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Assessing certainty and uncertainty in riparian habitat suitability models by identifying parameters with extreme outputs

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ABSTRACT

The aim of this paper is to introduce a computationally efficient uncertainty assessment approach using an index-based habitat suitability model. The approach focuses on uncertainty in ecological knowledge regarding parameters of index curves and weights. A case study determines which of two 15-year periods has more suitable surface water and groundwater regimes for riparian vegetation. The uncertainty assessment consists of defining constraints on index curves and weights. Linear programming is used to identify parameters that yield two extreme outputs: maximising and minimising differences between the two periods. Because they are extremes, if both outputs agree on which period is better (e.g. maximum and minimum differences are both positive), then all other models will also agree. Identifying models with extreme outputs prompts learning about the boundaries of our knowledge and identifies patterns about what is considered certain. It helps build an understanding of what is already known despite the high uncertainty.

1. Introduction

Riparian vegetation is increasingly under threat from human activities and climate change. Damming, surface water extraction, groundwater pumping and other human interventions have caused serious changes in the functioning of riparian ecosystems, resulting in widespread decline in the extent and health of riparian vegetation (Allan and Castillo, 2007; Ward and Stanford, 1995). This is especially so for riparian systems in arid and semi-arid regions where water can be more scarce, or at least more temporally variable, yet in high demand for human use, resulting in greater extraction of surface water and groundwater resources (Stromberg et al., 1996).

Maintaining the integrity of riparian ecosystems that provide valuable services whilst continuing to reserve and extract water for other purposes necessitates a greater understanding of relationships between riparian vegetation health and water regimes. Ecological models can be useful tools to investigate these relationships and assess the potential impact of water stress on riparian vegetation (Robson, in press). For example, empirical relationships between surface water hydrological variables and riparian vegetation cover (Auble et al., 1994), structure (Stromberg et al., 2010) and distribution (Camporeale and Ridolfi, 2006) have been developed based on monitoring data. These models have been used to quantify in-stream flow requirements of riparian vegetation or predict vegetation change resulting from a proposed upstream dam or diversion. Loheide and Gorelick (2007) developed empirical relationships between riparian vegetation type and depth to the water table to examine the impact of streambed incision on the composition of riparian vegetation communities. In the absence of sufficient monitoring data, however, an index-based approach can be a very useful way to evaluate habitat suitability based on literature and/or expert opinions (Yamada et al., 2003).

One of the major challenges in ecological modelling for understanding and managing riparian ecosystems is assessment of their uncertainties. These uncertainties can be high especially at large scales and when there is limited knowledge and informative data to quantify relationships between variables. High levels of uncertainty limit the use of models for assisting management and decision making. Traditionally, uncertainty analysis for ecological models has been used as an additional stage in evaluating model outputs using various approaches such as fuzzy bounds (Burgman et al., 2001), Monte Carlo simulations (Dietzel and Reichert, 2012; Straatsma et al., 2013; Van der Lee et al., 2006) and ensemble models (Estes et al., 2013). Those approaches can be limited by their computational cost, particularly where sampling methods such as

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Monte Carlo are used. Their application depends on the availability of sufficient data, models, expert knowledge and assumptions to define parameters such as probability distributions or possibility levels. Using ensemble models only considers a small set of models, which can limit exploration of uncertainty. These uncertainty analysis processes are typically not interactive, emphasising the creation of a final product rather than evolution over time. Their focus is typically on communicating uncertainty, leaving the end-user to understand and make use of that information.

The aim of this paper is to propose an additional uncertainty assessment approach, thereby bridging these gaps and inviting the modelling community to further test its usefulness in their own applications. In the paper, we illustrate a computationally efficient approach assessing uncertainty in index-based habitat suitability modelling, specifically addressing the situation where limited data are available and expert opinions differ significantly. The habitat suitability model estimates the suitability of surface water and groundwater for three riparian vegetation species. The focus of the uncertainty assessment is on what can be presumed certain in predicted model outputs given current agreed knowledge, thereby evaluating the state of knowledge, identifying knowledge gaps and reflecting on the impact of adding assumptions.

2. Study area

The Namoi River Catchment forms part of the Murray–Darling Basin and drains an area of approximately 42,000 km^2 in northern New South Wales (Fig. 1). Rainfall generally decreases from east to west across the catchment, with annual averages of 945 mm at Niangala near the headwaters, 620 mm at Gunnedah in the midsection of the catchment and 480 mm at Walgett in the low lying plains of the west. This study focusses on the mid to lower sections of the Namoi catchment, downstream of Gunnedah. The lower Namoi River is categorised as an anabranch and distributary river zone where the condition of the floodplain is important to river function (Lampert and Short, 2004).

The Namoi River has a long history of river regulation with the first dam having been constructed in 1960. The major impacts of river regulation in the Namoi include altered seasonal flow and reduced flood frequency and flows, most pronounced on the small to medium flood events (Sheldon et al., 2000). It also has the highest groundwater use in the Murray–Darling Basin. In 2004/05, groundwater extraction in the Namoi was estimated to be 255 GL, accounting for 15.2% of the total groundwater use in the Murray–Darling Basin. Some 35% of the groundwater extractions in the Namoi Catchment was from the Lower Namoi Alluvium Groundwater (CSIRO, 2007).

The major streams and rivers of the catchment are dominated by river oak (*Casuarina cunninghamiana*) and river red gum (*Eucalyptus camaldulensis*). Large areas of riverine land in the Namoi catchment have been converted to cropping and pastoral uses, effectively meaning that, except for habitat corridors and patches of riparian vegetation, most of the native vegetation has been cleared (Eco Logical, 2009). The lower Namoi does not have large wetlands, but contains many small lagoons, wetlands, anabranches and flood runners (Green et al., 2011). Although large in number (1829 natural and 937 artificial wetlands), most of the wetlands are small in size and scattered across the floodplain and major tributaries (Eco Logical, 2008).

3. Methods

This section defines terms that will be used, describes the habitat suitability model and introduces the uncertainty assessment approach.

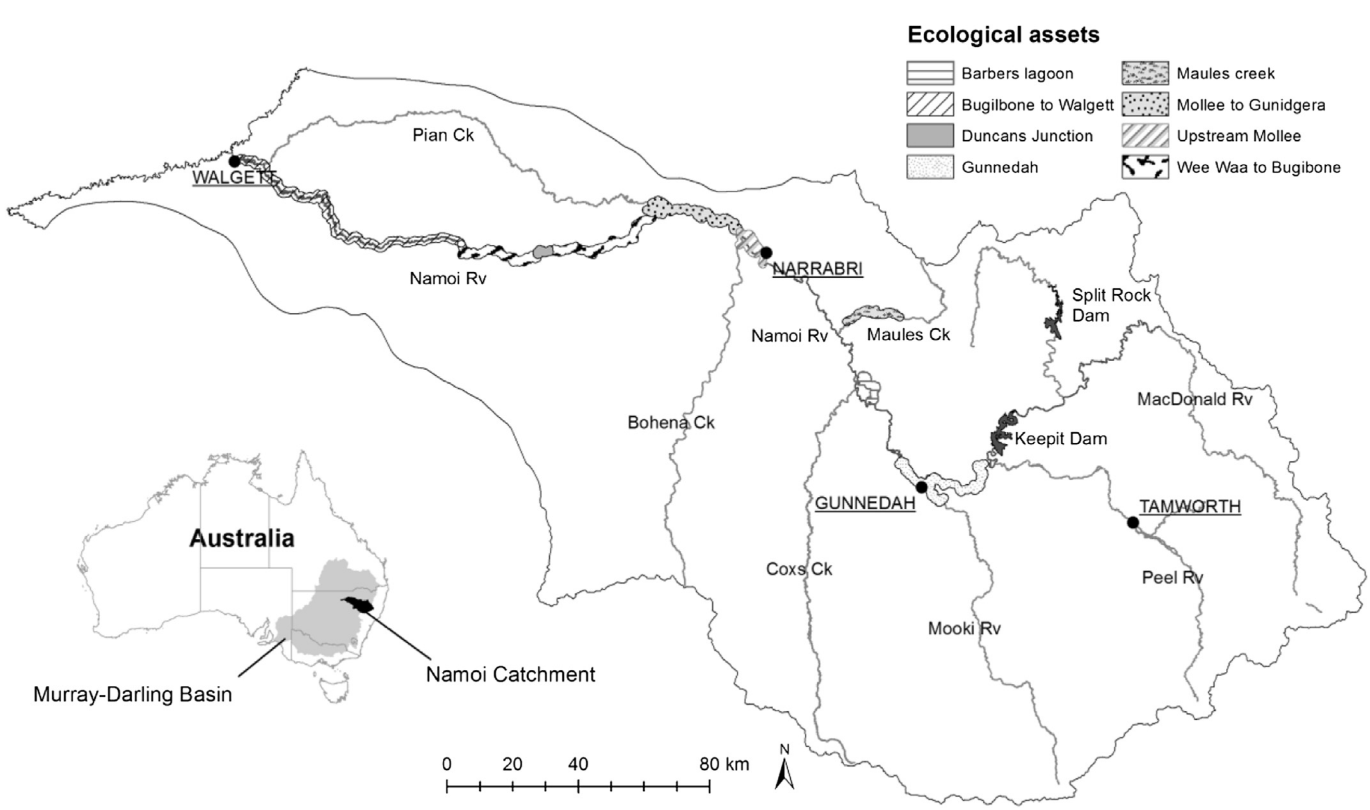


Fig. 1. Namoi River catchment, showing asset sections along the river.

3.1. Terminology in this paper

- Model – includes input variables, parameters and structure. Variation in any of these elements produces a new "model".
- Attribute – input variable used in a model. In our case, this includes flood duration, flood timing, inter-flood dry period and groundwater level.
- Index Curve – function converting attribute values to index values, approximated by piece-wise linear segment separated by "breakpoints".
- Parameters – this includes breakpoint coordinates and weights used to combine index curves into aggregate indices of suitability.
- Constraints – rules expressing knowledge of the system that limits the values of breakpoint coordinates and weights, and hence shape of index curves and possible model output values.
- Certainty – provisional certainty, conditional on the constraints specified, that could be altered as a result of new knowledge or addressing limitations of the analysis.

3.2. Habitat suitability model

The ecological model presented in this paper focuses on representing healthy river functions for riparian vegetation. This health is assumed to involve:

- regular flooding to sustain the growth of riparian vegetation and support regeneration;
- suitable groundwater levels to allow the access of water by riparian vegetation, particularly during drought.

The model therefore assesses the suitability of surface water and groundwater regimes for the maintenance and regeneration of riparian vegetation in the Namoi Catchment. It identifies characteristics of flooding events (e.g. duration, timing and inter-flood dry period) and groundwater levels (i.e. depth to water table), and generates suitability indices based on species' water requirements. Three vegetation species were modelled: *E. camaldulensis* (river red gum), *Muehlenbeckia florulenta* (lignum) and *Paspalum distichum* (water couch). These species were selected because they are some of the most common vegetation species identified at the modelled areas.

Eight ecological assets were selected (Fig. 1). Assets are areas in the catchment that have ecological significance. These assets were previously selected by another study researching watering needs in the Namoi Catchment for the development of broader environmental flow guidelines (Barma Water Resources et al., 2012). All assets have a history of river regulation, except that of Maules Creek, which is considered to be in relatively natural condition. All assets constitute important corridors of river red gum in the region. Some assets such as Barbers Lagoon (Asset 2) and Duncans Warrambool (Asset 6) contain wetlands which are important waterbird and fish habitats. Areas and ecological values of the assets are listed in Table 1.

For each species, a water suitability index was calculated as the weighted average of a groundwater suitability index and a surface water suitability index, viz.

$$I = w_g G(\text{groundwater level}) + w_s S \qquad (1)$$

where I denotes the water suitability index; G is a function of groundwater level which estimates groundwater suitability index; S is surface water suitability index and is described in Equation (2); w_g and w_s are weights for groundwater and surface water indices respectively.

Table 1
Areas and ecological values of the modelled ecological assets in the Namoi River catchment.

Asset ID	Name	Area (ha)	Main ecological values
1	Gunnedah	2012	River red gum riverine, testing site
2	Barbers Lagoon	134	River red gum, wetlands (water couch)
3	Maules creek	425	River red gum
4	Upstream Mollee	933	River red gum, wetlands
5	Mollee to Gunidgera	3195	River red gum, black box, coolabah, wetlands
6	Duncans Warrambool	301	River red gum, black box, coolabah, wetlands (lignum, billabong rush, nardoo, poison pratia)
7	Wee Waa to Bugilbone	3144	River red gum, coolabah, black box, wetlands (water couch, tall flat-sedge)
8	Bugilbone to Walgett	3570	Black box, coolabah, River red gum, wetlands (lignum, tussock rush, dirty dora, spiny sedge)

The groundwater suitability index was derived based on the suitability of groundwater level, which was generated from groundwater index curves that convert groundwater level into index values of 0–1, with zero indicating an unsuitable groundwater regime for the maintenance and regeneration of riparian vegetation and 1 being most suitable.

Mathematically an index curve can be defined as linear segments joined together at breakpoints (Fig. 2). Each piece-wise linear segment is defined by the coordinates of their end-points, (x_c, y_c) and (x_{c-1}, y_{c-1}). The suitability index a_c of an attribute falling within segment c is given by $a_c = m_c(x - x_c) + y_c$, $x_{c-1} < x < x_c$ where $m_c = (y_c - y_{c-1})/(x_c - x_{c-1})$. Groundwater index curves vary depending on species. Groundwater salinity is neglected in the model because the recorded salinity levels in the study area are lower than salinity tolerance thresholds identified in the literature.

The surface water suitability index was estimated based on weighted average of suitability of flood duration, flood timing and inter-flood dry period (Equation (2)).

$$S = w_d D(\text{flood duration}) + w_t T(\text{flood timing}) + w_f F(\text{inter} - \text{flood dry period}) \qquad (2)$$

where S is the surface water suitability index; D, T, F are respectively a function of flood duration which produces a flood duration index, a function of flood timing which produces a flood timing index, and a function of inter-flood dry period which produces an inter-flood dry period index; and w_d, w_t and w_f are weights for duration, timing and inter-flood dry period respectively.

Similar to the groundwater index, the suitability of flood attributes were estimated using index curves which convert each flood attribute (e.g. flood duration) into suitability indices. These flood attributes were generated from daily surface flow time series based on commence-to-flood levels, above which a flood or wetting event occurs. Thus a higher commence-to-flood level is interpreted as flooding of areas higher and further from the riverbank. Reference commence-to-flood levels are shown in results for each asset. They were defined by identifying benches and flood extent through field inspection and remote sensing (Barma Water Resources et al., 2012). We assumed that the minimum number of days in each flood event window is 3 days, and the minimum number of days that can separate events is 2 days.

In this paper, we compare mean surface water and groundwater suitability indices over two periods: Pre90 (1975–1989) and Post90 (1990–2005). This analysis is for illustrative purposes and can be easily extended to cover comparison of any hydrological regimes such as different environmental water release scenarios. The model inputs include daily surface flow and groundwater levels associated with respective ecological assets. Historical daily river flow data before 2008 was obtained from PINNEENA 9.2 (Department of Water and Energy, 2008); while more recent flow records (2008–2010) were obtained from the waterinfo website (waterinfo.nsw.gov.au). Historical groundwater bore data was obtained from Groundwater PINNEENA 3.2 (NSW Office of Water, 2010). The groundwater bore data was cleaned and then interpolated into daily time series using a linear regression (Blakers, 2011). River gauges and groundwater bores were selected based on their proximity to the assets and the completeness of the data within the testing period.

3.3. Uncertainty assessment

Model output is interpreted by comparing the mean suitability indices of two periods to determine which period results in a better habitat suitability outcome. There is however uncertainty in the definition of the index curves and their weights. Selecting different index curves and weights results in different models, which might give contradictory conclusions about which period is better. The uncertainty assessment aims to verify that all models that could plausibly be selected do give the same conclusion. Limitations of the approach will be discussed in Section 5.3.

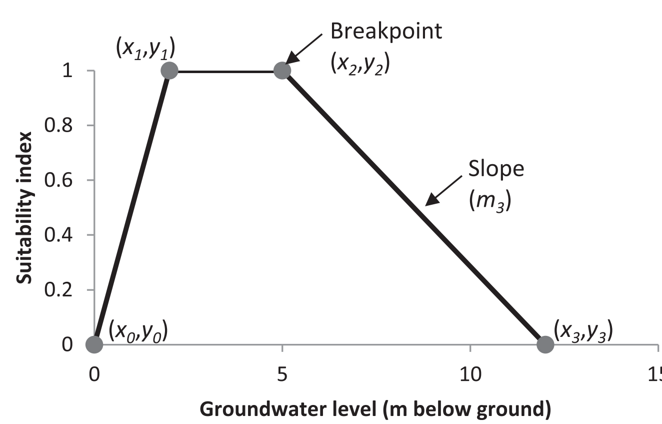


Fig. 2. A notional groundwater index curve showing breakpoints and slopes.

3.3.1. Characterising uncertainty of index curves and weights

The parameters of the model are defined directly by the modeller, expert or user, rather than by fitting of data. Uncertainty can therefore be characterised by setting constraints on the parameters' values, which define which models are plausible. Without constraints, any model and corresponding outcome is considered plausible; constraints are effectively assumed/agreed facts that permit the modelling to yield more precise predictions. In this paper, uncertainty is represented by a set of constraints on index curve breakpoints (either manually or using existing index curves), weights of attributes and the direction of the relationship between these parameters.

Constraints on the shape of the index curves are in practice implemented as restrictions on the coordinates of the breakpoints, either directly or relative to other breakpoints. To simplify the analysis, in this paper a fixed set of abscissa of breakpoints (i.e. x_c, see Fig. 2) are used, and constraints are defined on the ordinates (i.e. y_c). The modeller can specify four types of constraints manually (Table 2). Each of these rules is applied internally to the affected breakpoints. Rather than asking the modeller, expert or user to specify parameters of precise index curves, this method therefore asks them to specify knowledge of maximum and minimum suitability of attribute values, comparative suitability of attribute values, smoothness of changes in suitability and monotonicity of changes in attribute values.

Alternatively, if multiple index curves are already available, constraints can be determined from them by identifying what the curves agree on. This is done by comparing the suitability values of all the breakpoints (Fig. 3). Their minimum and maximum limits are determined. If all the index curves agree on the relationship between any pair of breakpoints, then this is added as a constraint. For example, if all curves agree that suitability increases, then the uncertainty analysis only considers curves where this holds true. This approach assumes that individual index curves implicitly capture the same knowledge that is explicitly requested when specifying index curves manually. It theoretically provides an equivalent means of eliciting that knowledge.

In this paper, multiple index curves for surface water attributes were derived from three sources: the Murray Flow Assessment Tool (Young et al., 2003, Rogers and Ralph, 2010 and Roberts and Marston, 2011). The constraints for these index curves were generated using the multiple curve method (see for example Fig. 3). Index curves for groundwater levels were initially defined based on literature (O'Grady et al., 2006; Roberts and Marston, 2011; Rogers and Ralph, 2010), and the constraints were added to each groundwater index curves using the manual constraints approach. An example of the constraints used for the maintenance of river red gum is shown in Table 3.

As discussed in Section 3.2, attribute suitability values are combined using weights. Constraints on weights are expressed manually in two ways. The first way consists of defining the minimum or maximum weight given to the ith attribute,

Table 2
Types of manual constraints and their mathematical translation.

Type of manual constraints	Examples	Mathematical translation
Bounds (max/min) suitability of attribute values	A given range of flood duration is highly suitable or that any flood lasting less than a given duration is not suitable.	$\forall\ x \in [x_{\min}, x_{\max}]$ $y_{\min} \le y \le y_{\max}$
Comparative suitability of attribute values	Some flood durations are better or worse than others, perhaps by a minimum difference Δy.	$\forall\ x_1 \in [x_{\min,1}, x_{\max,1}]$, $x_2 \in [x_{\min,2}, x_{\max,2}]$ $y(x_1) - y(x_2) \le \Delta y$
Smoothness of changes in suitability	Within a given range of flood durations, the suitability increases or decreases smoothly rather than with large jumps, with at most an increase of $\Delta y_{\max}$ or a decrease of $\Delta y_{\min}$ for a unit change in x.	$\forall\ x_1, x_2 \in [x_{\min}, x_{\max}]$, $x_2 > x_1$, $(y(x_2) - y(x_1))/(x_2 - x_1) \le \Delta y_{\max} \wedge (y(x_2) - y(x_1))/(x_2 - x_1) \ge -\Delta y_{\min}$ (This is analogous to constraining the derivative of the curve in a continuous function)
Monotonicity of changes in suitability	As flood duration increases within a range, suitability only increases (by at least Δy), it does not decrease or vice-versa.	$\forall\ x_1, x_2 \in [x_{\min}, x_{\max}]$, $x_2 > x_1$, $(y(x_2) - y(x_1))/(x_2 - x_1) \le -\Delta y$ to enforce a decrease in suitability index, and $\forall\ x_1, x_2 \in [x_{\min}, x_{\max}]$, $x_2 > x_1$, $(y(x_2) - y(x_1))/(x_2 - x_1) \ge \Delta y$ to enforce an increase in suitability index

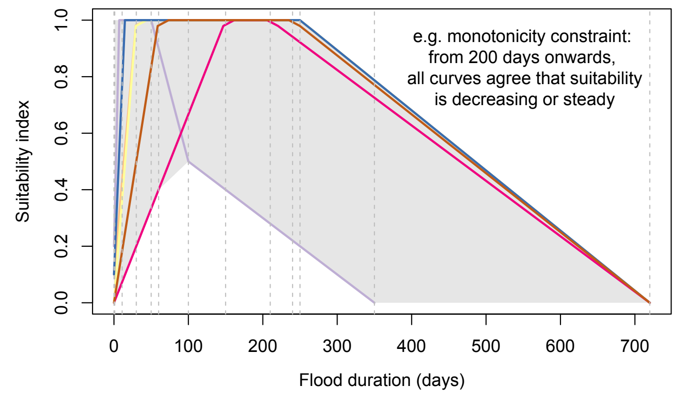


Fig. 3. An example of constraints generated from multiple flood duration index curves for the maintenance of river red gum. Dashed vertical lines are fixed abscissa values. Shading represents bounds on suitability values.

$w_{\min} \le w_i \le w_{\max}$. The second is to define the importance of attributes relative to each other, for example, that groundwater level must be less important than other attributes. Allowing for a minimum difference Δw, this is expressed for attributes i and j as $w_i + \Delta w \le w_j$. For practical reasons, we use $\Delta w = 0.05$ as a small value to enforce a strict inequality between the weights. To form a weighted average, the weights are also constrained to sum to unity. Rather than specifying weights directly, the user is therefore asked to specify either the range of importance or the importance of attributes relative to each other. In this paper, the weights were constrained as listed in Table 4. Knowledge in weights were derived from literature (Roberts and Marston, 2011; Rogers and Ralph, 2010). There are no constraints in weight for the regeneration of water couch because we do not have sufficient information. Therefore, the weight of any flood attributes can be between zero and 1 as long as the sum of the weights is 1.

3.3.2. Uncertainty analysis using linear programming

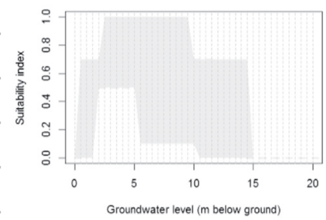
Having characterised the uncertainty as constraints, the aim is now to determine whether *all* models that can be defined within those constraints agree on which period is better. Rather than trying to exhaustively evaluate all the models, the simplest approach is to find the model where the one period has the greatest advantage in suitability compared to the other, and to find a model where the converse is true, where the period has the greatest disadvantage in suitability. If it turns out that both models show the period has better suitability, or both models show the period has worse suitability, then given that these are extreme cases, all other models will also agree on which period is better. In optimisation terms, this will involve selecting parameters that alternately maximise and minimise the advantage in suitability of one period over the other.

This optimisation problem is formalised as a set of linear programming problems in order to provide a fast, computationally efficient solution of the uncertainty analysis problem, minimising the need to sample parameter space. For each attribute, the formulation of the index curve as piece-wise linear segments and selection of fixed breakpoint abscissa allows the derivation of the difference in suitability Δa between periods, as a weighted sum of the ordinates of the breakpoints: $\Delta a = \sum_c \beta_c y_c$. The values β_c result from the substitution into the index curve of the breakpoint abscissa and flood attribute values for both periods. For each attribute, two linear programming problems are solved using the lpSolveAPI package in R (lp_solve and Konis, 2011; R Development Core Team, 2012). For this optimisation we select the ordinates of the breakpoints (y_c) that alternately maximise or minimise Δa, subject to the constraints on the breakpoints. Note that this approach can be extended to any additive model that is linear-in-parameters (Norton, 1996). The aggregated difference in suitability index can then be defined as the weighted sum $\Delta S = \sum_i w_i \cdot \Delta a_i$. This is in turn solved as a linear programming problem, selecting the weights (w_i) to maximise ΔS when using the maximum Δa_i for each attribute, and to minimise ΔS when using the minimum Δa_i for each attribute. Note that this multi-step linear programming approach is the result of the problem being a specific form of bilinear program (White, 1992). The original bilinear program is of the form $\Delta S = \sum_i \sum_c \beta_{c,i}\, w_i\, y_{c,i}$, selecting w_i and $y_{c,i}$ to maximise or minimise ΔS subject to independent constraints on w_i and $y_{c,i}$.

3.3.3. Interpreting the result of uncertainty analysis

The uncertainty analysis therefore consists of using linear programming to select index curves and weights that satisfy the constraints of knowledge and alternately maximise or minimise the advantage in suitability index of one period over another. This results in two models, defined by different index curves and weights. The outputs of these models define bounds on the advantage of one period over the other. However, the aim of the assessment is to determine which is better, not by how much. For this purpose, it is sufficient to assess whether the two

Table 3
Constraints in groundwater level used for the maintenance of river red gum.

Type	Ground-water level	Knowledge in groundwater suitability	Constraints on index value	Possible range for groundwater index curve (grey area)
Bounds	>=15 m	Unsuitable	= 0	
	0 m	Unsuitable	= 0	
	>=10 m	Less than ideal	<= 0.7	
	<=2 m	Less than ideal	<= 0.7	
	2-10 m	Not unsuitable	>= 0.1	
	2-5 m	Suitable	>= 0.5	
Monoto-nicity	0-2 m	Must increase/steady	Direction=1	(Monotonicity and smoothness not shown; vertical dashed lines indicate breakpoints; shading represents bounds on suitability values.)
	>= 5 m	Must decrease/steady	Direction= -1	
Smooth-ness	All range	Cannot jump sharply	Step=0.9/2 *	

*: Jumping from mostly unsuitable to ideal needs to be over at least 2m.

models agree on which period is better. If they agree (both outputs are positive or negative), the conclusion is certain, conditional on acceptance of the constraints and of the simplifying assumptions made. If they disagree (the bounds cross zero), neither period is clearly better.

The conclusion is summarised for multiple species and assets as a version of a "traffic light diagram", derived from the idea of an "Italian flag" (Davis et al., 2010). This paper shows in green where (that is for which asset and commence-to-flood threshold) the Pre90 period is better or the same (i.e. Pre90 is favourable); in light grey, the result is uncertain (i.e. cannot pick a favourable option), or in red, the Post90 period is better or the same (i.e. Post90 is favourable). If applicable, in "lemon chiffon" yellow, we add a fourth category where there is no difference between the periods (i.e. neither period is favourable). Note that the case where a model predicts both periods to be equal has been treated ambiguously as belonging in different categories, depending on what other models predict. We expect this would fit a manager's need to identify possibly favourable scenarios, rather than needing absolute certainty.

In analysing the traffic light diagram, the patterns shown are the result of constraints defined primarily by general ecological knowledge. The key contribution of this uncertainty assessment is therefore to be able to tell the user what uncertainty in general ecological knowledge allows the modeller to say about this case study. The resulting interpretation of certainty and uncertainty across species, assets and commence-to-flood levels will be discussed in Section 5.1.

Table 4
Weight constraints used in this study.

Species	Knowledge in weights	Constraints in weights
Maintenance of river red gum and lignum	Duration is more important than timing and inter-flood dry period.	- $W_{duration} \geq W_{timing} + 0.05$ - $W_{duration} \geq W_{dry} + 0.05$
Regeneration of river red gum	Timing and duration are both important.	- $W_{timing} \geq 0.3$ - $W_{duration} \geq 0.3$
Maintenance of water couch	Timing is more critical than duration or inter-flood dry period, but duration and inter-flood dry period cannot be neglected.	- $W_{timing} \geq W_{duration} + 0.05$ - $W_{timing} \geq W_{dry} + 0.05$ - $W_{duration} \geq 0.1$ - $W_{dry} \geq 0.1$
Regeneration of lignum	Timing is more critical than duration but duration cannot be neglected.	- $W_{timing} \geq W_{duration} + 0.05$ - $W_{duration} \geq 0.1$
All species	Groundwater cannot be more important than surface water.	- $W_{groundwater} \leq 0.5$

Additionally, singling out two extreme-case models rather than simply sampling models randomly allows these models to be analysed in more detail. The user can evaluate the plausibility of the resulting index curves and weights. If any behaviour is contrary to expectations, constraints might be added to eliminate it. If the conclusion is uncertain, and there is additional knowledge of lower confidence, additional constraints can be added that might reduce uncertainty. If it succeeds in making the result certain, then it indicates that additional work to improve confidence in this knowledge would be worthwhile. The uncertainty assessment therefore helps to critique and advance existing knowledge, rather than simply quantifying its consequences.

4. Results

4.1. Hydrology and groundwater

Average annual flows in the two test periods varied depending on the assets. At most assets average annual flows in the Pre90 period were higher than Post90. For example, in Gunnedah the average annual flow in Pre90 and Post90 were 716GL and 602GL respectively. Exceptions were Maules Creek, where the average annual flows were similar in the two periods (22GL and 21GL in Pre90 and Post90, respectively), and at Duncans Warrambool and Bugilbone to Walgett, where average annual flows in Post90 were higher than Pre90. For assets 1 to 8, respectively the ratios between Pre90 and Post90 average annual flow were 1.19, 1.24, 1.03, 4.35, 1.19, 0.71, 1.21, and 0.20. Wet periods were recorded in the late 1970s, mid 1980s, early 1990s and late 1990s. In most cases the Pre90 period had more low to medium flows (Fig. 4). However, the exceedance probabilities of high flows were less distinguishable between the two periods. At Bugilbone to Walgett, however, more frequent high flows were recorded for the Post90 period.

During the Pre90 period, groundwater levels ranged from 6 m below ground at Upstream Mollee to 16 m below ground at Bugilbone to Walgett. Most assets had deeper groundwater levels in the Post90 period (Fig. 5). Notable assets were Gunnedah and Wee Waa to Bugilbone, where average groundwater levels were 1.8 m deeper in Post90 than Pre90. Groundwater levels at Maules Creek and Bugilbone to Walgett were similar in the two periods. Groundwater at Duncans Warrambool was shallower in the Post90 period than that in Pre90, with mean groundwater levels rising from 14.8 m below ground to 11.5 m below ground.

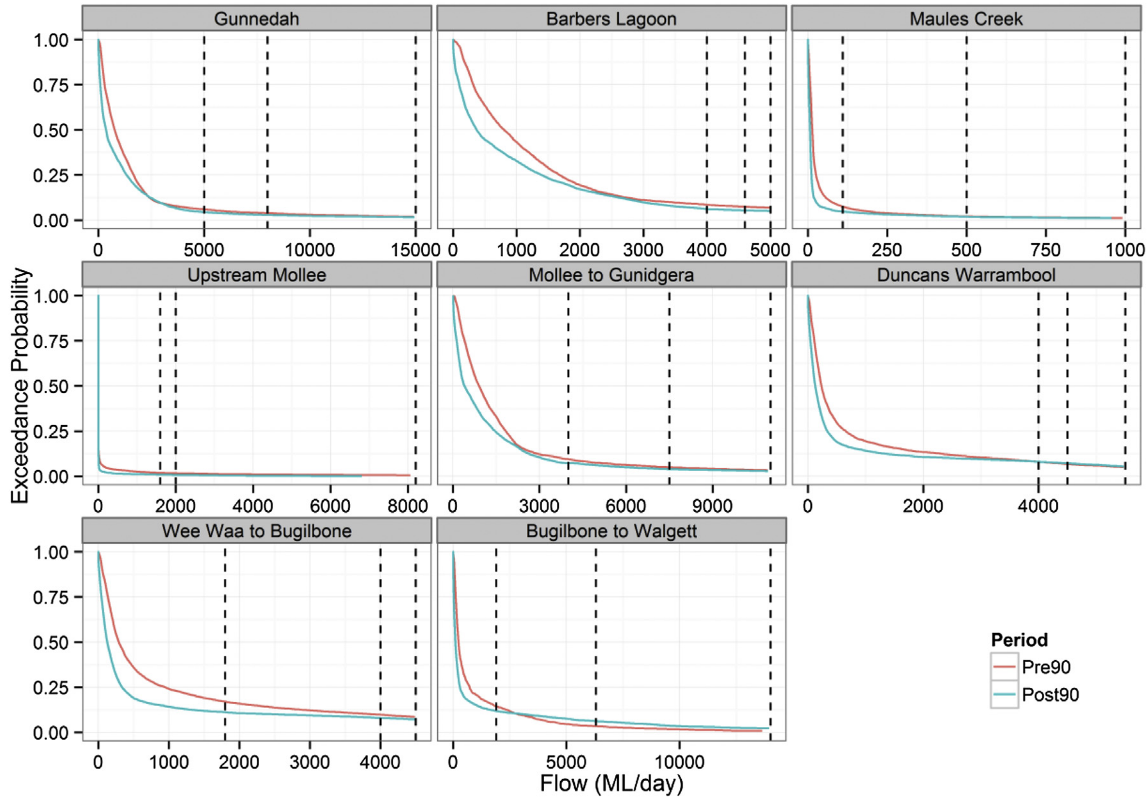


Fig. 4. Exceedance probability curves of daily flow at modelled assets during Pre90 and Post90 periods. Dashed lines are identified low, middle, and high commence-to-flood levels corresponding to flooding of different areas.

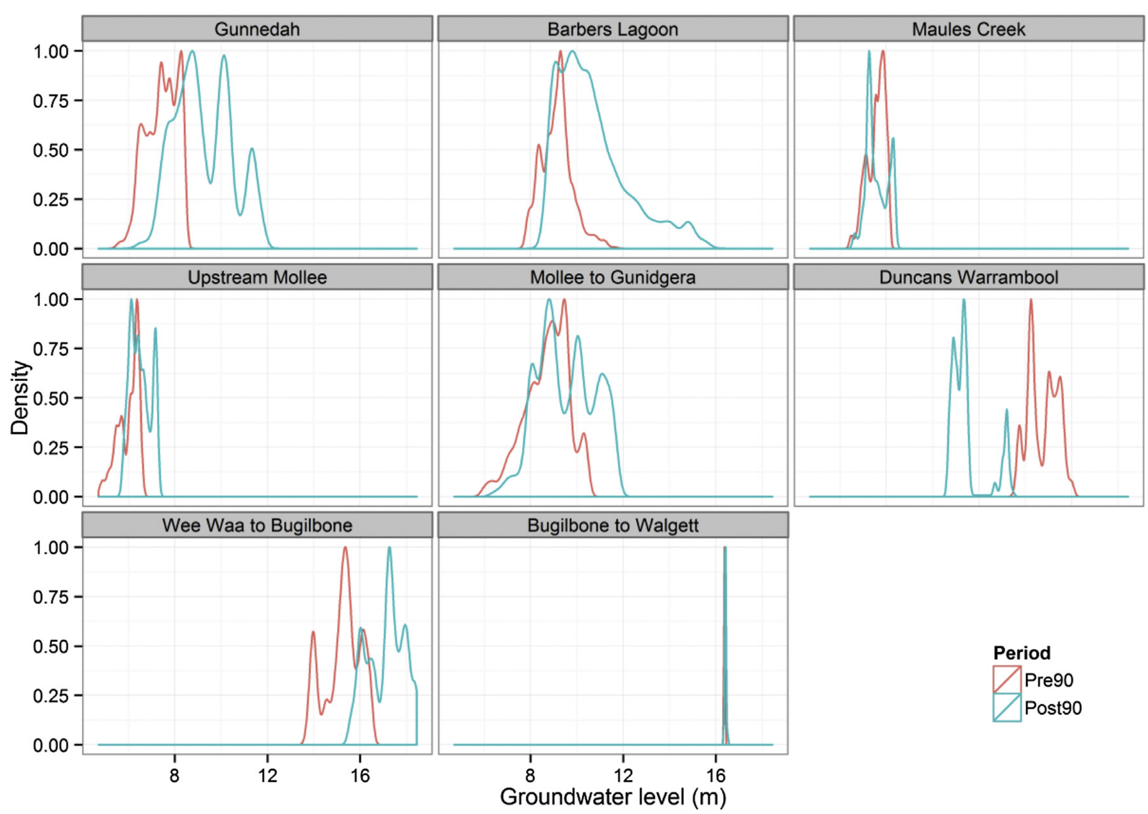


Fig. 5. Groundwater level distributions in Pre90 and Post90 periods.

4.2. Surface water suitability

Examples of constraints on the index curves (grey areas) of flood duration (days) and timing for the maintenance and survival of river red gum are shown in Fig. 6. Any index curve within the grey areas is considered plausible. The two dotted lines identify index curves for two extreme cases with the red line indicating the minimum difference between the Pre90 and Post90 periods and the green line the maximum difference between the two periods. When the minimum and maximum differences are both positive, then we are certain that the Pre90 period is always better taking all the uncertainties specified into account. When they are both negative, then we are certain that the Post90 period is always better.

In these examples, the water suitability index could favour either period depending on what we think is required for the maintenance of river red gum in terms of flood duration. If the flood duration requirement is as described as the red line in Fig. 6a where the "ideal" flood duration is between 60 and 150 days, then the surface water regime in the Pre90 period produces the best outcome in terms of suitability of flood duration for the maintenance of river red gum. However, if the "ideal" flood duration is between 11 and 50 days (green line in Fig. 6a), then the surface water regime in the Post90 period produces the best outcome. Note that the green line in Fig. 6a does not completely match our expectation because there is a slight rise in index curve between 60 and 100 days of flood duration before it drops again, and thus further investigation is warranted to adjust constraints.

Similarly, in terms of flood timing, if flooding during March and May is not suitable for the maintenance of river red gum (red line in Fig. 6b), then the Post90 period has the better surface water suitability outcome. Otherwise, if flooding between January and August is moderately suitable (green line in Fig. 6b), then the water suitability index is highest in the Pre90 period.

The results of uncertainty in surface water suitability are shown in Fig. 7, with no constraints on the relative importance of flood attributes (i.e. any flood attribute can have a weight between 0 and 1, but all weights for a species must sum to 1). The results suggested that given any possible weights and any possible index curves within the defined boundaries, at Upstream Mollee for example, the Pre90 period always had a higher mean water suitability index than the Post90 period at all commence-to-flood levels for the regeneration of river red gum, water couch and lignum. In terms of maintenance of these species, suitability was always better in Pre90s for areas further away from the banks, where the commence-to-flood level is above 4000 ML/day. Assuming current knowledge is correct, there was little benefit to further reduce uncertainty in weights and index curve for this asset, if areas that require higher commence-to-flood levels were of concern. However, for the areas closer to the river banks, there was still uncertainty in evaluating which period was better and further knowledge is needed. Similarly for Bugilbone to Walgett, given uncertainties in weights and index curves, at high commence-to-flood levels the Post90 period always had a better surface water regime for the maintenance and regeneration of river red gum, water couch and lignum.

Much higher uncertainties were found in the results for other assets (Fig. 7). In these cases, the current knowledge defined by our constraints was often insufficient to evaluate which period had a better surface water regime for different species. Variation between species became more visible. For example, in Gunnedah the uncertainty in evaluating periods was much lower for the regeneration of water couch (where the Pre90 period was better at most commence-to-flood levels). But for other species things were much more uncertain in Gunnedah. There were some cases where the outcome was certain for a given commence-to-flood level, but uncertain for higher and lower commence-to-flood levels. This means that the uncertainty becomes sensitive to the commence-to-flood level. For example, we were certain that the Pre90 period was better for the maintenance of water couch at Barbers Lagoon at commence-to-flood levels of 4000 and 4200 ML/day (assuming current knowledge in index curves is correct). However, it was uncertain which period is better for areas closer to the river bank or further away from it.

Overall, species within an asset exhibited similar direction of change. For instance, for Upstream Mollee the water regime in the Pre90 period generally produced better surface water suitability for all species; while for Bugilbone to Walgett the Post90 water regime was better for all species (Fig. 7). However, between locations in the catchment, different direction of change was detected. Bugilbone to Walgett had a noticeably favourable water regime in the Post90 period in comparison to other assets which favour the Pre90 period.

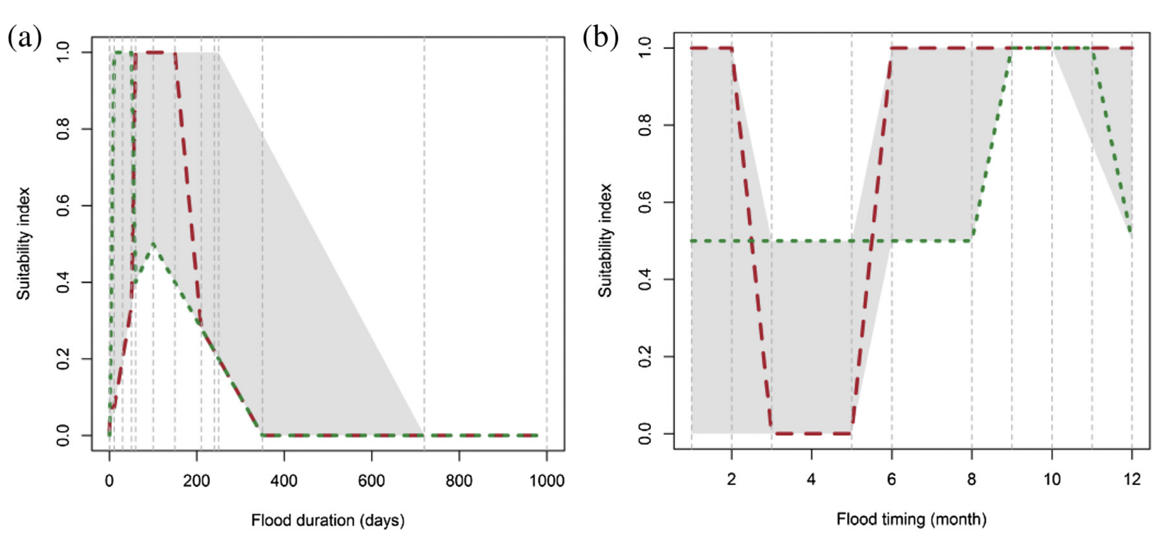


Fig. 6. Examples of constraints on the index curves (grey areas) of (a) flood duration (days) and (b) timing for the maintenance and survival of river red gum. It shows two generated extreme cases for Gunnedah with a commence-to-flood level of 3000 ML/day. The two dotted lines identify the index curves that yield the two extreme cases: the minimum difference between the Pre90 and Post90 periods (red index curve) and the maximum difference between the two periods (green index curve). Constraints on the slope of the index curves are not shown. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

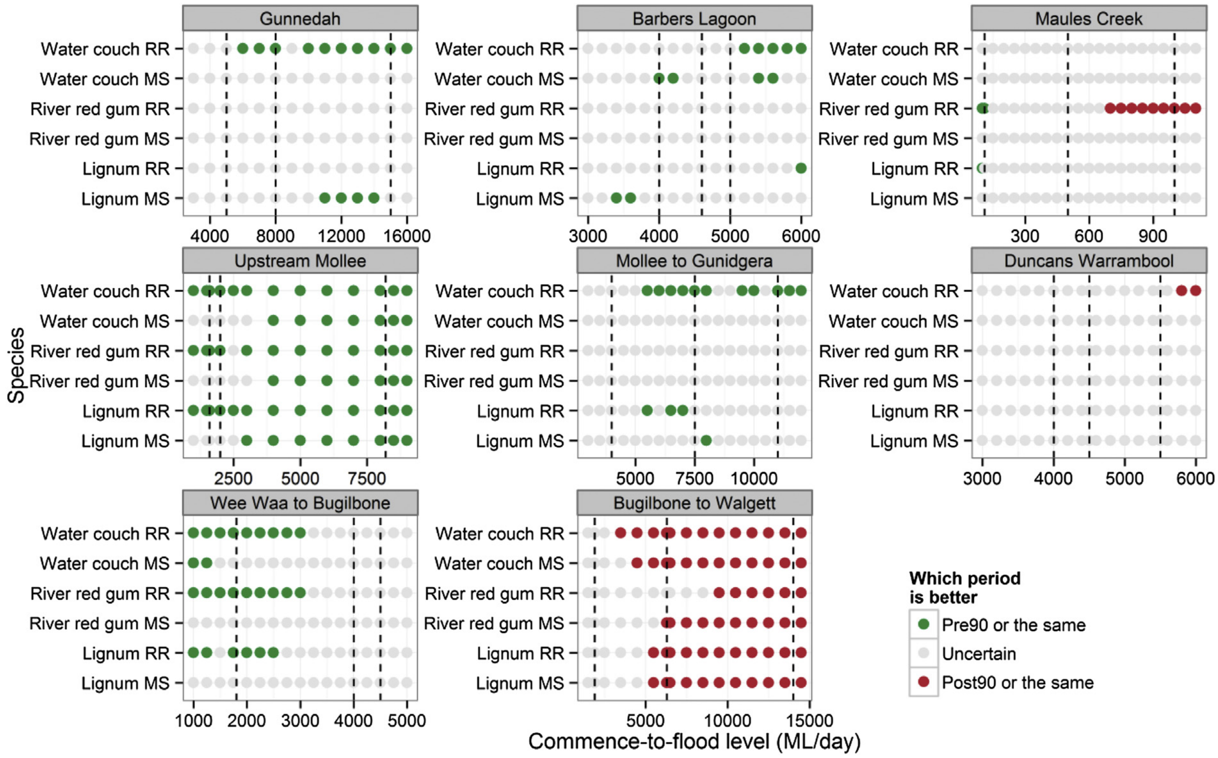


Fig. 7. Uncertainty in surface water suitability index at various commence-to-flood levels, given constraints in index curves. Weight constraints are not specified. Dashed lines identify low, medium and high commence-to-flood thresholds for that ecological asset. MS: denotes Maintenance and Survival, RR: Regeneration and Reproduction.

Adding additional constraints on the relative weights of each hydrologic attribute based on our assumed knowledge added additional certainty in discriminating between the two periods (Fig. 8). Overall, certain outcomes increased by 12.5% (over 810 data points). Noticeably, 33.3% improvement in certainty was found at Wee Waa to Bugilbone. At this asset, the Pre90 water regime was better than Post90 at any commence-to-flood levels for the maintenance of water couch and regeneration of river red gum, and at lower commence-to-flood levels for the maintenance of lignum. There were scattered improvements in certainty across other assets, mostly in the maintenance of lignum and water couch. Additional constraints in the weights for river red gum resulted in little gain in certainty when evaluating the surface water regime of the two periods.

4.3. Groundwater suitability

In terms of the uncertainty in the groundwater suitability index, it was found that in most cases the Pre90 and Post90 periods yield the same results as for the surface water case. This held especially for the regeneration of all species, the maintenance of water couch for all assets (except Upstream Mollee), maintenance of lignum for the western assets and maintenance of river red gum for Bugilbone to Walgett (Fig. 9). This occurred because the required groundwater levels were often shallower than the minimum observed groundwater levels. Groundwater levels in these cases were effectively all unsuitable. For the remainder of the species, given the current knowledge in groundwater requirements, we were certain that in most cases Pre90 period was better, with the exception of the maintenance of river red gum for Duncans Warrambool. Only three cases were found uncertain: maintenance of lignum and river red gum at Maules Creek, and maintenance of river red gum at Upstream Mollee.

4.4. Combined surface water and groundwater suitability

The uncertainty in combined surface water and groundwater suitability index was similar to that in surface water suitability with both weight and index curve constraints (Fig. 10). The only difference was that for Upstream Mollee the outcomes for the maintenance of river red gum were no longer as certain as for surface water suitability. This was because of the uncertainty introduced by groundwater suitability. The effect of groundwater uncertainty at Maules Creek was not seen for the maintenance of river red gum and lignum because these species were already uncertain according to surface water suitability. This result suggested that for the two periods evaluated uncertainty in groundwater levels had a small impact on the overall uncertainty of the water suitability index.

5. Discussions

This discussion interprets the implications of the preceding results for current knowledge (Section 5.1), describes points of difference to existing uncertainty analysis approaches and opportunities for other applications (Section 5.2), and identifies limitations of the approach and potential for future development (Section 5.3).

5.1. Evaluation of current knowledge

Broadly we could make conjectures about water suitability for riparian vegetation based purely on the volume of water, by assuming that more water is generally better. Under this assumption, we could reach conclusions about water suitability at the studied assets by simply comparing average annual flow in the Pre90 and Post90 periods (Fig. 4). The Pre90 period would be

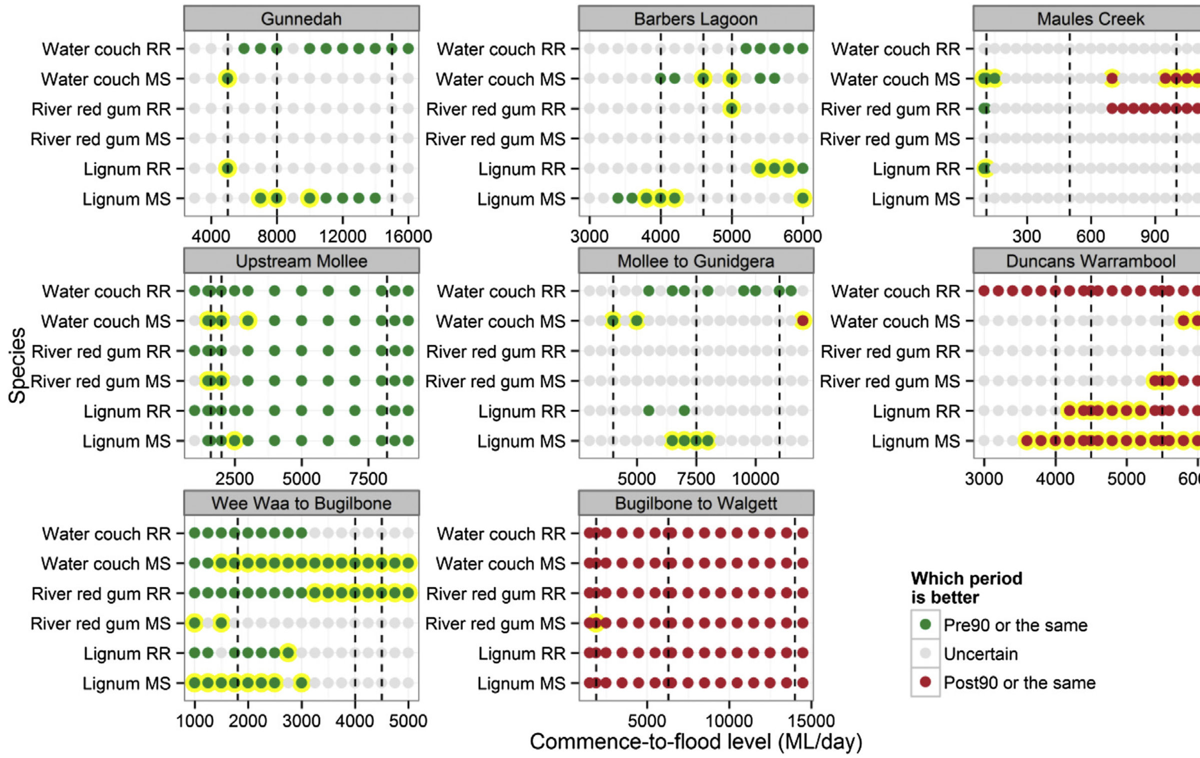


Fig. 8. Uncertainty in surface water suitability index at various commence-to-flood levels, given constraints in index curves and weights. Dashed lines identify low, medium and high commence-to-flood thresholds for that ecological asset. Yellow background highlights data points converted from uncertain in Fig. 7 to certain. MS: denotes Maintenance and Survival, RR: Regeneration and Reproduction. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

significantly better than the Post 90 at Upstream Mollee (ratio between Pre90 and Post90 average annual flow is 4.35); Post90 would be significantly better than Pre90 at Bugilbone to Walgett (Pre90/Post90 ratio is 0.20); while the differences between the two periods in other assets are probably marginal (Pre90/Post90 ratios range from 0.71 to 1.24).

However, there are two major limitations in adopting such a flow volume-based method. Firstly, the ecological knowledge is much more advanced, and in many cases it is known that volume of water is not the only factor contributing to the maintenance and regeneration of riparian vegetation. Too much water can have undesirable outcomes like tree die back due to prolonged flooding (Roberts and Marston, 2011). Other factors such as flood timing can also be important, particularly for regeneration (Roberts and Marston, 2011). Secondly, the flow volume-based method does not differentiate between different vegetation species, whereas many ecological studies have demonstrated different water requirements by different vegetation species (Rogers and Ralph, 2010). From a water management point of view, differentiating between species can help identify water management targets and monitoring strategies. Therefore, this valuable ecological knowledge should be used to help us better understand and predict water suitability for riparian vegetation. The question is, "Is the current state of ecological knowledge sufficient to help us make a robust decision about preferred water regimes" - is this illustrative case able to evaluate comparative water suitability between two periods?

Our results suggest that while the results are broadly consistent with the expected outcomes based on flow volume, they show variability and uncertainty due to the particulars of species, assets

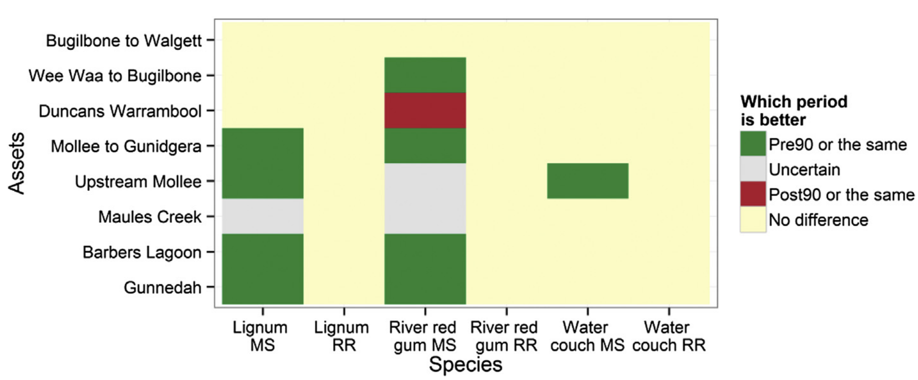


Fig. 9. Uncertainty in groundwater suitability index, given constraints in groundwater level index curves. MS: denotes Maintenance and Survival, RR: Regeneration and Reproduction.

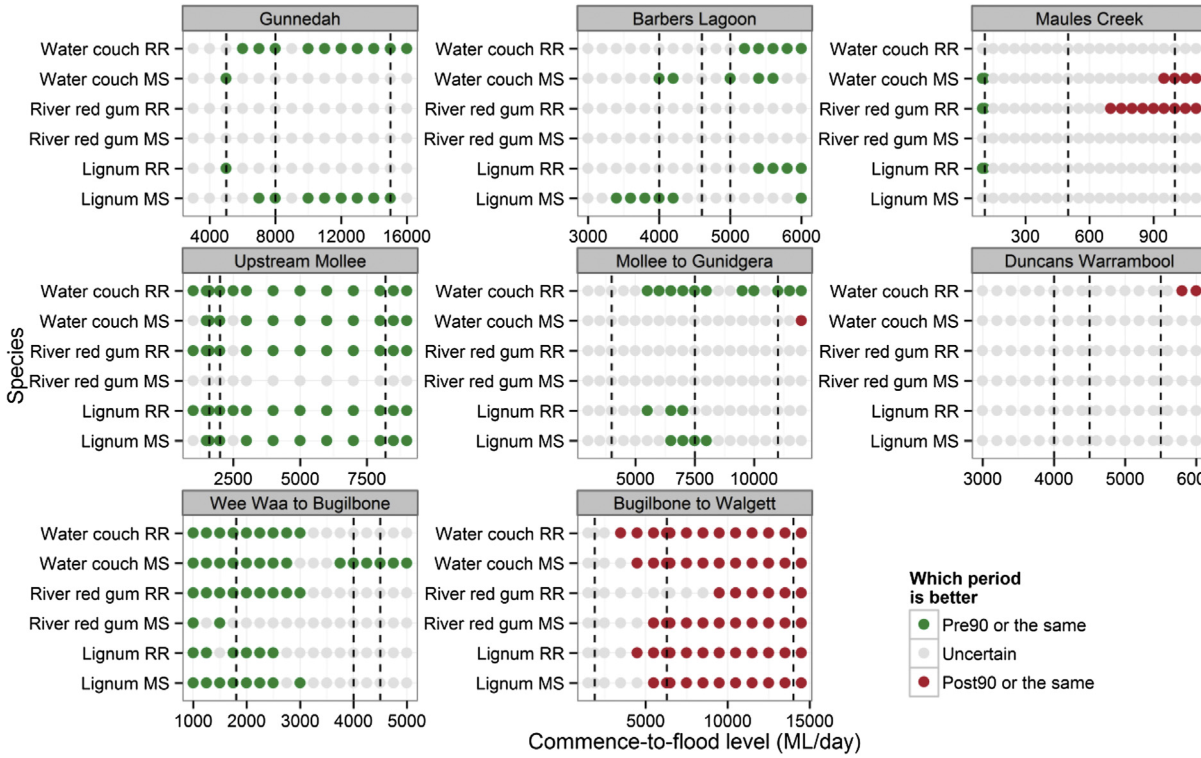


Fig. 10. Uncertainty in combined surface water and groundwater suitability index at various commence-to-flood levels, given constraints in index curves and weights. Dashed lines identify low, medium and high commence-to-flood thresholds for that ecological asset. MS: denotes Maintenance and Survival, RR: Regeneration and Reproduction.

and commence-to-flood thresholds. By considering this variation, we can identify useful differential impacts of a hydrological regime, as well as propositions as to where trade-offs may need to be made between protecting particular species or locations. With the hydrological inputs specifically used in this paper and the uncertainties in index curves and weights that were framed by current ecological knowledge, we still have relatively high certainty in discriminating between the two periods at Upstream Mollee and Bugilbone to Walgett (Fig. 10). As a result, little additional knowledge (i.e. tighter constraints) is needed. However, much higher uncertainties in model outputs are found for other assets, suggesting that current state of knowledge is insufficient in these cases to conclude which period is better. In these cases, better ecological knowledge in vegetation water requirements is needed to reduce uncertainty.

Note that the outcome of knowledge evaluation is case specific and thus only applies to the two water regimes (in this case, Pre90 and Post90) investigated. These results can be more useful when evaluating scenarios of different water management options. Identifying situations where knowledge is sufficient and conclusions are certain helps establish robust decision making; whereas identifying situations where current knowledge is insufficient helps direct monitoring and research efforts.

In this paper, we also demonstrate that a progression of additional knowledge can reduce or increase uncertainty in the model outputs, the extents of which vary on a case-by-case basis. For example, incorporating additional knowledge on the relative importance of flood attributes (i.e. weights) adds additional certainty in discriminating between the two periods. However, this added certainty is not distributed equally across assets and species. We found significant improvement in certainty in evaluating water suitability for some species at a specific asset (e.g. maintenance of water couch at Wee Waa to Bugilbone, Fig. 8), but little improvement in some other species or assets. In contrast, adding additional knowledge with respect to vegetation requirements on groundwater levels led to increased uncertainty in overall water suitability for the maintenance of river red gum at Upstream Mollee (Fig. 9). However, in other cases the effect of uncertainty in groundwater level is trivial because the surface water suitability is already highly uncertain.

In breaking down the uncertainty assessment, we are able to more specifically identify which component of the model is contributing to the uncertainty in the model outputs, and therefore not only identifying knowledge gaps but also recognising the different roles of these knowledge gaps for different species and assets. Consequently, research into closing knowledge gaps can be better targeted depending on desired outcomes in model certainty. A similar tactic has been used in system dynamics studies where parts of the model are turned on and off to examine its effect (Eberlein and Hines, 1987; Homer, 1983, 2012). Here we apply the tactic to uncertainty assessment and relate the outcomes to knowledge gaps.

5.2. Added value

The uncertainty assessment approach presented in this paper has several advantages over traditional approaches. On a technical level, it has efficiency gains over Monte-Carlo sampling approaches to uncertainty. Instead of time-consuming sampling, we use optimisation to identify two extreme cases, and algebraically simplify the optimisation problem to allow the use of efficient linear programming. More fundamentally, this approach can facilitate a change in the view of uncertainty.

Uncertainty is typically an after-thought. The traditional approach is to create a model with a specific set of parameters and structure, and then look for the effect of uncertainty (Jakeman et al., 2006; Refsgaard et al., 2006), and then perhaps iterate. Our approach instead assumes by default that little is known, and that everything is uncertain by providing no constraints. This way, any index curve and any weighting of attributes could be possible, and the generated models (i.e. the extreme cases) and the uncertainty results will reflect this. The focus is therefore on trying to reduce that uncertainty. By starting with a minimal set of constraints, our approach can be used in a precautionary way, naturally biased towards expecting an uncertain outcome. It is therefore less likely to give false confidence in the success of a management change.

Traditionally uncertainty is expressed as a distribution such as in fuzzy logic or Bayesian probability approaches (e.g. Garavelli et al., 1999; Vrugt et al., 2009) or as a range of outputs from ensemble models (e.g. Buisson et al., 2010). This paper addresses uncertainty by using optimisation to identify two models that produce extreme results. The emphasis on extremes helps identifies boundaries of what is considered certain in model outputs. These boundaries are valuable to scientists and managers alike in terms of identifying knowledge gaps and risk assessments (Norton, 1996). Changing these boundaries by adding constraints can show to what extent certainty can improve given additional information (as discussed for example by Dausman et al., 2010; Feyen and Gorelick, 2005; James and Gorelick, 1994).

In addition, the focus on the extreme helps draw attention to contested or marginalised views, raising them as a topic for debate (Midgley, 2000). This is facilitated by the simultaneous use of multiple models that show that multiple views of the system may be legitimate, and therefore in order to achieve reduction in uncertainty, requires a reflective approach that adjusts constraints to narrow down those multiple views. This process therefore emphasises awareness of limitations of our knowledge and reflection on the impact of adding assumptions. The method therefore makes learning about uncertainty part of the modelling process (Beven, 2007), considering the aim of modelling to be prediction of an uncertain outcome, rather than prediction followed by analysis of uncertainty.

In terms of potential opportunities for other applications, the approach described in this paper can be transferrable in different ways. Firstly, it can be readily applied to other habitat suitability models for comparing suitability of different water regimes for riparian and wetland vegetation, as a result of climate variability and/or water management. More generally, the approach can be used to assess uncertainty in index curves where two scenarios are compared. It might therefore also be applicable to many other index-based models, such as in habitat models (Burnett et al., 2007), environmental risk assessment (Buczko and Kuchenbuch, 2007), valuing ecosystem services (Van Houtven et al., 2014) and using indifference curves for economic and social studies (Kuminoff, 2009).

5.3. Limitations and future development

Typically, there are three main sources of uncertainty in environmental modelling: model inputs, parameters and model structure (Chatfield, 1995). Uncertainty in inputs (i.e. daily surface flow and groundwater levels associated with respective ecological assets) is not explicitly considered in this paper. Instead, our approach focuses on uncertainty derived from the estimates of the parameters and also some aspect of the model structure. The parameters considered are the weights and the parameters associated with defining index curves (e.g. x_c and y_c, Section 3.3.1).

There are several aspects to model structure uncertainty, including choice of variables, aggregation of attributes, and functional form of index curves. Uncertainty due to choice of variables (e.g. omitting groundwater salinity) is not considered in this approach. Historical observation suggested that the groundwater salinity level (NSW Office of Water, 2010) has been consistently lower than the minimum salt tolerance threshold for modelled vegetation species (Roberts and Marston, 2011). Therefore we assumed groundwater salinity is not a significant factor in determining the suitability of the groundwater to the vegetation. Alternate methods of aggregating attributes only need to be explored if any of the attribute suitability indices do not agree on which period is better. If they do agree, then it does not matter how these indices are aggregated, because the outcome will always be the same. However, model structure uncertainty associated with index curves has been considered. This is because the structure of the index curve is a piece-wise linear curve, which can approximate a broad range of functional forms, including threshold behaviours and multiple maxima or minima.

In terms of the nature of the uncertainty, three main categories can be identified: inherent variability (irreducible uncertainty), lack of knowledge (reducible uncertainty) and contradiction (ambiguity) (Brugnach et al., 2008; Guillaume et al., 2012). In this paper the uncertainty assessment approach addressed uncertainty arising from both inherent variability and lack of knowledge. For example, due to natural variability river red gum may exhibit a range of preferences for flood duration of 5 months. Instead of needing to define a specific index value for flood duration, this approach allows the variability to be represented by using bounds (e.g. index values can range from 0.5 to 1 when river red gum is flooded for 5 months). However, contradictory views are not addressed explicitly and this type of uncertainty needs to be handled separately by trying out alternate constraints interactively, which is enabled by computational efficiency of this analysis.

There are also a few limitations in the methodology itself. For example, constraints can be specified by the modeller by identifying bounds, monotonicity and smoothness. Or if multiple index curves are already available, constraints can be determined from them by identifying what the curves agree on (see Section 3.3.1). In the first method, the selection of constraints is left to the discretion of the modeller. Thus the results shown reflect a snapshot of ecological knowledge and suggest possible outcomes. In the second method, when multiple index curves are used, there remains a limitation that the automatically-generated constraints cannot be easily translated into understandings of smoothness or monotonicity of the index curve. This is fundamentally because these constraints do not have a unique interpretation. Constraints resulting from existing index curves are therefore more difficult to interpret and critique.

The second limitation is that the methodology is restricted by the use of piece-wise linear curves defined by abscissa of breakpoints. The piece-wise linear curves can be made to approximate more complex curves by adding breakpoints and the lack of continuity of derivatives is not a problem in this analysis. The use of fixed breakpoints is justified by its computational simplicity, though further work could examine this issue. In particular, the ability to represent uncertainty in the abscissa is dependent on the number of breakpoints used. A large number can be necessary for example to define the precise attribute values at which a non-linear change in suitability occurs.

Reflection on index curves is mentally demanding, particularly with a large number of assets and species. A well-designed user interface could facilitate the interactive editing of constraints and evaluation of the resulting models and outcomes. We developed a prototype interactive web application using the *shiny* package in R (Guillaume and Fu, 2013). The web application helps manage the user's focus by concentrating on elicitation of one relationship at a time, providing elicitation-specific visualisations of results and separating elicitation from diagnosis of necessary knowledge. This interface could be extended to allow multiple perspectives on constraints which may be assigned degrees of confidence, as per IPCC guidelines (Mastrandrea et al., 2010). Allowing multiple perspectives as opposed to using consensus can further emphasise alternate views (van Asselt and Rotmans, 1996). The increased diversity of views considered might also reduce the chance of being surprised by new information or a change in system behaviour.

6. Conclusion

This paper demonstrates a computationally efficient and precautionary uncertainty assessment approach for comparison of suitability of surface water and groundwater regimes for the riparian vegetation over two historical periods in the Namoi Catchment, Australia. Compared to traditional uncertainty analysis approaches, this approach identifies boundaries of what is considered certain in model outputs. These boundaries are valuable to scientists and managers alike in terms of identifying knowledge gaps and making risk assessments. The approach emphasises awareness and learning about boundaries of our knowledge, and reflection on the impact of adding assumptions. It is designed to deal with uncertainty as part of the model development process rather than as an afterthought. Implemented as a linear programming-based approach, it has efficiency gains over Monte-Carlo sampling approaches to uncertainty. The approach can be easily applied to other habitat suitability models for scenario evaluation. Indeed its philosophy would appear to have wide applicability as an additional means to characterising uncertainty in models generally.

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