LANDSCAPE LOGIC
LINKING LAND AND WATER MANAGEMENT TO RESOURCE CONDITION TARGETS

Technical Report No. 14

# Bayesian networks: A guide for their application in natural resource management and policy

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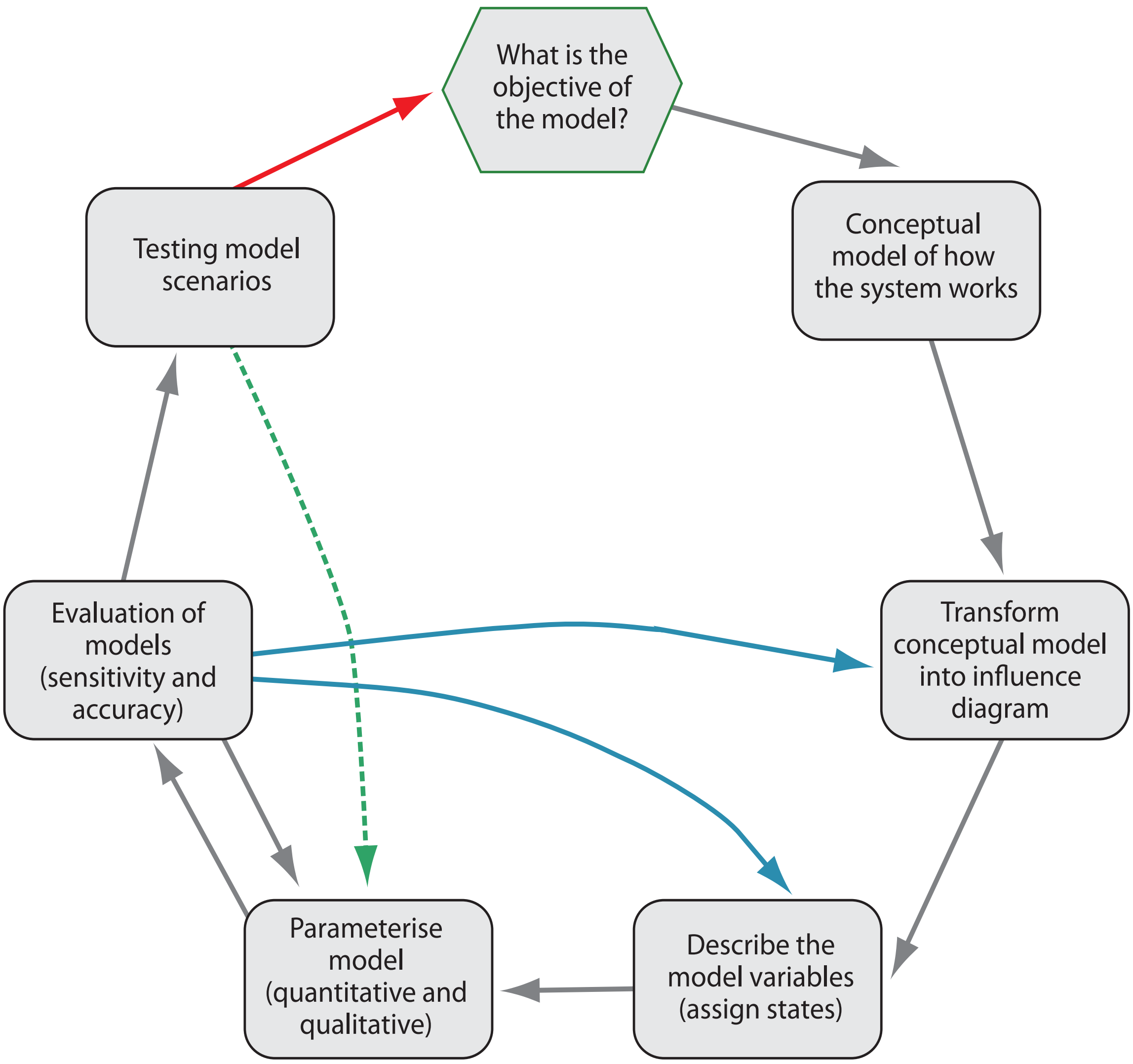



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Cover: Steps used to build a Bayesian network

**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.

# Bayesian networks:
# A guide for their application in natural resource management and policy

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## Executive summary

Bayesian networks have been successfully used to assist problem solving in a wide range of disciplines including information technology, engineering, medicine, and more recently biology and ecology. There is growing interest in Australia in the application of Bayesian network modeling to natural resource management (NRM) and policy. Bayesian networks offer assistance to decision-makers working in complex and uncertain domains by assembling disparate information in a consistent and coherent framework and incorporating the uncertainties inherent in natural systems and decision-making. Bayesian networks as modeling tools have been shown to fulfill the following needs:

- Integration –of models, data types and qualitative information;
- Prioritisation – through cost benefit analysis and ranking variables against a stated objective;
- Flexibility – as they can be modified to suit the context in which they are applied and can be updated as new knowledge is obtained; and
- Communication – as they are graphically based and allow explicit documentation of assumptions and uncertainties, making them easier to understand and use than most modeling frameworks.

A key feature of the successful adoption of Bayesian networks as a modelling tool in decision-making is their relative simplicity when compared with other modelling approaches. They are graphical models, capturing cause and effect relationships through influence diagrams. The use of probabilities to characterise the strengths of linkages between variables means that these can be defined using both quantitative and qualitative information while the use of Bayes' theorem (see Section 2.3.2) provides a formalised process to update models as new knowledge or data becomes available. Being probabilistic, Bayesian networks can readily incorporate uncertain information, with these uncertainties being reflected in model outputs. Sensitivity analysis tools allow characterisation of uncertainties so that key causal factors and knowledge gaps can be identified. Model outcomes are testable, both quantitatively and through formal review processes.

However, despite their advantages, it is important to be aware of several limitations. In their common form, Bayesian networks only poorly represent dynamic processes as continuous probability distributions require conversion into an equivalent discrete space for the purposes of easier calculation. Also exact algorithms are used for probability propagation which limits their representation of uncertainties, while complex networks are very data hungry. While their ability to incorporate qualitative (and possibly subjective) information is often seen as an advantage, the use of expert opinion is a potential source of bias and there is a tendancy to be overenthusiastic in the inclusion of such detail when data and knowledge is limited.

This report builds on an earlier report (Henderson *et al.* 2008). It overviews the role of models within environmental management (Section 1), the key components of a Bayesian network (Section 2), their benefits (Section 3) and limitations (Section 4), reviews past applications (Section 5) and discusses the potential roles for Bayesian networks in NRM and policy development (Section 6).

# Contents

# 1. The Context: Natural Resource Management

A regional-scale structure is used in Australia to plan, promote and deliver on natural resource management (NRM) priorities. This arrangement was formalised in 2000 with the formation of 56 regional bodies across Australia. The purpose of regionalisation was to facilitate a greater community involvement in NRM planning, priority setting and investment. Regional plans now form the basis for investment, with a focus on target setting, implementation and cooperative arrangements for catchment-wide activities. Plans address a broad range of issues including land, water and vegetation management, biodiversity conservation, and sustainable agriculture.

To develop and meet NRM objectives, the Australian government has invested almost $6 billion between 1996 and 2007. Despite this significant investment, delivery of tangible impacts through regional arrangements has proved difficult. Audits of public environmental programs (ANAO 2001, 2007, 2008) concluded that it was not possible to gauge the effectiveness of investment as there had been no provision for adequate monitoring of change on the ground. As reviewed in Hajkowicz (2009), although this outcome was not unique to Australia, it fell well short of community and government expectations.

In Australian landscapes demonstrating a measurable change in the health of natural resources as a consequence of public investment is exacerbated by: the 'tyranny of size', where physical area is large and dollars invested per unit area is low (Hajkowicz 2009); furthermore, it is difficult to gauge effectiveness of actions when there are long time lags in response; and the most insurmountable limitation is the general lack of any long-term monitoring programs that are dedicated to detecting a response. These factors make NRM a classic example of a 'wicked problem' where diverse interests, evolving understanding of a problem and its complexity combine to make problem resolution a challenging process (Rittel and Webber, 1973).

Uncertainties in environmental policy and management are usually addressed via one of the following five approaches (Peterman and Anderson 1999):

1. Using best estimates (usually point estimates) for parameters and state variables, ignoring uncertainties;
2. Uncertainties are acknowledged and used to justify status quo management actions because the outcomes of actions are uncertain;
3. Aggressive policies are introduced, e.g. for harvesting or pollutant release, as negative consequences cannot be demonstrated with certainty;
4. Arbitrary safety factors are applied that can over or underestimate reality; or
5. Explicitly considering and quantifying uncertainties.

While approach five is the most sensible, at present, there are few tools that can assist in planning, monitoring and evaluating the success of investments in an uncertain environment. Such tools are needed to better focus investments, more efficiently allocate scare resources and allow for ongoing improvements in resource condition through adaptive management. A modelling approach that is increasingly being regarded as useful in NRM, and which is explored further in this report, is Bayesian networks (BNs).

# 2. What is a Bayesian network?

Bayesian Networks (BNs), also known as Bayesian Belief Networks (BBNs) and Belief Networks, are probabilistic graphical models that represent a set of random variables and their conditional interdependencies via a directed acyclic graph (DAG) (Pearl 1988). They can be used to explore and display causal relationships between key factors and final outcomes of a system in a straightforward and understandable manner.

As BNs are causal, they can also be used to calculate the effectiveness of interventions, such as alternative management decisions or policies, and system changes, such as those predicted for climate change. Importantly, the uncertainties associated with these causal relationships can also be explored at the same time (see Section 3.1). BNs are able to maintain clarity by making causal assumptions explicit (Stow and Borsuk 2003) and are often used for modelling when the relationships to be described are not easily expressed using mathematical notation (Pearl 2000).

BNs emerged from research into artificial intelligence, where they were originally developed as a formal means of analysing decision strategies under uncertain conditions (Varis 1997). They have since proven to be applicable to a wide range of problems, discussed in greater detail in Section 5. They are particularly useful for diverse problems of varying size and complexity, where uncertainties are inherent in the system. However, it is only recently that they have begun to be adopted in the field of environmental modelling (e.g. Stassopoulou *et al*. 1998; Varis 1997).

Bayesian networks apply Bayes' Theorem (also known as Bayes' rule or Bayes' law). In Bayes' theorem, a prior (unconditional) probability represents the likelihood that an input parameter will be in a particular state; the conditional probability calculates the likelihood of the state of a parameter given the states of input parameters affecting it; and the posterior probability is the likelihood that parameter will be in a particular state, given the input parameters, the conditional probabilities, and the rules governing how the probabilities combine. The network is solved when nodes have been updated using Bayes' Rule:

$$P(A|B) = \frac{P(B|A)\,P(A)}{P(B)} \qquad \text{(Equation 1)}$$

where P(A) is the prior distribution of parameter A; P(A|B) is the posterior distribution, the probability of A given new data B; and P(B|A) the likelihood function, the probability of B given existing data A. Bayes' theorem was derived by the Reverend Thomas Bayes, and was first published posthumously in the essay *Towards Solving a Problem in the Doctrine of Chances* (1764). BNs use Bayes' Theorem to update or revise the beliefs of the probabilities of system states taking certain values, in light of new evidence (referred to as *a posteriori*) (see Section 2.3.2).

Unlike many other modelling techniques used for environmental applications, Bayesian networks use probabilistic, rather than deterministic, expressions to describe the relationships among variables (Borsuk *et al*. 2004b). Lack of knowledge is accounted for in the network through the application of Bayesian probability theory. This allows subjective assessments of the probability that a particular outcome will occur to be combined with more objective data quantifying the frequency of occurrence in determining conditional probabilistic relationships. Because uncertainty is accounted for in the model itself, Bayesian networks are a particularly appropriate method for dealing with systems where uncertainty is inherent, which tends to be a key issue in ecological systems. Communication of uncertainties is also essential when developing models for management.

Bayesian networks have a number of other appealing properties that make them particularly useful for data analysis and decision-making. In addition to their simple causal graphical structure: they can be readily extended and modified; they can readily incorporate missing data through the application of Bayes' theorem; they are able to be understood without much mathematical background; they have been shown to have good predictive accuracy with small sample sizes (Kontkanen *et al*. 1997); they can be used to forecast the likely values of system states given differing future scenarios; they can integrate different submodels, even if these operate on different scales; and they can be easily combined with decision analytic tools to aid management decision-making (Jensen 2001; Kuikka *et al*. 1999; Marcot *et al*. 2001). These advantages will be discussed in more detail in Section 3.

Bayesian networks are also useful for participatory processes. The process of setting up the model question and the influence diagram (or conceptual model) can be undertaken within a participatory environment; they can aid in examining alternative decisions for optimising a desired outcome; they can assist in the social learning processes; and they can be used to develop a broader understanding of a system across stakeholder groups.

The role of Bayesian networks, in comparison with other integration modelling approaches, is summarised in Table 1(Jakeman *et al*. 2007).

*Table 1: Functionality of selected methods of Integrated Modelling (Jakeman et al. 2007)*

| | | System dynamics | Bayesian networks | Meta models | Coupled complex models | Agent based models | Expert systems |
|---|---|---|---|---|---|---|---|
| **Model Purpose** | Prediction | | XXXX | XXXX | XXXX | | XXXX |
| | Forecasting | | | XXXX | XXXX | | XXXX |
| | Decision making | XXXX | XXXX | XXXX | XXXX | | XXXX |
| | System understanding | XXXX | | | XXXX | XXXX | XXXX |
| | Social learning | XXXX | | | XXXX | XXXX | XXXX |
| **Input Data Type** | Qualitative and quantitative | | XXXX | | | | XXXX |
| | Quantitative only | XXXX | | XXXX | XXXX | XXXX | |
| **Focal Range** | Focused and indepth | | | | XXXX | | |
| | General and broad | XXXX | | | | | |
| | Compromise | | | XXXX | | | XXXX |
| | Both | | XXXX | | | XXXX | |
| **Express uncertainty** | Yes | | XXXX | | | | XXXX |
| | No | XXXX | | XXXX | XXXX | XXXX | |
| **Model Output** | Individual | | | | | XXXX | |
| | Aggregated | XXXX | XXXX | XXXX | XXXX | | XXXX |

## 2.1 How to build a BN

The process used to construct a BN, and the associated feedbacks through model development, is shown in Figure 1 and outlined in the following sections.

The first steps of the process are to define the objectives for the model and the end users. At a minimum, the proposed model should have clear operational meaning to the modeller, the 'domain' experts and the model users. A poorly defined, unfocused objective will compromise the model development process. The objective should also include the temporal and spatial scales being considered in the model. Where possible, this process should be undertaken in a participatory environment to ensure the breadth of issues and potential inputs to the model are identified.

A conceptual model or influence diagram can focus the model developer, models users and other stakeholders in clearly defining focus issues and scales. The conceptual model can also be used directly to develop the BN. However, often

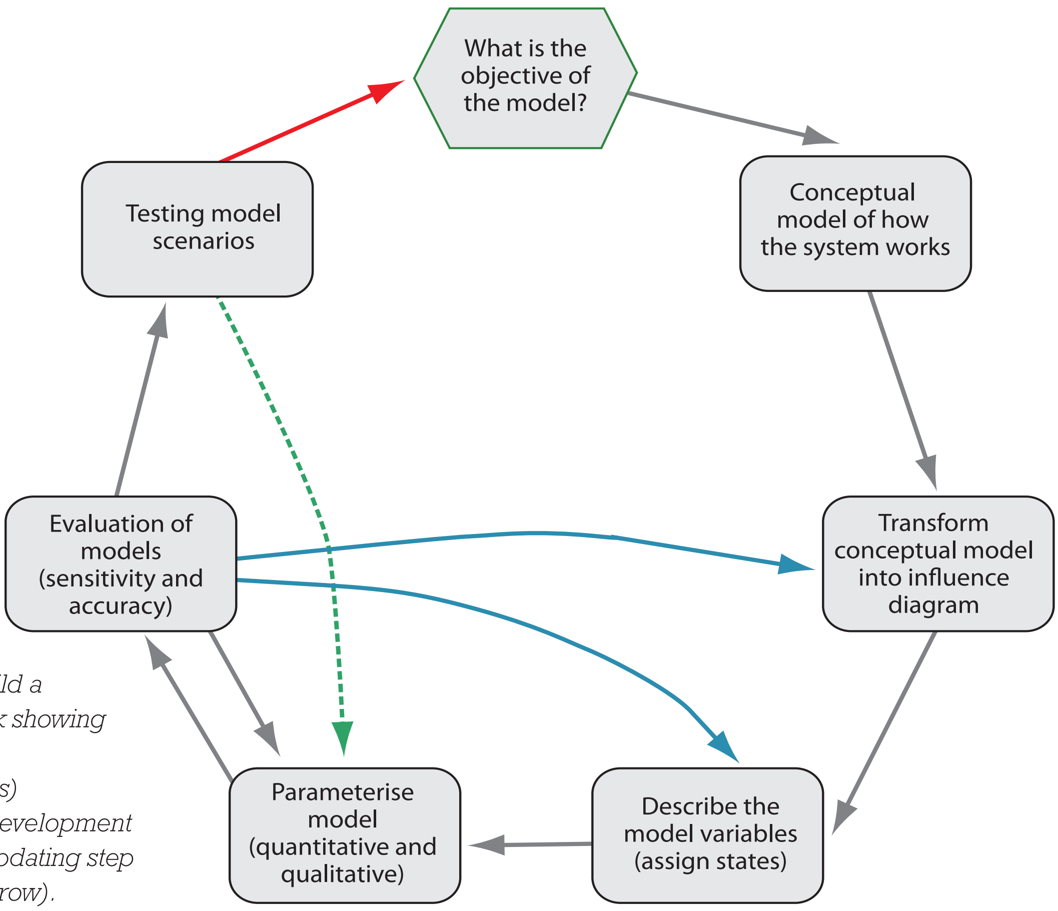



*Figure 1: Steps used to build a Bayesian network showing iteration steps (pale blue arrows) through model development and the model updating step (green dotted arrow).*

the conceptual model does require modifications. To avoid being overly complex, the aim of a model should be to describe important system features, rather than give a correct representation of reality (Jorgensen and Bendoricchio 2001).

## 2.2 Structure of a Bayesian network

In the majority of software platforms[1], the structure of a Bayesian network is defined graphically, where variables (or nodes) are connected by unidirectional arrows (or arcs). A BN is designed as a causal structure, where node A affects node B, which in turn may affect node C. In this case, A is referred to as a parent of B, with B being referred to as a child of A. B in turn will thus be a parent of C, and is also sometimes referred to as an intermediate node.


*Figure 2: Basic causal structure of a BN*

In a BN, the directions of arcs cannot loop back (i.e. cycle back into the model) and the form of the structure is a Directed Acyclic Graph (DAG). It is this acyclic nature that provides one of the limitations of BNs, particularly in ecological modelling (see Section 4.1). Loops can be represented using Dynamic Bayesian networks (see Section 4.1.1). But in its simple form, a Bayesian network needs to propagate probabilities to an endpoint or outcome.

The structure of a BN can be defined using a conceptual or influence "box and arrow" diagram. It is only when the network includes a set of probabilities, one for each node, specifying the belief that a node will be in a particular state given the states of those nodes that affect it directly (its parents), that it becomes a full Bayesian network

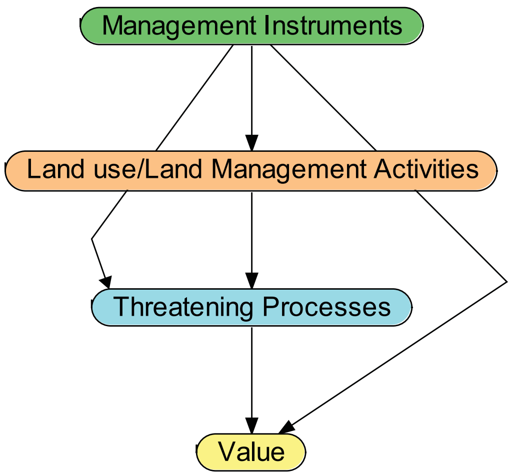



*Figure 3: Hierarchy describing the interactions between management instruments and how they affect an outcome to a system value (or asset). Only one outcome is shown here, but BNs can have multiple 'endpoints'.*

(Cain 2001). These probability sets are called conditional probability tables (CPTs), and are used to express and calculate the relationships between nodes (see Section 2.3).

When constructing a Bayesian network it is useful to consider the system in a structured, hierarchical manner. In the Landscape Logic project, the simple hierarchy of variables used to construct models for NRM is shown in Figure 3:

We can then extend this hierarchy to form a Bayesian network (see Figure 4):

As nodes in a BN structure can represent information from a range of scientific disciplines (e.g. hydrology, ecology, economic, social), it is possible to base the structure on a number of sub-models that are integrated to form a single BN. These sub-models can represent physical or chemical processes, or even political or socio-economic influences. The outcomes of the sub-models can be integrated into a set of endpoints (representing environmental, social or economic variables) that describe outcomes of the network model as a whole.

The goal in specifying a Bayesian network structure is parsimony, where the simplest structure should be used to describe the system under consideration (see Section 4.2.3). The reasons for this are pragmatic:

- Minimise specifying probabilities by having fewer nodes, fewer arcs, fewer states, so as to:
  - Not go beyond the 'power' of the data available;
  - Cut down computation processing time;
  - Minimise expert elicitation, including potential bias, going beyond expert knowledge base, overrepresentation of poor knowledge (Section 2.3.1.1); and remember
  - Too much detail can decrease model accuracy.

In developing models, tradeoffs between simplicity and complexity are also required, so it is important to maximise 'truthfulness' of model, which:

- May require more nodes, arcs, states;
- May require balancing benefit in model representative of current and/or future states against the cost of additional modelling; but
- Too little detail can decrease model representativeness and usefulness.

In artificial intelligence and Bayesian statistics, the principle of Occam's Razor where, all things being equal, the simplest solution tends to be the best one, is often used to simplify models (Pothos 2009; Schleip *et al.* 2008).

As discussed in (Woodberry *et al.* 2004b), due to the inherent difficulty involved in building a BN directly through elicitation from domain experts,

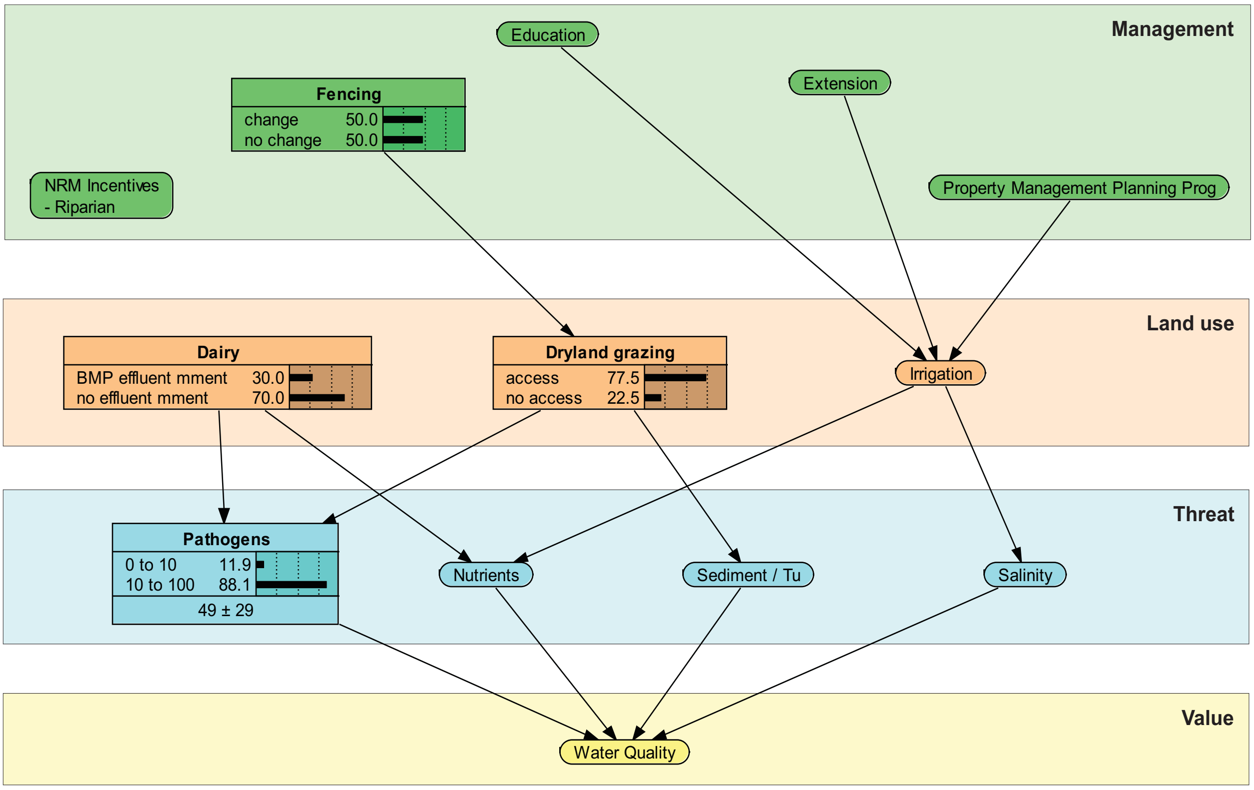



*Figure 4: An incomplete Bayesian network, showing the interactions between management actions and water quality outcomes.*

there is growing interest in developing machine learning of BNs using data. Increasingly, BN software packages can be used for data learning of a structure. However, as comprehensive data sets that describe all possible condition of an ecological system are rarely available, such a technique is less relevant for NRM purposes.

*Defining states on variables*

Each node in a BN represents an observable or measurable process. In a Bayesian network, with no decision or utility variables (see Section 3.2), we treat variables as random (termed a 'Chance variable'). The states of a variable can conceivably describe any state possible in the 'real world', but they must be defined as finite in number, discrete, and mutually exclusive. States of a variable can be Boolean (e.g. true or false), categorical (e.g. high, average, low), discrete (e.g. integers) or continuous. If a variable is continuous, it is generally handled by dividing its range into sub-ranges with discrete values. Discretisation of variables is not a requirement of BNs (Pearl 1998) but it is a common limitation in commercial programming shells, which use the junction tree algorithm (an exact approximation algorithm).

To obtain a robust and representative BN, setting discrete intervals in a BN should not be an arbitrary process. Data analysis, where important breakpoints in data distributions should be explored (e.g. plotting of data distributions, undertaking multivariate statistics or classification analyses of datasets, using percentiles of data) is recommended for empirical datasets. Where information is subjective, expert judgement can be used. Alternatively, if a model has a decision-making context, states that represent important regulatory thresholds, e.g. for water quality, can be used. Assessing the representativeness of states (e.g. too few, too many, poorly defined) should be reviewed as part of the model evaluation process (see Section 2.4).

In defining states, the accuracy and fineness of resolution will depend on how many nodes and arcs are used to model processes, and the number of discrete intervals used within each variable (see Section 4.2.1). By choosing too few states, the model can result in information loss, whereas too many states can overcomplicate the model. Although the potential loss of information can be a disadvantage of the process of discretisation (discussed in further detail in Section 4.2.1), this loss of information is less crucial where states are used to represent management objectives or outcomes. In documenting a BN, the process used to define states for each of the variables should be included.

## 2.3 Conditional probability tables

The relationship between a child node and all its parents is described by a Conditional Probability Table (CPT). The CPT describes the probability of being within a state, given a combination of values of parent states. Consequently, the size of the CPT for each variable is the product of the numbers of states of the child node and of all its parent nodes. If a node has no parents (i.e. it is a root node), it can be described probabilistically by a marginal probability distribution.

The following short example shows the process of inputting data into the CPTs for a simple Bayesian network consisting of only three nodes. In the network, nodes A and B (parent nodes) represent the causal factors of node C (child node). The example has been carried out using the programing shell Netica (www.norsys.com).

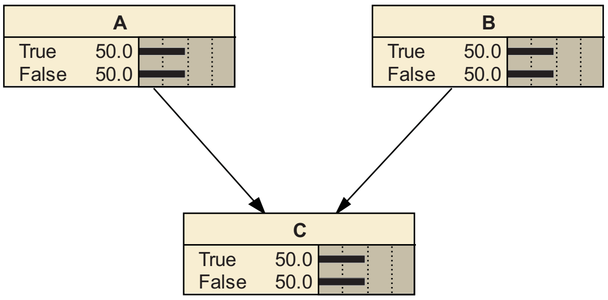



*Figure 5: Simple model structure showing nodes with 2 states*

In Figure 5, all nodes are binomial, with the states being defined as either true or false. A variable can be described by a finite number of states, which can be defined either qualitatively or quantitatively. The probability distributions for each node have not yet been specified. Thus this diagram is not yet a full BN but merely a Bayesian diagram. The nodes A and B are both root nodes, thus they can be defined by marginal probabilities. Node C, however, is the child of A and B, and so the probabilities of the states of node C are conditional on how the states of A and B combine.

The entries in a CPT can be 'parameterised' using a range and combination of methods, including directly observed data, probabilistic or empirical equations, results from model simulations, or elicitation from expert knowledge. In Figure 6, direct entry of probabilities (using expert elicitation) is used.

The elicitation process would usually take the form of scenarios as they appear in the table. For example, given that A is true and B is true, what is the probability that C is true (represented here as 100%). The fully parameterised CPT is shown in Figure 7. It is an important point to note that the method of probability generation must always be rigorously documented, including any assumptions and limitations.

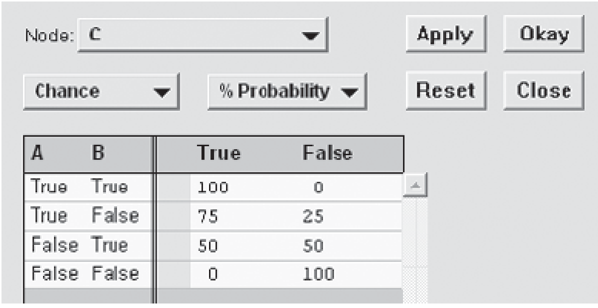



*Figure 6: CPT of node C, based on the simple model shown in Figure 7.*

When the probability distributions of each node have been defined, the network is able to be 'solved', as shown in Figure 7(a). After evaluation tests, the BN is complete and can be used for scenario analysis.

Individual scenarios, such as a set of management interventions or observations of the system, can then easily be examined. BNs provide a simple way of testing a scenario, allowing the user to input evidence into a node by defining a fixed distribution at a node. The effect of the scenario can then be examined by its effect on other nodes through the propagation of probabilities, as illustrated in Figure 7.

The rapid propagation of information through the network is one of the major advantages of BNs, in that they can be used to quickly view how decisions and observed conditions at one node will affect the system as a whole.

A specialisation of Bayesian Belief Networks exists, known as Bayesian Decision Networks (BDNs) that are discussed in greater detail in Section 3.2. BDNs can use two other types of nodes, 'Decision' nodes and 'Utility' nodes. Decision nodes do not have probabilities defining states, rather they display a number of possible decisions that a manager may take that will affect the system. Utility nodes represent the expected value, either cost or benefit, of a decision. Using a BDN, scenarios can be easily tested using these utility nodes to find an optimal combination of decisions in the decision nodes and the relative difference between these decision outcomes (for example alternative flow regimes) can be rapidly tested and outcomes communicated.

### *2.3.1 Methods for parameterisation*

There are a number of methods commonly used for calculating the conditional probabilities of the nodes within a BN. As demonstrated, probabilities can be obtained through expert elicitation. The accuracy of information obtained through elicitation can range from a deep understanding of the

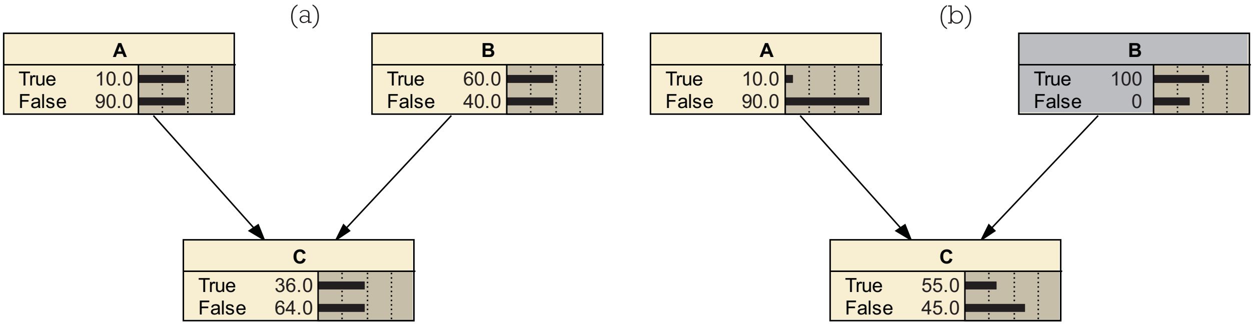



*Figure 7: BN before (a) and after (b) the propagation of new information.*

strength of the relationships, to a more heuristic estimate (e.g. an educated guess, or a general rule of thumb for the system). This information can also come from a diverse range of personal experiences of non-expert stakeholders in the system, such as anecdotal or contextual information.

Probabilities can also be obtained through the construction of equations, including probabilistic distributions, derived from fully peer-reviewed, or even simple conceptual, ecological theory. They can be obtained from the results of other ecological models. Additionally, they can also be obtained from sources of scientific data, including the frequency of observed conditions in monitored field or laboratory observations. This last point is one of the major advantages of BNs, in that, due to their inherent incorporation of uncertainty, incomplete data sets can be used to calculate conditional probabilities. A further benefit of BNs is that a combination of methods can be used to calculate conditional probabilities, for example, expert probabilities can be combined with observational data to describe outcomes of extreme events not represented in the dataset.

However, even though BNs are able to incorporate data from a wide variety of sources, it is important to keep in mind the risks and limitations of the different types. If information is obtained from scientific data or theory, it may be incomplete or unavailable in part. If information is obtained from elicitation of professional judgement or personal experience, on the other hand, high uncertainties can arise from epistemic uncertainty (incomplete knowledge or bias). Therefore, as previously stated, it is important to stress that all sources of information used in the creation of any model must be transparently documented.

As a guide, Table 2 shows a protocol on how to assign quality ratings to different evidence sources. The quality assessment can assist in determining the rigor and credibility of the model inputs, as well as outputs, where a model is only as reliable as its least reliable input (Jorgensen and Bendoricchio 2001).

*2.3.1.1 Expert elicitation*

Methods of elicitation can be found in Cooke (1991) and Morgan and Henrion (1990). Where possible, elicitation methods should be used to reduce ambiguity and bias in an assessment, and elicitation should use quantitative definitions for inherently numerical processes. Qualitative risk ratings rarely provide sufficient information to discriminate accurately between quantitatively small and qualitatively large risks (Cox *et al.* 2006). The use of qualitative rankings is also likely to result in linguistic ambiguities, value judgements and expert biases (Burgman 2005). If an ecological variable is defined qualitatively (e.g. low, medium, high), this will limit the potential for future updating of the model with

*Table 2: Quality ranking for different inputs to the risks analysis Bayesian networks (after(Bowden 2004))*

| Rank | Calibration – Statistical fit | Process-based model | Database | Literature | Expert |
|---|---|---|---|---|---|
| High | High calibration with data (≥95%) | Comprehensive validation using independent data set | Large sample, Multiple sites & times. Best practice design and collection methods | Published in peer reviewed forum | Multiple experts – high consensus |
| Medium | Moderately well calibrated with data (90 –<95%) | Some validation using independent data set | Limited sampling. Accepted design and collection methods | Non-peer reviewed publication | Multiple experts – partial consensus |
| Low | Poor calibration with data (≤ 90%) | No validation presented | Small sample, single site & time. Poor design and collection methods | Unreviewed publication | Single expert |

empirical data, so that the 'Bayesian' aspect of the BN is lost. Thus in BNs, as with any other modelling technique, expert judgment should not been seen as a substitute for data or research but rather as a way to assist decision-making before all the necessary science is known (Morgan and Henrion 1990). Because of this, all ecological models for environmental management should fit into a cycle of adaptive management (see Section 6.1).

To assist the elicitation process, it may be useful to map responses to probabilities, for example: Expert knowledge can be combined with sample data (Marcot *et al.* 2001) of varying levels of accuracy (Uusitalo 2007). Methods for combining qualitative and quantitative evidence sources can be found in Pollino *et al.* (2007b).

*2.3.1.2 Data learning*

Efficient algorithms allow for rapid inference and learning in Bayesian networks. Many common BN programing shells, such as Netica (Norsys 2005), can estimate conditional probabilities in a model using data learning algorithms. Some software types also require the model's causal structure to be defined before parameterisation. Netica has three automated algorithms: the Lauritzen Spiegelhalter method (LS) (Lauritzen and Spiegelhalter 1990); the expectation maximisation algorithm (EM) (Dempster *et al.* 1977); and the gradient descent algorithm (GD) (Norsys 2005).

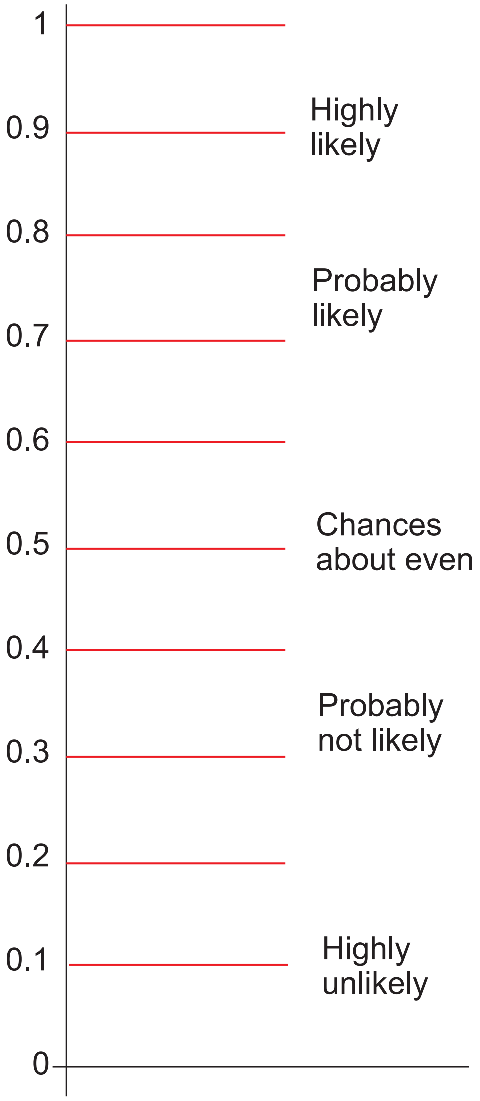
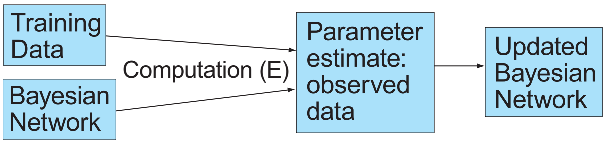
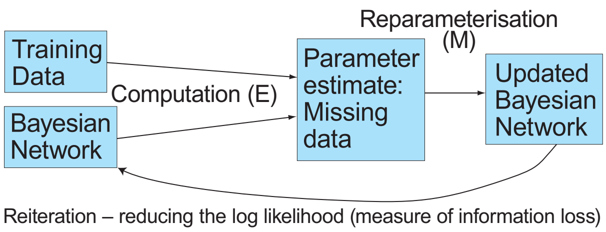



*Figure 8: Mapping probabilities to descriptive terms.*

The simplest method is LS; it uses frequency counts of child states given each possible parent instantiation (in a BN, instantiate represents an instance for a set of states). When using LS, problems arise when data lacks coverage across the diversity of model states and when data points are missing, as LS cannot estimate missing data points. The LS learning algorithm is shown diagrammatically below:




The EM algorithm deals with missing data by finding the parameterisations that yield the greatest likelihoods given the available information. EM alternates between performing an expectation (E) step, which computes an expectation of the likelihood by including the latent variables as if they were observed, and a maximisation (M) step, which computes the maximum likelihood estimates of the parameters by maximising the expected likelihood found on the E step. The parameters found on the M step are then used to begin another E step, and the process is repeated. As implemented in Netica (Norsys 2005), the EM algorithm solves a network by finding the posterior probability for each node based on information in the cases, where initial parameters are iteratively refitted to the data updated model until convergence is achieved (Kalacska *et al.* 2005). The EM learning algorithm is shown diagrammatically below:




GD works in a similar way to EM, but parameterisation trials with the GD method suggest that it is susceptible to local maxima (Woodberry *et al.* 2004a), which has also been observed when training neural networks using GD (Gori and Tesi 1992).

Environmental datasets often contain missing values. Where this occurs, the EM algorithm can be useful for data learning (Uusitalo 2007). However, limitations associated with EM arise when the data is sparse or biased; in such circumstances, missing data estimates will be only poorly estimated and outcomes would be generally unreliable. Also, given that the starting assumption of the EM algorithm (CPTs are blank) is different to LS (CPTs are equal), probability estimates are often much more certain (e.g. 100% for 1 observation), even where data coverage of a state is limited.

As with any modelling technique, it is possible to overfit a BN. Indeed, complex BNs can be more susceptible to overfitting where data is limited and model structures are complex. Overfitting occurs where random error or noise in data is represented instead of the underlying relationship. This can occur where too many parameters (i.e. too many nodes, states and/or arcs) are represented in the model and data are too few for model parameterisation. Evaluation tests (Section 2.4) should assist in identifying models that are subject to overfitting.

### *2.3.2 Propagation algorithms in BNs*

Downward propagation of evidence through the BN is based on the law of total probability, through a form of the joint probability calculation (Ames *et al.* 2003). Therefore, if a1 and a2 describe the variable A taking its first and second states respectively, then, in this example:

$$P(c1) = P(c1|a1,b1) \cdot P(a1,b1) + P(c1|a1,b2) \cdot P(a1,b2) + P(c1|a2,b1) \cdot P(a2,b1) + P(c1|a2,b2) \cdot P(a2,b2)$$

(Equation 2.)

Unlike a decision tree, a Bayesian network also has upward propagation of evidence, based on Bayes' Rule:

$$P(a1,b1|c1) = \frac{P(c1|a1,b1) \cdot P(a1,b1)}{P(c1)}$$

(Equation 3.)

Where P(a1) is the prior marginal distribution of the parameter value a1, and P(c1|a1,b1) is the conditional probability of c1 given a1 and b1. After collection of evidence c1, P(a1,b1|c1) represents the posterior distribution, given the new knowledge.

As the size of a BN grows, the propagation of information within the network might, at first, seem like it would require a vast amount of computational power. However, the scope of an update can be limited through the idea of conditional independence. Two nodes A and B are said to be conditionally independent if there is no way to get from A to B via the directed arcs in the network. When two nodes are conditionally independent, the network does not need to calculate conditional probabilities for the states of the two nodes. For a network with many nodes, this can drastically cut down on the computational power that would otherwise be required to update and use the network.

Conditional independence can arise even in direct causal chains (Norton 2010). For example, in Figure 9(a), nodes A and B may be conditionally independent, as if the value of C is known with certainty, then a change in A has no effect on B, and vice versa. It should be noted, however, that if an observation of C is subject to observational error, then knowledge of A can contribute to knowledge of B, and so the two are no longer conditionally independent. This is commonly referred to as d-separation in the AI literature.

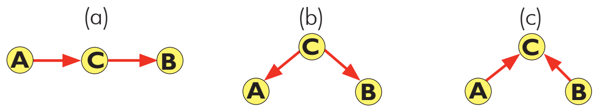


*Figure 9. Common dependence relationships in Bayesian networks.*

If two nodes have a common cause, such as node C in Figure 9(b), then A and B are again conditionally independent, since knowledge of A does not affect knowledge of B if C is known with certainty. On the other hand, if two nodes have a common effect, such as node C in Figure 9(c), this implies a conditional dependence between nodes A and B. For example, if it is known that P(c1|A) is low, this increases the probability that B has a state bx for which P(c1|bx) is high. In such a case as that illustrated in Figure 9(c), A and B in effect *compete* to explain C (Norton 2010).

## 2.4 Evaluation

An important aspect in building a Bayesian network is evaluation. Evaluation of a Bayesian network requires assessing the model behaviour to determine:

- Is the model doing the right job?
- Is the model doing a good job?

Evaluation can be undertaken at several levels. The first level is determining whether the model meets its stated purpose and operates at the right scales. This is particularly important for models that are constructed for decision support needs. An appraisal of the model structure should also be undertaken. Are the key variables, and their relationships, represented in the model? The BN review should ensure that variables and their states are defined unambiguously. If subjective terms are used (e.g. "low" or "high") these should have been clearly defined (e.g. below the 90th percentile, or below the 25 degree temperature threshold).

To evaluate the quantitative performance of the model three types of evaluation methods are discussed: sensitivity analysis, data-based evaluation and non-quantitative evaluation of model outputs using experts. Where possible, evaluation tests should be quantitative. However, in models for NRM, this is not always possible. In cases where large data sets are not available (especially common in complex systems such as ecological and biological systems), model review by an independent domain expert (e.g. an expert not engaged in constructing the model) can also be used. Because of the ability of BNs to incorporate information from various sources, it is possible to evaluate them via a combination of both statistical data and domain expert evaluation (Pollino *et al.* 2007b; Woodberry *et al.* 2004b). Further, this also means that Bayesian methods can be used to test expert predictions against empirical data, assess expert bias, and to provide a framework for the efficient accumulation and use of evidence (Newman and Evans 2002; Pollino *et al.* 2007b).

Where empirical data is not available for model evaluation, the accuracy of how well the model represents the system can only be poorly assessed. Therefore the acquisition of empirical data, collected via adaptive management processes, should be seen as a crucial component of model evaluation (Sobehart *et al.* 2001). Indeed, the use of Bayesian statistical inference demands that not only must models be confronted with empirical data, but their assumptions on how systems are structured must also be challenged. Thus, although peer review of models by independent domain experts is another form of model evaluation (Morgan and Henrion 1990; Pollino *et al.* 2007b), complex BN models that have not or cannot be tested with data should not be relied on for their management implications.

## Sensitivity analysis

Broadly, sensitivity analysis is a type of tool that can be used to explore the behaviour of complex models. It allows us to study how the variation (or uncertainty) in the output of a model can be apportioned to different sources of variation in the input of a model. Through sensitivity analysis, we can begin to identify which variables in our models have the greatest influence on our model endpoints, as well as ordering the importance, strength and relevance of the inputs in determining the variation of the output. Sensitivity assessment begins with sensitivity analysis but extends it to examine which hypotheses about model substructures are consistent with observations of system behaviours and knowledge about the system. It allows one to attempt to discriminate between alternative, outcome-sensitive representations in the model and/or to identify where new information is required to assist that discrimination. It is a powerful tool in model testing and simplification.

In models where a range of processes that affect an outcome are represented, sensitivity assessments using findings can assist in determining (a) how important are each of the driving variables, with respect to a given model result; and (b) how variables assessed as unimportant can be deleted or ignored, while the most important components are candidates for further model development or data gathering.

Two types of sensitivity analyses can be used in evaluating a Bayesian network. The first, ''sensitivity to findings,'' considers how the Bayesian network's posterior distributions change under different conditions, while the second, ''sensitivity to parameters,'' considers how the Bayesian network's posterior distributions change when parameters are altered. To date researchers appear to have employed only one or the other of these methods in any one study (e.g. Coupe and van der Gaag 2002; Laskey and Mahoney 2000; Rieman *et al.* 2001). Both are needed for a careful and thorough investigation of the properties of a network.

### *Sensitivity to findings*

Sensitivity to findings can use the properties of d-separation to determine whether evidence about one variable may influence belief in a query variable (Korb and Nicholson 2004). D-separation occurs when nodes in a causal graph are conditionally independent, given evidence (for more information see Korb and Nicholson, 2004). Using sensitivity to findings, it is possible to rank evidence nodes. This process allows the expert to identify whether a variable is sensitive or insensitive to other variables in particular contexts, which in turn may help to identify errors in either the network structure or the CPTs. The information can also be used to provide guidance for collecting further data or to direct expert elicitation and evaluation efforts.

Sensitivity to findings can be quantified using two types of measures, entropy and mutual information (also referred to as variance reduction for continuous variables). Both measures were implemented using algorithms in Woodberry *et al.* (2004a). Entropy, H, is commonly used to evaluate the uncertainty or randomness of a variable (X) characterised by a probability distribution, P(x) (Korb and Nicholson 2004; Pearl 1998):

$$H(X) = - \sum_{x \notin X} P(x) \log P(x) \qquad \text{(Equation 4)}$$

Entropy measures assess the average information required in addition to the current knowledge to specify a particular alternative (Das 2000).

Mutual information is used to measure the effect of one variable (X) on another (Y) (Korb and Nicholson, 2004):

$$I(X,Y) = H(X) - H(X|Y) \quad \text{(Equation 5)}$$

where I(X,Y) is 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 (Korb and Nicholson 2004). If I(X,Y) is equal to zero, X and Y are mutually independent (Pearl 1988).

*Sensitivity to parameters*

Sensitivity analysis can also be performed using an empirical approach in which each of the parameters of the query nodes are altered and the related changes in the posterior probabilities of the query node (such as the endpoint) are observed. To examine a complex Bayesian network, this type of analysis can be extremely time consuming. Coupe and van der Gaag (2002) seek to address this limitation by identifying a ''sensitivity set'' of variables, which are defined as being the most influential in a Bayesian network. This is done by calculating the posterior probability of a node by systematically changing conditional probabilities. It is these parameters that are most influential in calculating posterior probabilities, and it is on these parameters that quantification efforts should be focussed (Coupe *et al.* 1999). If the plotted sensitivity function does not behave as the expert expects (e.g. its slope, direction or range is unexpected), this may indicate errors in the network structure or CPTs.

A sensitivity set of nodes can be found using an adapted d-separation algorithm (see Equation 6). When evidence is entered into a Bayesian network (i.e. a Bayesian network is instantiated) the algorithm identifies the type of function of the parameters by checking whether the query node has any child nodes. Parameter changes are represented as linear if there are no child nodes or hyperbolic if there are child nodes.

A revised probability distribution of the test node is set by first selecting a new value, $P_{new}$ for the parameter under investigation, *Pj*. The remaining parameters, *Pi*, are normalised to retain relative values by the updating function:

$$Pi \Leftarrow Pi \times \frac{1-Pnew}{1-Pj}, i \neq j \quad \text{(Equation 6)}$$

before the parameter under study is updated.

$$Pj <= Pnew \quad \text{(Equation 7)}$$

### *Data-based evaluation*

Where possible, data should be used for evaluation. A common method of evaluation for a Bayesian network is to measure predictive accuracy. This method measures the frequency with which the predicted node state (that with the highest probability) is observed, relative to the actual value. If data are also being used to parameterise CPTs, it is necessary to divide data into a calibration/training set and a test set. Commonly, a calibration dataset would comprise 80% of data, and 20% would be used for testing. Independent datasets (e.g. other catchment areas) can also be useful for model testing purposes. Another output from predictive accuracy is a confusion matrix. This matrix identifies where model states were incorrectly predicted by showing the actual state versus predictive state.

Another metric that has some utility is Bayesian Information Reward, where Information reduces uncertainty about the world. This is explained in Hope and Korb (2002): ''When a [BN] correctly classifies an instance with probability *p*, *p* must be greater than the prior probability *p_* to inform, or reduce uncertainty. This is reflected in the definition of generalised *IR*; thus *p* > *p_* is rewarded and *p* < *p_* is penalised, given correct classification. Given misclassification, *p* < *p_* is rewarded and *p* > *p_* penalised. This can be interpreted as the following: the learning [algorithm for the BN] indicated that the probability *p* of the event was less than what you had expected (*p_*). That event did not occur, so the learner should be rewarded for reducing the expectation in the event, while if *p* was increased, the expectation was increased, and thus the learner should be penalised for its estimation'' (Hope and Korb 2002).

### *Non-quantitative evaluation using experts*

Bayesian network evaluation with experts is also important. This can be done via a structured review of the model with experts. The review should consider the model objectives, scales, structure (nodes and arcs) and conditional probabilities. Use of sensitivity analysis is a rapid style of analysis to check the relative strengths of relationships between variables.

Although the evaluation of a model is important, the accuracy of a BN should not be seen as the primary outcome of the exercise. An important outcome of a model may be a better understanding of a system, rather than a reliable, quantitative prediction (Jorgensen and Bendoricchio 2001). Indeed, often the outcomes of evaluation can guide future monitoring program designs or identify priority knowledge gaps (Pollino *et al.* 2007a), which is a important outcome for NRM and policy development processes. In the model developed by Barton *et al*. (2008), authors found that the integration and multi-disciplinary process of defining the network structure, determination of probability distributions and conducting sensitivity analysis were a more important outcome than the results of the analysis itself.

# 3. Benefits of Bayesian networks

In this section, we describe the benefits of Bayesian networks. Bayesian networks have become widely used and accepted in environmental applications due to their flexibility in being able to represent multifaceted systems. They can incorporate information of variable quality, and uncertainties in predictions are represented as the likelihood of being within a set of defined states. The process for developing a Bayesian network is fairly straightforward, and the software environments are user friendly. For these reasons, Bayesian networks are particularly useful for communication and educational purposes.

## 3.1 Complexity

Models can assist scientists and decision-makers in understanding complex systems. They are built to answer specific questions and to represent the relevant features of the system. The building blocks of systems models include: inputs, outputs, state variables, decision (control) variables, exogenous variables, uncertain variables and random variables (Haimes 2009). To structure and parameterise the model, the modeller needs to identify, understand and quantify the model building blocks. In complex integrated systems, where physical, biological and human systems interact, the model building system often requires the use of integrated models. Understanding and effectively modelling a system, where human and non-human systems interact, naturally requires a multidisciplinary approach (McCann *et al.* 2006). To be able to model such 'complex' or multifaceted systems, a flexible modelling approach, which can assemble diverse information into a coherent and systematic environment, is required.

Deterministic models only poorly represent complex systems. They are limited to relationships that are readily quantified, and only rarely is uncertainty or variability represented. Such models (e.g. climate, water quality, hydrology, etc.) seldom explore the connections between physical and biological systems, and the output of a physical model is used to infer changes in a biological process. In contrast, Bayesian networks readily integrate information from a range of disciplines, incorporating both quantitative and qualitative evidence across a range of scales, and do so without losing the uncertainties associated with this evidence. By building up an evidence base, we can explore the strength of interactions. Where deterministic models better represent the dynamism of a system process, this model can be used as an input to the Bayesian network (Merritt *et al.* 2010).

The simplicity of the links between variables in a BN allows a large number of state variables to be represented, often without too great an increase in complexity or computational power (Letcher *et al.* 2004). BNs can also be modular, where each important system component can be represented and developed independently, and integrated into a BN.

Previously, we have found that BNs can assist in promoting a better understanding of complex systems, while acknowledging the limitations and uncertainties that exist in our current understanding of system functions (Pollino *et al.* 2007a). Through adaptive management, uncertainties can be reduced. Using models within an adaptive management framework promotes: documentation of hypotheses; targeted monitoring; and allows management actions to be adjusted over time (Failing *et al.* 2004). BNs provide a framework for iterative updating as more knowledge becomes

| | | | |
|---|---|---|---|
| **Aleatory** | Quantifiable and irreducible | Heterogeneity<br>Fuzziness<br>Randomness<br>Inexactness<br>Variability<br>Imprecision | That which we know<br>(and include or don't use) |
| | Quantifiable and potentially irreducible | | |
| | Quantifiable, potentially irreducible, maybe irrelevant | | |
| | Quantifiable and potentially reducible | Incompleteness<br>Active Ignorance | That which we know we don't know |
| | | Inconsistency<br>Conflict | That which we can't agree that we know |
| **Epistemic** | Unquantifiable but potentially reducible | Incompleteness<br>Passive Ignorance | That which we know we don't know |
| | Unknowable and irreducible | Incompleteness<br>Indeterminacy | That which we could not possibly know |

*Figure 10: Mapping sources of uncertainty and uncertainty management capability on the states of knowledge (Curtis and Wood 2004).*

available, and consequently, the principles of adaptive management can be readily applied within a Bayesian network context (Pollino *et al.* 2007a; Prato 2005; Smith *et al.* 2007b). The potential use of BNs in Adaptive Management is discussed further in Section 6.1.

### *3.1.1 Uncertainty and variability*

Uncertainty is defined as a lack of knowledge about the accuracy of a measurement of a system and is an inherent property of the limitations of observing or understanding a system (Finkel 1996). Uncertainties can be classified into different types, as shown above in Figure 10, and as published first by (Curtis and Wood 2004).

In Bayesian networks, the most common sources of uncertainty we seek to represent is lack of knowledge and the inherent variability within natural systems. Other types of uncertainties that can be represented in a BN include: statistical variation; the subjectiveness of expert judgements; and disagreement between multiple experts. A description of uncertainties in models for conservation and NRM can be found in Burgman (2005) and Regan *et al.* (2002). As with Bayesian statistical approaches, it is not possible to identify or differentiate between sources of model uncertainty (i.e. delineating between lack of knowledge and natural variability). However, judgement of the model builder can be used to make a qualitative assessment on sources of uncertainty in the model. In representing uncertainty, Bayesian networks only estimate exact probabilities, such that credible intervals or imprecise probabilities are not given. This is a weakness of the BN approach (see Section 4.2) that can be addressed through model evaluation (see Section 2.4).

Technically, BNs have no minimum sample sizes and show good predictive accuracy even with only small sample sizes (Uusitalo 2007). They have the flexibility to be used in both data-poor and data-rich environments, and conditional probabilities do not need to be exact to be useful (Wooldridge 2003). BNs using approximate probabilities have been shown to give good results, as BNs are generally quite robust to imperfect knowledge. One drawback, however, is that imperfect knowledge of probabilities cannot be propagated through a network, a limitation of BNs discussed further in Section 4.2.3. Therefore, as with other modelling techniques, if attempting to model a data-poor system, caution is warranted (McCann *et al.* 2006).

In building a model, the modeller also has to continually make decisions on trade-offs in model complexity and performance. ''Any model should be as simple as possible and as complex as needed to answer the expected questions'' (Haimes 2009).

Although there are virtually no limits to the number of variables that can be included in a Bayesian network (Dorazio and Johnson 2003), parsimony is still the desirable outcome, smaller models are easier to interpret and communicate, leading to a better understanding of a system (Iwasa *et al.* 1987) and ability to communicate outcomes. Sensitivity analysis techniques for Bayesian networks can assist in determining the key variables influencing model outcomes, resulting in simpler models (Pollino *et al.* 2007b).

In complex Bayesian networks, such as those built for NRM, it is important to be able to assemble information so that it is logically consistent, compartmentalised (often using sub-model structures) so that is understandable to the model user, while being robust and parsimonious. To achieve these objectives, an understanding of the 'issue' for analysis, a clear focus of the model objectives (e.g. system understanding vs. decision-support) and good facilitation skills are essential. All Bayesian networks should also have thorough documentation. Part of this documentation should include the uncertainties in each part of the model.

Those involved in translating science into management are faced with the challenge of how to 'deal with' uncertainty. Bayesian networks can assist in determining how important threads of uncertainty are to the question at hand (e.g. does the uncertainty in data or knowledge pose a risk to not being able to define environmental flow needs?) and for assessing how uncertainty can effect a decision (i.e. How robust is a decision given modelled uncertainties? How sensitive is a model outcome to uncertainty?).

## 3.2 Bayesian Decision Networks

Up to this point, all Bayesian networks discussed have been Bayesian Belief Networks (BBNs), constructed solely using 'Nature' (also known as 'Chance') nodes. Nature nodes describe the empirical or calculated states that separate components of the system to be modelled may take, and associated with these states are probabilities of a state occurring. However, Bayesian Decision Networks (BDNs) use two other types of nodes. These are 'Decision' nodes, and 'Utility' nodes. (Barton *et al.* 2008) show the layout of a BDN in the context of Driver-Pressure-State-Impact-Response model (Figure 11).

Decision nodes represent two or more choices that a manager can make which can influence the values of other nodes. In a belief network, the parameters these nodes represent would simply be modelled by a Nature node. However, choices in a Decision node do not have probabilities associated

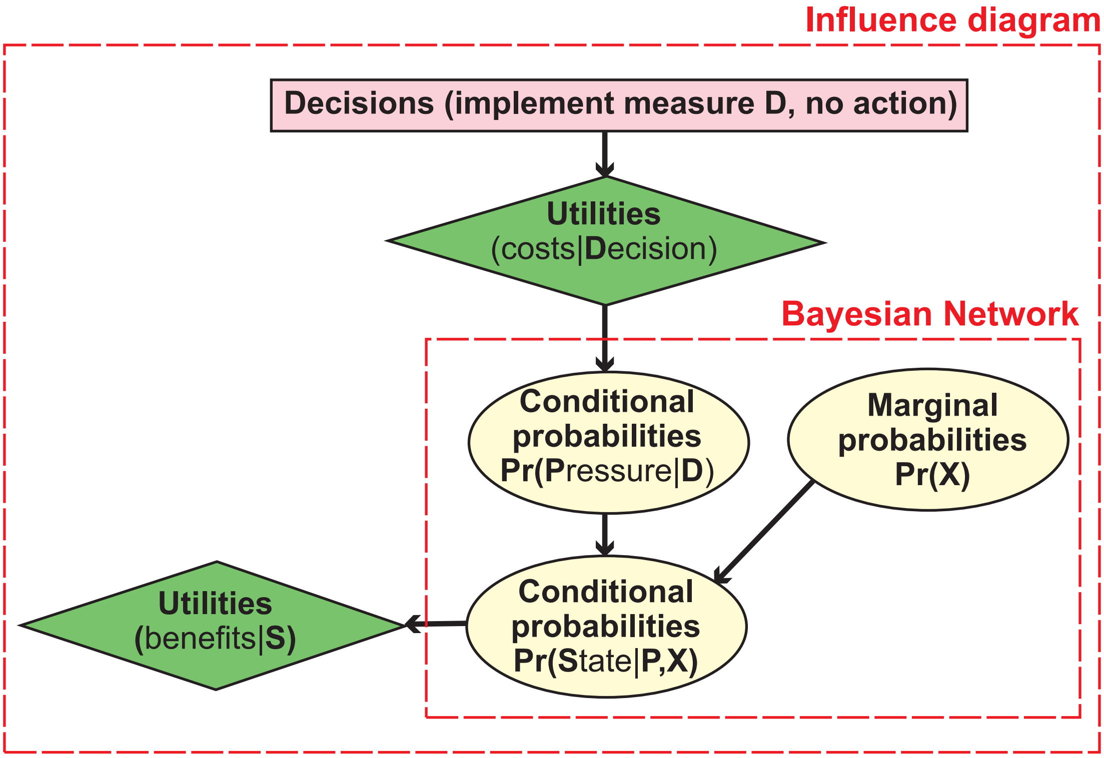



*Figure 11: The layout of a Bayesian Decision Network (BDN) showing utility nodes (green), decision nodes (pink) and nature nodes (yellow) in the context of a Driver-Pressure-State-Impact-Response model (Barton et al. 2008).*

with them. Instead, they can be used either to explicitly show the factors of the model that are able to be changed through management decisions, observe the effect a decision has on the system, or used in conjunction with Utility nodes to solve for some desired outcome, such as maximised benefits. In most software packages, the Decision node displays the total expected utility (Expected Utility(A) = Utility(A) x p(A)) for each decision modelled, allowing decisions to be optimised.

Utility nodes in BDNs are a way of explicitly representing the value, either cost or benefit, of some outcome or decision within the network of each possible outcome state. The Conditional Table for a Utility node describes the relevant expected cost or benefit for every possible combination of input states. Utility nodes can be linked to either outcome Nature nodes or Decision nodes. More

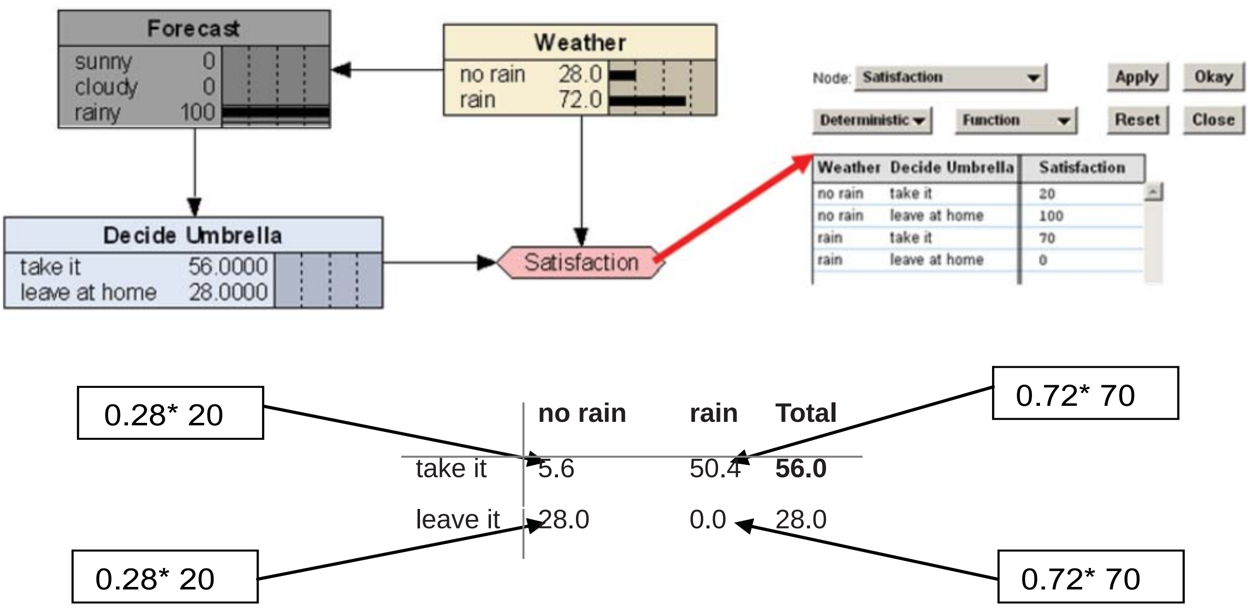



*Figure 12: Calculating utilities for optimising decisions.*

than one Utility node can be linked to the same node, and Utility nodes need not be parameterised on the same unit of measure, although doing so does make it easier to interpret model results. For example, one Utility node might represent an expected monetary outcome, whilst another represents a more subjective weighted measure of public happiness with the outcome.

An example of calculating expected utilities for deciding whether to take or leave an umbrella, given a forecast, is shown in Figure 12.

A simplified small example BDN incorporating both these types of nodes is shown in Figure 13. It illustrates the decision process where alternative environmental flow release scenarios can be explored. Utility nodes are ''Cost_Delivery'', 'Redgum_benefit' and 'Bird_benefit'. The values displayed in the Decision node ''Flow_release_scenarios'', reflects the expected utilities for each scenario and ecological outcome.

In this BDN, Scenario B is the optimal decision for the given flow-release scenarios. Multiple decision nodes for BDN can be used for sequential decision making.

Once parameterised and compiled, a BDN that contains both Utility and Decision nodes can be made to determine the optimum decision pathway (the best choice for each Decision node) that minimises costs, maximises benefits, or solves some other desired outcome. The sensitivity of these best decisions to changes in utility values and prior conditions can also be calculated. The BDN displays expected values for each choice in the decision nodes by combining all relevant utilities and their calculated probabilities.

Because of their explicit representation of the costs and benefits of certain decisions, BDNs produce information that is particularly well suited to decision support. The ability of BNs to update the whole network at the click of a button when a decision is entered makes examining the effects of various management decisions a quick and simple process. But with the inclusion of Utility nodes in a BDN, an estimate as to the relative value of the decision can be obtained at the same time. The ability to use the network to calculate a set of optimum decisions that will maximise benefits or minimise costs is also particularly useful in the support of decision-making.

An important point to note is that the inclusion of Utilities in a BN can make the network more subjective. Obtaining probabilistic data for the values of Nature nodes, whilst potentially difficult, is generally a rigorously defined process. When obtaining the utilities for the Utility nodes, on the other hand, there is no real scientific way to quantify the information because the values are subjective, psychological concepts, and thus intrinsically difficult to measure. For example, using the BDN shown in Figure 12, one user of the network might prefer walking in the rain, which would drastically change the expected utilities. Sometimes, monetary

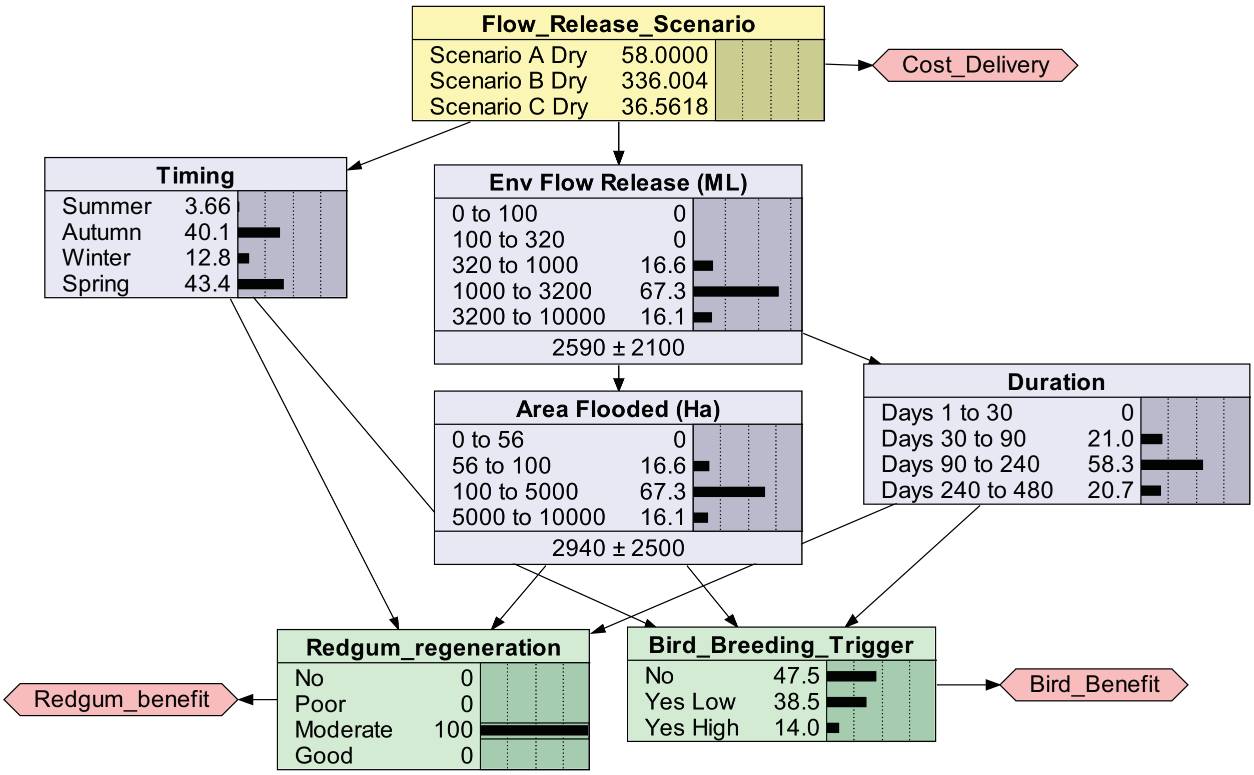


*Figure 13: Hypothetical BDN example, including expected utilities for Utility node.*

value can be used as a general measure to attempt to solve this problem. However, even a dollar can be worth more to one person than another, making its relative worth subjective. Thus it is important to note that the usefulness of Utility nodes should be dependent upon the degree of confidence in the representativeness of the utilities.

## 3.3 Adoption, Communication, Participation

When models are constructed in collaboration with users, they can be tailored to fit the needs of the users and are more likely to be adopted in decision making. When model are constructed with stakeholders, there is an increased likelihood the outputs of the model will be accepted (Hart *et al*. 2006).

BNs have the potential to allow the public to become better engaged in an informed discussion of tradeoffs, for example balancing water requirements for productivity and the environment. An effective community consultation process that addresses tradeoffs between resource users will enhance the prospect for less controversial outcomes, secure diverse input amongst the community, potentially advocate learning and change, and achieve better adoption and acceptance of policies by the community. Collaborative model development is also essential to ensure realistic bounding of management problems, constraints on possible actions, and identification of realistic outcomes (Schreiber *et al*. 2004). They also provide a platform in which disciplines can work together in a more integrative fashion.

After compiling a BN, a probability distribution is available for every possible combination of variable values, and is thus able to show any distribution instantly (Uusitalo 2007). Little formal training is required to use and understand a Bayesian network, particularly in their simplest form. As such, they are particularly suitable for communication, where management decisions need to be made. BNs can be readily used to examine scenarios, such as alternative management decisions or outcomes of system changes, and can be used in a timely manner to provide advice to decision-makers. This is in contrast to many other types of simulation models, in which the results would need to first be simulated and can take a long time depending on the size of the model.

# 4. Limitations of Bayesian networks: Description and solutions

In this section, we describe the limitations of BNs, and outline potential solutions. Limitations included are: representation of dynamics (temporal, feedbacks, spatial); representation of continuous probabilities; the size of CPTs in complex networks; the use of exact algorithms for probability propagation; and problems associated with use of subjective expert opinion.

## 4.1 Dynamics

As outlined above BNs are useful for modelling complex, multi-faceted systems. However, they are limited in their representation of dynamic systems. This is problematic for ecological applications, as ecological systems are complex, dynamic, and unpredictable across space and time (Moore *et al.* 2009).

### *4.1.1 Temporal dynamics*

A major limitation of Bayesian networks is their poor representation of temporal dynamics. Temporal representation in Bayesian networks is often done using a static representation, where time points or time slices are represented as static processes. A BN cannot be run over several iterations, but represents a change in outcome over a stated period, which needs to be pre-defined. Experience suggests that dynamic data for ecological systems is rarely available, and modelling the knowledge of temporal changes in systems where interventions are made is a task beyond most technical experts.

*Dynamic representation of changes through time*

If the Markov property applies to the system to be modelled, a way to work around this problem does currently exist. The Markov property holds for a system if, for every discrete time instant *k*, the values of any variable of the system at *k* depend only upon the values of that variable and any other related variables at time instants *k* and *k-1*, i.e. the states at *k* are not affected by the states at time instants *k-2* or earlier. Although the Markov property is restrictive, it is generally widely applicable, and if the Markov property does apply, the method of Dynamic Bayesian Networks (DBNs, not to be confused with Bayesian Decision Networks (BDNs)) can be used.

DBNs are able to model temporal relationships between variables at the same time as modelling any other relationships. They do this by breaking up time into relevant discrete time-steps, and placing a structurally similar copy of the network within each time-step. A causal relationship between output nodes in time-step *k* and relevant nodes in time-step *k+1* are then inserted. If some intermediate nodes in the network also affect nodes in the next time-step, these causal links are able to be modelled as well.

In this way, it is possible to model any number of required time-steps. DBNs are also able to update using the same algorithms as standard BNs. However, the example shown below in Figure 14 only has 3 nodes per time slice. For complex networks, 20 or more nodes would not be unfeasible. If only five time-steps are required to be modelled, this could conceivably make the network increase in complexity very quickly, in turn greatly increasing the amount of computational power required to run it. Thus DBNs can be a somewhat cumbersome method of dealing with temporal variability in an ecosystem.

However, if, as is often the case, the intra-timestep causal probabilities of the links retain their structure over every required time-step, and the inter-timestep causal probabilities also remain the same between each time-step, the computational power required can be greatly reduced. Most BN programming shells can be set to require only the CPTs of the intra-timestep causal links of the structure for one time-step, and the inter-timestep causal links between one time-step and the next, in order to create a DBN of a specified number of time-steps. Once this information is input, a large number of time-steps can be run with the same computational power requirements as that of a DBN with only a few.

Naturally, this solution only applies if the intra- and inter-timestep links remain constant over all time-steps to be modelled. This is generally widely applicable but, just like the Markov property, it can be somewhat restrictive. For this reason, as previously stated, dealing with temporal variability within BNs is currently an area of much research. Where temporal dynamics need to be well represented, systems dynamics models may be a more appropriate model approach to use.

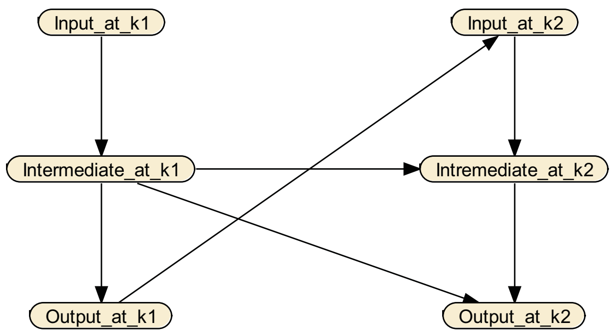



*Figure 14: Example of a simple DBN*

*Dynamic Decision Networks*

Just as a static BN can be extended by allowing for temporal variability to create a DBN, BDNs can be extended in the same way to create Dynamic Decision Networks (DDNs). This allows for sequential modelling and decision making to be performed, meaning that the effects and expected utilities of management decisions can be modelled not just in the immediate future but at any number of time-steps into the future as well.

As with BDNs, a DDN can have any number of utility nodes. Thus the network might have simply one or two distinct utility nodes at the end of all of the time-steps to be modelled, or a number of utility nodes within each time-step, or perhaps both. This greatly assists the decision-maker to find and take the optimum decision at each time-step, so as to maximise some desired outcome not only in this time-step, but into the future as well.

A simple Bayesian diagram of an example DDN is shown in Figure 15, spanning four time-steps. The intra-time-step causal structure of this DDN is comprised of 3 nature nodes A, B and C, as well as a decision node and a utility node. It can be seen that there exists some feedback between the variables A and C, showing how dynamic networks can be designed to incorporate feedback whilst retaining their acyclic graphical nature, if at the cost of increased complexity.

It can also be seen in Figure 15 that the inter-time-step causal links are repeated at each time-step. As previously discussed in Section 4.1, this is not necessary in the construction of a DDN, should causal links prove not to remain constant over time, but aids in greatly reducing the required complexity of a dynamical network.

*Static representation of changes through time*

If the model does not require changes to be represented dynamically, they can be simply represented by the addition of an additional variable, which can represent changes over time periods, represented as spans of time (Figure 16).

This style of approach is particularly useful when a 'parent' or input model is dynamic, so the dynamism of a system process can be represented 'statically' in a BN. The advantage of doing this is that the BN can link this process to other system processes (such as water quality) and to biological outcomes (such as changes in communities).

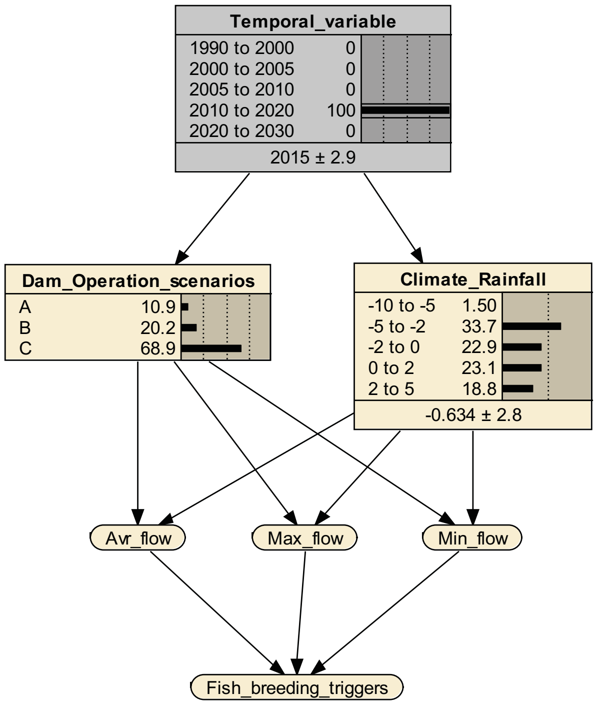



*Figure 16: Theoretical representation of temporal changes in dam operation and climate scenarios influencing flow metric and fish breeding triggers.*

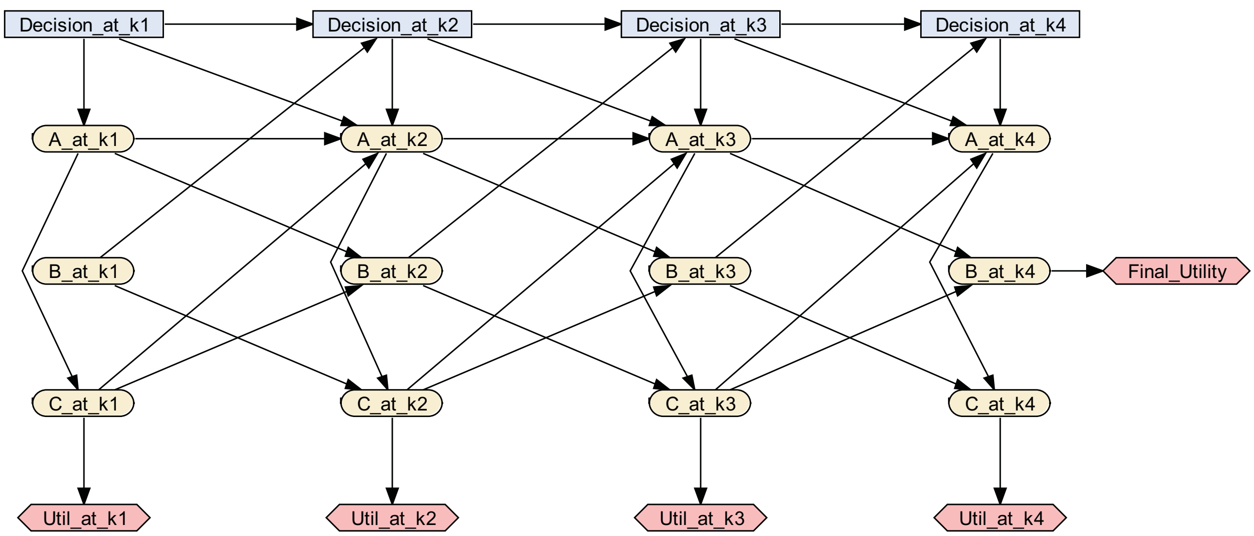



*Figure 15: Bayesian diagram of a simple 4 time-step DDN*

This style of approach is being used to develop the IBIS Decision Support Systems, which simulate environmental flows to, and predicts ecological outcomes in inland wetland systems (Merritt *et al.* in press).

### *4.1.2 Feedback loops*

Due to the acyclic nature of a BN's graphical structure, it is not possible to model cyclic loops, such as feedbacks, within a static BN. In other words, if node A affects node B, but is in turn affected by node B, this cannot be represented in a static BN. This represents another major problem for the adoption of Bayesian networks in ecological modelling, as feedbacks are an inherent component of many complex systems.

However, if the effect of the feedback occurs on the same general timescale as that of the timesteps being modelled in a Dynamic BN, it is then a straightforward process to include feedback loops. If node A is affected by node B at the same time as affecting node B, an inter-timestep causal link can be incorporated between node B at time-step *k* and node A at time-step *k+1*.

In this way, multiple feedback loops in the one system can be handled with relative ease, as can the same feedback loop over any number of timesteps. However, it is worth bearing in mind that with each addition of a causal link, the overall complexity of the DBN increases, as the size of a CPT within the network will increase. This problem of increasing complexity is discussed further in Section 4.2.

### *4.1.3 Spatial variability*

The states and values in ecosystems can also vary in space. Just as BNs have difficulty in dealing with temporal variability, representation of spatial variability is also limited. To represent spatial dynamics, the method can become excessively complex, depending on the accuracy required. To represent changes in space statically, the solution is straightforward.

*Dynamic representation of changes through space*

When dealing with temporal variability, the Markov assumption is used to greatly simplify the network. When dealing with spatial variability, an analogous assumption can be made: that is that the value of a variable at any location depends only on the variables at adjacent locations. Thus a Bayesian network designed to model spatial variability, or a sub-component thereof, could be set up in a similar fashion to a finite element analysis (FEA) model, where each node only affects adjacent nodes, only incorporating conditional probability tables instead of direct deterministic relations. However, due to the acyclic nature of Bayesian diagrams, feedback cannot occur in a single time-step. This means that, unless the model also incorporates temporal variability (further increasing the complexity), and if nodes A and B are adjacent, the network must be set up to allow only node A to affect node B, or node B to affect node A, not both ways.

It can perhaps be seen that the number of nodes and causal links required to incorporate spatial variability into a model will be large unless the spatial dependence is especially simple. An example of this is shown in Figure 17, where stream flow has only one spatial direction and thus only one dimension is required to be modelled. If two- or even three-dimensional spatial variability is to be modelled to any great detail, for example in modelling algal cells in a pond, the complexity required to construct a Bayesian network can quickly become unwieldy. This is especially the case if the conditional probabilities can only be obtained through expert elicitation.

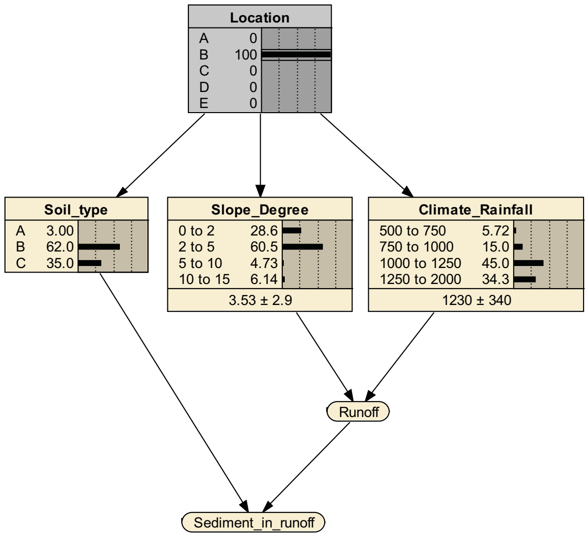



*Figure 17: Theoretical representation of spatial changes in soils, slopes and climate, and how these influence run-off (overland flow) and sediment volume in run-off.*

*Static representation of changes through space*

As described in the section describing temporal dynamics (Section 4.1.1), 'parent' models can be used to model spatial variability, and this can be used to calculate the conditional probabilities required for the Bayesian network.

If the inclusion of spatial variability into a BN does not require interaction of separate spatial components, a Bayesian network could be constructed using a spatial node (Figure 17).

This type of spatial representation has recently been extended to representation of BN outputs in GIS (McNeill *et al.* 2006; Samranpong and Pollino

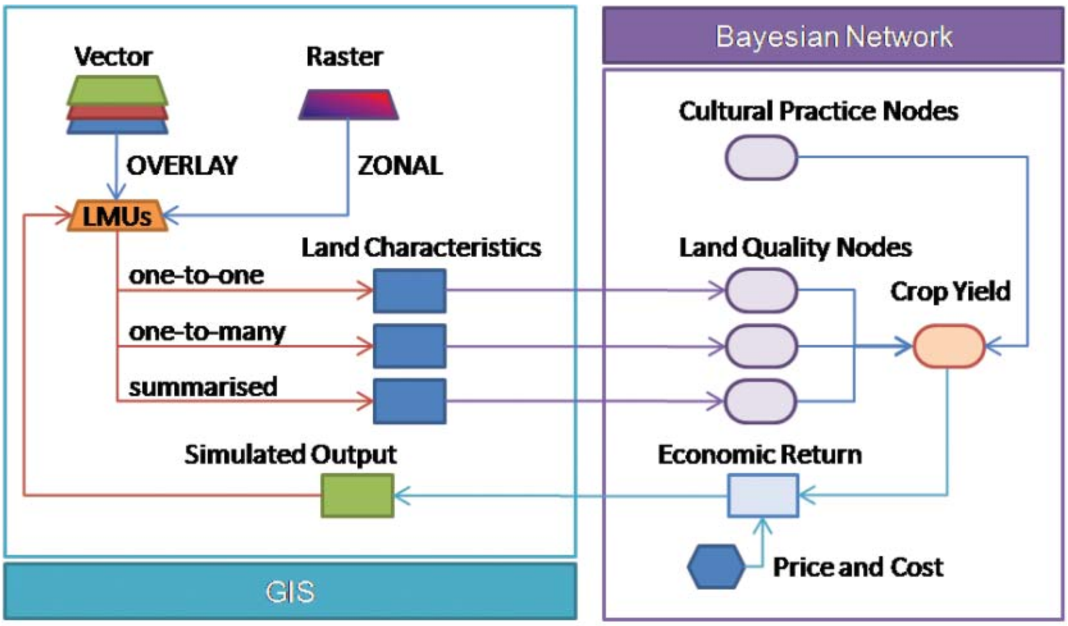



*Figure 18: Calculation of crop yields and economic returns, where GIS is used as inputs to the Bayesian networks, and outcomes are plotted back to GIS (Samranpong and Pollino 2009).*

2009; Smith *et al.* 2007b). An example of the interactions between GIS and Bayesian networks are shown in Figure 18 and an example of an output is shown in Figure 19.

### *4.1.4 Object Oriented Bayesian Networks*

An Object-Oriented Bayesian Network (OOBN) has an additional type of node called an instance node. An instance node represents an instance of another (nested) Bayesian network, which can also contain instance nodes. OOBNs allow a hierarchical representation of sub-models, which can be used to represent large and complex models, including those with spatial and temporal dynamics, in a way that is both parsimonious and easy to understand. At present few software applications can be used to construct OOBNs, the most popular commercial product for building OOBNs is Hugin (www.hugin.com).

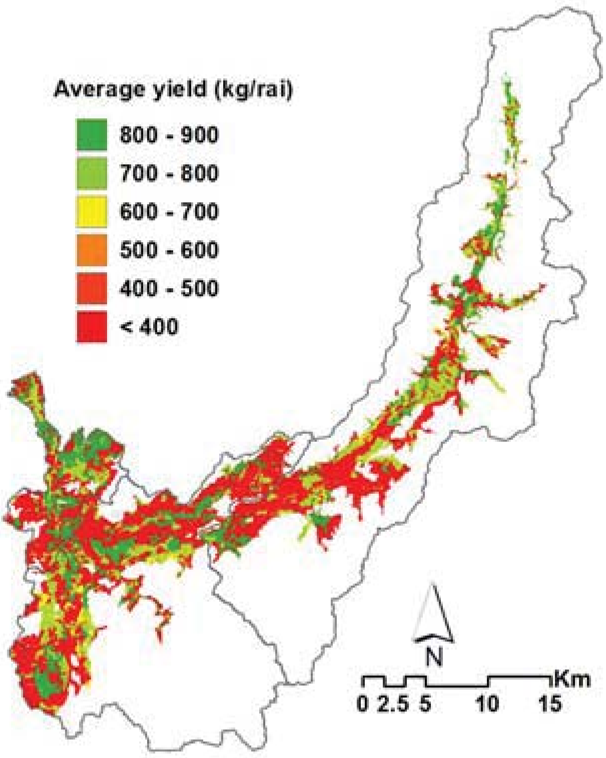



*Figure 19: Calculation of annual crop yields for rice (kg/rai) in the Mae Tha catchment in north Thailand, using GIS (Samranpong and Pollino 2009)*

## 4.2 Limitations in defining probabilities

In this section, the limitations defining probability distributions, and how these are represented in a Bayesian network, are discussed.

### *4.2.1 Discretisation of variables*

Many parameters modelled in BNs have continuous values. However, as stated in Section 2.2, most commercial BN programing shells can only deal with these continuous variables through discretisation[2]. By choosing too few states, this can result in information loss, where as too many states can overcomplicate the model. An example showing the representation of a normal distribution over different number of states is shown in Figure 20.

The resolution of distribution should reflect the quality of information available and the degree of complexity, which can be limited by the issues under consideration, system understanding and the computing load available.

Because of this, a BN may only be able to capture rough characteristics of the original distribution which can cause the BN to lose statistical accuracy (Friedman and Goldszmidt 1996). This is particularly the case should the underlying relationship between two variables prove to be linear (Myllmäki *et al*. 2002). By discretising values, it is also possible to capture non-linear relationships between variables in an easier way than would be required for continuous values, and without too much computational power (Myllmäki *et al*. 2002).

If a model requires particularly high statistical accuracy, depicting a well-defined discretisation of variables is an important task. The method and data used to discretise a variable, including the number of intervals and their division points can make a notable difference in the resulting model (Uusitalo 2007). The method of discretisation used therefore needs to consider the shape of the data distribution and the number of categories/intervals needed to capture the distribution, the significance of the breakpoints, and preferably try to guarantee that each of the intervals has a reasonable number of observations. This can, depending on the complexity of the system to be modelled, be a task that requires much time and examination on the part of the expert team working on it. The software Genie (http://genie.sis.pitt.edu/) contains a tool to explore discretisation in BNs.

Discretisation can be useful where a variable has a particular breakpoint significant to management, as discussed in Section 2. Other methods include using classification methods to explore datasets, defining thresholds using expert input and defining ranges using percentiles of data. The greater the number of discrete states, the greater the model complexity, and the more power you need in your data to support the increase in model complexity.

### *4.2.2 Exponential growth of CPTs*

As stated in Section 2, Bayesian networks use conditional independence to simplify the computational power required to run models. However, where the node in a BN has a large number of parent nodes, the conditional probability table can become overly complex, which increases the computational power to update a BN, increases the data requirements to parameterise the model and leads to difficulties in parameterising CPTs that are derived using expert elicitation. As parent variables are linked to child nodes, the size of the CPTs increase exponentially.

Where previously derived equations or parent models are used to characterise CPTs, an overly complex BN will only be affected by computational time. Where data learning algorithms are used, effectively, the data needs to represent every possible condition that has been established in the model. Ecological data is rarely that comprehensive. Poor data leads to poor statistical power, and can potentially lead to an erroneous interpretation of relationships. This is particularly the case for data learning algorithms that handle missing data (Section 2.3.1). Where expert opinion is used, the quality of that information rarely supports such complexity.

Techniques that can be used to simplify

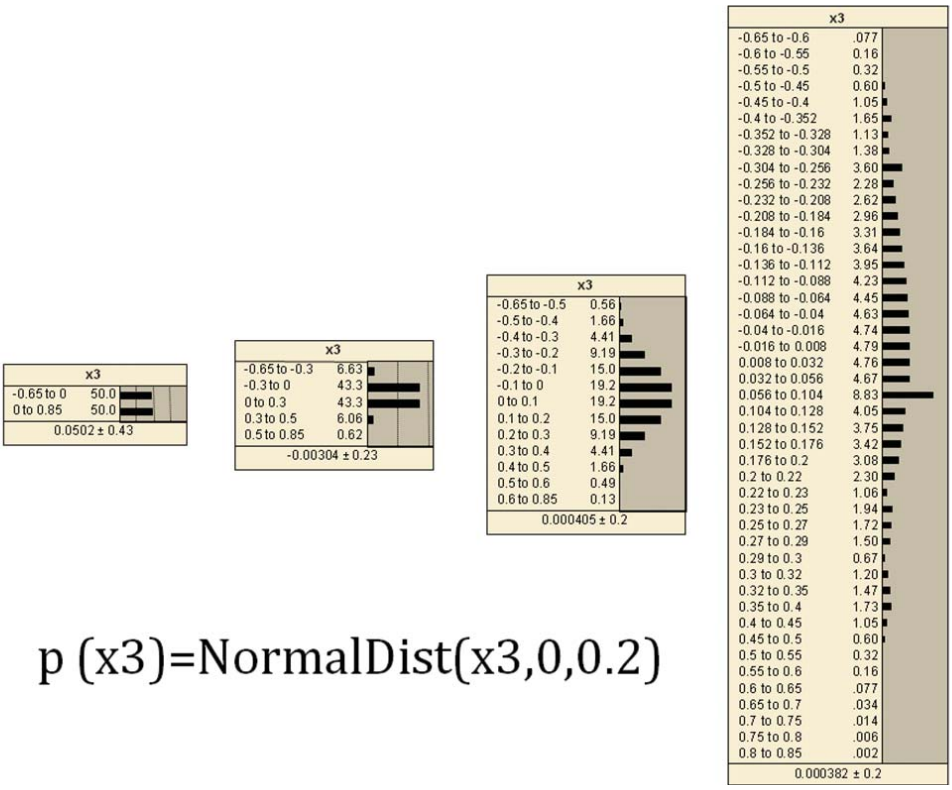



*Figure 20: Normal distribution for variable x3, with a mean of 0 and, a standard deviation of 0.3. The numbers of states are altered for x3..*

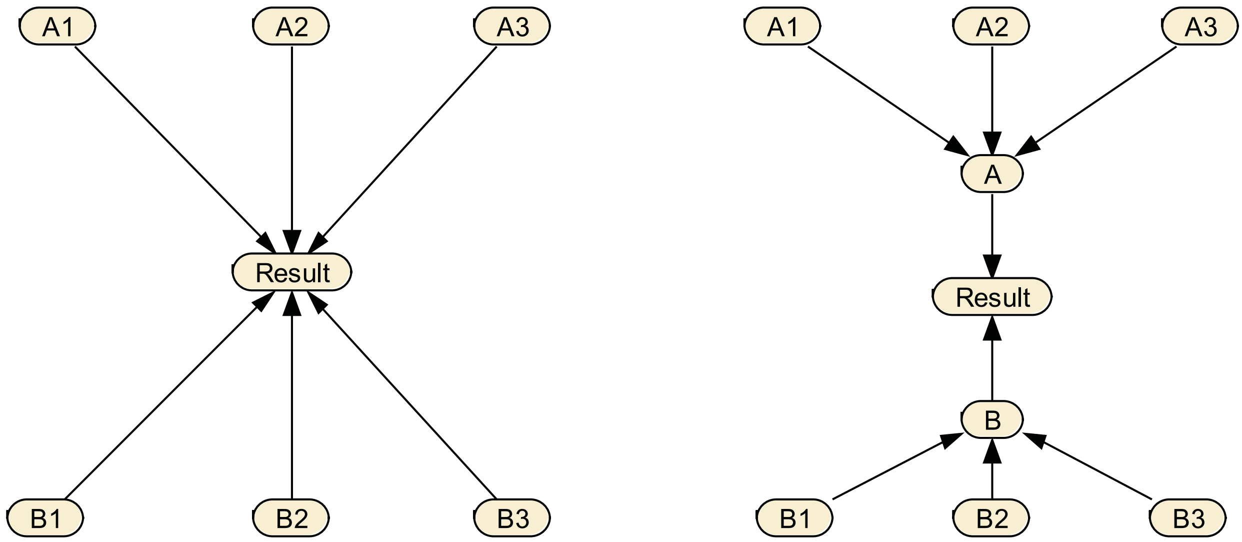



*Figure 21: Divorcing, where nodes A1, A2 and A3 and B1, B2 or B3 in (a) are "divorced" from the node Result by including intermediate nodes 'A' and 'B' (b).*

overly-complex node structures include: using divorcing nodes; removing factors that are not consistent with the model objective; and re-focusing the model scope. "Divorcing" (Figure 21) simplifies CPTs by intervening where too many nodes feed directly into a one child node. In Figure 21, rather than having the nodes A1, A2 and A3 all feeding into 'Result', they are aggregated into a summary node 'A', thus they are "divorced" from the node Result. The same can be done for the three B nodes at the bottom, which might represent factors related to a different process that also affects the Result.

Although divorcing does add nodes to a network, which may not intuitively seem to be the best way of simplifying it, the combined size of the CPTs underlying all the nodes can be greatly reduced. This is because the size of a CPT is determined both by the number of states that node has, and the number of states each of its parents has. For example, if all nodes in the two networks in Figure 21 had 3 possible states, then in Figure 21(a), the size of the CPT for the node Result would be the number of states in Result multiplied by the number of states in each separate parent, i.e. (3*3*3*3*3*3*3)=2187. In Figure 21(b), the size of the CPT for node A is (3*3*3*3)=81, likewise for node B, and as nodes A and B only have 3 states each, the size of the CPT for Result would be (3*3*3)=27. Thus the total number of entries in the whole network of (b) would be 189, resulting in a decrease in the number of required CPT entries by (2187-189) = 1998 entries.

Furthermore, divorcing can make the network easier to understand, as the new variables added will group the BN into logical sub-sections or sub-models. This type of compartmentalised approach to modelling is consistent with the goals of integration, where certain aspects of a system are described as individuals, and the outcomes of these are aggregated into a final outcome. For example, water quality parameters can be aggregated into a 'summary' water quality node prior to feeding into an endpoint node. This can be done for other physical variables, such as hydrology and physical habitat, as well as policy, planning and implementation of model components. A limitation of this approach is the potential for "diluting" the impact of the interventions on the objectives, particularly if the CPT underlying the divorcing node is specified with uncertainty (Cain 2001). Where this occurs, sensitivity analysis of the sub-components of the BN can assist in identifying the important driver(s).

When building a BN in a participatory environment, the desire generally is to include too much detail to the model. However, it is important to ensure that the objectives and scope are well defined so that unwarranted additional complexity can be removed. For models that are solely or partly expert based, a child node should have no more than four parents (most people cannot interpret information beyond four dimensions).

Where it is not possible to simplify a BN through compartmentalisation, it suggests that the system to be modelled is overly complex, the objectives are too opaque, or the knowledge for that system is poor. Where this occurs, it may suggest that a BN is not the right type of modelling tool, the model objectives need refinement or further background work is required before the model can be constructed.

### 4.2.3 Chain lengths in BNs

Generally, but not always[3], the most sensitive variables in a BN tend to be the immediate parents of the child nodes. As you move further away from the endpoint node, the sensitivity of variables to the endpoint declines. This is to be expected as uncertainty is propagated through chains. Consequently, a long chain of nodes will, in general, have a reduced sensitivity to model drivers due to propagation. In designing a BN, long causal chains with little to no branching should be avoided so that any input evidence will not be 'diluted' (Cain 2001).

Aggregation of groups of parameters forming a causal chain, or simply removing variables that are found to be redundant in the process being modelled, can increase the sensitivity of a BN. For example, as shown in Figure 22, the process represented in the node "disturbance of sediments" can be fully captured by a causal link between "Dredging" and "Release of Nutrients," and so does not need to be included in the network. The system states of the node "increase in bio-available nutrients" can be captured within the states of the node "release of nutrients", so these two nodes can be integrated together. In this way, nodes that have little to no impact on the network can be lumped together or even removed completely. Such unnecessary nodes can be found through sensitivity analysis, or simply constant checking of the BN structure during construction.

The length of causal chains should be addressed in the design of the BN structure. A conceptual model/influence diagram only rarely translates as a BN structure.

#### *4.2.4 Probability intervals/Imprecise probabilities*

Probability intervals provide a more realistic and flexible modelling approach for applications with uncertain and imprecise knowledge (Thone *et al.* 1997). Bayesian networks are often criticised for relying on exact probabilities. This is a result of the use of the junction tree algorithm (an exact approximation algorithm) in the majority of BN software packages. Most BN applications require reasoning techniques for coping with incomplete or imprecise information about the involved probabilities. Often subjective information, elicited from an expert, is acquired in the form of an interval, e.g. between 80 and 90 percent. Using a decision tree (Failing *et al.* 2004) elicited quantitative estimates of fish biomass responses to flow regimes but bounded these estimates within a confidence interval. It is possible that a similar approach could be applied for BNs, so as to allow the incorporation of probability intervals.

However, to date, estimation and propagation of probability intervals (credible intervals) has yet to be implemented in the majority of BN programing shells, even though algorithms exist to do this. The major problem with the implementation of many of these algorithms is the computational load.

### 4.3 Subjective input into BNs

Analyses of historical and comparative empirical data rarely provide the range and resolution of data needed for predictive ecological models (Pollino and Hart 2005). Often, such data is also situation-specific and scale-dependent, not accommodating the range of influences that can operate in different settings across scales (Clark 2005). Further, available empirical data can also be of variable quality and relying on limited or suspect data alone can have implications for the accuracy and reliability of models (Pollino and Hart 2005; Sobehart *et al.* 2001).

Where data for developing a BN is inadequate or lacking, the development and evaluation of a BN model can continue using heuristic methods and elicitation from domain experts. Bayesian models offer a process where quantitative knowledge or data can be integrated with expert knowledge, as has been previously discussed (Pollino *et al.* 2007b; Sikder *et al.* 2006). Thus, there is no doubt that the use of expert judgement has an important

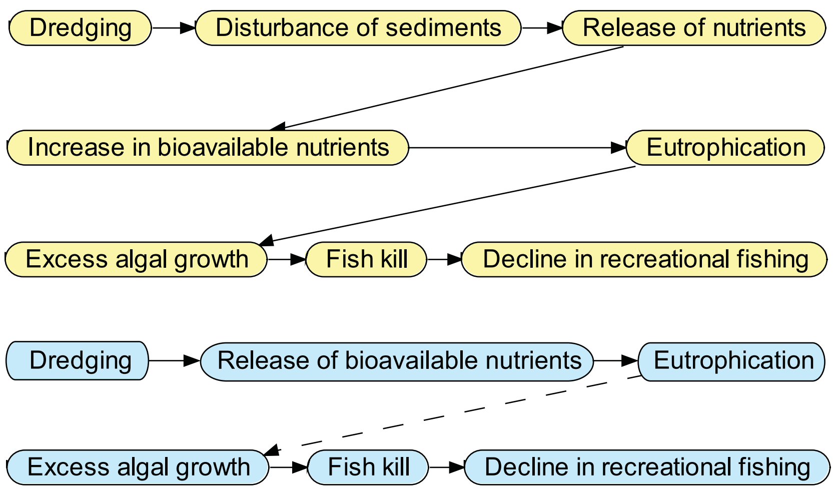



*Figure 22: Propagation example showing long (yellow) and short (blue) causal chains describing the same outcome.*

role, particularly in environmental management (Rykiel 1989). The quality of expert knowledge (Table 2) should be reported, and caution should be exercised, particularly where the BN is used in a decision making context. As discussed below, the use of expert judgement also has the potential to introduce bias into a BN.

#### *4.3.1 Expert bias*

The role of experts in ecological assessments is not to make value judgements but to present information about consequences and probabilities in a manner clear enough to allow decision-makers to make better decisions (Burgman 2005; Failing *et al.* 2004). For this to be possible, well-reasoned, probabilistic judgements must have the potential to guide the evolution of scientific thought, be formed as rationally as possible and be able to coincide with some unobservable but objective reality (Baddeley *et al.* 2004). Despite this rhetoric, expert opinion is still subject to cognitive and knowledge-based bias (Anderson 1998; Baddeley *et al.* 2004; Burgman 2005). Given this, it is useful to understand the typical human biases that may occur in the opinion-forming cognitive processes used by experts so that their effects can be reduced rather than propagated (Baddeley *et al.* 2004).

In establishing a prior (see Section 2), Bayesian approaches assume some sort of order in the process of forming subjective beliefs. Unfortunately, human cognitive processes can jar with Bayesian concepts (Anderson 1998; Baddeley *et al.* 2004; Piattelli-Palmarini 1994). Indeed, there is considerable research showing that most people make mistakes in probabilistic judgements (Anderson 1998; Bier *et al.* 1999; Piattelli-Palmarini 1994). These mistakes or biases reflect the cognitive limitations of processing ability in the human mind (Anderson 1998; Baddeley *et al.* 2004). Experts are similarly susceptible to bias, both as individuals and in groups, perhaps suggesting that expert opinion may not be the outcome of rational, systematic calculation.

As reviewed in other papers, (e.g. Pollino and Hart 2006b), the two main sources of expert bias are motivational bias and cognitive bias (Baddeley *et al.* 2004; Burgman 2005), which are defined as follows:

*Motivational biases* reflect the interests and circumstances of the expert. For example, technical experts can advocate a position or underestimate potential risks because their research and career prospects are tied to an outcome (Walters 1997). As motivational biases are often under rational control, they can be manipulated. In these circumstances, incentive structures can be used to encourage honest assessments.

*Cognitive biases*, on the other hand, are more problematic because they emerge from incorrect processing of the information and are not under conscious control. In making judgements, humans employ heuristics (rules of thumb) to aid analysis and interpretation of data. Heuristics are commonly used to make relatively quick decisions in uncertain situations. These are used because a full assessment of available information is difficult, time consuming or information is sparse.

In making judgements, at least four types of heuristics are commonly employed (Baddeley *et al.* 2004; Burgman 2005). *Availability* is the heuristic of assessing an event's probability by the ease with which an occurrence of the event is recalled. *Anchoring and adjustment* involves making an initial estimate of a probability using an anchor and then revising or adjusting it up or down in the light of new information. This typically results in assessments that are biased towards the anchor value. *Control* is the tendency of people to respond where they consider their ability to influence a situation. If it is perceived that a person can control a situation, consequences are quantified as being lower. *Representativeness* is where people use the similarity between two events to estimate the probability of one from the other. This is linked to *conjunctive fallacy*, where the probability of two co-occurring events is erroneously considered to be more probable than a single event.

In employing these heuristics, experts are also often *overconfident* about their knowledge (Anderson 1998; Baddeley *et al.* 2004; Burgman 2005). Biases are believed to be amplified when probabilities are extreme (i.e. at the tails of a distribution – close to 0 or 1) (Baddeley *et al.* 2004).

To limit individual bias, it is widely recommended that elicitation of probabilities should involve multiple experts (see Table 2). In addition to addressing bias, it is best to obtain a diversity of independent judgements as previous research suggests that accuracy of experts is not necessarily a function of the level of expertise (particularly for extreme events) (Bier *et al.* 1999). However, when experts collect and confer in groups, they can generate and perpetuate complex forms of bias associated with group interactions (Baddeley *et al.* 2004), resulting in lack of independence (Burgman 2005).

Group biases can be compounded when mistakes and misjudgements are communicated amongst experts (Baddeley *et al.* 2004). If group expert opinion evolves along a particular path just because others have started on that path, then the link between subjective probabilities and underlying objective probability distributions may be completely broken (Baddeley *et al.* 2004). If a situation arises where there is substantial differences of opinion amongst experts, it is preferable that these differences be kept explicit in a BN model (Pollino *et al*. 2007a).

Obviously, given these multiple sources of biases, the question of how best to elicit and incorporate expert input into a BN model is crucial, having implications for the model's overall robustness and representativeness of a system (Pollino and Hart 2006b). In Bayesian statistical models, where enough information is known about a problem to define an appropriate probability distribution, then formal methods of elicitation are considered appropriate (Bier *et al*. 1999). Expert judgements are used to define parameters quantitatively (e.g. probability distribution function with moments). A number of formal methods for eliciting probabilities have been described previously (e.g. Baddeley *et al*. 2004; Cooke 1991; Morgan and Henrion 1990; Savage 1971; Wang *et al*. 2002). Such methods for probability elicitation should be applied within a Bayesian network context, to limit the sources of bias (Pollino and Hart 2006b).

Therefore, because of the potential for expert bias in models of ecological systems, the optimal solution for limiting this bias is to both combine expert opinion parameter estimations with actual observed data and to evaluate parameter values with data, where possible (Pollino *et al*. 2007b), rather than relying wholly on expert judgement.

# 5. Applications of Bayesian networks

Due to the flexibility of BNs, they have been implemented in a wide range of disciplines. As BNs were initially largely developed through research into artificial intelligence, the majority of applications have been in the fields of Engineering and IT. However, BNs have steadily begun to find use in many other areas of science, they have been proven to be particularly useful in medicine, due to their ability to be used in aiding diagnosis. Other areas where BNs have been developed and have found a use include military applications, space shuttle propulsion systems, applications in Microsoft Office (e.g. software troubleshooting, 'the paper clip'), financial market analysis, risk assessments of nuclear power plants, pattern analysis and robotics. Likewise, BNs are increasingly being used for biological and ecological applications.

## 5.1 Assessment frameworks

Most assessment frameworks aim to bring together disparate knowledge for a problem domain and make it relevant for decision-making processes. Whether an assessment is focussed on conservation, assessing risk, or aimed at integrating information across disciplines, complexity, tradeoffs and uncertainty are common features. Within each of these frameworks, BNs have proved particularly useful for focussing issues by clearly structuring the formulation of a problem within a participatory-style and transparent process. NRM BN applications included in this review are listed in Table 3. Select functionality of each of the applications is shown in Table 4. Papers, within the context of their assessment framework, are reviewed.[4]

### *5.1.1 Conservation assessment and planning*

A sense of urgency surrounds the management of many of our threatened ecological species and systems. The traditional response to this uncertainty is to conduct further research, where the aim is to collect more data to reduce uncertainty in decision-making. However, given that data on threatened species and habitats is often patchy in quality and quantity, rarely is it suitable for use in more tradition analysis approaches. In conservation decision-making, BNs can be used to assist in better targeting and prioritising investments in research and decision-making. They can guide the collection and structuring of knowledge, existing data and future data collection within an adaptive learning-management framework, and allow conflicts to be examined (Pollino *et al.* 2007a).

*5.1.1.1 Terrestrial ecology*

Prior to 2008, there were few applications in terrestrial ecology. As BN technology has advanced, and the ability to interface spatial and BN software has progressed, there has been an increase in the number of applications.

(Smith *et al.* 2007b) developed a BN that interfaced with GIS spatial data and expert knowledge on preferred habitats to map habitat suitability of the Julia Creek dunnart (*Sminthopsis douglasi*), in north-west Queensland. The species was previously thought to be extinct.

The use of Bayesian networks for testing the criteria for threatened species to be listed on the IUCN Red List was tested by Newton (2010), where he compared the approach to the standard method of fuzzy numbers. Newton (2010) found that the BN approach was a more transparent method of analysis in its treatment of data which was incomplete or lacking. Incomplete survey data was used by Wilson *et al.* (2008) for amphibian populations, in the context of meeting objectives given constrained circumstances.

This BN was developed within WinBUGS (www.mrc-bsu.cam.ac.uk/bugs/) to exploit the use of MCMC to derive model parameters for habitat variables. Knowledge of co-occurring species was used to strengthen parameters for shared habitat areas. BNs are useful for decision-making where knowledge is incomplete, but decisions are required. As Newton (2010) found, they offer a transparent process for decision making, and can draw on both expert knowledge (Smith *et al.* 2007b) and incomplete survey data and complimentary data (Wilson *et al.* 2008).

Galan *et al.* (2009) developed a basin scale reforestation model, where spatial data was trained against existing woodland areas and types, and predictions were used to guide reforestation activities in deforested areas. This method is a simple, self-contained and straightforward approach to guiding management activities. A BN meta-model was constructed by Steventon and Daust (2009) to model the outbreak of the mountain pine beetle. This model integrated results from other spatial and analytical models and was used to test scenarios for management and climate change, with parameter uncertainty built in. These 2 approaches contrast the use of BNs, where Galan *et al.* (2009) construct a self-contained modelling tool for data analysis and decision making, whereas Steventon and Daust (2009) use the BNs as an integrator of other 'parent' models into a single framework, but again for decision-making purposes.

*Table 3: List of BN papers according to type of assessment framework (TDML = Total Daily Maximum Load, LUIM = Land Use Impact Model, Lyngbya = a toxic marine cyanobacterium, IUCN = International Union for the Conservation of Nature)*

| **Application** | **Conservation Planning** | **Risk Assessment** | **Integration: Environmental, Socio-Economic** | **Integration: Experts and Models** |
|---|---|---|---|---|
| Fish (Rieman *et al*., 2001) | | | | X |
| Land use change (Bacon *et al*., 2002) | | | X | |
| Fish (Borsuk *et al*., 2002) | X | | | X |
| Coral (Wooldridge & Done, 2003) | X | X | | |
| TDML (Borsuk *et al*., 2004b) | | X | | X |
| Fishery (Little *et al*., 2004) | X | | | |
| Fish (Baran *et al*. 2003) | X | | | X |
| Pollution (Stiber *et al*., 2005) | | X | | |
| Water management (Bromley *et al*., 2005) | | | X | X |
| Wimmera (Chee *et al*., 2005) | X | X | | |
| Pollution (Dorner *et al*., 2006) | | X | | X |
| Water management (Olalla *et al*., 2006) | | | X | |
| Water management (Varis *et al*., 2006) | | | X | X |
| LUIM (McNeill et., 2006) | | X | | |
| Coastal management (Ticehurst *et al*., 2007) | | | X | X |
| Dunnart (Smith *et al*. 2007b) | X | | | |
| Fire (Smith *et al*. 2007a) | X | | | |
| Koalas (Pullar and Phan 2007) | X | | | |
| River management (Reichert *et al*., 2007) | | | X | X |
| Climate change (Tighe *et al*., 2007) | | X | | X |
| Fish (Pollino *et al*. 2007b) | | X | | |
| Eucalypt A (Pollino *et al*. 2007a) | X | X | | |
| Eucalypt B (Hart *et al*., 2007) | X | X | | |
| Fish (Menke *et al*., 2007) | X | X | | |
| Mining (Pollino *et al*. 2008) | | X | | X |
| Amphibians (Wilson *et al*. 2008) | X | X | | |
| Invasive fish (Peterson *et al*. 2008) | X | X | | |
| Lyngbya (Johnson *et al*. 2009) | | | | X |
| Groundwater (Farmani *et al*. 2009) | | | | X |
| Macroalgae (Renken and Mumby 2009) | | | | X |
| Pest outbreak (Steventon and Daust 2009) | | | | X |
| Reforestation (Galan *et al*. 2009) | X | | | |
| Cropping (Samranpong and Pollino 2009) | | | X | |
| IUCN Red List (Newton 2010) | X | | | |
| Groundwater (Molina *et al*. 2010) | | | X | X |
| Coastal Management (Lynam *et al*. 2010) | | | | X |
| Flow – River restoration (Arthington *et al*. 2010) | X | | | X |
| Flow – River restoration (Stewart-Koster *et al*. 2010) | X | | | X |
| Wetlands – Environmental flows (Merritt *et al*. in press) | X | | | X |

Table 4: *List of BN papers according to model features (G = GIS capability, D = DBN, TDML = Total Daily Maximum Load, LUIM = Land Use Impact Model, Lyngbya = a toxic marine cyanobacterium).*

| Application | Participatory process | Temporal | Spatial | Utilities (BDN) | OOBNs | DSS[5] |
|---|---|---|---|---|---|---|
| Fish (Rieman *et al.*, 2001) | | | | | | |
| Land use change (Bacon *et al.*, 2002) | X | | | X | | |
| Fish (Borsuk *et al.*, 2002) | X | | | | | |
| Coral (Wooldridge & Done, 2003) | | | | | | |
| TDML (Borsuk *et al.*, 2004b) | X | | | | | |
| Fishery (Little *et al.*, 2004) | | X | X | | | |
| Fish (Baran *et al.* 2003) | X | D | | | | |
| Pollution (Stiber *et al.*, 2005) | | | | | | |
| Water management (Bromley *et al.*, 2005) | X | | | X | | |
| Wimmera (Chee *et al.*, 2005) | | | | X | | |
| Pollution (Dorner *et al.*, 2006) | | X | | X | | |
| Water management (Olalla *et al.*, 2006) | X | | | X | | |
| Water management (Varis *et al.*, 2006) | X | | | X | | |
| LUIM (McNeill et., 2006) | | | G | | | |
| Coastal management (Ticehurst *et al.*, 2007) | X | | | X | | X |
| Dunnart (Smith *et al.* 2007b) | | | G | | | |
| Fire (Smith *et al.* 2007a) | X | | X | | | |
| Koalas (Pullar and Phan 2007) | | | X | | | |
| River management (Reichert *et al.*, 2007) | X | | | X | | |
| Climate change (Tighe *et al.*, 2007; Fu *et al.*, 2009) | X | X | X | | | X |
| Fish (Pollino *et al.* 2007b) | | | X | | | |
| Eucalypt A (Pollino *et al.* 2007a) | X | | X | | | |
| Eucalypt B (Hart *et al.*, 2007) | X | X | X | | | |
| Fish (Menke *et al.*, 2007) | | | | | | |
| Mining (Pollino *et al.* 2008) | | | | | | |
| Amphibians (Wilson *et al.* 2008) | X | | X | | | |
| Invasive fish (Peterson *et al.* 2008) | | | X | | | |
| River Basin Management (Barton *et al.* 2008) | X | | | X | X | |
| Lyngbya (Johnson *et al.* 2009) | | X | X | | X | |
| Groundwater (Farmani *et al.* 2009) | X | | | X | | |
| Pest outbreak (Steventon and Daust 2009) | | X | X | | | |
| Reforestation (Galan *et al.* 2009) | | X | G | | | |
| Cropping (Samranpong and Pollino 2009) | | | G | X | | |
| Groundwater (Molina *et al.* 2010) | X | | X | X | X | |
| Flow – River restoration (Stewart-Koster *et al.* 2010) | | | | X | | |
| Wetlands – Environmental flows (Merritt *et al.* in press) | X | X | X | | | X |

Bayesian networks can also operate within existing modelling frameworks, as demonstrated by Bashari *et al.* (2008) who developed state and transition models in rangelands. Generally, state and transition models are considered to be descriptive in their application, but within a Bayesian network, they can be used in a predictive capacity.

*5.1.1.2 Aquatic ecology*

One of the earliest BN frameworks constructed for modelling habitat and population viability of selected at-risk fish species was developed by Marcot *et al.* (2001). Marcot focussed his frameworks based on population viability and habitat suitability. The BN Marcot created is shown in Figure 23.

These methods were used by Rieman *et al.* (2001) to model habitat suitability for salmonoid fishes as a representative indicator of the condition of an aquatic ecosystem. Both Marcot and Rieman found BNs to be a particularly useful way of modelling complex issues, assessing land management strategies for the Columbia River basin in the USA. The process of creating the BNs targeted the collection of information at better understanding the system and allowed for more explicit documenting of assumptions. Marcot further developed these methods for developing and evaluating BNs in Marcot *et al.* (2006).

Borsuk *et al.* (2002) constructed a BN to investigate all possible causes of a decrease in the health status of brown trout populations in Switzerland. As the primary cause of the decline in the trout fishery was unknown, twelve hypotheses were obtained through expert elicitation, which were tested through laboratory and field research projects. In order to apply the results of these investigations a BN was constructed and the strength of each hypothesis was tested by updating the network with data and examining the relative probabilities. The investigation was continued in Borsuk *et al.* (2004a), where the network was used to assess the historical causal importance of anthropogenic changes, as well as predict the effect of proposed management actions.

Peterson *et al.* (2008) used a BN to examine trade-offs in decision-making, where the removal and the placement of barriers was used to manage threats from habitat fragmentation and invasion by non-native trout species. Management actions to address one issue may create or exacerbate the other, and therefore a BN was used to formalise a systematic analysis and consistent decision process for assessing the most appropriate action. Likewise, Stewart-Koster *et al.* (2010) developed a theoretical BN to examine how the technique can be used to examine the relative importance of investments in flow restoration and riparian and catchment land use, to assist in structuring tradeoffs in decision-making. Arthington *et al.* (2010) consider the use of BNs in environmental flow studies, amongst other methodologies.

Using a BN, Little *et al.* (2004) created a hypothetical simulated fishery, based on a real fishery on the Great Barrier Reef, to examine the effect of information flow among fishing vessels. The BN was useful in capturing the reaction of fishers to the implementation of fishery management decisions and the model was used to compare

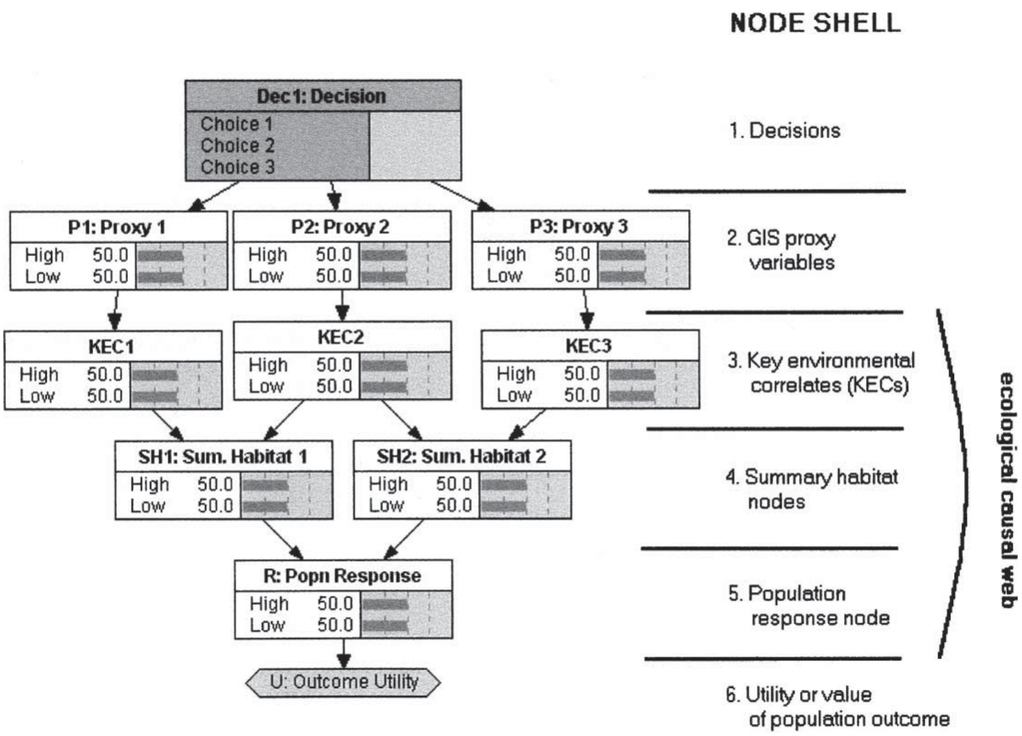



*Figure 23: General structure of a BN model for evaluation population viability for wildlife species (Marcot et al. 2001).*

the behaviours of vessels acting independently with behaviours displayed when vessels 'watch' each other. This was linked to the effect that such information flow can have on a resource and thus the BN was able to show that information flow among fishing vessels can have an effect on the dynamics and resource exploitation of a simulated fishery, given fishery management regimes.

One of the limitations of BN models in representing ecological processes has been the inability to easily demonstrate dynamic processes (see Section 4.1). Baran *et al.* (2003) constructed a DBN to model fish populations on a tropical floodplain, including feedback loops. The model integrated a combination of biological and physical parameters, including hydrological factors, environmental factors and fish migrations. Because of the wide range of information that needed to be included to produce an effective model of the whole system, the BN approach proved to be particularly useful and because of the ease with which system states could be varied the consequences of various management scenarios on fish production could be rapidly examined.

### *5.1.2 Integrated assessment*

Integrated modelling is referred to as a type of assessment because the activity aims to generate useful information for policy making, rather than to advance knowledge for knowledge's sake (http://en.wikipedia.org/wiki/Integrated_assessment_modelling). Integrated environmental modelling aims to develop interdisciplinary frameworks and methodologies that integrate models and software tools across issues, scales, disciplines and stakeholders with respect to resource and environmental issues. As integration models, BNs are ideal as they can integrated data and knowledge from a range of sources in a parsimonious and consistent framework.

BNs were developed for integrated management of four basins across Europe, with the focus on water management (Bromley *et al.* 2005). The project aimed to develop a practical and effective methodology to assist managers in making multi-objective decisions while at the same time ensuring that stakeholders became actively involved in the decision-making process. BNs were considered ideal for fulfilling this need. A simple BN developed by Bromley is shown in Figure 24.

The focus of the case study in Bromley *et al.* (2005) is water resources in the UK Loddon catchment, which are under increasing stress. Planning application in the region are likely to only add to the pressure and the water supply companies are legally obliged to provide more water. Bromley *et al.* (2005) examined examples of how best to achieve such a reduction considering trade-offs between installing more boreholes or increasing reservoir capacity (which is expensive and encounters environmental concerns) or reducing domestic demand (which accounts for the bulk of consumption in the region).

Similar to the Steventon and Daust (2009) described above and Borsuk *et al.* (2004b)

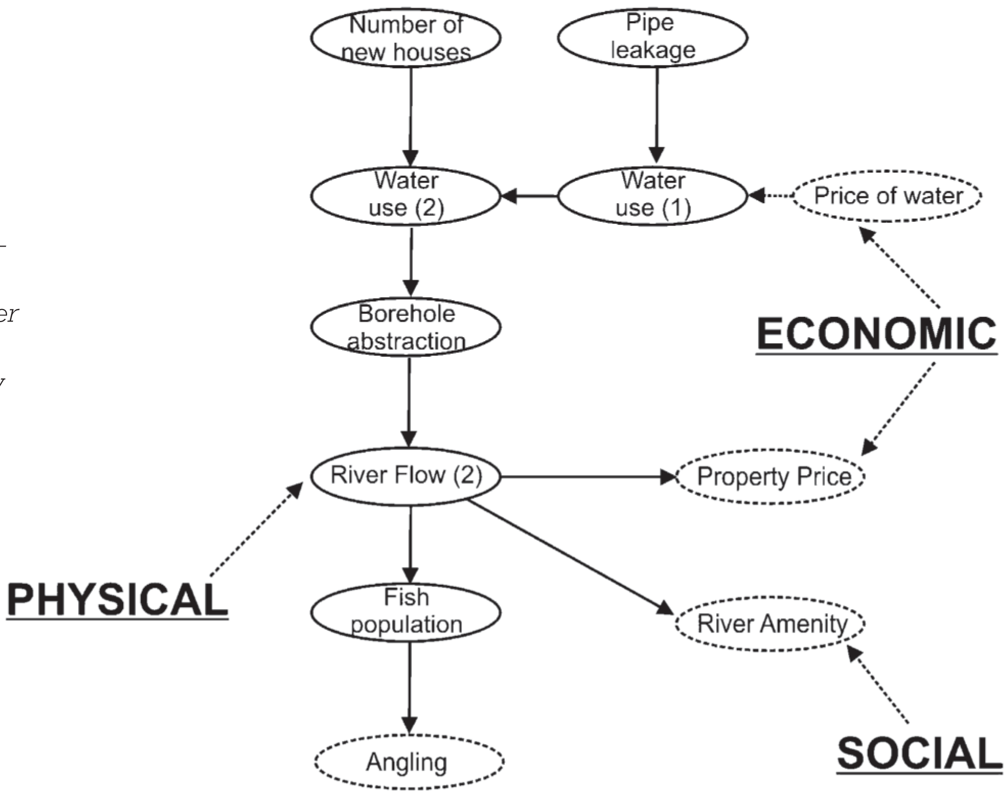



*Figure 24: A simple BN examining trade-offs between water use, water price, river amenity and fish population (Bromley et al. 2005).*

described below, BNs have again been used as an integration meta-modelling tool (Barton *et al.* 2008), where the approach was considered to be alternative to scenario analysis in deterministic models, enabling a more complete accounting of integrated model uncertainty. The case study focused on evaluation of eutrophication mitigation costs relative to benefits, as part of the economic analysis under the EU Water Framework Directive (WFD). The advantages of using Bayesian networks were reported as: promoting integrated, inter-disciplinary evaluation of uncertainty in river basin management and advantages in communicating risks with stakeholders. The limitations were reported as the cost of obtaining reliable probabilistic data and meta-model validation procedures. Barton *et al.* (2008) concluded that the integration and multi-disciplinary process of defining the network structure and probability distributions and conducting sensitivity analysis were more important than the results of the analysis itself.

Likewise, Martin de Santa Olalla *et al.* (2006) also created a BN with a high level of stakeholder involvement, so as to fulfil legal requirements within the EU Water Framework Directive (Directive 2000/60/EC), but with a focus on groundwater. The BN was constructed to model water resource management in a region faced with the risk of overexploitation of the local aquifer, brought about by a considerable increase in the surface area of irrigated arable land over the last 25 years. A similar application with OOBNs has also been trialled (Molina *et al.* 2010). The BN was able to show that the current level of aquifer exploitation was not sustainable and tested scenarios of future management. Because of the high level of stakeholder involvement, the probability of adoption of proposed solutions was considered to be increased. BNs have also been used to analyse contamination of groundwater in Copenhagen as a multi-objective optimization problem (Farmani *et al.* 2009). The goal of the model was to maximise farm income, minimise compensation and maximise water quality.

Integration in a policy context using BNs was also the focus of Varis and Keskinen (2006). They constructed a BN to assist in finding a way of attaining a combination of the three development goals of economic growth, poverty reduction and environmental sustainability at Ton Le Sap Lake in the Mekong Basin. Due to the conflict associated with these three goals, the BN proved to be particularly useful for policy scenario analysis. Bacon *et al.* (2002) constructed a two-stage BN to model the risks of land use change. The BN stage was used to assess if a manager was currently satisfied with the present situation, and in the second stage a BDN was used to estimate how dissatisfied the manager was and whether the costs of changing from the present use to a potentially better one would be out-weighed by the anticipated benefits, using a variety of cost and benefit criteria (e.g. financial, social and ecological). Likewise, Ticehurst *et al.* (2007) used BNs for integration purposes, modelling sustainability-based management issues and decisions regarding coastal lakes in New South Wales (the DSS is referred to as CLAM: Coastal Lake Assessment and Management tool). These BNs included environmental, economical and social elements, with an emphasis on stakeholder participation and adoption of model for coastal lake planning. Using a similar process, an integrated BN was also constructed for the management of dryland salinity in New South Wales (Sadoddin *et al.* 2004) and water resource management along the Senegal River (Varis and Lahtela 2002).

Recognising that historically many of the river rehabilitation decisions made by authorities have had insufficient transparency, Reichert *et al.* (2007) outlined a process of decision analysis to structure scientist and stakeholder involvement in river rehabilitation decisions. The steps outlined in the paper were:

Step 1: Definition of the decision problem
Step 2: Identification of objectives and attributes
Step 3: Identification and pre-selection of alternatives
Step 4: Prediction of outcomes
Step 5: Quantification of preferences of stakeholders and decision makers for outcomes
Step 6: Ranking of alternatives
Step 7: Assessment of results.

These steps are not unlike existing decision-analysis methodologies. The process aims were: (i) to analyse synergies and conflict potential between stakeholders, (ii) to analyse the sensitivity of alternative-rankings to uncertainty in prediction and valuation, and (iii) as a basis for communicating the reasons for the decision (Reichert *et al.* 2007).

A proposed output of the process is an integrative probability network model for the prediction of the consequences of rehabilitation alternatives and a mathematical representation of preferences for possible outcomes elicited from important stakeholders. The form of a proposed network is shown in Figure 25. In the paper by Ticehurst *et al.* (2007), the advantages of using a BN within a DSS context were shown. The CLAM DSS allowed for rapid scenario comparisons and reporting for use in coastal lake planning, as well as providing easy access to, and thorough documentation of, the BN. Similar to the CLAM DSS, the EXCLAIM (EXploring

CLimAte Impacts on Management) DSS has been developed to explore climate change predictions and impacts on flows, water quality and ecology of the Macquarie River and Macquarie Marshes (Tighe *et al.* 2007). The BN acted as an integration tool, linking the OzClim climate model (Page and Jones 2001) to the IQQM flow model (Jones and Page 2001), to water quality and ecological outcomes. The original EXCLAIM DSS has since been updated with new data and parent climate and hydrology models to address knowledge gaps identified with the first release. This DSS has been successful in promoting an adaptive learning process (Fu *et al.* 2009).

IBIS[6] is a DSS designed for annual and long-term (decadal) environmental flow planning. There are 3 applications[7] being built for inland RAMSAR wetlands. IBIS is a significant advance from EXCLAIM and CLAM, where only the ecological component models of the DSS are Bayesian networks (Merritt *et al.* 2009; Merritt *et al.* 2010). IBIS provides a framework for interacting models: with individual components models for climate/hydrology, hydro-dynamic and ecological outcomes (Figure 26).

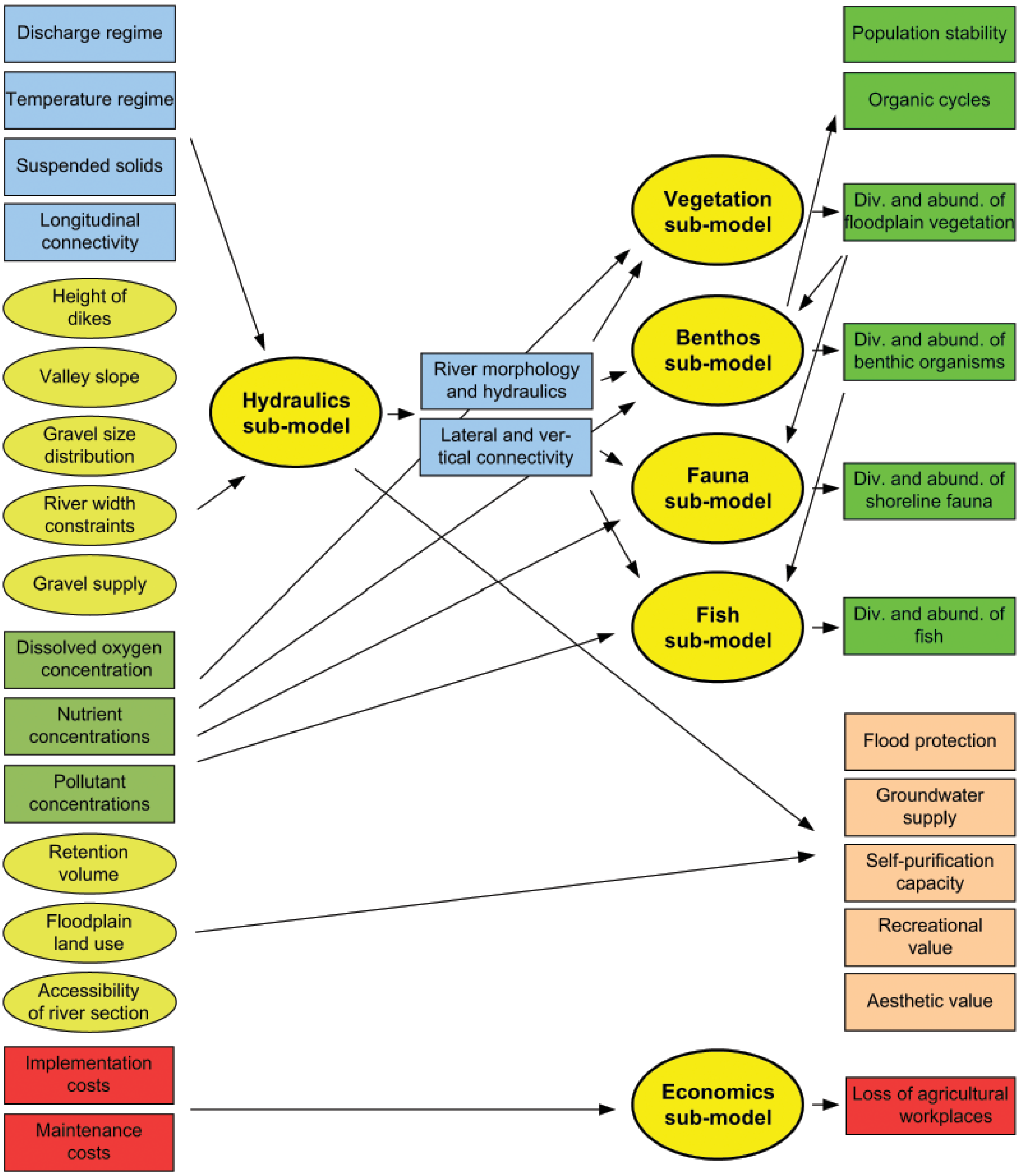



*Figure 25: Overview of the integrative model for the prediction of outcomes of decision alternatives for river rehabilitation (Reichert et al. 2007).*

### *5.1.3 Risk assessment and Risk Management*

Risk assessment is a process used to collect, organise, integrate and analyse information for use in a planning environment, where the outcomes is the analysis and prioritisation of risks or hazards to a stated objective. In its simplest form, risk assessment involves the evaluation of likelihoods and consequences, where likelihood implies probabilities. Risk management involves the development of strategies to minimise, monitor, and control the probability and/or impact of adverse events. The outcome of a risk assessment and risk management process is an improved understanding and prioritisation of risks for a given system, and guidance on the implementation of appropriate risk reduction strategies.

Until recently, the ability to predict risks in dynamic ecosystems was limited. The difficulties arose in quantifying the causal relationships between multiple interacting threats or stressors to outcomes. Risk implies uncertainty, and few modelling approaches could represent ecosystem complexity with associated uncertainties. However, the recent growth in the use of Bayesian network tools for ecological risk assessments has resulted in major advances in better understanding and managing ecosystems despite their inherent complexity (Hart and Pollino 2008).

The risk assessment–management cycle and the process used to build Bayesian networks are highly complementary (Figure 27), where the outcome of each part of the risk assessment cycle can be formalised within a Bayesian network. BNs directly apply the conceptual model from the problem formulation step, and primary and secondary information sources can be used to derive the strengths of relationships for risk analysis and characterisation. Using scenario and sensitivity analysis, priority knowledge gaps and priority risks can be identified. Models can be used in development of strategies to treat/manage. The likely success of strategies can be assessed in the BN using scenario analysis (Pollino *et al.* 2008).

As outlined previously, BNs are useful as metamodels, where they can bring together existing models into a single framework. Borsuk *et al.* (2004b) is one of the first papers to use BNs in this way. Authors' exploited the BN cause-and-effect assumptions to develop an eutrophication model for the Neuse River estuary of North Carolina (Figure 28). The model was also compared to other total maximum daily load models, and although it was not to outperform any of the other water quality modelling approaches, it fulfilled the needs of adaptive management (Stow *et al.* 2003).

This BN was used to generate predictions of the policy-relevant ecosystem variables under alternative nutrient management strategies. As predictions were expressed as probability distributions, stakeholders and decision-makers had a realistic prediction of the chances of achieving desired outcomes.

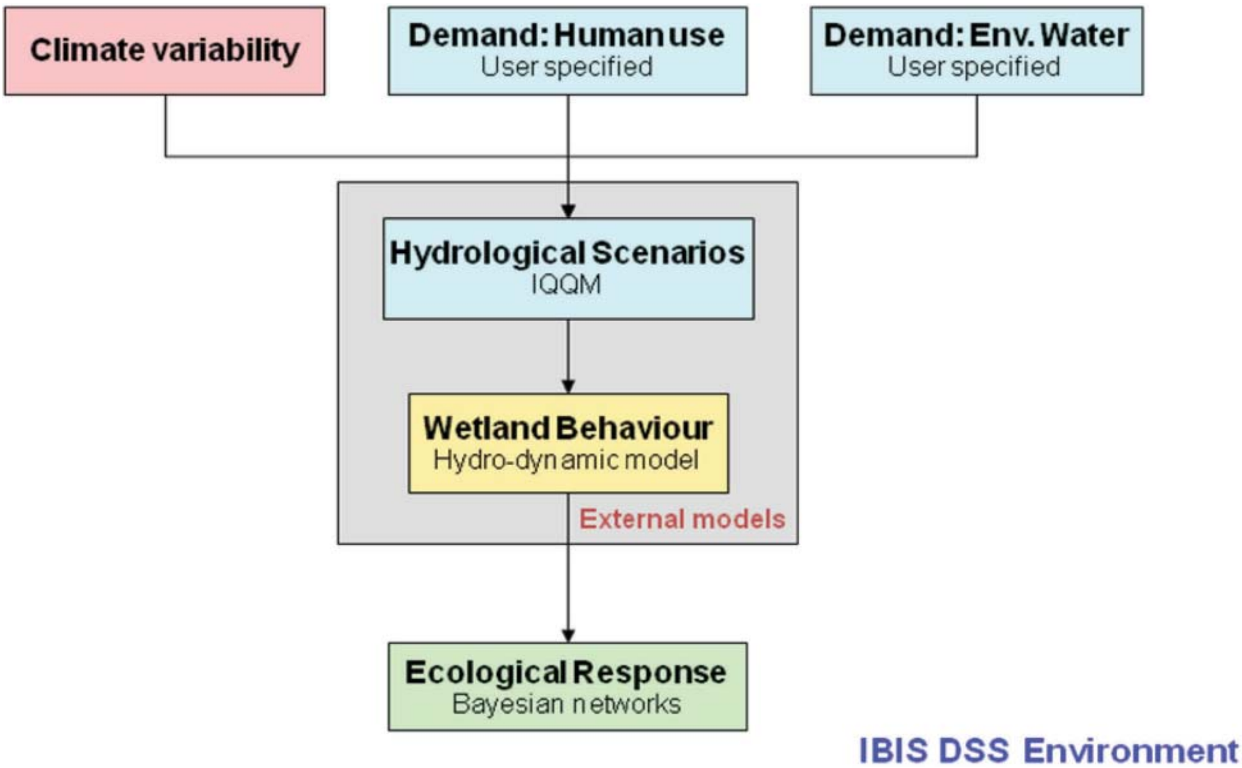



*Figure 26: Component model of the IBIS DSS (unpublished figure).*

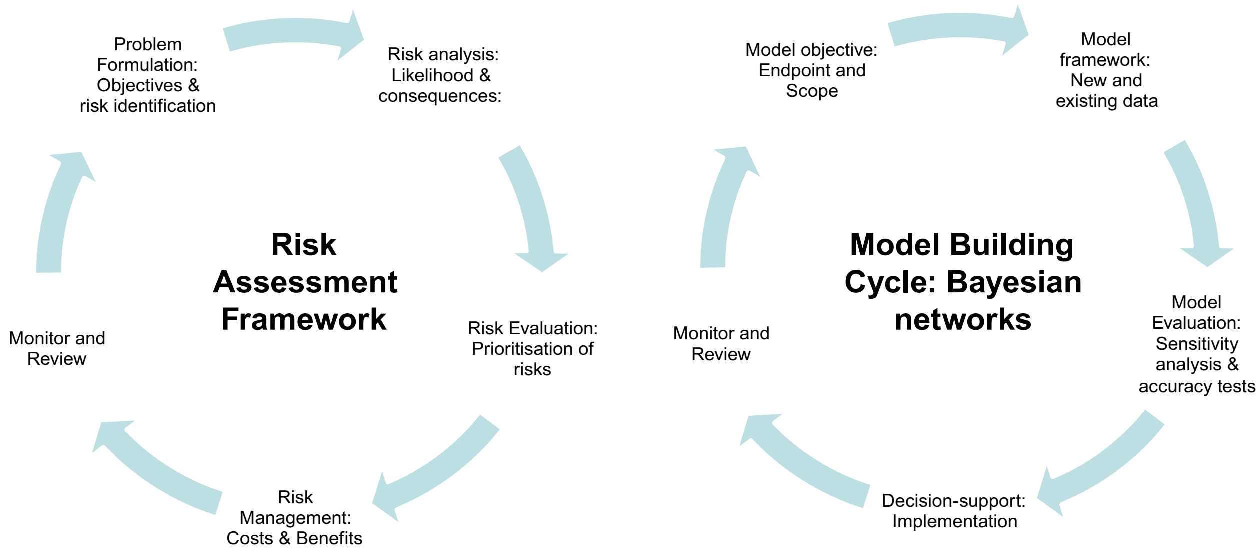



*Figure 27: Risk Assessment and Bayesian network building cycle (Pollino and Hart 2008).*

In Stiber *et al.* (2004), a BN was constructed to combine multiple expert opinions on cleaning up hazardous chemicals at a site with contaminated groundwater. Probabilities were obtained for this BN from a number of experts. The final BN incorporated all the elicited probabilities, with higher weightings given to those probabilities that proved to be more reflective of actual observed data. Similarly, Dorner *et al.* (2006) developed a dynamic BN to assess the possible effects of non-point source pollution transport in aquatic systems, within a multi-objective context. The non-point source BN was joined to a separate sub-model BN based on a simplified crop rotation revenue model. The model can be used for multi-year analysis.

A BN was developed to prioritise causative factors contributing to the decline in native fish communities in the Goulburn Catchment (Victoria, Australia) (Pollino *et al.* 2007b). The BN (shown in Figure 29) considered habitat suitability of native fish communities in a multi-stressor environment, and was useful for prioritising stressors at different sites and reaches across the catchment, considering two time scales. In developing the model, information gained through expert elicitation and quantitative data was combined using parameterisation algorithms to parameterise and evaluate the BN.

Using the methods from Pollino *et al.* (2007b), a BN was developed for assisting in the management of a threatened tree species, the Swamp Gum (*Eucalyptus camphora*) (Pollino *et al.* 2007a). Pollino *et al.* (2007a) also found that BNs can be used to analyse conflict situations, modelling conflicting hypotheses independently or integratively, focussing future planning efforts and investments in management and data collection. Using a similar approach, a BN was constructed for Black Box (*Eucalyptus largiflorens*) depressions on the NSW Murray floodplain. The BN was built via community consultation, which resulted in an unnecessarily complex model. Using sensitivity analysis techniques, a simpler model was constructed showing the major factors influencing tree health and recruitment were flooding frequency and grazing pressure (Hart *et al.* 2007; Pollino *et al.* 2009).

The final application is a suite of BNs that were developed for testing risk management strategies for the mining industry (Pollino *et al.* 2008). Models integrated sediment transport and water quality models, toxicological data and ecological monitoring data. Model scenario tests of alternative management strategies (Pollino and Hart 2006a) along with other studies, resulted in mine rehabilitation works, which were last estimated to have cost $US 170 million (*www.oktedi.com*). Four BNs (three aquatic resource models – drinking water, fish and algae, and one terrestrial resource model) were constructed considering multiple time periods and river reaches under a range of climates, each undergoing a rigorous evaluation process. The author of this paper has also developed risk assessment BNs for evaluating risks to water resources in the Murray Darling Basin, as required by the *Water Act 2007*. These BNs were used to target risk management strategies. The results of the tool are being used in the relevant section of the Basin Plan, which is a Commonwealth legal instrument.

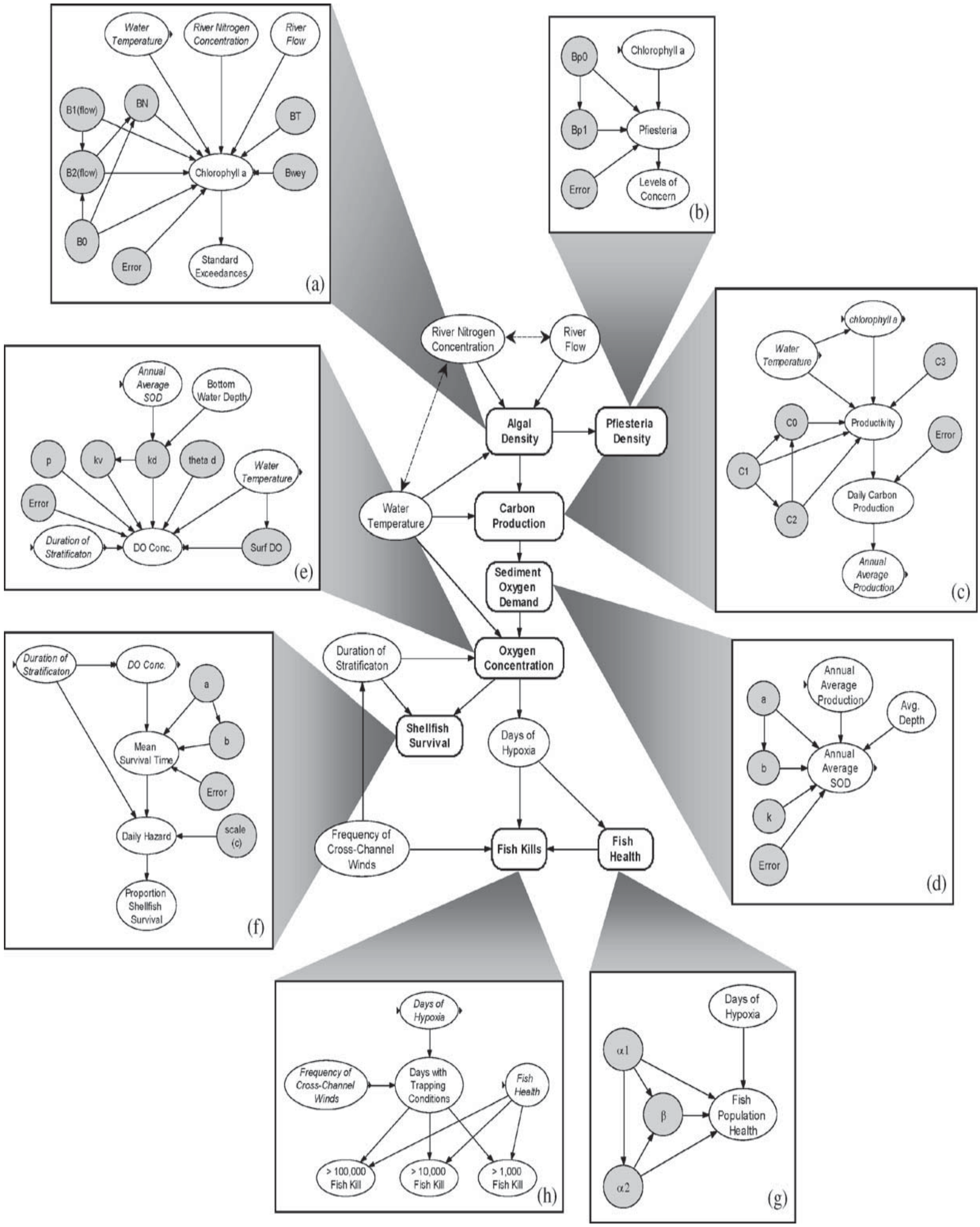



*Figure 28: Neuse River estuary eutrophication BN from (Borsuk et al. 2004b).*

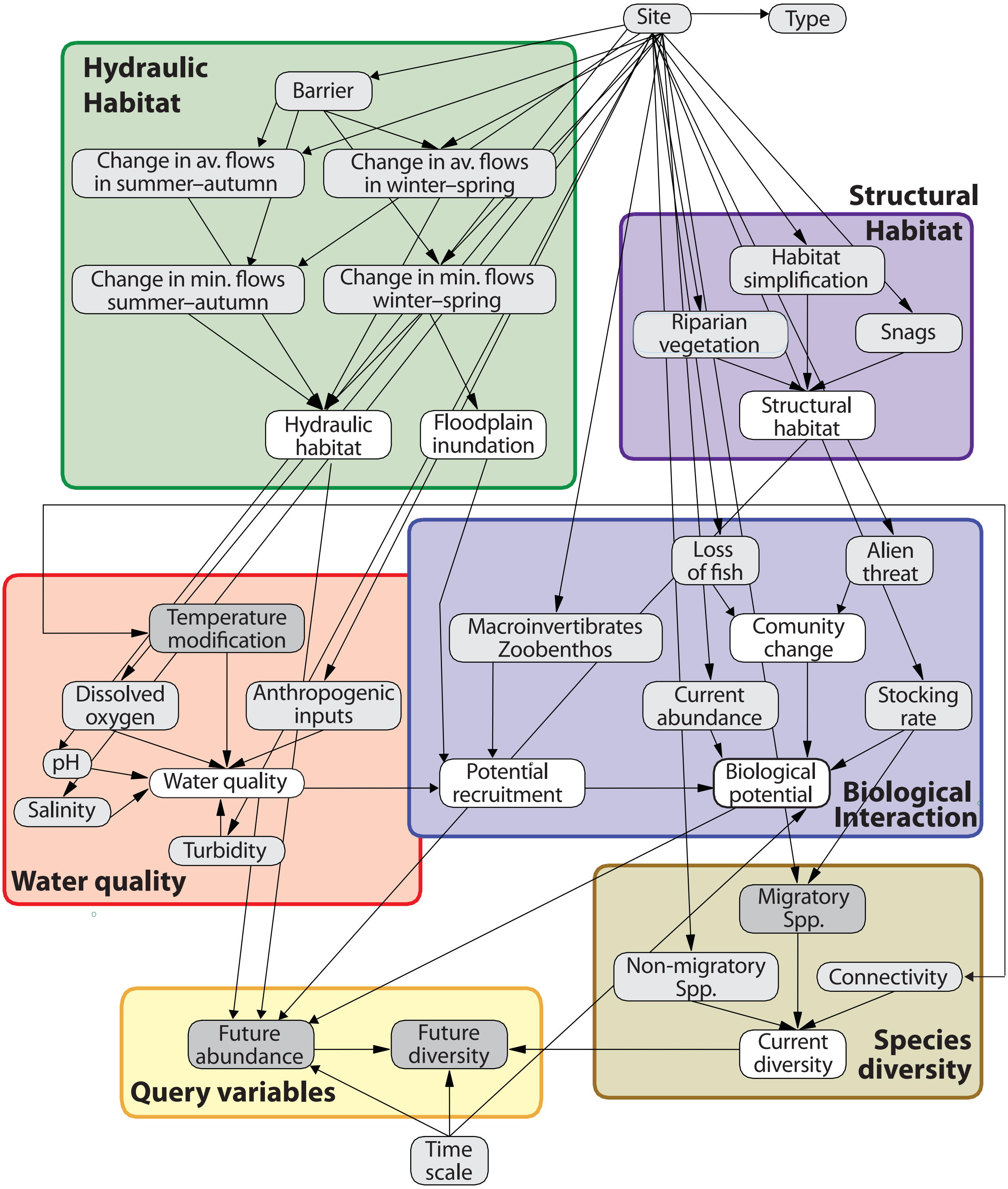



*Figure 29: BN for native fish in the Goulburn Catchment, Victoria (Pollino et al. 2007b).*

# 6. Using Bayesian networks for decision-making

Limited understanding of ecosystems and overconfidence in the effectiveness of environmental policy and management has lead to some unwelcome surprises (Sainsbury et al. 2000). To deal with the various sources of uncertainties in decision-making, scientists advocate the implementation of adaptive management frameworks. An adaptive management framework involves the documentation of hypotheses, monitoring responses and adjusting management actions over time (Failing et al. 2004). The appeal of adaptive management is driven by three factors: our rudimentary knowledge of natural systems; systems being in a constant state of disequilibrium; and community goals and management expectations always being in flux.

The appeal of using BNs within an adaptive management framework lies in their ability to be maintained over time with little effort. They fulfill the integration and modelling requirements of adaptive management (Walters 1997, Holling 1978, Walters 1986, Van Winkle et al. 1997) and can be directly applied within a decision-theoretic framework to address environmental policy needs (Bradshaw and Borchers 2000). Modelling within an adaptive management framework allows us to replace management learning by trial and error with learning by careful tests (Walters 1997); avoids reinventing the wheels of science and policy; facilitates a greater understanding of the links between policy, management and resource condition; promotes a robust, defensible and tractable decision-making process; and as evidence accumulates to support the underlying hypotheses of the model, provides greater confidence in its representations increase (Bradshaw and Borchers 2000).

The BN review in this report details how BNs have been used to implement the principles of adaptive management, encouraging an active learning environment that ensures models have an extended life span. Unfortunately, to the knowledge of the authors', there are few if any BNs maintained and used in an adaptive context. This is unfortunate given that the majority of BN papers expound the virtues of their use in just this manner.

High natural variability in ecological systems, long time lags, the high costs of experimentation, intervention and monitoring, and institutional barriers have resulted in low success rate for the implementation of adaptive management strategies (Walters 1997). Frameworks for environmental policy and management are generally quite static, reflecting the need for certainty amongst resource users and policy makers. Consequently, translating scientific uncertainty into policy still remains a challenge. Adaptive management in policy and planning is generally limited to vague endorsements of the approach, whereas in practice management at best may be adjusted according to changing climatic conditions (e.g. State water sharing plans).

## 6.1 Frameworks for decision-making in NRM: The Landscape Logic experience

Landscape Logic (www.landscapelogic.org.au) is a collaboration between researchers and environmental managers that, aims to improve our understanding of NRM issues by testing assumptions that link interventions to outcomes. BNs are the primary tool being used to achieve this outcome. Through the use of conceptual models, project teams have been able to refine their understanding of NRM issues, develop an evidence base to describe and test the interactions and strengths of relationships in conceptual models through data mining, modeling, experimentation and survey, and through model evaluation processes, identify key uncertainties and pathways for linking interventions to outcomes. Through adaptive learning processes, we can use Bayesian networks to explore alternative actions (or policies) and monitor and evaluate outcomes post-implementation.

The steps used within Landscape Logic are explored further below.

### *Defining the problem*

Problem definition focussed on identifying specific targets or objectives and identifying causal pathways and their interactions (e.g. social, biophysical, political). In Landscape Logic, we have found that conceptual models or 'influence diagrams' developed jointly with environmental management, experts and other stakeholders, were invaluable in capturing a whole of system perspective of an NRM problem. We have used a simple hierarchy (landscape context > investments > system changes > resource condition) for structuring NRM issues. This hierarchy is developed in a 'bottom up' fashion, where resource condition is used to bound the suite of preceding variables. Within resource condition, we define a target value, which represents a well articulated and achievable outcome, usually one already defined through statutory or consultative processes (such as the Tasmanian River Condition Index).

This problem definition phase was undertaken with people from a broad spectrum of disciplines to ensure that problem definition occurs within an appropriate system boundary. Through stakeholder engagement processes, it allowed us to focus on issues of community concern, and avoids bias in the representation of a system. These conceptual models formed the basis for collection and integration of evidence. Out of this process came a better collective understanding of the system complexity that can exist in linking cause-and-effect (e.g. investments to outcomes) in NRM.

### *Building the evidence base*

A strong evidence-base is important for characterising NRM problems, planning interventions, monitoring impacts, and evaluating and reporting to funders. Building an evidence-base requires assembling existing knowledge and hypotheses, identifying critical knowledge gaps, and targeting focused data collection and modelling. Such evidence can range from expert knowledge, monitoring data, and theoretical concepts to complex quantitative models.

In Landscape Logic, the aim was to assemble multiple lines of evidence to characterise the strength of causality between variables in conceptual models through the use of 'integration models', where integration included NRM processes, datasets, models, scales and stakeholder concerns (Greiner 2004). The choice of integration model was Bayesian networks, where models are built using existing data supplemented by targeted data collection and modelling to establish an evidence base. The choice of Bayesian networks was guided by their previous use in NRM decision making (e.g. Pollino et al. 2007a and b; Ticehurst et al. 2007 and Jakeman et al. 2007).

An advantage of using Bayesian networks was their hierarchical nature and their simplicity in describing inherently complex relationships, while avoiding over-representation of mechanistic detail.

### *From complexity to simplicity*

Ecological models should not seek to replicate complex systems but to represent a robust simplification of system behaviour. Models constructed for management purposes should represent the needs of the decision maker. Where possible, it is important in natural resource management to strive for simpler models, as they are easier to comprehend (Iwasa *et al.* 1987) and more amenable to being adopted.

In Landscape Logic, we adopted the concept of the simplicity cycle (Lefroy *et al* 2009) to guide us from a starting point of naive simplicity in our assumptions about how to influence environmental condition to one of informed simplicity. To do this, the BNs allowed us to negotiate inevitable periods of confused complexity as conceptual models incorporated the data from multiple domains and the assumptions of multiple experts. The primary tool used to achieve simplicity was sensitivity analysis, which allowed us to study how the variation (or uncertainty) in the output of a model can be apportioned to different sources of variation in the input of a model. Through sensitivity analysis, we were able to identify which variables in our models have the greatest influence on our model endpoints, as well as ordering the importance, strength and relevance of the inputs in determining the variation of the output.

### *Adaptive learning: Management, monitoring and modelling*

The BNs from Landscape Logic aim to promote and facilitate an adaptive learning environment. Adaptive learning is a structured, iterative process that explicitly recognises uncertainty in our understanding and the inherent variability of natural systems, which aims to reduce epistemic uncertainty over time. Adaptive learning should be applied synergistically with adaptive monitoring and modelling. Adaptive modelling allows us to test the validity of assumptions and hypotheses in decision-making, promotes continual learning as system changes take place and allows monitoring to be targeted at reducing uncertainties, including knowledge gaps, in models. By promoting adaptive management through models, the learning process can be interactive, iterative and meaningful in a positive and constructive way.

A major challenge to the wider adoption of adaptive management is the long time lag between intervention and response that is characteristic of ecological systems at landscape scales. This is turn poses a challenge for the education and training of environmental managers as each new cohort of managers will need to be familiar with prior work in their field, have the knowledge and skills to update the models that represent our understanding of NRM systems, which requires training in integrated environmental modeling techniques such as Bayesian networks.

# 7. Concluding remarks

As outlined in this report, BNs have the potential to play an increasing role as a useful tool for decision-making processes. Their increased use reflects their ability to tie together different bodies of data, aiding in the identification of salient, necessary and sufficient features of a system within a pragmatic and scientific environment. Their value in decision-making is in their ability to provide direct answers to environmental management assessment and planning processes using the best information available, and building on this evidence base over time.

By no means are they a panacea for either the modelling or decision-making communities but, used in the correct way and for the right purpose, they can fulfil the needs of the NRM community by addressing decision-making needs in complex environments, they make use of the evidence available, and they can promote and assist the adaptive learning process. A summary of the strengths and weaknesses of BNs are summarised in Table 5.

*Table 5: A summary of the strength and weaknesses of BNs, as outline in this report*

| Criteria | BNs |
|---|---|
| Transparency | ✓ |
| Multiple hazards/risks | ✓ |
| Communication tool | ✓ |
| Integration tool | ✓ |
| Adaptive Management | ✓ |
| Scenario management and analysis | ✓ |
| Representation of dynamic systems (& loops) | Research |
| Representation of Continuous distributions | Research |
| Representation of Imprecise Probabilities | Research |

# Endnotes

1. A list of Bayesian network software, with information on availability and functionality, can be found at: http://people.cs.ubc.ca/~murphyk/Software/bnsoft.html.
2. A limitation of the junction tree algorithm used in BN software packages.
3. See Pollino CA, White AK, Hart BT. (2007a). Examination of conflicts and improved strategies for the management of an endangered Eucalypt species using Bayesian networks. *Ecological Modelling* 201:37–59.
4. Some papers in the review could fit into multiple assessment frameworks, and the choice of these have been made at the discretion of the authors of this report.
5. Here a DSS is defined as an interactive software-based system intended to help decision makers compile information from a combination of raw data, documents, personal knowledge, or models to identify and solve problems and make decisions (http://en.wikipedia.org/wiki/Decision_support_system).
6. IBIS is not an acronym.
7. Narran Lakes, Gwydir wetlands, Macquarie Marshes.

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