Environmental Modelling & Software 88 (2017) 188–199

Contents lists available at ScienceDirect

Environmental Modelling & Software

journal homepage: www.elsevier.com/locate/envsoft

Using optimization to develop a "designer" environmental flow regime

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ARTICLE INFO

Article history:
Received 15 June 2016
Accepted 18 November 2016

Keywords:
Environmental flow
Conditional probability network
Bayesian network
Optimization
Designer flow
Mixed integer programming

ABSTRACT

There are increasing numbers of rivers with large storages, resulting in changes to environmental condition downstream. In these systems, environmental flow regimes that are specifically designed to meet environmental management objectives, whilst continuing to support economic needs, may be the best approach. A challenge remains as to how best to design these novel flow regimes. Decision support tools such as optimization provide a potential tool to achieve this. In existing tools environmental outcomes are not represented with sufficient realism and this is a major barrier to successful adoption by decision-makers. Here, we employ conditional probability networks as a promising approach that provides both ease of modelling and a direct link to ecological outcomes and processes. We present a generic model that can be used to represent any ecological endpoint within a river system. We then demonstrate the approach using two fish species in the Yarra River, Victoria.

1. Introduction

The worlds water resources are becoming increasingly stressed as human demand for water increases (Vorosmarty et al., 2010). Many of the worlds rivers are managed through infrastructure such as dams to help secure a reliable human resource for agriculture and urban centers, to manage flooding risk, and to support hydropower. Although estimates vary, there are currently in the order of 50,000 large dams worldwide (defined as those higher than 15 m), capturing around 20% of the natural river discharge to the worlds oceans (ICOLD, 2007). There are also a considerable number of smaller dams (Lehner et al., 2011), and in the order of 3700 new major dams in planning (Zarfl et al., 2015).

At the same time, there is a growing awareness of the impacts of these impoundments on instream environments, often as a result of altered water regimes (Dudgeon et al., 2006; Poff et al., 1997). These systems require managers to balance the human livelihood objectives supported by water and river development and the ongoing sustainability of the river ecosystems.

In these modified systems, the downstream environments remain valuable, but are significantly modified from their natural state. It therefore may be more appropriate to an environmental flow regime that meets the multiple objectives (consumptive and environmental) of the system rather than basing environmental flows on the natural flow paradigm (Acreman et al., 2014). *The idea of being able to define and quantify the components of the flow hydrograph and assemble them into an environmental flow regime that meets a particular set of ecological and social objectives can be thought of as a designer approach, producing environmental flows that support desired ecosystem states or provide desired ecosystem services* (Acreman et al., 2014, p 486).

A significant challenge however remains as to how to design and manage a flow regime to ensure that the complex needs of the environment are supported in the longer term (Acreman et al., 2014; Arthington et al., 2006; Arthington, 2012; Harman and Stewardson, 2005). This will require a trade-off between different river-level objectives (e.g. agriculture, hydropower, urban and environmental), and indeed between different elements of the environment (e.g. fish and vegetation). A water resource manager will need to decide how to operate the water resource system and its storages to achieve the best overall outcome for the environment and society (Poff et al., 2016). This challenge has been highlighted in Australia with the implementation and active and ongoing management of environmental water rights, which require

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http://dx.doi.org/10.1016/j.envsoft.2016.11.020
1364-8152/

an environmental manager to decide upon and implement flow releases continually throughout the year.

Optimization provides one approach for systematically and transparently developing a designer flow regime and assessing tradeoffs within a system. Indeed, an increasing number of studies have already applied optimization to the challenge of designing an environmental flow regime (for a review of these studies refer to Horne et al., 2016).

The consistent challenge for these studies is how best to incorporate and model the environmental objectives (Horne et al., 2016). An optimization tool must be able to assess the relative benefit of providing water to the environment at one time-step or location over another, between different environmental endpoints, or between the environment and other water users (depending on the model objective) (Horne et al., 2010).

While human water uses such as hydropower and agricultural water are generally trying to maximize relatively simple endpoints (e.g. electricity production, irrigated crop production), it is more complicated to develop a measure of ecological outcome from a flow regime. The approach must recognize the complex interaction between flow components and the nature of the non-linear flow responses (Horne et al., 2016, 2010). To date, methods have either allowed for non-linear flow responses but grossly simplified the aggregation of flow components (Chen, 2011; Horne, 2009) or have assumed a linear-flow response (Chang et al., 2010; Han et al., 2012; Ringler and Cai, 2006; Shiau and Wu, 2013).

Understanding relations between flow and ecology has improved in recent decades (Arthington, 2012). The highly complex and dynamic dependencies of aquatic flora and fauna, ecological processes and the multiple components of a flow regime (and the challenges in defining them) are discussed in an extensive and rapidly expanding literature (Arthington, 2012; Poff and Zimmerman, 2010; Webb et al., 2010). A clear challenge exists in translating or incorporating this complex knowledge into models that can inform management decisions.

In this paper we highlight the challenges and critical elements in representing ecological outcomes to support the design of novel environmental flow regimes. We then address the key question of how environmental outcomes can be incorporated into optimization-based decision support tools in a way that allows trade-off decisions. We propose Conditional Probability Networks (CPNs) as a possible way forward for representing ecological responses in such tools, and this is demonstrated through a case study.

2. The challenge of representing ecological outcomes

Optimization tools to support environmental flow design are mostly structured to include a model or representation of the physical water resource system and operational constraints, a model of ecological outcome or response to flow for each relevant species, and an objective function that links these species outcomes together considering spatial and temporal information. Here, we focus on the challenge of representing ecological outcomes and any implications for the objective function (shown in grey in Fig. 1). There is a clear trade-off between representing the ecosystem response in all its complexity, and developing a model that is manageable in its data requirements, implementation, computational complexity and interpretation of results. Ideally, we require an approach that:

- Shows the flow-ecology cause effect relationship (including the relationship between flow components)
- Shows the marginal benefit of flow
- Allows for links between ecological endpoints or species
- Allows for temporal sequences or changes in ecological outcome arising from past flow conditions and those likely to occur in the near future
- Is sufficiently computationally tractable to allow multiple endpoints or species to be considered simultaneously

A number of different approaches have been used to represent environmental outcomes in optimization-based decision support tools for management of flow regimes. Horne et al., (2016) reviewed optimization models where the environmental flow was part of the decision (i.e. where it is included as a decision variable). They found that most existing studies have adopted hydrological indicators as a surrogate for environmental outcomes (25 out of 40 papers). This most common approach to representing environmental outcomes is the simplest to implement (requiring no ecological data), but also the least ecologically realistic, with a number of limitations when applied within optimization (Horne et al., 2016). Firstly, in the context of developing a designer regime, hydrological indicators compare key elements of the regime to a target flow regime, usually based on the natural flow regime. The very premise of a designer regime is that a natural or unimpacted conditions are not necessarily an appropriate objective in systems heavily regulated by large storages /citepAcreman2014. Secondly, there is an implicit assumption of a linear response to changes in flow; for a given indicator of the flow-regime (usually a characteristic of the readily-available discharge flow time-series). For example, a high flow event might be characterised by the peak flow magnitude or total flow volume during the event, but this assumes that half the flow provides half the benefit. However, we know in reality that there will be non-linearities and thresholds (for example exceeding the height of the river channel) that affect the benefit of any component of the flow regime (Turner and Stewardson, 2014). This is a major limitation for trade-off decisions, because the shape of the marginal benefit curve (i.e. the benefit of each additional unit of water at a particular time) has considerable influence on how limited water is allocated between flow components (Horne et al., 2010). An assumption of linearity will affect this.

Ecological responses have been modelled directly using flow-response curves (Young et al., 2003). These relate a metric of ecological performance to variation in a single flow component. Such curves can include thresholds and non-linearities not possible with hydrological indicators. However, most ecological responses will be driven by combinations of different flow response curves, and flow components are rarely independent in their effects upon an individual species. A challenge of using flow-ecology response curves is how best to combine responses to individual flow components to provide an overall outcome for a particular species. Existing studies that have linked flow-ecology response models together have primarily used a geometric mean or the minimum of component measures as representing the most limiting factor (Marsh et al., 2007; Bryan et al., 2013). Other tools allow combination methods based on expert judgement usually in the form of weighting response curves (Young et al., 2003).

A limitation in these approaches is the failure to recognize event connectivity or interactions between species (Lester et al., 2011). To demonstrate this, consider how an optimization model would decide between a flow to trigger fish spawning and a flow to trigger recruitment back into the system. If the benefits of these two flow components are averaged, the model would assume the same outcome is achieved when providing one flow component and not the other as providing half of each. However, in reality, there will be no benefit of providing a fish recruitment flow if there has not previously been spawning. A further limitation is the assumption that the environmental response will remain constant over time.

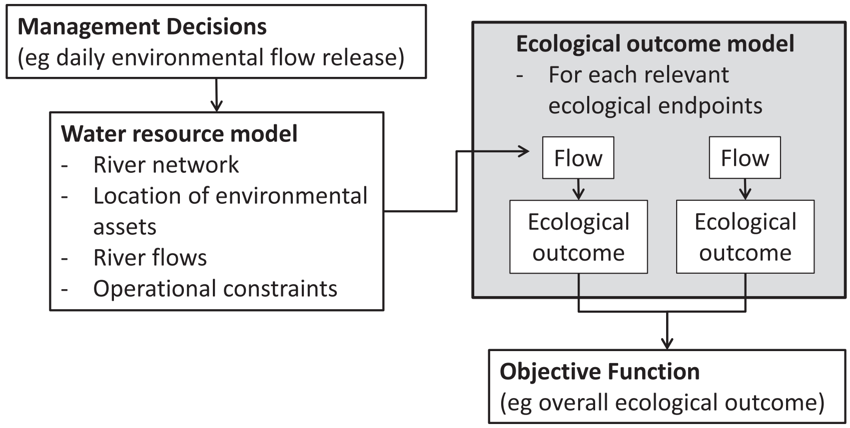

Fig. 1. Overview of optimization model structure to support environmental flow regime design downstream of a storage.

However, species respond differently to flow depending on their antecedent condition and resilience.

The approach to representing ecological outcomes to inform the design of a flow regime downstream of storage requires both a representation of the marginal value of flow events at different times and locations (analogous to flow-response curves), but also needs to allow for the complex interaction between flow components and species (the way in which the curves are combined). A small number of studies have addressed the challenges outlined through the use of population demographic models where the focus is on abundance or densities, usually of a single fish species (for example Jager, 2014; Jager and Rose, 2003). However the difficulty of the modelling, the advanced ecological knowledge required, and sheer computational complexity for the optimization mean that it is unlikely that such an approach would be possible in systems where multiple environmental objectives exist.

The existing approaches therefore present a dilemma. In the majority of cases, environmental outcomes are not captured with sufficient realism and complexity to allow the trade-off required to design a flow regime. However, a process-based model such as a population demographic approach is computationally infeasible or too knowledge and data intensive for most multi-objective applications. We believe that conditional probability networks provide a wy of navigating this dilema.

3. Do conditional probability networks (CPNs) provide a way forward

Broadly, a Conditional Probability Network represents the probabilistic cause-effect relationships between driver variables (in this context, flow and other ecological drivers) and one or more outcomes (here, ecological condition). The most familiar use of CPNs is within Bayesian network models (Pearl, 2000). The network is represented by a series of nodes and links. For each node there is a predefined conditional probability table with a finite set of input states and output states. These probabilities define the outcome of that node given the condition of the parent nodes that feed into it (Hart and Pollino, 2009).

This approach to representing the relationship between flow regime and ecological outcomes lends itself to decision making and can be embedded within an optimization tool. Importantly, these networks explicitly represent the interactions between multiple flow components to produce a single ecological outcome (i.e. each flow component is a separate parent node). This approach highly flexible to represent ecological knowledge concerning these interactions in contrast to the common simplification of using an average value. In the context of optimization, this means that the environmental outcome is defined based on the full structure of the node-link network. The predefined conditional probability tables for each link-node relationship also allow the inclusion of non-linear responses.

The benefits of CPNs include that they (Henderson et al., 2008):

- show cause-effect relationships through a simple graphical structure;
- are easily constructed, extended and modified;
- incorporate uncertainty in relationships through the use of probabilities;
- allow the conditional probabilities between variables to be constructed using either observed data, other models, or expert knowledge (or any combination of these); and
- are an accessible and intuitive modelling approach.

The use of CPNs within Bayesian network models is increasing in natural resource management (McCann et al., 2007), and the use of such models in environmental flows is also gaining momentum (Hart and Pollino, 2009; Arthington et al., 2010). To date, the use of Bayesian networks for environmental flows has been for multi-year flows planning (for example Chee et al., 2005; Pollino et al., 2007; Stewart-Koster et al., 2010), using a constant set of rules over a long term flow sequence where the resulting flow release recommendations remain the same each year. Here, we are proposing to use CPNs within an optimization framework to inform within-year decision making for active flow management. By embedding a CPN within an optimization framework, the optimization tool can identify the flow release decisions that would lead to the best predicted outcome, trading off multiple endpoints, and taking into account the specific climatic conditions being experienced at the time. This approach also allows seasonal and annual decisions to vary each year to favour different species or objectives.

The probabilistic relationships within CPNs can be populated using data and information from a number of sources. When extensive data are available, algorithms such as the expectation maximization (Dempster et al., 1977) algorithm embedded in the Netica Bayesian Network software can be used to populate a CPN directly. Where data are lacking, expert knowledge can be used to parameterize relationships. Formal expert elicitation methods (for example Speirs-Bridge et al., 2010) can be employed to reduce the bias and overconfidence that often affects expert-based estimates, and methods have been developed specifically aimed at eliciting flow-ecology relationships (de Little et al., 2012). Interpolation of linear relationships among multiple discrete states in nodes can be used to reduce the number of questions needed for elicitation, thereby reducing expert fatigue (Cain, 2001). Ideally, knowledge of the relationships in a CPN builds over time, with new information able to be used to update the probabilities via application of Bayes rule.

4. How can CPNs be included within optimization models of environmental flow decisions?

We present a generic model using Mixed Integer Programing (MIP), focusses on the representation of CPNs (the constraints used to determine the link-node relationships) and incorporation within the objective function. We have chosen MIP as it is one of the less flexible optimization methods that have been used in previous studies (Horne et al., 2016), and if CPNs can be implemented within an MIP-based optimization, they should be amenable to other optimization algorithms as well. The case study (Section 5) and supplementary material provide detail of this generic model as applied to a real catchment, and provide the complete MIP model (including water resource system constraints applying to the case study) that optimizes the design of the environmental water releases.

The design of an environmental flow regime, in the context of optimization, can be considered as a series of decisions around which flow components to provide, at which time of year, and to what duration and magnitude. A conditional probability network for a given species provides the relationship between the provision of flow components (for example, low flows or high pulse events) and the overall ecological outcome for the species (for example, condition of adult population) through a set of nodes and directed links. The nodes represent the flow components and other ecological state variables relevant to the life history of the species (for example, spawning) and directed links represent cause-effect relations between "parent" nodes and "child" nodes. Each node in the CPN can be in a finite number of states. In the case of parent nodes, for example, a flow pulse event node could include a number of different possible flow thresholds. The states of these nodes can be described relative to natural flow metrics (NFM), with different percentile flows relevant to each flow component. Each node representing an intermediate ecological stage (for example, habitat quality or spawning condition) also has a set number of possible states. For example, a node describing *instream habitat* may be "adequate" or "inadequate", or similarly a node representing *spawning* may be "triggered" or "not-triggered" etc. The nodes representing the overall ecological outcome of a species could have states such as "good, average or poor" condition or "increasing, decreasing or maintained" population. The CPN includes a conditional probability table (CPT) for every node, which quantifies the strength of the cause-effect relation between the parents of that node and the node itself. The CPT for a node specifies, for each possible combination of states of its parent nodes, the probability of the given node being in various states.

Using the node link structure and the underlying CPTs of a CPN, the probability distributions for the final ecological outcomes can be derived once the probability distributions of the flow component nodes are known. Different environmental water release schedules will lead to different probability distributions of the flow component nodes, and hence will imply different distributions for the nodes representing the final outcomes for that species.

Below, we show how the CPNs for all relevant species or environmental endpoints can be incorporated within an MIP optimization model to inform the design of environmental flow releases (including volume and timing). The aim is to produce a flow series such that the nodes representing the flow components in the CPN of each ecological endpoint have probability distributions that lead to the maximal outcome across the different species and locations at which these occur. There are three key steps:

- Based on the flow regime in the river reach (the sum of environmental releases and "exogenous" flows provided for consumptive and other purposes) the optimization model must calculate the probability distribution for the parent node Section 4.1
- The distributions for the parent node must be propagated through the CPN to derive the overall ecological outcome for a given species (Section 4.2)
- Outcomes for individual species are combined in the objective function (Section 4.3).

4.1. Determining probability distribution for the parent (flow component) nodes

Broadly, flow components can be divided into two main classes (1) base flows (for example low flows in summer or winter) that provide continuous instream flow over a season, or (2) pulse events (sometimes referred to as 'freshes' or 'spells') which are a higher pulse of flow through the river, described in terms of both magnitude and frequency. The implementation of these two classes of flow components differs.

4.1.1. Base flow components

Many species require a continuous river flow throughout the year, often distinguished into two seasons (for example, summer and winter low flow requirements). A CPN node representing a base flow component has a number of states defined by various flow thresholds (derived hydrologically for the species and the river reach). The probability distribution for nodes representing base flow delivery would be based on the distribution of flows during the relevant season in the planning horizon. Specifically, the probability of the base flow node in a particular state in a reach is given by the proportion of days the flow in the reach lies between the flow thresholds defining the state. These probabilities can be computed within a MIP model with the help of following set of constraints, where Constraints (1)–(3) count the number of days the low flow lies in each state, and Constraints (4) calculate the probability of low flow node in each of its states.

$$x_{ad} \geqslant b_{qai}\beta_{qadi} \quad \forall\ i \in \mathscr{S}_{qa}(LF), a \in A_r^q, d \in \mathscr{D}_{q(LF)}, q \in \mathscr{Q}_{LF} \tag{1}$$

$$x_{ad} \leqslant b_{qa(i+1)} + M\left(1-\beta_{qadi}\right) \quad \forall\ i \in \mathscr{S}_{qa}(LF), a \in A_r^q, d \in \mathscr{D}_{q(LF)}, q \in \mathscr{Q}_{LF} \tag{2}$$

$$\sum_{i \in \mathscr{S}_q(LF)} \beta_{qadi} = 1 \quad \forall\ a \in A_r^q, d \in \mathscr{D}_{q(LF)}, q \in \mathscr{Q}_{LF} \tag{3}$$

$$\rho_{qa}^{(LF)}(i) = \frac{1}{\left|\mathscr{D}_{q(LF)}\right|} \sum_{d \in \mathscr{D}_{q(LF)}} \beta_{qadi} \quad \forall\ i \in \mathscr{S}_{qa}(LF), a \in A_r^q, q \in \mathscr{Q}_{LF} \tag{4}$$

where $\mathscr{Q}_{LF}$ is the set of species or endpoints requiring the low flows, $\mathscr{A}_r^q$ is the set of river reaches that are relevant to species q, $\mathscr{S}_{qa}(LF)$ is the set of states for the summer low flow node for species $q \in \mathscr{Q}_{Lf}$ in reach $a \in \mathscr{A}_r^q$, b_{qai} is the flow threshold defining state $i \in \mathscr{S}_{qa}(LF)$, $\mathscr{D}_{q(LF)}$ is the set of days relevant for low flows for species q, M is a sufficiently large real number, and β_{qadi} are bookeeping binary variables that take value one only if the total flow in reach $a \in \mathscr{A}_r^q$ on day $d \in \mathscr{D}_{q(LF)}$, denoted by x_{ad}, lies in the i^{th} state, i.e.,

$$\beta_{qadi} = \begin{cases} 1, & \text{if } b_{qai} \leqslant x_{ad} \leqslant b_{qa(i+1)} \\ 0, & \text{otherwise.} \end{cases}$$

4.1.2. Pulse or fresh events

Fresh or *pulse events* are defined as periods where flow exceeds a certain threshold for a minimum duration. The states of the nodes representing the fresh flow components are defined by the flow thresholds, and frequencies at which a fresh event for a species would have a positive effect on its overall condition. The optimization model chooses a release pattern, and this will result in exactly one scenario from the possible combinations of frequency and magnitude of fresh events. Thus, the model will know definitively that there are *X* fresh events over threshold *Y*. Thus for each release pattern, each node representing a fresh flow component (fresh threshold and fresh frequency) one state will have a probability of one and the remaining states will have probability zero. In an MIP model, this can be captured with the help of the following set of constraints.

Constraints (5) and (6) note whether the total flow in a reach is above or below the given flow thresholds. Constraints (7) model the minimum duration of a fresh event. These constraints require that if in reach *a*, a fresh event above threshold *t* starts on day *d* for species *q* and fresh flow component *n*, then the flow must remain above the threshold *t* for the minimum duration of the fresh event after day *d* as required by species *q* for the flow component *n*. Constraints (8) impose that a fresh event for species *q* and fresh flow component *n* happens within relevant days (for example, autumn freshes must occur within March to May for Australian grayling - one of the fish species modelled in the case study presented below). Constraints (10) model the independence of two fresh events requiring that the flow must fall below the threshold for a given number of consecutive days immediately before the beginning of next independent fresh event. Constraints (11) count the number of independent fresh events above all suitable thresholds for each species and flow components in reaches relevant for species *q*, and finally Constraints (12) gaurantee for every node in the CPN corresponding to a fresh flow component node only one state can have a probability of one and all other states have a probability of zero.

$$x_{ad} \geqslant t\alpha_{adt} \quad \forall\ d \in \mathscr{D}_{at}, t \in \mathscr{T}_a, a \in \mathscr{A}_r \tag{5}$$

$$x_{ad} \leqslant t + M\alpha_{adt} \quad \forall\ d \in \mathscr{D}_{at}, t \in \mathscr{T}_a, a \in \mathscr{A}_r \tag{6}$$

$$\sum_{p=d}^{d+F^{MinDur}_{qan}-1} \alpha_{apt} \geqslant F^{MinDur}_{qan} Z_{qantd} \quad \forall\ t \in \mathscr{T}_{qan}, a \in \mathscr{A}^q_r, n \in \mathscr{N}_q, q \in \mathscr{Q}, \quad d \in \mathscr{D}_{qn} : d + F^{MinDur}_{qan} - 1 \leqslant \max_{d \in \mathscr{D}_{qn}} d \tag{7}$$

$$Z_{qantd} = 0 \quad \forall\ t \in \mathscr{T}_{qan}, a \in \mathscr{A}^q_r, n \in \mathscr{N}_q, q \in \mathscr{Q}, \quad d \in \mathscr{D}_{qn} : d + F^{MinDur}_{qan} - 1 > \max_{d \in \mathscr{D}_{qn}} d \tag{8}$$

$$\sum_{p=d+1}^{d+F^{I}_{qan}} Z_{qantp} \leqslant 1 - \alpha_{adt} \quad \forall\ t \in \mathscr{T}_{qan}, a \in \mathscr{A}^q_r, d \in \mathscr{D}_{qn}, n \in \mathscr{N}_q, q \in \mathscr{Q} \tag{9}$$

$$\sum_{p=d}^{d+F^{MinDur}_{qan}+F^{I}_{qan}-1} Z_{qantd} \leqslant 1 \quad \forall\ t \in \mathscr{T}_{qan}, a \in \mathscr{A}^q_r, n \in \mathscr{N}_q, q \in \mathscr{Q}, \quad d \in \mathscr{D}_{qn} : d + F^{MinDur}_{qan} + F^{I}_{qan} - 1 \leqslant \max_{d \in \mathscr{D}_{qn}} d \tag{10}$$

$$\sum_{d \in \mathscr{D}_{qn}} Z_{qantd} \geqslant \sum_{k' > k} W_{qantk'} \quad \forall\ t \in \mathscr{T}_{qan}, a \in \mathscr{A}^q_r, n \in \mathscr{N}_q, q \in \mathscr{Q}, \quad k \in \left\{0, 1, \ldots, F^{MaxNum}_{qan}\right\} \tag{11}$$

$$\sum_{t \in \mathscr{T}_{qan}} \sum_{k=1}^{F^{MaxNum}_{qan}} W_{qantk} = 1 \quad \forall\ a \in \mathscr{A}^q_r, n \in \mathscr{N}_q, q \in \mathscr{Q} \tag{12}$$

where $\mathscr{N} = \{\text{Autumn freshes}, \text{Spring freshes}, \text{Bankfull events}\}$ is the set of fresh flow components, $\mathscr{N}_q \subseteq \mathscr{N}$ is the set of flow components in $\mathscr{N}$ that are relevant for species *q*, $\mathscr{D}_{qn}$ is the set of days relevant for flow component $n \in \mathscr{N}_q$ for species *q*, $\mathscr{T}_{qan}$ is the set of thresholds relevant for species *q* in reach $a \in \mathscr{A}^q_r$ for provision of flow component $n \in \mathscr{N}_q$, $\mathscr{T}_a$ is the set of thresholds that are relevant for the reach arc $a \in \mathscr{A}_r$, which is given by union of all thresholds in reach *a* over all species $q \in Q$ and flow components $n \in \mathscr{N}_q$, $\mathscr{D}_{at}$ is the set of days relevant for threshold *t* in reach *a*, F^{MinDur}_{qan} denotes the minimum duration of a fresh event for species *q* and flow component $n \in \mathscr{N}_q$ in reach *a*, where F^{I}_{qan} is the minimum number of fresh independence days required by species *q*, and F^{MaxNum}_{qan} is the maximum frequency of fresh events for species *q* in reach *a*. Here we have used the following three types of binary variables to compute the probability distributions of CPN nodes representing fresh flow components:

- α_{adt} which can be one only if the flow in reach *a* is above threshold *t* on day *d*,
- Z_{qantd} which can be one only if a fresh event over threshold *t* starts on day *d* for species *q* and flow component $n \in \mathscr{N}_q$, and
- W_{qantk} which are used to select the optimal states for the flow events for each species *q* in each relevant reach $a \in \mathscr{A}^q_r$ and flow component $n \in \mathscr{N}_q$ (W_{qantk} can be one only if at least *k* events over threshold $t \in \mathscr{T}_{qan}$ are selected for flow component $n \in \mathscr{N}_q$).

4.2. Linking the nodes: constraints for evaluating ecological outcomes

Assume that three flow components (for example summer low flow, spring fresh magnitude and frequency) affect the likelihood of good habitat and likelihood of spawning, which in turn influence the probability of recruitment for a fish species. The probability distribution of the recruitment node (*R*) thus depends on the probability distributions of the Habitat node (*H*) and the Spawning node (*S*), the nature of which are affected by the probability distribution of the summer low flow node (*SLF*), and the probability distributions of spring fresh threshold and frequency node respectively. Using the knowledge of flow drivers outline above, we can obtain the probability of the recruitment node being in a given state using the following constraints. Note that the left hand side of the following constraint is bounded by the value of the first term on the right hand side corresponding to the combination of threshold and frequency for the spring fresh for which the binary variable *W* takes value one. Since the objective is to improve overall recruitment, the model will choose that combination of spring fresh threshold and frequency that maximizes the objective:

where $\rho^{(R)}_{qa}(i)$ is the probability the recruitment node in the CPN of species *q* is in state *i* in reach *a*.

$$
\begin{aligned}
\rho_{qa}^{(R)}(i) \quad & \leqslant \sum_{h\in\mathscr{S}_q(H)} \sum_{s\in\mathscr{S}_q(S)} P_{qa}^{(H)}(h) P_q^{(S)}(s|t,k) P_q^{(R)}(i|h,s) + M\left(1 - W_{qankt}\right) \\
& = \sum_{h\in\mathscr{S}_q(H)} \sum_{s\in\mathscr{S}_q(S)} \left(\sum_{j\in\mathscr{S}_{qa}(SLF)} \rho_{qa}^{(SLF)}(j) P_q^{(H)}(h|j) \right) P_q^{(S)}(s|t,k) P_q^{(R)}(i|h,s) + M\left(1 - W_{qankt}\right) \\
& \qquad \forall\ i\in\mathscr{S}_q(R), k\in \left\{0,\ldots,F_{qan}^{MaxNum}\right\} \\
& \qquad t\in\mathscr{T}_{qan}, a\in\mathscr{A}_r^q, n = \text{Spring fresh}
\end{aligned}
\tag{13}
$$

4.3. Designing an objective function

Each species may be located at multiple locations throughout a river system. The objective function must ensure an appropriate aggregation of this spatial information. For example, for bird breeding, it may be sufficient to ensure that appropriate breeding conditions occur at one location within the catchment. This could be represented in an objective function as the maximum breeding outcome across all locations in the catchment. In contrast, the objective for fish species may be to ensure a health population throughout the river channel, and so averaging of outcomes across spatial locations may be more appropriate. Every river system has a number of key species and assets that environmental water managers are seeking to protect or restore. This results in a multi-objective consideration of the problem of optimizing the environmental water releases. One approach adopted in the Water resources management literature is to combine the multiple objectives into a single objective by taking a weighted average of the outcomes of the multiple objectives (Horne et al., 2016). We have adopted this approach to design an objective function for the MIP optimization model. The main challenge then is to determine the weights for the species. This is informed by management and stakeholder priorities within the system.

While maximizing overall ecological outcomes in the river is the primary objective in optimizing environmental water releases in a river, it must be noted that different release patterns can potentially lead to the same ecological benefit. In this case, the optimal release pattern is one that uses the least volume of water to achieve the optimal benefit. This can be achieved using a two-step approach. At step 1, one solves the optimization model to obtain the optimal ecological benefit. Then at step 2, an additional constraint is added to the model requiring that the overall ecological benefit be same as the one obtained at step 1, and the optimization model is then solved again with the objective of minimizing the total volume of the environmental releases.

5. Demonstration - native fish in the Yarra River, Victoria, Australia

The Yarra River originates in a steep forested region and extends 120 km downstream to Port Phillip Bay in the city of Melbourne, Victoria, Australia (Fig. 2). The catchment is highly regulated with a

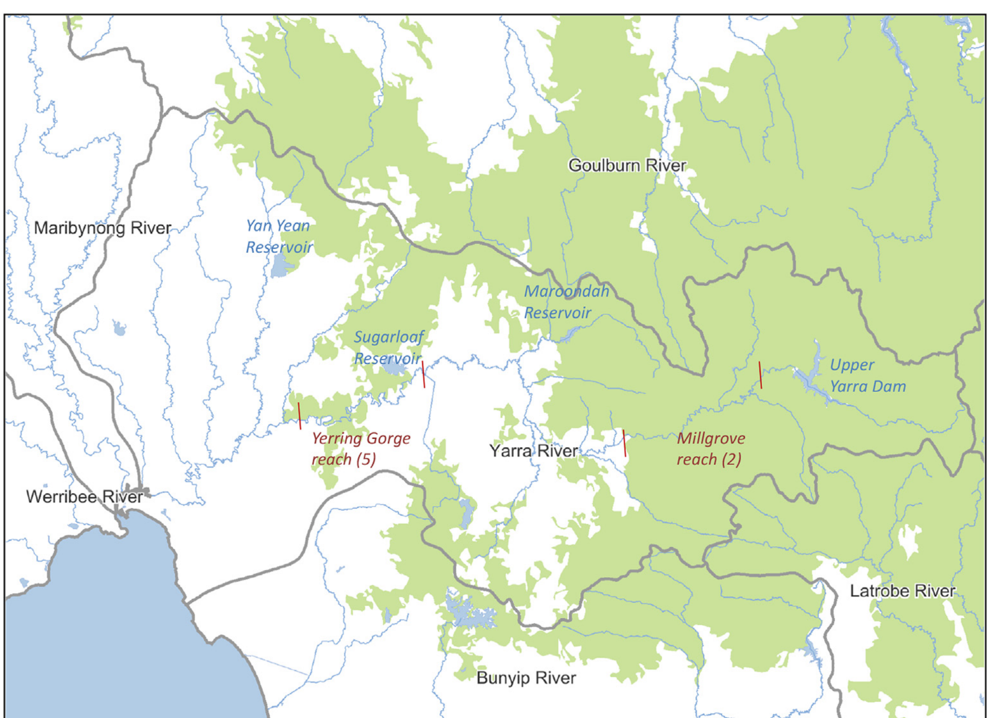

Fig. 2. Map of the Yarra River system.

number of large urban storages that provide water supply for Melbourne. There are also a number of irrigation diversions along the river. This level of development has altered in-stream flow, with annual flow at some locations reduced to half the pre-development flow (SKM, 2012).

The Victorian government holds an environmental water entitlement in the Yarra system that is actively managed to achieve multiple environmental outcomes. However, a range of delivery constraints apply to different parts of the system (Water, 2014). Within these constraints, the manger must decide when to release environmental water from the various storages to achieve best environmental outcomes downstream. Environmental outcomes are represented by two key reaches: Yering Gorge and Millgrove (Water, 2014). The Yarra River supports a range of environmental values, including a number of nationally significant fish species (Water, 2014). This paper focuses on two of these fish species; River Black fish (*Gadopsos marmoratus*) and Australian Grayling (*Prototroctes maraena*).

5.1. Development of the Yarra optimization model

The optimization model developed for the Yarra River is structured as shown in Fig. 3. The detailed optimization model and constraints are provided in supplementary material. Importantly, the modelling of the water supply system was limited to those allow representation of reaches of environmental significance (thus the urban water supply network was not necessary to include in the model). The model was implemented using the Mosel XPRESS program. The constraints to represent the CPNs and objective function follow the approach outlined in Section 4.

5.2. Ecological assets in Yarra river and their conditional probability networks

River Blackfish are potamodromous, spending their entire life in freshwater (Koster and Crook, 2008). They spawn in spring (October to January) when water temperatures exceed 16 °C (Lintermans, 2007). Spawning is likely triggered by temperature and habitat type rather than a specific flow event (Koehn et al., 1994). Once hatched, larvae remain in the area for around three weeks. During this time, it is important that flows do not flush larvae from the nursery habitats (SKM, 2005).

In contrast, Australian Grayling are diadromous, moving to and from the marine environment. Movement of adults downstream and subsequent spawning is triggered by fresh or pulse flow events in autumn (specifically in April or May) (O'Connor and Mahoney, 2004) and a fall in water temperature (Shenton et al., 2011). These same flow events also transport eggs and larvae downstream to the estuary (SKM, 2005). Juveniles are then believed to return upstream in response to a spring fresh event, four to six months after spawning (Koster et al., 2013). Australian Grayling are panmictic and spawning and recruitment do not necessarily occur in the same river (Shenton et al., 2011).

Shenton et al. (2011) developed Bayesian network models for Australian Grayling and River Blackfish based on expert elicitation and existing conceptual models (Chee et al., 2009). These models have been adapted for use within the optimization tool. It is important to note that the parent nodes (i.e. descriptors of flow) of the Bayesian network models include probabilities based on long-term analysis of flow data and models. As noted in 4, this is a point of differentiation when adopting this model in an optimization model for seasonal environmental watering decisions. In the optimization model, the conditional probability relationships that link elements of the ecological response model are retained, but the long-term probability distributions for flow conditions at parent nodes are replaced by specific representations of the flow regime at that time step. The flow regime is the decision variable in the optimization model; optimization searches for an environmental flow delivery pattern that will provide the best result given the conditional probabilities that links flow to ecological outcome.

Fig. 4 shows the conceptual models that underlie the Shenton et al. (2011) Bayesian network models. The conditional probability tables used to populate this model were taken from Shenton et al. (2011) without modification. The assessment is based on daily flow requirements. In these models, there are four relevant flow components: Autumn Fresh, Spring Fresh, Summer Low and Winter Bankfull. There are seven possible states for flow magnitude for each component (the median natural flow (NFM), NFM minus 10 percent, NFM minus 20 percent etc.) and four possible states for frequency (three, two, one and none). These flow components are represented as parent nodes in the networks. Each transitional node (in-stream habitat, pre-spawning condition, transport larvae,

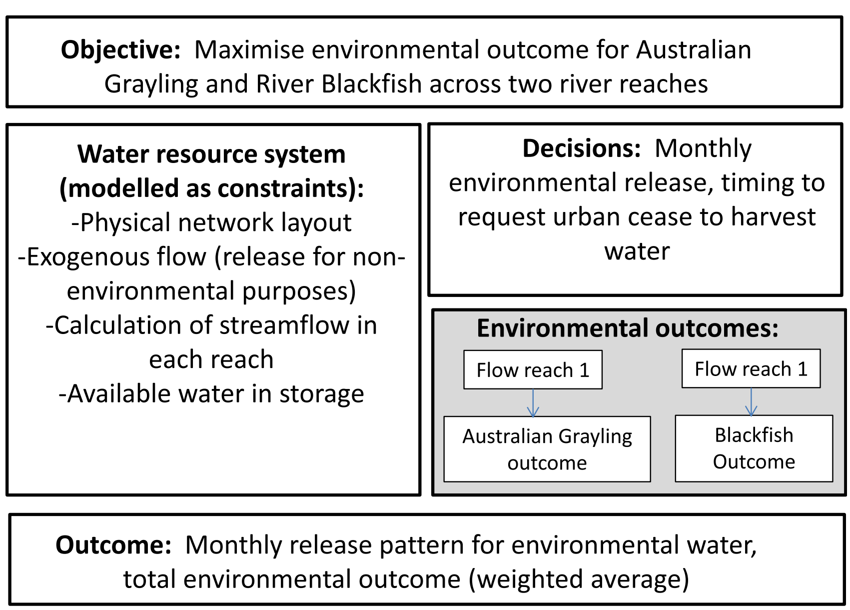

Fig. 3. Structure of the Yarra River Environmental Water Optimization model.

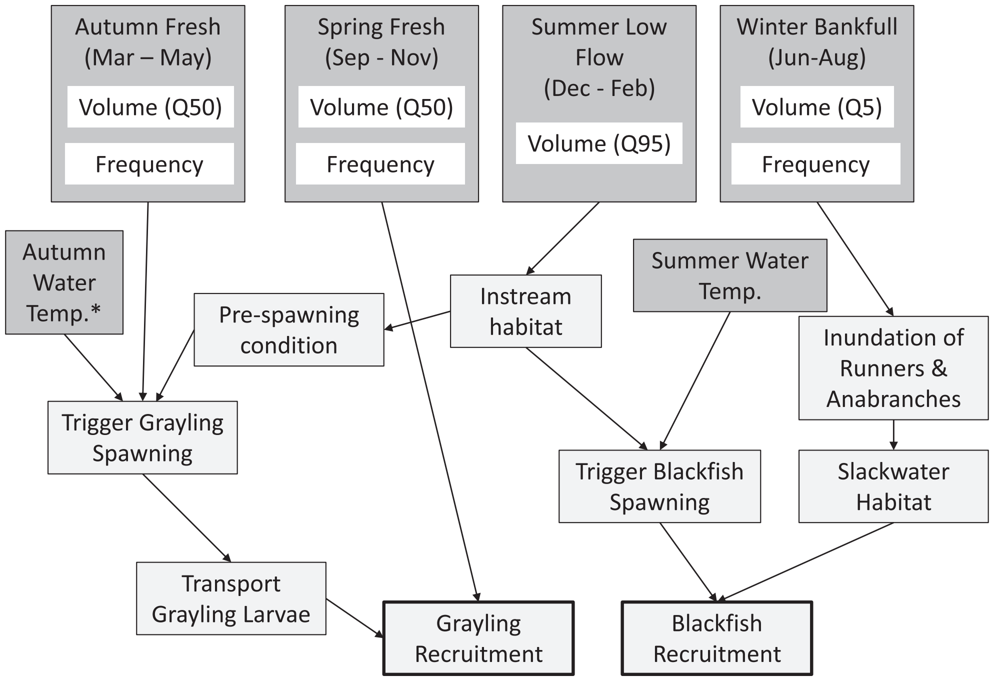

Fig. 4. Conceptual models for Australian Grayling and River Blackfish (adapted from Shenton et al. (2011)). Q50 refers to the 50th percentile flow, Q95 to the 95th percentile flow and Q5 to the 5th percentile flow for the corresponding time period. Darker grey boxes represent parent nodes and bold bordered boxes represent child nodes. *Note that Autumn water temperature is taken to refer to temperature at the time of the autumn fresh event (Anabranches and Runners refer to sections of a river or stream that divert from the main channel and rejoin further downstream).

etc.) has two possible states (adequate/inadequate, good/poor, triggered/not triggered, etc.) The CPNs in our application have only one child node for each species, representing the recruitment of the fish species, which has three possible states: increasing, decreasing and maintained.

Water temperature is a key element in the conceptual models for both Australian Grayling and River Blackfish. For River Blackfish, summer water temperature is aimed at maintaining adequate habitat, and is therefore included in the model a parent node populated using the distribution of temperature over summer. For Australian Grayling water temperature was included as a constraint for an autumn fresh event. This reflects that spawning is triggered with a rise in flow and drop in temperature occurring concurrently (Shenton et al., 2011), rather than the average autumn temperature.

6. Results and analysis

The optimization model was run for the six years where flow and corresponding water temperature data are available for the Yarra River system (1998–2003). These years represent the water planning year which runs from July to June, encompassing the Australian summer peak irrigation season (ie. 1998 represents the water year from July 1998 to June 1999). The years 2000 and 2003 experienced close to the average annual flow in the Yarra River, while the other years in this period were drier than average. No water temperature data were available that corresponded to a year with high annual flow.

We investigate the benefits of providing additional environmental water in different years by looking at the overall

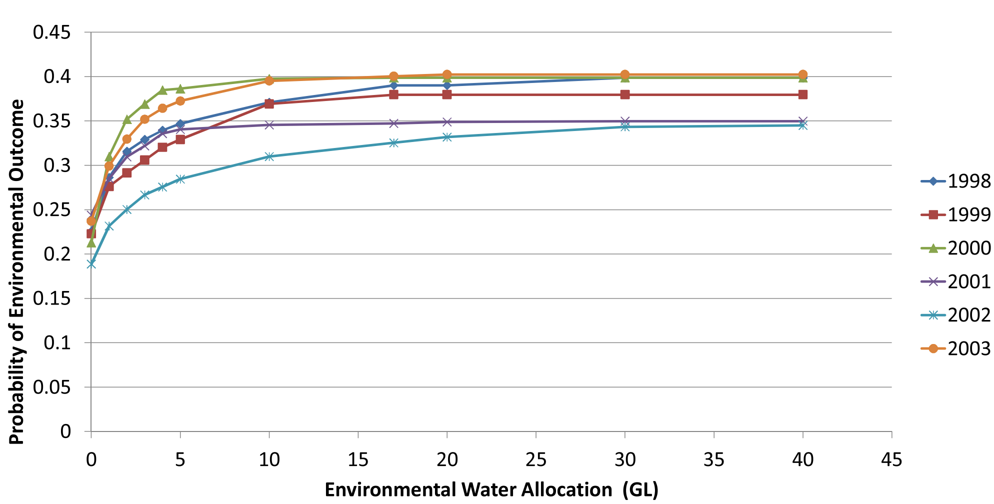

Fig. 5. The overall environmental outcome for Australian Grayling and River Blackfish in different years with increasing volumes of environmental water available.

environmental outcome with increasing volumes of environmental water available. Fig. 5 shows how the overall environmental outcome (a combined score across the two species shown on the y-axis) changes as more water is provided (with volume of environmental water shown on the x-axis). Each curve in the figure represents the outcomes from a different year of flow data. The slope of the curve shows the marginal value (the additional environmental outcome per unit of additional water); where the curve is steep there are large gains for a small additional amount of water and where the curve flattens there is little marginal gain. The figure shows that for these two species, the majority of environmental outcome is achieved with only 10 GL of water with little returns for additional volumes.

Fig. 5 shows clear variation between the overall outcome in the different years. This can not readily be explained by the annual stream flow for each of these years. To look at this further, Table 1 shows how water is used in each year when the environmental entitlement of 17 GL is available. Note it is only the years 1998, 2001 and 2002 that the full 17 GL is required to achieve the optimal environmental outcome based on the requirements of the two fish species (noting that in reality Melbourne Water also manages the system for a number of other environmental objectives). The table shows that across all years, the recommended number and magnitude of Autumn freshes are provided in the Millgrove reach, with a relatively fewer number of events provided in Yerring Gorge but at the recommended threshold. Spring freshes are then provided usually at a reduced threshold and frequency and highly dependent on the timing and duration of exogenous flow pulses in the river upon which such freshes can be "piggy-backed". Bankfull events at a reduced threshold (50% of the recommended volume) are provided in a number of years, again where there is a significant exogenous flow pulse event in July that can be used to achieve a smaller top-up volume from the environmental water account. The way in which environmental releases take advantage of exogenous flow patterns and opportunistically add fresh events is shown in Fig. 6.

In 2001, there is a reduced frequency of autumn freshes in Yerring Gorge, and a reduced frequency of spring freshes in the Millgrove reach, both of which contribute to a lower probability of Australian Grayling recruitment. This is similar to the year 2002 where reduced frequency and magnitude of spring freshes limits recruitment. On this basis, the overall probability of a good environmental outcome in these years remains below that of other years. The table shows that the outcomes for Australian Grayling

Table 1
Targeted flow components for each year (1998–2003) (Shaded cells indicate that the full possible flow recommendation or probability of environmental outcome has not been achieved, Reach 2 refers to Millgrove and Reach 5 refers to Yerring Gorge).

	Year	1998	1999	2000	2001	2002	2003
Amount of water used		17	13.73	10.94	17	17	15.18
Total Benefit		0.390	0.379	0.399	0.347	0.325	0.400
Flow components provided	**Reach**						
Autumn Fresh Threshold	2	Q50	Q50	Q50	Q50	Q50	Q50
	5	Q50	Q50	Q50	Q50	Q50	Q50
Autumn Fresh frequency	2	3	3	3	3	3	3
	5	3	3	2	1	2	2
Spring Fresh threshold	2	Q50 minus 20%	Q50 minus 20%	Q50	Q50	Q50 minus 40%	Q50
	5	Q50	Q50	Q50	Q50	Q50 minus 20%	Q50
Spring Fresh frequency	2	3	1	2	1	1	3
	5	1	1	3	3	1	3
Bankfull threshold	2	*	*	Q50 minus 60%	Q50 minus 60%	Q50 minus 60%	Q50 minus 50%
	5	*	Q50 minus 50%	Q50 minus 50%	Q50 minus 60%	Q50 minus 60%	*
Bankfull frequency	2	*	*	1	1	1	1
	5	*	1	1	1	1	*
Australian Grayling outcome							
Probability of adequate habitat	2	0.950	0.950	0.950	0.950	0.950	0.950
	5	0.950	0.950	0.950	0.936	0.799	0.936
Probability that spawning is triggered	2	0.889	0.889	0.889	0.889	0.889	0.889
	5	0.889	0.889	0.768	0.628	0.715	0.763
Probability that larvae transport occurs	2	0.895	0.895	0.895	0.895	0.895	0.895
	5	0.895	0.895	0.672	0.458	0.629	0.668
Probability that recruitment increases	2	0.542	0.470	0.587	0.542	0.390	0.631
	5	0.542	0.542	0.487	0.348	0.346	0.484
Probability that recruitment maintained	2	0.139	0.184	0.184	0.184	0.184	0.139
	5	0.184	0.184	0.117	0.096	0.144	0.117
Maximum possible prob. of recruitment increasing*	2 & 5	0.631	0.631	0.631	0.631	0.631	0.631
Blackfish outcome							
Probability of adequate instream habitat	2	0.950	0.950	0.950	0.950	0.950	0.950
	5	0.950	0.950	0.950	0.936	0.799	0.936
Temperature $\geq 16°$	2	0.856	0.769	1.000	0.722	0.889	0.945
	5	0.933	1.000	1.000	1.000	1.000	1.000
Probability that spawning is triggered	2	0.679	0.615	0.785	0.581	0.703	0.745
	5	0.736	0.785	0.785	0.781	0.740	0.781
Probability of natural slackwater habitat	2	0.283	0.283	0.283	0.283	0.283	0.335
	5	0.283	0.335	0.335	0.283	0.283	0.283
Probability that recruitment increases	2	0.356	0.335	0.391	0.324	0.364	0.382
	5	0.375	0.396	0.396	0.389	0.368	0.389
Probability that recruitment maintained	2	0.234	0.225	0.248	0.220	0.237	0.244
	5	0.241	0.249	0.249	0.247	0.238	0.247
Maximum possible prob. of recruitment increasing*	2	0.411	0.386	0.452	0.372	0.420	0.436
	5	0.433	0.452	0.452	0.452	0.452	0.452

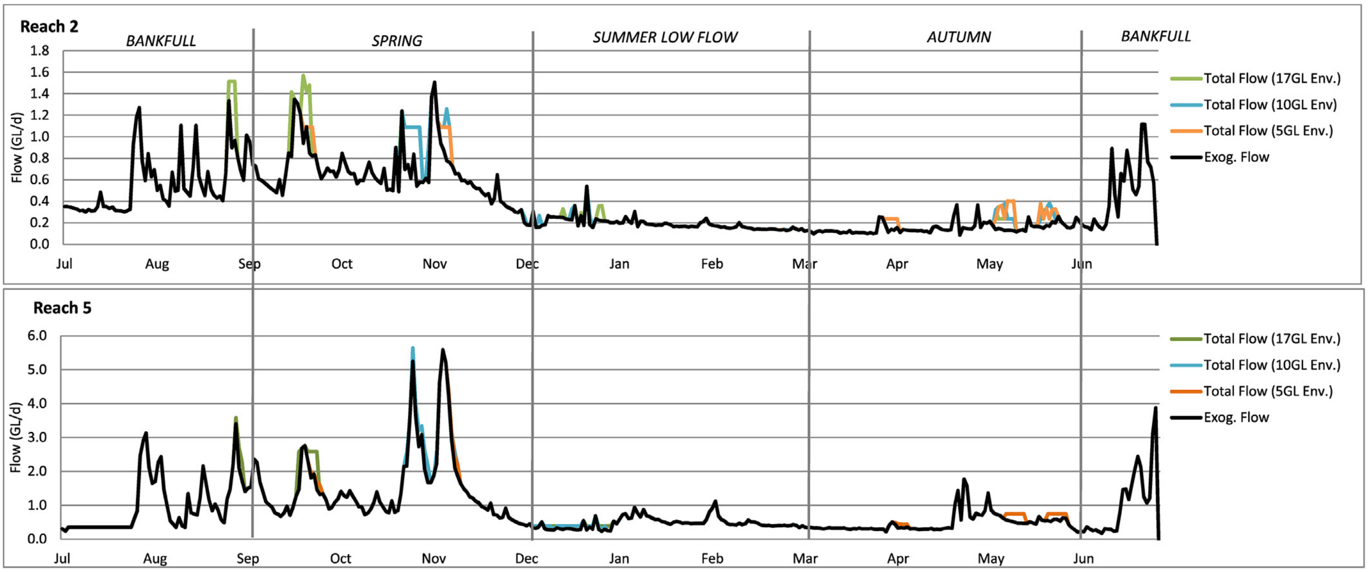

Fig. 6. Exogenous flow and environmental releases in Millgrove (reach 2) and Yerring Gorge (reach 5) for the year 2003, with varying levels of environmental water available.

are affected more significantly by the environmental watering than Blackfish. This analysis highlights one of the advantages of representing ecological outcomes using CPNs- the ability to track how individual flow components are affecting the probability of adequate habitat, spawning and ultimately recruitment.

It is important to note that the maximum possible probability of recruitment for both species is less than one, that is, the CPN specifies that even if all flow components are provided, there is still a reasonable probability that recruitment will not occur. For Blackfish, the maximum possible probability of recruitment varies, depending on the summer temperature for that year. If temperatures during summer are low, additional flow will not improve the likelihood of spawning. The maximum possible outcomes are shown in Table 1.

7. Discussion and conclusions

Managing environmental flows downstream of storages presents a particular set of challenges. In these systems, an environmental flow regime that is designed to achieve a specific set of environmental objectives may be more appropriate than a flow regime based on the natural flow paradigm. Translating these management objectives into a designer flow regime requires an understanding of the relative benefits of providing flow at different times and places throughout the year. Decision support tools such as optimization can play a role in informing the design and implementation of these novel flow regimes, but representing ecological outcomes within these models has been a challenge. The CPN approach illustrated here offers potential as an approach that provides a representation of how flow release decisions link to a given management objective and include information on the marginal value of flow at different times. These models directly predict the ecological effects, rather than having to rely on surrogates like hydrology.

There are a number of advantages we see in the use of CPNs within environmental flow decision support models. As the information within the conditional probability network can be revised over time as new knowledge becomes available, the approach lends itself to adaptive management and allows a degree of flexibility that has been lacking in previous approaches. Indeed, the outcomes from the optimization model can be used with an expert group to assess whether the conceptual model is behaving as expected in terms of the recommended flow release patterns, and this information can then be used to revise the models as required. They can also incorporate data and information from multiple sources.

CPNs are transparent and provide useful outputs for communication and analysis. For example, they allow the tracking of how individual flow components are affecting the probability of adequate habitat, spawning and ultimately recruitment. This may be particularly relevant when comparing multiple environmental endpoints with competing needs at a particular time of year. The case study also demonstrated the ability to incorporate temperature as another factor influencing environmental outcome. The CPN structure supports analysis to understand whether flow or another environmental driver is the limiting factor for a particular outcome.

A potential limitation of the CPN approach is that the tabular format creates a piece-wise linear relationship that risks creating thresholds on what would otherwise be a smooth response function. This effect can be reduced by having a larger number of states in the node, but this might make the conditional probability table difficult to parameterize. The potential effect of discretization would require investigation at the model development stage to test the sensitivity of the model outcomes to the number of states in each node.

The process outlined in this paper (and implemented in the case study with the two fish species in the Yarra) includes only two species and a relatively simple spatial network (two reaches in series). The two species are separate and independent ecological endpoints. In many cases, there will be multiple ecological endpoints and it is likely that at least some of these ecological endpoints will not be independent of one another (for example, frogs might rely on adequate riparian vegetation, which would require a link between vegetation and frog models). Developing these more complex interactions and river networks and implementing them within an optimization tool to determine environmental watering decisions is an area for further research. It will increase the computational complexity, and the CPNs themselves may be more challenging to parametrize. However, these are just extensions of the approach demonstrated here, rather than being qualitatively more difficult. In particular, the concept of interaction between ecological endpoints is straightforward using CPNs.

A key limitation of the Bayesian networks that have previously been adopted in natural resource management applications, is their inability to consider temporal sequencing (Hart and Pollino, 2009). Incorporating a CPN within an optimization approach can overcome this, as feedback loops and time series of flow can be incorporated. Temporal sequencing would be included by adding an antecedent ecological condition node to the network. If ecological condition for an endpoint starts out in a good state, then providing flows might only cause a small extra increase. In contrast, if ecological condition starts out poor, ecological improvements will be greater, and flows will be more highly prioritized. In this way, temporal sequencing within CPNs will facilitate year-to-year changes in priority among endpoints, focusing on those that need water the most for the current time period. There is a major opportunity to refine this approach and consider how antecedent conditions and resilience can be considered when designing environmental flow regimes downstream of major storages.

The results from the Yarra case study clearly show that there is variation across years in how environmental water can be used for best ecological effect. This shows the importance of considering individual years rather than long term averages when determining release patterns and designer flow regimes. It also suggests that there may be advantages in considering hydrological forecasting approaches when determining environmental water use for the coming season, rather than relying on historical long-run average information. Analysis of a longer period of record would help assess this in more detail, and it may be possible to move to a stochastic modelling framework to address these challenges.

The real success of optimization models in supporting the design of environmental flow regimes will only be tested when such models are used by water managers. While CPNs can be readily updated and used within an adaptive management context, the models need to be translated into usable tools and work within the institutional settings that are present. This will require ongoing collaboration with water resource managers to ensure the modelled decisions and objectives align with their management needs.

Acknowledgements

This study was funded by the Australian Research Council (ARC Linkage project LP130100174) and a number of partner agencies.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.envsoft.2016.11.020.

References

Acreman, M., Arthington, A.H., Colloff, M.J., Couch, C., Crossman, N.D., Dyer, F., Overton, I., Pollino, C.A., Stewardson, M.J., Young, W., 2014. Environmental flows for natural, hybrid, and novel riverine ecosystems in a changing world. Front. Ecol. Environ. 12 (8), 466–473. http://dx.doi.org/10.1890/130134.

Arthington, A., 2012. Environmental Flows - Saving Rivers in the Third Millennium. University of California Press.

Arthington, A., Bunn, S., Poff, L., Naiman, R., 2006. The challenge of providing environmental flow rules to sustain river ecosystems. Ecol. Appl. 16 (4), 13111318.

Arthington, A.H., Naiman, R.J., McClain, M.E., Nilsson, C., 2010. Preserving the biodiversity and ecological services of rivers: new challenges and research opportunities. Freshw. Biol. 55 (1), 1–16.

Bryan, B., Higgins, A., Overton, I., Holland, K., Lester, R., King, D., Nolan, M., Hatton Macdonald, D., Connor, J., Bjornsson, T., Kirby, M., 2013. Ecohydrological and socioeconomic integration for the operational management of environmental flows. Ecol. Appl. 23 (5), 999–1016.

Cain, J., 2001. Planning Improvements in Natural Resource Management: Guidelines for Using Bayesian Networks to Support the Planning and Management of Development Programmes in the Water Sector and beyond. Centre for Ecology and Hydrology, Wallingford.

Chang, L.-C., Change, F.-J., Wang, K.-W., Dai, S.-Y., 2010. Constrained genetic algorithms for optimizing multi-use reservoir operation. J. Hydrology 390, 66–74.

Chee, Y., Burgman, M., Carey, J., 2005. Use of a Bayesian Network Decision Tool to Manage Environmental Flows in the Wimmera River, Victoria. Report.

Chee, Y., Webb, A., Stewardson, M., Cottingham, P., 2009. Victorian Environmental Flows Monitoring and Assessment Program: Monitoring and Assessing Environmental Flow Releases in the Thomson River. Report. E-Water Cooperative Research Centre.

Chen, D. (2011), Optimization of reservoir operation considering both hydropower generation and ecological flow requirements, in 34th IAHR World Congress - Balance and Uncertainty, 33rd Hydrology and Water Resource Symposium and 10th Hydraulics Conference, Engineers Australia.

de Little, S.C., Webb, J.A., Patulny, L., Miller, K.A., Stewardson, M.J., 2012. Novel methodology for detecting ecological responses to environmental flow regimes: using causal criteria analysis and expert elicitation to examine the effects of different flow regimes on terrestrial vegetation. In: Mader, H., Kraml, J. (Eds.), 9th International Symposium on Ecohydraulics 2012 Proceedings. International Association for Hydro-Environmental Engineering and Research (IAHR).

Dempster, A., Laird, N.M., Rubin, D., 1977. Maximum likelihood from incomplete data via the em algorithm. J. R. Stat. Soc. Ser. B Methodol. 39 (1), 1–38.

Dudgeon, D., Arthington, A.H., Gessner, M.O., Kawabata, Z.-I., Knowler, D.J., Lvque, C., Naiman, R.J., Prieur-Richard, A.-H., Soto, D., Stiassny, M.L.J., Sullivan, C.A., 2006. Freshwater biodiversity: importance, threats, status and conservation challenges. Biol. Rev. 81, 163182.

Han, J.-C., Huang, G.-H., Zhang, H., Zhuge, Y.-S., He, L., 2012. Fuzzy constrained optimization of eco-friendly reservoir operation using self-adaptive genetic algorithm: a case study of a cascade reservoir system in the yalong river, China. Ecohydrology 5, 768–778.

Harman, C., Stewardson, M., 2005. Optimizing dam release rules to meet environmental flow targets. River Res. Appl. 21, 113–129.

Hart, B., Pollino, C., 2009. Bayesian Networks for Risk-based Environmental Water Allocations. Report. National Water Commission.

Henderson, C., Pollino, C., Hart, B.T., 2008. Bayesian Modelling as a Basis for Risk-based Environmental Flow Assessment a Review. Report. National Water Commission.

Horne, A., 2009. An Approach to Efficiently Managing Environmental Water Allocaitons (Thesis).

Horne, A., Stewardson, M., Freebairn, J., McMahon, T., 2010. Using an economic framework to inform management of environmental entitlements. River Res. Appl. 26 (6).

Horne, A., Szemis, J.M., Webb, J.A., Stewardson, M.J., Costa, A., Boland, N., 2016. Optimization tools for environmental water decisions: A review of strengths, weaknesses, and opportunities to improve adoption. Environmental Modelling & Software 84, 326–338.

ICOLD, 2007. World Register of Dams. Report.

Jager, H., 2014. Thining outside the channel: timing pulse flows to benefit salmon via indirect pathways. Ecol. Model. 273, 117–127.

Jager, H., Rose, K., 2003. Designing optimal flow patterns for fall cinook salmon in a central valley, California river. North Am. J. Fish. Manag. 23, 1–21.

Koehn, J., OConnor, N., Jackson, P., 1994. Seasonal and size-related variation in microhabitat use by a southern victorian stream fish assemblage. Aust. J. Mar. Freshw. Res. 45, 1353–1366.

Koster, W., Crook, D., 2008. Diurnal and nocturnal movements of river blackfish (gadopsis marmoratus) in a south-eastern australian upland stream. Ecol. Freshw. Fish 17, 146–154.

Koster, W., Dawson, D., Crook, D., 2013. Downstream spawning migration by the amphidromous australian grayling (prototroctes maraena) in a coastal river in south-eastern Australia. Mar. Freshw. Res. 64, 31–41.

Lehner, B., Liermann, C.R., Revenga, C., Vorosmarty, C., Fekete, B., Crouzet, P., Doll, P., Endejan, M., Frenken, K., Magome, J., Nilsson, C., Robertson, J.C., Rodel, R., Sindorf, N., Wisser, D., 2011. High-resolution mapping of the world's reservoirs and dams for sustainable river-flow management. Front. Ecol. Environ. 9 (9), 494–502. http://dx.doi.org/10.1890/100125.

Lester, R., C. Pollino, and C. Cummings (2011), Improving ecological outcomes by refining decision support tools: A case study using the murray flow assessment tool and the sustainable rivers audit, in 19th International Congress on Modelling and Simulation, Perth, Australia.

Lintermans, M., 2007. Fishes of the Murray-Darling Basin: an Introductory Guide.

Marsh, N., Grigg, N., Arene, S., 2007. A Framework for Capturing and Applying Models of Biological Response to Natural Resource Management MODSIM. International congress on modelling and simulation. Modelling and Simulation Society of Australia and New Zealand, pp. 74–80.

McCann, R., Marcot, B., Ellis, R., 2007. Bayesian belief networks: applications in ecology and natural resource management. Can. J. For. Res. 36, 3053–3062.

Melbourne Water, 2014. Yarra River Seasonal Watering Proposal 2014-2015. Report, Melbourne Water.

O'Connor, J., Mahoney, J., 2004. Observations of ovarian involution in the austgrayling (prototroctes mareana). Ecol. Freshw. Fish 13, 70–73.

Pearl, J., 2000. Causality: Models, Reasoning, and Inference. Cambridge University Press, Cambridge, UK.

Poff, N., Zimmerman, J., 2010. Ecological responses to altered flow regimes: a literature review to inform the science and management of environmental flows. Freshw. Biol. 55 (1).

Poff, N., Allan, J., Bain, M., Karr, J.R., Prestegaard, K., Richter, B., Sparks, R.,

Stromberg, J., 1997. The natural flow regime: a paradigm for river conservation and restoration. 47. BioScience 47, 769–784.
Poff, N.L., Brown, C.M., Grantham, T.E., Matthews, J.H., Palmer, M.A., Spence, C.M., Wilby, R.L., Haasnoot, M., Mendoza, G.F., Dominique, K.C., Baeza, A., 2016. Sustainable water management under future uncertainty with eco-engineering decision scaling. Nat. Clim. Change 6, 25–34.
Pollino, C., Woodberry, O., Nicholson, A., Korb, K., Hart, B., 2007. Parameterisation and evaluation of a bayesian network for use in an ecological risk assessment. Environ. Model. Softw. 22, 11401152.
Ringler, C., Cai, X., 2006. Valuing fisheries and wetlands using integrated economic-hydrologic modeling-mekong river basin. J. Water Resour. Plan. Manag. 132, 480–487.
Shenton, W., Hart, B.T., Chan, T., 2011. Bayesian network models for environmental flow decision-making: 1. latrobe river Australia. River Res. Appl. 27, 283–296.
Shiau, J.-T., Wu, F.-C., 2013. Optimizing environmental flows for multiple reaches affected by a multipurpose reservoir system in taiwan: restoring natural flow regimes at multiple temporal scales. Water Resour. Res. 49.
SKM, 2005. Determination of the Minimum Environmental Water Requirement for the Yarra River: Minimum Environmental Water Requirement and Complementary Works Recommendations. Report, Report prepared for Melbourne Water.
SKM, 2012. Yarra River Environmental Flow Study Review: Flow Recommendations Report. Report, Report prepared for Melbourne Water.
Speirs-Bridge, A., Fidler, F., McBride, M., Flander, L., Cumming, G., Burgman, M., 2010. Reducing overconfidence in the interval judgments of experts. Risk Anal. 30, 512–523.
Stewart-Koster, B., Bunn, S., MacKay, S., Poff, N., Naiman, R., Lake, P., 2010. The use of bayesian networks to guide investments inflow and catchment restoration for impaired riverecosystems. Freshw. Biol. 55, 243–260.
Turner, M., Stewardson, M., 2014. Hydrologic indicators of hydraulic conditions that drive flow-biota relationships. Hydrological Sci. J. 59 (3–4), 659–672.
Vorosmarty, C.J., McIntyre, P.B., Gessner, M.O., Dudgeon, D., Prusevich, A., Green, P., Glidden, S., Bunn, S.E., Sullivan, C.A., Reidy Liermann, C., Davies, P.M., 2010. Global threats to human water security and river biodiversity. Nature 467, 555–561.
Webb, A., Stewardson, M., Koster, W., 2010. Detecting ecological responses to flow variation using bayesian hierarchical models. Freshw. Biol. 55 (1), 108–126.
Young, W., Scott, A., Cuddy, S., Rennie, B., 2003. Murray flow Assessment Tool a Technical Description. Report, CSIRO Land and Water.
Zarfl, C., Lumsdon, A.E., Berlekamp, J., Tydecks, L., Tockner, K., 2015. A global boom in hydropower dam construction,. Aquat. Sci. 77 (1), 161–170. http://dx.doi.org/10.1007/s00027-014-0377-0.