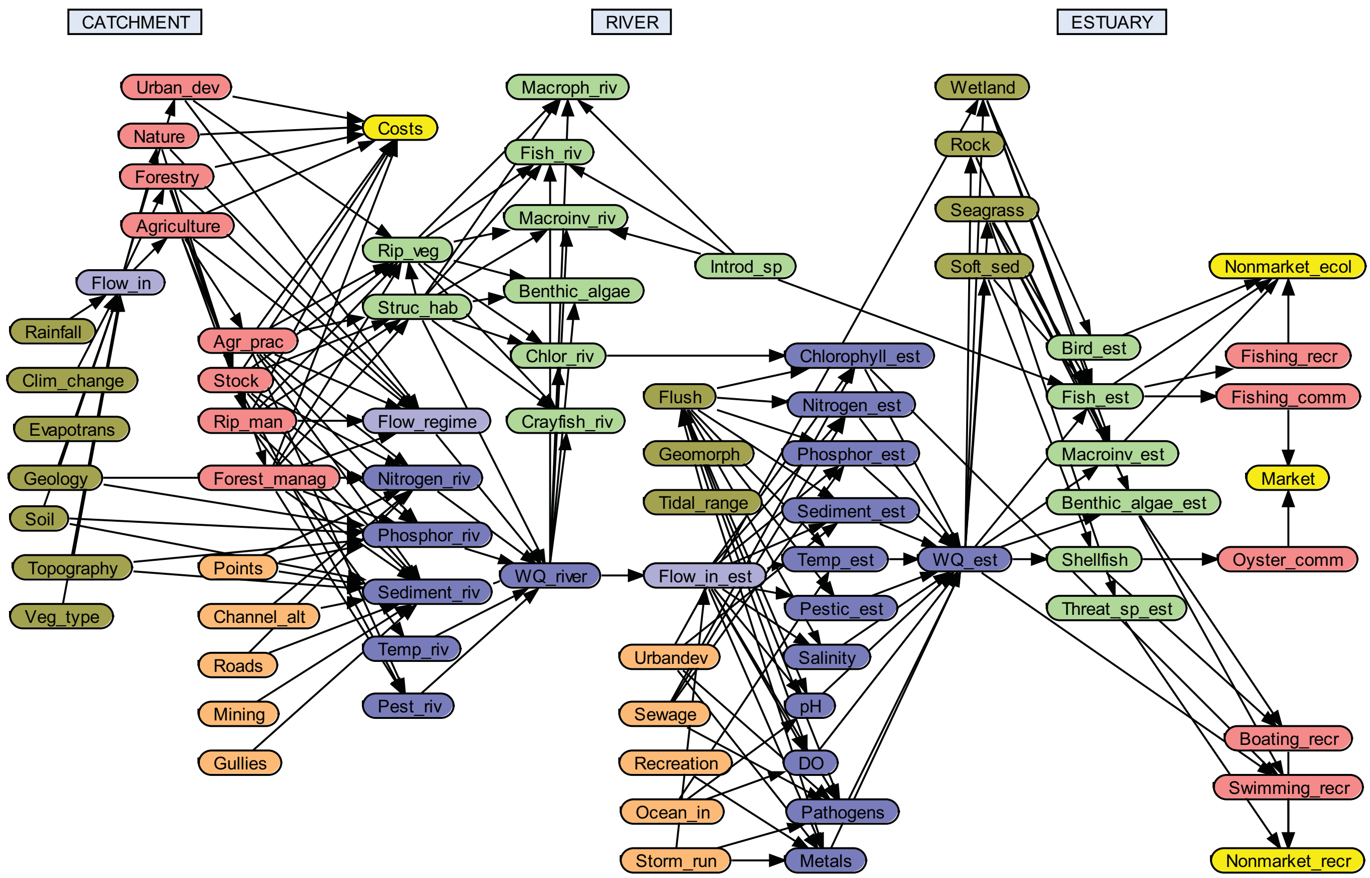
LANDSCAPE LOGIC

LINKING LAND AND WATER MANAGEMENT TO RESOURCE CONDITION TARGETS

Technical Report No. 9

A beginners guide to Bayesian network modelling for integrated catchment management



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Cover image: Conceptual influence diagram for the George catchment Bayesian Network, expert workshop, October 2007.

LANDSCAPE LOGIC is a research hub under the Commonwealth Environmental Research Facilities scheme, managed by the Department of Environment, Water Heritage and the Arts. It is a partnership between:

- **six regional organisations** – the North Central, North East & Goulburn–Broken Catchment Management Authorities in Victoria and the North, South and Cradle Coast Natural Resource Management organisations in Tasmania;
- **five research institutions** – University of Tasmania, Australian National University, RMIT University, Charles Sturt University and CSIRO; and
- **state land management agencies in Tasmania and Victoria** – the Tasmanian Department of Primary Industries & Water, Forestry Tasmania and the Victorian Department of Sustainability & Environment.

The purpose of Landscape Logic is to work in partnership with regional natural resource managers to develop decision-making approaches that improve the effectiveness of environmental management.

Landscape Logic aims to:

1. Develop better ways to organise existing knowledge and assumptions about links between land and water management and environmental outcomes.
2. Improve our understanding of the links between land management and environmental outcomes through historical studies of private and public investment into water quality and native vegetation condition.

A beginners guide to Bayesian network modelling for integrated catchment management

By Marit E. Kragt

Summary

Catchment managers often face multi-objective decision problems that involve complex biophysical and socio-economic processes. In recent years, it has been acknowledged that the interrelationships between these biophysical and socioeconomic systems require integrated approaches to catchment management. The Landscape Logic research hub aims to develop tools that aid such integrated assessment, using Bayesian Network (BN) modelling approaches.

In this report, the theory behind BNs, and the steps involved in developing a BN model are reviewed. A number of example BNs related to catchment water resource management are discussed.

The examples show that BNs offer a comprehensive way to portray the complex systems associated with catchment management. The simple graphical representation in BNs can help stakeholders to understand the trade-offs involved in multi-objective catchment management. BNs also have the advantage that their structure can accommodate a variety of knowledge sources and data types. Furthermore, the explicit recognition of uncertainty can help decision-makers to identify the risks associated with different management strategies.

Reviewing existing BNs aids in the identification of current knowledge gaps and some challenges involved in BN development that researchers need to be aware of when developing their own BN model. Two prominent issues that are apparent from the reviewed literature is the lack of knowledge and experience about the ecological and socio-economic systems that are influenced by catchment management changes.

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Contents

Introduction

Catchment managers in Australia are faced with complex decision problems that involve multiple systems and stakeholders, varying from environmental and ecological issues to social and economic concerns. To support decision-making, modelling tools have been developed that aim to capture system complexities by incorporating the hydrological, ecological, economic and social processes impacted by changed catchment management (Argent, 2004, Hajkowicz *et al*, 2005). However, many of these tools are limited to either biophysical models that assess environmental changes, or to economic models focussing on socio-economic systems.

Despite the policy interest in integrated catchment management, and the identified need for decision support tools, there is still limited experience in developing catchment models that evaluate environmental and economic trade-offs in one framework (Reinhard and Linderhof, 2006).

Integrated modelling approaches are needed that capture the complex interactions between biophysical and socio-economic processes to enable an assessment of alternative catchment management policies.

The Landscape Logic CERF program aims to develop evidence-based tools to enable more informed integrated catchment management. The objective of the study of which the present report forms a part is to demonstrate how different processes associated with catchment management actions can be integrated into one framework using a case study in the George catchment, Tasmania. The outcomes of the study will enable decision makers to analyse the tradeoffs between the costs and benefits associated with changes in catchment management and environmental conditions.

A major challenge for the projects in the Landscape Logic program is the combination and translation of knowledge from many different academic disciplines, and from non-academic fields, into single, logically consistent frameworks. The models that are part of such integrated frameworks need to accommodate a suite of catchment processes. Some processes (for example, in catchment hydrology) may be clearly described by deterministic models or can be derived from observational data. However, many biophysical and socio-economic processes impacted by changes in catchment management actions are not well understood and are inherently subject to uncertainty. Using a deterministic model that relies on quantitative data will not be useful when there is limited information about the system. The analyst may need to rely on expert judgment to assess uncertain processes. The integration framework needs to have the capacity to handle uncertainty in the data and accommodate different data sources. One useful method for combining deterministic models with observations and expert knowledge is the use of Bayesian Networks (Pearl, 1988).

As part of the Bayesian Network (BN) development in the George catchment case study, existing BNs were reviewed. The present report presents relevant results of this review. In the next section, the concepts behind BNs will be introduced, while section three describes the steps in BN model development. Section four discusses some noteworthy examples of BNs that have been used to assess changes in water quality or catchment management. The last section summarises and outlines some implications for developing integrated modelling tools for catchment management.

Bayesian Networks

Bayesian Networks (sometimes called belief networks or causal probabilistic networks) are probabilistic graphical models, widely used for knowledge representation and reasoning under uncertainty in natural resource management. There is a rising interest in BNs as tools for ecological and water resource modelling (see, for example, McCann *et al*, 2006, Castelletti and Soncini-Sessa, 2007, Ticehurst *et al*, 2007). BNs provide a method for representing relationships between variables (called 'nodes' in the BN) even if the relationships involve uncertainty. They can be a useful modelling tool in situations where different types of variables and knowledge from various sources need to be integrated within a single framework (Pearl, 1988, and Jensen, 1996).

BNs have been applied to a variety of natural resource management issues. Applications in ecological modelling include, for example, the modelling of responses of Brown Trout to habitat patterns (Borsuk *et al*, 2006); assessment of native fish communities (Pollino *et al*, 2007) and the response of wildlife species to environmental conditions (Marcot *et al*, 2001). Applications to catchment management issues are presented in Dorner *et al* (2007), who employed a BN to assess the impacts of agricultural non-point source pollution on a catchment scale, and Sadoddin *et al* (2005) who used a catchment-scale BN to assess the ecological impacts of dryland salinity. Water resource management and stakeholder involvement in decision making was the focus of projects described in Bromley *et al* (2005) and Hendriksen *et al* (2007). In the context of coasts and estuaries, BNs have been applied by Borsuk *et al* (2004) to assess the causes and effects of eutrophication of the Neusa River estuary, by Hamilton *et al* (2007) to model the risks of *Lyngbya majuscula* blooms in Deception Bay, Queensland and by Ticehurst *et al* (2007) to assess the sustainability of coastal lakes in New South Wales.

In the following sections, the theory behind BNs and their strengths and weaknesses are described. Further details about Bayesian Networks and probability calculus can be found in Pearl (1988) and Jensen (1996).

Bayesian Network theory

A Bayesian Network consists of a directed acyclic graph of 'nodes' and 'links' that conceptualise a system. The values of the nodes are defined in terms of different, mutually exclusive, 'states' (McCann *et al*, 2006). The relationships between nodes are described by conditional probability distributions that capture the dependences between variables. If there is a link going from node *A* to node *C*, then *A* is said to be a 'parent node' of *C*, and *C* is said to be a 'child node' of *A*. In Figure 1(a), parent nodes *A* and *B* represent the causal factors of child node *C*. The states of nodes *A* to *C*, arbitrarily selected for ease of demonstration here, are depicted in Figure 1(b). Node *A* can assume the discrete states 'high' or 'low' and node *B* can assume discrete states 'true' or 'false'. The states of variables *A* and *B*[1] will determine whether variable *C* is in state 'high', 'medium' or 'low'. The conditional relationship between parent nodes *A* and *B* and child node C is defined by a conditional probability table (CPT). The CPT in Figure 1(c) can be interpreted as the probability that *C* will be in its High, Medium and Low states, given the states of *A* and *B*.

Figure 2 shows another example of a BN structure where Erosion is the parent node of *Sediment* and *Nutrient concentrations* in water. Changed nutrient concentrations will impact upon child node *Algae growth*. Sediment concentrations in the water affects *Turbidity* (an intermediate node), which in turn impacts algae growth.

Different types of nodes can be included in a BN: 'nature' nodes, 'decision' nodes and 'utility' nodes. *Nature* nodes are variables that can be controlled by actions of the decision-maker (for example, *sediment* or *nutrient concentrations* in river water). Nature nodes are used to represent the empirical or calculated parameters and the probabilities that various states will occur. Input nodes (nodes without parents) can either be structured as constants or as categorical states with associated marginal probability distributions. A *decision node* represents control variables or events that can directly be implemented by the decision maker (for example, *erosion control* measures in Figure 2). These nodes

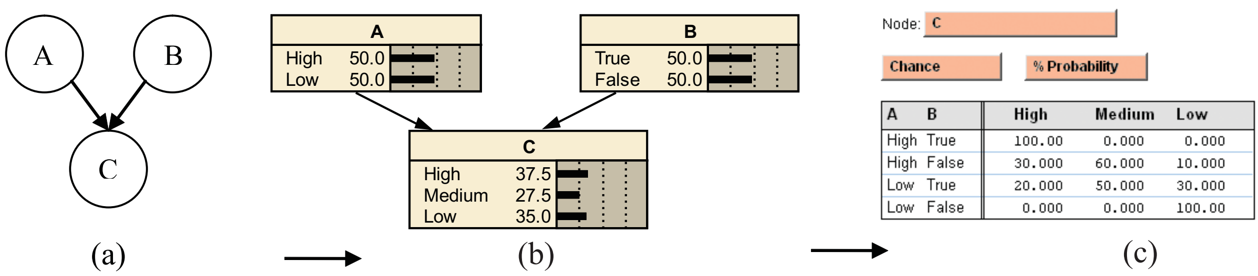


Figure 1. Example Bayesian Network structure.

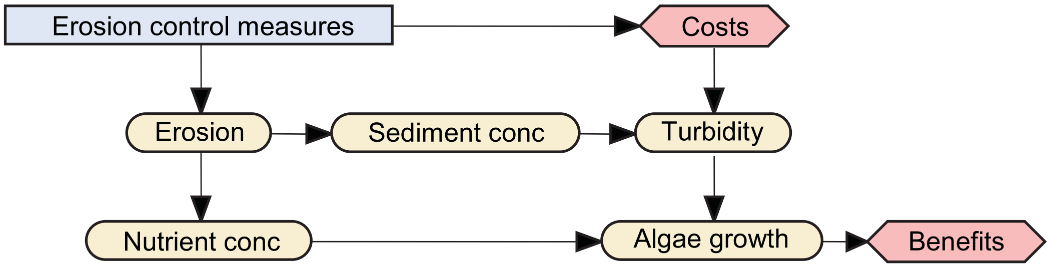


Figure 2. Example Bayesian Network structure for erosion, water quality and algae growth.

typically represent the suite of available management actions. Decision nodes should always be accompanied by utility nodes. These *utility* nodes represent the value of the decisions or outcomes. A utility node can be linked directly to the decision node (for example, costs in Figure 2), or to the outcome node (for example, *benefits* in Figure 2). The utility nodes are used to assess the optimal decision rules in the network that will maximise the sum of expected values of the utility nodes.

Bayesian Networks rely on Bayes' theorem of probability theory to propagate information between nodes. Bayes' theorem describes how prior knowledge about hypothesis *H* is updated by observed evidence *E*. The theorem relates the conditional and marginal probabilities of *H* and *E* as follows[2]:

$$P(H|E) = \frac{P(H) \cdot P(E|H)}{\int P(H) \cdot P(E|H) \cdot dE} \qquad (1)$$

where P(H) is the prior probability of the hypothesis (the likelihood that H will be in a particular state, prior to consideration of any evidence); P(E|H) is the *conditional probability* (the likelihood of the evidence, given the hypothesis to be tested); and P(H|E) is the *posterior probability* of the hypothesis (the likelihood that H is in a particular state, conditional on the evidence provided). The integral in Equation 1 represents the likelihood that the evidence will be observed, given a probability distribution. The presentation in the form of probabilities gives an explicit representation of uncertainty (Bromley *et al*, 2005).

Advantages and disadvantages of Bayesian Networks

There are some obvious advantages of working with BNs (Table 1). BNs can facilitate learning about causal relationships between variables (Uusitalo, 2007) and can easily be converted into decision support tools to aid natural resource management (Marcot *et al*, 2001). The graphical nature of a BN clearly displays the links between different system components. This can facilitate discussion of the system structure with people from a wide variety of backgrounds and can encourage interdisciplinary discussion and stakeholder participation (Martín de Santa Olalla *et al*, 2005). The use of Bayesian inference means that a BN can be readily updated, when new knowledge becomes available (Ticehurst *et al*, 2008).

Natural resource management deals with complex and heterogeneous issues. There is often a lack of information about one or more processes involved in natural systems. Models that rely on data alone (e.g. traditional deterministic or process models) are not suitable to assess uncertain processes in the system. BNs provide a way to overcome data limitations by incorporating input data from different sources. BNs are therefore useful tools for addressing uncertainty in data and combining observations, model simulation and expert knowledge (Uusitalo, 2007).

A convenient feature of BNs is the ability to learn about the structure and parameters of a system based on observed data. Knowledge of the structure of a system can reveal the dependence and independence of variables and suggest a direction of causation. It evaluates the 'optimal' BN structure, based on the highest probability score for possible candidate structures, given the data provided and perhaps penalised for the level of complexity (Norsys, 2005). Different score metrics can be used to evaluate the BN structure, varying from entropy methods (Section 3.4) to genetic algorithms. Parameter learning entails estimating the CPT at each node, given the link structures and the data. Parameter learning is based on Bayesian learning algorithms[3] that aim to find the maximum likelihood for the CPTs in a given BN. Of course, 'sufficient' observations are needed to enable an estimation of conditional probabilities and the availability of 'enough' observed data is precisely a limitation in many natural resource management issues. If there are lots of missing observations, BNs can use complex learning algorithms to learn the tables. The distribution of the missing data needs to be defined and may be dependent on the states of other variables or they can be randomly distributed. Kontkanen *et al* (quoted in Uusitalo, 2007) demonstrate that BNs can yield good prediction accuracy using learning algorithms, even if sample sizes are small.

Table 1. Strengths and limitations of Bayesian Networks.

Strength	Limitations
Transparent representation of causal relationships between system variables	Difficult reaching agreement on the BN structure with experts
Use a variety of input data	Difficult defining the CPTs with expert opinion
Representation of uncertainty	Continuous data representation
Visual decision support tool	Spatial and temporal dynamics
Can handle missing observations	No feedback loops
Structural and parameter learning	
New evidence can be incorporated	

There are also some clear limitations to BN models. While Bayesian models are a useful way to model expert knowledge, it may be difficult to get experts to agree on the structure of the model and the nodes that are important to be included. Furthermore, experts may be challenged to express their knowledge in the form of probability distributions (Uusitalo, 2007). Elicitation of expert knowledge requires an iterative process, to ensure that experts are comfortable with the nodes, their states and interrelationship in the BN, before they can make statements about distributions and confidence intervals of variables (Pollino, 2008).

Furthermore, some BN software packages may have limited ability to deal with continuous data. Such data generally needs to be 'discretised' (broken up into discrete states). The states need to comprise interval values that define the total range of values the continuous variable can assume. Although discretising is a convenient way to control the size of the network, discrete states may not capture the original distribution of the variable completely and can lead to lower precision of variable values (Nyberg *et al*, 2006). Barton *et al* (2008) show how discretisation assumptions can significantly affect the outcome estimates.

Another limitation that has been defined in the literature stems from the acyclic nature of BNs. The acyclic property is required to carry out probability calculus, but implies that feedback effects cannot be included in the network (Barton *et al*, 2008). There is also a limit to the spatial and temporal scales that can be modelled within one BN. The usual approach to account for different scales is to develop a network for each geographical site or time period, and running these separately, inevitably increasing the size of the model.

Software

A number of commercial software packages are available for developing BN based models. The most popular ones are Analytica (Lumina, 2004); Netica (Norsys, 2005); Hugin (Hugin Expert A/S, 2004); and GeNie (DSL, 2005). Each package has its own strengths and disadvantages (Table 2). Information about some different software packages available for BNs is provided by Murphy (2007).

The Netica application was used to develop many of the Bayesian models in the Landscape Logic project (Landscape Logic, 2008). The Netica software tool can build, learn, modify, transform and store nets, as well as answer queries or find optimal solutions (Norsys, 2005). Netica performs standard belief updating which solves the network by finding the marginal posterior probability for each node (Marcot *et al*, 2001). One advantage of Netica is the comprehensive, flexible and user friendly graphical user interface included in the package (Uusitalo, 2007).

Table 2. Some software packages available for building Bayesian Networks.

Package	Graphical User Interface?	Parameter learning?	Structural learning?	Utility nodes supported?	Free?	Inference algorithm
Analytica	Yes	No	No	Yes	No	MC sampling
GeNie	Yes	Yes	Yes	Yes	Yes	Various[a]
Hugin Expert	Yes	Yes	Yes[b]	Yes	No	Junction tree
Netica	Yes	Yes	No	Yes	No	Junction tree

a GeNie supports many different inference algorithms, see http://genie.sis.pitt.edu/wiki/GeNIe_Documentation.

b Using conditional independency tests.

Bayesian Network development

Figure 3 outlines the major steps in constructing a BN. Model development is an iterative process that may need to be repeated several times before a valid and useful BN is established (Farmani *et al*, 2009).

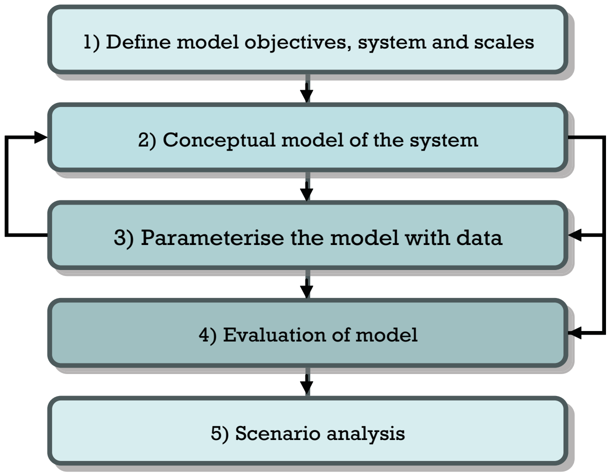


Figure 3. Major steps in developing a Bayesian Network. (Adapted from Ticehurst et al, 2008.)

Model objectives

As stressed by Jakeman *et al* (2006), any model development process should start with a definition of the model's objective and the scope of the system to be considered. First of all, there needs to be agreement about the aim of the model, the system under consideration and the issues involved. Model developers generally need to decide on the selection of stakeholders that will be consulted in the modelling process. These could range from local councils, landholders and community organisations to State governments and scientists.

Various stakeholders may consider a multitude of issues related to the system, which could lead to different modelling objectives for different stakeholders. Where scientists may be interested in increasing their understanding of the system, decision makers may be more concerned with prediction or forecasting. The issues considered in the model will affect the management decisions that will be included in the Bayesian network. Engagement with end-users is required to ensure that management scenarios to be considered are relevant to stakeholders.

The definition of the system under consideration may also differ between stakeholders and even between the different scientific disciplines involved in developing a Bayesian model. Agreement is needed about the spatial and temporal scales that are relevant to the system. The scope of the system needs to be defined in terms of the assets or values that will be considered in the modelling. This first phase of model development should result in a clear picture of the system that is to be modelled, its scale and scope, the discrete environmental condition or endpoint, which stakeholders will be involved and the management scenarios that are relevant to the system.

Conceptual model development

When the model's objectives are defined, a conceptual BN can be developed. The initial conceptualisation includes: (1) Identifying the important system variables; and (2) Establishing the links between variables.

Identifying the variables ('nodes') that are important for the system that is being modelled is typically based on a literature review, expert opinion and consultation with stakeholders. Included nodes should at least be measurable, observable or predictable and should have unambiguous definitions (Borsuk *et al*, 2004). 'Oyster populations', for example, could mean oyster size, oyster hatching success or oyster quality. Nodes should be defined such that all model users understand what variable is represented. Once the variables are chosen, the links between them need to be identified. It is recommended that the number of parent nodes is kept to three or fewer, to limit the size of the CPT (Marcot *et al*, 2006).

The identification of nodes and the links between them should result in a conceptual influence diagram representing the system under consideration. The conceptual model development may involve iterative rounds of expert meetings and stakeholder consultation and is refined in the model evaluation stage. Conceptual models should capture the objective and scales of the model, provide a clear (graphical) representation of the system and address stakeholder concerns and needs. Conceptual models can assist with clarifying system understanding and identifying priorities and knowledge gaps.

Parameterising the model

The third step involves assigning states and probabilities to each variable. The states for each node represent the potential values or conditions that the node can assume. States can be of different types, such as one numerical value, an interval, a probability distribution or a categorical definition (Martín de Santa Olalla *et al*, 2005). The state types and the number of states for a node[4] is based on the type and quality of data available, and on the level of model parsimony desired by model developers and its users. Both node state types and 'coarseness' are finetuned at the model evaluation stage. The initial starting values for each node can be elicited from literature, using existing data sets or models or by discussions with experts or stakeholders.

Once the state type and number of states have been defined, the conditional probabilities for the states of each child node are specified for all combinations of states of their parent nodes. A prior expectation of the probability of a node being in a certain state can be elicited from known frequencies, or can assume a uniform distribution to represent total uncertainty (Nyberg *et al*, 2006). The estimation of probabilities associated with each state can be elicited from experts, obtained from existing process models, learned from data or a combination of these three sources (Pollino *et al*, 2007). Uncertainties associated with each relationship are quantified in the probability distribution.

Model evaluation and testing

After developing the model's structure and estimating the conditional probabilities, the BN needs to be evaluated. Model evaluation tools include qualitative feedback from experts and stakeholders, or by comparing model predictions with literature data or with results from similar models. Quantitative model evaluation should include sensitivity analyses and assessments of predictive accuracy. Predictive accuracy refers to a quantitative evaluation of the model, by comparing model predictions with observed data (Pollino *et al*, 2007). Sensitivity analysis tests the sensitivity of model outcomes to variations in model parameters. Sensitivity analysis in BNs can measure the sensitivity of outcome probabilities to changes in input nodes or other model parameters, such as changes in node's type of states and their coarseness. Sensitivity analysis can be performed using two types of measures; entropy and Shannon's measure of mutual information (Pearl, 1988). The entropy measure is based on the assumption that the uncertainty or randomness of a variable *X*, characterised by probability distribution *P(x)*, can be represented by the entropy function *H(X)*:

$$H(X) = -\sum_{x \notin X} P(x) \cdot \log P(x) \qquad (2)$$

Reducing *H(X)* by collecting information in addition to the current knowledge about variable *X* is interpreted as reducing the uncertainty about the true state of *X* (Barton *et al*, 2008). The entropy measure therefore enables an assessment of the additional information required to specify a particular alternative. Shannon's measure of mutual information is used to assess the effect of collecting information about one variable (*Y*) in reducing the total uncertainty about variable *X* using:

$$I(Y, X) = H(Y) - H(Y|X) \qquad (3)$$

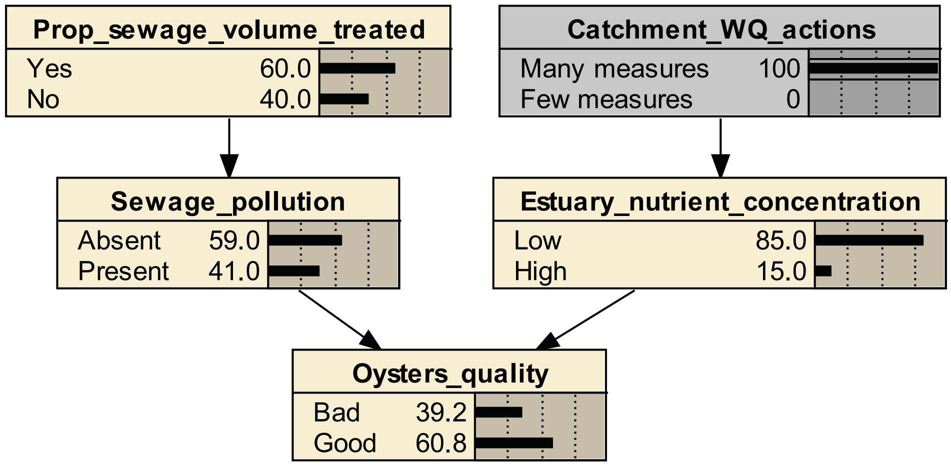
where I(Y,X) = the mutual information between variables. This measure reports the expected degree to which the joint probability of *X* and *Y* diverges from what it would be if *X* were independent of *Y*. If *I(Y,X) = 0, X* and *Y* are mutually independent (Pearl, 1988). Another way to use the mutual information measure is to compare the impact of gathering information on variables *Y* and *Z* on reducing the uncertainty in *X*. For example, if *I(Y,X)* > *I(Z,X)*, then the uncertainty in variable *X* would be reduced more by increased observations about *Y* then by increased information about *Z* (Barton *et al*, 2008).

Coupé and van der Gaag (2002) and Pollino *et al* (2007) propose an additional empirical approach to sensitivity analysis, based on changing each of the parameters and observing the related changes in the posterior probabilities. This approach can be used to identify the most 'sensitive set' of variables in the BN; those that are most influential in affecting change and those that are most affected by variations in parameters. Note that assessing the influence of every single parameter can be a time-consuming process, especially in large networks.

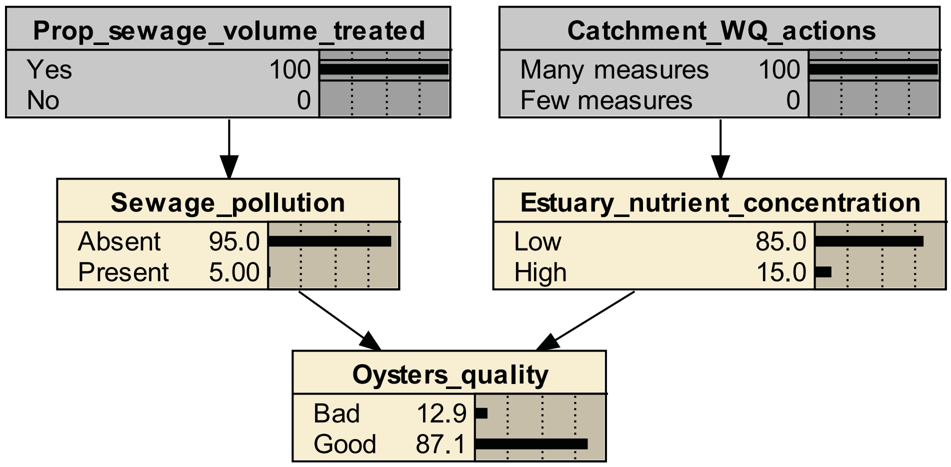
Scenario analysis

BNs can be useful decision support tools as they allow an assessment of the relative changes in outcome probabilities, associated with changes in management actions or system parameters. By specifying the state for one or more input nodes, the impacts on other nodes can easily be predicted. In Figure 4, this is shown for a hypothetical example of oyster production. Catchment management actions that aim to improve water quality will impact the concentration of nutrients in the estuary, which subsequently impacts on oyster quality. The pollution from a (hypothetical) sewage treatment plant also impacts oyster quality and is dependent on the proportion of effluent treated. It is shown in Figure 4(a), that if many water quality control actions are taken, but only 60 percent of the sewage volume is treated, the likelihood that oyster quality is good is 60.8 percent. If water quality control measures are accompanied by treatment of all sewage, the probability that oyster quality is good increases to 87.1 percent (Figure 4b).

In addition to prediction, BNs can be used for *diagnostic analyses*. By selecting a specific state of an output node, the probability that the input nodes need to be in a particular state can be observed. In Figure 4(c), it is shown that to obtain good oyster quality, the most likely states for sewage treatment and water quality control measures are 'yes' and 'many measures'. Figure 4(c) also shows the uncertainty associated with the impacts of sewage treatment and water quality control on oyster quality. The likelihood that good oyster quality depends on many water quality control measures is 64.6 percent, whereas the impact of sewage treatment is more explicit at 87.5 percent.



(a)



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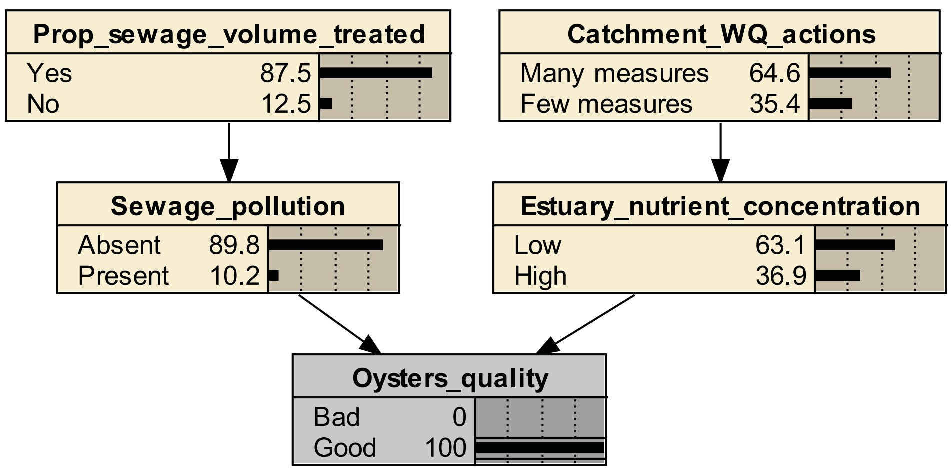

(c)

Figure 4. Scenario and diagnostic analysis for a hypothetical Bayesian Network for oyster quality.

Examples of Bayesian Networks in Catchment Management

Bayesian Networks have been used to model a variety of environmental systems. This section will describe a selected number of BNs that have been developed in the context of catchment water resources management. The focus of this review is on models that aim to understand catchment processes and riverine or estuarine ecology. It is shown how BNs can be coupled with other modelling approaches and how they can be used to support catchment decision making. A review of existing BN models can assist the identification of a catchment model structure and will provide information about nodes and states that are typically included in catchment models. In this review, current knowledge gaps and some challenges involved in BN development are identified.

An integrated BN of estuary eutrophication

Borsuk *et al* (2004) developed a BN that integrated process-based models, regression analysis and expert opinion to predict eutrophication processes in the Neuse River estuary, North Carolina. Nodes were defined through consultation rounds with local stakeholders and decision makers. The attributes of concern to stakeholders included water quality, ecosystem conditions and human health (Table 3). Fish populations were one of the most important attributes in the Neuse River estuary.

The basic network structure is depicted in Figure 5. Input variables are indicated with rounded nodes. These are river nitrogen concentrations, flow, water temperature, cross-channel winds and the duration of stratification. Management actions (not explicitly represented in the model) were assumed to affect nitrogen concentrations in the river. The two output nodes in the network were '*Pfiesteria* Density' and 'Fish Kills'.

The nodes in squared boxes depict intermediate and output variables whose values were determined using sub-models. Clarity, taste, odour, aquatic vegetation and faecal coliform were not included in the final BN, because they were not affected by nitrogen control, the management action under consideration. Algal density was modelled as a function of water temperature, river flows and total nitrogen concentration using a regression model developed using available monitoring data. The *Pfiesteria* density sub-model was developed using experimental results of the correlation between *Pfiesteria* and phytoplankton biomass. Carbon production was assumed to be a function of algal biomass and water temperature, whereas sediment oxygen demand was expressed as a probabilistic function of annual average carbon production and water depth. A process-based sum-model of oxygen depletion was specified to estimate oxygen concentrations in bottom waters. Shellfish abundance was related to oxygen status using a survival model for the clam species *Macoma balthica*. The survival of *M. balthica* further depended on the duration of stratification (Figure 5).

Predictions of fish population health and fish kills were based on expert opinion. Decline in fish population health and increased fish kills were correlated to low oxygen levels. Fish kills were further related to the occurrence of strong cross channel winds

Table 3. Ecosystem attributes of the Neuse River estuary (Source: Borsuk et al, 2001).

Concern	Measurement variables
Water quality	Water clarity Taste, odour Dissolved oxygen levels Chlorophyll a levels Algal toxins
Biological quality	Algal blooms Fish and shellfish abundance and health Species diversity Human-induced fish kills Submerged aquatic vegetation
Human health	Faecal coliform Pathogenic micro-organisms (e.g. *Pfiesteria*)

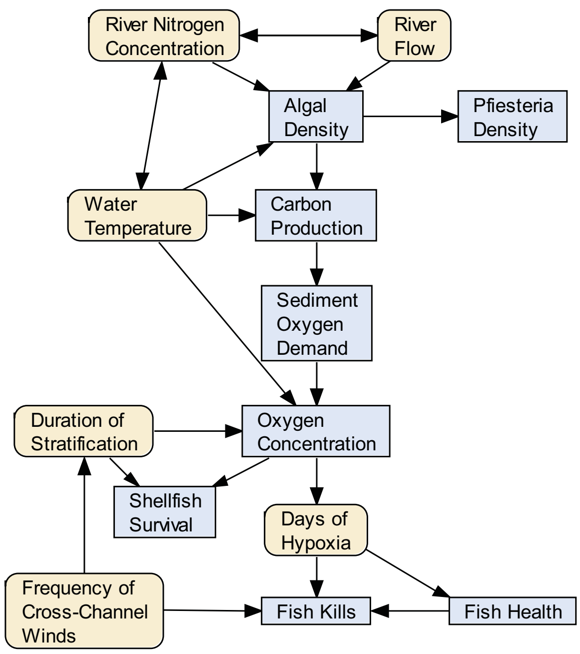

Figure 5. Bayesian network for Neuse estuary eutrophication (Source: Borsuk et al, 2004).

causing stratification and subsequent reduction in available oxygen. A scenario of a 50% reduction in riverine nitrogen inputs was run in the software program Analytica. The results showed that reductions in nitrogen loads may limit the number of fish kills in the estuary. The authors note, however, that the predictive uncertainty in the model is high, mostly due to a lack of information on the ecological processes in the system. Although fish population health may have been the most relevant attribute for stakeholders, the use of fish kills as an output node may have compromised the predictive precision achieved by the model. The Neuse estuary Bayesian Network is being used as a decision making tool, to determine total maximum daily nitrogen loads and the impacts of changes in daily loads on fish populations. An extension to the model could include management nodes that link into river nitrogen concentrations and flows to enable an assessment of the effectiveness of alternative management actions on the model outcomes.

Stakeholder participation in BN development

The project 'Management of the Environment and Resources using Integrated Techniques' (MERIT) attempted to provide a methodology for integrated water resources management. MERIT was a joint project by institutions in Denmark, Italy, Spain and the UK (www.merit-eu.nl). The project aimed to develop a generic integrated management tool based on the concept of Bayesian Networks.

Stakeholder consultation was a major focus in each country, however the issues being addressed varied from case to case (Bromley *et al*, 2005). The BNs developed in the UK and Italy considered competing water demands by a variety of users (hydroelectric facilities, tourism, urban households and irrigation). The Spanish project involved a BN of agricultural groundwater extraction in the Júcar catchment in central Spain. This network focused on competing water demands for domestic, agricultural and environmental uses, examining the likely impact of various management interventions on different stakeholder groups (Bromley *et al*, 2005).

The Danish project considered the issues of pesticide and nitrate contamination of ground and surface waters in the Northeast Zealand catchment in Denmark. Water flow and particle transport models provide inputs to the BN probability tables. The Danish study aimed to engage stakeholders in all stages of model development (Henriksen ed., 2004). Stakeholder groups included local and regional governments, farmers and local landholders, scientists, industry and environmental organisations.

The conceptual framework presented in Figure 6 shows how changing agricultural land use and practices may affect groundwater quality. The management action being considered was the implementation of compensatory payments to landholders for changing their land use and pesticide application practices. The BN showed how introduction of pesticide application in agricultural areas would affect farming economy, groundwater quality, biodiversity and the aquatic environment (Figure 6).

Results showed that high compensations (up to 600 Euro/ha/yr) would be needed to achieve a 95 percent probability that water supply would be safe. Assessments of the BN focused primarily on the stakeholder consultation processes (see, for example, Henriksen *et al*, 2007, and Henriksen and Barlebo, in press). There was disagreement between farmers and hydrologists about the extent of pesticide leaching to groundwater. To represent this disagreement between stakeholders, a variable 'perception' was included that allowed the model user to view the results from both viewpoints.

The results of the Danish groundwater protection BN has been evaluated using an optimisation technique in Farmani *et al* (2009). The authors show how the BN can be coupled with an optimisation tool for groundwater management. The technique aims to optimise safe water supply, farm income and compensation, allowing for multiple criteria assessment.

The authors conclude that adding the optimisation tool to the BN allows for participatory integrated assessment of the impacts of groundwater protection measures, and for improved validation of the constructed BN. However, it is unclear how safe water supply (in per cent) and monetary cost and benefits (compensation and farm income) can be compared when the objectives are measured in disparate units.

BNs as a decision support tool for coastal lake management

Ticehurst *et al* (2007 and 2008) developed a decision support tool to analyse the impacts of management decisions in coastal catchments of New South Wales. The Coastal Lake Assessment and Management tool (CLAM) made use of Bayesian Decision Networks (BDNs) to integrate social, environmental, and economic systems associated with coastal lake development in several case-study catchments.

The CLAM development process involved intensive stakeholder participation, expert feedback and an open documentation of the assumptions and data sources underlying the model structure and input parameters. Every CLAM case-study had a different model structure, dependent on the system, stakeholder needs and data availability.

Figure 7 shows an example CLAM developed for Merimbula Lake (Ticehurst *et al*, 2008). The shaded ovals represent the different management scenarios,

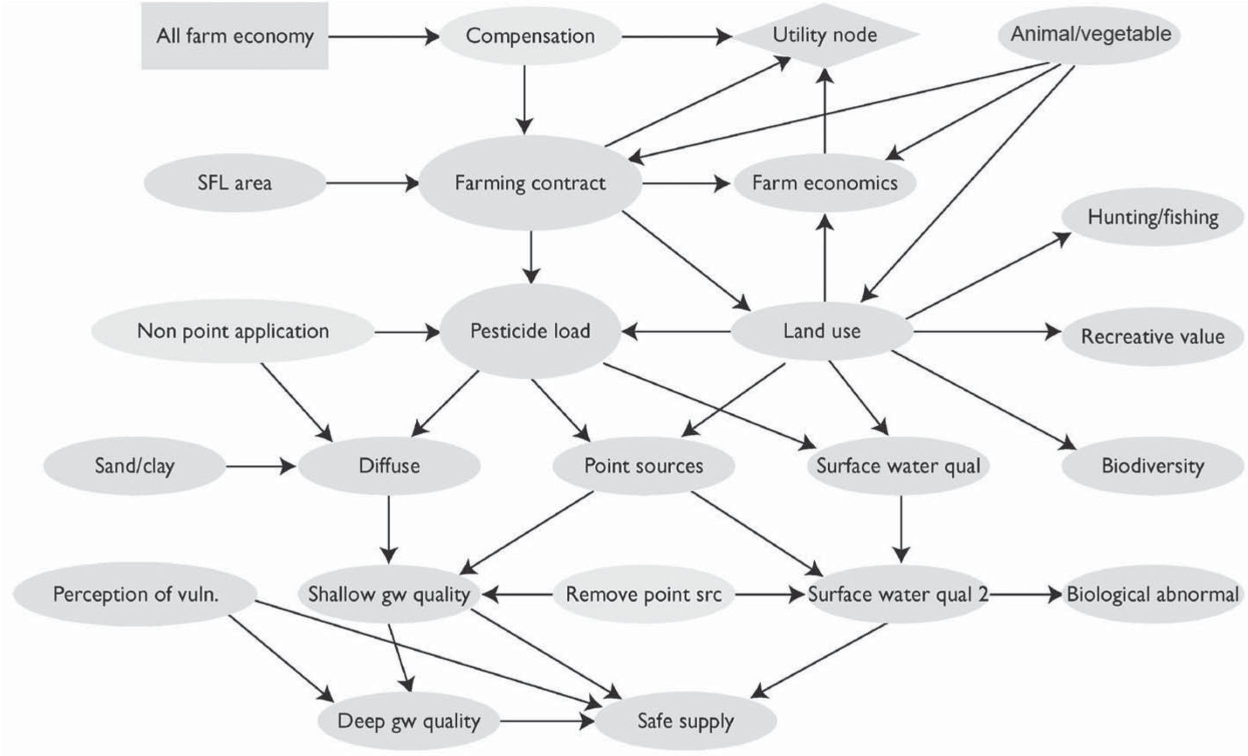

Figure 6. Bayesian network for groundwater protection using voluntary farming contracts (Source: Henriksen and Barlebo, 2008).

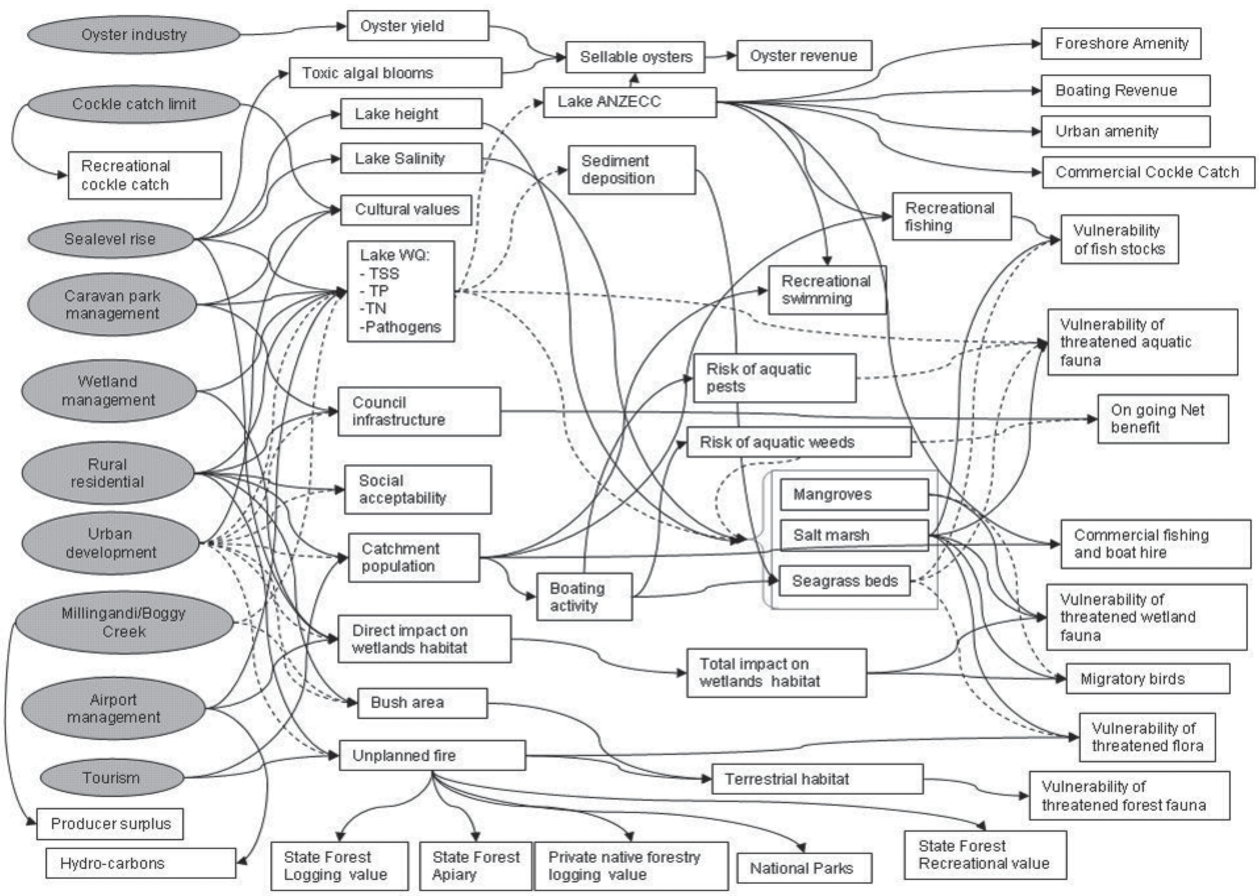

Figure 7. Bayesian Decision Network for the Merimbula lake CLAM (Source: Ticehurst et al, 2008).

including sea-level rise, wetland management and urban development. The framework integrated hydrodynamics, water quality and ecological data. Social components included population or institutional structures. Economic costs included in the network were the costs of management actions, changes in revenue from commercial fishing or oyster production and changes in recreational usage of the lake. Probability distributions of parameter values were obtained through data analysis, assumptions, literature reviews, model simulations and expert opinion (Ticehurst *et al*, 2008).

The CLAM development process followed an open, trans-disciplinary modelling approach that involved stakeholders in all stages of the model development process. The use of Bayesian Decision Networks enabled CLAM to take uncertainty in the input data into account and provided a decision support tool for coastal managers. Modelling results showed that the certainty of the state of the output nodes was dependent on the information in the causal links of the lower order variables. Hence, the certainty in the input nodes and the interrelationships between nodes will have a substantial impact on the model results (Ticehurst *et al*, 2008).

The data underpinning the current CLAM models is limited and it is recommended to extend the ecological and economic information when better data becomes available. Current economic information is rather coarse and could be refined using extended market analysis and by including an assessment of non-market values. Most notably, the impacts of alternative management scenarios are represented by a variety of output nodes, ranging from qualitative measures of threatened species vulnerability to monetary benefits. The model user needs to decide which of the CLAM output nodes is most relevant for making policy decisions. A direct comparison of the various outcomes is difficult if nodes are measured in disparate units.

Prioritising market based instruments to catchment management

Bryan and Garrod (2006) report on a project in the Onkaparinga catchment, South Australia. The aim of the project was to develop a decision framework in prioritising stream protection measures taken by private landholders in a public auction bidding procedure. Measures such as exclusion of livestock from streams and revegetation were analysed in terms of costs and their impacts on stream health. The BN was used to assess the probabilities that a certain level of measures would result in the desired protection of the stream.

Figure 8 shows the BN. Nodes that could be influenced by management actions include grazing pressure, riparian vegetation condition and buffer width and length. The cost impacts are expressed as the marginal costs of taking measures. The environmental impacts are expressed in terms of river health attributes: ecological condition and the likelihood of degradation. The river health condition nodes were assessed using expert opinion, based on information on river style, hydrological intactness and habitat conditions. The utility node in the model measured whether the cost-effectiveness of management would warrant funding the landholder's activities.

Coupling hydrology models with BNs

The French Agire project aimed to develop a decision support tool for integrated water resources management. A quasi-distributed hydrological model was developed for the Hérault River catchment. This model was linked to models of water extraction by irrigators and recreational water uses (Giraud *et al*, 2002). The model includes three hydrological models specifying water movements, and modules of farmers' behaviour. A component of recreational utility was included to represent canoe renters who derive satisfaction from specified levels of water flow. Development of the model was supported by intensive stakeholder consultation. Simulations were aimed at assessing the impacts of alternative levels of water use for irrigation versus recreational benefits.

The quasi-distributed model did not include ecological impacts. Further development of the model by Lanini (2006) involved the construction of a BN that aimed to assess the ecological quality of the catchment (Figure 9). This BN comprised 9 input nodes: gravel pit regulation, groundwater level, bank degradation, land use, tourism, population, impervious surface, water discharge and hydraulic works. Several of these input nodes can be influenced by management activities.

Each node had a limited number of two or three states in order to reduce the number of possibilities in the CPT. The CPTs were separated by ecological experts, and then calibrated by comparing the results from the model with observed ecological data (http://agire.brgm.fr).

Three output nodes were considered: landscape aesthetics, ecological value and fishermen satisfaction. These final output nodes were assumed to synthesise the environmental criteria. Model results showed that the two hydrological input nodes 'groundwater level' and 'water discharge' had the biggest influence on the output indicators. It was recognised by Lanini (2006) that further research is needed to populate the CPTs with data and to validate the model to real observations.

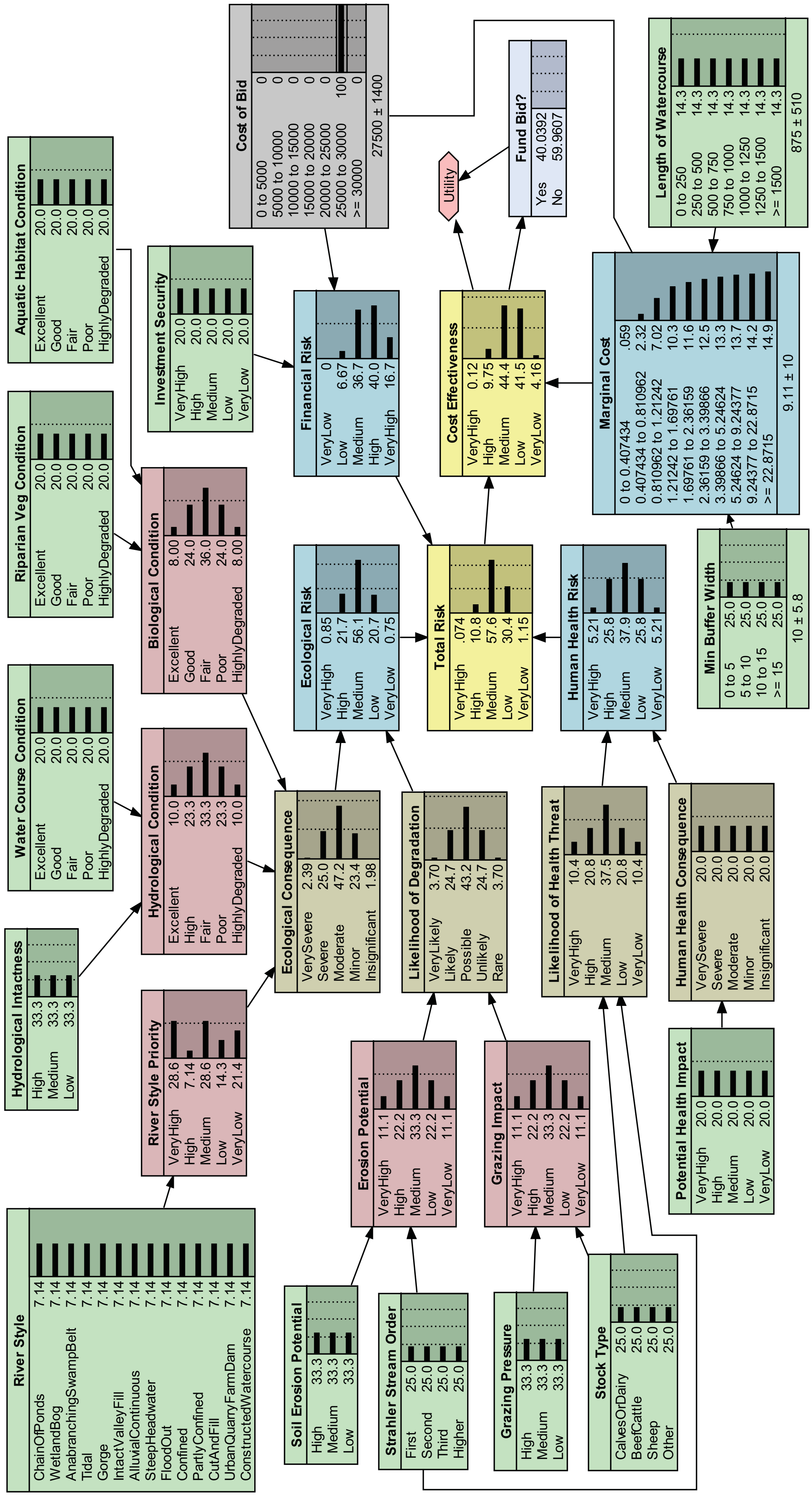

Figure 8. Bayesian network for prioritising landholder fencing bids (Source: Bryan and Garrod, 2006).

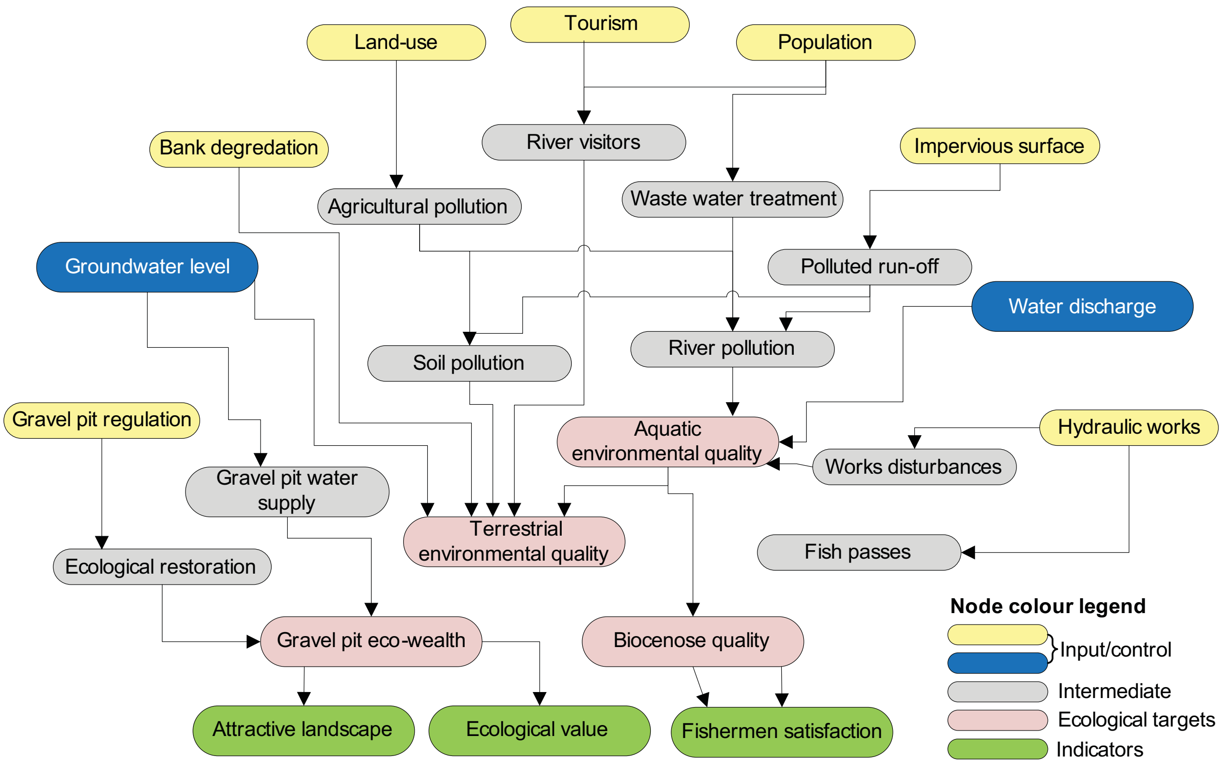

Figure 9. A Bayesian Network for the Hérault River catchment.

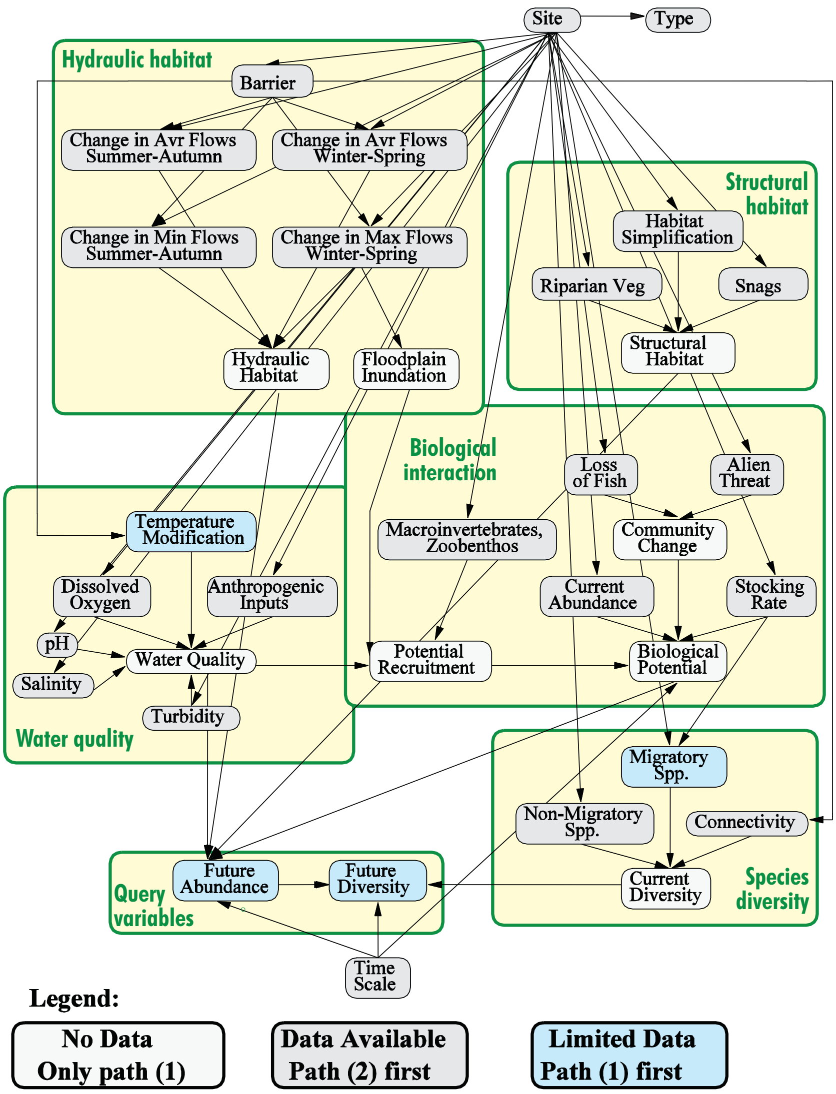

Figure 10. Native fish BN structure for the Goulburn catchment (Source: Pollino et al, 2007).

Bayesian ecological modelling

Pollino *et al* (2007) developed a BN to assess the impacts of human-related activities on native fish communities in the Goulburn catchment, Victoria, Australia. The development of a conceptual model of native fish communities in the catchment and the conditions required to establish sustainable populations followed an iterative process of expert workshops. The BN represented multiple locations and two time periods by including 'site' and 'time scale' as separate nodes in the framework.

The model consisted of five interacting sub-models: water quality, hydraulic habitat, structural habitat, biological potential and species diversity (Figure 10). The model parameters were estimated using only available scientific data, a combination of data and expert information, and where no data were available, expert information alone. Two end-points were defined: Future Abundance and Future Diversity.

The model was evaluated by comparing results with fisheries data from different sites. This assessment showed that the model results were consistent with observed data. Further assessments of model performance included a structural review with experts and sensitivity analyses. The sensitivity analyses were performed using the 'sensitivity to findings' function in Netica and using an empirical approach. Results showed that the hydraulic habitat, biological potential and water quality were the variables having the greatest influence on future fish abundance and diversity. If decision-makers are aiming to protect fish populations, management actions should therefore be targeted at restoring water quality and flows, improving biological potential and rehabilitating structural habitat in the rivers (Pollino *et al*, 2007).

Integrating a BN with cost–benefit analyses

Barton *et al* (2008) used a BN approach to analyse the costs and benefits of nutrient abatement measures in the Morsa catchment, South Eastern Norway (Figure 11).

The costs of changing four management practices (tillage land use, buffer strips, sedimentation dams and wastewater treatment) were analysed using data from a separate cost-effectiveness study. This information fed into four separate BNs that evaluated the effectiveness for each action in reducing phosphorus and nitrogen loadings to the river. Probability distributions in these networks were elicited using a variety of data sources, including expert opinion, empirical data and regression model results.

The information about abatement measures fed into a larger BN framework that modelled the impacts of nutrients on lake euthropication. A dynamic, process-based model (MyLake) was used to simulate the effects of changes in chemical water quality indicators on the suitability of lake water for recreational use.

Running the dynamic model repeatedly with Monte Carlo simulations provided the CPTs for bathing suitability in terms of temperature, total P, chlorophyll a, water clarity and pathogen concentrations (Barton *et al*, 2008). The benefits of recreation were evaluated using results from a 1994 contingent valuation survey of households in the Morsa catchment.

In this study, households' willingness to pay was estimated for the scenario of moving from lake water quality that was unsuitable for recreation to water quality that was 'well suited' for bathing, boating, fishing and drinking. Because of the binary nature of the valuation study (moving from unsuitable to suitable for recreation), the output node 'suitability' had two states zero and one.

Results of the management cost-effectiveness sub-models indicated that implementing buffer strips was the most cost-effective way to reduce nutrient loadings to rivers and lakes. While the ranking of measures was similar to the original deterministic cost-effectiveness study, the uncertainties represented by using the BN approach can help to identify which assumptions dominate the uncertainty in cost-effect when implementing different management actions.

Where the cost-effectiveness of catchment management actions to reduce nutrient levels was positive, the effectiveness of measures on improving lake water quality to suitable recreation conditions was generally low. This was due to the combined effect of poor current lake conditions and the low probabilities of achieving large enough water quality changes.

In a deterministic cost-benefit analysis, such low probabilities would not have been accounted for, resulting in a positive net benefit from management actions. The BN accounted for uncertainty, which in this case cancelled out the net benefits of implementing catchment management actions. The propagation of uncertainties through the model and the coarse discretisation of the output nodes (suitable and unsuitable) were the principle explanation for this lack of sensitivity.

This study showed the benefits of using a BN approach in addition to (or over) deterministic cost-effectiveness or cost-benefit analyses. BNs can help to ''identify and visualise which assumptions dominate the cost-benefit uncertainty and where to gather more information'' (Barton *et al*, 2008:99). The authors stressed the information loss due to the discretisation of nodes in the BN. A valuation approach that can account for step-wise improvements in lake water quality would be desirable to define less coarse states for the 'suitability' node[5].

Also, further integration and multi-disciplinary model development is recommended to reduce the uncertainty in the structure and probability distributions of the Bayesian models.

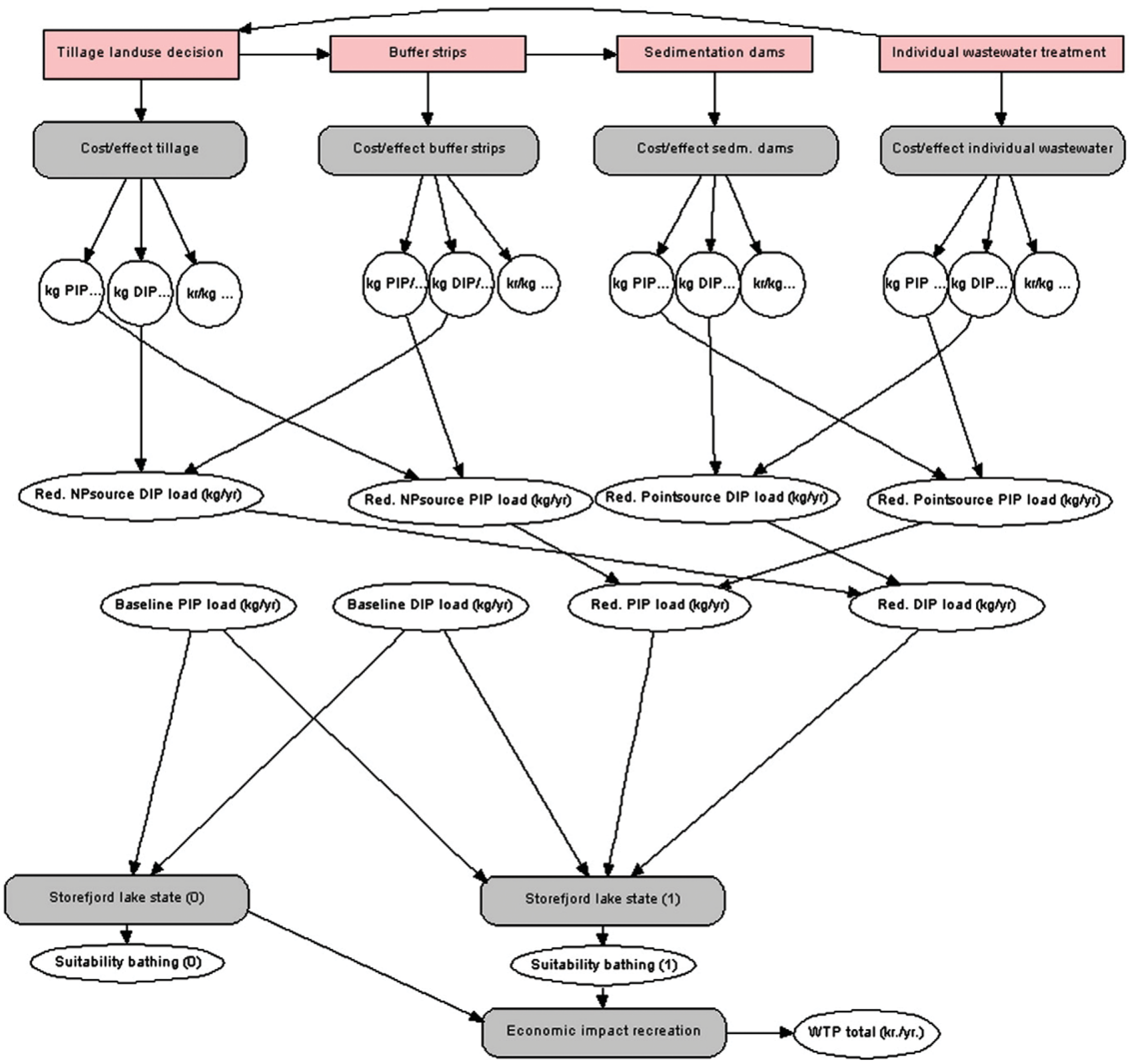

Figure 11. A BN for nutrient abatement in the Morsa catchment (Source: Barton et al, 2008). [* Pink boxes represent management actions; grey ovals represent underlying sub-networks; white ovals represent nature nodes with conditional probability distributions.]*

Discussion

This review of existing Bayesian Networks showed how they can be used as a tool to support the development of integrated catchment policies. BNs offer a comprehensive way to portray the complex system interaction involved in catchment management. BNs have advantages over other decision support tools in that they are able to represent the catchment system as a whole. BNs can be used to aid cost benefit analyses of catchment management actions that inevitably have environmental, social and economic consequences. The simple graphical representation in BNs can help stakeholders to easily assess the trade-offs involved in multi-objective catchment management.

In the absence of knowledge, conventionally physically-based modelling tools may not be appropriate when describing catchment processes. BNs can be developed even if insufficient data is available through the inclusion of various information sources and quantitative data. Furthermore, the explicit recognition of uncertainty can help decision-makers to identify the risks associated with different management strategies.

The limitations of BNs should, however, be recognised. They have limited ability to represent spatial and temporal dynamics within a system. Some BN applications have overcome these limitations, for example by using nodes to indicate changes in specific catchment areas (Pollino *et al*, 2007), by linking BN nodes to GIS data layers (Smith, 2007) or by including nodes to represent the duration of events (Merritt *et al*, 2009). Results are sensitive to the type of node states, the coarseness in state discretisation and the propagation of uncertainties. Also, the use of expert knowledge and stakeholder consultation requires the model developer to have considerable communication and elicitation skills, or to engage specialists to assist in the collection of information and assemble it in the appropriate form.

The examples reviewed in this report show how BNs can be coupled with other modelling approaches and how they can be used for a variety of management issues in river catchments and estuaries. Many of the reviewed studies use physical observations or process-based sub-models to provide inputs into the network. The representation of ecological systems is often limited due to a lack of knowledge or observable data. Although BNs can account for such data limitations, further information about the dynamic relationships between water quality parameters and ecological parameters in rivers, lakes and estuaries, as well as additional collection of baseline ecological data, would improve the performance of most reviewed catchment models. Some of the studies that are being undertaken within the Landscape Logic research hub will address these information gaps. [See Landscape Logic Technical Reports 4 and 5.]

The BNs reviewed in this report typically aim to represent catchment systems by addressing a number of environmental issues, but are limited in their description of the social and economic processes involved. On the input side, additional information could include the impacts of catchment management on local communities, landholder uptake of catchment management initiatives and improved analysis of the management costs of alternative policy actions (e.g. direct implementation, maintenance and extension costs). On the output side, existing BNs often fail to incorporate non-market impacts of catchment management changes. If BNs are to aid cost-benefit analysis of integrated catchment management actions, such non-market impacts need to be included. It is essential that cost-benefit analyses are carried out in cooperation with the BN model developers, to ensure that the results are attuned to the needs of the BN model (and vice versa). For example, a valuation study should address the same variables as the parameter nodes in the BN. Furthermore, the valuation should provide results in terms of marginal changes, to enable a finer discretisation of output nodes.

Several Landscape Logic projects aim to develop BN models that include input from a variety of process-based models and represent a diversity of systems. In the George catchment study, for example, a BN approach will be used to model hydrologic, ecologic and economic processes in the catchment. The review of existing BNs in the context of catchment management shows the benefits of using BN models but also serves to identify challenges and knowledge gaps related to integrated BN model development.

End notes

1. Or, more accurately, the *marginal probabilities* that parent nodes A and B are in a certain state.
2. Note that P(E) needs to be normalised such that P(E) = 1.
3. For example, Netica uses three main types of algorithms to learn CPTs: counting, expectation-maximisation (EM) and gradient descent (Norys, 2005).
4. The number of states defines the 'coarseness' of the node and its representation of the parameter distribution.
5. Choice Experiments (also known as Choice Modelling) provide a valuation technique to assess the marginal values of water quality improvements.

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