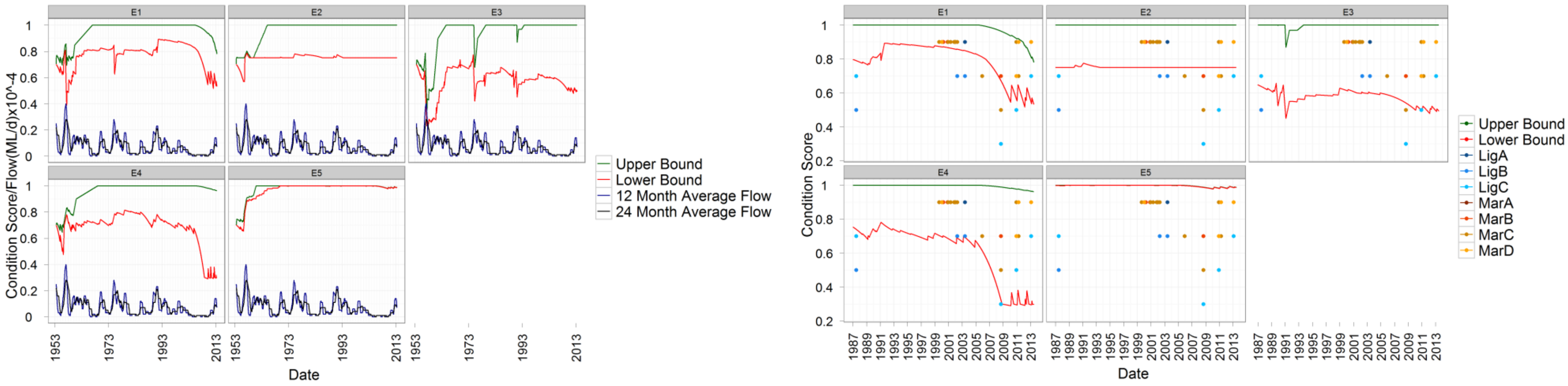


Figure 93 Hydrological Assumption Set 6: 15m GW access with rain and 2700ML/d for 30 days flow threshold

The difference in results between the visual assessment and Bayesian analysis can be explained by referring back to Figure 79b, which shows modelled condition scores using hydrological set 6 compared with bias corrected observations. It can be seen from Figure 79b that with bias correction, the *values* of the modelled condition scores are within or close to the modelled bounds using a Δ of 0.04. However, what the Bayesian analysis has not captured is the *pattern* of change to reflect the decline and recovery of River Red Gum. Given the pattern of change occurs within the width of the upper and lower limits of the modelled condition scores, the model is insensitive to any changes in condition within these bounds.

This difference raises some interesting questions regarding what criteria should be used to identify the best performing model, and what the trade-off is between representation of uncertainty and predictive capacity.

6.5 Discussion and Conclusions

Comparison of model performance with observed data has long been standard practice within the modelling community through calibration and validation/verification processes. It is essential in developing further understanding of system behaviour; model improvement and refinement; building model credibility; and understanding uncertainties and limitations in model application (e.g. Clark *et al*., 2011; Schoniger *et al*., 2014).

The development of models of increasingly complex systems presents significant challenges to the process of model evaluation, where observational data are limited or absent, system understanding and representation is incomplete, and uncertainties are significant and difficult to define or quantify. Whilst model refinement is still essential, greater focus is needed on improving model and system understanding, and gaining awareness about the limitations in model use.

Despite these challenges, the majority of studies focus on comparing different parameter values without considering the impact of model conceptualisation or different types of uncertainty on results (Butts *et al.*, 2004; Clark *et al.*, 2011). This study complements the work of those such as Butts *et al*. (2004) and Buytaert and Beven (2011) in demonstrating the impact of conceptualisation on model results, as well as in exploring the different views of experts (Foglia *et al*, 2013).

The application of Bayesian statistics in this study enabled a systematic analysis of large sets of scenarios with a variety of uncertain inputs. Different sources of uncertainty are explicitly considered, including both model and observational uncertainty. The analysis provides additional insight into model behaviour above and beyond that provided by the visual analysis of model performance compared with observations. However, comparison between the visual and Bayesian analyses highlights the need to consider what constitutes acceptable model performance where there is significant uncertainty – representation of pattern of change (e.g. E1 in Figure 91), approximate representation of observed values (e.g. E2 in Figure 91), or broad encapsulation of observed data in wide uncertainty bounds (e.g. E1 in Figure 93). It explores the question of accuracy versus usability, where wide uncertainty bounds are more likely to ensure a model captures actual events yet is less informative, compared with a precise model which is at greater risk of being wrong.

The use of uncertainty bounds can also introduce additional uncertainty, where some experts may be better at estimating upper limits than lower limits, or vice versa. The comparison of model performance using both uncertainty bounds, just one uncertainty bound, or an average of the lower and upper bounds, led to different outcomes in which set of assumptions performed best.

Exploration of model performance in this chapter has not provided clear support of which set of assumptions performs best, but instead has shown the importance of considering a range of model uncertainties when evaluating different management alternatives. Comparison of expert models has suggested that some perform better under different hydrological conditions, such as accessibility to groundwater. This may provide a justification for the use of model averaging methods to combine alternative models (e.g. Jordan and Jacobs, 1994; Marshall *et al*., 2007 and Hsu *et al*., 2009). However, in this case it is argued that the uncertainty is too great to warrant model averaging. There is insufficient confidence in the hydrological and ecological assumptions to determine which model should be used when, as well as insufficient data to adequately test model performance. For example, greater certainty in the flow threshold would be needed to reduce the possible set of expert models which performed well, and vice versa. In addition, combining parts of different models may lead to internal inconsistencies, where experts have assumed different response mechanisms and behaviours.

The analysis demonstrated that the set of assumptions which performs best is also influenced by the likelihood function used, and it is recommended that this is further explored in future work. The poor performance of all expert models combined with the paucity of observed data limit the construction of a reliable likelihood function, and the degree to which uncertainty can be adequately represented. The inability of the likelihood functions to clearly distinguish between expert models indicates further development would be needed to extend the current analysis for use in a predictive capacity, and the estimation of posterior predictive distributions.

Despite the significant variability in performance of both expert models and hydrological model assumptions, some conclusions can be drawn from the analysis. Evaluation of all models and assumptions suggested that access to groundwater is important in influencing ecological response. Whilst it is recognised that the uncertainties involved in such a model make it difficult to disentangle the influence of single drivers, it provides reason for further investigation given very few ecological response models consider access to groundwater as an important determinant of condition.

It could also be argued that the majority of expert models are somewhat pessimistic in their estimates of River Red Gum condition (although these are also dependent upon the hydrological model). Many of the lower bound estimates fall to zero during the Millennium drought, if not before. Whilst observations suggest that a number of individuals did die during the drought, on average the community survived and recovered. It is also noted that there is uncertainty in the observed dataset, and variation between the two locations and seven sites demonstrates variability in River Red Gum condition and resilience across the Great Cumbung Swamp is significant. As highlighted in the expert interviews, questions such as resilience to water stress based on average access to water are still underexplored.

This analysis demonstrates the challenges of modelling hydrological and ecological response in complex systems such as the Great Cumbung Swamp. It highlights the importance of using multiple models in evaluating management alternatives. Undertaking a comprehensive evaluation of model performance considering uncertainty is essential to ensure models are appropriately applied, yet relatively few studies undertake such a rigorous analysis. The use of Bayesian statistics in model evaluation can lead to additional insights into model behaviour and system processes. The method developed here can be easily adapted and applied to the evaluation of other models to test different sets of assumptions.

Given the lack of a single ‘best’ performing set of assumptions based on the analysis above, the exploration of different environmental flow rules using multi-objective optimisation in Chapter 8 compares multiple expert models and multiple hydrological assumptions. This enables the impact of model assumptions on management decisions to be explored.

Part C

Evaluating Environmental Flows Through Multi-objective Optimisation

Evaluating Environmental Flows Through Multi-objective Optimisation

The primary objective of Part C is to examine the application of multi-objective optimisation for environmental flow management. Building upon Part B, it explores some of the uncertainties identified in representing ecological systems in a modelling framework, and the impact of these uncertainties on management decisions. In addition to uncertainties in objective setting and problem framing applicable to any modelling exercise, the use of optimisation introduces additional considerations regarding the specification of objectives in mathematical terms, the identification of decision options, and the evaluation of what is considered to be a 'better' outcomes. Part C contains two chapters:

- **Chapter 7**: Optimisation as a process for ecological management in river systems
- **Chapter 8**: Using optimisation to explore opportunities and trade-offs in environmental flow management

Chapter 7 reviews previous studies which have applied optimisation for evaluating ecological objectives in river system. The chapter evaluates approaches used for objective setting through to identifying impacts on actual management outcomes in the context of significant and multiple sources of uncertainty. In doing so, a number of existing challenges are identified, and strategies for addressing these challenges are proposed.

Chapter 8 builds upon the development and evaluation of the expert derived ecological response models in Part B to assess the impact of the uncertainties identified on management decisions for the Lachlan case study. In addition, it addresses the challenges identified in Chapter 7 through adopting the proposed strategy.

The focus of Part C is on developing a methodological approach to examining uncertainty in the assessment of environmental flows. For the purpose of the current work, the exact operation of the Lachlan system is not replicated and hence the results should be viewed in this context. However, the methodology developed could equally be applied to the actual Lachlan system (or other river systems) in future work.

Chapter 7: Optimisation as a process for understanding and managing river ecosystems

7.1 Aim and Overview

Part B developed and evaluated a set of five expert derived ecological response models for the purpose of evaluating different environmental flow alternatives. The analysis identified a number of significant uncertainties in representing ecological response in a quantitative model. These include uncertainty in estimating inundation patters and uncertainty in estimating River Red Gum response to water availability. Whilst the sensitivity analysis in Chapter 5 and the Bayesian analysis in Chapter 6 evaluated the impact of different assumptions on estimated ecological condition, there is still a need to identify how these assumptions impact upon environmental flow decisions, and trade-offs with non-ecological objectives.

Optimisation provides one approach for exploring multiple alternative management strategies and evaluating trade-offs. In addition, it can facilitate learning about the system and aiding communication. This chapter reviews and synthesises a number of optimisation papers to gain a better understanding of the opportunities and challenges in applying optimisation to explore different environmental flow rules. The synthesis focused on optimisation studies which considered at least one ecological objective, and assessed the strengths and weaknesses of different approaches in setting objectives and representing the system in an optimisation framework.

The Chapter provides two main contributions. Firstly, it identifies four major challenges which currently influence the effectiveness of optimisation to aid in decision making for environmental flows. These are: identifying and quantifying ecosystem objectives; use of predictive models to evaluate objectives associated with different management alternatives; representing the management problem in an optimisation framework; and evaluating model results in terms of actual ecological outcomes. Secondly, the chapter provides a strategy for addressing these challenges through increased consideration of the impacts of problem framing and uncertainties on the analysis. Drawing upon literature from ecology, optimisation and decision science, it highlights the need for better recognition and analysis of assumptions in optimisation modelling as part of a process that generates and shares knowledge, and that enables a better understanding of how well the results represent plausible outcomes to meet the needs of decision makers.

The content of this chapter is largely based on a published journal article, with minor adaptations to fit within the current thesis: Barbour, E.J., Holz, L., Kuczera, G., Jakeman, A. J., Pollino, C. A., and Loucks, D. P. (2016). Optimisation as a process for understanding and managing river ecosystems, *Environmental Modelling & Software*, **83:** 167-178.

7.2 Introduction

A greater recognition of the ecological value of river systems has introduced a number of challenges for the development of robust, adaptable and socially acceptable management strategies. Ecological objectives can be difficult to define and model, and often present a trade-off with other river management objectives such as agricultural yield or hydropower production. Optimisation is one method which can assist in identifying and evaluating alternative management policies, and trade-offs among multiple objectives. Whilst it has been widely applied to both water resource (see reviews by: Labadie, 2004; Nicklow *et al*., 2010 and Maier *et al*., 2014) and ecological management problems independently (e.g. Sarkar *et al*., 2006; Nicholson *et al*., 2006; Lee and Iwasa, 2014), fewer studies have utilised optimisation for the ecological management of river systems (e.g. Sale *et al*., 1982; Shiau and Wu, 2009; Suen at al., 2009; Yang and Cai, 2011; Rheinheimer *et al*., 2013).

The use of optimisation to aid decision making for ecological and other complex systems has been facilitated by the development of metaheuristics, a class of optimisation methods which use pre-defined rules to search for preferred solutions, and provide flexibility in problem definition. Metaheuristic methods overcame many of the restrictions on problem formulation and complexity required by earlier methods, such as linear and dynamic programming. However, the application of optimisation to increasingly complex systems has also required it to be redefined: from a tool used to find a single definitive solution; to one which aids in the exploration of different possible solutions, and facilitates learning and communication (Jacoby and Loucks, 1972; Liebman, 1976; Walters and Hilborn, 1978; Brill Jr, 1979).

The focus on finding a single ‘optimal’ solution was often appropriate for early applications of optimisation, which were largely simple engineering or logistical problems. However, the concept of optimality becomes less clearly defined for complex systems, where there are multiple, ill-defined and often conflicting objectives,which can only be partially represented in a modelling framework. The optimisation of these systems requires greater consideration regarding problem definition, model representation, and the impact of uncertainties and assumptions on actual management outcomes (Liebman, 1976; Haimes and Hall, 1977; Brill Jr, 1979).

The challenge of problem definition and representation of complex systems has been recognised and discussed in the context of planning and public policy since the 1960’s and 70’s (e.g. Hitch, 1960; Rittel and Webber, 1973; Liebman, 1976; and Brill Jr, 1979). These so called ‘wicked problems’ are applicable to ecological systems due to: inadequate knowledge of the system; lack of clear criteria by which to define objectives and measure outcomes; decisions having significant and often irreversible impacts; and each decision occurring in a unique context (Rittel and Webber, 1973; Metrick and Weitzman, 1998; Possingham *et al.*, 2001; Failing and Gregory, 2003; Tear *et al.*, 2005; Nicholson and Possingham, 2006; Nicholson and Possingham, 2007; Game *et al.*, 2008; Hirsch *et al.*, 2011; Game *et al.*, 2014).

The use of optimisation introduces additional challenges through the need to specify objectives in a series of mathematical equations, and to develop an adequate model representation of the system such that 'optimal' solutions represent desirable outcomes to the actual problem (Ackoff, 1962; Haimes and Hall, 1977). This requires an understanding of how these formulations influence the resulting decisions, and consequently the management of the ecosystem (Wilson *et al*., 2009; Nicholson and Possingham, 2006). Whilst these challenges are well recognised, there has been limited discussion regarding the use of optimisation for ecological objectives in river basin management.

Defining ecological objectives is complicated by the existence of many and often conflicting social values regarding what is considered to be a 'preferred' environmental outcome. Preference for a particular outcome is also context dependent, and is influenced by factors such as a country's wealth, level of development, and competing requirements to fulfil basic needs. Added to this is the dynamic nature of many ecological systems, making it difficult to identify an ideal state in time and space. Representation of riverine ecological systems in a modelling framework requires an understanding of these dynamics and the relationship between river flow and ecological response, as well as the role of other influencing factors such as land management, climate, and disease (Shenton *et al.*, 2012; Acreman *et al.*, 2014b). It is therefore essential that the outcomes of any optimisation are critically evaluated in terms of the assumptions made, to identify what the likely actual outcomes will be. Assumptions can include conceptualisation of the problem, adequacy of the data, predictive capacity and suitability of the model for the decision being made, as well as set-up of the optimisation framework. Ideally, optimisation outcomes should be compared with actual ecological outcomes, to improve our understanding of ecological systems and improve the effectiveness of modelling and optimisation tools in aiding decision making.

Until recently, the majority of optimisation research has remained largely focused on algorithm development and application to different types of problems (Reed and Kasprzyk, 2009; Maier *et al*., 2014). Where optimisation has been employed to assist in ecosystem management, there has been little focus on the explicit challenges of ecological optimisation. Exceptions include Walters and Hilborn (1978), who reviewed different optimisation methods and approaches for ecological management considering uncertainty. More recently, Nicholson and Possingham (2006) examined the impact of translating management goals into specific mathematical objective functions. Whilst they did not use optimisation directly, they examined different objective function formulations for conservation planning, and the effect of these on preferred management strategies. Probert *et al*. (2011) demonstrated the effect of different optimisation algorithms (focusing on adaption to new knowledge), and different project objectives for conservation management.

In the context of river system optimisation, Jager and Smith (2008) reviewed 29 optimisation studies which considered both hydropower and environmental criteria. The review identified the need for further research to adequately account for ecosystems in multi-objective optimisation, including: the need for a better understanding of flow-ecology relationships; tools to model such relationships; and the development of methods for valuing the environment.

In this synthesis, we draw upon literature from ecology, optimisation and decision science to discuss and evaluate different approaches for the optimisation of riverine ecosystems. The paper discusses four key challenges throughout the optimisation process which are considered essential for effective river basin management:

1. Ecological objectives - defining ecological objectives for optimisation studies and the role of social values.
2. Ecological models – limitations and strengths of different types of models used for river system optimisation
3. Optimisation of ecological objectives – challenges in defining objective functions and decision variables; and
4. Ecological outcomes – how wellmodelled results are evaluated in terms of actual outcomes.

In the following sections each of the four challenges is discussed through critical evaluation of previous studies. The paper concludes with an overview of key outcomes and recommendations.

7.3 Defining ecological objectives

Defining objectives is one of the first steps in any study or management activity. In the case of ecological systems, this presents a major challenge, yet is generally given insufficient attention in optimisation studies. Setting ecological objectives is largely a subjective process involving social values as much as scientific knowledge, and these values often differ between stakeholders and experts (Voinov and Bousquet, 2010; Liebman, 1976; Davis and Slobodkin, 2004). The selection of who to involve in defining objectives can therefore ultimately influence the final management outcome.

Identifying broad, high level goals for ecological management is important in providing context and justification for a particular study, yet these require translation into clear, specific, quantifiable objectives which can be used within the modelling process and to measure the success of outcomes (Metrick and Weitzman, 1998; Richter *et al*., 2003; Tear *et al*., 2005; Palmer *et al*., 2005; Nicholson and Possingham, 2006; Fischer *et al*., 2009). It is essential that the assumptions required in translating broad goals into specific objectives are transparent, well recognised, and inclusive, in order to achieve the best possible management outcomes with minimal unintended consequences. Assumptions may include focusing on a desired ecological state, or a particular species at a specific timeframe or location (e.g. Nicholson and Possingham, 2006). Identifying specific objectives can assist in selecting the most appropriate modelling and optimisation approaches, and enabling optimisation outcomes to be evaluated. Conversely, limitations in model, optimisation and implementation capabilities need to be considered to ensure objectives are realistic and achievable.

Previous optimisation studies have focused on human water objectives which are often specific and well known. For example, basic water needs can be roughly estimated on a per capita basis dependent upon the time of day, temperature and other climatic variables. Similar estimates can be made for other water users such as industry, agriculture and hydropower. In contrast, defining ecological objectives and objectives incorporating social values (such as cultural flows – see Jackson, 2006; Finn and Jackson, 2011; Jackson *et al.*, 2015) is far less straightforward.

Ecological systems include multiple species which respond to external drivers, complex internal interactions and have lags in response. Ecosystem needs and optimal states are difficult to identify, being highly variable and often dependent on antecedent states, as well as operating at different scales (Holling, 1973). Whilst defining objectives for a single species, habitat or population may be quantifiable, at a community scale, ecosystem needs become harder to define, as they depend on composition, interactions, redundancies and dependencies across time and space (Poiani *et al.*, 2000; Naiman *et al.*, 2008). At ecosystem scales, consideration of additional factors such as connectivity between habitats and meta-populations is required, and hence it can be harder still to identify what constitutes an ideal state. Ecosystems are constantly in flux, where their composition may change over time as biota evolve and environmental conditions change (Cropp and Gabric, 2002), and questions of whether one type of composition is more desirable than another become largely subjective.

Given the challenge of defining ecological objectives, the use of high level, all-encompassing goals that focus on the concept of ecosystem health has been widely adopted. Whilst this approach has a number of advantages such as being holistic, and engaging the public through the metaphor with human health (Rapport, 1989; Boulton, 1999), it also has a number of disadvantages. Ecosystem health is a largely subjective concept which is dependent upon society's values, yet is often applied with the misleading assumption that it is objective and measurable (Steedman, 1994; Wicklum and Davies, 1995; Davis and Slobodkin, 2004). Consequently, there has been much debate around the meaning and usefulness of ecosystem health as a management objective (e.g. Suter, 1993; Steedman, 1994; Wicklum and Davies, 1995; Lancaster, 2000; Lackey, 2001), as well as more specifically around river health (e.g. Karr, 1999; Boulton, 1999; Norris and Thoms, 1999).

Defining socially acceptable, ecologically robust and relevant objectives therefore remains a challenge, as further demonstrated in the following section.

7.3.1 Defining ecological objectives for river system optimisation

A selection of previous optimisation studies which examined ecological objectives for river system management were analysed in terms of the ecological objective, modelling method and optimisation approach adopted. The papers examined spanned the period from 1982 to 2015, and reflected changes in river system management and optimisation approaches, as well as changes in available methods and technology. Papers were selected based on the use of different approaches for ecological management in river systems with varying levels of complexity. They included different types of ecological objectives and models such as the use of flow based metrics, species based flow preferences, and economic valuation. The papers covered different aspects of river system management, including reservoir operations and trade-offs with non-ecological objectives, environmental flow allocations, and the use of flow control structures for wetlands and floodplains. Furthermore, they adopted different optimisation approaches including classical and metaheuristic methods, with different formulations of single or multiple objectives. In covering this range of studies, the synthesis aims to identify some of the key trends and differences in methods, whilst not claiming to be an exhaustive coverage of the optimisation literature.

Papers were firstly evaluated using two main criteria: (1) the type of ecological objective used, which is indicative of a particular approach to ecological management; and (2) how specific the objective is, which influences what assumptions are needed for quantitative modelling and optimisation. Both of these criteria can influence the modelling and optimisation process, and hence impact upon the resulting management strategies. These are discussed in more detail below.

Types of ecological objectives

Based on the papers examined, two main types of ecological objectives were identified: achieving hydrological metrics; and targeting ecological needs directly. Hydrological metrics are frequently used for defining ecological water needs in river system models and optimisation. This flow-based approach relies on identifying key components of the hydrograph, such as events of a particular magnitude, duration and seasonality, to meet the ecological needs of a river system (Poff *et al*., 1997). Where indicators aim to represent all aspects of a natural (unimpaired) flow regime, the water requirements of multiple species and locations can be met. This type of approach can be easy to implement where there is little ecological data or knowledge of which ecosystems are most highly valued, and can be quantified using flow data.

Examples of hydrologic metric-based objectives include minimising hydrologic alteration (Shiau and Wu, 2006; Yin *et al*., 2012; Shiau and Wu, 2013), maintaining the variability of the natural flow regime (Dittmann *et al*., 2009), maximising instream flow benefits (Sale *et al*., 1982), and providing an ecological flow regime (Suen and Eheart, 2006).

Challenges in using hydrological metrics include: defining appropriate flow indicators that capture key ecological functions and achieve the intended ecological outcome; and identifying an acceptable deviation from baseline values (Richter *et al*., 1997). What constitutes an appropriate baseline can also be debated, given some ecological communities that have adapted to modified flow regimes may be highly valued. Consequently, returning these systems to a more natural state may not be socially acceptable (e.g. Rapport, 1989; Hobbs *et al*., 2006; Hobbs *et al*., 2009; Acreman *et al*., 2014b).

The second type of objective focuses on directly targeting ecological needs (or assets), and identifying the flow required to meet these needs. Environmental water requirements are typically defined for a particular ecological attribute (e.g. species, communities) at a defined location(s). Examples of these objectives (as defined in the papers examined) include: meeting the flow needs of native fish species (Suen *et al*., 2009); maximise riverine fish biodiversity (Tsai *et al.*, 2015); meeting the water requirements of a range of flora and fauna (Szemis *et al*., 2012; Szemis *et al*., 2014); meeting downstream ecosystem needs (Yin *et al*., 2012); and meeting in situ uses (Grafton *et al*., 2011).

A challenge of this approach is the reliance on selecting a range of indicators that are representative of the diversity of water requirements within an ecosystem (Davies *et al*., 2010; Bunn *et al*., 2010). The approach can also require prioritising between different species and locations given it may not be feasible to specify objectives for all ecological components, thereby introducing trade-offs. Additionally, the ecological flow requirements of key species may not be well understood.

Level of specificity

In addition to distinguishing between hydrological metrics and ecological needs objectives, it can be seen from the examples above that some objectives are more general and holistic (such as meeting downstream ecosystem needs), whilst others are much more specific (such as meeting the flow requirements of specific flora and fauna). This distinction has important implications for modelling and optimisation. More general objectives can be informative in providing a holistic, overall goal, and can assist in engaging with decision makers and stakeholders. However, a number of assumptions are required to translate these into quantitative objectives which can be modelled and optimised (Metrick and Weitzman, 1998; Nicholson and Possingham, 2006). These assumptions can involve value judgements and can impact upon the resulting management solutions, yet are rarely discussed in optimisation studies.

More specific objectives such as to 'return the natural flow regime of key components of river ecosystems in terms of flood timing, flood duration, and inter-flood period' (Higgins *et al*., 2011), or to 'design optimal seasonal flow patterns for salmon' (Jager and Rose, 2003) can provide greater detail regarding what will actually be modelled and optimised.

Defining specific objectives is often more challenging at larger temporal and spatial scales which encompass multiple ecological and non-ecological components and multiple stakeholder perspectives. However, it is equally relevant for smaller scale analyses focusing on individual species or communities, where assumptions are still required to define quantitative functions.

7.3.2 Evaluation and recommendations for defining ecological objectives

All but two of the papers examined contained limited discussion of the assumptions and implications of the specified ecological objectives, highlighting a gap in the current literature. Exceptions include Dittmann *et al*. (2009), who identified that maintaining natural flow variability did not encompass all biological requirements for water, but provided a first step approach. Rheinheimer *et al*. (2013) identified that the use of minimum flow objectives did not capture important higher natural flows which are also ecologically important.

Despite the subjectivity of defining objectives and the reliance on social values, none of the papers referred to stakeholder engagement in the derivation of objectives. Rheinheimer *et al.* (2013) referred to stakeholders advocating for greater consideration of the natural flow regime in the study area as motivation for the analysis, although any direct involvement in the modelling and optimisation was not discussed. Involving stakeholders in the derivation of objectives is considered essential for effective and transparent management of ecological systems (Loucks, 2006).

The identification of appropriate, specific and measurable objectives within a broader environmental context is important for ensuring the modelling and optimisation framework is most effective in aiding management decisions. This requires careful consideration of the desired ecological outcome, and explicitly stating the assumptions made to model the identified objectives.

7.4 How well can we model ecological systems for river system optimisation?

Although optimisation can assist in identifying management strategies for meeting ecological objectives, the ability to do so is dependent upon how well the model represents the ecological system. Solutions identified as being 'optimal' may be infeasible and suboptimal in reality if the problem is not appropriately represented. However, an iterative process of evaluating model solutions and model behaviour through optimisation can assist in improving knowledge of the system. This section evaluates the advantages and disadvantages of different types of ecological models used in river system optimisation.

The ecological models examined were classified into two groups: (1) hydrological methods and (2) species preferences (see also Chapter 4, with the ecological response model developed in this thesis classified as a species preference approach). These categories align with the two types of objectives described in Section 7.3.1. Hydrological approaches were the most frequently used for representing ecological systems, and included the natural flow approach as well as other types of flow metrics. The use of these two approaches in river system optimisation is explored in the following two sections.

7.4.1 Hydrological methods

It has been well established that flow is one of the key determinants of riverine and floodplain structure, function, and ecology (Poff *et al*., 1997; Bunn and Arthington, 2002; Arthington *et al*., 2006). The natural flow approach provides a holistic way of capturing ecological water requirements. It is reliant on the use of flow metrics to describe the key features of the flow regime which are ecologically significant. The natural flow approach can be used for both instream and overbank flows, but has been predominantly applied to instream requirements.

One of the most commonly used set of metrics for evaluating the environmental impacts of river regulation is the Indicators of Hydrologic Alteration (IHA) method (Richter *et al*., 1996). IHA includes 32 indicators based on the magnitude, timing, frequency, duration and rate of change in flows. IHA is often used in conjunction with the Range of Variability Approach (Richter *et al*., 1997) which provides a method for identifying an acceptable deviation in IHA values between baseline and altered flows.

The IHA and RVA methods are also frequently used in the optimisation of ecological objectives (e.g. Dittmann *et al*., 2009). Variations on the IHA and RVA approach include different methods of aggregating indicators to give greater sensitivity to high scoring values (with high levels of alteration) (Shiau and Wu, 2006); and the use of frequency histograms to consider variations of indicator values within and outside a target range, thereby overcoming limitations of the RVA approach (Shiau and Wu, 2008). Four alternative flow metrics were used by Yin *et al*. (2012) along with a modified RVA approach, whilst Yang and Cai (2011) used IHA in combination with fish data to generate a fish diversity index.

An alternative set of indicators (the Taiwan Ecohydrology Indicator System, TEIS) has been developed using fish data to create fuzzy and non-fuzzy membership functions using the intermediate disturbance hypothesis (which assumes an average level of variation in flow metrics is desirable) (Suen and Eheart, 2006; Suen *et al*., 2009). A flow alteration metric was also developed by Hurford *et al*. (2014) to focus on seasonal variation between regulated and unregulated flows.

IHA and TEIS metrics use daily flow data to evaluate ecological impact, with fewer studies examining sub-daily impacts due to limited availability of suitable metrics and data (Olivares *et al.*, 2015). Sub-daily alterations in flow due to hydropower and dam operations can have significant impact on downstream ecosystems which is not reflected in daily flow metrics (Cushman, 1985; Zimmerman *et al*., 2010; Haas *et al.*, 2014; Bevelhimer *et al.*, 2015). Optimisation studies which consider sub-daily ecological impacts include Shiau and Wu (2013), who explore the use of hydrological metrics at different temporal scales including sub-daily, daily, seasonal, annual, and inter-annual scales. Sub-daily impacts are assessed using the Richards-Baker flashiness index (Baker *et al.*, 2004), which is also used by Olivares *et al.* (2015) to analyse the economic and environmental efficiency of sub-daily flow constraints for hydropower operation.

The use of the natural flow approach in modelling ecological systems requires consideration of: (1) whether natural flow based indicators are appropriate for the particular case study; (2) how to define the natural flow hydrograph, such as what length of time should be considered, and how long term variability (such as wet and dry periods) should be captured; (3) the location at which actual flows are measured (typically just downstream of the dam), and how these releases are influenced by additional non-environmental releases; (4) how to compare indicators representing a natural and altered flow regime; and (5) how to meaningfully aggregate the indicators.

In many river basins, identifying a time series of natural flows is limited by the extent of human impact. Even where there has been minimal infrastructure development or extractions, changes in land use can significantly impact on rainfall-runoff patterns. In areas of highly variable precipitation, flow records of sufficient duration to capture this variability may not exist. This is further complicated by the effects of climate change, and the need to distinguish between natural variability and anthropogenic induced long term change.

Other hydrologic approaches used in previous studies include the setting of flow targets. These targets include static minimum flows (e.g. Yeh and Becker, 1982; Wang *et al*., 2009; Rheinheimer *et al*., 2013); static seasonal flows (e.g. Tilmant *et al*. (2010) used 50% of pre-development seasonal flows as a target); monthly flow targets (Xevi and Khan, 2005); and optimal dry periods (Grafton *et al*., 2011). Whilst the effectiveness of these targets is very much dependent upon the particular ecosystem and management objectives, the implications of such approaches is worthy of investigation. For example, minimum flows can provide for instream biota during critical periods, but do not provide the variability required by many species. In addition, minimum flows can have a detrimental impact by reducing variability, and are often of insufficient magnitude to meet floodplain and wetland water requirements. The use of monthly flow targets enables some intra-annual variability to be maintained, which may be adequate in some systems with little inter-annual variability but are insufficient in highly variable systems (Poff *et al*, 1997).

Hydrologic targets have been used in optimisation studies to evaluate the economic impact of different management alternatives. For example, Grafton *et al*. (2011) specified optimal durations for ‘dry’ periods, and applied an exponential cost function where this was exceeded. Tilmant *et al*. (2010) calculated the economic value of flows within a specified range using a two-step marginal benefit function. Rheinheimer *et al*. (2013) applied an economic value to unmet minimum flow requirements, based on relative value to hydropower.

The benefits of using economic valuation methods include ease of comparison with non-environmental objectives valued in monetary terms, which can assist in engaging policy makers and generating greater awareness of environmental values (Costanza *et al*., 1997). However, economic valuation can be highly subjective and result in the undervaluing of resources (e.g. Costanza *et al*., 1997; Fisher *et al*., 2009). This is particularly true for environmental flows, which have intrinsic and indirect value through supporting ecological function and processes, rather than providing more direct services such as water supply for domestic and agricultural purposes.

7.4.2 Species Preference

Species preference-based methods are often used when umbrella or keystone species are targeted, or used to represent wider environmental water requirements. However, the selection of appropriate indicator species and locations that are representative of the entire system (or specified objectives) is critical to the success of this approach (Rogers *et al*., 2012). Where multiple indicator species and locations are used, the method of aggregation requires careful consideration and raises the question of the relative importance of one species/location compared with another (Davies *et al*., 2010). This approach can also be significantly more data intensive, which may further limit study size and number of species/locations.

The Murray Flow Assessment Tool (MFAT) described in Chapter 4 is an example of a species preference tool, as it consists of a set of preference curves for depth, duration, magnitude, frequency and rate of change to relate flow and habitat condition for a particular species. MFAT has been used in optimisation by Higgins *et al*. (2011) to assess the location and operation of weirs and regulators to improve ecological outcomes. MFAT was also used by Szemis *et al*. (2012) to compare different environmental flow allocations, and demonstrate the sensitivity of solutions to different species and weightings. In Szemis *et al*. (2014), MFAT was used to evaluate the ecological outcome of different dam releases allowing for adaptive information on available environmental allocations.

Other examples of species preference methods include the Weighted Usable Area (WUA) discussed in Chapter 4, and was used by Sale *et al*. (1982) to develop a habitat condition index for different fish species. Tsai *et al.* (2015) used artificial neural networks to generate a relationship between flow based metrics (using TEIS) and fish diversity. Fish diversity was calculated using the Shannon Index (Shannon, 1948), which compares the number of individuals of different species relative to the total number of all individuals. Jager and Rose (2003) and Jager (2014) used population based models to relate salmon survival to flow releases, considering spatially explicit habitat and different life stages.

7.4.3 Evaluation and recommendations for modelling ecological systems for river system optimisation

The majority of papers which were examined identified limitations and uncertainties associated with their modelling approach. For example, Szemis *et al.* (2012) used sensitivity analysis to identify the impact of different species, locations, and method of aggregation. Tsai *et al.* (2015) refer to the uncertainty in estimating ecological response, with fish biodiversity not representing all ecological requirements. Olivares *et al.* (2015) refer to the lack of evidence regarding sub-daily flow indicators and thresholds for estimating ecological impacts. However, a limited number of studies undertook a comprehensive evaluation of the impact of model behaviour on ecological objectives, despite the need for rigorous assessment of assumptions being well recognised (e.g. Jakeman *et al*., 2006).

Given the considerable uncertainty involved in representing ecological systems in a quantitative model, greater consideration is needed in identifying and testing model behaviour and implications for optimisation outcomes. This was demonstrated by Norton and Andrews (2006), who found that MFAT habitat condition scores were sensitive to the method of aggregating individual preference curves. A wide variety of methods exist for model assessment, including comparing model output with observed data, sensitivity analysis, error propagation, Bayesian analysis, scenario analysis, and multi-model simulation (see for example Jakeman *et al*., 2006; Refsgaard *et al.*, 2007; Matott *et al.*, 2009; and Bennett *et al.*, 2013). In addition, optimisation can also be applied as a process for better understanding model behaviour and system understanding (Jacoby and Loucks, 1972; Liebman, 1976).

Model development can be aided by frameworks such as the Ecological Limits of Hydrological Alteration (ELOHA) (Poff *et al*., 2010), which provides a strategy for improving the local relevance of flow alteration – ecology relationships through using local hydrologic and geomorphologic data. Stakeholder input to defining ecological objectives can also guide which indicators are most appropriate and what level of alteration is considered acceptable (e.g. SUMHA, Pahl-Wostl *et al*., 2013).

7.5 *Representing ecological requirements in an optimisation framework*

The use of optimisation to evaluate ecological objectives requires the identification of appropriate optimisation algorithm(s), objective function(s) and decision variables. Each of these is evaluated below with reference to previous studies.

7.5.1 Optimisation algorithms for ecological management in river systems

Metaheuristics and their hybrid variations are being increasingly used in river system optimisation, due to their greater flexibility and capacity to handle complex systems (e.g. Maier *et al*., 2014). A number of river system studies have used metaheuristics to examine trade-offs between ecological and non-ecological objectives (e.g. Dittmann *et al*., 2009; Suen and Eheart, 2006; Suen *et al*., 2009; Yang and Cai, 2011; and Tsai *et al*., 2015). In comparison, there appear to be fewer applications of metaheuristics in studies focusing on ecological systems in conservation planning (Sarkar *et al*., 2006; Possingham *et al*., 2001). Although a number of limitations remain in the use of metaheuristics (see Maier *et al*., 2014), the capacity to incorporate more complex models and explicitly represent multiple objectives makes them well suited to ecological models and objectives.

As an alternative to metaheuristic optimisation methods, earlier 'classical' methods place restrictions on problem formulation and level of complexity, and hence often require simplifications to model structure and objective functions. Developed prior to metaheuristic methods, they retain the advantages of being capable of greater efficiency, providing exact solutions for linear problems, handling many decision variables. Classical methods can therefore provide an effective approach for problem formulations and objectives which do not require the greater flexibility of metaheuristic methods, such as in cases where there is insufficient knowledge to support complex models of environmental systems (e.g. Biegler and Grossmann, 2004; Labadie, 2004). A number of optimisation studies have utilised classical methods to examine ecological objectives, including Yeh and Becker (1982), Sale *et al*. (1982), Shiau and Wu (2006), Xevi and Khan (2005), Ringler and Cai (2006), and Rheinheimer *et al*. (2013).

7.5.2 Objective functions

Optimisation requires user-defined objectives to be specified in a mathematical format. This can be particularly challenging in defining ecological objectives. Formulation of objective functions typically requires the aggregation of values over time and space, with the method of aggregation having the potential to significantly impact on the resulting optimal solutions. This includes: aggregation of time series values such as through summation, averaging, or selecting a subset of values exceeding a threshold; aggregation over different locations; as well as aggregation of multiple objectives. Aggregation can also involve the use of weights, which introduce further subjectivity and can bias solutions that more closely match a desired outcome.

Whilst there has been some evaluation of different aggregation methods for combining objectives, no thorough assessment of the effect of objective function formulation on river system management outcomes has been identified. Examples of evaluation which has been undertaken include: Higgins *et al.* (2011), who discussed the use of multiplication for different indicators to give the lowest scoring value a greater impact; and Sale *et al*. (1982), who maximised a minimum habitat value based on the assumption that fish production is controlled by the most limiting conditions.

There has been greater focus on objective setting in conservation management (e.g. Ellison, 1996; Wilson *et al*., 2009; Nicholson and Possingham, 2006). For example, Nicholson and Possingham (2006) evaluated the performance of three conservation management scenarios using seven different objective function formulations, all considering risk of extinction. All but two of the seven objective functions returned different rankings of preferred management scenarios, demonstrating the significance of objective function formulation on resulting solutions.

Of the papers examined for this synthesis, there were four main types of ecological objective functions used: (1) Maximise/minimise totals or averages; (2) Maximise/minimise differences between actual and target values; (3) Objectives framed as constraints; and (4) Maximise a minimum/minimise a maximum. The likely effect of these formulations of optimisation results and ecological outcomes is discussed below.

7.5.2.1 Maximise/minimise totals or averages

Maximising or minimising a total or average value has the effect of giving greater focus to large increments in values. In the case of maximisation, greater total or average scores may be achieved through increasing a small subset of individual scores by large amounts, rather than increasing all scores by small amounts. Whilst this effect can be influenced by scale and how the scores are defined, there is potential for short periods of time with ‘good’ ecological outcomes being given priority over maintaining condition above critical values. As an example of this type of objective function, Equation 46 below was adopted by Szemis *et al*. (2012) and Szemis *et al.* (2014) to calculate ecological condition based on the MFAT model (Young *et al*., 2003), for different species, locations, and years:

$$\max\left(\sum_{i=1}^{q} w_{1i} \sum_{r=1}^{s} w_{2r} \sum_{v=1}^{K} \frac{w_{3v} E_{i,r,v}}{Y_K}\right) \tag{46}$$

where:

$E_{i,r,v}$ = indicator for ecological asset *i*, indicator type *r*, in the time interval *v*

Q = total number of wetlands, floodplains and river reaches

S = total number of indicators

Y_K = years, ranging from 1 to a total of K years

w = weights

In addition to Equation 46, Szemis *et al.* (2014) included a second objective function to minimise the difference in environmental flow operations between time steps accounting for updated environmental allocation forecast information. This objective function used a similar method of aggregating over time and management alternatives.

As an alternative, Grafton *et al*. (2011) combined environmental cost and irrigation profit into a 'social return' index. This social return was then summed for each year over the total simulation period using a discount rate to provide an expected net present value which was maximised. The use of a discount rate to apply greater weight to more recent outcomes may have advantages in placing more focus on managing environmental assets in the short term, when there is greater certainty about ecological requirements. However, ecosystems operate on long term cycles, hence reducing water delivery and sacrificing short term condition for long term outcomes may provide greater overall benefit.

7.5.2.2 Maximise/minimise differences between actual and target values

The success of any approach based on outcomes relative to a target relies greatly on how the target is defined. The same principle applies when setting constraint values. Objective functions which compare actual values with target values summed over time focus on deviations from this target. For example, Yin *et al*. (2012) used the RVA approach to minimise the difference between the number of years each indicator value fell within a target range for an altered hydrograph compared with a natural hydrograph, as shown below:

$$D = \frac{1}{H}\sum_{m=1}^{H}\left|\frac{N_{o,m} - N_{e,m}}{N_{e,m}}\right| \times 100\%$$

where:

D = degree of flow regime alteration

m = hydrological indicator, with a total of H indicators

$N_{o,m}$ = number of years where hydrological indicator falls within the target RVA range

$N_{o,m}$ = expected number of years where the hydrological indicator falls within the RVA target range

Whilst the approach used by Yin *et al.* (2012) recognises that even the natural hydrograph may not always meet target values, it penalises the number of years which fall outside the natural range irrespective of whether the number falls short of, or exceeds the natural range. This raises the question of whether a modified flow regime can (and should) be able to perform 'better' than natural based on these indicators. As identified by Shiau and Wu (2009), values falling outside the target range are treated the same irrespective of their magnitude, as are those within the target range. Indicators are combined by averaging their values, which assumes all indicators have equal value.

Higgins *et al*. (2011) also minimised the difference between altered and natural flows but using species preference curves from MFAT for flood timing, duration and inter-flood period. Differences between natural and actual values were squared, giving greater emphasis to larger differences. Separate MFAT curves were multiplied together, which gives greater weight to smaller scores as changes become proportional rather than additive (for example, an increase in score from 0.2 to 0.4 has the same outcome as increasing a score from 0.4 to 0.8). In optimisation, this may be advantageous in reducing the times at which the ecosystem is in a poor condition. However, it also means that the same effort is used to reducing small differences between actual and natural indicators compared with larger differences.

The way in which differences in target values are aggregated is another key consideration where a sequence of failures in meeting a target in multiple consecutive years has a different outcome compared with a few poor years interspersed amongst a number of good years.

7.5.2.3 Objectives framed as constraints

Some studies specify ecological targets as constraints rather than independent objective functions. The effectiveness of this approach relies on how this target is defined. The advantage of this method is that a particular ecological outcome is achieved for all management solutions considered. However, it also means that the outcome is unlikely to ever be better than this minimum value, particularly if it conflicts with the objective(s), as the optimiser will have no incentive to find solutions with greater values. This raises the question of what level of ecological outcome is considered acceptable.

Ecological constraints were used by Yeh and Becker (1982), who used a minimum flow constraint for fish protection. The value of this constraint was not discussed, with the implication that it would be identified external to the optimisation process. Constraint values were varied to develop a trade-off curve with other objectives. Olivares *et al.* (2015) also used constraints to represent ecological requirements using a combination of minimum flows and maximum ramping rates for hydropower generation (which control the difference in flow at the current time step compared with the previous time step). Multiple solutions were obtained by varying constraint thresholds.

7.5.2.4 Maximise a minimum/Minimise a maximum

Similar to the constraint method, maximising a minimum value places emphasis on avoiding worst case conditions rather than focusing on maximising optimal conditions. However, unlike the constraint method, this has the advantage of not setting a fixed minimum value, and provides incentive to improve this minimum value as much as possible. In a multiple objective setting, it also allows trade-offs to be generated, which is not possible when objectives are specified as constraints.

This form of objective function was used by Sale *et al*. (1982) to maximise the minimum habitat suitability condition, calculated using WUA. This has the advantage of reducing the likelihood of any critically poor habitat condition from occurring. The disadvantage is that short periods of low habitat availability may be tolerated by some species, and it gives less incentive for the optimiser to maximise good conditions at other times.

7.5.3 Decision variables

The choice of decision variables can also greatly influence which management solutions are considered optimal. This was demonstrated by Kasprzyk *et al*. (2012) for a water supply case study, where different sets of decision variables were selected based on a sensitivity analysis, and their impact on management strategies compared.

The number and type of decision variables used can influence the degree of variability and control captured within the management strategies. For example, Sale *et al*. (1982) used 12 decision variables to define the target reservoir volume for each month over a one year period; whilst Shiau and Wu (2009) also used 12 decision variables to define monthly environmental flow releases. In comparison, Suen and Eheart (2006) and Suen *et al*. (2009) used 36 decision variables to represent 10 day release volumes, thereby deriving operating rules at a finer resolution. At the other extreme, Grafton *et al*. (2011) defined a yearly environmental release for a simulation period of over 100 years. In this case, any representation of intra-annual variability would have required a significant increase in the number of decision variables.

A different approach was adopted by Dittmann *et al*. (2009), who defined a piecewise linear function to dictate what percentage of the inflow should be released at different storage levels over a 39 year simulation period. By defining decision variables which are a function of the inflow, fewer variables can be used with a greater capacity to incorporate both intra-annual and inter-annual variability. This becomes particularly useful when multi-year simulations are used.

7.5.4 Evaluation and recommendations of representing ecological requirements in an optimisation framework

Metaheuristics are being increasingly used in optimisation studies for complex systems given their greater flexibility in problem formulation (Maier *et al.*, 2014). However, the most appropriate optimisation algorithm is dependent upon the particular objectives, problem context, available information and modelling framework. Both metaheuristic and classical optimisation methods have been successfully applied to investigate improved ecological outcomes in river systems (e.g. Yeh and Becker, 1982; Shiau and Wu, 2006; Dittmann *et al*., 2009; Rheinheimer *et al.*, 2013; Tsai *et al.*, 2015). Irrespective of the algorithm used, of key importance is identifying the impact of different assumptions and uncertainties on results.

Although the impact of objective functions and decision variables has been widely discussed, it is rarely considered in the context of ecological objectives for river system management. Objective function formulation can affect whether greater focus is given to periods of good ecological conditions; to avoiding worst case scenarios; or to maintaining moderate conditions. The choice of decision variables can limit the type of management solutions found if they do not describe sufficient variability in flow release strategies, but can increase computational time as additional decision variables are introduced. It is recommended that the sensitivity of optimisation solutions to objective function and decision variable formulation is examined as part of any optimisation study, with particular consideration given to the ecological implications of different formulations.

7.6 How well are ecological modelling outcomes evaluated in terms of actual outcomes?

An assessment of actual ecological outcomes compared with modelled predictions is essential in the management of ecosystems, as well as in improving future modelling capabilities and understanding of the system (Davies *et al.*, 2014). However, field-based evaluations of ecological outcomes are rarely reported in river system optimisation studies due to the large investments needed; the lag time in ecological response; monitoring not being robustly designed to detect change; and the challenge in attributing ecological outcomes to a specific action (Lindenmayer and Likens, 2010). Of the papers reviewed, none identified whether the modelled outcomes had been applied in practice, and hence the performance of the model relative to actual ecological response was not evaluated. This lack of evaluation in the context of the real system is seen as a major limitation in the assessment of model performance.

Where evaluation of model performance against actual ecological outcomes is not possible, a comprehensive and systematic analysis of the model and optimisation framework can aid in understanding the impact of uncertainty on management strategies. It is recommended that this type of evaluation follows a similar approach to the analysis outlined in this chapter and in Part

B of this thesis, where assumptions in objective setting, model representation and application in an optimisation framework are identified. This can lead to greater understanding of model behaviour and the context in which it can be applied. A key element of model evaluation is in identifying major assumptions (such as system conceptualisation) and how they are likely to alter the model outcomes and recommended management actions.

Frameworks and tools such as those described by Walker *et al*. (2003), Refsgaard *et al*. (2007), van der Keur *et al*. (2008), O'Hagan (2012) and Bastin *et al*. (2013) provide guidance on identifying critical model assumptions. Bennett *et al*. (2013) also summarise and categorise a range of model evaluation metrics and methods. Of the optimisation papers reviewed, the majority did incorporate some sensitivity analysis (e.g. Sale et al., 1982; Xevi and Khan, 2005; Shiau and Wu, 2006; Shiau and Wu, 2009; Tilmant et al, 2010; Yang and Cai, 2011; Grafton et al, 2011; Yin et al, 2012; Jager, 2014). The majority of these papers examined sensitivity to different objective function weights, whilst others considered the impact of constraint values, decision variables and the optimisation algorithm. Some papers also tested the sensitivity to model parameters or input drivers, for example, the impact of different habitat functions (Sale *et al*., 1982), ecological model input parameters (Jager, 2014), different economic values for a wetland (Tilmant *et al*., 2010), and the impact of different water availability or allocations (Grafton *et al*., 2011; Szemis *et al*., 2012).

The application of robust optimisation and decision making can also incorporate model uncertainty through the use of multiple scenarios, where optimisation outcomes are evaluated against a range of possible futures to assess sensitivity to different assumptions (e.g. Lempert, 2002; Lempert *et al*., 2003; Deb and Gupta, 2006; Lempert and Groves, 2010; Hall *et al*., 2012; Kasprzyk *et al*., 2013).

It is argued that a greater focus on comparing results to actual ecological outcomes is critical for bridging the gap between research and management, and for more informed application of modelling tools. This can be assisted through ongoing adaptive management, where different strategies are tested and evaluated, and used to improve future model predictions. This requires models to be adaptable to incorporate new information as it becomes available.

7.7 Conclusions

Using optimisation for ecological management in river systems presents both opportunities and challenges. Opportunities lie in the exploration of system behaviour and the facilitation of learning, communication, and ultimately decision making (Liebman, 1976; Brill Jr, 1979; Maier *et al*., 2014). Optimisation can increase transparency in the decision making process, encompass multiple stakeholder inputs and perspectives, as well as highlight data and knowledge gaps for future research. It provides a framework for formulating assumptions, and can be used in an iterative and adaptive process in conjunction with sources of information that are not directly included within the model.

Many of the challenges in using optimisation stem from the subjectivity in defining and representing objectives and objective functions, and the gaps in contemporary knowledge describing ecological systems. Given subjectivity is an inherent component of objective setting, better recognition of this subjectivity and its role in, better recognition of this subjectivity and its role in the decision making process can assist in identifying appropriate management strategies (Beven, 2002; Loucks, 2006). The issues pertaining to ecological systems discussed in this paper apply more widely, displaying characteristics of 'wicked problems' as identified by Rittel and Webber (1973).

This synthesis explored the use of optimisation for the management of riverine ecosystems, by drawing upon papers covering a range of ecological modelling and optimisation approaches. Whilst previous studies demonstrate innovative ways of incorporating ecological objectives to improve river system management, this paper argues that more critical analysis is needed to examine how the objectives, model(s), optimisation approach, and results represent and influence ecological outcomes. Few previous studies critically evaluated the major assumptions throughout the optimisation process, and there was limited discussion regarding the impact of these assumptions on modelled solutions. In addition, there is a lack of evaluation of modelling results against actual ecological outcomes, which is considered necessary to further advance the effectiveness of optimisation to aid decision making.

Whilst many of the challenges identified in this chapter are not unique to ecological systems, additional challenges are introduced due to the complexity and uncertainty inherent in understanding ecosystem behaviour, the social values attached to defining desirable ecological states, and the difficulty in measuring cause/effect relationships to evaluate outcomes (Davis and Slobodkin, 2004; Naiman *et al.*, 2008). Many non-ecological water requirements such as for domestic, agricultural, or hydropower purposes, are more easily estimated due to less variability in demands, and greater control through systems which are designed, constructed and operated to meet these requirements. In comparison, ecosystems change and adapt in response to prevailing conditions in ways that are generally less predictable (Holling, 1973). In addition, valuation of non-ecological objectives such as irrigation net profit or flood damage is often more straightforward than valuing an ecosystem.

The following recommendations draw on approaches for applying best practice for environmental modelling (e.g. Jakeman *et al*., 2006; Loucks, 2006), but with greater focus on identifying assumptions and uncertainties for optimisation:

(1) Identifying ecological objectives which consider both the overarching goal as well as the specific objective which is modelled and measured. It is recommended that the

assumptions required in specifying these objectives are explored, as well as the role of social values in defining desired ecological outcomes.

(2) Further evaluation of the impact of limitations and assumptions on modelled outcomes, and consequently how well the modelled results can inform the stated objectives. It is recommended that the evaluation includes an assessment of the indicators used, and the use of multiple scenarios to identify the impact of different model conceptualisations, as undertaken in Chapters 5 and 6 in this thesis.

(3) Consideration of the impact of objective functions and decision variables on ecological outcome. It is recommended that multiple formulations are tested as part of any optimisation studies.

(4) Evaluation of results within the context of assumptions in objective setting and problem formulation, with greater consideration of likely actual ecological outcomes. This type of evaluation can also assist in identifying requirements for additional data collection/investigations to improve the reliability of results.

The process of setting objectives through to evaluating results needs to be adaptive and allow for multiple iterations as the understanding of the system improves throughout the modelling and optimisation process, as well as over time (Loucks, 2006). In addition, there is a need for better integration of modelling and optimisation in the decision making process such that these tools can be tailored to the specific context, and can be complementary to other sources of information. It is believed that the above recommendations can improve the effectiveness of optimisation to aid decision making, both in terms of exploring different options which warrant further investigation, and in better understanding the system (Liebman, 1976; Brill Jr, 1979). The use of optimisation as part of a process that informs and enriches decision making rather than a purely predictive tool, allows the appreciation of limitations and uncertainties to be shared among stakeholders, thereby facilitating more widely acceptable decisions (Dunn *et al.*, 2008; Gupta and Nearing, 2014).

Chapter 8: Using optimisation to explore opportunities and trade-offs in environmental flow management: case study

8.1 Aim and Overview

This chapter brings together the different elements of work presented so far. Chapters 3 to 6 describe the development of an ecological response model using a systems approach to understanding water availability and the impact on River Red Gum condition. These chapters explore some of the significant uncertainties that still remain in our understanding and modelling of ecological response; they outline strategies for developing a deep insight into model behaviour to facilitate learning about the system; and they enable more informed interpretation of model results. Chapter 7 then presents a synthesis of the opportunities and challenges in using multi-objective optimisation to aid decision making for ecological management in river systems. It identifies the importance of clearly identifying objectives and the assumptions inherent in objective statements. It also highlights the need for greater consideration of the assumptions in representing ecosystems within a modelling and optimisation framework, and the impact these assumptions have on management decisions.

The aim of this chapter is twofold:

- Firstly, to evaluate the effectiveness of optimisation in aiding decision making for environmental flows using a case study. In doing so, challenges identified in Chapter 7 are addressed, including the specification of clear objectives, and the examination of how model and optimisation assumptions impact on decisions.
- Secondly, to identify environmental flow rules which have potential for improved outcomes for both River Red Gum and agriculture within the case study, and to explore trade-offs between objectives.

Given that Chapter 7 provided a comprehensive overview of relevant literature, this chapter focuses on the application of optimisation, and demonstration of an approach for improved consideration of uncertainties.

An early version of this analysis was presented in the conference paper Barbour *et al*. (2011). However, both the model and the optimisation implementation have significantly changed since this paper was published.

8.2 Introduction

The Lachlan catchment presents an ideal case study for exploring the use of optimisation in ecological river system management, where multiple competing water use objectives exist in a context of significant river and basin development, high variability in available water, and periods of extreme water scarcity. The presence of shallow groundwater in the Great Cumbung Swamp also enables the examination of groundwater dependency by River Red Gum, a novel component of the current work as previously discussed. Whilst a more detailed description of the case study is provided in Chapter 2, a schematic of the catchment is repeated here in Figure 94 to show the major land use types, irrigation districts, and the two most significant wetlands, Booligal Wetlands and the Great Cumbung Swamp. Major reservoirs are also shown, which control approximately 68% of annual inflows (CSIRO, 2008) and divide the system into three main sections – the upper headwaters above the Belubula-Lachlan confluence; the mid-Lachlan above Lake Brewster; and the lower Lachlan.

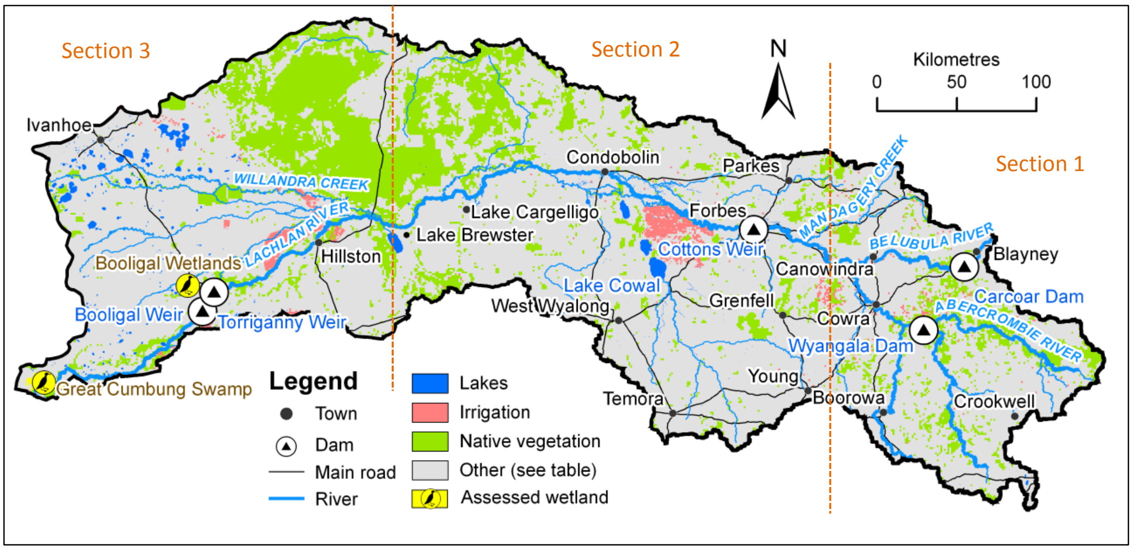


Figure 94. Lachlan river basin showing major reservoirs and land type/land use. For the purpose of this thesis, the catchment is described using three sections – Section 1: upper Lachlan; Section 2: mid-Lachlan; and Section 3: lower Lachlan (source: adapted from CSIRO, 2008).

Given the aim of this chapter is to explore the use of optimisation as well as investigate environmental flow management strategies and trade-offs, a simplified model of the Lachlan catchment was applied instead of the full model used for management. Results should therefore be interpreted in this context.

The two main objectives examined in the case study consider: (1) River Red Gum condition in the Great Cumbung Swamp; and (2) available water for irrigation (the primary water user) in the Lachlan catchment. These are intended to be representative of the broader trade-offs between riverine ecosystems and human water use, and can be readily extended to include other objectives in future work. The main decisions considered were reservoir releases and agricultural extractions. The model was run on a daily time step for 108.5 years from

1/1/1898 to 31/7/2006, utilising data provided by Department of Primary Industries Water (DPI Water), Australia.

The following sections provide an overview of the modelling framework used, followed by application of optimisation to the Lachlan case study. The case study addresses challenges identified in Chapter 7 through the exploration of objective and problem formulation. Six optimisation scenarios are used to identify the sensitivity of the results to different objective functions, hydrological model assumptions, ecological model assumptions, and optimisation algorithm performance. The chapter finishes with a discussion of management implications and conclusions.

8.3 Modelling framework for the Lachlan

The Lachlan model used for the current work consists of two components: a simplified river model which has been adapted from that used by DPI Water; and the ecological response model (ERM) developed in Part B of this thesis. Figure 95 shows the integration of these two components, whereby the river model is run for the complete 108.5 years to generate daily flows that are then used as an input to the ERM.

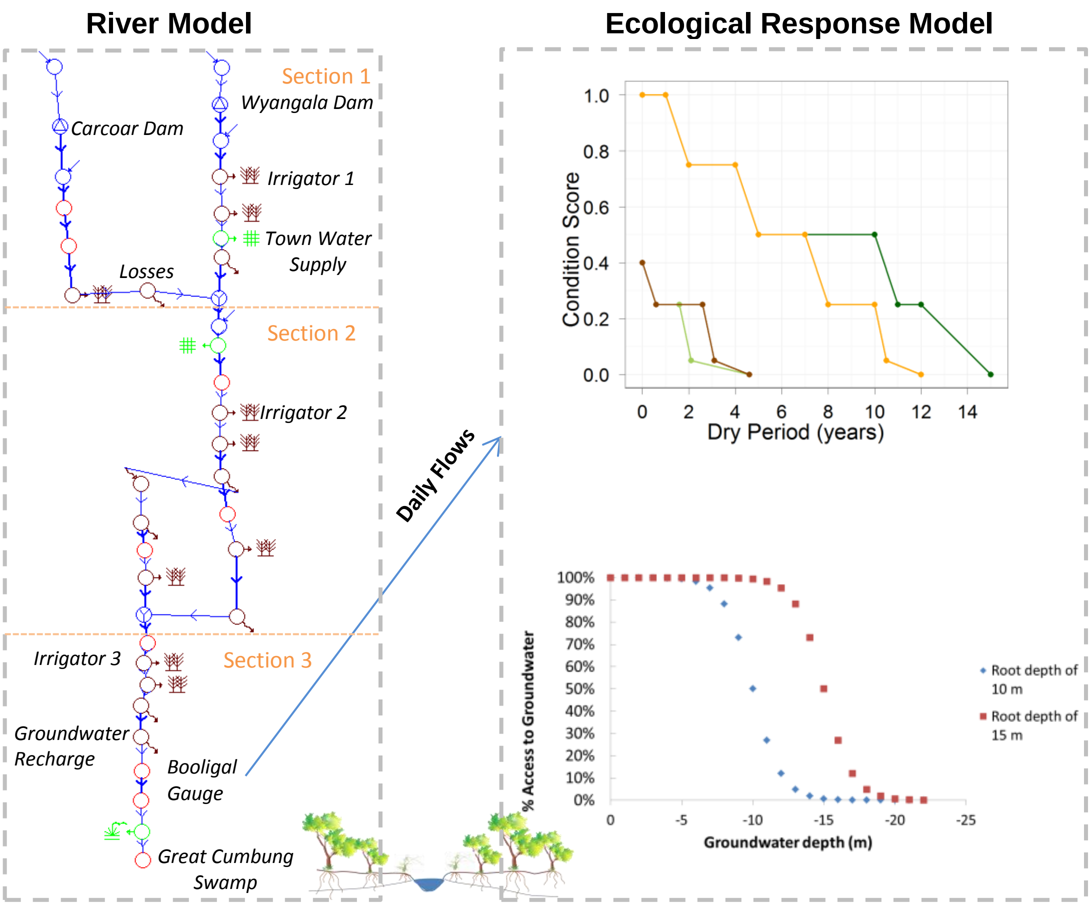


Figure 95. Integration of the simplified Lachlan river model and River Red Gum Ecological Response Model for the Great Cumbung Swamp.

The Lachlan river model was implemented using the Integrated Quantity and Quality Model (IQQM) developed by DPI Water, Australia (Hameed and Podger, 2001; Simons *et al.*, 1996; Podger and Hameed, 2000; DPI Water, 2007). IQQM is a process based model where nodes represent river elements such as inflows, losses, extractions, storages, wetlands, confluences or bifurcations; and links represent river reaches with delay and attenuation of flow. There are two main calculation steps, the first begins at the most downstream end of the system and calculates total water demands moving up the system to each storage; and the second which releases water from the storages, routing it through the river reaches considering any extractions, losses or inflows. The actual volume released from storage is dependent on the total demands, release constraints and the storage operating rules.

The simplified Lachlan river model used here (Figure 95) incorporates two major headwater dams, three main irrigation regions, two town water supplies, and one downstream wetland. In addition, major inflows and losses are included, as well as groundwater recharge upstream of the wetland. The model structure was developed to represent the three main sections of the Lachlan, where irrigator extraction nodes represent an aggregate of the main irrigators within a region. The three irrigators labelled in Figure 95 represent an aggregation of the main *general security* irrigators, where water is used for planting annual crops. Some additional smaller general security irrigators as well as an aggregation of the main high security irrigators were also included to approximate the total agricultural water requirements in the system.

The first section of the model consists of the headwater inflows and storages, and extends to the confluence between the main Lachlan River and the Belubula River (shown in Figure 94). The second runs from the Belubula confluence to upstream of Lake Brewster, and the third from downstream of Lake Brewster to the Great Cumbung Swamp (Figures 94 and 95). Whilst the complexity of the simplified model is greatly reduced compared with the full Lachlan model, it was considered adequate for the current purpose of exploring the application of optimisation in investigating environmental flow management. To reduce the impact of these differences, loss and routing parameters in the simplified model were selected based on minimising the different in flow at key locations between the two models (described further in Section 8.4).

A summary of each of the primary river system model components is provided below.

8.3.1 Inflow nodes

Major headwater and tributary inflows were included in the simplified model using the same input data as in the full Lachlan model. Combined, these represent 95% of the major tributary inflows in the full model, with the inflow to Wyangala being approximately 82% of the total major inflows (Figure 96).

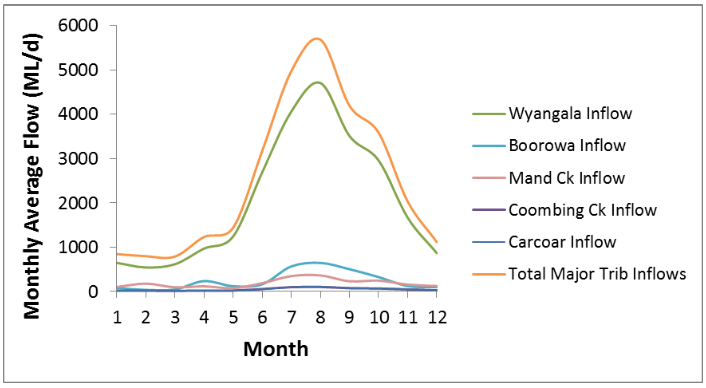


Figure 96. Major tributary inflows included in the simplified model compared with the sum of all major tributary inflows in the full model. Values represent the *average* monthly flow from the full Lachlan model (DPI Water, 2007).

8.3.2 Loss nodes

The full Lachlan model includes twenty loss and distributary nodes. Given that the aim of the simplified model is primarily to explore the use of optimisation with representative elements, only six losses were used. These include two loss nodes, two unregulated distributaries, a groundwater recharge node (Section 8.3.3), and a calibration loss node. The calibration loss node was used to account for other system losses not explicitly modelled, to obtain the closest possible match between the simplified model and full model.

Loss nodes were specified using monotonically piecewise linear relationships between river flow and loss, in keeping with the full Lachlan model.

8.3.3 Groundwater recharge

There are high levels of surface water – groundwater connectivity in the lower Lachlan (CSIRO, 2008). Whilst it was beyond the scope of the current work to develop a comprehensive representation of surface water - groundwater interactions, a single groundwater recharge point was included in recognition of the importance of groundwater in estimating water availability and ecological outcomes. This is an advance on the existing full Lachlan IQQM model, where groundwater recharge is often incorporated in generic loss parameters due to a lack of available data. Limitations in representing surface water – groundwater interactions are now being addressed through the development of the eWater Source model (Welsh *et al.*, 2013; Rassam *et al.*, 2013). However, this model was not available at the time the current work was undertaken.

For the single groundwater node included here, recharge was estimated using data from two boreholes (GW036721 and GW090056) to provide an average representation of groundwater at two different depths and locations within the Great Cumbung Swamp (see Chapters 2 and 3 for more information on groundwater in the Great Cumbung Swamp). First, the change in groundwater level was estimated using a Nash cascade of two storages (Nash, 1958), based on the same approach used in Chapter 3 for examining River Red Gum uptake of groundwater:

$$GW_t = m\left[2aQ_{t-1} - a^2 Q_{t-2} + (1-a)^2 Q_t\right] + c \tag{47}$$

where:

GW_t	=	Groundwater level at time *t* (m)
t	=	Time (days)
Q	=	Booligal flow (ML/d)
$\tilde{Q}$	=	Output flow from the second storage (ML/d)
a	=	$e^{\frac{-1}{\tau}}$
τ	=	storage delay constant
m, c	=	constants to convert values from ML/d to level (m)

For borehole GW036721, the parameters $\tau, m,$ and c had values of 1950, 0.0075, and -17.86 respectively, as discussed in Chapter 3. The same process was used to identify parameter values for borehole GW090056, with values of τ = 1050, m = 0.0151, and *c* = 9.85.

The second step was to estimate monthly change in groundwater volume averaged across the two boreholes using a simple bucket style representation of the aquifer underlying the Great Cumbung Swamp:

$$\Delta GW^{vol}_{t,b} = \frac{\left(GW^d{}_t - GW^d{}_{t-1}\right) \times A \times \phi}{1000} \tag{48}$$

$$\Delta GW^{vol}_{m} = \sum_{t=1}^{D}\left(\frac{\sum_{b=1}^{2} \Delta GW^{vol}_{t,b}}{2}\right)$$

where:

$\Delta GW^{vol}_{t,b}$	= daily change in groundwater volume at time *t* for borehole *b* (ML)
GW^d	= groundwater depth (m)
A	= aquifer area (taken to be the surface area of the Great Cumbung Swamp – $1.5\text{x}10^8$ m^2)
ϕ	= porosity (0.5)
ΔGW^{vol}_{m}	= net monthly change in groundwater volume (ML)
D	= days per month

Figure 97a shows the estimated net monthly change in groundwater volume plotted against the total monthly surface water flow at Booligal. This relationship was used to generate a piecewise linear pattern between surface flow and groundwater recharge. Figure 97b shows the same relationship between estimated change in groundwater volume and surface flow divided into moderate, wet and dry years (classified using a frequency distribution curve). The variation in groundwater change under different climatic conditions highlights the need to consider loss relationships which are climate dependent as well as flow dependent in future work (Barbour *et al.*, 2011).

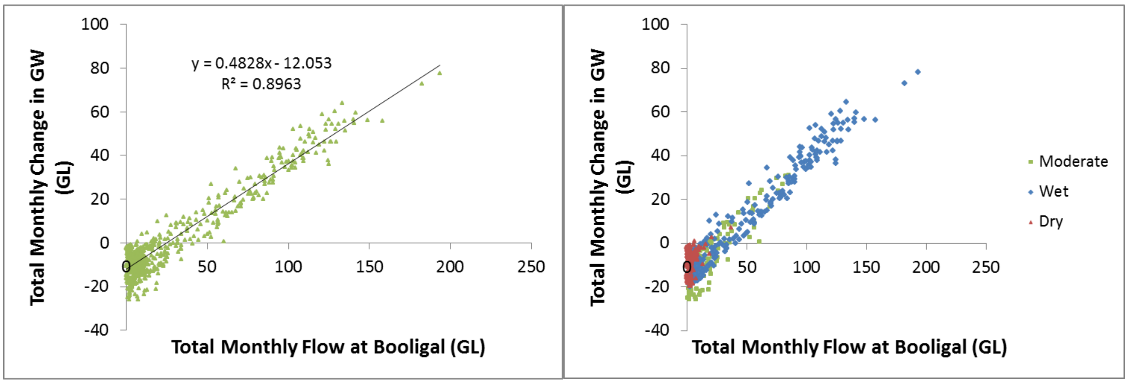


Figure 97. Estimation of groundwater recharge based on monthly surface water flow for (a) all years combined; and (b) separately for moderate, wet and dry years.

8.3.4 Dams

The two major headwater dams in the Lachlan, Wyangala and Carcoar, are both represented within the simplified model. Wyangala is the primary headwater storage dam, with a capacity of 1220 GL. It is operated in conjunction with two re-regulating storages – Lake Cargelligo and Lake Brewster (not included in the simplified model). Wyangala is a multi-purpose dam, and is operated to meet extractive uses including town water supply, industry and agriculture, as well as for flood mitigation and environmental flows. Releases made to meet these requirements are used to generate hydropower with a capacity of 22.5 MW (State Water Corporation, 2009). For the purpose of this research, re-regulating storages and other infrastructure have not been included in the simplified model.

8.3.5 Extraction nodes

Two types of extraction nodes were included in the simplified model: town water supply and irrigation. The two town water supply demands represent the townships of Cowra and Forbes in the mid and upper Lachlan (Figure 94). Water demands were specified using a monthly pattern.

Ten irrigator nodes were included, of which three are high security and seven are general security. High security licences are typically for perennial plantations such as fruit trees, where a lack of water in one season will result in the loss of the entire crop. General security licences are used for annual crops, where the decision to plant, the type of crop, and the area planted vary each year based on the available water. For this reason, meeting the water requirements of high security licences is given a higher priority than general security.

IQQM estimates water requirements for irrigation using an in-built crop model, which calculates soil moisture for each day based on rainfall and evapotranspiration data. The user specifies the crop type and maximum crop area, which are used to estimate water demand based on a crop factor and potential reference crop evapotranspiration (see Podger (2004) for more information on IQQM crop modelling). Once the projected soil moisture falls below a specified target, a water order is generated. The total amount of water which can be used by each irrigator is controlled by their licence entitlement and the current allocation.

8.3.6 Translucent demand

As described in Chapter 2 (Section 2.2.2), translucent dam releases are one of three methods used in the Lachlan to meet environmental water requirements. The term 'translucency' is used to reflect dam operations which have only 'partial' impact on headwater inflows – making the dam appear 'translucent' (i.e. releasing a proportion of the inflow). Translucent flows are defined by a lower and upper flow threshold where inflows less than the lower threshold are stored, inflows between lower and upper thresholds are released, and flows above the upper threshold are released at the upper threshold rate (Figure 98). More information on translucency rules is provided in Podger and Hameed (2000).

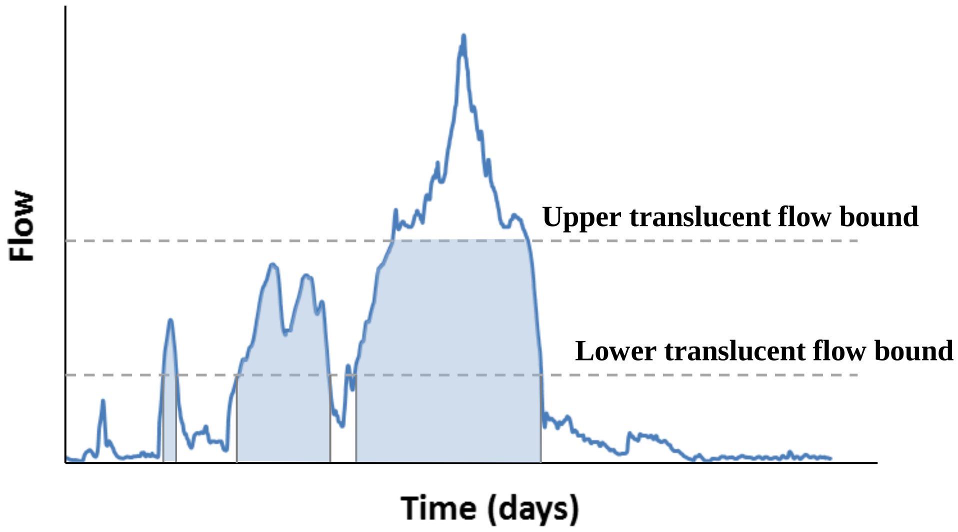


Figure 98. Translucency flow rules, where inflows to a dam (blue line) falling between a lower and upper flow threshold are released as outflows (shaded blue). Adapted from Podger and Hameed (2000).

In the full Lachlan model, translucent releases occur between mid-May and mid-November such that they arrive at Lake Brewster between early June and late November accounting for travel time. Releases are dependent on the storage volume in Wyangala Dam and the flow downstream of Lake Brewster to ensure that there is sufficient water remaining for irrigation (G. Podger, pers. comm., 2015). Operating under these conditions, the lower and upper translucency flow bounds are 3500 ML/d and 8000 ML/d respectively, with a maximum annual translucency volume of 350,000 ML (DIPNR, 2004; Driver *et al.*, 2005a).

In the simplified model, translucency rules consider the time of year and the minimum and maximum translucency release. A base case scenario was run using the same lower release bound of 3500 ML/d and an upper bound of 8000 ML/d, with releases occurring between June and November (a monthly rather than daily pattern was used in the simplified model). However, both flow bounds (lower and upper) and the timing of translucency rules were varied during optimisation considering both environmental and agricultural water requirements. Instead of capping the maximum annual translucency volume at 350,000 ML, an arbitrarily high maximum volume of $1x10^{11}$ ML was used such that translucent releases are only constrained by dam outlet capacity.

8.3.7 Links

Non-linear routing was used to delay and attenuate flow through the model using Equation 49, where outflow is dependent upon the inflow, the storage within the reach, and two parameters which define the degree of delay and attenuation (generally determined through calibration):

$$S = kQ^m \tag{49}$$

where:

S = reach storage

k = storage delay parameter

m = non-linearity measure, generally based on the shape of the channel cross section

Q = flow

Due to the simplified nature of the model, routing parameter values were selected based on giving the best match between the simplified and full model, rather than being representative of any specific part of the system. More detail on the selection of parameter values are provided in the following section.

8.4 Model parameterisation

As described above, the majority of inputs and parameter values used in the simplified model were based on the full Lachlan model, with some aggregation applied in the case of the irrigation nodes. However, the reduced number of nodes and links resulted in significant differences in flow reaching Booligal gauge in the simplified model. Whilst the primary purpose here is to demonstrate the *application* of multi-objective optimisation to aid decision making, some calibration of parameter values was undertaken to ensure that the volume and pattern of flows were approximately similar. This is important for assessing the behaviour of the ecological response model, which was developed specifically for River Red Gum in the Great Cumbung Swamp using knowledge of historical response to water availability.

Calibration involved varying a loss node just upstream of Booligal gauge, as well as varying a selection of link parameters throughout the system. Model outputs for different parameter values were evaluated based on comparison with the full Lachlan model at three key locations relevant to the study objectives: (1) flow at Booligal gauge, relevant for calculating ecological response; (2) flow entering the Irrigator 2 node, relevant for calculating available agricultural water; and similarly, (3) flow entering the Irrigator 3 node. Irrigator 1 was not included in the calibration as the simplified model is identical to the full model upstream of Irrigator 1.

The calibration process was iterative, involving optimisation and manual adjustment of loss and link parameter values as well as model refinement. Optimisation was firstly used to identify approximate parameter values using the following single objective function:

$$\text{Min } D = \sum_{i=1}^{3} d_i$$

$$d_i = w_i \sum_{t=1}^{T} \left| Q_F^t - Q_S^t \right|$$

where:

d_i = Difference in flow at the three calibration locations: Booligal, Irrigator 2 and 3

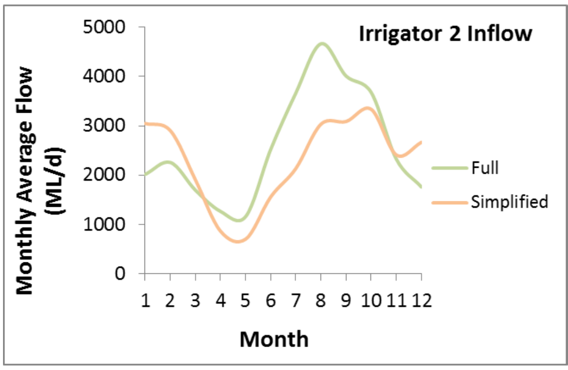
Q_F^t = Flow from the full Lachlan model

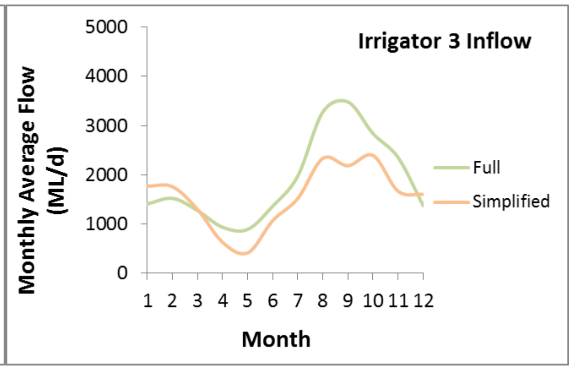
Q_S^t = Flow from the simple Lachlan model

w = weight to combine the difference in flow at location *i*

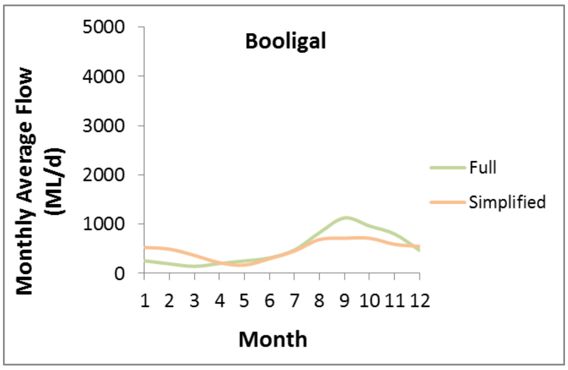
The optimisation results provided an improvement in the fit to the full model, but revealed that the simplified objective function did not capture sufficient detail to achieve the goal of representing a similar pattern and volume of flow at the key locations. In addition, it was identified that minor modifications to the model were needed. Parameter values were therefore further adjusted manually.

The results from the calibration process are shown in Figure 99, where average monthly flows from the simplified and full model are compared. It can be seen that the seasonal pattern of flow is represented, with high flows in July to November and lower flows from January to June. However, the simplified model underestimates the volume of flow particularly during the winter months. The calibration could be further improved, but was not considered warranted for the purpose of the current analysis.





(a) (b)



(c)

Figure 99. Model parameterisation – comparison of the simplified and full Lachlan model at three key locations: (a) inflow to Irrigator 2; (b) inflow to Irrigator 3; and (c) flow at Booligal gauge.

To compare the effect of the simplifications on ecological response, the time series of River Red Gum condition using both the full Lachlan model and simplified model were examined (Figures 100 and 101 - note that figures are shown starting in 1/1/1900 rather than 1/1/1898 as the first two years are more sensitive to initial conditions). For the simplified model, the base case translucent rules were adopted. A starting condition score of 0.7 was used for both models. Due to the absence of any available flow data prior to 1898, the same starting condition score applied in Chapter 4 was adopted. This was considered reasonable as it assumes a moderate-good condition score indicating some system resilience without being overly high or low.

In evaluating the results from both the full and simplified models, it should be noted that the model set-up is stationary over time for both models, given IQQM does not have capacity for time varying parameters. The model set-up and calibration assume all current development and operations have been in place throughout the entire simulation period. This has important implications in assessing available water. Firstly, the construction of major dams in the MDB began in the mid 1930's and continued until the late 1970's (Leblanc *et al.*, 2012). In the Lachlan, construction of Wyangala dam was completed in 1935 and upgraded in 1972. Irrigation development also underwent significant expansion during this time, with total water use across the Basin peaking in the late 1990's (Leblanc *et al.*, 2012). Changes in infrastructure development and water use have directly impacted upon the flow regime in the Lachlan, as well as indirectly through changes in geomorphological processes such as sediment transport (Driver *et al.*, 2002). Secondly, river operations have also changed significantly based on different water reforms (see Section 2.1), such as the introduction of the basin wide cap in 1995, and the implementation of Water Sharing Plans. However, of particular importance is the alteration of operations during drought, where contingency measures are implemented to reserve more water in storage and limit extractions. For the purpose of the current research, it was not feasible to capture these actual operations within the model, which impacts upon the estimation of ecological condition.

It can be seen from Figures 100 and 101 that the most observable difference between the full and simplified model is for Expert Model 1, where the upper bound shows survival of the River Red Gum community using the full Lachlan model, whilst in the simplified model the community collapses in the mid-1940's. However, it can also be seen that River Red Gum condition using the full model also approaches zero during the mid-1940's for the upper bound, reaching a minimum score of <0.01. Meanwhile, the lower bound shows collapse. This suggests that the ecological model is highly sensitive to the estimated available water during this period, and hence is not surprising that there is no survival using the simplified model using the current calibration. It should also be noted that the model has only been evaluated against observed data from 1987 onwards, as no data were available prior to this (see Chapter 6). Consequently, the occurrence of extremely low modelled condition scores of < 0.1 in the earlier part of the century could not be verified.

What can also be observed from Figures 100 and 101 is that none of the other four expert models estimate survival past the early 1900's. Consistent with the evaluation of the expert models in previous chapters, the simulated condition shown below highlights the significant impact of different system conceptualisations on results.

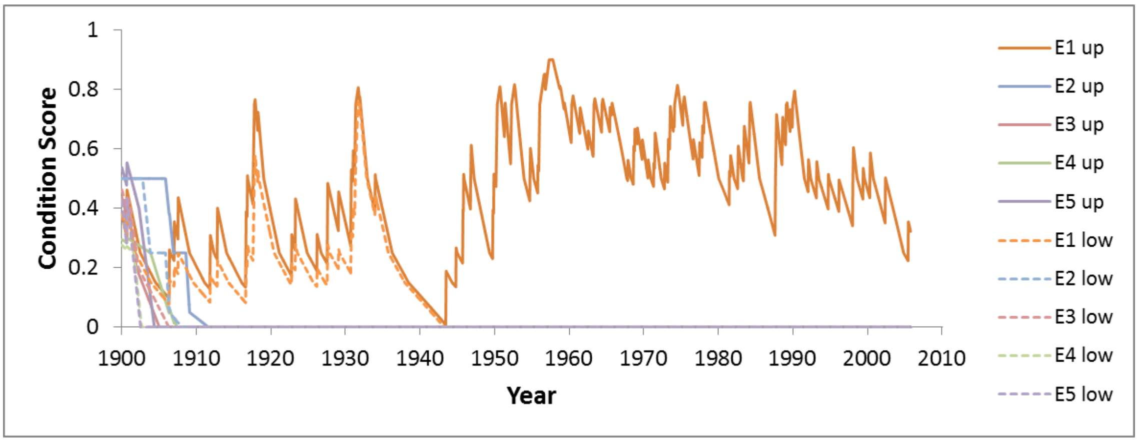


Figure 100. River Red Gum condition score estimated using the five ERMs for the full Lachlan model

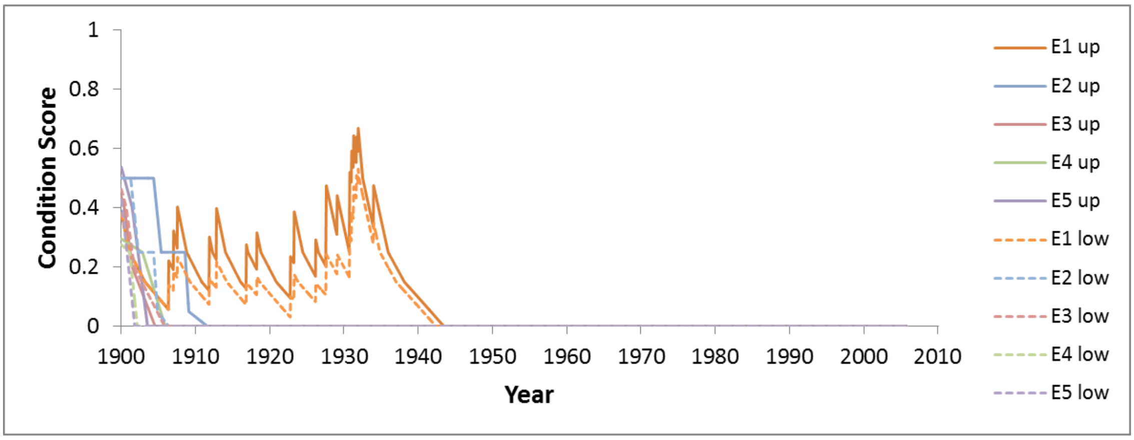


Figure 101. River Red Gum condition score estimated using the five ERMs for the simplified model

To better understand the behaviour of the simplified model, a without development scenario was also run. This involved removing all regulated structures and extractions. The resulting time series of condition scores for the five expert models is shown in Figure 102. It can be seen that the removal of structures and extractions resulted in an improvement in the upper bound curve for Expert Model 1, whilst the lower bound still collapses in the mid-1940's.The minimum condition score was marginally higher than that in the full Lachlan model (developed scenario), being approximately 0.02 rather than 0.01. However, all other expert models still predicted a collapse in the early 1900's.

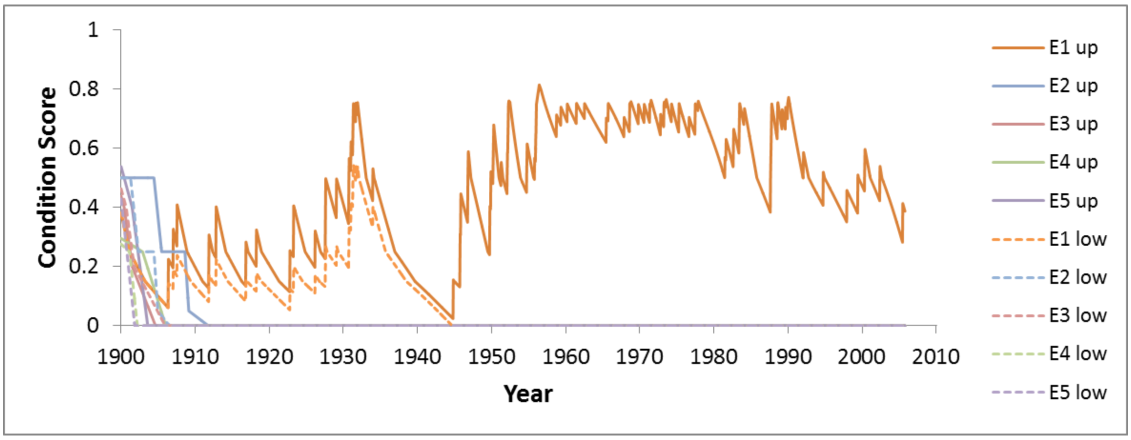


Figure 102. Simplified model with a no development scenario (no regulation or water extractions)

Examining the pattern of change in ecological response in Figure 100, three main periods of decline can be observed. The most severe decline occurs in the mid-1940's, followed by the turn of the century (noting that the starting condition in 1898 was 0.7), and lastly from the 1990's onwards until the end of the simulation in mid-2006. These changes are consistent with the three major historical droughts occurring in the MDB: the Federation drought (mid-1890s to early 1900s); the World War Two (WWII) drought (c. 1937-1945); and the Millennium drought

(Ummenhofer *et al.*, 2009; Verdon-Kidd and Kiem, 2009; Timbal and Fawcett, 2013). Figure 103 shows the twelve month moving average flow at Booligal gauge for both the full and simplified Lachlan models, where it can also be seen that below average flows occur from the start of the time series to mid-1910; from the mid 1930's to mid-1940's; and from the late 1990's onwards.

Given the water scarcity during these three droughts, they provide critical periods for the analysis where there are likely to be trade-offs between environmental flows and agriculture. Whilst the Millennium drought is often referred to as being the worst drought on record (since the 1890's) (e.g. Leblanc *et al*., 2012; Ummenhofer *et al*., 2009), analysis of rainfall data and climatic drivers of the three droughts highlight that both the cause and effect have differed significantly (Verdon-Kidd and Kiem, 2009; Ummenhofer *et al.*, 2009; van Dijk *et al.*, 2013). There is consequently some debate as to whether the Millennium drought was the worst on record given factors such as spatial and seasonal variability in length and severity, as well the capacity of the system to respond (Ummenhofer *et al.*, 2009; Verdon-Kidd and Kiem, 2009; Timbal and Fawcett, 2013; Leblanc *et al.*, 2012).

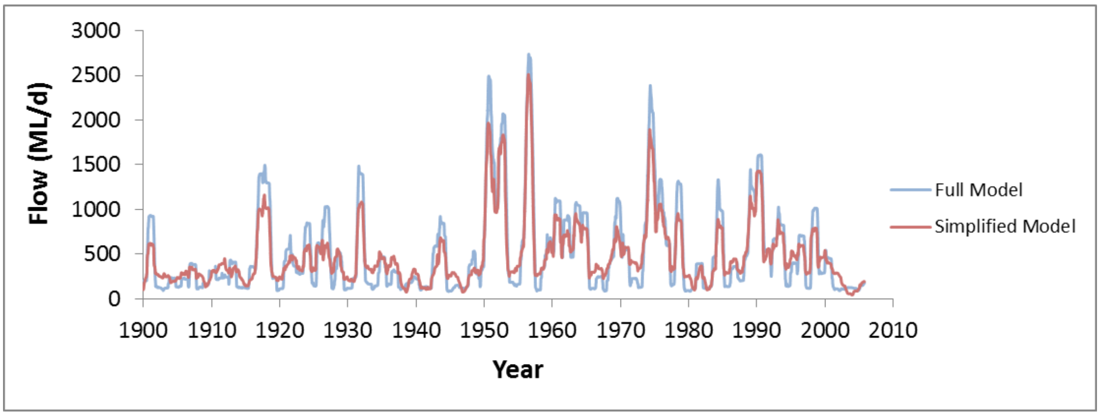


Figure 103. Twelve month moving average simulated flow at Booligal gauge using the full and simplified Lachlan models.

It can be seen from Figure 103 that the differences in flow between the full and simplified models are reflected in reduced peak flows, increased base flows, and some variation in pattern. Whilst these differences are likely to impact on environmental and agricultural outcomes in the simplified model, the representation of the major periods of drought and flood are largely consistent with the full model. The simplified model is therefore considered adequate for the purpose of exploring optimisation as an approach for investigating environmental flows, and investigating the impact of different sources of uncertainty.

The following section describes the application of multi-objective optimisation to the Lachlan case study, beginning with an overview of the problem formulation and finishing with a discussion of results and implications for decision making.

8.5 Using multi-objective optimisation to explore ecological river management in the Lachlan

The optimisation case study aims to address a number of limitations identified in Chapter 7, by identifying and evaluating assumptions in objectives and system representation. In Section 8.5.1, the overall objective is defined and discussed, which sets the context for the analysis. The integrated river system and ERM model is only briefly discussed in Section 8.5.2 to highlight some of the key assumptions, having already been presented in greater detail in previous chapters. Sections 8.5.3, 8.5.4, 8.5.5 and 8.5.6 describe the optimisation framework, including the optimisation algorithm and parameters, objective functions, decision variables and constraints. Section 8.5.7 then describes six different scenarios which were used to investigate the impact of assumptions on optimisation results.

8.5.1 Objectives

The high level objective for this case study was to maximise ecological condition within the Lachlan catchment having minimal impact on non-ecological objectives. Given the estimation of ecological condition throughout the entire Lachlan catchment was outside the scope of the current work, this high level objective was constrained to maximising River Red Gum condition in the Great Cumbung Swamp whilst simultaneously maximising the total water available to three irrigation districts during the primary and secondary growing season. As discussed in previous chapters, River Red Gum was selected given its role as an umbrella species in the Great Cumbung Swamp, hence it is assumed that meeting the water requirements of River Red Gum will also support the broader vegetation community of the Great Cumbung Swamp, and provide habitat for other species. However, it is also recognised that each species within the Great Cumbung Swamp has distinct water requirements which may not always be met by providing for River Red Gum alone (Rogers *et al.*, 2012).

The Great Cumbung Swamp was selected as the focal point of the case study given its ecological significance both nationally and regionally. In addition, its location at the end of the Lachlan system means it can be assumed that delivering environmental water for the Great Cumbung Swamp can also sustain upstream ecosystems. In reality, this assumption may not always hold true, given that water diverted to upstream wetlands and floodplains may reduce the total surface water reaching the Great Cumbung Swamp, although recharge of shallow and deeper aquifers will still have regional benefits.

Irrigation was used as a test case for examining ecological and non-ecological trade-offs in the Lachlan, being the largest water consumer in the catchment and hence having the greatest impact on altering the flow regime. Given a simplified version of the Lachlan river system model was used, the largest general security irrigators were identified in the three main sections of the Lachlan, and aggregated to form three total irrigation demands. In doing so, there will be some variation in system behaviour compared with representing each irrigator independently.

General security rather than high security irrigators were selected for the case study as they have larger licence volumes, as well as being more adaptive to available water given the use of annual crops rather than perennial plantations. They are also the first to be impacted by water shortages.

Whilst the objective stated above has been constrained to River Red Gum in the Great Cumbung Swamp and three irrigator regions, it can be seen that additional ambiguity remains in how to define River Red Gum condition, total water availability for irrigators, and how these should be maximised. Further specification is therefore required to formulate mathematical objective functions, taking into consideration model formulation and constraints. These are described in the following sections.

8.5.2 Integrated river system and ecological model

The integrated model has been specifically formulated for investigating different environmental flow rules to meet the objective described above. It estimates River Red Gum response to water availability as well as the total water available for the three irrigator regions. Given four of the five expert models predicted an ecological collapse in the early 1900's, the majority of optimisation scenarios only used Expert Model 1, with a single scenario using Expert Model 2 as a comparison (see Section 8.5.7 for details on scenarios).

A number of model limitations influenced the formulation of objective functions and decision variables, as well as the resulting solutions. These are important to consider when evaluating the optimisation results. The primary limitations are listed as follows:

River system model

- Translucent flows released from Wyangala can be extracted by users upstream of the Great Cumbung Swamp should the orders placed by other users not be met – environmental water is therefore not protected from other users once it is released.
- Environmental flow releases are only made based on translucent flow rules, and do not incorporate additional discretionary releases based on the current state of the ecosystem (such as through licences or annual environmental flow allocations – see Section 2.2.2 for more detail). The current IQQM model structure does not allow for direct feedback between ecological condition and dam releases. However, the optimisation process searches for translucent rules which have better ecological outcomes based on the defined metrics.
- As discussed above, the model assumes there are no structural or operational changes to the system over the simulation time (108.5 years). In reality, licence volumes and irrigation patterns have changed over this time. In addition, there

have been changes to the standard operating rules during times of drought and flood which are not reflected in the model.

- As with all river system models, flows are an estimate only and some differences would be expected compared with the actual observed flows. The same applies to the agricultural model within IQQM.

Ecological Response Model

- Only a single species in a single location was modelled, consequently limiting the problem formulation.
- Sensitivity to surface water inundation and groundwater level estimates suggest these are likely to impact upon the predicted ecological outcome.
- Differences in expert conceptualisation of ecological response are significant, suggesting there is high uncertainty in the estimate of ecological response.
- Uncertainty bounds in ecological response limit the informative nature of the model.
- A lack of adequate observational data limits the capacity to evaluate model performance.

8.5.3 Optimisation algorithm and parameters

The multi-objective genetic algorithm eMoga (Laumanns *et al.*, 2002) was used based on demonstrated performance in previous studies (Mortazavi-Naeini *et al.*, 2015). Given that the focus of the current work is on problem formulation rather than algorithm performance, the selection of an optimisation algorithm was based primarily on adequate prior performance, the capacity to evaluate multiple objectives, and the inclusion of an 'epsilon' parameter which can improve search efficiency (Laumanns *et al.*, 2002). There have been many previous studies devoted to the improvement and evaluation of optimisation algorithms (e.g. see review by Maier *et al*., 2014). Table 16 summarises the values used for the main optimisation parameters.

Table 16. eMoga optimisation algorithm parameter values

Parameter	Parameter value
Population	100
Maximum generations	2500
Probability of crossover	1.0
Probability of mutation	0.025
Epsilon value	5

It is recognised that the maximum number of generations used here is relatively small and was not sufficient for convergence for some of the optimisation scenarios. However, it was adopted due to the significant computational times involved in running multiple optimisation scenarios, and given the focus of the current work was on exploration of different types of problem formulation rather than on finding the trade-off curve closest to the actual Pareto front.

8.5.4 Objective functions

Two objective functions were used in each scenario, one to represent River Red Gum condition and one for irrigator water availability. These were defined through an iterative process, involving consultation with water managers in NSW government departments, the Murray-Darling Basin Authority, as well as fellow researchers in hydrology and ecology. This iteration included trialling and rejecting different objective functions as a greater understanding of the system and model was gained. The two types of objective functions are described below.

8.5.4.1 Ecological Objective Function

Four different ecological objective functions were examined to explore the impact on management strategies and trade-off curves. EcoObj(1) in Equation 50 was defined to incorporate two important ecological characteristics – minimising the occurrence of very low condition scores which could lead to system collapse, and maximising the occurrence of high condition scores, noting that natural variability is desirable. As described in Chapter 7, an objective function focusing only on low condition will not provide incentive to identify solutions which have a ‘good’ ecological outcome, whilst focusing only on high condition scores may ignore the community dying during the simulation.

Low condition scores are considered by taking the minimum value from the twelve month moving average condition score for the entire simulation ($\tilde{C}_{UL}$). In this case, the condition score was taken as the *average* of the lower and upper ecological condition bounds. The use of the moving average has the effect of smoothing the data such that it is not driven only by a single daily condition score, for which there is insufficient accuracy in the model to adequately estimate. High condition scores are considered by counting the number of times the average of the lower and upper bound score is above or equal to 0.7. A threshold of 0.7 was used to represent a ‘good’ condition, which is consistent with information obtained during expert elicitation.

Given the ecological objective function returns values between 0 and 2 (in the case of EcoObj(1), otherwise between 0 and 1 for the other three ecological objectives), a scaling factor of 10,000 was applied to increase the magnitude of values in the optimisation decision space. This was done to improve the optimisation search process by magnifying differences between ecological objective values. The same effect could have been equally achieved by reducing the epsilon value to a value <<1 rather than 5 as used here (see Table 16).

Limitations of Equation 50 are twofold: there is no consideration of moderate condition scores; and the assumption is that as long as some good periods are found and poor periods are minimised, that the condition will be adequate based on flow alone. In addition, it only considers the average of Expert Model 1, and assumes that there is a distinct difference between ≥0.7 and <0.7 which disregards scores close but not equal to 0.7.

As an alternative to objective function 1, EcoObj(2) (Equation 51) computes the average ecological condition over both lower and upper ecological bounds *and* the total simulation time *T*. Similarly, EcoObj(3) and (4) (Equations 52 and 53) compute the average for either the lower or upper bound over *T*. In contrast to objective function 1, objectives 2 to 4 consider the full range of condition scores but are less sensitive to either high or low scores. This type of formulation with averaging over the simulation period was also used by Grafton *et al*. (2011) and Szemis *et al*. (2012) as discussed in Chapter 7.

$$\mathrm{EcoObj}(1) = \max\left(10{,}000 \times \left(\tilde{C}_{UL} + \frac{c_{ul}(0.7)}{T}\right)\right) \tag{50}$$

$$\mathrm{EcoObj}(2) = \max\left(10{,}000 \times \frac{\sum_{t=1}^{T} 0.5 \times (C_U^t + C_L^t)}{T}\right) \tag{51}$$

$$\mathrm{EcoObj}(3) = \max\left(10{,}000 \times \frac{\sum_{t=1}^{T} C_L^t}{T}\right) \tag{52}$$

$$\mathrm{EcoObj}(4) = \max\left(10{,}000 \times \frac{\sum_{t=1}^{T} C_U^t}{T}\right) \tag{53}$$

where:

$\tilde{C}_{UL}$ = 12 month moving average of condition score for Expert 1

$c_{ul}(0.7)$ = count of days where the average of the upper and lower bound condition score is above or equal to 0.7

n = length of time over which the data are averaged, in this case 365 days

T = total number of time steps (days)

C_U^t = upper bound condition score at time t

C_L^t = lower bound condition score at time t

$C_{UL,t}$ = average of lower and upper bound condition score at time t

$\tilde{C}_{UL}$ is defined as:

$$\tilde{C}_{UL} = \min_{t=1,T}\left(\frac{C_{UL,t} + C_{UL,t-1} + ... + C_{UL,t-(n-1)}}{n}\right)$$

Equation 50 describes the main ecological objective function used in all but one of the six scenarios, whilst the remaining three were tested as part of Scenario 2 (see Section 8.5.7).

8.5.4.2 Irrigation Objective Function

A single objective function was used for irrigation water availability for all scenarios (Equation 55). The objective function counts the number of years where the water available for each irrigation region is considered to be either 'good' or 'bad', where 'good' is defined as years when the total volume of water available during the primary or secondary growing season is greater than or equal to 30% of the maximum possible volume for that irrigator, whilst 'poor' is defined as years when the total volume is less than or equal to 10% of the maximum possible:

$$c_{i,g} = \sum_{y=1}^{Y} y \text{ where } V_{i,y} > 0.3L_i^{\max}$$

$$c_{i,p} = \sum_{y=1}^{Y} y \text{ where } V_{i,y} \leq 0.1L_i^{\max}$$

$$c_{i,p3} = \sum_{y=1}^{Y} y \text{ where } V_{i,y} \leq 0.1L_i^{\max} \text{ for } y, y+1, y+2$$

$$c_{i,p5} = \sum_{y=1}^{Y} y \text{ where } V_{i,y} \leq 0.1L_i^{\max} \text{ for } y, y+1, y+2, y+3, y+4$$

where:

$c_{i,g}$ = number of 'good' years for irrigator i over the total number of years Y

$c_{i,p}$ = number of 'poor' years for irrigator i over the total number of years Y

$c_{i,p3}$ = number of times there are three consecutive 'poor' years for irrigator i over the total number of years Y

$c_{i,p5}$ = number of times there are five consecutive 'poor' years for irrigator *i* over the total number of years Y

i = Irrigator

Y = Total number of *y* years (108 for September and 109 for March given the simulation runs from 1/1/1898 to 31/7/2006)

$V_{i,y}$ = Volume water available for Irrigator *i* for year *y*:

$$V_{i,y} = A_y \times L_i \tag{54}$$

A_y = Allocation for year *y*

L_i^{max} = Maximum possible allocation volume for Irrigator *i*

L_i = Actual licence volume for Irrigator i

The definitions above are based on consultation with commonwealth and state government water managers as well as fellow researchers, but given there has been an aggregation of feedback from multiple sources, these should not be assumed to represent the opinion of any department or organisation. It is also recognised that many irrigators may view 30% of maximum water as being sub-optimal rather than 'good'. However, it should be noted that 'good and 'poor' are defined based on a single day at the start of the primary or secondary growing season, when allocations for the upcoming water year are intended to be conservative. Hence a starting allocation of 30% may still increase significantly during the season.

In addition to considering single 'poor' years, water managers indicated that the sequence of 'good' and 'poor' years was equally important. Where there are three or more consecutive poor years, this can result in farmers going out of business. As such, occurrences of consecutive poor years were given a higher weight. A higher weighting is also given to the primary growing season in September, with the secondary season being less critical in the Lachlan given higher flows and rainfall over winter.

Given irrigator licence volume is used as a decision variable (see Section 8.5.5), the total volume of water available is defined in Equation 54 as the allocation multiplied by the licence volume as determined by the optimiser. This is then compared with 10% and 30% of the current (i.e. maximum) licence volume assuming 100% maximum allocation.

Limitations of the irrigation objective function include: each irrigation region is not considered separately; available water at the start of the growing season does not necessarily correlate with the total crop production (not currently calculated in IQQM); and the method of aggregation is subjective.

$$\mathrm{IrrObj}(1) = \max\left(1000 \times \frac{0.3\left(c^m_{T,g} - c^m_{T,p} - 3c^m_{T,p3} - 5c^m_{T,p5}\right)}{I \times Y^m} + \frac{0.7\left(c^s_{T,g} - c^s_{T,p} - 3c^s_{T,p3} - 5c^s_{T,p5}\right)}{I \times Y^s}, 0\right) \quad \ldots(55)$$

where:

$c_{T,g}$ = sum of 'good' years for all three irrigators, $c_{T,g} = \sum_{i=1}^{I} c_{i,g}$

$c_{T,p}$ = sum of 'poor' years for all three irrigators, $c_{T,p} = \sum_{i=1}^{I} c_{i,p}$

$c_{T,p3}$ = sum of times there are three consecutive 'poor' years for all three irrigators, $c_{T,p3} = \sum_{i=1}^{I} c_{i,p3}$

$c_{T,p5}$ = sum of times there are five consecutive 'poor' years for all three irrigators, $c_{T,p5} = \sum_{i=1}^{I} c_{i,p5}$

I = Number of irrigators (in this case three)

m = 15 March, start of the secondary growing season

s = 1 September, start of the primary growing season

8.5.5 Decision variables

The decision variables represent what can be controlled within the system to meet the specified objectives. There are three main controls within a regulated river system which can be modified to influence ecological condition and irrigator water availability: infrastructure; extractions; and operations. Infrastructure can include storages and regulators such as weirs and offtakes for irrigation, as well as structures such as wetland regulators which are directly intended to improve ecological outcomes (e.g. Higgins *et al*., 2011). Outside the river system, ecological and agricultural outcomes can be significantly impacted by many additional factors such as land ownership, access and use, and floodplain connectivity.

As this case study was focused on environmental flow rules, decision variables were limited to infrastructure operations and irrigator extractions with other factors being outside the scope of work. Seven decision variables were used, four defining translucent releases, and three defining irrigator licences:

Table 17. Decision variables with lower and upper decision bounds

	Decision Variable	Decision lower bound	Decision upper bound
Translucent releases	*Lower translucency bound (ML/d)*	0	1000
	Upper translucency bound (ML/d)	Lower translucency bound	Lower translucency bound + 11000
	Start month	1	12
	End month	1	12
Irrigator licences	*Reach 1 Irrigator*	0	38,025
	Reach 2 Irrigator	0	314,020
	Reach 3 Irrigator	0	217,300

The translucency flows given in Table 17 give a much larger upper bound than what currently exists (8000 ML/d), to explore the effect of releasing larger flows. The upper bound for the irrigator licences is based on an aggregation of current licences for each region. It can be seen that the Reach 1 Irrigator licence is much smaller than those further downstream.

8.5.6 Constraints

A single constraint was used to ensure the volume in Wyangala Dam does not fall below 1000 ML, which is just below 0.1% of the full storage volume. This small volume was used given the simplified model estimates that storage volumes were only just over 1000 ML during the Federation drought. This is likely to be a result of drought saving measures not being reflected in the model, as discussed in Section 8.4. In reality, changes in operations are likely to have prevented such low storage volumes. Further to this, the Federation drought occurred at the start of the simulation period (late 1890's to early 1900's), hence storage volumes are likely to be sensitive to the specified starting storage volume. For this reason, the starting volume was taken to be the same as in the full Lachlan model.

Given the modified drought operations could not be reflected in the model, a minimum storage value of 1000 ML was used to ensure feasible solutions were still obtained in the optimisation. It is recommended that this is revisited in future work.

8.5.7 Scenarios

Six scenarios were used to investigate the impact of three main sources of uncertainty: objective formulation; model assumptions (hydrological and ecological); and optimisation parameters (Table 18). Objective formulation was evaluated through the comparison of different objective functions which vary in their definition of what constitutes a 'good' ecological outcome. Evaluation of the model assumptions considered the influence of rainfall and groundwater in supporting River Red Gum condition; the impact of different expert conceptualisations of ecological response; the influence of upper and lower uncertainty bounds; and the influence of ecological condition at the start of the simulation. The first three of these were considered to have the most impact on estimation of River Red Gum condition based on the sensitivity and Bayesian analysis in Chapters 5 and 6, whilst the influence of ecological starting condition was examined given the collapse of the River Red Gum community in the base case scenarios described in Section 8.4. Thirdly, a different random seed number (used by the eMoga algorithm to sample the initial population) was tested to evaluate the impact of an optimisation parameter. Previous studies have identified that this can have a significant impact on the Pareto front (Kollat and Reed, 2006; Reed *et al*., 2013).

For all scenarios, the same irrigation objective function (Equation 55) was used, and all other model and optimisation components were kept the same as the base case unless specified.

Table 18. Optimisation scenarios used to investigate the impact of different assumptions

Scenario	Ecological Objective	Hydrology	Eco start condition	Expert model	Random seed number
1	1	Rain + GW	0.7	1	Base
2	**2** **3** **4**	Rain + GW	0.7	1	Base
3	1	**1. No rain** **2. No GW** **3. No rain, no GW**	0.7	1	Base
4	1	Rain + GW	**0.9**	1	Base
5	1	Rain + GW	**0.9**	**2**	Base
6	1	Rain + GW	0.7	1	**Modified**

The first scenario shown in Table 18 uses the aggregated ecological objective function to explore model behaviour and trade-offs in detail. It is then used as a comparison for the remaining scenarios to evaluate the impact of changing different assumptions. Scenario 2 evaluates the impact of different ecological objective functions using an average ecological condition score over the entire simulation, and also examines the impact of focusing on either the upper or lower ecological uncertainty bound. Scenario 3 explores the impact of groundwater and rainfall on optimisation results by firstly excluding rainfall from the River Red Gum ecological model, secondly excluding groundwater, and thirdly excluding both rainfall and groundwater.

Scenarios 4 and 5 investigate assumptions associated with the ecological response model. In Scenario 4, a higher starting condition of 0.9 is used instead of 0.7, given the decline of condition scores using the base case. In Scenario 5, objective function 1 is used to optimise for Expert Model 2 condition scores instead of Expert Model 1.

The final scenario examines the use of a different initial random seed number.

8.6 Results

Results from the five scenarios demonstrate the sensitivity of environmental flow rules to the formulation of objective functions and model assumptions. Nevertheless, the use of optimisation can assist in identifying trends in system behaviour, and insight into the performance of different management alternatives. Details of each of the six scenarios are provided below.

8.6.1 Scenario 1: Ecological and agricultural trade-offs

Optimisation of the aggregated irrigator and ecological objective functions in Equations 50 and 55 demonstrate a clear trade-off between objectives, where increases in the ecological objective coincide with decreases in the irrigator objective (Figure 104a). Three breakpoints in the trade-off curve can be observed, one near the maximum irrigator objective, one near the maximum ecological objective, and one at an ecological objective of around 470. At the two extremes, the breakpoints are likely to be a result of the shift to a single objective problem – either maximising the ecological objective or the irrigator objective. The breakpoint close to an ecological objective of 470 is caused by a significant drop of approximately 30% in the total irrigator licence volume, and is likely to result from a lack of convergence given the number of generations used.

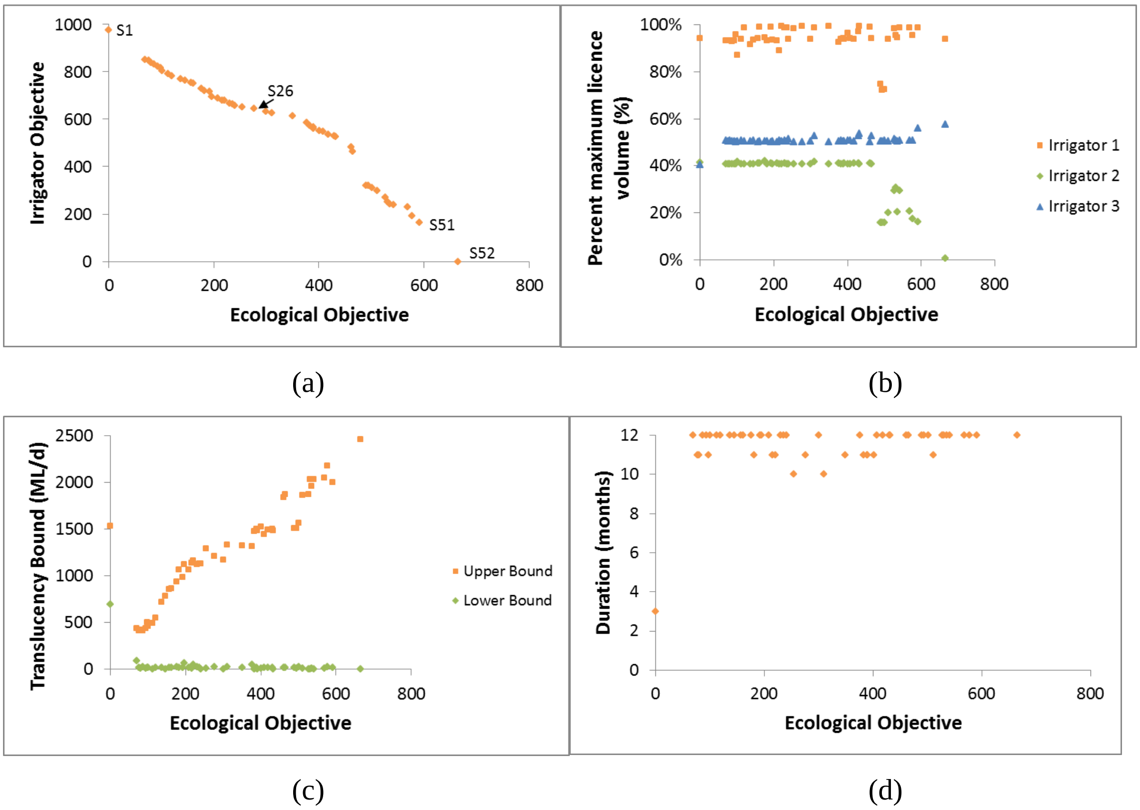


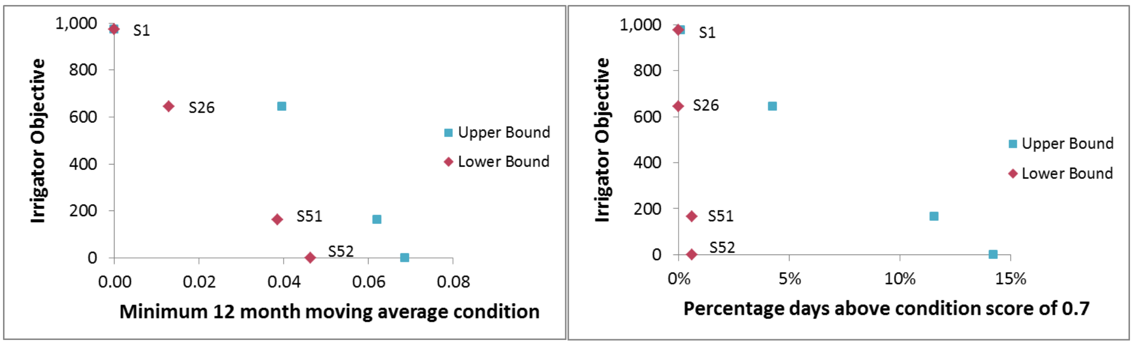
Figure 104. Trade-off curves showing (a) irrigator and ecological objectives; (b) changes in irrigator licence volume for different ecological objective values; (c) upper and lower translucency flow bounds; and (d) duration of translucency rule operation. S1, S26, S51 and S52 represent solutions which are used for further analysis.

Figures 104b to d show the decision variables which lie along the trade-off curve. Figure 104b shows the irrigator licence volume as a percentage of the current licence volume (given in Table 17). It can be seen that Irrigator 1 has close to 100% of the current licence volume for the majority of solutions. Irrigator 1 has the smallest current licence volume of the three irrigators (7% of the total), and hence the water demands are more easily met. In comparison, Irrigator 2 has the largest current licence volume (55% of the total), and consequently has the largest reduction of approximately 40% of the current volume. At low ecological objective values, irrigator licence volumes are relatively similar for all solutions, however at high ecological values there is a trade-off between Irrigator 2 and the ecological objective.

Translucency flow bounds and duration are shown in Figures 104c and d, where it can be seen that the upper translucency flow bound shows the greatest trade-off with the irrigator objective function, where a larger upper bound results in a better ecological objective score. The majority of lower translucency bound values fall below 30 ML/d, which is much smaller than the base case scenario of 3500 ML/d. There is a lack of sensitivity of the lower bound to the irrigator objective function, except for the highest scoring irrigator objective function where the lower bound is much higher (975 ML/d).

The duration of the translucency rules was generally 12 months, with a minimum of 10 months (except where the ecological objective was zero). This suggests that translucency rules should operate throughout the entire year, again with minimal impact on irrigation except at the maximum irrigation objective function.

Given the irrigator and ecological objectives consist of an aggregation of different metrics, component metrics were calculated for a subset of four solutions on the trade-off curve – one at the highest irrigator objective (solution S1), one in the middle of the trade-off curve (solution S26) and the two highest ecological objectives (solutions S51 and S52) (Figures 105 and 106).

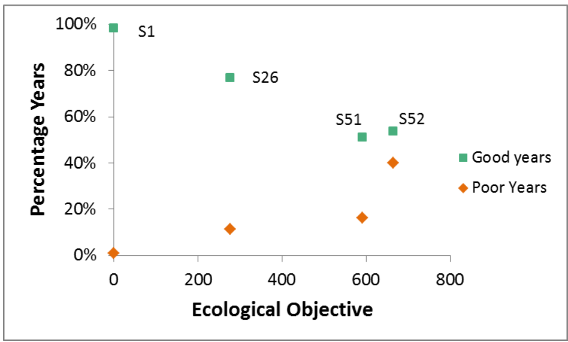


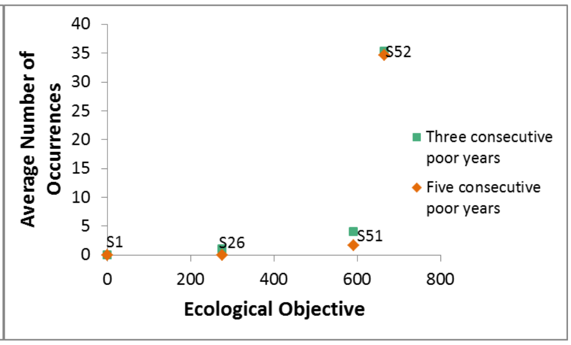
(a) (b)

Figure 105. Trade-off curves for constituent ecological objectives using four example solutions (S1, S26, S51 and S52): (a) minimum twelve month moving average for upper and lower ecological condition scores; and (b) the percentage of days in the total simulation where ecological condition was equal to or above 0.7.

Figure 105a shows the minimum moving average for both upper and lower ecological bounds. For all four solutions, the minimum moving average for both upper and lower bounds was below a condition score of 0.1. This low score is a result of the WWII drought where there was minimal water available for both the environment and human water use. Even so, the difference between a condition score of 0 and 0.07 is the difference between survival and collapse of the River Red Gum community in the case study model, and hence presents a significant trade-off with irrigation water requirements.

For the higher condition scores, Figure 105b shows that a condition of 0.7 was only exceeded 15% of the entire 108.5 years of simulation for the upper bound with the best ecological objective (S52), suggesting that the ecological model is somewhat pessimistic. There was also a large difference between upper and lower ecological bounds, with the lower bound being relatively insensitive to the irrigation objective compared with the upper bound. This is likely to be a result of a hard threshold of 0.7 being used (Equation 50), where the upper bound may be just above but the lower bound just below, whereas the moving average is not threshold dependent.





(a) (b)

Figure 106. Trade-off curves for constituent irrigator objectives for the primary growing season (September): (a) percentage of good years (available volume > 30% maximum possible) and poor years (available volume <10% maximum possible); and (b) the average number of occurrences of three and five consecutive poor years for all irrigators.

Figure 106a shows the average percentage of good and bad years across the three irrigators. It can be seen that the number of good years varies between 100% and 50% of the time, noting that ‘good’ is defined here as >30% of maximum possible available water considering both the licence volume and current allocation. The number of poor years (<10% maximum possible available water) also increases to 40% of the time for S52, hence having a significant impact on irrigation at high ecological objectives.

Figure 106b shows the number of consecutive poor years, which is low for all solutions except S52. At the highest ecological objective there is a step change, with a 35% occurrence of three and five consecutive poor years. Referring back to Figure 104, this occurs when the upper translucency flow bound is largest, the lower bound is smallest, and there is the lowest irrigator licence volume. This solution is the closest to the without development scenario of all the trade-off solutions, and suggests that it is not viable to support irrigation for this case study. However, referring to Figure 107 below which shows the number of occurrences of three consecutive poor years for each irrigator separately, it can be seen that it is only the largest irrigator, Irrigator 2, which is affected. This is consistent with the trade-off curve in Figure 104b.

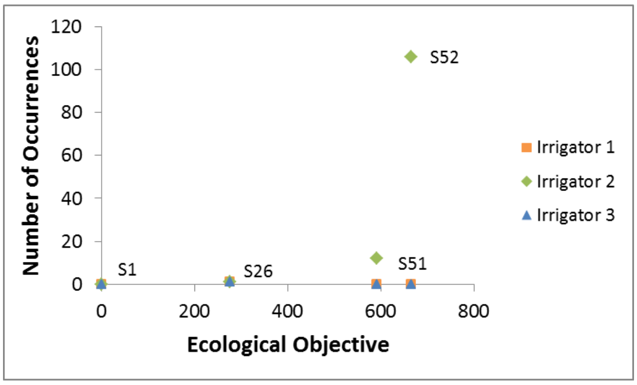


Figure 107. Number of three consecutive poor years for the three irrigator regions

These results can be further explored by investigating the time series of ecological condition scores, available water for irrigation, and changes in dam storage volume for the four example solutions. These are described in Sections 8.6.1.1 to 8.6.1.3.

8.6.1.1 Ecological condition

The change in ecological condition for the five expert models using solution 52 is shown in Figure 108. Whilst the objective function only considered Expert Model 1, the difference in performance of the five models reflects that of the developed base case (Figure 101). However, the optimised solution 52 shows a significant departure from the base case for Expert Model 1, where the River Red Gum community survives the WWII drought for both upper and lower bounds. This is also an improvement on the ecological outcomes used with the full Lachlan model, where only the upper bound survives (Figure 100). Meanwhile, the remaining four expert models still predict a collapse in the River Red Gum community during or shortly after the Federation drought.

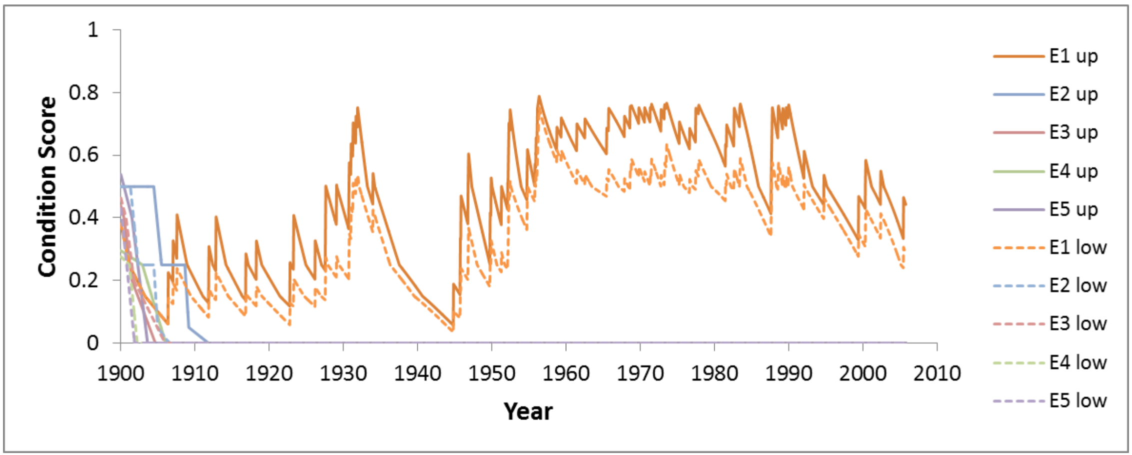
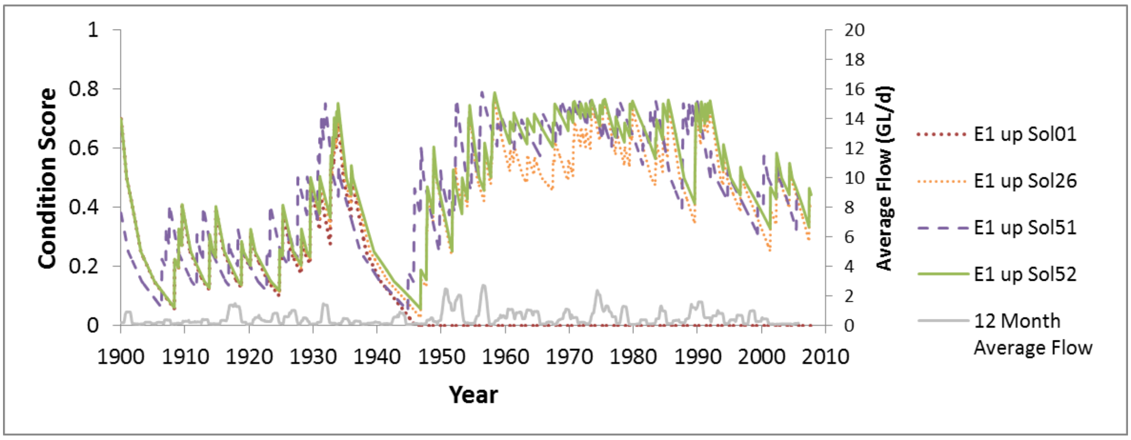


Figure 108. Comparison between the five expert models for solution 52 (highest ecological objective value)

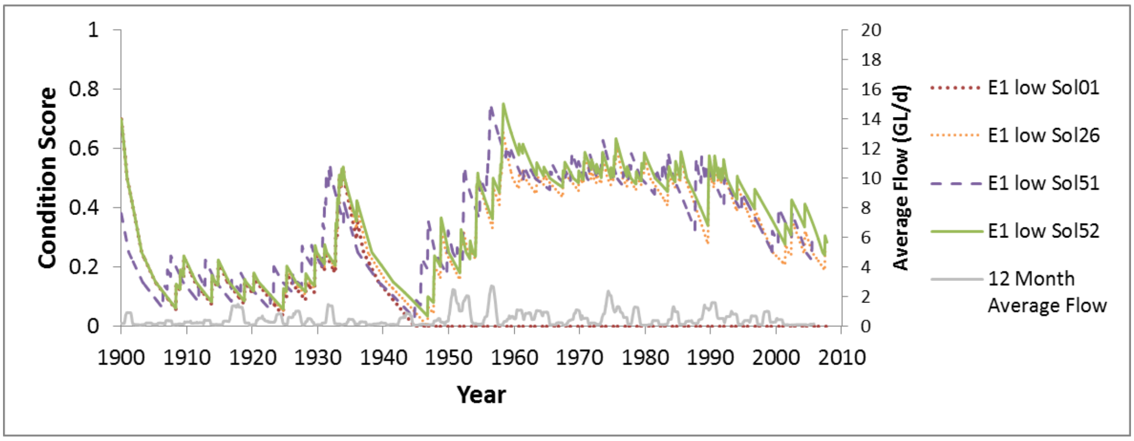
Comparing the four solutions S1, S26, S51 and S52 for Expert Model 1 only, it can be seen from Figure 109 that changes in ecological condition are largely similar for S26, S51 and S52, whilst S1 drops to zero for both upper and lower bounds during the WWII drought. In all four cases, condition scores decline during the Federation drought, followed by oscillation in condition primarily due to intermittent rainfall events (shown in Figure 110) and some flow events (with the twelve month moving average flow shown in Figure 109).

After the Federation drought, the second major decline in condition began in the 1930's and continued until the late 1940's. Based on the model used here, this drought was the most severe in terms of ecological impacts, due to the extended duration of low flows and low rainfall. Estimated groundwater levels were also low during this period, although not as low as during the Federation drought. An example of groundwater levels for S52 is shown in Figure 111, which is the best case scenario of the four solutions given it favours ecological outcomes (and hence more water reaching the Great Cumbung Swamp). It can be seen from Figure 111 that groundwater levels remain below the threshold of 12m up until 1954, although the model assumes some groundwater can still be accessed below 12 m but at a reduced rate (see Chapter 4).

Interestingly, for this model the Millennium drought had less impact on ecological condition compared with the WWII drought, despite it being referred to as the Murray-Darling Basin's most severe hydrological drought (Bond *et al.*, 2008; Leblanc *et al.*, 2012). However, the model was only run until 31 July 2006 and hence did not capture the end of the drought.



(a)



(b)

Figure 109. Ecological condition score for the four sample solutions showing (a) upper bound condition scores; and (b) lower bound condition scores. The twelve month moving average flow at Booligal based on the full Lachlan model is also shown for comparison (DPI Water, 2007).

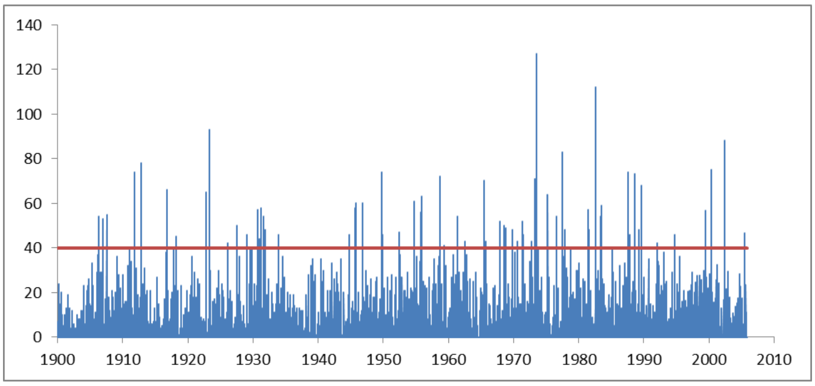


Figure 110. Rainfall from 1900 to 2006 at 75007.06 (source: Jeffrey *et al*., 2001) with the 40mm rainfall inundation threshold shown.

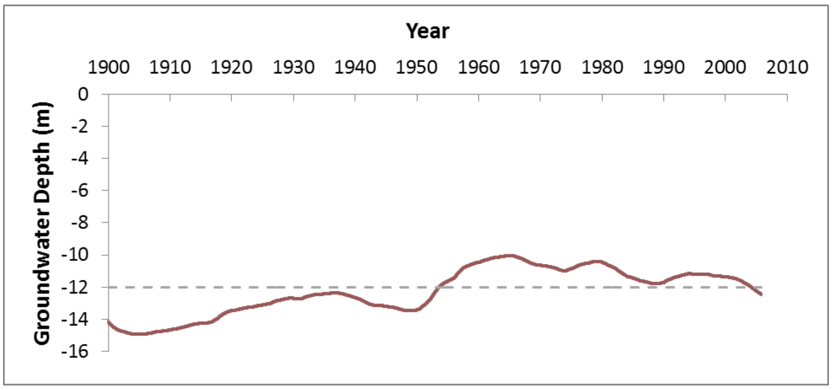


Figure 111. Groundwater levels for Solution 52, Scenario 1.

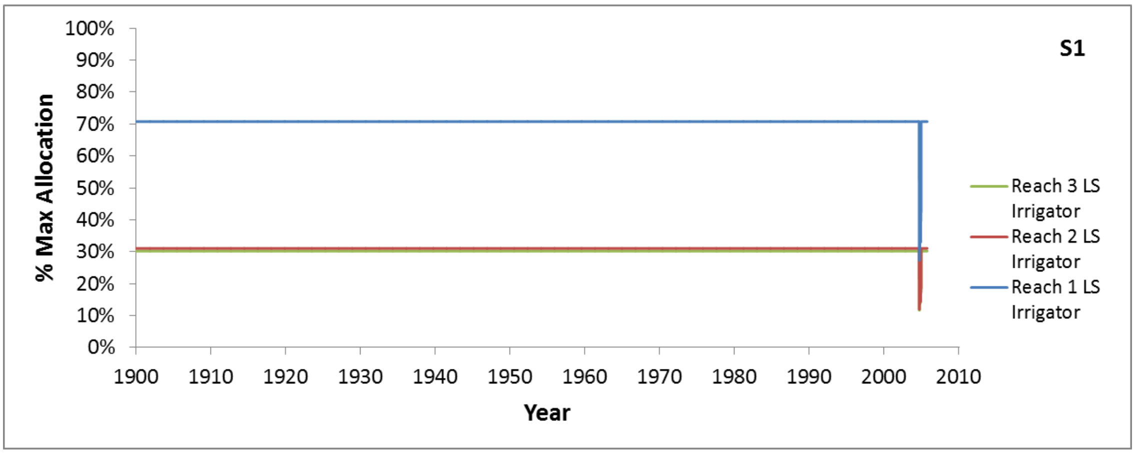
8.6.1.2 Irrigator water availability

The total water available to the three irrigators (based on licences and allocations) for solutions S1, S26 and S52 is shown in Figure 112. For S1 (highest irrigator objective, Figure 112a), all irrigators are within the 'good' category of >30% until the Millennium drought, although the two larger irrigators are no greater than 30%. During the Millennium drought, water availability drops but remains above 10% for all irrigators.

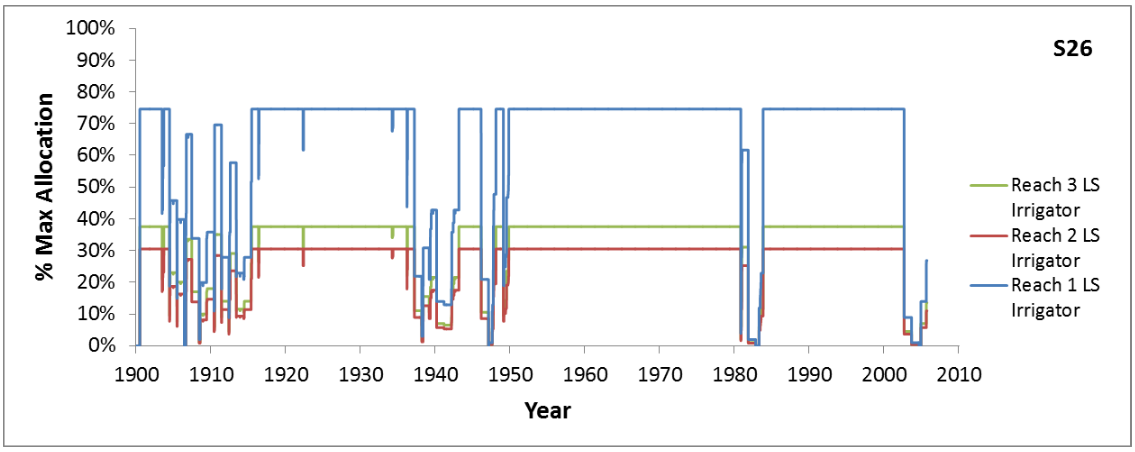
Where there is a compromise between the irrigator and ecological objectives in S26 (Figure 112b), available water for irrigation is more reflective of the total water available in the system. The longest period of zero allocations occurs during the Federation drought, lasting a total of two years. During the WWII drought, allocations dropped to ≤1% for six months, whilst in 1982 they dropped below 3% for approximately 1.5 years. During the Millennium drought, from mid-2004 onwards allocations were ≤1% for approximately 1.25 years, but were preceded by allocations of only 9% for the full year prior to mid-2004. This duration is also likely to be longer given the drought ended in late 2010 for the Lachlan.

For the lowest scoring irrigator objective in S52 (Figure 112c), the Federation, WWII and Millennium droughts all had zero allocations for two years. In reality, these allocations would have generally been higher, given there were changes in operations and the implementation of water saving measures during drought which are not reflected in the model. However, the results provide some insight into the impact of drought and different environmental flow rules on allocations, and the difference in drought severity experienced by irrigators and the environment. For the River Red Gum community in the Great Cumbung Swamp, the WWII drought was the most severe (although it is possible that the Federation drought may have been equally severe if more data were available to capture the lead up to the drought). It is likely that the higher groundwater levels resulting from the larger flows and rainfall in the second half of the 20th century played an important role in sustaining River Red Gum during the Millennium drought using the current model. In comparison, irrigation is affected by multiple droughts, with the WWII and Federation droughts impacting through both severity and duration.

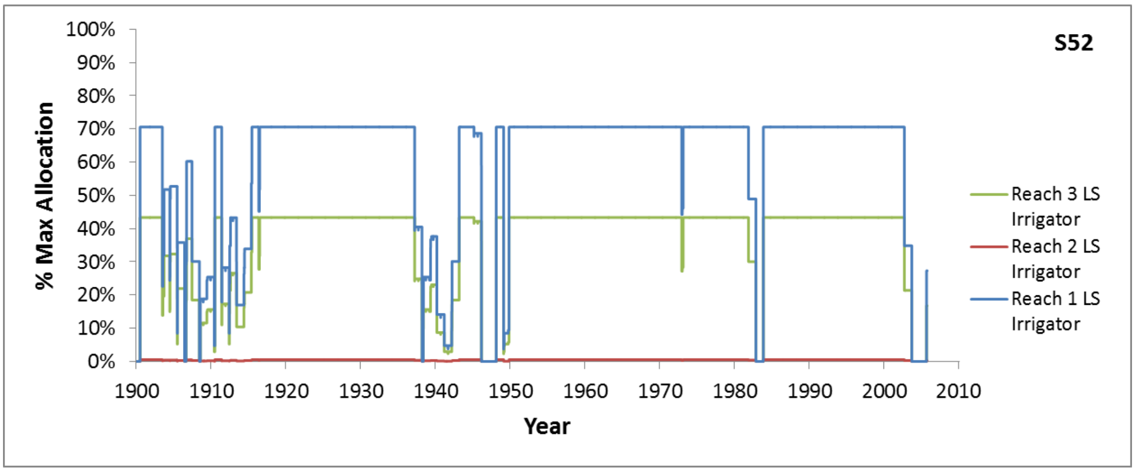
Comparing the three irrigators, it can be seen that the water available for the largest irrigator (Irrigator 2) falls to zero or close to zero for the entire simulation for solution 52, representing a trade-off between the three irrigators. In both solutions 26 and 52, Irrigator 3 increases in amount of water available where less water is available to Irrigator 2. In addition to Irrigator 2 having a maximum licence volume of 45% more than that of Irrigator 3, Irrigator 2 also has a maximum planted area twice that of Irrigator 3, and hence a greater water demand despite higher rainfall in the mid-catchment.



(a)



(b)



(c)

Figure 112 Allocations for Scenario showing trade-off solutions for (a) S1: favouring irrigator objectives; (b) S26: compromise between ecology and irrigation; and (c) S52: favouring ecological objectives.

8.6.1.3 Dam 1 storage volume

Figure 113 shows the change in Wyangala storage volume for the three solutions S1, S26 and S52. For S1, it can be seen that storage volume remains above 50% capacity for the majority of the simulation, except during the Federation drought, WWII drought, early 1980's, and during the Millennium drought. The greater storage volume is a reflection of minimal translucent flows, hence water is primarily released to meet agricultural water requirements and during times of flood. In comparison, S26 and S52 both show much greater fluctuations which largely correspond to changes in inflow to Wyangala. The larger translucency flows in these solutions represent a higher risk operational strategy, where lower storage volumes are tolerated compared with S1.

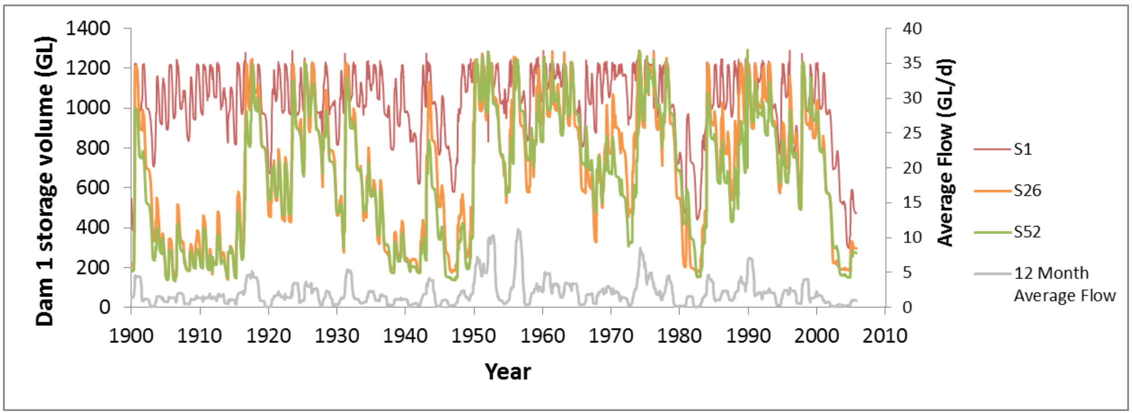


Figure 113. Storage volume for Wyangala in Scenario 1, showing trade-off solutions for S1: favouring irrigator objectives; S2: compromise between ecology and irrigation; and S3: favouring ecological objectives. The twelve month moving average inflow to Wyangala is also shown.

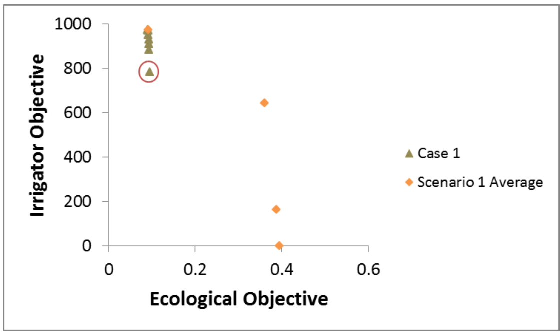
8.6.2 Scenario 2: Impact of different objective functions

The impact of changing the objective function to an average ecological condition over the entire simulation (using the same irrigation objective) is shown in Figure 114. Equations 51, 52 and 53 described earlier calculate either the average condition score for the average of upper and lower bounds ('Case 1'); for the lower bound only ('Case 2'); or for the upper bound only ('Case 3'). For comparison, the same equations were applied to the four sample results from Scenario 1. Note that whilst the objective functions scaled condition scores by 10,000, the values presented in Figure 114 are for the actual average condition scores rather than the scaled values.

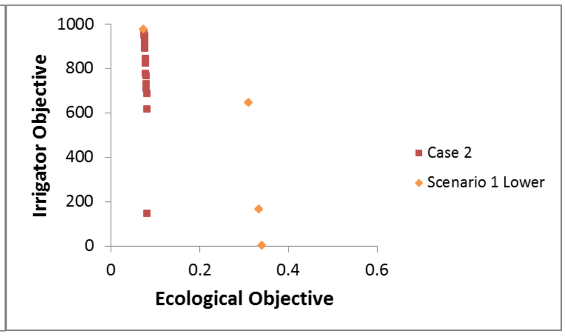
It can be seen that in all three cases there has been a significant impact on the resulting trade-off curve, with the ecological objective falling below that obtained using Scenario 1. This is also reflected in the time series of condition scores for the highest scoring ecological objective in Case 1 (Figure 115), where none of the expert models show survival of the River

Red Gum community throughout the entire simulation. The WWII drought acts as a breakpoint in the optimisation search, where in this case no solutions are found where the River Red Gum survives. It is possible that a different optimisation algorithm or parameters may identify the set of solutions where River Red Gum does survive. In this case, the lack of convergence is not a concern given all three cases converge in less than 2500 generations.

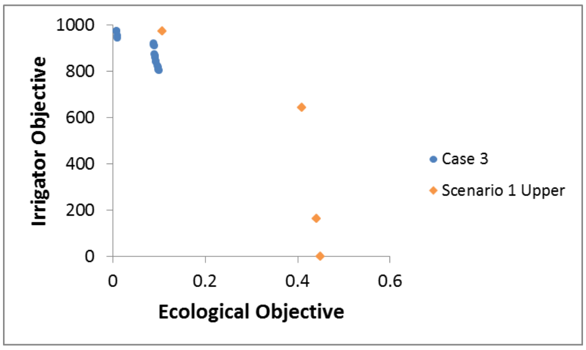
Interestingly, use of just the lower bound finds the greatest spread of irrigator objective values, whereas it can be seen that there is minimal change in the average ecological condition for different irrigator outcomes. The lack of sensitivity of solutions to different ecological condition scores is at least in part due to averaging across the 108.5 year simulation where more than 50% of scores are equal to zero. In comparison, use of the upper bound finds the greatest spread of ecological objective values of the three cases, although this is still small compared with Scenario 1.



(a)



(b)



(c)

Figure 114. Impact of objective functions based on average ecological condition compared with the aggregated objective function used in Scenario 1, showing: a) averaging of lower and upper condition bounds, with the highest ecological objective value circled; b) lower condition bounds only; and c) upper condition bounds only.

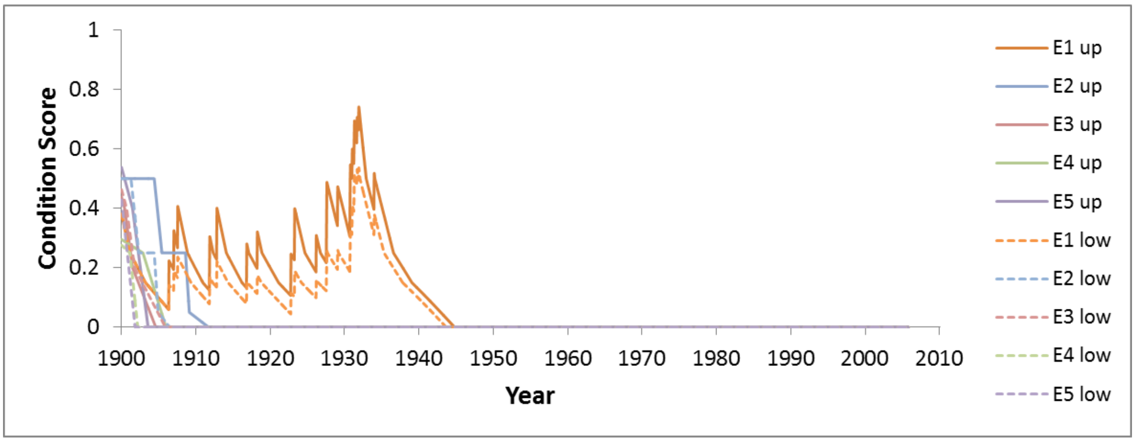


Figure 115. Change in ecological condition scores for the highest ecological objective value in Case 1 (circled in Figure 114)

The impact of using the three different objective functions on decision variables can be seen in Figure 116. Both ecological and irrigator decision values are plotted against the irrigator objective as this is consistent across all three cases as well as Scenario 1. It can be seen that the three cases generally have a higher upper translucency flow bound (Figure 116a) than Scenario 1 (not to be confused with the upper ecological bound). This is particularly evident for Case 1 at high irrigator objective values, where it appears that the optimiser is releasing as much water as possible in an attempt to survive the WWII drought. In comparison, there is greater similarity between the three cases and Scenario 1 for the lower translucency bound (Figure 116b), the translucency rule duration (Figure 116c), and the average available water across the three irrigators (Figure 116d).

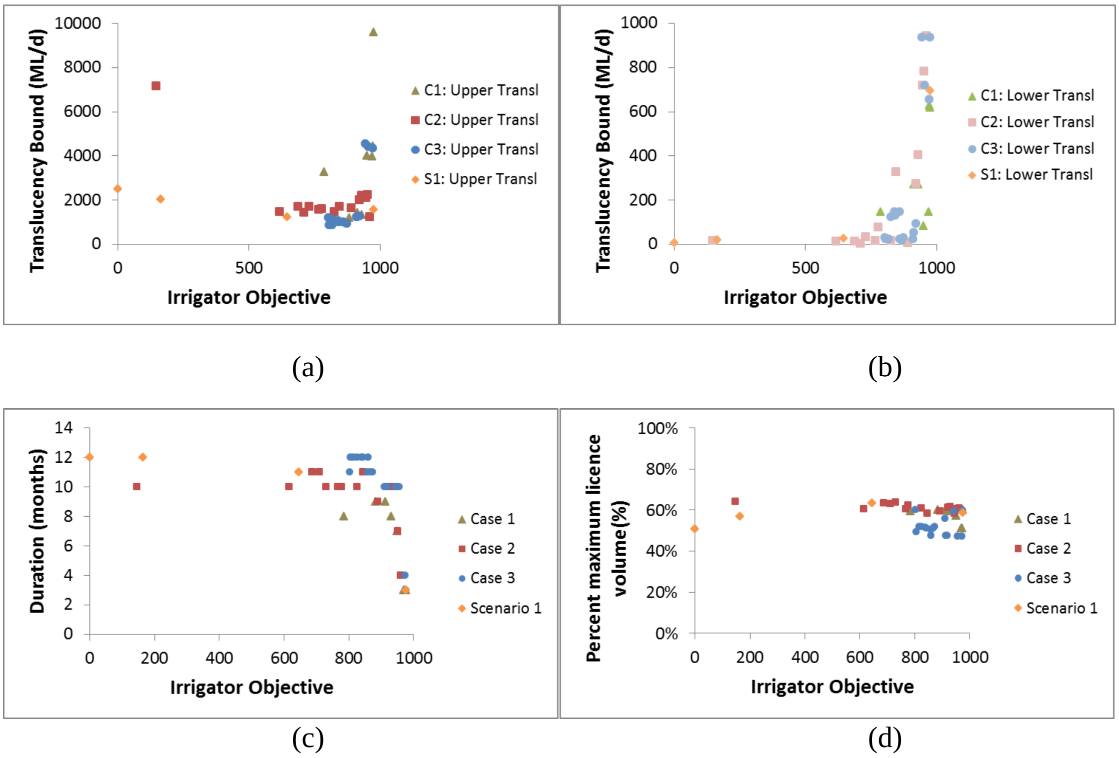


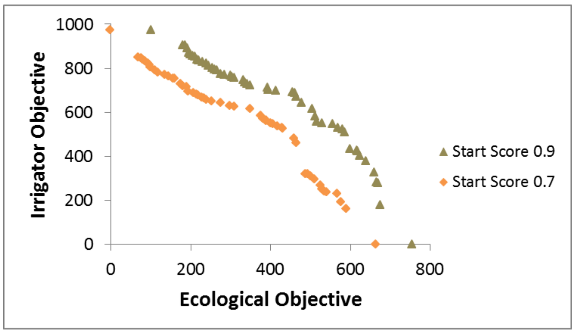
Figure 116. Impact of objective functions (Case 1, 2, 3) on decision variables compared with Scenario 1, showing: a) the upper translucency flow bound; (b) the lower translucency flow bound; (c) the translucency rule duration; and (d) the water available to irrigators (averaged across the three irrigators).

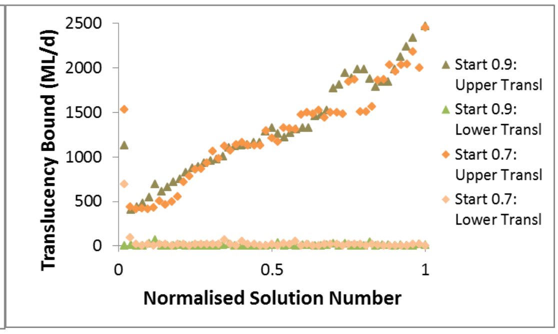
8.6.3 Scenario 3: Impact of hydrologic model assumptions

Removal of rainfall and groundwater from the ecological response model resulted in no solutions being found by the optimiser for ecological objective values >0, using the same objective functions as Scenario 1 (Equations 50 and 55). The optimisation therefore became a single objective problem, with the same irrigator objective value of 955 being found for all three cases (Case 1: without rainfall, Case 2: without groundwater, Case 3: without rainfall and groundwater). However, this irrigator objective value is smaller than in Scenario 1 (975) for the same ecological objective of zero. The decision variables were similar between the three cases but also differed from the equivalent solution in Scenario 1, with a larger total licence volume across the three irrigators (c. 28,400 in Scenario 3, c. 25,400 in Scenario 1), and larger lower and upper translucency bounds. The start and end months for the translucency rules also varied, with December to January in Scenario 3, and April to June in Scenario 1. Releases during the winter months are more aligned with the winter dominant rainfall in the catchment, although less preferable for supporting agricultural water requirements over summer.

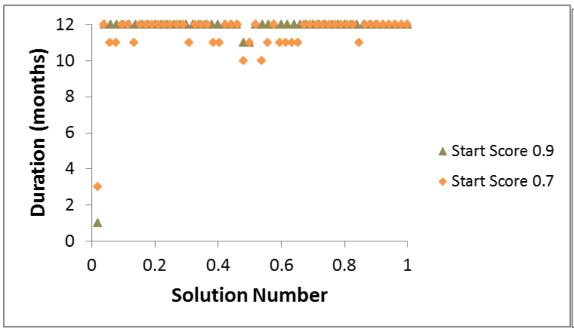
8.6.4 Scenario 4: Impact of initial ecological condition

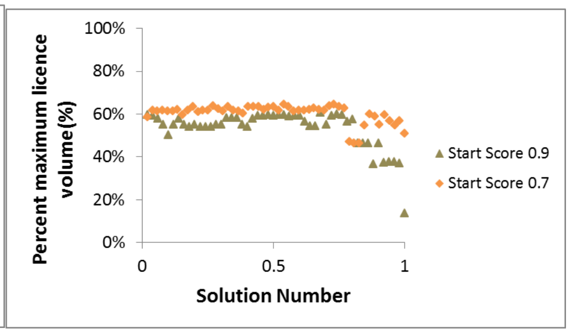
Increasing the initial ecological condition from 0.7 to 0.9 had a significant impact on the resulting trade-off curve, as shown in Figure 117a. However, by looking at the time series of ecological condition for the highest scoring ecological objective in Scenarios 1 (start score 0.7) and 4 (start score 0.9) in Figure 118, it can be seen that there is minimal impact on condition from about 1908 onwards (for Expert models 1 and 2, with changes being smaller still for other experts). The difference in trade-off curve can therefore be attributed primarily to the first c. 10 years of simulation. As the ecological objective calculates the number of days with condition >0.7, a start score of 0.9 disproportionately increases the objective relative to the remaining simulation. The range of ecological decision variables was also similar between the two scenarios, as shown in Figure 117b and c, although there was some reduction in available water for irrigation using a start score of 0.9 (Figure 117d).





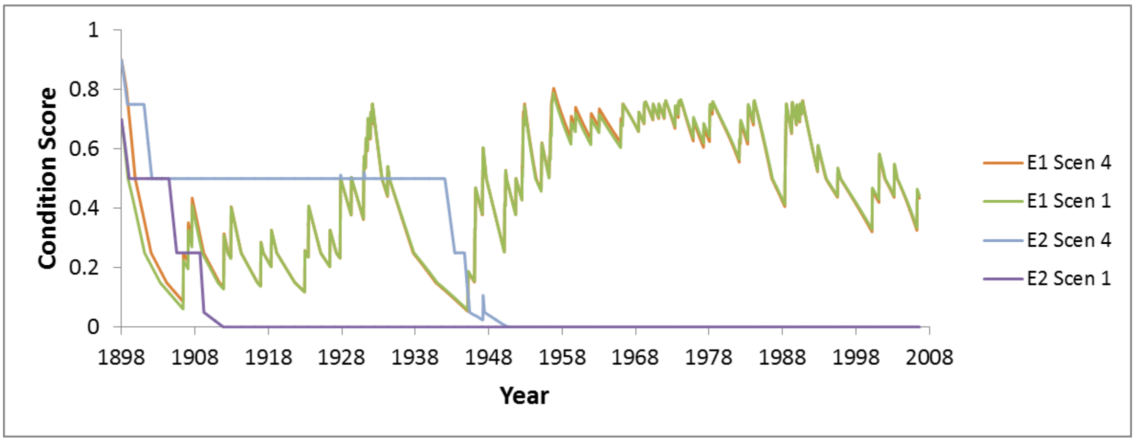
(a) (b)



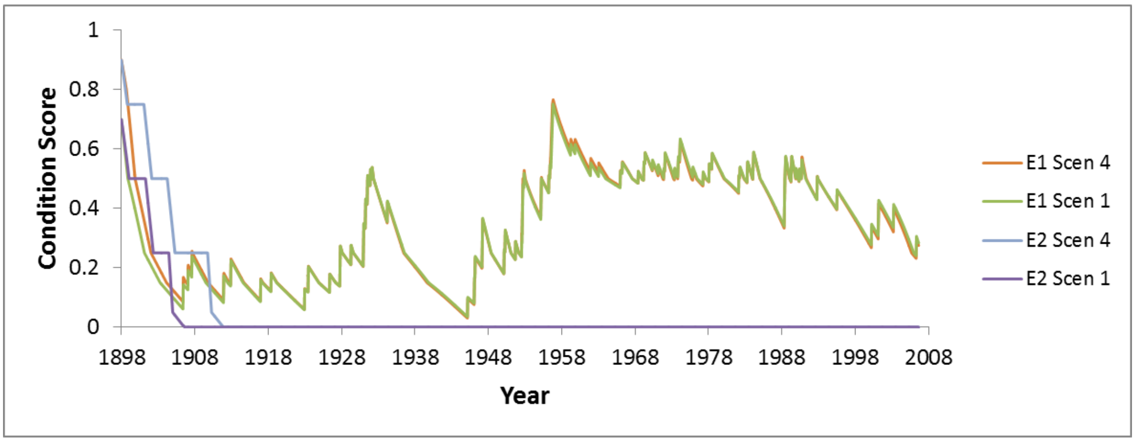


(c) (d)

Figure 117. Comparison in objective functions and decision variables using a starting ecological condition of 0.9 (Scenario 4) and 0.7 (Scenario 1), showing: a) trade-off curve; b) translucency lower and upper flow bounds; c) translucency rule duration; and d) water available for irrigators.



(a)



(b)

Figure 118. Comparison in ecological condition for Expert Models 1 and 2 for different starting condition scores (Scen 4: 0.9; Scen 1: 0.7) showing: a) upper condition bound; and (b) lower condition bound.

Whilst there was minimal impact on condition scores for Expert Model 1, it can be seen from Figure 118 that a starting score of 0.9 had a significant impact on Expert Model 2. Whilst condition still declined to zero in 1950 (upper bound), this is nearly 39 years longer than using a starting condition score of 0.7.

8.6.5 Scenario 5: Impact of different expert models

Using the same objective function formulation as in Scenario 1, Expert Model 2 was used in place of Expert Model 1 to explore whether improved ecological values can be obtained for Expert Model 2. Figure 119 shows the difference in condition scores for all expert models optimised either for E1 or E2. It can be seen that specifically optimising for E2 results in lower condition scores for both Expert Model 2 and Expert Model 1, with minimal impact on the remaining expert models. This is a result of the optimiser not being able to find a solution where Expert model 2 survives the full simulation, hence there is greater focus on finding the best irrigator outcome. In addition, an epsilon value of 5 means that the solutions are not sensitive to differences in objective functions of <5, hence whilst there may have been slightly better solutions for E2 that were discarded.

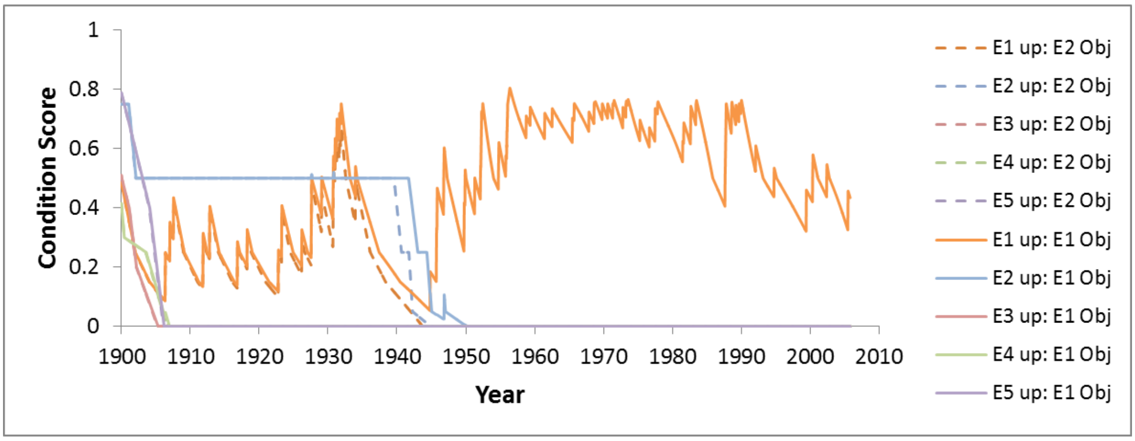


Figure 119. Comparison between optimising for Expert Model 1 and Expert Model 2 using a start score of 0.9 – upper bounds for all models.

8.6.6 Scenario 6: Impact of random seed number

Changing the random seed number had an observable impact on both the trade-off curve and the decision variables (Figure 120). In general, the alternative random seed number resulted in higher objective values, except for the highest ecological objective (Figure 120a). This is likely to be due to a higher upper translucency bound (Figure 120b), although interestingly there was less water available for irrigators (Figure 120d). The duration of the translucency was largely similar between the two scenarios, as was the lower translucency flow bound.

However, comparison between the scenarios suggest that the random seed used here had significantly less impact than the different objective functions, starting ecological condition, use of lower and upper ecological bounds, and inclusion/exclusion of groundwater and rainfall. It is also likely that the difference can be attributed to the small number of generations used, where the optimisation did not converge. This could also be further explored by testing additional random seed numbers, as it is difficult to draw a conclusion from a single test.

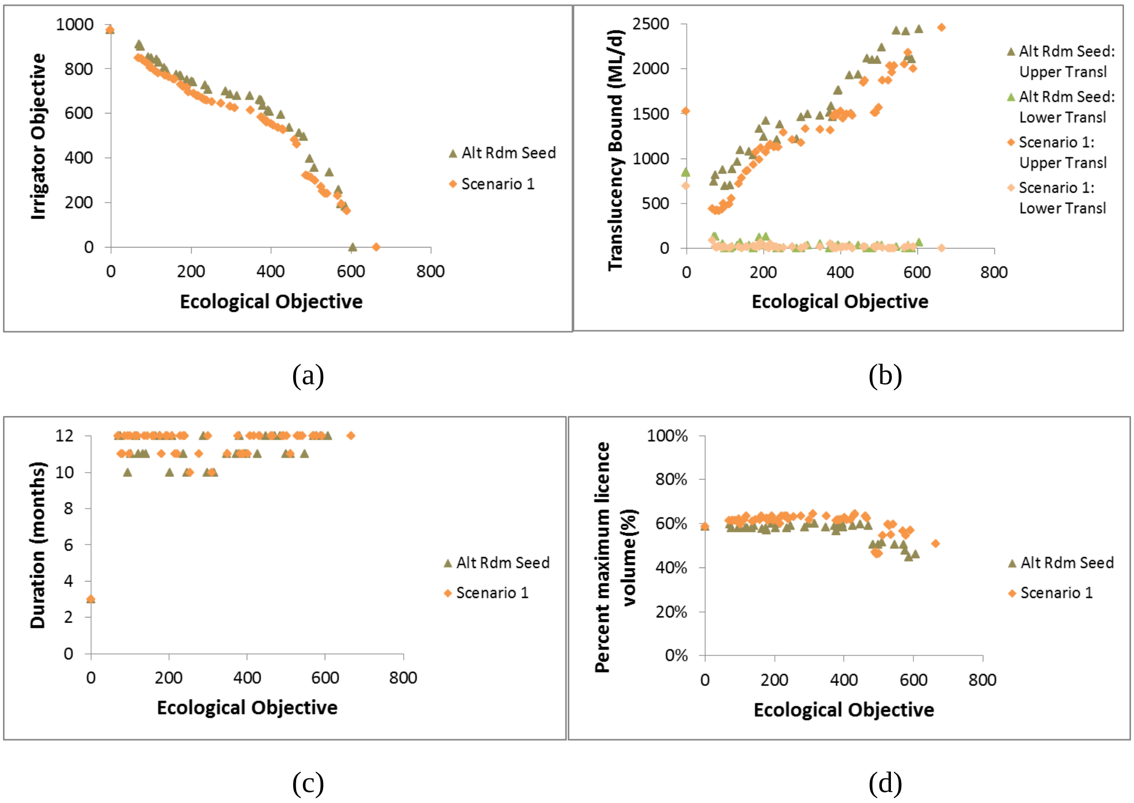


Figure 120. Impact of a different random seed number on objectives and decision variables showing: a) trade-off curve; b) translucency lower and upper flow bounds; c) translucency rule duration; and d) water available for irrigators.

8.7 Implications for decision making

This analysis demonstrates the applicability of optimisation for aiding decision making in environmental flow management, through: (1) facilitating the investigation of alternative management solutions; (2) providing further understanding of system behaviour; and (3) providing insight into existing uncertainties and knowledge gaps and their implications for decision making, as well as the need for future research and data collection. The optimisation process can therefore complement other sources of information and facilitate discussions with stakeholders. These contributions are demonstrated as below.

8.7.1 Investigating management solutions

There are a number of consistent findings across the six scenarios, despite variability in results across different objective functions, problem formulation, and (to a lesser degree) random seed number. As with any model outcomes, these findings are to be interpreted in the context of the assumptions described in Section 8.7.2 and throughout the thesis, but provide alternatives which warrant further investigation.

Firstly, the system appears to be over-allocated given that none of the scenarios had Pareto solutions where 100% of the current licence volume was met for all three irrigators, even where the ecological objective was zero. This is not entirely inconsistent with the actual situation in the Lachlan, as allocations are often below 100%. A trade-off was observed between the smallest irrigation region (Irrigator 1) and the two larger irrigation regions (Irrigators 2 and 3), where close to 100% of the full licence volume was often maintained for Irrigator 1, whilst licence volumes were generally close to or below 50% for Irrigators 2 and 3. This inequality is not reflected in the actual Lachlan catchment, where the system of allocations means that all licence holders share the cost of insufficient water.

Secondly, the model suggests that changes to the baseline translucency flow rules may improve River Red Gum condition in the Great Cumbung Swamp whilst having minimal impact on water available for irrigators (except in the extreme case where only irrigators are considered). The majority of solutions across all scenarios indicated preference for a translucency rule which continues throughout the entire year, rather than the current baseline of May to November. Given the system is largely dominated by winter rainfall, the additional benefit from translucent releases over December to April would need further investigation. That said, the high variability of flows within the system mean that large flows can occur over the summer months, as occurred during the break of the Millennium drought at the end of 2010.

The results also suggest that the lower flow bound for the translucency rules should be decreased to <30 ML/d (i.e., as close to zero as possible). Whilst the model suggests this reduction would have minimal impact on irrigators, it is likely to lead to lower water levels in storages, and higher risk in managing for future severe droughts.

The upper translucency bound displayed a direct trade-off with irrigation objectives, and hence is the main decision lever resulting in ecological – agricultural trade-offs in the current case study (along with Irrigator 2 licence volumes at high ecological values). The upper translucency bound therefore becomes a reflection of different values toward the two objectives, and would require a public decision regarding the relative importance of irrigation compared with the environment. Referring back to the without development scenario presented in Figure 102, the survival of River Red Gum using Expert Model 1 in the optimised solutions raises some interesting questions regarding the role of river regulation and alteration and what is considered to be a desirable ecological outcome. In the context of the case study, river regulation made the difference between survival and collapse of the River Red Gum community during the WWII drought. Whilst in this case the collapse of River Red Gum in the without development scenario is more likely attributed to model assumptions, there are numerous examples of human alteration 'improving' ecological outcome beyond what would have naturally occurred (see discussion in Chapter 7 on novel ecosystems).

Consistent with findings in earlier chapters, the evaluation of rainfall and groundwater impacts on results provide further indication that multiple sources of water are essential for River Red Gum survival in the case study used here. Not only did a lack of rainfall and groundwater result in a zero ecological objective value, it also impacted upon the decision variables identified for the equivalent solution with rainfall and groundwater. This suggests that model assumptions can impact both on the predicted outcome, but also recommended management strategies.

8.7.2 Exploring uncertainties

The optimisation process has further demonstrated the significant impact that conceptualisation of ecological response has on results. Only Expert Model 1 estimated survival of the River Red Gum throughout the entire simulation, even when independently optimising for Expert Model 2. These results are likely to be influenced by the inclusion of only translucency rules in the model, without accounting for additional environmental flow releases which may have been instrumental in ensuring survival during extreme drought. As previously discussed, the model also does not account for water saving measures and suspension of water sharing plans, with alternative operations put in place during drought.

Evaluation of different ecological starting conditions suggested that despite an initial change in condition, this difference was negligible after approximately 10 years of the simulation using Expert Model 1. However, the effect of the starting condition was highly sensitive to the choice of expert model, where River Red Gum survived for an additional 39 years with a higher starting condition score using Expert Model 2.

In addition to model assumptions, different objective functions also had a significant impact on objective values, and more importantly, on decision variables. The use of average condition scores influenced the optimisation search process, resulting in no solutions being identified where the River Red Gum community survives the WWII drought. The Pareto solutions also identified higher upper translucency bounds compared with Scenario 1 for the same ecological objective value.

Whilst the use of a different random seed number also impacted upon results (and warrants further investigation), the solutions here suggest that this impact is minimal compared with that of conceptual assumptions regarding the simulation model, and assumptions in the formulation of the optimisation problem.

In addition to the uncertainties and limitations discussed in previous chapters, the findings above highlight key considerations for the evaluation of different management alternatives. Whilst many of these considerations are specific to the model and optimisation formulation presented here, subjectivity in objective specification and uncertainty in conceptualisation of ecological response are applicable outside the modelling process, and are essential to the management of environmental flows.

8.8 Conclusions

This chapter presents an approach to applying optimisation for investigating different environmental flow rules. It advances upon previous studies in bridging the gap between optimisation and decision making, both in terms of building system understanding and in the consideration of uncertainties in problem formulation. This includes examination of the assumptions in objective setting, from defining a high level qualitative objective through to a specific quantitative objective function. The impact of model assumptions on both objectives and decision levers are explored, and include differences in system conceptualisation as well as parameter values. Unlike the majority of previous studies, multiple ecological response models are applied and evaluated (Clark *et al.*, 2011; Foglia *et al.*, 2013). Lastly, the implications of identified assumptions and uncertainties are discussed with reference to actual decisions.

In addition to presenting an alternative approach to applying optimisation, this chapter identified a number of key management outcomes for environmental flows, which are recommended for further investigation. These include: extension of the current translucency rules to between 10 and 12 months; a reduction of the lower translucency bound, noting that this needs to be tested using the actual, more complex translucency rules; and wider discussion regarding upper translucency bounds and limits to extraction licences. Review of current water extractions has already been undertaken as part of the Murray-Darling Basin Plan, and the developed of Sustainable Diversion Limits (SDLs). This work is still ongoing.

These recommendations are based on modelled estimates of River Red Gum condition based on flow only, and it is recognised that there are many additional considerations required in setting environmental flow rules. For example, the current translucency rules for the Lachlan consider additional factors not included here, such as: ensuring flows entering the Great Cumbung Swamp are of sufficient magnitude to minimise carp breeding (which cause significant ecological impact, Gehrke *et al*., 1995); ensuring releases do not cause unintended flooding; and reducing the impact on irrigators (G. Podger, pers. comm., 2015). It is also recommended that additional species, locations, and water user requirements are considered to enable the examination of intra-catchment trade-offs spatially and temporally.

This chapter demonstrates that optimisation can be a valuable tool to explore alternative management options as well as better understand system behaviour and the impact of conceptual uncertainties through an iterative learning process. It also demonstrates that greater focus is needed in optimisation studies on problem formulation.

Part D

Chapter 9: Discussion and recommendations

As the impacts of river alteration, extraction and pollution become more severe and widespread, there is an increasing need to identify alternative management strategies. Environmental flows are being increasingly adopted in river management world-wide as one strategy to reduce these impacts (Acreman *et al.*, 2014b; Poff and Matthews, 2013). However, a number of limitations remain which can lead to uninformed decisions and unexpected outcomes which do not meet the desired objectives. These limitations include: lack of clear identification of objectives; limited knowledge of ecological response to different water sources; minimal assessment of uncertainty in estimating ecological response; and lack of identification of what impact this uncertainty has on model outcomes, and more importantly, on actual management decisions.

These limitations apply irrespective of the people, tools and information used in the decision process. Quantitative models provide one approach which can assist in formalising existing knowledge, data and assumptions, and form a shared understanding between stakeholders (Jakeman *et al.*, 2006; Loucks, 2006; Voinov and Bousquet, 2010). As demonstrated throughout this thesis, model development and application can bring new insight and learning about the system, can identify and evaluate alternative management strategies under a range of assumptions, and can be used as a platform for communication and negotiation (Jacoby and Loucks, 1972; Liebman, 1976; Gupta and Nearing, 2014).

However, the modelling community has a responsibility to facilitate the modelling process in a way that is more accessible, inclusive and transparent, with greater focus on problem definition and context setting. This research endeavours to address this challenge by demonstrating the application of modelling tools using a systems approach to environmental flow management, focusing on the limitations described above. It explores some of the challenges involved in defining ecological objectives, modelling ecological response, and evaluating alternative environmental flow rules considering multiple sources of uncertainty. It provides a new approach to modelling ecological response, both in terms of estimating water availability, and subsequent change in ecological condition. Model behaviour is then explored through sensitivity and Bayesian analysis, to identify the impact of model conceptualisation and parameterisation on results, and to evaluate model performance compared with observed data. The ecological response model is then coupled with a river system model to evaluate different environmental flow rules using multi-objective optimisation. This considers the impact of problem formulation on management decisions drawing upon a synthesis of previous optimisation studies.

Three key outcomes were identified, which address the objectives and hypotheses described in Chapter 1 (Section 1.2):

1. *Significance of problem formulation in evaluating environmental flows*

The development of increasingly advanced computational tools has enabled the exploration of more complex systems in modelling and optimisation frameworks. This is reflected in the expansion of ecological response models developed for environmental flow management and investigating trade-offs between multiple objectives (Poff and Matthews, 2013). However, along with this increase in computational capacity is a need to revisit fundamental questions regarding objective definition and system conceptualisation in quantitative form. Whilst these issues were recognised and discussed by those such as Rittel and Webber (1973) and Liebman (1976) in the 1960's and 70's, until recently the application of optimisation has focused primarily on algorithm development rather than problem formulation (Maier *et al.*, 2014). Consequently, a primary focus of this research was to explore the impact of problem formulation on the management of environmental flows.

First, the impact of different expert based conceptualisations of ecological response was examined using both sensitivity and Bayesian analysis. The analysis identified that expert based conceptualisation had a greater impact on ecological condition scores compared with model parameters, although there was some variation depending on the comparison metric used. It is recognised that whilst there is no clear distinction between model conceptualisation and parameterisation, the results here demonstrate that different representations of system processes can significantly impact on model outcomes. These findings are supported by studies such as Saltelli *et al*. (2000), Butts *et al*. (2004), Buytaert and Beven (2011), and Foglia *et al*. (2013). However, there has been limited previous research examining how problem formulation can influence results, particularly in the field of environmental flows (Butts *et al.*, 2004; Clark *et al.*, 2011; Refsgaard *et al.*, 2006).

Secondly, the management implications of differences in problem formulation were explored through multi-objective optimisation. The use of optimisation can facilitate problem definition through the requirement to specify the objectives, decision levers, and the system in mathematical equations. However, an assessment of previous optimisation studies highlighted that until recently, there has been limited consideration of how problem formulation can impact upon results.

Through the use of a case study, it was demonstrated that different objective functions, hydrological model assumptions and ecological model assumptions all impacted on the management outcomes identified. In addition, assumptions influenced which management decisions performed better (based on the stated objectives). Whilst further evaluation is needed, the preliminary assessment presented here supports the hypothesis that the primary challenge for environmental flow management lies in problem conceptualisation rather than optimisation algorithm performance.

2. Quantitative modelling tools for supporting environmental flow management

Three types of quantitative modelling tools were applied and examined in this research. The first type was a dynamic system model, which in this case consisted of an ecological response model and a river system model. A new ecological response model was developed specifically for the purpose of evaluating different environmental flow rules in the Lachlan catchment, Australia. Through the process of model development, new insight was gained regarding the key factors influencing ecological response to water availability. The quantification of system processes also assisted in identifying gaps in knowledge and data, an outcome which was reflected in feedback from the expert elicitation process.

Modelling tools for assessing model behaviour were the second type which were applied, and included both sensitivity analysis and Bayesian analysis. Sensitivity analysis provided insight into the impact of problem formulation on estimating ecological condition, as highlighted above. It also identified which model parameters had the greatest impact on ecological condition scores. The analysis demonstrated that modelled ecological condition was highly sensitive to a number of hydrological model assumptions, suggesting that ability to accurately predict ecological outcomes can be highly dependent upon the capacity to represent water availability.

Comparison against observed data using Bayesian analysis further supported these findings, as well as highlighting the challenge of evaluating ecological model performance where there are multiple sources of uncertainty. Consideration of multiple sources of uncertainty is essential when evaluating model results, and can lead to greater insight into model behaviour, and more informed assessment of different management alternatives (Jakeman *et al.*, 2006; Ascough *et al.*, 2008). The analysis applied here demonstrates that the range of model assumptions investigated here were largely inadequate for accurately representing the pattern of ecological decline during drought and recovery post drought. However, the analysis was based on limited observed data which did not capture low ecological condition scores. The level of uncertainty in estimating ecological response warranted the use of multiple models in assessing different management interventions, as opposed to selecting a single model or model averaging which is more frequently applied (Jordan and Jacobs, 1994; Madigan *et al.*, 1996).

The third type of modelling tool aimed at examining environmental flow management through multi-objective optimisation. Drawing upon outcomes from the model development and evaluation process, further exploration of problem formulation was undertaken. Whilst the results are not representative of the full Lachlan system, optimisation identified improved environmental flow rules for the simplified system (based on River Red Gum condition scores). The analysis provided further insight into model behaviour, as well as an understanding of system trade-offs based on the case study used. This research supports previous studies in demonstrating the value of optimisation in exploring different solutions and improving system understanding (Liebman, 1976; Kasprzyk *et al.*, 2013). However, it is essential that any application of optimisation considers the broader decision-making context, where social values, political context and governance often play a greater role in the decision process compared with model outputs (Pahl-Wostl *et al.*, 2013).

3. *Advancing modelling tools for environmental flow management through a systems approach*

In developing an ecological response model for investigating environmental flows, a number of limitations of existing models were addressed. The first of these was the application of a systems approach to considering water availability for River Red Gum. The model considered rainfall and groundwater in addition to river flows in estimating water availability and changes in ecological condition. Whilst previous research has demonstrated the importance of rainfall and groundwater in supporting wetland and floodplain vegetation (Thorburn and Walker, 1994; Mensforth *et al.*, 1994; Jolly *et al.*, 2008), these have not been considered in the majority of ecological response models. Model analysis including sensitivity analysis, Bayesian analysis and optimisation, identified that rainfall *and* groundwater were critical for the survival of River Red Gum during periods of low water availability.

The ecological component of the model also advanced upon previous models through the consideration of antecedent conditions, the impact of ecological condition at the start of each wet and dry period, as well as the pattern of change during decline and recovery. In addition, the model explicitly considered uncertainty in ecological response through the development of multiple expert-based conceptualisations, and the use of lower and upper bound response curves.

The key outcomes described above have important implications for environmental flow decision making. First, greater focus is needed on problem formulation, particularly in modelling and optimisation applications. This includes clearly identifying and defining objectives, and the assumptions that are involved when translating broad, qualitative objectives to quantitative metrics which can be modelled and measured (Hitch, 1960). Secondly, whilst there have been substantial advances in the field of environmental flows and ecological response modelling, significant uncertainties remain in our knowledge of ecosystem response to available water. For this reason, rigorous evaluation is required considering system conceptualisation, parameterisation, and input data in the use of modelling tools (Bennett *et al.*, 2013). Although the need for such evaluation is well recognised, application in practice remains limited.

The current research demonstrates a systems approach to assessing uncertainty from problem formulation through to application. Whilst it is recognised that specific case study results entail a number of simplifications and assumptions, they highlight the importance of considering uncertainties at each step of the decision making process. The process also demonstrates the learning process which was facilitated by the use of quantitative modelling tools, with greater insight gained as to the key factors likely to influence ecological response, and the need for further research to reduce existing uncertainties.

There remain many unanswered questions, and there is scope for further research to test and evaluate the ideas presented here. These include further exploration of: the role of rainfall and groundwater in supporting wetland and floodplain ecosystems; the impact of life history and the sequence of past events in determining ecological response; the pattern of ecological response under different hydrologic conditions; the balance between explicit incorporation of uncertainty in ecological response models and usefulness in decision making; and the impact of different uncertainties on resulting decisions regarding environmental flows.

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Appendix B1: Comparison of hydrological model results with expert observations

Year	Landholder/ environmental water manager observation	Modelled inundation (Reed Bed) (no rain)	Matches Obs?	With rain (Reed Bed)	Matches Obs?
1967	Reed bed was dry but the river still had some water	Dry	Yes	Dry	Yes
1968	Reed bed filled	Dry	No	Wet for 17 days in Dec	Yes
1989	1989 was a bigger event than 1990, as Marrool Creek also flooded. Flooding in the Cumbung highly influenced by flooding in Marrool.	Wet for 181 days from Jun-Dec	Yes but not bigger than 1990	Wet for 21 days Mar-Apr plus 184 days from Jun-Dec	Yes but not bigger than 1990
1990	Didn't flood.	Wet for 239 days from Jun 1990 to Feb 1991	No	Wet 18 days Apr-May plus 240 days from Jun 1990 to Feb 1991	No
1996	Stayed within the main channel	Dry	Yes	Dry	Yes
1998	Everywhere got wet, including the floodplain. Stayed wet for approximately 6 months. Marrool and Toopuntal wet, but didn't extend much further	Wet for 103 days Oct 1998-Jan 1999	Yes but duration too short	Wet for 106 days Oct-Jan	Yes but duration too short
2000	Similar water levels as now (i.e. just extending onto floodplain – March 2013)	Dry	Yes? Some water in reed bed but not full March 2013	16 days inundation Feb-Mar	Yes? Or maybe too wet?
2001	Drought started end 2001	Dry from Jan 1999 to May 2012	?	Dry 2001, one 16 day event in 2000	?
2002	2002 - still water in the lakes but no rainfall	Dry	Yes	16 days inundation from rain Feb- Mar 2002	No – rainfall did occur
2005	2005 the Lachlan within channel was completely dry	Dry	Yes	Dry	Yes
2006	Early 2006 some water in the Lachlan channel.	Dry	Yes	Dry	Yes
2009	Some rain in 2009, but the Lachlan had dried up again	Dry	Yes	Dry	No
	At the end of 2009, the system was incredibly dry, with sparse vegetation coverage – lots of busy groundsel, a little Cumbungi hanging on, and effectively no reeds.	Dry	Yes	Dry	Yes
2010	Approximately 300 ml rain. Inundation from flows also occurred, but stayed within channels and lakes	Dry	Yes	49 days Feb-Mar 2010	Yes
2011	The 2011 event was primarily rainfall driven, again no flooding.	Dry	Yes	47 days Jan – Mar 2011	Yes
2010/ 2011 and 2012	Events didn't extend as far as expected, largely due to the dryness of the system prior to 2010 event, and in particular to re-filling of the GW stores.	Dry	Yes	Wet for 49 days total 2010 and 47 in 2011	Yes
2010/ 2011	For the 2010/2011 events, the red bed was wet, and water extended out to Cockatoo area and Longneck. Some River Red Gum areas also got wet, in some places for a few months. Marrool and Lignum lake also got wet. Water didn't get as far as Boocathan	Dry	No	As above	Yes

	Lake to the north (past Lignum Lake). Most places dried out between the 2010 and 2011 event, only the channel stayed wet although the flows were very low. Both the 2010/11 and 2012 events put water into Bunumbert, Brittons, Clear Lakes.				
2012	The 2012 event was the only one since the drought to wet Boocathan. The 2012 event was preceded by large rainfall which had already started to fill areas. However, even so, the 2012 event still didn't wet all areas. Some black box was inundated for a couple of months as a result of both rainfall and flow. Need to consider both for an accurate picture. After the inundation, was incredibly dry with only 50% of average rainfall, hence the inundation didn't last as long. The reed bed was wet from about end March until sometime between Nov and Feb. Flows in the lower Lachlan were being maintained until about Oct/Nov 2012.	Wet 153 days May-Oct	Yes – although duration maybe too short	Wet 28 days Mar 2012 and 162 days May-Oct	Yes – although April not wet in model, and finished before Nov
2012	Most recent event started in Feb/March 2012, and peaked around June 2012 for Clear Lake. Approximate inundation extent for Toopuntal shown on map. Water went out of channels and lakes, based on approximate extent likely to have inundated black box areas (my interpretation of map).	As above	Probably too short	As above	Yes
2012	The 2012 event which began in Feb/March has receded but most lakes/channels still have water based on our observations: - Clear lake full (duration > 12 months) - Lake near Charlies Point maybe around 80% full (duration > 12 months) - Lignum Lake – c. 30% full (duration a bit longer than 12 months) - Marrool Lake – c. 10% full (duration c. 12 months) - Reed bed – dry at IMEF site (duration <12 months)	Doesn't refer to River Red Gum areas, but given some lakes only partially full wouldn't expect River Red Gum areas to have been inundated for long.	As above	As above	No – states reed bed dry

Appendix B2: Expert Elicitation Interview Questions & Supporting Material

Questionnaire 1: Ecologists with limited local knowledge of the GCS

Questionnaire

Influence of flooding

1. How much of an influence do you think wet and dry cycles have on river red gum condition, compared with other factors such as disease, temperature, animals etc?
2. How much influence do you think rainfall has on ecological condition?

Ecological response

1. How much difference does the initial condition make to response during drought/inundation?
2. During drought, how long does it take before river red gum condition deteriorates? Does this happen:
   a) gradually, or
   b) no change followed by rapid change, or
   c) rapid change followed by gradual change?
3. After inundation begins, how long does it take for river red gum condition to improve? Does this happen:
   a) gradually, or
   b) no change followed by rapid change, or
   c) rapid change followed by gradual change?
4. After extended inundation, after how long does vegetation begin to deteriorate due to being too wet?
5. If inundation has extended beyond 7 months with an associated decrease in condition for river red gum;
   - Once the wetland becomes dry, does the condition initially improve?
   - How long does this improvement last for before it decreases again due to drought stress?
6. How does tolerance to drought change depending on the distance from the river?

Groundwater

1. If river red gum has access to groundwater, how much longer can it survive compared with no access to groundwater?

Questionnaire 2: Landholders & ecologists with local knowledge of the GCS

Questionnaire

Influence of flooding

1. How much of an influence do you think wet and dry cycles have on river red gum condition, compared with other factors such as disease, temperature, animals etc?
2. How much influence do you think rainfall has on ecological condition?
   Is there much variation in rainfall across the Great Cumbung Swamp?

Flooding patterns

1. During different flood events, how far did the water get to?
2. How long were the following areas wet for:
   a. Channel
   b. Low lying areas around the channel
   c. Low lying areas in the reed bed
   d. The whole reed bed and some river red gum areas
   e. All river red gum areas
   f. River red gum areas and partial black box areas
   g. All river red gum and black box areas
3. During flood events in particular years, how long did it take with high flows at Booligal, for the channel within the Great Cumbung Swamp to stay wet and overflow? (days, weeks, months?)
4. How much longer did this take after it had been dry for a while?
5. How long did it have to be dry to make a difference?

Ecological response

7. What was the river red gum condition at the start/end of different drought periods?
8. How much difference does the initial condition make to response during drought/inundation?
9. During drought, how long does it take before river red gum condition deteriorates?
   Does this happen:
   d) gradually, or
   e) no change followed by rapid change, or
   f) rapid change followed by gradual change?
10. After inundation begins, how long does it take for river red gum condition to improve?
    Does this happen:
    d) gradually, or
    e) no change followed by rapid change, or
    f) rapid change followed by gradual change?
11. After extended inundation, after how long does vegetation begin to deteriorate due to being too wet?

12. Have there been any periods where the inundation has extended beyond 7 months, with an associated decrease in condition for river red gum?
    - If so, once the wetland becomes dry, does the condition initially improve?
    - How long does this improvement last for before it decreases again due to drought stress?
13. Are there any differences in river red gum response depending on the location within the Great Cumbung Swamp?

Groundwater

1. Are there areas where vegetation seems to maintain a better condition for longer than other areas, yet there is no surface water?
2. If so, how much longer is the condition better for? How much better is the condition?

Supporting Information 1: Response curves for completion by all experts

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These images are taken from Souter et al. (2009) and Roberts and Marston (2011)

River Red Gum deterioration

Optimal condition - maximum crown extent and maximum crown density

Abundant leaf die off, large number of dead leaves at the bottom left of the crown

Long-term dead river gum

River Red Gum recovery

River red gum in poor condition with some epicormic growth

Common active epicormic growth

Abundant active epicormic growth

Optimal condition - maximum crown extent and maximum crown density

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Supporting Information 2: Feedback on initial ERM from ecologists
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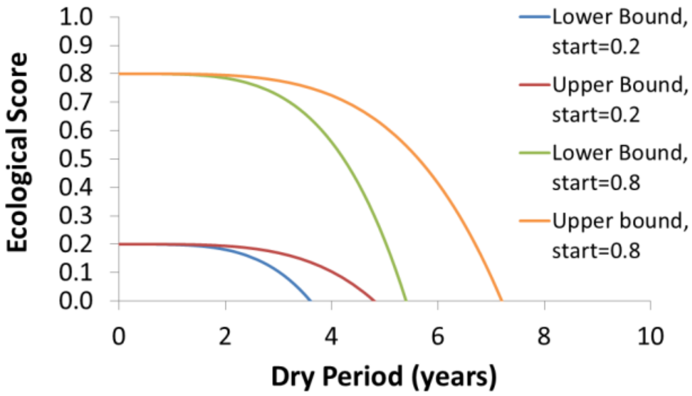
Questionnaire Supporting Information

Flooding patterns

Flow rate (ML/d)	Duration	Area wetted	Duration wet	Source
700	6 weeks	'core reed bed'	?	2005 Env Water All.
700	90 days	Reed bed: 4000ha	?	Ch12 ERMs, GCS water balance, Ref&Mod Flows…
3000	30-90 days	RRG area, 15,000 to 30,000 ha	?	GCS water Balance, Ch 12 ERMs,Ecological Character…

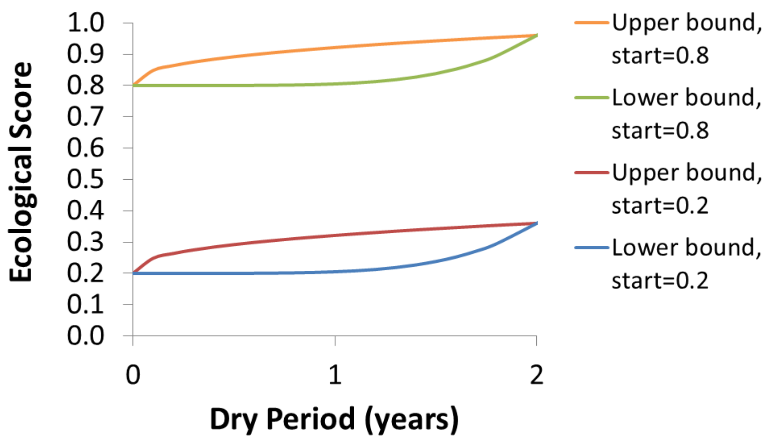
Ecological response – River Red Gum Forest maintenance

Dry periods

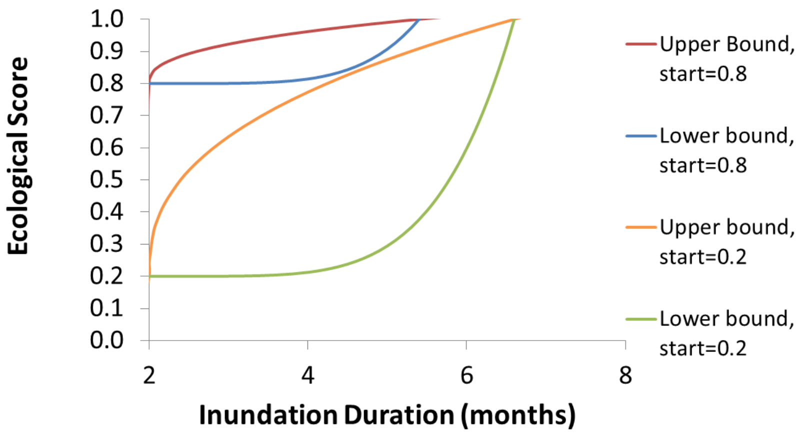


Score	Condition	Seddon et al. (2002) score
0.9-1.0	Vigorous, abundant foliage	1
0.7-0.8	Foliage beginning to die from tips, partially dead branches	2
0.5-0.6	Thin canopy, some completely dead branches	3
0.3-0.4	Many dead branches	4
0.1-0.2	Leafless	5
0	Dead	

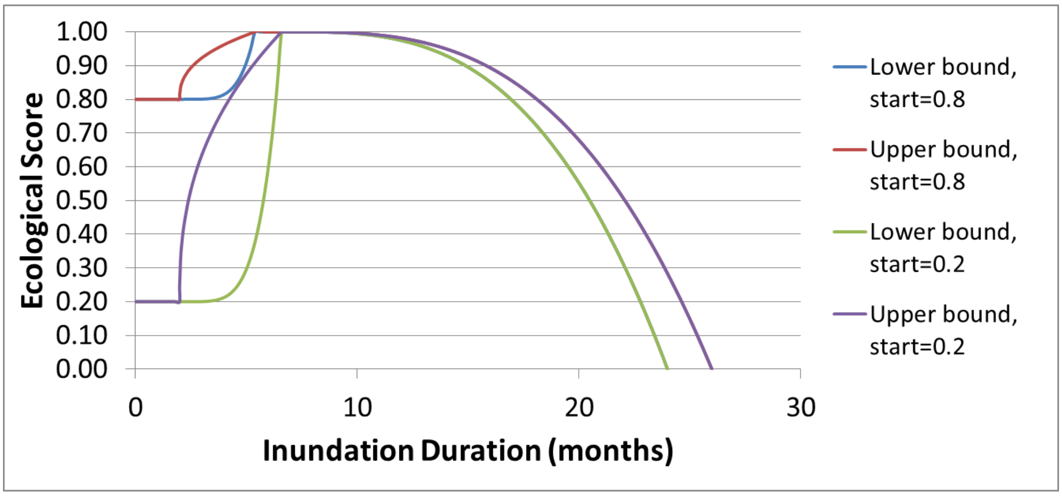
Initial two years of dry period following extended inundation



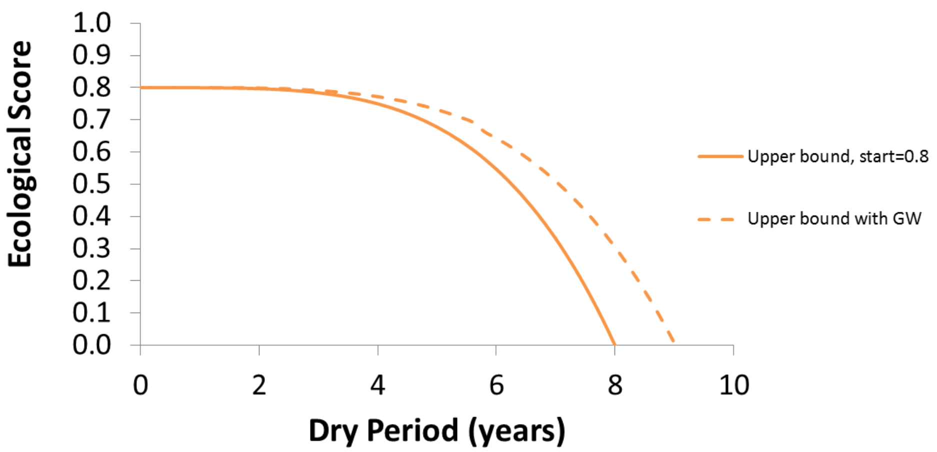
Inundation period (ideal period)



Combined inundation period (ideal and extended inundation)

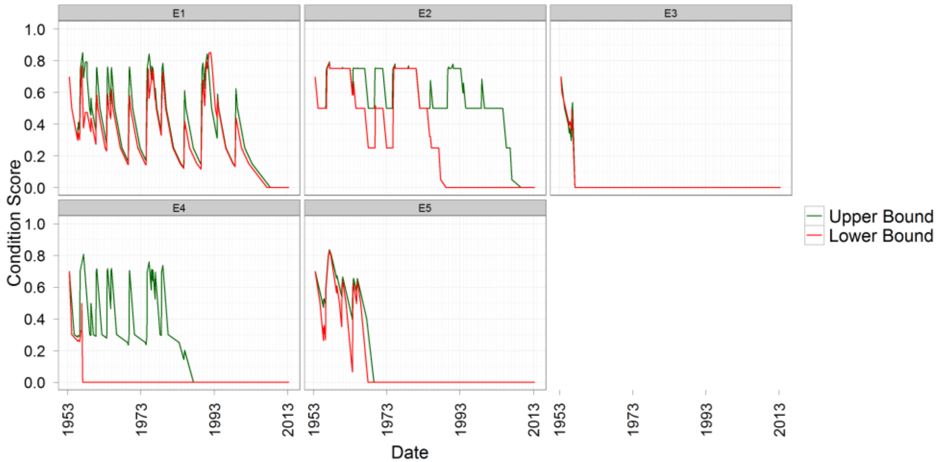


Groundwater

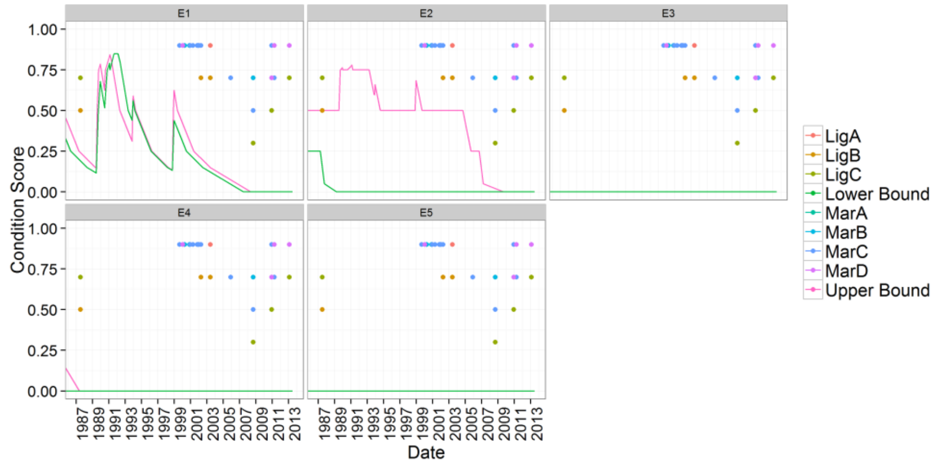


Appendix B3: Expert model performance for hydrological assumptions

Set 1: 2700ML/d 30d No Groundwater, No Rain

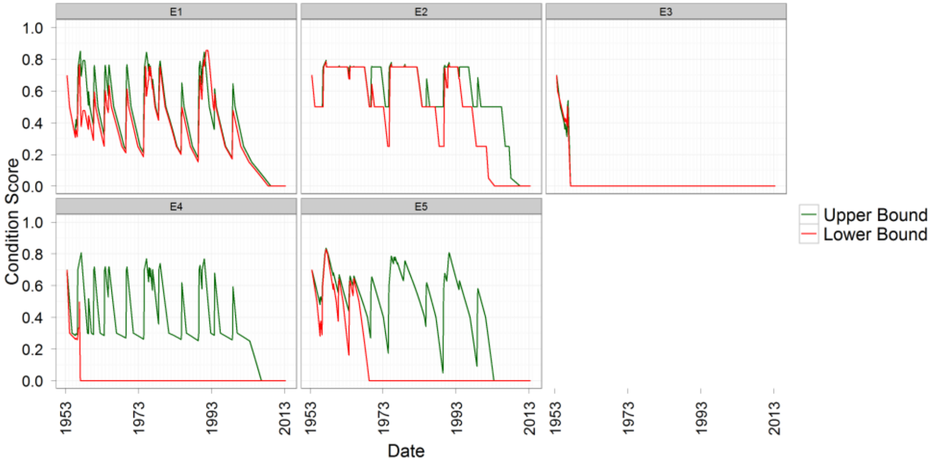


Modelled ecological condition for 1953 to 2013

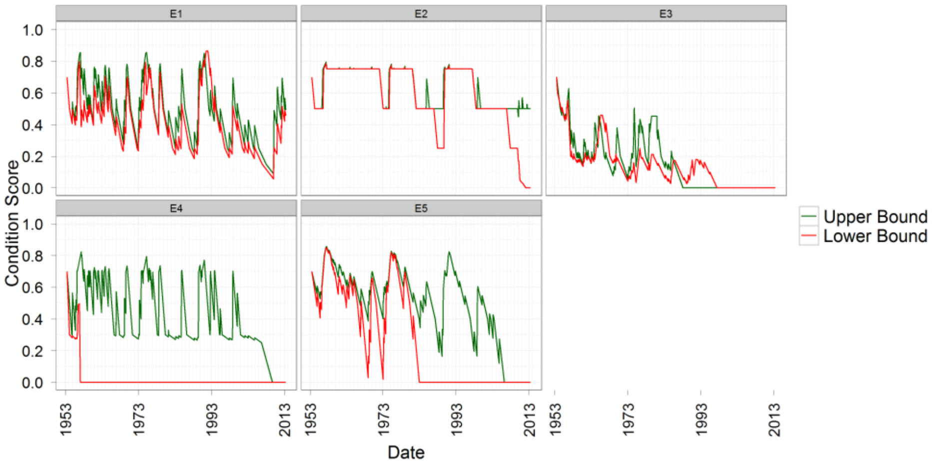


Modelled and observed ecological condition from 1999 to 2013

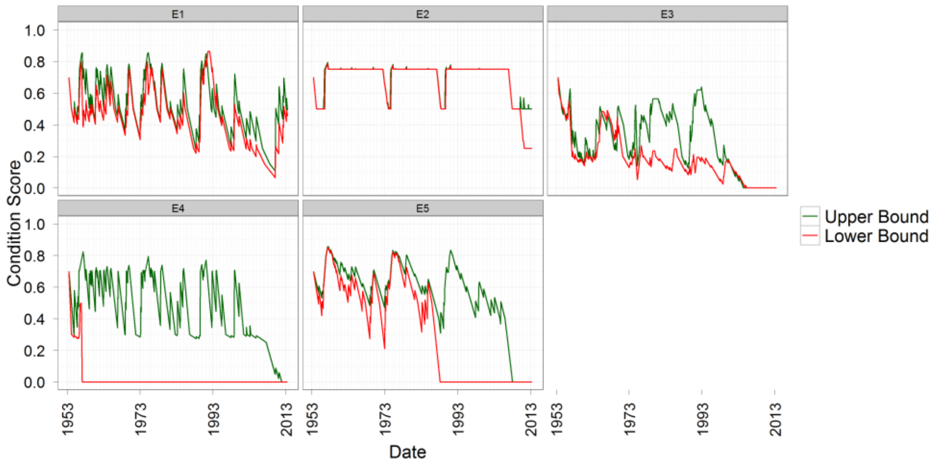
Set 2: 2700ML/d 30d 10m Groundwater access, No Rain



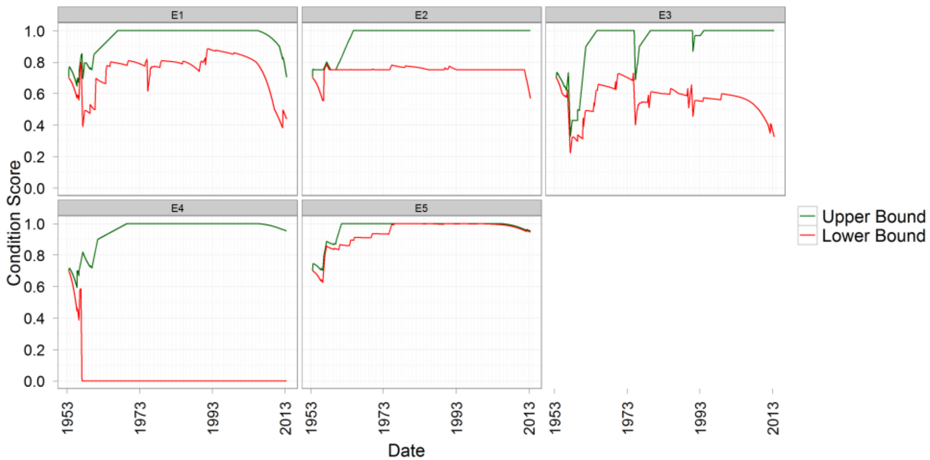
Set 3: 2700ML/d 30d No Groundwater, with Rain



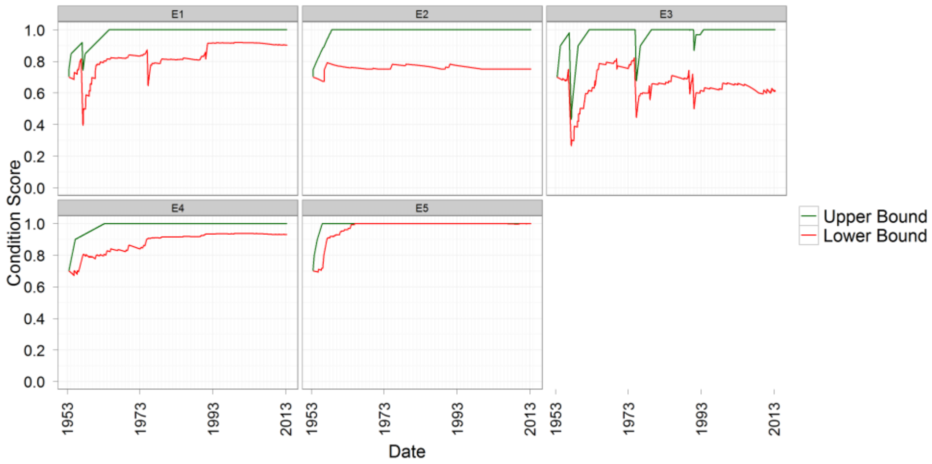
Set 4: 2700ML/d 30d 10m Groundwater access, with Rain



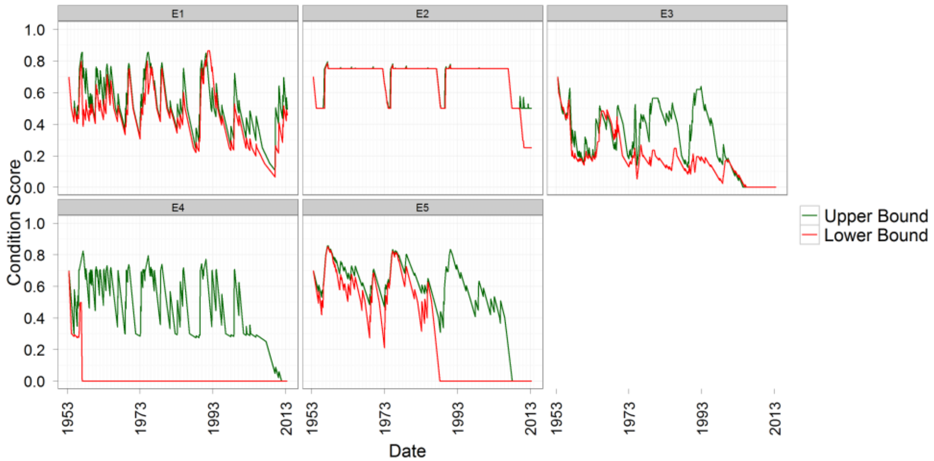
Set 7: 2700ML/d 30d 15m Groundwater access, no Rain



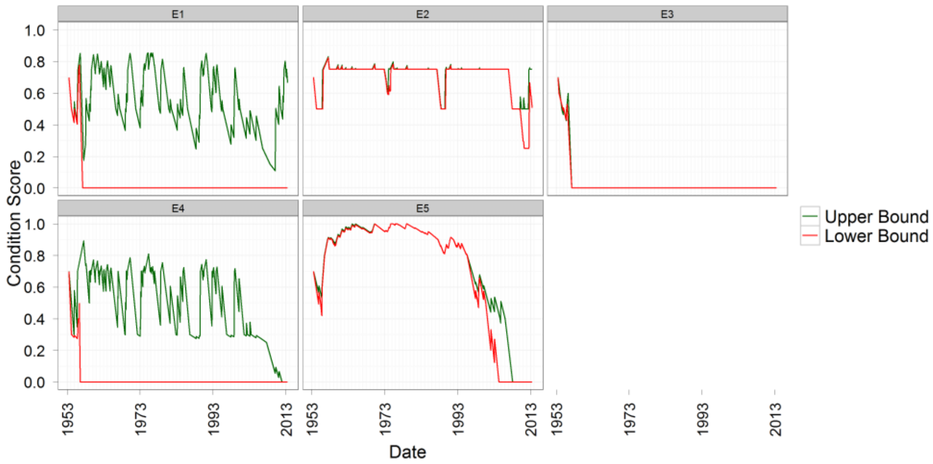
Set 8: 2700ML/d 30d 10m GW access, with rain, GW depths halved (half as close to the surface)



Set 9: 2700ML/d for 90 days flow threshold, 10m GW access with rain



Set 10: 700ML/d for 90 days flow threshold, 10m GW access with rain



Set 12: 700ML/d for 90 days flow threshold, 15m GW access with rain