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A GENERAL APPROACH TO PREDICTING ECOLOGICAL RESPONSES TO ENVIRONMENTAL FLOWS: MAKING BEST USE OF THE LITERATURE, EXPERT KNOWLEDGE, AND MONITORING DATA

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ABSTRACT

Around the world, governments are making huge investments in environmental flows. However, much of the rationale for these releases is based on expert opinion and is thus open to challenge. Empirical studies that relate ecological responses to flow restoration are mostly case studies of limited generality. Radically, different approaches are required to inform the development of general models that will allow us to predict the effects of environmental flows. Here, we describe the modelling framework being used in a major study of environmental flows in the Australian state of Victoria. The framework attempts to make best use of all the information available from the literature, experts, and monitoring data, to inform the development of general quantitative response models. It uses systematic review of the literature to develop evidence-based conceptual models, formal expert elicitation to provide an initial quantification of model links, and data derived from purpose-designed monitoring programs over large spatial scales. These elements come together in a Bayesian hierarchical model that quantifies the relationship between flow variation and ecological response and hence can be used to predict ecological responses to flow restoration. We illustrate the framework using the example of terrestrial vegetation encroachment into regulated river channels. Our modelling framework aims to develop general flow-response models and can immediately be used to demonstrate the ecological return on investment from environmental flow programs. However, the framework also has the potential to be incorporated into planning and decision-making processes, helping to drive a transformation in evidence-based practice for environmental flow management. © 2014 The Authors. *River Research and Applications* published by John Wiley & Sons, Ltd.

KEY WORDS: flow-response modelling; monitoring and assessment; hierarchical Bayes; Eco Evidence

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INTRODUCTION

Worldwide, the regulation of freshwaters for humanity's benefit has been associated with severe ecological impacts (Vörösmarty *et al*., 2010). Over the past 15–20 years, there has been a growing realization that protecting and restoring the ecological integrity of freshwater systems relies largely on providing flows that contain biologically important components of the natural flow regime of that system (Poff *et al*., 1997). This concept has proved appealing, and today, there are dozens of countries around the world that have adopted policies to provide such 'environmental flows' to protect and restore river systems.

Among these, Australia is a world leader in the implementation of large-scale environmental flows programs. Most notable among a number of initiatives, the Basin Plan has recently passed into law and aims to return 2750 Gl of environmental water to the Murray and Darling river system. The re-allocation of such a large volume of water from productive (i.e. agricultural) uses has caused controversy, and images of protest have echoed around the world.

One of the key points of contention in the Basin Plan has been the credibility of the process used to determine the environmental water allocations and particularly the use of expert opinion. The majority of environmental flow assessment methods rely on an expert-based approach to predict ecological effects (Stewardson and Webb, 2010). The experts involved are usually experienced and well-respected researchers, but the utility of such knowledge is dependent on the rigour with which it is elicited (Martin *et al*., 2005). Informal techniques that are implicit, unstructured and

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undocumented are prone to cognitive biases, overconfidence effects and information cascades (Fidler *et al.*, 2012). Environmental flow assessments rely on experts because, despite a large and rapidly increasing body of literature on the ecological impacts of flow *degradation* (Stewardson and Webb, 2010), we have learned much less regarding general ecological effects of flow *restoration* (Souchon *et al.*, 2008). Instead, the literature is dominated by papers examining responses to individual flow alterations at small numbers of sites on individual rivers and over relatively short periods (Webb *et al.*, 2010a). Such studies cannot be used to make defensible quantitative predictions of the likely ecological benefits of flow restoration in new situations.

It would be naïve to suggest that a strong ability to predict the ecological benefits of flow restoration would resolve the controversy associated with large-scale water reforms like the Basin Plan. As a ‘wicked problem’, debates around the relative merits of different water resource management schemes will always continue. However, a strong basis in evidence of the general effectiveness of environmental flows would support the large investments of public funds in flow restoration programs.

Such predictive ability will only be gained by moving away from the current model of individual case studies of environmental flow effects and embracing new methods for large-scale synthesis of information from diverse sources. In this paper, we illustrate the modelling framework being used in a major study of ecological effects of flow alteration in the Australian state of Victoria. The framework improves the synthesis of information from small-scale case studies available in the literature, uses rigorous approaches to extract and synthesize expert knowledge, and employs data from large-scale purpose-designed monitoring programs to form general predictive models of ecological responses to flow variation. These models can then be used to make quantitative predictions of the likely ecological benefits of environmental flows.

The modelling framework consists of five main steps that each provides input into the final ecological response models (Figure 1). Below, we provide a brief description of the motivation and background for each of the steps. This is followed by a section that provides an overview of the results of each step for an illustrative case study—the encroachment of terrestrial vegetation into regulated river channels. In the discussion, we examine how the steps complement each other but also ask under what circumstances individual steps could be omitted and how we might approach that question. As this paper attempts to provide an overview of the framework, it does not cover any of the individual steps in great detail. Interested readers are directed towards the primary sources provided.

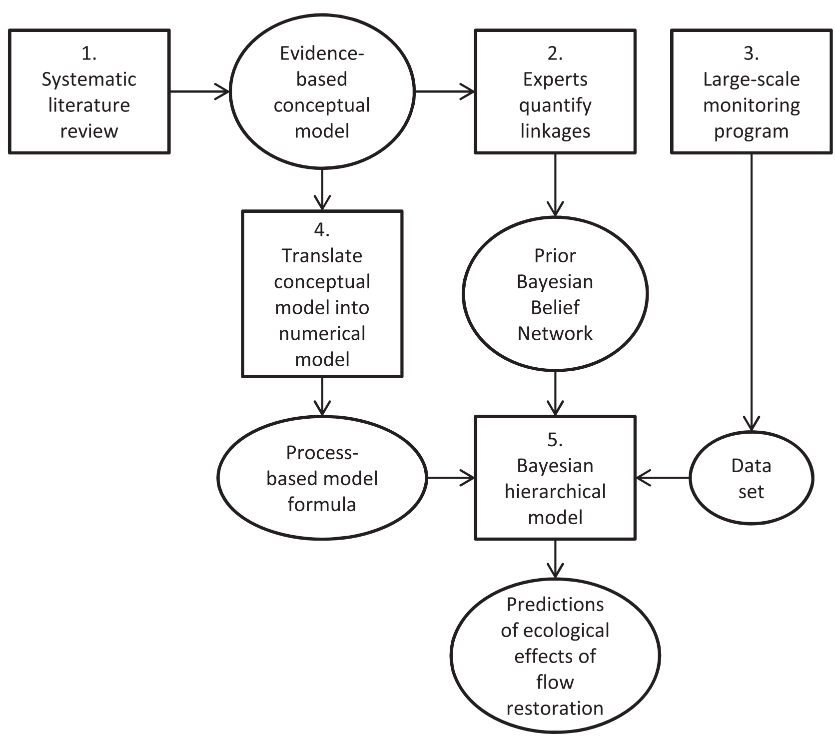

Figure 1. Work and information flow for the framework presented in this paper. Boxes are tasks and correspond to the step numbers listed below. Circles are outputs from each step

GENERAL PRINCIPLES OF THE MODELLING FRAMEWORK

Step 1. Develop an evidence-based conceptual model

Conceptual models, either explicit or implicit, underpin any analysis of data. In environmental flow research, the great majority of conceptual models are developed with little formal assessment of the evidence for causal linkages within them. Stewardson and Webb (2010) proposed that systematic reviews be used to develop evidence-based conceptual models underpinning any model of ecological response to flow alteration. Systematic reviews treat the literature as data and use analytical methods to test hypotheses (e.g. the causal links in the hypothesized conceptual model) across an objectively collected set of literature (Khan *et al.*, 2003).

Step 2. Quantify linkages in the conceptual model using expert elicitation

The systematic review assesses the validity or otherwise of cause–effect hypotheses within the conceptual model but does not provide any quantification of these relationships. Our framework employs expert elicitation to provide an initial quantification (for a full explanation refer to de Little *et al*., in review). Unlike the unstructured use of expert knowledge criticized early in this paper, expert elicitation is a formal process developed by cognitive psychologists that is designed to take advantage of the considerable knowledge of experts but reduce the problems associated with unstructured approaches (Kuhnert *et al*., 2010). For example, expert estimates often suffer from overconfidence (i.e. uncertainty of estimates is underestimated). The four-point elicitation method we employ has been shown to reduce such overconfidence (Speirs-Bridge *et al*., 2010). Similarly, estimates derived from informal group discussions can be biased through dominance of individual personalities, groupthink, and information cascades (Burgman, 2005). By requiring experts to provide independent estimates prior to any group discussions, this effect is reduced.

Step 3. Collect monitoring data across wide spatial scales using compatible methods

It is only possible to conduct large-scale analyses if monitoring data collected from different rivers are compatible. However, different rivers are commonly managed by different management agencies, creating a jurisdictional barrier to achieving compatible monitoring. This can lead to multiple individual monitoring programs, all attempting to detect the same types of responses but using different methods to do so. Separately, large-scale data analyses are not simple to conduct, and the experience necessary to undertake high-level statistical analyses (e.g. the Bayesian hierarchical model presented here) will typically reside in academic institutions rather than management agencies. These issues can be overcome by strong and enduring partnerships between management agencies and academic institutions. Such partnerships move away from the dominant model (in Australia, at least), where the data from small-scale government-funded monitoring programs are analyzed under short-term contracts with academics or consultants.

Step 4. Translate the conceptual model into a process-based expression of the relationship between flow and ecological response

Translation of a conceptual model to a numerical model for statistical analysis is an important step in data analysis. However, statistical models are often developed without due consideration of the ecological processes they are trying to capture. We thus believe it worthwhile to describe a separate step in our framework focused on development of the numerical model but independent of the statistical analysis.

Stewardson and Webb (2010) examined issues around the choice of model complexity and suggested that the underlying conceptual model needs to play a greater role in development of the statistical model. In general, we believe that statistical models that are based upon hypothesized ecological processes will have a greater chance of being able to be extrapolated to new sites than models that simply test for associations.

Step 5. Parameterize Bayesian hierarchical flow-response models using all previous outputs

In recent years, there has been a large increase in the use of Bayesian statistical models for the analysis of ecological data (Clark, 2005). Bayesian hierarchical models, in particular, have the ability to model processes at multiple scales simultaneously (Gelman and Hill, 2007), and can reduce some of the issues associated with low replication in analysis of environmental flow responses. They do this by assuming 'exchangeability' (partial dependency) among experimental units. The practical effect is that both within-unit and among-unit unexplained variations are reduced relative to an analysis that treats experimental units independently (Webb *et al*., 2010b). Because of these inferential advantages and because they can combine expert opinions with monitoring data, we believe that Bayesian hierarchical models are the best option for the statistical analysis phase of this framework.

CASE STUDY: TERRESTRIAL VEGETATION ENCROACHMENT INTO REGULATED RIVER CHANNELS

We illustrate the framework using the example of terrestrial vegetation encroachment into regulated river systems. In

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south-eastern Australia, decades of river regulation, coupled with 10 years of drought, left many river channels colonized with terrestrial vegetation. While environmental flow assessments frequently propose that flow releases be used to remove this vegetation and to prevent it from re-establishing, the evidence for these predictions has not been rigorously tested. Here, we demonstrate that flow management can be used to prevent terrestrial vegetation encroachment into Victorian river systems and provide quantitative estimates of how vegetation can be expected to respond to different flow scenarios.

Step 1. Conceptual model of vegetation encroachment

We employed the Eco Evidence method (Norris *et al.*, 2012) and software (Webb *et al.*, 2011; Webb *et al.*, 2012) to conduct the systematic literature review. The Eco Evidence method has been fully described elsewhere (Norris *et al.*, 2012), as has the detail of the systematic review on terrestrial vegetation encroachment (Miller *et al.*, 2013). We provide here a summary of the results. Miller *et al.* (2013) assessed five hypotheses relating to the effects of inundation on terrestrial vegetation (Figure 2). The keyword-based search of literature databases identified 489 papers. Upon reading the titles and abstracts of these papers, 29% were deemed potentially useful for the review. Detailed examination of these papers resulted in 58 ‘evidence items’—individual instances of cause–effect associations that either help to support or refute a hypothesis. Overall, the review found support for three hypotheses: that scouring flows increase plant mortality, that inundation increases plant mortality, and that inundation (regardless of mechanism) leads to lower abundance of terrestrial vegetation. One hypothesis was refuted; rather than finding that inundation reduced germination success, the review found more evidence of either no effect or of positive effects of inundation on germination. There was insufficient evidence to reach any conclusion regarding whether inundation reduces plant reproduction (Figure 2). The resulting evidence-based conceptual model was used as the basis of the next stage of the framework. More specifically, we chose to focus the statistical analysis on the general ‘non-mechanistic’ link between inundation and abundance of terrestrial vegetation (bold link in Figure 2).

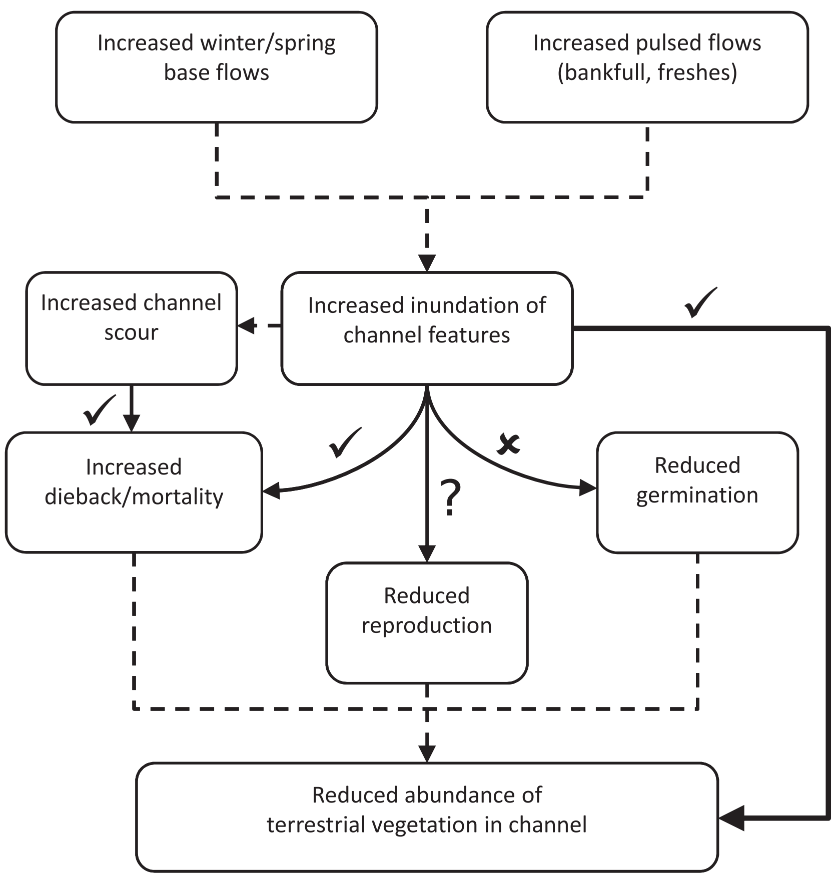

Figure 2. Conceptual model of the responses of terrestrial vegetation to inundation. Solid links are hypotheses tested by the systematic review. Ticks, crosses and question marks denote hypotheses that were supported, refuted, and for which insufficient evidence was available to reach a conclusion, respectively. Dashed lines represent assumed links that were not tested. Modified from Miller *et al.* (2013)

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Step 2. Expert-based quantification of environmental effects on encroachment

To generate a quantitative model, the conceptual model was re-expressed as a Bayesian belief network (BBN). BBNs are graphical models, in which nodes (model state variables) are linked by arcs (probabilistic relationships) to form a directed acyclic graph (Pearl, 2000). They can combine information of multiple types and are very useful for modelling complex systems with uncertain relationships.

The structure of the BBN is shown in Figure 3. Effects of inundation duration and frequency (whether inundation was continuous or episodic) were included as separate state variables. We also included the season of inundation and the non-flow variable of stock grazing. These four variables form the 'parent' nodes of the network, with the 'child' node—the abundance of terrestrial vegetation within the river channel—being dependent on the states of the parents (Figure 3). Discretizing continuous probability distributions of the nodes (i.e. dividing them into ordered states) is a requirement of the Netica (www.norsys.com) software that we used for this analysis. This allows rapid updating of probability distributions for child nodes when the state of one or more parent nodes changes (Pearl, 2000). More importantly for our purpose, discrete probability states can be used to form a small number of mutually exclusive questions for expert elicitation. It is desirable to have as few states as possible for both parent and child nodes, because this reduces the complexity of the underlying conditional probability table (Cain, 2001) and hence the number of questions that the experts need to be asked. Here, we defined two states for each of inundation frequency, season of inundation, and presence of stock; and three states for each of inundation duration, and terrestrial vegetation abundance (Table I).

To populate the conditional probability table that describes the relationship between parent and child nodes, we followed the expert elicitation methods outlined by Patulny (2012). Questions followed the four-point format developed by Speirs-Bridge *et al*. (2010). In a workshop setting, experts were individually asked to provide (in this order) the lowest vegetation cover they would expect to see given a particular combination of parent states, the highest cover, their best estimate, and the probability that the interval between low and high estimates contained the true amount. The 'group-level' opinion was derived by averaging across the group, resulting in the elicited probabilities in Table I (de Little *et al*., in review). It is desirable to interpolate probabilities where possible rather than risk 'expert fatigue' by eliciting all possible combinations of parent states (F. Fidler, University of Melbourne, personal communication). We used the methods outlined in Cain (2001) to interpolate some of the probabilities (Table I).

Overall, the expert-based BBN indicated that medium and high covers of terrestrial vegetation are likely under most combinations of parent states. The lowest cover of vegetation is expected when the river channel is inundated continuously for a long period during the winter and when stock have access to the river (Table I).

Step 3. Collect large-scale monitoring data: the Victorian Environmental Flows Monitoring and Assessment Program

The data analyzed in this paper were collected through the Victorian Environmental Flows Monitoring and Assessment Program (VEFMAP; Webb *et al*., 2010a). In light of

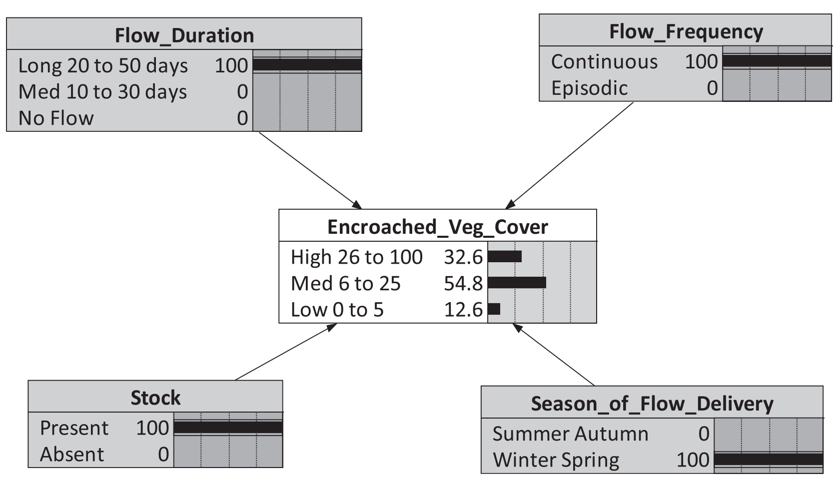

Figure 3. Structure of the BBN. Grey nodes are parent nodes. The central node is the child node. The discrete states of all variables are shown (e.g. 'low' cover is 0–5%). This example shows the predicted probabilities of the different cover classes of vegetation cover for a long duration, continuous inundation event in winter/spring, with stock present. Under these conditions, the experts' collective opinion is that there is a 12.6% chance of low vegetation cover, etc.

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Table I. Conditional probability table underlying the BBN (modified from de Little *et al*., 2012)

	State of parents				Probability of state of vegetation cover		
Method	Duration of inundation	Delivery of flows	Season of inundation	Stock	Low (0–5%)	Medium (5–25%)	High (25–100%)
E	Long (20–50 days)	Continuous	'Summer' (Nov–Apr)	Present	0.08	0.59	0.33
E	Long	Continuous	Summer	Absent	0.04	0.58	0.38
E	*Long*	*Continuous*	*'Winter' (May–Oct)*	*Present*	*0.13*	*0.55*	*0.32*
I	Long	Continuous	Winter	Absent	0.06	0.54	0.40
E	Long	Episodic	Summer	Present	0.08	0.54	0.38
I	Long	Episodic	Summer	Absent	0.04	0.53	0.43
I	Long	Episodic	Winter	Present	0.13	0.50	0.37
E	Long	Episodic	Winter	Absent	0.11	0.54	0.35
E	Medium (10–30 days)	Continuous	Summer	Present	0.02	0.45	0.53
I	Medium	Continuous	Summer	Absent	0.01	0.44	0.55
I	Medium	Continuous	Winter	Present	0.00	0.08	0.92
E	Medium	Continuous	Winter	Absent	0.03	0.49	0.48
E	Medium	Episodic	Summer	Present	0.03	0.47	0.50
I	Medium	Episodic	Summer	Absent	0.01	0.47	0.52
I	Medium	Episodic	Winter	Present	0.00	0.08	0.92
E	Medium	Episodic	Winter	Absent	0.03	0.47	0.50
E	No inundation	NA	NA	Present	0.00	0.25	0.75
E	No inundation	NA	NA	Absent	0.00	0.08	0.92

'State of parents' columns denote the states of the four parent variables. 'Probability of state of vegetation cover' columns show the expert-based probability of different levels of terrestrial vegetation cover within river channels. Probabilities sum to 1 across the three potential child states for each combination of parent states. 'Method' denotes whether the probabilities were directly elicited (E) during the expert workshop or whether they were interpolated (I) following the methods of Cain (2001). The scenario expected to result in minimum vegetation cover is printed in italics.

previous poor monitoring of environmental flow programs (Souchon *et al*., 2008), VEFMAP was established in 2005 to maximize the Victorian government's chances of being able to detect effects of the state's environmental flow program. The program is a partnership between the state-level river manager (Department of Environment and Primary Industries), six catchment management authorities responsible for the individual rivers in the program, researchers from the University of Melbourne, and the environmental consultant Sinclair Knight Merz (recently taken over by Jacobs). For full details, refer to Webb *et al*. (2010a, 2014). Briefly, the state-level manager provides overall leadership and funding for monitoring; the catchment management authorities implement the monitoring programs; the researchers use novel approaches (as described in this paper) to conduct much stronger data analyses than would otherwise have been possible; and the consultant acts as a go-between among the other partners, facilitating interactions and helping to translate the differing priorities and goals of managers and researchers. Although these are the main roles, all partners have been centrally involved in the design of the monitoring programs, the collection and collation of the data, and the analysis and interpretation of results (Webb *et al*., 2014).

The involvement of both researchers and managers ensures that the monitoring is sufficiently sophisticated to detect effects of flow variation but still practical and affordable to implement. Local managers' expertise is used in the design of individual river-level monitoring programs to address local priorities, but the involvement of state-level managers and researchers ensures that the data can also be used to reach large-scale conclusions.

While VEFMAP is collecting data across a wide variety of environmental endpoints, here, we concentrate on the vegetation data. For the analysis presented below, data were collected up to three times (2008, 2010, 2012) from 27 sites across seven different river systems spread across the state. At each site, 1×1 m quadrats were assessed for vegetation cover along ten cross-sectional transects, with the number of quadrats per cross section varying among and within sites. Overall, the analysis incorporated data from 9465 quadrats. Surveys of channel features and water level measurements taken under different flow conditions were used to develop hydraulic models of each site. The location of each vegetation quadrat was linked to the hydraulic model so that an analysis of hydrological data could determine inundation history for that quadrat.

Step 4. Process-based model of the effect of inundation duration and frequency on terrestrial vegetation encroachment

For the statistical analysis, we were primarily interested in the effects of inundation on vegetation cover. In light of the results of the literature analysis and also from the quantified Bayesian network, we developed a heuristic model of change in cover (Figure 4). We expected that terrestrial vegetation cover within river channels will attain a maximal

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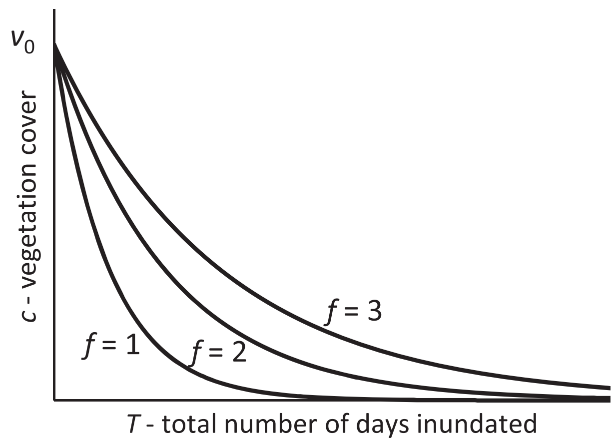

Figure 4. Diagrammatic representation of the relationship between vegetation cover and the duration and frequency of inundation. Abbreviations are explained in the text

value with no inundation, drop rapidly with short durations of inundation, and level off at zero with longer durations. If the same total duration of inundation is experienced as several separate inundation events, the reduction in vegetation cover will not be as great (Figure 4). This heuristic model of the expected joint effects of inundation duration (T) and frequency (f) on terrestrial vegetation cover (c) can be expressed as the following mathematical form suitable for analysis,

$$c = v_0 e^{\left(-m\frac{T}{f}\right)} \quad (1)$$

where m is a parameter that describes the steepness of the curve from maximal vegetation cover (v_0) down to 0 with increasing inundation.

Step 5. Bayesian hierarchical model of vegetation encroachment

We modelled cover of terrestrial vegetation primarily as a function of inundation duration and frequency as described in the previous section. Consistent with the parameterized BBN, the effect of season of inundation (Se) was quantified as an additive effect (α), as was the presence or absence of stocking (St) at the site (β). The experts at the elicitation workshop suggested that steep banks are likely to have lower vegetation cover, and so we also quantified the effect of bank slope (Sl) from which the monitoring data were collected as a covariate (γ) to reduce unexplained variation. Thus, overall

$$\begin{aligned} &c \sim N(\mu, \sigma^2) \\ &\mu = v_0 e^{\left(-m\frac{T}{f}\right)} + \alpha Se + \beta St + \gamma Sl \end{aligned} \quad (2)$$

Cover is modelled as a normally (N) distributed random variable with mean μ, and variance σ^2 and the other terms are described in the preceding text. There were also several other variables in the model that are beyond the scope of this overview paper (refer to de Little *et al.*, 2013). The hierarchical structure of the model is also beyond the scope of the present paper. However, several of the parameters were modelled hierarchically, with site-level parameters being assumed to be drawn from either river-level or state-level distributions.

All parameters in a Bayesian model require a prior probability distribution. We used minimally-informative priors for γ, but for the other parameters shown here, we used the expert-derived BBN to produce prior distributions informed by the experts' knowledge (de Little *et al.*, 2013). Using informative prior distributions, along with good empirical data, results in the strongest possible outcome from the analysis. All model fitting was done using the OpenBUGS software package (Lunn *et al.*, 2009). We used a comparison of the observed data to 'fake data' produced by the model (Gelman and Hill, 2007) to confirm that the model was an adequate fit to the data.

Model results

The fitted values of parameters from the model have little intuitive meaning. The most effective way to present the results is to use the model to predict what vegetation cover will be seen under different inundation scenarios. We present here example predicted vegetation covers (mean ± SD) for one site on each river under four inundation scenarios (no inundation, 50-day continuous inundation in winter, 50-day continuous inundation in summer, 50-day inundation in summer divided into three events). Fifty days is the recommended length of a high-flow event for one of our rivers (the Wimmera), and so, the scenarios are consistent with flow recommendations designed to prevent terrestrial vegetation encroachment. However, the model could be used to predict response for any flow scenario.

It is important to note that none of the results presented represent the measured conditions at any of the sites. Rather, they are all predictions from the model fitted to those data. The results show that 50-day inundation will be effective at reducing terrestrial vegetation encroachment for these sites. The uncertainty of predictions was also low, with standard deviations of cover estimates generally around 10% or less and mostly substantially less than the means (Figure 5). Under zero inundation, sites had between 18% (Wimmera) and 96% (Macalister) predicted mean cover of terrestrial vegetation within the channel. With 50-day continuous inundation, these cover figures dropped away to near zero for sites on the Broken and Thompson rivers, by approximately three quarters on the Wimmera and Goulburn rivers, and by approximately half on the McKenzie and Macalister rivers. Only for the site on the Yarra River was 50-day continuous inundation predicted to have little effect on terrestrial

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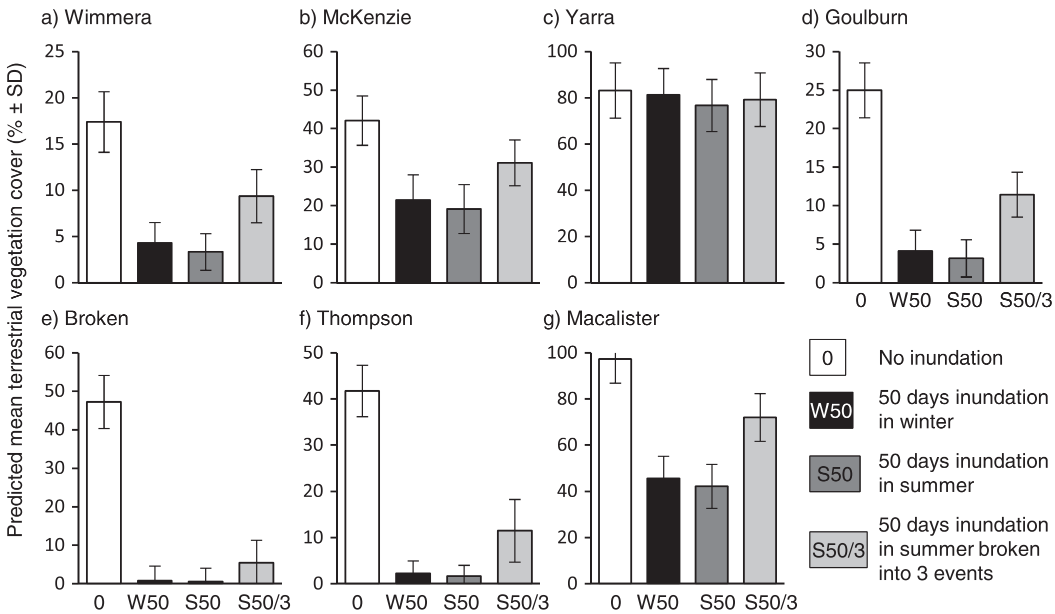

Figure 5. Graphs of predicted cover of vegetation under four different inundation scenarios, for one haphazardly chosen site on each of the seven rivers. Bars show mean estimated cover ± SD. Different inundation scenarios are indicated by different fills, as described in the key

vegetation cover. Inundation in summer led to slightly lower predicted cover than inundation in winter, and breaking the summer inundation into three distinct events reduced its effectiveness.

This set of results is not necessarily indicative of the entire 27 sites. They are presented to give an idea of the types of results available from the Bayesian hierarchical model. Closer examination of model predictions also showed that by taking a hierarchical approach to data analysis, predictions were more precise than was the case when data from individual rivers were analyzed separately and that using expert-derived priors also resulted in an improvement of predictive precision relative to minimally informative priors (results not shown; refer to de Little *et al*., 2013).

DISCUSSION

The modelling framework outlined in this paper makes exhaustive use of all the information that can be brought to bear when predicting the likely ecological effects of environmental flows. Systematic review of the literature results in an evidence-based conceptual model. Structured expert elicitation can be used to provide an initial quantification of the links in the model. These initial parameterizations can be used to produce prior probability distributions for a Bayesian hierarchical model. Large-scale monitoring informs statistical analysis, but it is important to have coordinated data collection, with contractors using compatible methods. All the previous steps' outputs come together in the Bayesian hierarchical model, which can be used to make specific predictions (together with the uncertainties of those predictions) of ecological response to environmental flow regimes. This is exactly the type of general quantitative ecological response model that environmental flow science has lacked until now.

We focus on predicting ecological responses to environmental flows because of the pressure that environmental water managers are under to justify investment of public funds in environmental flows. However, because we have derived few general principles from studies of flow restoration (Souchon *et al*., 2008), our new approach also makes use of the much more considerable information (literature, opinions, data) concerning ecological responses to natural (or semi-natural) changes in flow.

Benefits of the framework

Existing approaches to detecting effects of environmental flows mostly rely on small-scale comparisons of data before or after a flow event or between a flow-restored river and a control (Webb *et al*., 2010a). However, such studies cannot make predictions of environmental flow effects in new situations. Thus, the predictive ability of the approach detailed in this paper provides considerable advantages over these other methods. Beyond this, there are several other advantages of our modelling framework. The Bayesian approach allows great flexibility in model structure, which means that models can reflect ecological processes, rather than testing for associations. Bayesian methods also allow the

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combining of expert opinion with data to make maximal use of both these sources of information. Coordinated data collection over large scales provides much more information than small-scale monitoring programs. Here, the case study demonstrates that strong results emerge when large amounts of data are combined within a hierarchical modelling framework. A hierarchical model also provides a mathematically valid framework for making predictions at sites that *have not been monitored*. The river-level distributions of parameters can be sampled to provide predictions for a new hypothetical site on that river, or the state-level distributions can be used to similarly make predictions for another river entirely. Such predictions are less precise than those produced for sites where monitoring data have been collected. However, the predictions are non-biased and provide a solution to the well-known problem in ecology of scaling up small-scale results to larger scales.

Are different parts of our framework more important than others, and could individual components be omitted? We believe that the core of the approach lies in the Bayesian hierarchical analysis of data collected over large scales. It could be argued that if one already had a very strong idea of what processes to model and/or hypotheses to test, then the systematic review component is not required. Similarly, if one is very confident in the quality and precision of the data collected, then the effort involved in conducting expert elicitation to develop informative prior distributions may have marginal benefits.

Such considerations are important because the workload involved in implementing the full framework is considerable. As described above, some 10,000 quadrats worth of vegetation cover data were included in the case-study analysis. The systematic review consumed approximately 200 h of person time for an experienced researcher, with a similar amount spent on data cleaning, model building, and running and analyzing the results of the expert workshop. The amount of time and effort (and therefore funds) to invest in the evaluation of monitoring data could be determined using principles of risk assessment. For outcomes at smaller scales and of interest to fewer stakeholders, a simpler analysis may be appropriate. Conversely, for important ecological outcomes over large scales, there is an argument to invest considerable resources in the evaluation and employ the full framework described here. Even in such cases, the effort and expense involved in such an assessment are dwarfed by the expenditure of taxpayer funds on the environmental water released.

Potential applications

The predictive model offers a number of different potential applications. We do not yet know which of these applications will be most common or most useful.

It can be used to determine the effectiveness of an environmental flow program, even when no control sites are available and before-flow data have not been collected. The model can be re-run with an artificial hydrograph, removing the environmental water component from the flow regime. The difference between model predictions for the two flow scenarios is the benefit of the environmental flows.

In a similar fashion, it can be used to test the predictions of environmental flow assessments, by making quantitative predictions of the ecological outcomes from recommended flow regimes. In the specific example presented here, the frequent qualitative predictions in environmental flow assessments—that flow management can be used to reduce terrestrial vegetation encroachment—have been borne out. However, the results go much further. We are now able to make specific quantitative predictions of the expected effect of inundation, both at sites where data have been collected and for new sites and new rivers. This type of quantitative predictive ability can provide for much more rigorous planning of environmental flows in the future.

Such predictions can also be used in multi-criteria analysis, trading off (for example) ecological benefits versus economic returns from irrigated agriculture (Powell *et al*., 2013). This type of analysis has the potential to identify where water could have multiple benefits both for environmental and consumptive uses.

More generally, predictive quantitative models similar to that developed here have the potential to help move environmental flows into a new era of 'evidence-based' environmental management. Managers are already required to use 'best available science' when making decisions (Ryder *et al*., 2010). However, there has been little advice as to how to recognize best-available science or how it should be synthesized to inform decision-making. Our framework provides one solution to both of these issues. It therefore has the potential to inform evidence-based management, providing substantive accountability for the expenditure of public money and improving our ability to plan environmental flows into the future.

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