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The use of Bayesian networks to guide investments in flow and catchment restoration for impaired river ecosystems

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SUMMARY

1. The provision of environmental flows and the removal of barriers to water flow are high priorities for restoration where changes to flow regimes have caused degradation of riverine ecosystems. Nevertheless, flow regulation is often accompanied by changes in catchment and riparian land-use, which also can have major impacts on river health via local habitat degradation or modification of stream energy regimes.
2. The challenges are determining the relative importance of flow, land-use and other impacts as well as deciding where to focus restoration effort. As a consequence, flow, catchment and riparian restoration efforts are often addressed in isolation. River managers need decision support tools to assess which flow and catchment interventions are most likely to succeed and, importantly, which are cost-effective.
3. Bayesian networks (BNs) can be used as a decision support tool for considering the influence of multiple stressors on aquatic ecosystems and the relative benefits of various restoration options. We provide simple illustrative examples of how BNs can address specific river restoration goals and assist with the prioritisation of flow and catchment restoration options. This includes the use of cost and utility functions to assist decision makers in their choice of potential management interventions.
4. A BN approach facilitates the development of conceptual models of likely cause and effect relationships between flow regime, land-use and river conditions and provides an interactive tool to explore the relative benefits of various restoration options. When combined with information on the costs and expected benefits of intervention, one can derive recommendations about the best restoration option to adopt given the network structure and the associated cost and utility functions.

Keywords: cost-benefit, environmental flows, multiple stressors, riparian revegetation, river restoration

Introduction

There is little doubt that flow regulation has impaired river ecosystems globally (Nilsson *et al.*, 2005) via the alteration of natural hydrologic regimes (Magilligan & Nislow, 2005; Poff *et al.*, 2007). In recognition of the widespread degradation of rivers due to flow regulation there have been increasing calls to include aquatic

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ecosystems as legitimate users of water and to improve methods for the allocation of environmental flows (Naiman *et al*., 2002; Arthington *et al*., 2006; Poff *et al*., 2010). Considerable investments have been made in some countries to release water as environmental flows intended to restore aquatic habitat and biotic assemblages (Richter *et al*., 2006). These environmental flow releases are often controversial (Poff *et al*., 2003), particularly in dry regions (Arthington & Pusey, 2003; Bond, Lake & Arthington, 2008).

Flow regulation seldom occurs in isolation from changes in catchment and riparian land-use with vegetation removal, intensive agriculture and urbanisation also having wide ranging and cascading effects on river ecosystems (Strayer *et al*., 2003; Allan, 2004; Dolédec *et al*., 2006; Paul, Meyer & Couch, 2006). To address these and other related land-use impacts, a range of strategies has been used by river managers to improve water quality and river conditions. These strategies include the construction of artificial wetlands and other water-sensitive urban design measures (e.g. Mitchell *et al*., 2007) and the creation of buffer strips and replanting of riparian vegetation (Lowrance, 1998; Broadmeadow & Nisbet, 2004).

While it is well recognised that river conditions, including biodiversity, are affected by a combination of land-use and flow-related drivers; restoration efforts are often focused on one or the other. In some instances it may be relatively clear as to which has the overriding influence (e.g. increased urban development compared to riparian degradation, Walsh *et al*., 2007), but the interaction among key drivers in many systems may be less apparent (Bunn & Arthington, 2002; Allan, 2004). Constrained by limited budgets, it can be difficult to determine objectively the most effective restoration approach when faced with multiple drivers of river condition decline.

Our objective is to outline an approach that may be used as a decision support tool to identify an appropriate restoration strategy in the presence of multiple drivers of a river's ecological condition. We use Bayesian networks (BNs) to model key ecological relationships in terms of their potential for restoration in impaired streams. The use of BNs in natural resource management has grown rapidly in recent years, either to model the system under study or as a decision support tool (Varis & Kuikka, 1999; Borsuk, Stow & Reckhow, 2004; Arthington *et al*., 2007; Castelletti & Soncini-Sessa, 2007). Examples of BNs as decision support tools in aquatic ecosystem management include the evaluation of different management scenarios for in-stream phosphorus loadings (Ames *et al*., 2005), the ecological impact of dryland salinity management (Sadoddin *et al*., 2005), competing stream flow allocations (Said, 2006) and different water treatment sequences (Zhu & McBean, 2007). Although many published examples apply to single response variables, the BN framework also can be used to identify effective management actions for multiple response variables, such as water quality and quantity (e.g. Said *et al*., 2006).

In this study, we present two case studies using BNs where flow and land-use related factors combine to influence a specific aspect of river health. The first is a hypothetical example to demonstrate the modelling approach, focused on dissolved oxygen (DO) in a small regulated and degraded stream. The second is based on empirical data on factors influencing aquatic macrophytes in coastal streams in south-east Queensland, Australia (Mackay, 2007). Finally, we illustrate how the costs of restoration can be incorporated into these conceptual models to identify the most cost-effective restoration approach and to help prioritise competing management actions using Bayesian decision networks (BDNs).

Methods

We constructed BNs and BDNs using the software package, NETICA (Norsys, 2005). A BN is a graphical

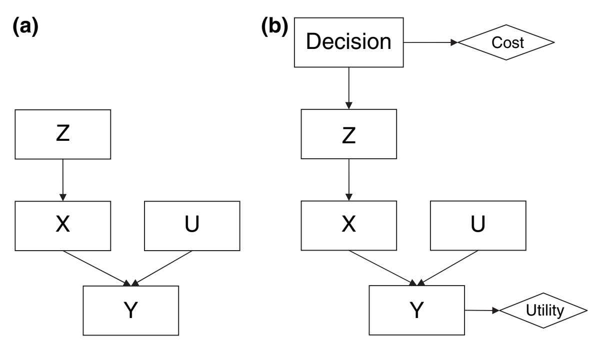

Fig. 1 (a) An example of the structure of a Bayesian network with common parent nodes (*X* and *U*) and potentially conditionally independent nodes (*Y* and *Z*) and (b) an example of a Bayesian decision network, showing a decision node with associated *cost* node representing the costs of implementing the states of the decision node and a *utility* node representing the desirability of the states of the child node.

model representing the key factors of a system (nodes) and their conditional dependencies (Fig. 1a; Varis, 1997; Korb & Nicholson, 2004; Jensen & Nielsen, 2007). The dependencies are depicted as directed links or arrows connecting a 'parent node' to a 'child node', resulting in a directed acyclic graph (DAG). In a DAG, no path starts and ends at the same node and no feedback loops are allowed so that connecting nodes do not become ancestors of their ancestors (Jensen & Nielsen, 2007). The network is quantified by populating conditional probability tables (CPTs) associated with the nodes in the network. The CPTs can be specified by experts or learned from data using one of several learning algorithms depending on the complexity of the network, such as the Bayesian counting–learning algorithm or the expectation-maximisation algorithm (Korb & Nicholson, 2004; Jensen & Nielsen, 2007).

Conditional independence is fundamental to BNs (Korb & Nicholson, 2004). This property allows an examination of both the independent and interactive (conditional) effects of some environmental change on the modelled response variable. Furthermore, a BN requires the assumption of the Markov property which means that each CPT can be populated by only considering the immediate parent nodes of the node being quantified. By specifying the probabilities of the states of a parent node(s) in a BN, the probabilities of any child nodes are updated via the process of *belief updating*. Thus, when a particular state of a parent node is observed, subsequent probabilities of any child nodes, $P(Y \mid X = x)$, are estimated using Bayes Theorem (eqn 1) and the chain rule from probability theory (Korb & Nicholson, 2004).

$$P(y|x) = \frac{P(x|y)P(y)}{P(x)} \tag{1}$$

where $P(y)$ is the prior probability of the child node and $P(x)$ is a normalising constant. Prior probabilities can come from expert opinion, preliminary data from the system or data from research on similar systems. Prior probabilities can be informative, thereby influencing model outputs, or uninformative, making little or no difference to model outputs. The use of Bayes theorem to estimate the CPTs provides the opportunity to use data and expert opinion, together or in isolation, to populate the network (Korb & Nicholson, 2004; Pollino *et al.*, 2007). Further information on BNs and their development can be found in Charniak (1991), Reckhow (1999), Korb & Nicholson (2004) and Jensen & Nielsen (2007).

In addition to modelling relationships between environmental drivers and ecological response variables, we modified the BNs to incorporate the relative costs and benefits of potential management actions (e.g. Ames *et al.*, 2005; Said, 2006). Such models are known as BDNs (Fig. 1b), and are used to identify the most appropriate decision (here, restoration action) given estimated costs and benefits (Korb & Nicholson, 2004; Jensen & Nielsen, 2007). A *decision* node(s) is included in the network whose states are the possible restoration actions; for example, different kinds of environmental flow releases. The effect of the decision node is to alter the states of its child nodes according to the possible restoration actions. Decision nodes can have an associated *cost* function that represents the actual or relative cost of each decision state (Jensen & Nielsen, 2007). The terminal node or response variable can have an associated *utility* function that reflects how desirable each management intervention is in terms of its modelled outcome (Zhu & McBean, 2007). By including a cost and utility node in the network, the BDN can identify the most cost-effective restoration decision, that which maximises the expected *utility* within the network (Jensen & Nielsen, 2007). The expected utility is the sum of the possible utilities associated with the terminal node resulting from each restoration action, weighted by the probabilities of each state of the terminal node (Jensen & Nielsen, 2007). The restoration decision that maximises the expected utility is that which provides the most desirable ecological outcome relative to its costs, thereby combining ecological response with economic constraints.

Case study 1 – reducing low DO extremes

The concentration of DO in a stream can fluctuate widely in response to physical factors that influence solubility (e.g. temperature, atmospheric pressure, turbulence and re-aeration), chemical factors (e.g. oxidation of pollutants) and biological factors (e.g. photosynthesis and respiration). In degraded streams and rivers, low oxygen can result from a combination of low flows, high water temperatures and/or excessive aquatic plant or organic matter respiration. Some of these causal factors, such as in-stream temperature, are in turn a function of other physical factors such as riparian shading and groundwater inputs (Rutherford *et al.*, 2004; Webb *et al.*, 2008). Similarly, aquatic plant production and respiration are primarily driven by light regime (e.g. turbidity and riparian shading), temperature and nutrients (Bunn, Davies & Mosisch, 1999; Wetzel, 2001).

The relationship between DO and these environmental factors can be summarised in a conceptual model which shows causal linkages between numerous factors that exert a positive or negative influence on each other and ultimately on DO (Fig. 2a). To show how these interactions can be modelled in a BN we simplified the conceptual model to include only the major factors that would influence DO in a hypothetical small, regulated river: riparian cover (including light and temperature and its influence on plant photosynthesis/respiration) and flow (Fig. 2b). These are two of the primary factors that a manager may be able to manipulate through stream restoration to prevent low oxygen extremes. In this example, each of the nodes in the model comprises two or three states.

In this hypothetical example of a small, degraded and regulated river, we have set the CPTs for demonstration only with the probability of high water velocity below the reservoir to be 10% and low velocity as 70%, and the probability of poor riparian cover to be 70% (Fig. 2b). In a real example, these could be informed by available flow release data and assessments of riparian condition. These nodes both contribute directly to water temperature, which in turn influences the DO concentrations. Riparian cover influences light regime and aquatic plant photosynthesis/respiration, which can also lead to extremes in DO. Stream flows also directly influence DO through turbulent mixing and re-aeration (Fig. 2a). The network has three categories of DO concentration; good

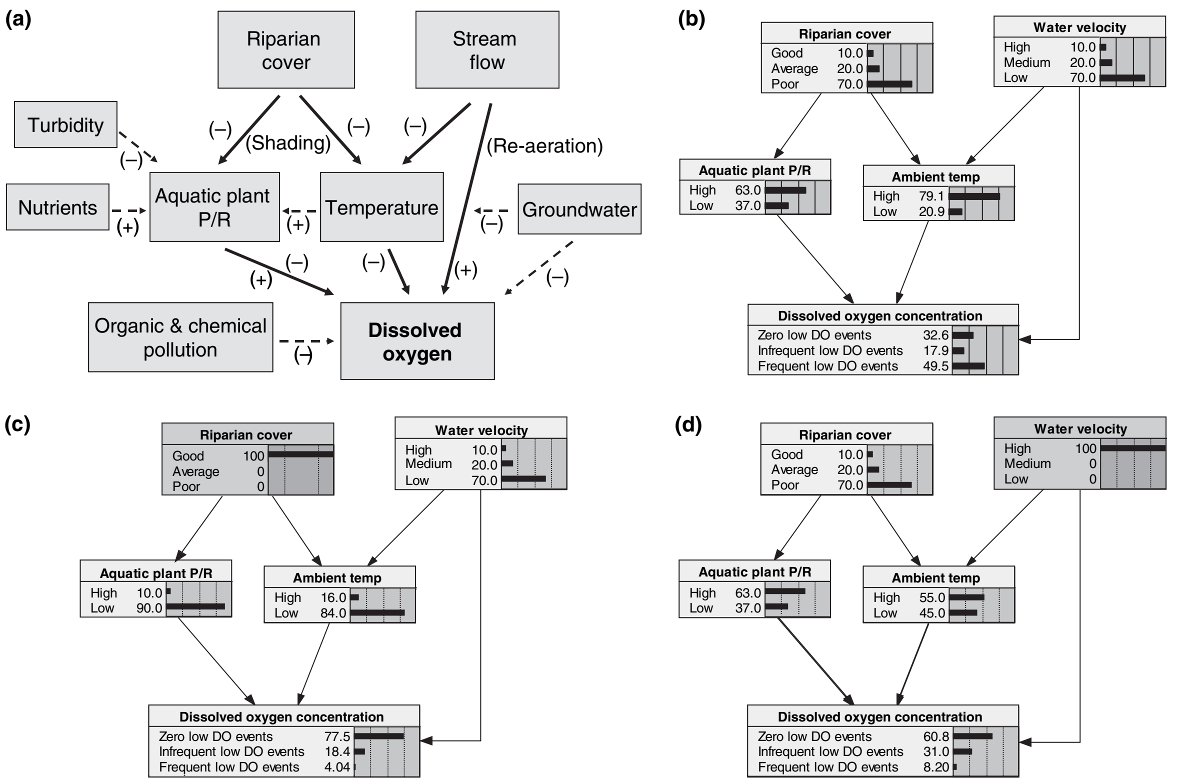

Fig. 2 (a) A conceptual diagram of the major environmental factors that influence DO concentrations in streams including biotic factors such as aquatic plant photosynthesis/respiration and abiotic factors such as temperature. Solid arcs indicate the causal relationships included in the subsequent networks. (b) Simplified network showing key factors and their interconnectedness affecting DO concentrations in a small, regulated stream. The histograms in each node are a graphical representation of the probabilities of each category of each node. (c) BN showing conditional probabilities of the three states of DO concentration given good riparian cover. (d) BN showing conditional probabilities of the three states of DO concentration given high water velocity.

water quality throughout the year (zero low DO events), episodic poor water quality (infrequent low DO events) or persistent poor water quality (frequent low DO events).

The property of conditional independence means the conditional probability of each category of DO depends directly on the states of the three parent nodes only (water velocity, aquatic plant photosynthesis/respiration and ambient temperature). Therefore, each DO state has a conditional probability for each combination of these nodes, as specified in Table 1. Again, the values in this CPT are hypothetical and intended for illustrative purposes only. The probabilities of each state of the temperature and plant nodes, represented by CPTs that are not shown, depend on their parent nodes: riparian cover and water velocity. It is via this causal pathway that riparian cover and flow releases can influence DO.

Identifying potential management options for reducing low DO events

In this hypothetical example, the goal of reducing the frequency of low DO events in a degraded stream can be accomplished by increasing flows (to increase re-aeration and reduce heating) and/or by increasing riparian canopy cover to reduce temperature and aquatic plant growth (Fig. 2). BNs such as this can be used to identify key drivers of ecological health that

Table 1 Conditional probability table for dissolved oxygen (DO) concentrations with respect to stream temperature, aquatic plant photosynthesis/respiration (P/R) and water velocity

Water velocity	Ambient temperature	Aquatic plant P/R	No low DO events	Low frequency of low DO events	High frequency of low DO events
High	High	High	20	60	20
High	High	Low	70	30	0
High	Low	High	90	10	0
High	Low	Low	100	0	0
Medium	High	High	10	50	40
Medium	High	Low	50	40	10
Medium	Low	High	80	20	0
Medium	Low	Low	90	10	0
Low	High	High	0	0	100
Low	High	Low	60	30	10
Low	Low	High	50	30	20
Low	Low	Low	80	20	0

Probabilities in this table are hypothetical and devised for illustrative purposes only.

are under some control by river managers. These networks can then be explored to understand the interrelationships among the nodes and their influence on the response variable of interest. It is possible to specify observed conditions by setting 100% probability of a specific state of any given node in the network (Fig. 2c,d). The probabilities of the states of any conditionally dependent nodes are subsequently updated via belief updating. If riparian cover were observed to be in 'good' condition, then according to the BN the probability of zero low DO events would be 77.5%, and there would be only a 4% probability of frequent low DO events (Fig. 2c). If our hypothetical stream were observed to have 'high' water velocity, under this network there would be approximately 61% probability of zero low DO events (Fig. 2d). Each network can be manipulated as such to evaluate the expected influence on the target ecological endpoint for any given scenario, including combined changes in riparian condition and water velocity (not shown).

The simple networks in Fig. 2 allow us to illustrate the assumed causal relationships between DO concentration and important environmental drivers that river managers might manipulate through restoration. However, they do not reflect the relative costs associated with these investments. Prioritising investment between two (or more) potential management options (levers) may also require consideration of the relative economic and social costs of restoration alternatives. These costs are not necessarily linear in relation to increasing management intervention. For example, we might expect that the cost function for improving riparian condition will be related to land tenure (ownership) and initial condition (Fig. 3a). At one extreme, improvements to riparian condition on well-managed public land might be achieved at a relatively low cost (e.g. maintenance of fences, weed control). At the other extreme improvements in riparian condition on poorly managed private land might be possible only with expensive restoration requiring physical works to restore stream banks, fencing, planting and weed control and stewardship payments (Qureshi & Harrison, 2001).

In contrast, we might expect the cost function for improvements to the flow regime to have a distinctly stepped function (Fig. 3b). For example, initial changes to the flow regime might be achieved through manipulation of the operational rules of the reservoir

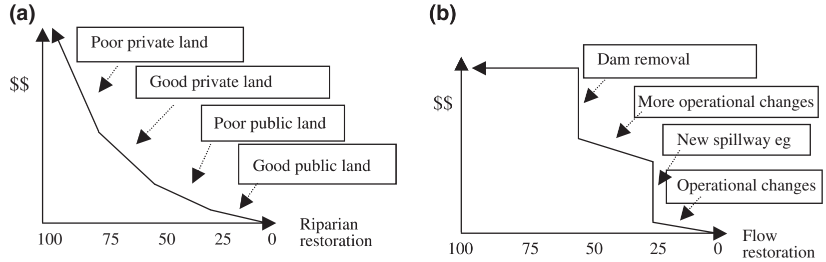

Fig. 3 Hypothetical cost functions for (a) riparian restoration whose costs increase in a relatively linear and incremental way depending on initial riparian condition and land tenure status, (b) flow regime restoration whose costs increase in a more stepped manner depending on the degree of infrastructure change that may be required to restore a more natural flow regime.

with little cost other than the volume of water used. Further gains might only be possible if an investment in infrastructure is made, such as a new spillway, after which additional improvements may be possible because of increased flexibility in releases. Ultimately, further restoration of the flow regime might only be possible by completely removing the infrastructure at significant cost (Fig. 3b). Thus, Fig. 3 is a simple illustration of how costs of river restoration might vary according to the initial conditions at any given stream reach. These cost functions can be integrated into a BN along with utility values for restoration outcomes to develop BDNs.

To illustrate this, we continue with the hypothetical example of a small regulated river in a disturbed catchment with poor riparian cover (Fig. 2). This BDN is somewhat more complex than the initial BN because it incorporates the pre-restoration riparian and water velocity conditions (Fig. 4). There is also an additional set of nodes reflecting the decision to be made between the available restoration options (decision node, 'restoration decision'), the costs of available actions (cost node) and the value or utility of the management outcomes (utility node). Since the initial BN (Fig. 2b) was developed for an impaired site with a highly modified catchment, we assume that the most expensive level of riparian restoration would be required to attain a desirable state of DO. The restoration options we include in the decision node are complete riparian restoration alone, the first two flow options identified in Fig. 3b (changing operational rules; modifying infrastructure) and the combinations of these actions. The 'no restoration' action is also included, for a total of eight options (Fig. 4).

Hypothetical examples of the relative costs for each of the eight restoration options (cost node) are listed in Table 2. These values are standardised on a scale of 0 to −1, with the most expensive option (full riparian restoration and modifying dam infrastructure) having the greatest relative cost (−1). Less expensive options would have values greater than −1; operational changes to the reservoir would be the least expensive intervention with a cost of −0.15 (Table 2). Relative utility is also assigned on a standardised scale, but with positive values (0–1) to reflect the desirability of the outcomes, and high water quality having the maximum utility of 1 (Table 2). It is worth noting that a high frequency of low DO events incurs a negative utility due to the likelihood of additional costs associated with water quality treatment or removal of nuisance algae and dead fish, to remediate poor water quality.

The numbers in the decision node in Fig. 4 show the expected utility of each restoration action according to the BDN, without specifying a specific ecological state (as in Fig. 2b). Under this model, operational changes to the reservoir and to a lesser extent riparian restoration are sensible options to manage DO levels, with the highest utilities of 0.48 and 0.4, respectively. It is possible to specify ecological states in the network represented in Fig. 4, in the same way as in Fig. 2c,d, to identify which of the eight restoration strategies maximises return (utility) for a specified set of historical conditions (Table 3). For example, where the preceding conditions were good riparian cover and a low water velocity, the restoration option with the maximum utility in the BDN (0.783) is a flow operational change, but followed closely by no restoration (0.776). By contrast, when preceding conditions were poor riparian cover and a high water velocity, the recommendation that would come out of the BDN would be no restoration (0.583); however, riparian restoration would also yield a relatively high expected utility (0.552). Where preceding conditions are poor

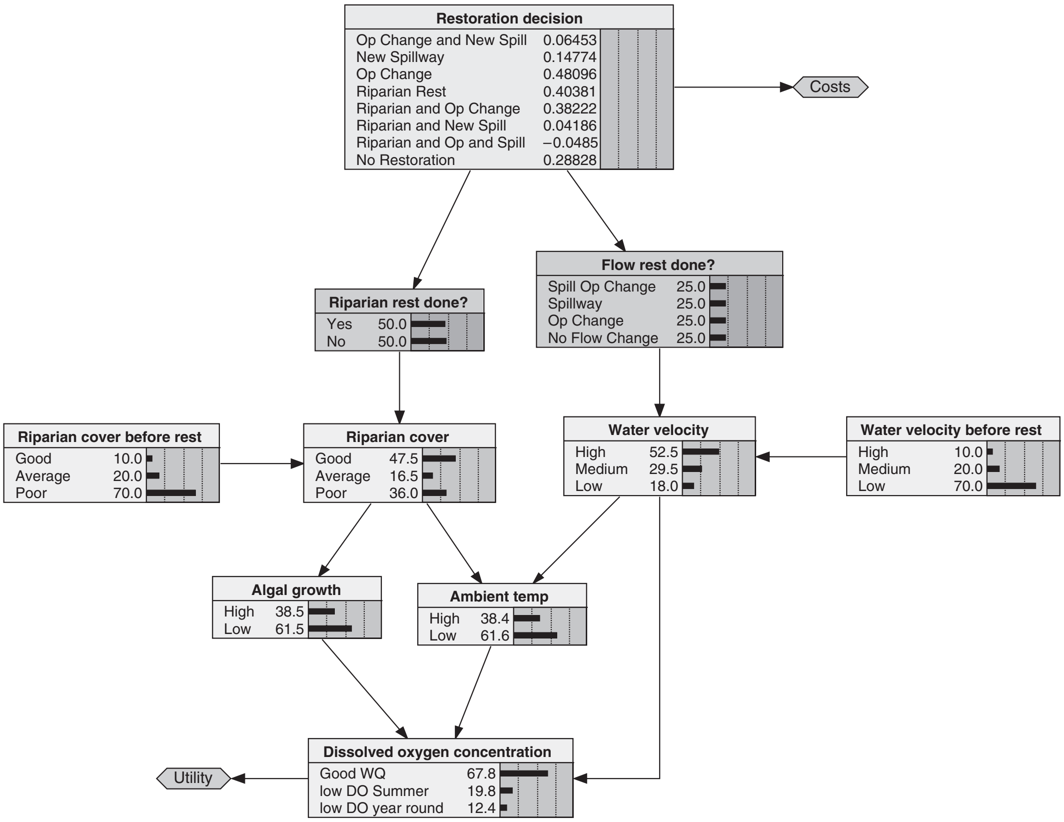

Fig. 4 Bayesian decision network incorporating costs of flow release versus riparian revegetation and the utility of each state of DO concentration. The decision node, restoration decision, illustrates the decision that maximises the utility based on costs and utilities from Table 2 averaged across all conditions in the network, operational changes to the reservoir (utility = 0.481).

riparian cover and low water velocity, the restoration action that maximises utility within the BDN would be operational changes to the reservoir (0.373), while combining this with riparian revegetation would also result in a relatively high expected utility (0.369). Of course, these outcomes reflect the information contained in the model and would be sensitive to the cost and utility functions used as well as the ecological relationships described in the CPTs. Nonetheless, these illustrative examples demonstrate how a BN and BDN can be used to assess restoration options in a systematic and quantitative fashion.

Case study 2 – managing nuisance aquatic macrophytes in rivers

Macrophytes are key components of aquatic ecosystems and their biomass, species composition, structure and distribution in the water column may strongly influence hydraulic habitat availability, water quality and the structure of other biotic assemblages (Dodds & Biggs, 2002; Strayer *et al.*, 2003; Taniguchi, Nakano & Tokeshi, 2003). However, anthropogenic disturbance to riverine ecosystems can result in excessive macrophyte growth, loss of native macrophyte species and invasion by alien species (Bunn *et al.*, 1998; Demars & Harper, 1998; King & Buckney, 2000). Excessive macrophyte growth can impede water flow and increase flood risks in canals and rivers, obstruct water intake pipes, reduce the recreational value of waterways and taint water intended for human consumption (Dunderdale & Morris, 1996; Acosta *et al.*, 1999; Sosiak, 2002).

In this example we illustrate the Bayesian approach with a more complex network describing the relationship between light availability, hydrology and aquatic macrophyte cover in streams. The majority of CPTs in this network are populated by observed data on the influence of flow regulation and riparian canopy cover on stream macrophyte communities in south-east Queensland, Australia (Mackay, 2007).

Table 2 Cost and utility functions for the restoration options in Fig. 4

Restoration action	Cost
Operational changes + new spillway	−0.6
New spillway	−0.5
Initial operational changes	−0.15
Riparian restoration	−0.4
Riparian + initial operational changes	−0.55
Riparian + new spillway	−0.9
Riparian + operational change + new spillway	−1
No restoration	0
Water quality outcome	**Utility**
No low DO events	1
Low risk of low DO events	0.4
High risk of low DO events all year	−0.2

Relative costs are standardised from 0 to −1 and devised from the cost functions illustrated in Fig. 3 with the most expensive restoration action, riparian revegetation + operational changes + new spillway assigned a value of −1. The utility function is also on a (0, 1) interval with the best water quality outcome assigned a value of +1. The most undesirable water quality outcome has a utility of −0.2 which represents likely costs of clean up due to poor water quality.

Table 3 Expected utilities of different restoration options for dissolved oxygen under three scenarios of preceding conditions from Fig. 4

Preceding conditions			
Water velocity	Low	High	Low
Riparian cover	Good	Poor	Poor
Restoration option	Utility	Utility	Utility
Spill Op Change	0.354	0.024	−0.036
Spillway	0.443	0.124	0.043
OpChange	**0.783**	0.474	**0.373**
Level 4 Riparian	0.402	0.552	0.349
Level 4 Rip OpChange	0.397	0.424	0.369
Level 4 Rip Spill	0.057	0.074	0.03
Level 4 Rip SpillOp	−0.034	−0.025	−0.059
No restoration	0.776	**0.584**	−0.02

Utility values for the restoration option with the maximum expected utility for each scenario are bolded.

Data collection

Data for the network were obtained from macrophyte surveys conducted at 19 locations (32 sites) in regulated and non-regulated river systems in south-east Queensland, Australia (Mackay, 2007). Sixteen of the 32 sites were regulated directly by dams or weirs. All sites were surveyed on two occasions (November 2003 and February–March 2004). Each site was an individual hydraulic unit (riffle, run, pool) varying in length from 20 to 40 m. Macrophyte cover was estimated in 10 randomly positioned belt transects (1 m wide) at each site as a proportion of the substrate covered by macrophytes. Macrophyte cover exceeded 100% when multiple layers of macrophyte growth occurred within a transect. The wetted width of each transect was measured to the nearest 0.1 m with a tape. Riparian canopy cover was estimated using a spherical densiometer (Lemmon, 1956). Three measurements were taken at equally spaced points on each belt transect. Turbidity was recorded *in situ* with a TPS WP89 data logger and TPS 125192 turbidity probe (TPS, Brisbane, Australia) three measurements per site, recorded in NTUs. Discharge data were supplied by the Queensland Department of Natural Resources and Water. A full description of data collection methods is outlined in Mackay (2007).

Description of the macrophyte network

The BN describing macrophyte cover (MAC_COV) is based on the conceptual model of Riis & Biggs (2001), which describes the key environmental drivers of macrophyte assemblage structure in terms of resource supply (nutrients, light) and disturbance frequency (hydrologic and hydraulic factors; Fig. 5), which can be characterised by a variety of variables. We have chosen factors that influence light conditions and availability (LIGHT_AVAIL) and those that influence hydrologic conditions (FLOOD_DIST) as drivers of MAC_COV (Fig. 5), as these variables are known to influence macrophyte assemblage structure in south-east Queensland (Mackay, 2007) and they represent environmental drivers potentially under management control.

LIGHT_AVAIL is a function of two observed predictor variables, riparian canopy cover (RIPCOV) and turbidity (TURB; Fig. 5). RIPCOV indicates the percentage of stream area that is directly covered by the riparian canopy. As such RIPCOV is a function of stream width and has a single parent node in the network, (WIDTH). LIGHT_AVAIL has three categories (high, moderate, low). High LIGHT_AVAIL represents favourable light conditions for macrophyte growth (i.e. low riparian canopy cover and turbidity) whereas low LIGHT_AVAIL represents poor light conditions for macrophyte growth (i.e. high riparian canopy cover and turbidity). The

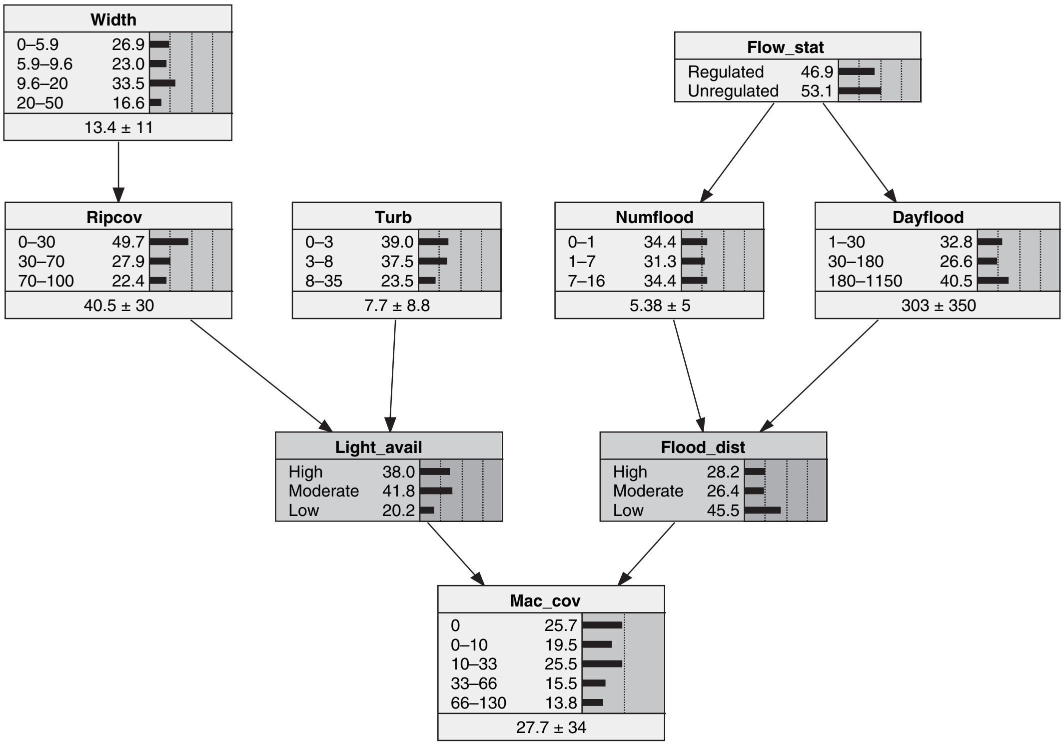

Fig. 5 Bayesian network of aquatic macrophyte cover based on data collected from streams in south-east Queensland. The network shows two distinct constraints on aquatic macrophyte cover, resource limitation through shading and turbidity and disturbance regime through flood frequency. Where continuous nodes are populated by data, the mean ± SD of the data is shown in the lower part of the node itself.

variable FLOOD_DIST is a function of two observed variables, NUMFLOOD and DAYFLOOD, which describe the frequency and timing of high flow events respectively (Fig. 5). A high flow event, or spate, is defined as an event where mean daily discharge is seven times the long-term median daily flow (Riis & Biggs, 2003) and independent events had to be separated by at least 7 days. NUMFLOOD indicates the number of spates that occurred in the 12 months prior to sampling, whereas DAYFLOOD indicates the number of days since the last spate prior to sampling. FLOOD_DIST has three categories (high, moderate and low). Low FLOOD_DIST indicates no flooding or that the last spate occurred more than 180 days prior to sampling. This represents hydrologic stability and hence opportunities for macrophytes to recover from prior flood disturbance and/or colonise new habitats (Biggs, 1996). High FLOOD_DIST indicates high spate frequency and a spate(s) occurring in the 30 days prior to sampling. Both NUMFLOOD and DAYFLOOD are a function of FLOW_STAT, which indicates whether the stream is directly regulated by either a dam or a weir. Regulated sites experience reduced flood frequency and reduced flood magnitude. CPTs for this BN were learned from data using the counting–learning algorithm in NETICA (Norsys, 2005).

Identifying potential management levers for aquatic macrophyte control

Having developed a BN that predicts the response of macrophyte cover to multiple drivers relating to light availability and hydrologic disturbance, it is now possible to incorporate cost and utility nodes to identify an effective approach for aquatic macrophyte control. In this example, we have made specific assumptions about the utility of the presence of different levels of macrophytes in the stream: that the presence of a relatively low density of macrophytes is desirable to increase habitat heterogeneity and biotic diversity but that excessive macrophyte cover is detrimental to ecosystem structure and function. A utility value of −0.2 is assigned to high macrophyte cover to reflect the cost of manual removal that may be necessary with excessive macrophyte growth. A utility of 1 is assigned to zero macrophyte cover and values in the low range, which provides some habitat and structural diversity without clogging the channel. Finally, a utility of 0 is assigned to intermediate cover values as this level of cover is approaching the level of infestation. However, the utility values assigned to cover values in practice would depend upon the position of the site(s) of interest within the stream network. In heavily shaded headwater streams that are naturally devoid of vascular macrophytes (or characterised by non-vascular macrophytes) greater utility value would be assigned to zero or low cover categories. The utility values used in this example are representative of lowland streams.

In our example, several management interventions are available to control aquatic macrophytes, again based on riparian restoration and providing high flows through environmental flow releases. We defined a BDN to allow for environmental flows to be provided monthly, bimonthly or infrequently; alternatively, investment can be made in riparian restoration, thereby influencing light conditions and flood disturbance (Fig. 6). The cost function used for these interventions is again scaled from 0 to −1 (*sensu* Zhu & McBean, 2007). The relative cost of environmental flow delivery was scaled according to stream size, based on the hydraulic geometry relationship between discharge and channel width (Newbury & Gaboury, 1993). The impact and cost of riparian revegetation depended on initial riparian condition (Fig. 6, Table 4). It is unlikely that in monetary terms, the cost of flow restoration will equal riparian restoration. Flow restoration costs could include significant capital works and ongoing payments for water allocation whereas riparian restoration might require some initial capital costs and minor ongoing maintenance. In the absence of cost data, we explore the impact of the relative weighting of these cost functions with two different scenarios: (i) cost function 1 where the most expensive riparian revegetation is half the cost of the most expensive environmental flow regime and (ii) cost function 2 where the most expensive riparian revegetation is a quarter of the cost of the most expensive flow regime (Table 4).

Each environmental flow regime will change the probability of each category of NUMFLOOD and DAYFLOOD (Table 5). For NUMFLOOD we have set the delivery of monthly flows to result in 100% probability of 7–16 spates per year, delivering bimonthly flows will provide between 1–7 spates per year while infrequent environmental flows will provide a maximum of one spate per year (Table 5a). Riparian restoration will not alter the flow regime itself and therefore the elements of Table 5a relating to riparian restoration are blank. Conditional probabilities for 'no restoration' are taken from the observed probabilities of each category of NUMFLOOD for regulated and unregulated streams respectively in Fig. 5. The CPT to illustrate the effect of monthly flooding to the number of days since the last flood, DAYFLOOD, (Table 5b) follows a similar pattern to Table 5a with the probabilities for the 'no restoration' option taken from the observed probabilities of each category of DAYFLOOD in Fig. 5. Since it is not possible to provide environmental flows of this magnitude in an unregulated stream, these elements of Table 5a,b are marked with an '*x*' and are removed from subsequent belief updating.

The potential impact of riparian revegetation (RIPCOV) on light conditions in the stream will depend on channel width (Table 6). The probabilities of different levels of RIPCOV after restoration across all stream widths were derived from expert knowledge of the potential for canopy closure in south-east Queensland streams (see Bunn *et al*., 1999). Levels 1–2 riparian restoration increases vegetative cover from 0–30% to 30–70%, levels 1–3 riparian restoration increases vegetative cover from 0–30% to 70–100% and levels 2–3 riparian restoration increases vegetative cover from 30–70% to 70–100% (Table 6). Empty cells in Table 6 indicate that in this example we have assumed that the environmental flow regime will not affect riparian cover, however, given the extensive literature that exists on this ecological interaction (Nilsson & Svedmark, 2002; Latterell *et al*., 2006), these relationships could be included in the CPT if desired.

The decision network in Fig. 6, with assumptions of responses to interventions outlined in Tables 3–6 (cost function 1), suggests that overall infrequent environmental flow releases and to a lesser extent riparian restoration (levels 2–3) would yield the greatest utility when controlling aquatic macrophyte cover. As in the

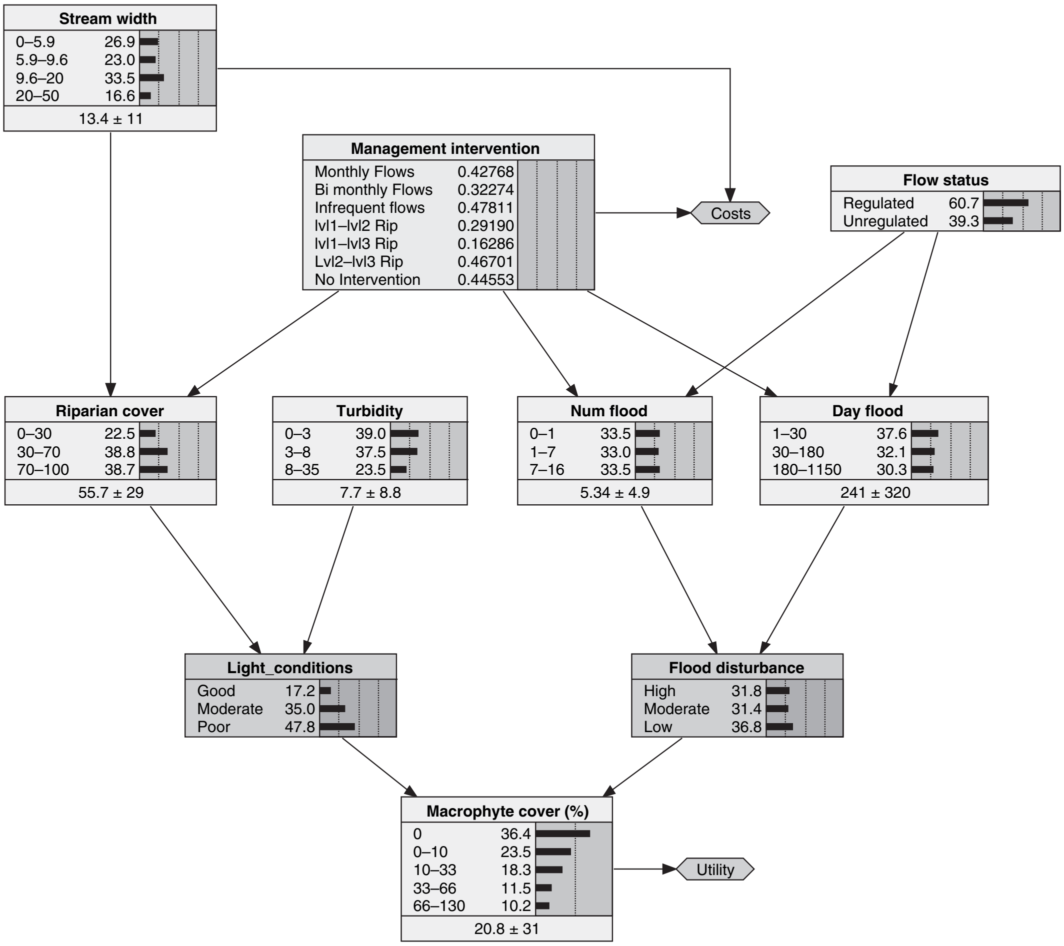

Fig. 6 Bayesian decision network for the control of aquatic macrophytes in south-east Queensland streams. The decision node, Management Intervention, illustrates that based on cost function 1 from Table 4 and utilities described in text, the decision that maximises utility averaged across all conditions in the network is infrequent flows (utility = 0.478).

first case study, it is possible to manipulate the network to identify the management action that maximises utility at different stream types. It is also apparent that predictions of maximum expected utility depend on the cost function used (Table 7). In narrow regulated streams, where the volume of water required for a flood (and therefore the cost of delivering it) is relatively low, the decision network suggests that the provision of monthly environmental flows is the management action that maximises utility, under cost functions 1 and 2. Note that utility is comparably high (0.638) for levels 2–3 riparian restoration under cost function 2. However, in large streams under cost function 1, providing infrequent environmental flows maximises the expected utility in the network, while levels 2–3 riparian restoration maximises utility under cost function 2 (Table 7). Thus there are recommendations of which restoration option to adopt given the BDN and the associated cost and utility functions.

Discussion

Anthropogenic impacts to rivers, such as flow regime changes from river regulation and catchment and riparian changes from land-use, seldom occur in isolation from each other. However, in the presence of multiple drivers of river health decline, it is often difficult to identify a primary cause–effect relationship to make rational decisions about river restoration approaches. It therefore becomes necessary to incorporate ecological theory and understanding into the restoration process (Lake, Bond & Reich, 2007). Even if the potential causal factors are known, there is a

Table 4 Two possible cost functions for the control of aquatic macrophytes standardised to a negative (0, 1) interval where the action with the greatest cost, monthly floods in the widest stream, has a cost of −1

Restoration action	Stream width (m)	Cost function 1	Cost function 2
Monthly floods	0–5.9	−0.02	−0.02
Monthly floods	5.9–9.6	−0.05	−0.05
Monthly floods	9.6–20	−0.2	−0.2
Monthly floods	20–50	−1	−1
Bimonthly floods	0–5.9	−0.01	−0.01
Bimonthly floods	5.9–9.6	−0.025	−0.025
Bimonthly floods	9.6–20	−0.1	−0.1
Bimonthly floods	20–50	−0.5	−0.5
Infrequent floods	0–5.9	−0.0002	−0.0002
Infrequent floods	5.9–9.6	−0.005	−0.005
Infrequent floods	9.6–20	−0.02	−0.02
Infrequent floods	20–50	−0.1	−0.1
Levels 1–2 Rip Rest		−0.25	−0.125
Levels 1–3 Rip Rest		−0.5	−0.25
Levels 2–3 Rip Rest		−0.25	−0.125
No intervention		0	0

Costs of flooding decrease according to the relationship between channel width and discharge volume. The cost of riparian revegetation is assumed constant across stream widths. Under cost function 1, the most expensive riparian revegetation is half the cost of the most expensive flood regime and under cost function 2, the most expensive riparian revegetation is a quarter of the cost of the most expensive flood regime.

need to consider the costs of available river restoration options with respect to their efficacy. BNs and BDNs can be used to incorporate the costs of restoration actions as well as the expected benefits (utility). Using BNs in this way allows managers to make decisions based on the ecological understanding of a system with a quantitative basis.

Selecting restoration strategies under multiple stressors

We have demonstrated how BDNs can be used to determine a restoration decision in the common situation of multiple stressors impacting riverine conditions. In this context, there can be various restoration options available to a river manager. However, it may not be clear as to which is going to be the most effective relative to the costs of implementation and the expected ecological response. Implementing a BDN approach provides decision makers with a method of combining ecological responses with budget constraints. We used simple examples of specific ecosystem health goals, minimising low DO events and reducing nuisance macrophytes, to illustrate the approach without requiring detailed and potentially confusing descriptions of network structure and CPTs. As a consequence, the results from the BDNs we developed may seem unsurprising. However, in other scenarios with different river health goals such as biodiversity outcomes or multiple indices of ecosystem health (e.g. Borsuk *et al*., 2004; Said *et al*., 2006) the most effective restoration option is unlikely to be so obvious. This approach encourages river managers to consider multiple stressors and potential restoration measures in a transparent framework incorporating costs, benefits and expected ecological response.

Dealing with the different timing of investment for restoration strategies

When investing in vegetation restoration a large proportion of the investment is incurred in the initial phases, whereas the delivery of environmental flows is likely to incur costs on an ongoing basis with costs dependent on the volume of water released over time. This presents an important challenge to consider as it is difficult to incorporate temporal dynamics or feedback loops in BNs (Uusitalo, 2007). However, accounting for the difference in timing of the costs of restoration and the accrual of utilities can be approached in various ways. In the networks presented in this paper, we have treated costs and utilities over the long-term assuming they will eventually be recouped or incurred by including total costs and utilities in a single node for each. An alternative approach would be to include one utility node for each time step over which the network was developed (e.g. monthly) to represent the accrual of economic benefits through a given year (Ames, 2002). Each separate utility node then contributes to the overall utility within the BN. The same approach can be used for costs incurred over time. It is important to consider the timing of the costs and utilities to be incurred when developing the cost and utility functions to successfully implement a BDN approach and ensure transparent decision making.

Challenges when using Bayesian networks

It is clear that the nature of the cost and utility functions will influence any conclusions about optimal restoration options (Table 7); therefore it is

Table 5 Conditional probability tables for (a) NUMFLOOD and (b) DAYFLOOD in the decision network for the control of aquatic macrophytes

Flow status	Management intervention	0–1	1–7	7–16
(a)				
Regulated	Monthly floods	0	0	100
Regulated	Bimonthly floods	0	100	0
Regulated	Infrequent floods	100	0	0
Regulated	Levels 1–2 Rip Rest			
Regulated	Levels 1–3 Rip Rest			
Regulated	Levels 2–3 Rip Rest			
Regulated	No restoration	63.0363	16.8317	20.132
Unregulated	Monthly floods	*x*	*x*	*x*
Unregulated	Bimonthly floods	*x*	*x*	*x*
Unregulated	Infrequent floods	*x*	*x*	*x*
Unregulated	Riparian restoration	*x*	*x*	*x*
Unregulated	Levels 1–2 Rip Rest			
Unregulated	Levels 1–3 Rip Rest			
Unregulated	Levels 2–3 Rip Rest			
Unregulated	No restoration	9.03788	44.0232	46.9389
		1–30	30–180	180–1150
(b)				
Regulated	Monthly floods	100	0	0
Regulated	Bimonthly floods	50	50	0
Regulated	Infrequent floods	0	50	50
Regulated	Levels 1–2 Rip Rest			
Regulated	Levels 1–3 Rip Rest			
Regulated	Levels 2–3 Rip Rest			
Regulated	No restoration	26.7327	10.231	63.0363
Unregulated	Monthly floods	*x*	*x*	*x*
Unregulated	Bimonthly floods	*x*	*x*	*x*
Unregulated	Infrequent floods	*x*	*x*	*x*
Unregulated	Levels 1–2 Rip Rest			
Unregulated	Levels 1–3 Rip Rest			
Unregulated	Levels 2–3 Rip Rest			
Unregulated	No restoration	38.1924	41.1079	20.6997

Where a flooding regime is prescribed by the Management Intervention decision node, there is a probability of 100% for that level of the node, NUMFLOOD or DAYFLOOD. For 'No restoration' probabilities are the observed probabilities for regulated and unregulated streams respectively, taken from the Bayesian network in Fig. 5. Since riparian revegetation has no effect on flooding, these probabilities are blank and therefore assumed uniform. Probabilities for flow releases in unregulated streams are marked with an '*x*' as this is impossible.

imperative that they be as accurate as possible. Where possible, it is preferable to use economic data based on estimated costs of restoration or environmental flow delivery to generate cost nodes and estimated revenues to generate utility nodes (e.g. Ames *et al.*, 2005). However, such information may not always be available or there may be no direct economic benefits resulting from the restoration, in which case alternative approaches based on the ecological value of each restoration outcome may be used to develop a standardised index of cost and utility. There is no one right way to develop such subjective cost and utility functions and many approaches could be used. For example, standardising utility values across the categories of the restoration target, or devising a scale of acceptability based on what would be an acceptable outcome to society for any given restoration problem. There is considerable scope for error in subjective utility nodes, making full disclosure of their structure a vital aspect of transparent decision making.

In addition to limitations associated with temporal dynamics and the difficulty of deriving cost and utility functions in the absence of data, there are other limitations that must be considered when developing

Table 6 Conditional probability table for Riparian Cover in the decision network for the control of aquatic macrophytes

Width (m)	Management intervention	0–30	30–70	70–100
0–5.9	Monthly floods			
0–5.9	Bimonthly floods			
0–5.9	Infrequent floods			
0–5.9	Levels 1–2 Rip Rest	0	100	0
0–5.9	Levels 1–3 Rip Rest	0	0	100
0–5.9	Levels 2–3 Rip Rest	0	0	100
0–5.9	No restoration	29.1429	29.7143	41.143
5.9–9.6	Monthly floods			
5.9–9.6	Bimonthly floods			
5.9–9.6	Infrequent floods			
5.9–9.6	Levels 1–2 Rip Rest	0	100	0
5.9–9.6	Levels 1–3 Rip Rest	0	0	100
5.9–9.6	Levels 2–3 Rip Rest	0	0	100
5.9–9.6	No restoration	32	38	30
9.6–20	Monthly floods			
9.6–20	Bimonthly floods			
9.6–20	Infrequent floods			
9.6–20	Levels 1–2 Rip Rest	0	100	0
9.6–20	Levels 1–3 Rip Rest	0	50	50
9.6–20	Levels 2–3 Rip Rest	0	30	70
9.6–20	No restoration	55.5046	31.6514	12.844
20–50	Monthly floods			
20–50	Bimonthly floods			
20–50	Infrequent floods			
20–50	Levels 1–2 Rip Rest	80	20	0
20–50	Levels 1–3 Rip Rest	70	30	0
20–50	Levels 2–3 Rip Rest	0	100	0
20–50	No restoration	95.4128	3.66972	0.917432

Where riparian revegetation is prescribed by the Management Intervention decision node, a probability of 100% for that level of the node is the result. For 'No restoration' probabilities are the observed probabilities for each category of stream width taken from the Bayesian network in Fig. 5. We have assumed that flooding has no effect on Riparian Cover; therefore these probabilities are blank and assumed uniform.

BNs to guide stream restoration decisions. In most commonly available software packages there is a restriction to using categorical variables, requiring continuous variables to be converted to categories or states (Korb & Nicholson, 2004). To retain parsimony, the fewest states required to reflect assumed causal relationships should be used for each node (Marcot *et al.*, 2006). While algorithms that automatically categorise continuous nodes do exist (e.g. Norsys, 2005), specifying the appropriate number and levels of states for each node can be challenging. Scientific interpretability may provide a useful guideline (Uusitalo, 2007) with defensible ecological boundaries identified *a priori*. As with all modelling approaches the balance between parsimony and precision must be found (Levin, 1992), and this applies to network structure as well as the number of states within each node (Marcot *et al.*, 2006).

'All models are wrong, but some are useful' – Box (1979)

With any BN there is the possibility that the network does not reflect the modelled ecosystem processes; even the most accurate BN is still only a model of the ecosystem. Therefore, an important aspect of the use of BNs is eliciting information from experts regarding the structure of the network or prior probabilities, or to populate the CPTs in the absence of data (Uusitalo, 2007). There is a body of literature devoted to the elicitation of probabilities for Bayesian modelling (Kadane & Wolfson, 1998; Clemen & Winkler, 1999). For any BN that is largely populated by expert opinion it is important to consider the possibility of error in the experts' opinions. To place trust in a BN based on invalid or error-prone expert opinion could lead to potentially costly management decisions. Therefore, the selection of experts for expert opinion is an important phase of network development and must be undertaken carefully to ensure information upon which the BN is based is reliable with key uncertainties acknowledged (Ayyub, 2001). Developing the BN with a thorough literature review, possibly in tandem with expert elicitation would help to improve the accuracy of the network. Sensitivity analysis, the process of analysing how sensitive any conclusions are to minor changes in network structure and/or CPTs (Jensen & Nielsen, 2007), can be used to understand the impact of key uncertainties and also to identify potential errors in the network (Reichert *et al.*, 2007). Where possible, updating the network with newly collected data from monitoring programs would improve the network. Thus, following a rigorous process of expert selection, undertaking sensitivity analysis and updating the probabilities in the network with data as they become available in the future, will help to ensure the network reflects the ecosystem processes under study as accurately as possible and ensure greater confidence in and reliability of the BN or BDN and its outputs.

Recognising the uncertainty of our understanding of ecological processes is an important aspect of environmental decision making (Reckhow, 1994). A key advantage of BNs is that these models propagate predictive uncertainty (Borsuk *et al.*, 2004). Conceptual ecological models (Fig. 2a) generally assume a

Table 7 Cost and utility of each restoration action to control aquatic macrophytes in regulated streams at two different widths

Prevailing conditions				
Stream width	0–5.9 m		20–50 m	
Flow status	Regulated		Regulated	
Restoration option	Cost 1	Utility	Cost 1	Utility
Monthly floods	−0.02	**0.658**	−1	−0.322
Bimonthly floods	−0.01	0.438	−0.5	−0.052
Infrequent floods	−0.0002	0.502	−0.1	**0.403**
Levels 1–2 Rip Rest	−0.25	0.341	−0.25	0.048
Levels 1–3 Rip Rest	−0.5	0.263	−0.5	−0.166
Levels 2–3 Rip Rest	−0.25	0.513	−0.25	0.341
No intervention	0	0.531	0	0.231
Restoration option	Cost 2	Utility	Cost 2	Utility
Monthly floods	−0.02	**0.658**	−1	−0.322
Bimonthly floods	−0.01	0.438	−0.5	−0.052
Infrequent floods	−0.0002	0.502	−0.1	0.403
Levels 1–2 Rip Rest	−0.125	0.466	−0.125	0.173
Levels 1–3 Rip Rest	−0.25	0.513	−0.25	0.084
Levels 2–3 Rip Rest	−0.125	0.638	−0.125	**0.466**
No intervention	0	0.531	0	0.232

The two cost functions outlined in Table 4 are compared for each stream type, with the maximum utility for each scenario in bold text.

directional relationship between two or more ecological factors or processes, such as aquatic plant photosynthesis/respiration and riparian shading. However, there may be uncertainty around the nature or strength of these relationships due to limited understanding of the system or due to the exclusion of certain causal processes from the BN (Fig 2b). Using a BN for modelling these relationships ensures the propagation of uncertainty that may arise from these issues. For example, Fig. 2a suggests that increasing stream shading will decrease aquatic plant photosynthesis and respiration. While this may generally be true, increasing riparian shading may not always dramatically alter aquatic plant growth. Other factors that may not be included in the BN such as stream orientation, flow regime or instream nutrient concentrations also regulate aquatic plant growth. In the BN probabilities of all levels of plant growth under higher levels of riparian shading are estimated and propagated through subsequent child nodes, thereby incorporating any uncertainty that may exist about the nature of that ecological process as represented in the network (e.g. Fig. 2c,d). Therefore, while any BN will be subject to error, this method can also explicitly incorporate any uncertainty in the understanding of the ecological process under study.

We encourage river managers to consider modelling approaches such as those outlined here in restoration planning. The use of BNs is not the only approach available to ecosystem managers for decision support; however, it is a relatively straightforward method to capture the conceptual understanding of a system. This approach will not solve river restoration problems itself, but rather it provides a framework in which to consider the problem in the context of known and uncertain ecological relationships. The development of conceptual models ensures that the specific goals are clearly articulated and that likely cause–effect linkages are identified. For most environmental management problems, direct experimentation to infer causality between disturbance factors and river health indicators is limited. Nevertheless, in some instances there may be strong correlative evidence and/or expert understanding of these relationships. In these cases BNs represent an attractive approach to explore how multiple environmental drivers may affect ecosystem health goals allowing managers to consider the impacts of flow-related and land-use related stressors together. The provision of flow is an essential prerequisite for maintaining the health of a river, even where other environmental factors may be limiting (Poff *et al.*, 1997, 2010; Bunn & Arthington, 2002). However, in heavily regulated and sometimes over-allocated systems, the costs and benefits of purchasing water for the environment need to be compared with the costs and benefits of investing in other forms of restoration. The use of BDNs provides a transparent, probabilistic approach to support such decisions.

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