Australian Government
National Water Commission

Bayesian modelling for risk-based environmental water allocation

Barry T Hart and Carmel A Pollino
Water Science Pty Ltd and the Australian National University

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Waterlines

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Waterlines

This paper is part of a series of works commissioned by the National Water Commission on key water issues. This work has been undertaken by Water Science Pty Ltd and the Australian National University on behalf of the National Water Commission.

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Contents

List of tables

List of figures

Australian Government

National Water Commission

National Water Commission
Water-dependent ecosystems position statement

Water-dependent ecosystems in Australia

Water-dependent ecosystems include wetlands, floodplains, riparian areas, estuaries and springs. They provide many important services including provision of good quality water for irrigation and domestic use, habitat for fish and other aquatic fauna and flora, removal of wastes and contaminants, and aesthetic, cultural and recreational benefits. Without adequate and timely water these ecosystems lose their capacity to provide such services. In some cases, the losses may be irreversible; in others, they may be difficult and costly to reverse. Under current conditions, many significant water-dependent ecosystems are under threat.

Commitments under the National Water Initiative to water-dependent ecosystems

Striking a balance between water for consumptive uses and water for ecosystem health—so that environmental, social and economic outcomes are optimised—is integral to the National Water Initiative Agreement. Water planning is the fundamental means for achieving this balance. Overallocated water systems need to be restored to environmentally sustainable levels of extraction; in other systems, crucial environmental assets and ecosystem services need to be protected.

The National Water Initiative calls for:

- environmental water to enjoy the same security as water for consumptive uses
- environmental water managers to be established and equipped with the necessary authority and resources
- water market and trading arrangements to protect the needs of the environment
- environmental water to be included in water accounts and audited
- periodic assessments of river and wetland health to be conducted so that adaptive management can be undertaken on an evidence basis.

Progress on water-dependent ecosystems

The National Water Commission's 2007 First Biennial Assessment of Progress in the Implementation of the National Water Initiative found that all states had made statutory provision for water to meet environmental and public benefit outcomes within water plans, however:

- over-allocated systems were not always adequately identified
- environmentally sustainable levels of extraction were poorly defined
- there was considerable variability in the quality of the science underpinning water plans
- in many cases the trade-offs between environmental and consumptive uses were not transparent
- there was often a lack of specificity in the environmental outcomes.

The Commission considers that the protection of threatened water-dependent ecosystems, including the recovery of overallocated systems, continues to be a major challenge in implementing the National Water Initiative Agreement.

The Commission's water-dependent ecosystems activities

Over the past three years, the focus of Commission activities has been on filling knowledge gaps and promoting science to support good decisions about environmental water. These activities have included:

- commissioning the synthesis of existing knowledge about specific aspects of water-dependent ecosystems and their management

- commissioning scoping studies to identify critical knowledge gaps and provide guidance on research priorities
- providing grants to research programs addressing issues such as the formation of acid sulfate sediments, water requirements for native fish populations and the use of aerial surveys of waterbirds as indications for wetland health
- supporting environmental water managers by establishing a 'community of practice' where they can share experiences
- undertaking trials of a national framework for assessing river and wetland health (FARWH), with the intention that an agreed framework will be delivered in 2011.

Future directions for water-dependent ecosystems
The Commission will continue to build on these activities. However improved knowledge alone will not ensure that environmental outcomes are achieved. The Commission has therefore adopted the following six priorities to guide future work involving the management of water-dependent ecosystems:

1. *Help develop and implement national guidelines and procedures for determining environmentally sustainable levels of extraction of water.* A nationally agreed method will expedite the formulation of water plans that protect water-dependent ecosystems and include a pathway to recover overallocated systems. The methods will include guidelines for establishing clear environmental outcomes.
2. *Pursue an agreed national inventory of over-allocated water systems together with commitments by governments to return them to sustainable levels of extraction.* Identifying overallocated systems and recording agreed actions to recover the water needed to restore sustainability is central to achieving environmental outcomes contained in the NWI.
3. *Improve the security of environmental water.* In spite of the legislation now passed in all jurisdictions, environmental water allocations often lack specificity and there is uncertainty around the status and security of environmental water holdings.
4. *Support more effective management of environmental water.* There are many shortcomings in the governance and operations of environmental water managers. Statutory empowerment, funding, skills and access to science, data and best practice guidelines all require urgent attention. The development of a national community of practice in environmental water management is an important initiative that will support these water managers.
5. *Strengthen the role of adaptive management of environmental water.* Recent work commissioned by the Commission[1] showed there is a deficiency in monitoring and reporting on plan implementation. This is a significant weakness when coupled with gaps in ecological knowledge and the occurrence of climatic conditions outside the planned-for circumstances. More systematic monitoring and reporting is essential to enable the water management regime to be adapted intelligently in the light of experience.
6. *Implement the Framework for the Assessment of River and Wetland Health.* While the Commission will continue to support the implementation of the Framework for the Assessment of River and Wetland Health, its successful adoption rests with the parties to the National Water Initiative Agreement.

By pursuing these priorities, the Commission will play its part in promoting the enduring objective of the National Water Initiative to manage water–dependent ecosystems to best effect. We urge the parties to the National Water Initiative Agreement to do likewise.

National Water Commission
1 September 2008

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[1] Hamstead M., Baldwin, C. and O'Keefe, V. (2008) Water allocation planning in Australia – current practices and lessons learned. Waterline Occassional Paper No. 6, April 2008. National Water Commission.

Executive summary

This *Waterlines* report is part of a series of papers commissioned on issues relating to Australian aquatic ecosystems. These *Waterlines* reports will contribute to improved environmental water management by stimulating discussion, synthesising current thinking, identifying knowledge gaps and highlighting areas that warrant further investigation.

There is a growing recognition that many of Australia's rivers and wetlands are significantly degraded. In an effort to rehabilitate these stressed systems, much effort has been put into reinstating a reasonable environmental flow regime since many of these systems occur where water has been overallocated to consumptive uses.

Many of the approaches available in Australia for determining environmental flow allocations suffer from a lack of data, transparency, and knowledge about important aspects of the ecosystem. Additionally, few methods easily account for an adaptive management approach. An adaptive approach is prefereable given our poor knowledge of and the inherent variability in Australian ecosystems. An adaptive approach for environmental flow assessment and management methods would allow for flow allocations to be refined over time as new information is gained and to account for changes in ecosystems.

This report explores the potential for Bayesian modelling approaches (specifically Bayesian networks although Bayesian hierarchical models are considered to a minor extent) to be a key tool in the determination and management of environmental flow allocations. Bayesian approaches are now used in many areas of natural resource management. Some of the uses and benefits of using Bayesian approaches include:

- prioritisation of risks to aquatic ecosystems from multiple threats, such as flow changes, excessive nutrients, degradation of instream habitat, riparian vegetation and pest fauna and flora
- integration of qualitative and quantitative information (such as hydrology, hydraulic and ecological response models) across a range of disciplines and stakeholders
- prioritisation of management activities (such as maintaining or restoring certain parts of the flow regime) and investments, within an adaptive management context, to achieve the best outcomes when resources (either capital or natural) are limited
- informing risk management strategies through scenario analysis.

The National Water Commission (the Commission) has been approached to fund work on the use of Bayesian approaches for assisting decision-making related to environmental water requirements for ecosystems. To determine the suitability of the approach, the Commissioners have decided to draw together current thinking, identify the knowledge and methodological gaps, and propose the best way forward. The Commission has contracted Water Science Pty Ltd and the Australian National University to undertake a project—Bayesian modelling as a basis for risk-based environmental flow assessment—to address these needs.

The project objectives are:

- to prepare a review of the application of Bayesian models for assessing risks in natural resource management, with particular focus on applications in assessing environmental flows
- to run a workshop (roundtable) of relevant experts to: (a) discuss current thinking in the application of Bayesian decision models in risk-based flow assessments for aquatic ecosystems, (b) identify gaps in knowledge, and (c) discuss how these gaps might be addressed
- to prepare a final report covering: (a) opportunities for the application of Bayesian approaches to environmental flow assessments in Australia, (b) what can be done right now, and (c) suggestions for future work to extend the application of Bayesian approaches in flow assessments.

This report summarises the main points to emerge from the review (Henderson et al. 2008, also Appendix A of this report). It provides a short summary of the main discussion points from the workshop and finally provides a set of suggestions to interested parties on a possible way ahead.

Key findings

It is clear that Bayesian modelling approaches could play an important in environmental flow assessment and decision-making in Australia.

In particular, they can improve current methods by:

- providing simple, visual representation of conceptual models and causal links that are easily communicated
- documenting the rationale behind environmental flow recommendations (in flow–ecology links and notes that accompany them) for future use
- validating the science underpinning individual flow recommendations, and testing the effectiveness of an implemented flow regime (for example, VEFMAP using Bayesian statistical models)
- facilitating adaptive management by using the data collected in monitoring programs to iteratively improve the models used to estimate the flow requirements for different parts of the ecosystem
- predicting and demonstrating the risks associated with not providing the agreed environmental flow regime
- providing potential for stakeholders representing different interests (urban water, irrigation, environment) to use a single tool in scenario analysis and decision-making, thereby promoting a common understanding. This need will become increasingly important as the impacts of climate change become more apparent.

Bayesian network (BN) models are relatively simple to develop and use. They can be used to integrate flow information (such as from existing hydrological and hydraulic models) and other biophysical factors (such as water quality, habitat, predation) with measurable ecological responses (such as bird breeding, fish migration). They can also be used to integrate social and economic drivers and management outcomes.

Thus, BN models can provide a tool for environmental flow assessment and decision-making in Australia as well as a decision-support tool to integrate flow requirements with other biophysical and socio-economic information.

Although several individual projects are currently underway in Australia to develop and apply Bayesian network models (and other Bayesian statistical models) for environmental flow assessment decision-making, we believe opportunities exist to stimulate a more coordinated approach to the development and application of Bayesian approaches for environmental flow assessments throughout Australia.

Opportunities exist in facilitating the following:

- a national approach to achieve greater consistency in approaches to environmental flow assessments and decision-making throughout Australia, which could involve establishing consistent methodologies, guidelines for best practice, and promoting a role for Bayesian modelling in facilitating adaptive management of environmental flows
- the establishment and promotion of a network for Bayesian modellers and users of Bayesian models to ensure that the learning and experiences from local and international studies are captured and built upon
- the funding of a well-coordinated series of national case studies to provide real examples of Bayesian approaches in environmental water allocation processes, and developing and road testing consistent methodologies and guidelines for best practice. The approach should involve: (a) building upon existing Bayesian environmental flow projects that are underway, which incorporate state-based environmental flow assessment methodologies (such as projects in Victoria, New South Wales, Queensland and Western Australia); and

(b) developing and applying a series of new Bayesian models incorporating biophysical, socio-economic and policy aspects

- the establishment of a capacity building process for Bayesian approaches in environmental flows through a nationally coordinated training program and establishing an accreditation process via an auditing process
- the establishment of a central knowledge manager for Bayesian approaches in environmental water allocation processes in Australia. This could involve: (a) providing a repository for conceptual models, time-series response models and Bayesian models; and (b) establishing a network of Bayesian modellers and users to ensure that the learning and experiences from these and other studies are captured and passed on.

Research and training needs

Some key research and training needs were identified to ensure continual improvement of Bayesian approaches in environmental flow assessment, management and monitoring of outcomes. These include:

- **National case studies program**—a series of coordinated case studies to provide real examples of Bayesian approaches in environmental water allocation processes, and in developing and road testing consistent methodologies and guidelines for best practice
- **Integrated Bayesian network models**—a series of new integrated Bayesian network models be developed and applied to decision-making related to maintaining (and perhaps rehabilitating) the ecological health of rivers and wetlands, incorporating flow, other biophysical drivers and socio-economic factors
- **Bayesian hierarchical modelling**—Bayesian hierarchical models be applied to extract more information from monitoring data about the relationships between flow and environmental endpoints
- **Climate change and environmental flows**—research is needed to develop a generic Bayesian network for undertaking risk-based assessments for assess the resilience and vulnerability of species under plausible scenarios of climate change
- **Software development**—to complement and improve available BN software by formalising the process of developing a BN using tools (such as ‘wizards’) that guide the BN developer through the process and that assist the model developers in documenting the model building process
- **Capacity building program**—a nationally co-ordinated training program is needed to increase the capacity of modellers, environmental managers and policy-makers and assist them to better accept and use Bayesian network approaches in environmental flow allocation decision-making,
- **Central knowledge manager**—there is a need to establish a central repository for conceptual models, time-series response models and Bayesian models, and a network of Bayesian modellers and users to ensure that the learning and experiences from relevant studies are captured and passed on.

1. Introduction

There is a growing recognition that many of Australia's rivers and wetlands are significantly degraded. In an effort to rehabilitate these stressed systems, much effort has been put into reinstating a suitable environmental flow regime, particularly where water has been overallocated to consumptive uses.

Reinstating components of the environmental flow regime is well suited to an adaptive management approach, where an environmental flow regime is determined using the best available knowledge, legal entitlements are negotiated, a flow regime is then implemented through allocation or water sharing, the results are carefully monitored and evaluated, and then on the basis of this scientific information, the environmental flow regime may be refined over time (Richter et al. 2006). The potential role of Bayesian modelling approaches in this adaptive management process is discussed in Section 4.2.

This report focuses on the potential application of two Bayesian modelling approaches (Bayesian hierarchical models and Bayesian network models) in the determination and management of environmental flow allocations. There are now a number of applications of Bayesian approaches in natural resource management (Nyberg et al. 2006; Henderson et al. 2008). Some of the benefits of using Bayesian approaches (Henderson et al. 2008) include:

- prioritisation of risks to aquatic ecosystems from multiple threats, such as flow changes, excessive nutrients, degradation of instream habitat, riparian vegetation and pest fauna and flora
- integration of qualitative and quantitative information (such as hydrology, hydraulic and ecological response models) across a range of disciplines and stakeholders
- prioritisation of management activities (such as maintaining or restoring certain parts of the flow regime) and investments, within an adaptive management context, to achieve the best outcomes when resources (either capital or natural) are limited
- informing risk management strategies through scenario analysis.

Natural resource managers increasingly need tools to guide decisions where considerable uncertainty exisits, particularly in understanding how a system works and how particular management actions will influence the system. Although our understanding of cause-effect relationships between the threats and ecosystem outcomes is increasing, our systems are constantly changing. In such situations, Bayesian modelling approaches are seen as having value as decision support tools.

To determine the suitability of the approach, the Commission decided to draw together current thinking, identify the knowledge and methodological gaps, and propose the best way forward. The Commission has contracted Water Science Pty Ltd and the Australian National University to undertake a project—Bayesian modelling as a basis for risk-based environmental flow assessment—to address these needs.

The project objectives are:

- to prepare a review of the application of Bayesian models for assessing risks in natural resource management, with a particular focus on applications in assessing environmental flows[2]
- to run a workshop (roundtable) of relevant experts to: (a) discuss current thinking in the application of Bayesian decision models in risk-based flow assessments for aquatic

[2] The Commission requested that we also consider situations where recycled water can be used as environmental flows. Given the current lack of information on the environmental risks associated with this management action, it was not possible to adequately address this situation. We note that the Victorian Department of Environment & Sustainability is currently (May 2008) developing a business case for the possible recycling of 100 gigalitres per year of treated water from the Eastern Treatment Plant in Melbourne to the Yarra River.

ecosystems, (b) identify gaps in knowledge, and (c) discuss how these gaps might be addressed

- to prepare a final report covering: (a) opportunities for the application of Bayesian approaches to environmental flow assessments in Australia, (b) what can be done right now, and (c) suggestions for future work to extend the application of Bayesian approaches in flow assessments.

This report firstly summarises the main points to emerge from the review, then provides a short discussion on the main discussion points from the workshop, and finally provides a set of findings to the Commission and other interested parties on a possible way ahead. Appendix A contains a review of what Bayesian networks are and documents recent applications in the environmental literature.

This report focuses largely on Bayesian networks as the approach most likely to find application with environmental water allocation managers, although we recognise that there are other Bayesian approaches that are being used and can also assist (Henderson et al. 2008).

2. Available environmental flow assessment methods

2.1 General

The objective of an environmental flow assessment is to determine a flow regime[3] that will ensure that a healthy aquatic ecosystem[4] is sustained into the future. There are four main approaches to modelling used in environmental flow assessments (see Arthington et al. 2007 for more detail), which are discussed below. It is important to note that for every modelling approach, lower order modelling approaches can be used as tools within them.

- Hydrological models—these comprise the most basic desktop methods, where modellers or system managers perform simple analysis of hydrological data such as flow duration curves, and estimate annual or monthly flow statistics. Because of their focus on hydrological data, rapidity of construction, and typically their consequent lack of ecological relevance, these low-resolution methods are appropriate only at the planning level of water resource management and development (Tharme 2003; Arthington et al. 2007).
- Hydraulic rating models—these represent the next level of complexity for environmental flow assessments s (Arthington et al. 2007) and incorporate hydraulic parameters, such as maximum depth or wetted perimeter, in addition to the information captured in the lower order hydrological models. These hydraulic parameters are used as surrogates for information on aquatic habitat structure and habitation, and although they are still useful and remain in use in some situations, higher order models are needed to model the effects of flow regime change on biological diversity and ecological processes.
- Habitat simulation models—these provide a more refined analysis of both the quantity and sustainability of the physical habitat available to target species (or taxonomic groups) at different levels of flow. These models include system parameters (such as stream width, depth, substrate characteristics, instream cover) that can be used to estimate flow-related changes in physical habitat; these are usually measured at the scale of representative sites within a number of stream reaches. They enable a prediction of the loss of particular types of habitat structure in relation to change in stream discharge. These simulation models require access to data on the habitat requirements of the target species (usually fish or invertebrates).
- Holistic models—these are based on the premise that the sustainability of an aquatic ecosystem depends on the characteristics of the entire flow regime in its natural state (Arthington et al. 1992; Poff et al. 1997), and they attempt to consider the flow requirements of all system components (channels, habitat, water quality, all aquatic taxa, dependent vertebrates, foods webs, even estuaries and downstream coastal systems). Interactions between the physical features of river systems, target flora and fauna and any predator/prey or symbiotic biota may also be addressed. These approaches aim to provide the most informed and precise estimates of the flow requirements of the river ecosystem and its biological communities. Two main types are available—proactive and reactive methods. Proactive methods explore how much a river's flow regime can be altered before undesirable ecological change becomes evident. Reactive methods address how the flow regime of a regulated river can be 'restored' in whole or part to achieve improvements in ecological condition.

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[3] The flow regime is defined by the magnitude, frequency, timing, duration and rate of change of flow (or water level) for the various flow components required to sustain a healthy aquatic ecosystem.
[4] A healthy aquatic ecosystem is one in which the structure, ecological processes, resilience and the ecological services that sustain the ecosystem are maintained.

Because holistic methods aim to incorporate such a high number of separate components, the increased accuracy of these higher order models generally comes at the cost of greatly increased complexity and cost. Several holistic modelling approaches are available, although all these suffer from either a lack of knowledge about the system or a lack of data (or both) and so must rely heavily on expert opinion and the collective judgements of scientific panels.

This reports explores the potential for Bayesian modelling approaches to be a key tool in the determination and management of environmental flow allocations in Australia, potentially complimenting and being appied within the methods described above.

2.2 Environmental flow assessment methods used in Australia

All Australian states and territories have at least some process in place for determining the environment's water needs (Jones et al. 2001). However, there is little consistency between these methods, and the methods are (mostly) poorly documented. This lack of consistency in the different determination methods used makes it very difficult to determine whether the environmental flow requirement for a river in one state or territory is the same as that required for an equivalent river in another state or territory.

The decision-making for determining environmental flow requirements is mostly expert-based: the flow components are determined using hydrological and hydraulic models (for example, IQQM, REALM, BigMOD, HEC-RAS, MIKE FLOOD), and the ecological responses to these flow components are inferred by a technical panel. The documentation of the expert assumptions or rules used is off poor or non-existent.

Two environmental flow methods that are particularly well documented, scientifically-based, and well tested are the FLOWS method used in Victoria and the Murray Flow Assessment Tool (MFAT) developed by the Murray-Darling Basin Commission. These are summarised below. Other methods in use in Australia are the Queensland 'Benchmarking' method (Arthington et al. 2007) and the 'Macro water planning' process used in New South Wales.[5] Some states use more than one method, and this can be an advantage when different levels of detail are required for particular systems.

In Section 4.2, we discuss how Bayesian modeling approaches can assist this process of determining the flow regime that is required to satisfy the environmental needs of particular river systems (environmental flow regime).

FLOWS method (Victoria)

In Victoria, environmental flow requirements are determined using the Victorian FLOWS methodology (DSE 2002). The FLOWS methodology establishes a series of environmental objectives for each river reach as the basis for developing the final environmental flow recommendations. The ecological objectives are linked to a particular environmental asset, such as native fish, water quality, stream channel form or macro-invertebrates. The water requirements of the environmental asset are linked to particular flow components, which include low and high flows for summer and winter, freshes and cease-to-flow (Figure 1).

A technical panel is employed to determine the objectives and flow components required in each reach of the river. the panel also determines the volume, timing, duration and frequency that are associated with each flow component. See SKM (2005) for the process leading to the environmental flows recommended for the Yarra River.

The FLOWS method is currently (May 2008) being reviewed.[6]

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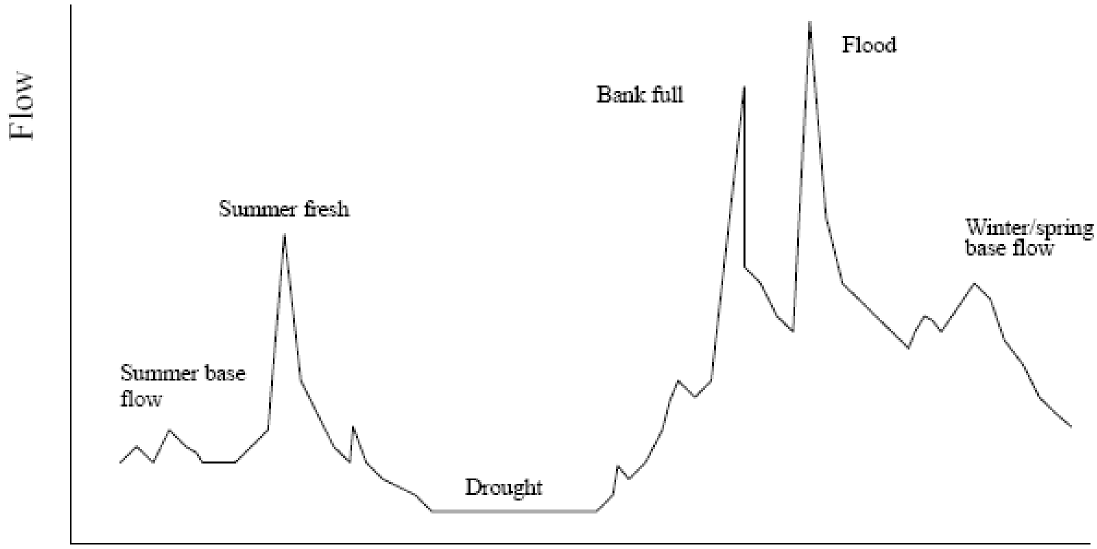
[5] For details see: *http://203.3.195.251/water/macro_sharing_plans.shtml*
[6] Details of the review process can be obtained from Department of Sustainability and Environment or Melbourne Water.

Figure 1: Natural flow regime, identifying important flow components

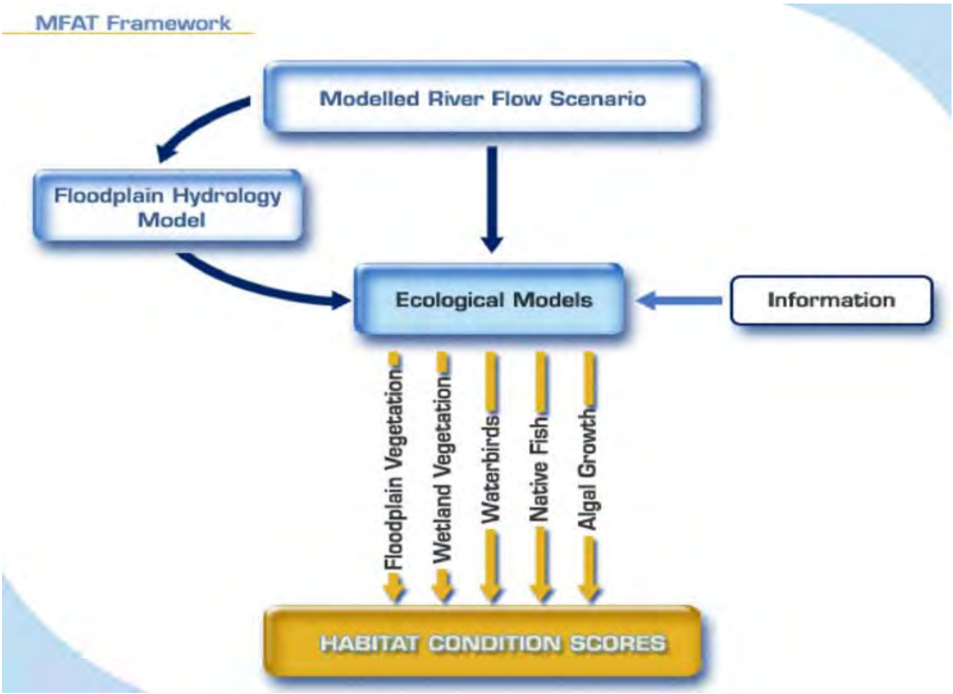


Source: Poff et al. (1997); Richter et al. (1997)

Murray Flow Assessment Tool (Murray–Darling Basin Commission)

The Murray Flow Assessment Tool (MFAT) (Young et al. 2003) is a decision support system developed by CSIRO for the Murray-Darling Basin Commission. It is designed to support environmental flow assessments within the Living Murray Initiative. MFAT relates river flow to potential habitat conditions for river and floodplain environments. It assesses the impacts and benefits of different flow scenarios on the condition of physical habitat for native fish, waterbirds and vegetation communities and the growth of algal blooms for the River Murray system (Figure 2).

Figure 2: Murray Flow Assessment Too (MFAT) framework



Source: Murray Darling Basin Commission website, 'What is MFAT?'
http://www.mdbc.gov.au/subs/information/mfat/what.htm, accessed March 2008

MFAT uses daily river flows as the primary input to ecological models that are largely parameterised on the basis of expert knowledge. It integrates the assessments across spatial scales ranging from a single locality to the entire river system. The results can then be used to facilitate an informed trade-off process between the allocation of water for environmental and human requirements.

2.3 Implementation of environmental flow regimes

Determination of the environmental flow regime is often only the first of many steps required to actually secure and deliver additional water for the environment in an overallocated system.

A single set of environmental flow recommendations (such as that determined by the Victorian FLOWS method) may be used repeatedly in several decision-making processes over many years. These processes can include: negotiating legal entitlements, developing water sharing agreements, defining operation rules, ongoing management planning, drought contingency plans, emergency response plans, and monitoring plans.

Each of these processes will involve negotiations and trade-offs, so that environmental flow recommendations are rarely implemented in full. It is vital that the environmental managers involved in these discussions are able to articulate the rationale behind individual recommendations (particularly the hydraulic requirements and flow-ecology relationships that underpin recommendations) in a transparent and easily communicated way. Further, if they cannot clearly demonstrate the ecological risks associated with not fully implementing the flow regime, the environment will continue to lose out in these negotiations.

Section 4.2 considers the role of Bayesian modeling approaches in assisting environmental managers in influencing decision-making once the initial environmental flow recommendations are set.

3. Potential application of Bayesian approaches

This section covers two Bayesian modelling approaches that have potential for assisting decision-making in relation to environmental water requirements for river and wetland ecosystems—these are Bayesian statistical modelling and Bayesian network (BN) modelling.

3.1 Bayesian statistical modelling

During the past ten years Bayesian statistical modelling has established a strong following, being used in a number of applications, including environmental applications. The approach is often supported by integration of expert opinion and with quantitative information (Clark 2005).

In terms of there use for environmental flow studies, Bayesian statistical approaches are mostly useful in the analysis of monitoring data from environmental flow programs. They are suited to fitting models and testing hypothesis concerning the effects of flow on ecosystem endpoints. Bayesian statistics are being used for data analysis of the Victorian Environmental Flows Monitoring and Assessment Program (VEFMAP; Cottingham et al. 2005, Chee et al. 2006), analysing trends in ecological systems in response to flow.

Bayesian statistical approaches have an advantage over more familiar ‘frequentist’ approaches in that the approach is inherently flexible and the models are built to match the requirements of the data. In contrast, when using standard statistical approaches (such as ANOVA or regression), the data are assumed to conform to the requirements of a relatively small number of models (McCarthy 2007).

One form of Bayesian statistical modelling—Bayesian hierarchical modelling—is particularly suited to the spatio-temporal complexities often present in ecological investigations (Clark 2005). Bayesian hierarchical models can be used for small sample sizes by assuming partial dependence of sampling units (for example, individual sites). This is particularly useful for analysing ecological datasets, which are often limited. Additionally, they offer a mathematically and intuitively satisfying solution to the problem where few data have been collected at several different sampling sites (Gelman et al. 2004). Bayesian hierarchical models solve pseudo-replication (*sensu* Hurlbert 1984) and low statistical power by assuming monitoring sites are related through their prior distributions of parameter values.

Webb et al. (submitted) provide an explanation of the mechanism of Bayesian hierarchical modelling for the non-expert, while Gelman et al. (2004) provide an excellent explanation of the more detailed mathematics.

Preliminary work undertaken through the VEFMAP program has demonstrated the efficacy of Bayesian hierarchical models for assessing the relationships between environmental endpoints and flow (Webb et al. submitted; workshop presentation by Dr Angus Webb). Webb et al. (submitted) analysed relationships between summer low flow volumes and: (a) salinity and (b) fish abundance (Australian Smelt *Retropinna semoni*). The latter analysis provided a good demonstration of the power of the hierarchical approach using a small data set and concluded that higher-than-recommended summer flows in the Thomson River have a negative impact on the abundance of Australian Smelt.

Bayesian statistical approaches, and in particular Bayesian hierarchical modeling, offer a way to complete the adaptive management cycle and iteratively improve environmental flow assessments. By using gradient-based models to quantify relationships between flow and ecosystem response (see Webb et al. submitted, Cottingham et al. 2005, Chee et al. 2006), it is possible to use the data collected during monitoring programs to iteratively improve the models used to estimate the flow requirements of different parts of the ecosystem. The use of Bayesian networks in environmental flow assessments are reviewed below.

3.2 Bayesian network modelling

Bayesian network (BN) models are being increasingly used in natural resources management (McCann et al. 2006; Nyberg et al. 2006) and more recently, specifically for determining environmental flow allocations. In Australia, BN-based environmental flow studies have been undertaken or are underway in Queensland, New South Wales and Victoria.

In this section, we describe the advantages and limitations of BNs and how they are currently being used in natural resource management. Here we use the generic term BN to cover two types of Bayesian network models—Bayesian belief networks (BBNs) and Bayesian decision networks (BDNs). BDNs contain decision nodes (and optionally utility nodes) and are described in Henderson et al. (2008).

What are Bayesian networks?

Bayesian networks are graphical models that can be adapted for use in a wide variety of applications. BNs emerged from research into artificial intelligence, where they were originally developed as a formal means of analysing decision strategies under uncertain conditions. They have since proven to be applicable to a wide range of problems (see Section 5 in Henderson et al. 2008).

BNs are able to explore and display causal relationships between key factors and final outcomes of the responses of a species, assemblage or ecosystem in a straightforward and easily understood manner. They are often developed simply from a conceptual model of the system.

Figure 3 shows a simple BN for linking management flow release options for a wetland, showing changes in the ecological system responses.

Figure 3: Hypothetical Bayesian network linking management flow release options for a wetland showing change in system responses

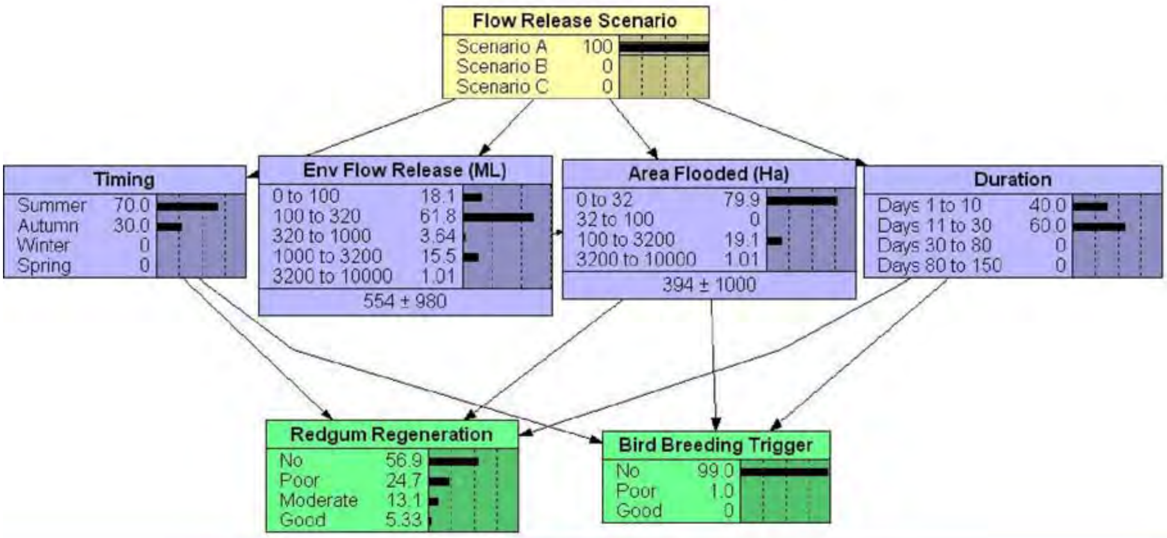


Table 1: Portion of a hypothetical condition probability table describing the probability of a bird breeding event given system conditions

Node: Breeding_Trigger   Apply   Okay

Chance   Percentages   Reset   Close

Timing	Duration	Area Flooded (Ha)	No	Poor	Good
Summer	Days 1 to 10	0 to 32	99.000	1.000	0.000
Summer	Days 1 to 10	32 to 100	99.000	1.000	0.000
Summer	Days 1 to 10	100 to 3200	99.000	1.000	0.000
Summer	Days 1 to 10	3200 to 10000	99.000	1.000	0.000
Summer	Days 11 to 30	0 to 32	99.000	1.000	0.000
Summer	Days 11 to 30	32 to 100	99.000	1.000	0.000
Summer	Days 11 to 30	100 to 3200	99.000	1.000	0.000
Summer	Days 11 to 30	3200 to 10000	99.000	1.000	0.000
Summer	Days 30 to 80	0 to 32	99.000	1.000	0.000
Summer	Days 30 to 80	32 to 100	20.000	70.000	10.000
Summer	Days 30 to 80	100 to 3200	20.000	70.000	10.000
Summer	Days 30 to 80	3200 to 10000	20.000	70.000	10.000
Summer	Days 80 to 150	0 to 32	99.000	1.000	0.000
Summer	Days 80 to 150	32 to 100	20.000	70.000	10.000
Summer	Days 80 to 150	100 to 3200	10.000	60.000	30.000
Summer	Days 80 to 150	3200 to 10000	10.000	60.000	30.000
Autumn	Days 1 to 10	0 to 32	99.000	1.000	0.000

Bayesian networks can be used to assemble knowledge to explore system interactions (for example: investments -> activities -> processes/impacts -> outcomes), while capturing the uncertainties in this knowledge. As BNs are causal, they can also be used to calculate the impact or effectiveness of interventions, such as management decisions or system changes (such as those predicted for climate change). Importantly, the uncertainties associated with causal relationships and BN predictions, and the sensitivity of model predictions to uncertainty, can also be assessed (see Section 3.1 of Henderson et al. 2008).

BNs apply Bayes' Theorem to update or revise beliefs about the probabilities of system states taking certain values in the light of new evidence.

A well-developed BN can assist both researchers and decision-makers to document knowledge, interrogate system interactions and guide investment strategies.

What are their advantages?

In contrast to most environmental modelling techniques, Bayesian networks use probabilistic, rather than deterministic, expressions to describe the relationships among variables. Lack of knowledge is accounted for in the network through the application of Bayesian probability theory. This allows subjective assessments (for example, expert opinion) of the probability that a particular outcome will occur to be combined with objective data to quantify the frequency of occurrence in determining conditional probabilistic relationships.

Uncertainty is a major issue in modelling ecological systems. A common source of uncertainty that can be represented in a BN is the lack of knowledge of natural systems and the inherent variability within these systems. Other sources of uncertainty that can be represented in a BN include: statistical variation (for example, parameter measurements); the subjectiveness of judgements ranging from expert elicitation of model structure and estimation of probabilities; the inherent randomness of some complex systems; and also any disagreement that may arise between multiple experts. As with other Bayesian statistical approaches, differentiating between the sources of model uncertainty (by delineating between lack of knowledge and natural variability) is not possible.

Bayesian networks have a number of properties that make them particularly useful for ecological data analysis, as well as management decision-making. In particular, they (Section 3 of Henderson et al. 2008):

- show cause–effect relationships directly through a simple causal graphical structure, but they are also easily constructed, extended and modified
- have a natural way to handle missing data
- incorporate uncertainty in relationships
- are an accessible and intuitive modelling approach

- can show good predictive accuracy even with rather small sample sizes
- allow the conditional probabilities between variables to be constructed using either observed data, other models, or expert knowledge
- are modular (composed of a set of submodels)
- can be easily used to aid management decision-making (particularly when embedded within an decision support system environment).

Relatively inexpensive and simple-to-use software packages are now available for developing and applying BNs (such as Netica).

Limitation of Bayesian networks

As noted above, BNs are useful for (a) displaying and quantifying (using actual or simulated data or expert opinion) the interactions between key variables, and (b) determining the implications of management decisions on ecological outcomes.

However, it is important that users of current software (such as Netica) recognise that they also have several limitations, in particular feedback loops and time-dependency. These limitations are covered in Section 4.3 of this report.

3.3 Applications of Bayesian networks in natural resource management

Due to their flexibility, BNs have been used by a wide range of disciplines, namely engineering, information technology, medicine, and more recently in biology and ecology. Applications introduced below are divided into ecological applications and assessment frameworks. A more comprehensive review of applications can be found in Henderson et al. (2008).

Ecological applications

BNs are proving to be particularly useful tools for assisting and prioritising investments in research and decision-making by structuring knowledge and focusing new and existing data collection. BNs are also useful where uncertainties in decision-making cannot be reduced in a timely manner by collecting more data (as in the management of an endangered species or habitat). In such cases, often decisions cannot wait for a definitive understanding of current or future system processes, and a risk-based approach is required.

Section 5 of Henderson et al. (2008) reviews some recent applications of BNs in terrestrial and aquatic ecology.

Assessment frameworks

As noted elsewhere in this report, BNs are particularly useful for focusing issues by clearly structuring the formulation of the problem using a transparent process.

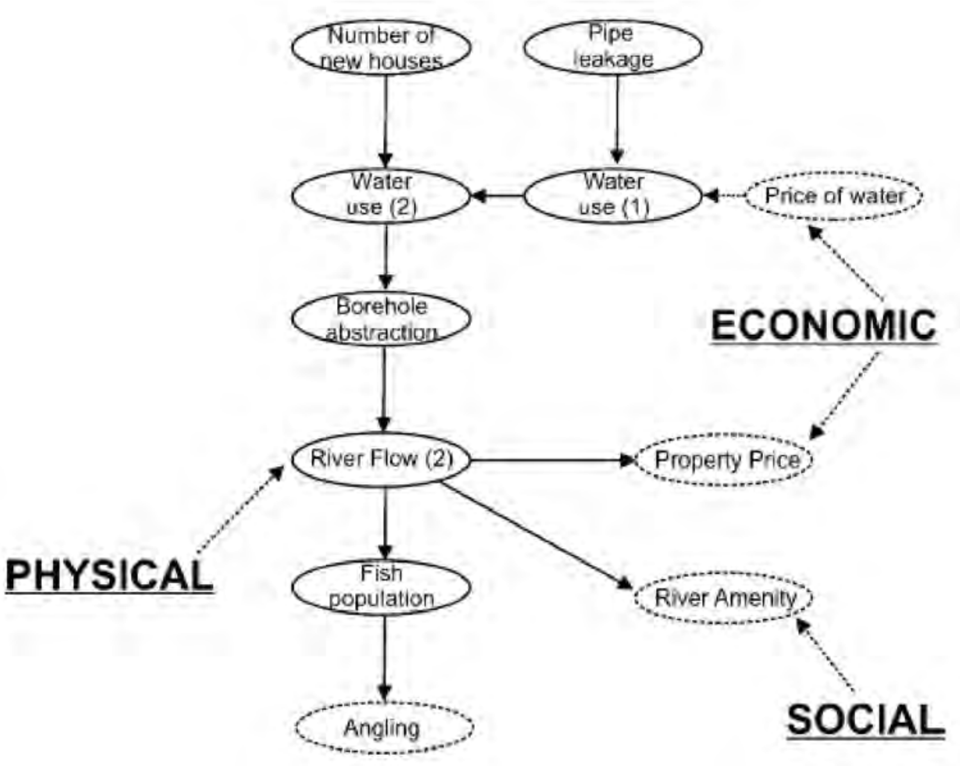
There are now many interesting applications for which BNs have been used as a framework to integrate biophysical, socio-economic and policy aspects of an issue (see Section 5 of Henderson et al. 2008). For example, Bromley et al. (2005) developed a BN to assist in assessing the trade-offs between water use, water price, river amenity and fish population. A simple version of this BN is shown in Figure 4.

Additionally, BNs are increasingly being used in risk assessment to examine the effects of both human and non-human stressors on ecological systems (see Section 5 of Henderson et al. 2008). Risk-based decision-making aims to quantify the likelihood of a threat occurring, the consequences of this threat to an ecological system, process or value, and the associated uncertainty in the predictions.

Until recently, the ability to predict changes in dynamic ecosystems due to stressors was limited by both the poor understanding of the drivers of ecological processes and structure, and the lack of modelling tools that could represent such complexity with associated uncertainties. However, the recent growth in the use of BN models for ecological risk assessments has resulted in major advances in better understanding and managing ecosystems despite their inherent complexity and variability.

For a complete overview of Bayesian networks, and their use in environmental flow assessments, please see (Henderson et al. 2008).

Figure 4: A simple BN examining trade-offs between water use, water price, river amenity and fish population



Source: Bromley et al. (2005)

4. Key points from the workshop

4.1 Critical needs for environmental flow assessments

To provide an understanding of the potential role of Bayesian models in environmental flow assessments, we asked workshop participants to summarise the critical needs involved in assessming and implementing environmental flows.

Environmental flow assessments: Process requirements

The needs for each step in assessing environmental flows are outlined in Table 2.

Bayesian models (with a focus on BNs) have the potential to meet these needs by:

- articulating conceptual models (generalised and specific)
- incorporating concepts of risks, uncertainty and risk management in an assessment
- integrating information from other models and other sources
- integrating other factors (biophysical, social and economic) into an assessment
- assisting trade-off processes by assessing the risks to the ecological health
- enabling scenario testing (event-based and long term) for decision-making.

Table 2: Critical needs in the environmental flow assessment process

Defining the problem	Clear ecological objectives (regional register of flow-dependent ecological assets?) Methods for defining environmental watering options Better methods for specifying environmental flow regimes
Understanding flow responses	Methods for prioritising environmental water delivery options· Common and clear flow-ecology conceptual models (and information about other drivers) Better use of available causal evidence linking flow alteration to ecological responses
Quantitative flow-ecology models·	Risk-based environmental flow assessment, including considerations of uncertainty, prioritisation of actions and adaptive management Integrating information Methods and institutional structures for inter-river, -basin and -jurisdictional learning from environmental flow monitoring and assessment·
Integrated allocation (and operation) of water for the environment and human use·	Coordinate environmental flow decisions, monitoring and assessment by different agencies at different temporal and spatial scales· Integrated environmental flow decisions, monitoring and assessment with other river restoration activities
Scenario testing	Assessing flow alternatives for optimising the likelihood of meeting multiple ecological objectives· Assessing trade-offs between meeting outcomes for ecological and urban–rural water needs

Source: information modified from material presented at the Workshop by Dr Michael Stewardson and Dr Simon Treadwell

Environmental flow assessments: Data and model requirements

The workshop identified four types of riverine systems that could need an environmental flow assessment: regulated rivers that are either not fully allocated or are overallocated to consumptive uses, and unregulated rivers that are either not fully allocated or are overallocated to consumptive uses.

Specific data and modeling needs are as follows:

- Hydrology—need to understand the site hydrology to enable current condition to be placed in some sort of flow context. This requires:
  - high-quality streamflow records
  - high-quality, daily time-step models of the systems (which include natural inflows, current levels of demand, current system operating rules)
- Hydraulics—need accurate relationships between streamflows and water levels, including:
  - sufficient number of surveyed cross-sections to capture detailed hydraulic controls and ecological or geomorphic points of interest
  - effective downstream control to accurately set boundary conditions
  - surveys at more than one discharge level to enable improved model calibration
- Ecological value and condition—need good ecological data to be able to:
  - accurately identify ecological values and describe their existing condition. This requires an understanding of the biota that we think should occur (or that do occur, or we want to occur, or in some cases that we want to exclude) in a particular system
  - understand the key factors influencing condition, both flow and non-flow related
  - set meaningful ecological objectives
- Ecological response—need a good understanding of ecological response to flow and habitat requirements. This can be gained through conceptual models and site-specific studies
  - assessments are often biased by species and processes about which we have the most understanding
  - need to know system failure thresholds
  - need to understand temporal dynamics
  - need to document risks and uncertainty around the responses
- Quantitative flow-ecology models—that can be used for:
  - assessing environmental flow requirements
  - evaluating proposed environmental flow provisions
  - informing the release of environmental water
  - model-based environmental flow monitoring and assessment
  - integrating hydrology, hydraulics and ecological responses
  - integrating temporal variability patterns and their impact on population dynamics
  - dealing with spatial linkages
- Methods and institutional structures—for inter-river, inter-basin and inter-jurisdictional issues that should incorporate shared learnings from environmental flow monitoring and assessment. This could involve:
  - common flow-ecology conceptual models
  - consistent or complementary measurements, data infrastructure and assessment techniques

- institutional infrastructure to share models, data and results

- Methods for integrated allocation (and operation) of water for the environment and human use, including:
  - finding the 'sweet spots' in the multi-dimensional solution space
  - representing environmental water demand in water allocation models

Environmental flow assessments: End-user requirements

Further, the workshop identified the following critical needs for environmental flow assessments:

- Managers need advice that is:
  - timely and cost-effective—they often do not have the luxury of time or unlimited budget
  - transparent and defensible—the recommendations will be scrutinised by many parties and need to be defensible, the processes used to develop recommendations need to be transparent and repeatable, and the risks and uncertainties need to be well defined
  - pragmatic—the recommendations need to be relatively easily implemented, complicated recommendations will be ignored at best. Information needs to assist in making trade-offs between available water and ecological outcomes.

4.2 How can Bayesian network approaches help?

BN models offer a number of potential advantages as decision-support tools for environmental flow assessments, in that they:

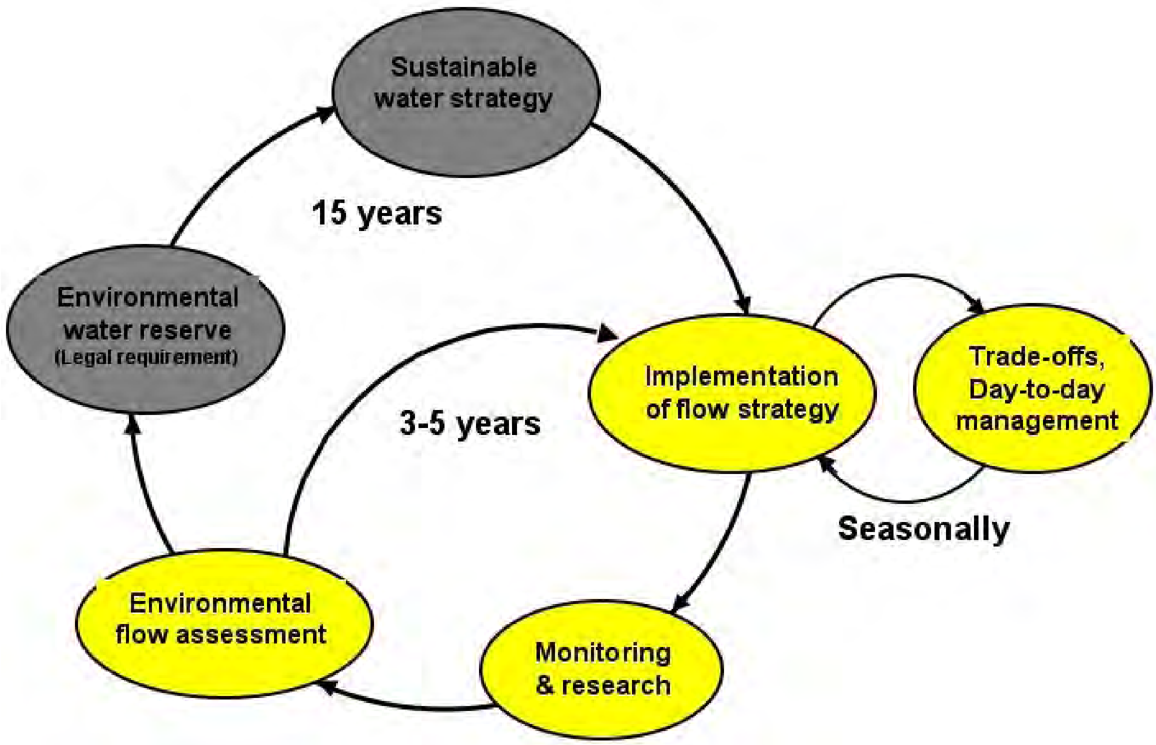
- can build upon the conceptual model(s) of the system, and upon existing state-based environmental flow processes and methodologies (such as the Vic FLOWS method), not re-inventing the wheel
- can provide a means for linking existing hydrological and hydraulic models with ecological response models, thus operating as an integrated decision-support tool
- can integrate the effect of flow and other biophysical factors (such as water quality, habitat, predation) on the ecosystem
- can integrate social and economic drivers and outcomes
- can provide a platform to document and interrogate assumptions in models and decision-making processes, replacing conceptual models with a more interactive approach
- can make the cause-effect linkages more transparent and understandable, thus removing the 'black-box' approach associated with most models
- allow model structures and findings to be demonstrated to contributors and stakeholders, encouraging agreement or correction and facilitating updating
- can be updated as new information becomes available
- can serve as an interim stage between conceptual model and quantitative model development to develop quantitative relationships, which could then be further examined using Bayesian statistical modeling, dynamic projection modeling approaches, or spatial modeling approaches, or combinations of all those
- can provide rapid and integrated assessments of risk and uncertainty, and provide standardisation in execution and documentation
- can provide a knowledge system to better understand and transfer information between catchments and states over time

Thus, BN approaches can assist environmental water managers, by:

- optimising the likelihood of meeting ecological objectives
- providing a decision-making tool to assist the process of achieving a balanced share of the resource between the environment and consumptive uses
- assisting in analysing trade-offs for ecological water requirements during extreme weather events (and also climate change scenarios)
- assisting in establishing a best-practice monitoring and assessment program
- assisting in evaluating the outcomes of environmental flow allocations.

Figure 5 provides an example of where Bayesian modelling approaches could assist in the adaptive management of water resources. The example relates to the environmental flow allocation and management process in place in Victoria, where the overall planning framework is a 15-year sustainable water strategy for each river system. An environmental water reserve specifies the legal entitlement of water for the environment, and a bulk entitlement specifies the legal entitlement of water for consumptive uses. Within this long-term sustainable water strategy, there is an adaptive management process by which changes can be made (within an overall cap and on the basis of monitoring and research) to the water regime required by the environment during a 3–5 year period. Furthermore, implementation of the flow regime will involve trade-offs and management decisions about flow releases during shorter periods, such as within a particular season or year. The yellow boxes in Figure 5 represent the decision points that could be assisted by Bayesian modelling approaches.

Figure 5: Schematic of the environmental flow allocation and management process in place in Victoria



Note: The yellow boxes represent decision points that could be assisted by Bayesian modelling approaches.

4.3 Limitations of Bayesian networks

There are several limitations that users of current software packages (such as Netica) need to recognise:

- feedback loops—BNs do not permit feedback functions either within a node or from output variable back to input variables. Feedback can be important in many ecological systems
- time-dynamic functions—BNs handle time functions poorly. The BN model structure needs to be replicated, and specific time-dependant nodes should be linked between the replicates
- discretised probability distributions—most BN software requires that continuous probability distributions be discretised, which can result in the state variable being over-simplified
- spatial detail—representing spatial detail, including spatial interactions, can affect the simplicity of BNs.

Methods are available for handling feedback, time dimensions and hierarchical structure (which can be used to represent different spatial dimensions), and some of these are now available in BN software (such as Netica, Hugin). However, such solutions are still limited and are less than optimal.

A non-software limitation relates to the quality of the information used to derive relationships within a BN model. BNs that are developed using largely expert opinion (qualitative data) can certainly assist the decision-making process, but it is important that the outputs from such models are used with caution. Quantitative relationships in BNs can be developed by coupling a BN with other models (for example, numeric deterministic models such as hydrology models, and Bayesian statistical models) (Merritt et al., in press).

4.4 What can be done now?

Several BNs have been developed (or are being developed) in recent years to assist in environmental flow assessments. These are discussed in Henderson et al. (2008) and include:

- Chee et al. (2005) explored decision-making in ecosystem management as a process of balancing multiple objectives, constraints, trade-offs and uncertainties against a complex backdrop of socio-economic, cultural and political considerations and limited ecological understanding. In the context of the ecological risk assessment framework, the authors modelled environmental flows in the Wimmera River in Victoria, a degraded, semi-arid lowland river. Stakeholder engagement and consideration of uncertainties were particularly important aspects of the ecological risk assessment process, and the BN proved to be a particularly good method for modelling the system.
- In Queensland, a Bayesian network is currently being trialed for assessing and determining environmental flow requirements within the Fitzroy River catchment (Menke et al. 2007). Important limitations discovered are the autocorrelation of climatic conditions, particularly in drought situations, which were addressed using dynamic modeling, and complex spatial processes for migratory life forms and local extinction processes, which require a spatial approach. Bayesian belief networks were found to provide an effective link between freshwater experts and modelers, helping with the rapid and transparent construction of the model structure, which was then utilised in dynamic and spatial models.

- A Bayesian network model based on the Victorian FLOWS methodology has been developed, and is being tested on the lower Latrobe River (Victoria) and the Daly River (Northern Territory).[7]
- A Bayesian network is currently being constructed, using the Murray-Darling Basin Commission Sustainable Rivers Audit data (CERF project: Landscape Logic). The network, which will form a decision support system, is being developed in two stages. A generic model is being developed to describe fish community responses to changes in habitat (water quality, flow, physical, competition, predation). The model will link to existing models (such as those for hydrology and climate), management activities and climate change. The generic model will be calibrated for two Victorian catchments. The outcomes will be (a) a generic model and a process for calibrating this model across the Murray-Darling Basin, and (b) two decision support tools for select catchments. The model is being constructed using the Goulburn Catchment fish BN as a starting point (Pollino et al. 2007).
- Hybrid models with hydrology–hydraulic–ecology linkages are being constructed for testing environmental flow allocation scenarios in the Narran Lakes and Gwydir wetland. The ecological components (bird, fish vegetation responses) are BNs. The models are embedded within a decision support system and will be used to guide flow event and long-term strategic time frames for managing (and purchasing) water (Merritt et al., in press).[8]

The current focus of the environmental flow BN models being developed in Australia is on relating flow regime to biophysical aspects of ecosystems and testing various flow scenarios. There is still some way to go, although there is good potential, before socio-economic and policy aspects can be incorporated into these biophysical models.

4.5 What is needed in the future?

It is clear that there are a number of individual projects underway to develop BN models (and other Bayesian statistical models) that will assist in the environmental flow assessment decision-making processes in parts of Australia. Individual projects will continue with funding provided through a variety of sources.

However, the workshop was focused on what could be done to stimulate a more coordinated approach to the development and application of Bayesian approaches for environmental flow assessments throughout Australia.

The workshop identified the following points:

- Bayesian modelling approaches are an important new tool for environmental flow assessment and decision-making in Australia.
- Bayesian network models in particular are relatively simple and can integrate flow information (for example, from existing hydrological and hydraulic models) and other biophysical factors (for example, water quality, habitat, predation) with ecological responses, thus providing an integrated decision-support tool. BN models can also integrate social and economic drivers and outcomes with the biophysical information, although there are few existing examples.
- There would be advantage in achieving greater consistency in approaches to environmental flow assessments and decision-making throughout Australia. This could involve establishing more generic methodologies and guidelines for best practice.
- Additionally, there are currently no established networks for Bayesian modellers and users of Bayesian models to ensure that the learning and experiences from local and

[7] Contact Dr Will Shenton, Water Studies Centre, Monash University for details. Email: *will.shenton@sci.monash.edu.au*
[8] Contact Dr Carmel Pollino, The Fenner School of Environment and Society, ANU for details. Email: *carmel.pollino@anu.edu.au*

international studies are captured and built upon.[9] Establishing and promoting such a network is recommended.

- The workshop participants recommended that a well-coordinated series of case studies should be funded to provide real examples of Bayesian approaches in environmental water allocation processes, with an emphasis on innovative approaches suitable of enhancing the value of BNs for water resources assessment and environmental flows planning. The approach could involve: (a) building upon existing Bayesian environmental flow projects that are underway which incorporate state-based environmental flow assessment methodologies (such as projects in Victoria, New South Wales, Queensland and Western Australia), (b) developing and applying a series of new Bayesian models incorporating biophysical, socio-economic and policy aspects, and (c) focusing on developing modelling techniques to better represent the integration of Bayesian belief networks with dynamic, spatial and generally quantitative modelling approaches.
- Currently, there are relatively few groups in Australia with the skills to develop and apply Bayesian network models, although the number of groups is rapidly increasing. Even fewer groups have skills in other Bayesian modelling approaches. If BNs are to be more widely used in environmental flow assessments (and natural resource management in general), a nationally co-ordinated training program needs to be established to increase the capacity of people with the skills to develop, use and update BN models.
- This training program could also include an auditing process for accrediting professionals wishing to develop BN models. We expect an increasing number of consulting companies will see value in developing such capacity in the near future.
- Additionally, there would be considerable advantage in establishing a central knowledge manager for Bayesian approaches in environmental water allocation processes in Australia. This knowledge manager could act as the central repository for conceptual models, time-series response models and Bayesian models associated with environmental flow allocations. Possible organisations in which such a position could be located include the Commission, Land & Water Australia and the eWATER Cooperative Research Centre.
- The workshop identified a number of key research and development needs to ensure more effective utilisation and continual improvement of Bayesian approaches in environmental water allocations. These are listed in Section 6 of this report, and they can be used to inform investment priorities for national research and development funding agencies (such as Land & Water Australia and the Australian Research Council), and state and territory agencies.

[9] A Bayesian Networks Discussion Forum was established in late 2007
Website: *http://dbl-dev.lafs.uq.edu.au/mbnm2007/*

5. Key report findings

It is clear that Bayesian modelling approaches could play an important in environmental flow assessment and decision-making in Australia.

They can improve current methods by:

- providing a simple, visual representation of conceptual models and causal links that are easily communicated
- documenting the rationale behind environmental flow recommendations (in flow-ecology links and notes that accompany them) for future use
- validating the science underpinning individual flow recommendations, and testing the effectiveness of an implemented flow regime (for example, VEFMAP using Bayesian statistical models)
- facilitating adaptive management by using the data collected in monitoring programs to iteratively improve the models used to estimate the flow requirements for different parts of the ecosystem
- predicting and demonstrating the risks associated with not providing the agreed environmental flow regime
- providing potential for stakeholders representing different interests (such as urban water, irrigation, environment) to use a single tool in scenario analysis and decision-making, promoting common understanding. This need will become increasingly important as the impacts of climate change become more apparent.

BN models are relatively simple to develop and use, and can be used to integrate flow information (from existing hydrological and hydraulic models) and other biophysical factors (water quality, habitat, predation) with measurable ecological responses (such as bird breeding, fish migration). They can also be used to integrate social and economic drivers and management outcomes.

Thus, BN models can provide a tool for environmental flow assessment and decision-making in Australia, and as well a decision-support tool to integrate flow requirements with other biophysical and socio-economic information.

Although a number of individual projects are currently underway in Australia to develop and apply BN models (and other Bayesian statistical models) for environmental flow assessment decision-making, we believe a role exists for agencies to assist in stimulating a more coordinated approach to the development and application of Bayesian approaches for environmental flow assessments throughout Australia.

Opportunities exist for facilitating the following:

- a national approach to achieve greater consistency in approaches to environmental flow assessments and decision-making throughout Australia, which could involve establishing consistent methodologies, guidelines for best practice, and promoting a role for Bayesian modelling in facilitating adaptive management of environmental flows
- the establishment and promotion of a network for Bayesian modellers and users of Bayesian models to ensure that the learning and experiences from local and international studies are captured and built upon
- the funding of a well-coordinated series of national case studies to provide real examples of Bayesian approaches in environmental water allocation processes, as well as developing and road-testing consistent methodologies and guidelines for best practice. The approach should involve: (a) building upon existing Bayesian environmental flow projects that incorporate state-based environmental flow assessment methodologies (such as projects in Victoria, New South Wales, Queensland and Western Australia); and (b) developing and applying a series of new Bayesian models incorporating biophysical, socio-economic and policy aspects

- the establishment of a capacity-building process for Bayesian approaches in environmental flows through a nationally co-ordinated training program and establishing an accreditation process through an auditing process.
- the establishment of a central knowledge manager for Bayesian approaches in environmental water allocation processes in Australia. This could involve: (a) providing a repository for conceptual models, time-series response models and Bayesian models; and (b) establishing a network of Bayesian modellers and users to ensure that the learning and experiences from these (and others) studies are captured and passed on.

6. Research and training needs

Key research and training needs were identified to ensure continual improvement of Bayesian approaches in environmental flow assessment, management and monitoring of outcomes. These are presented below, and they could be used to inform the investment priorities of national research and development funding agencies (for example, Land and Water Australia and the Australian Research Council) and state and territory agencies.

National case studies program

A series of coordinated case studies should be funded to provide real examples of Bayesian approaches in environmental water allocation processes. This will contibute to developing and road testing consistent methodologies and guidelines for best practice.

This program would have three components:

- a series of national case-studies (for example, in Victoria, Queensland, Western Australia) to develop and road test methods for building BN models for environmental flow assessment and management. Note that at least some of these case-studies should adopt a 'whole of management cycle' approach so that BNs are used to develop environmental flow recommendations, then monitoring data are analysed using Bayesian hierarchical models that feed back to the next iteration of the assessment models
- preparation of a document ‘Framework for building Bayesian networks for environmental flow assessments and management’ that will seek to achieve some national consistency
- a series of capacity-building workshops to introduce practitioner and decision-makers to Bayesian network approaches for environmental flow assessment and management.

Integrated Bayesian network models

Funding is required to support the development and application of a series of new integrated BN models for decision-making related to maintaining (and perhaps rehabilitating) the ecological health of rivers and wetlands. These would seek to integrate environmental flows regimes with other biophysical drivers (water quality, habitat, predation), and socio-economic and policy aspects.

Bayesian hierarchical modelling

Further research is required on the application of Bayesian hierarchical models for assessing the relationships between flow and environmental endpoints. Webb et al. (submitted) has shown the power of this approach using small data sets and sensible hypotheses to analyse the likelihood of relationships between flow and: (a) salinity; and (b) fish abundance (Australian Smelt). The latter analysis concluded that higher than recommended summer flows in Victoria’s Thomson River have a negative impact on the abundance of Australian Smelt.

Climate change and environmental flows

The impact of climate change on environmental flows is likely to be significant over much of Australia during the next 20–30 years. Research is needed to:

- build an information base on climate change predictions
- generate information on species-based environmental flow requirements
- develop a generic BN for undertaking a risk-based assessment for assess the resilience and vulnerability of species under plausible scenarios of climate change.

Software development

There is a need for a new level of BN software support. Currently available BN software offers little guidance in how to structure, develop, use and document models. The process could be improved using using tools (like wizards) to walk the BN developer through the process, semi-automatically documenting during the process, and also making developers document the process fully. Research is needed on the development of methodologies for: (a) knowledge engineering with BNs; and (b) software tools to support that knowledge engineering process.

Capacity building program

A nationally co-ordinated training program will need to be established to increase the capacity of modellers, environmental managers and policy makers and assist them to better accept and use BN approaches in environmental flow allocation decision-making.

Central knowledge manager

The development and application of BN approaches in environmental water allocation processes in Australia could be enhanced by providing funds to establish: (a) a central repository for conceptual models, time-series response models and BNs; and (b) a network of Bayesian modellers and users to ensure that the learning and experiences from relevant studies are captured and passed on.

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Appendix A: The review—Workshop discussion document

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Contents

Executive summary

Currently, there is much interest in Australia in the application of Bayesian modelling approaches to many areas of natural resource management. A particular focus is in determining the risks to aquatic ecosystems from multiple threats, such as flow changes, excessive nutrients, degradation of instream habitat and riparian vegetation, and the introduction of pest fauna and flora.

Managers of aquatic and terrestrial resources need to make decisions for situations in which there is considerable uncertainty in understanding how the system works and how particular management actions will influence the system. It is rare to have well understood cause–effect relationships between the threats and the ecosystem. In these situations, Bayesian models are increasingly being used as decision support tools, particularly where the risks are such that quantitative methods are warranted.

The National Water Commission (the Commission) has been approached to fund work on the use of Bayesian approaches for assisting decision-making related to environmental water requirements for ecosystems. However, the Commissioners have decided before this can occur, there is a need for work to draw together current thinking, identify the gaps, and propose the best way forward. The Commission has contracted Water Science Pty Ltd and the Australian National University to undertake a project—Bayesian modelling as a basis for risk-based environmental flow assessment—to address these needs.

This report contains information on Bayesian networks and their applications that will support an expert workshop to be held in Canberra 4–5 March 2008, the objectives of which are:

- to discuss current thinking in the application of Bayesian decision models in risk-based flow assessments for aquatic ecosystems (benefits and challenges), identify gaps in knowledge, and discuss how these gaps might be addressed
- to identify opportunities for the application of Bayesian approaches to environmental flow assessments in Australia, what can be done right now, and recommend future work needed to extend the application of Bayesian approaches in flow assessments.

The report starts with a brief discussion on what Bayesian networks are and their benefits and limitations. Bayesian decision networks are graphical models used to establish the causal relationships between key factors and final outcomes (cause–effect relationships). A particular advantage of Bayesian decision network models that makes them attractive for natural resource managagement applications, is that they can incorporate both quantitative information (obtained from existing models, monitoring and from site-specific investigations) and qualitative information (obtained mostly from expert opinion), and they can be updated as new information or data becomes available. Also, they can readily incorporate uncertain information, with these uncertainties being reflected in model outputs, and sensitivity analyses can be used to identify key risks and knowledge gaps. They are particularly useful in modelling ecological processes because Bayesian inference provides a probability-based approach that can update scientific knowledge when new information becomes available.

There are some limitations to Bayesian networks discussed in the report. These include: (a) difficulties in representing dynamic processes, both temporal and spatial, including feedback loops; (b) poor representation of continuous variables; (c) the size of conditional probability tables in complex networks; (d) the use of exact algorithms for probability propagation; and (e) problems associated with the use of subjective expert opinion.

Bayesian networks have been used in a wide range of disciplines (for example, IT, engineering, medicine), including more recently biological and ecological applications. The report summarises some of the more recent applications of Bayesian networks in conservation assessment, terrestrial and aquatic ecology, integrated assessment and risk assessment. The report also summarises the small number of applications of Bayesian networks in environmental flow assessments.

Finally, the report identifies the main reasons for using Bayesian networks in determining risk-based environmental flow assessments as their ability to be used for both adaptive management and integrated management and for use in policy development.

1. Introduction

Currently, there is much interest in Australia in the application of Bayesian modelling approaches to a number of areas of natural resource management. A particular focus is in determining the risks to aquatic ecosystems from multiple threats, such as flow changes, excessive nutrients, degradation of in-stream habitat and riparian vegetation, and the introduction of pest fauna and flora (see Section 5 of this Appendix).

Managers of aquatic and terrestrial resources need to make decisions for situations where there is considerable uncertainty in understanding how the system works and how particular management actions will influence the system. It is rare to have well understood cause–effect relationships between the threats and the ecosystem. In these situations, Bayesian models are increasingly being used as decision support tools, particularly where the risks are such that quantitative methods are warranted.

A particular advantage of Bayesian decision network models is that they can incorporate both quantitative information (obtained from existing models, monitoring and from site-specific investigations) and qualitative information (obtained mostly from expert opinion), and can be updated as new information or data becomes available. Additionally, Bayesian decision networks are graphical models used to establish the causal relationships between key factors and final outcomes (cause–effect relationships). They can readily incorporate uncertain information so the uncertainties are seen in the results of model outputs, and sensitivity analyses can be used to identify key risks and knowledge gaps. They are particularly useful in modelling ecological processes because Bayesian inference provides a probability-based approach that can update scientific knowledge when new information becomes available.

The Commission has been approached to fund work on the use of Bayesian approaches for assisting decision making related to environmental water requirements for ecosystems. However, the Commissioners have decided before this can occur, there is a need for work to draw together current thinking, identify the gaps, and propose the best way forward. This project—Bayesian modelling as a basis for risk-based environmental flow assessment—will aim to address these needs.

1.1 Methods for environmental flow assessments

There are four main approaches to modelling using environmental flow assessment, a method for calculating an optimum level of flow through a river or stream, such that it can sustain some level of its ecological diversity. These approaches, outlined in greater detail in (Arthington et al. 2007), are (ordered in terms of increasing complexity): 1) hydrological models; 2) hydraulic rating models; 3) habitat simulation models; and 4) holistic approaches. This ranking is set up so that for every modelling approach, lower-order modelling approaches can be used as tools within them.

Hydrological models, as labelled in Arthington et al. (2007), comprise the most basic desktop calculations, where modellers, or even non-expert system managers, collect and perform basic analysis on simple hydrological data such as annual flow. Because of their rapidity of construction, and their consequent lack of ecological refinement, these low-resolution methods are appropriate only at the planning level of water resource management and development. If the results of such a model were to be used for actual catchment management, any calculated outcomes from a hydrological model should thus be regarded only as preliminary targets to be refined with a higher-order model at a later date.

Hydraulic rating models are defined as the next level up in complexity for environmental flow assessment in Arthington et al. (2007), and they incorporate other hydraulic parameters, such as maximum depth or wetted perimeter, on top of those used in the lower order hydrological models. These parameters are used as substitutes for information on aquatic habitation, and although they are still in use in some situations, higher-order models are better suited to modelling flow change effects on ecological diversity. Habitat simulation models provide a far more detailed model-based analysis of both the quantity and sustainability, at different levels of flow, of physical habitat available to a select species. These models directly calculate flow-related changes for the suitability of the physical habitat, rather than relying on hydraulic parameters as an approximation.

Holistic models take the approach that the sustainability of an aquatic habitat depends not only on the flow, but on the interactions between the target biota and any predator/prey or symbiotic biota. As Sparks (1992) stated, 'rather than optimising water regimes for one or a few species, a better approach is to try to approximate the natural flow regime that maintained the entire panoply of species'. Thus these approaches will provide the most accurate results of an optimum flow level for sustaining the biodiversity of the river.

However, because they incorporate such a high number of separate components, the increased accuracy of these higher order models generally comes at the cost of greatly increased complexity. One potential solution to the problem of this forced trade-off between modelling accuracy and complexity may come in the form of Bayesian networks. Bayesian networks are a modelling technique that are able to incorporate information from a number of varying sources; but due to their simplified structure, this high level of data does not necessarily come at the cost of greatly increased complexity. More information about methods for environmental flow assessments is available in Section 6 [of this workshop report].

2. What is a Bayesian network?

Bayesian networks (BNs), also known as Bayesian belief networks (BBNs) and belief networks, are graphical models that can be adapted for use in a wide variety of applications. They are able to explore and display causal relationships between key factors and final outcomes of a system in a straightforward and easily understood manner. As BNs are causal, they can also be used to calculate the effectiveness of interventions, such as management decisions, 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 of this workshop report). BNs are able to maintain clarity by making causal assumptions explicit (Stow and Borsuk 2003) and are often used for modelling when 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 of this workshop report. 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 (for example, Stassopoulou et al. 1998; Varis 1997).

BNs apply Bayes' Theorem (also known as Bayes' rule or Bayes' law), a result from probability theory, to relate the conditional and marginal distributions of random variables that represent system states (see Section 2.2.2 of this workshop report). 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*).

Thus, in contrast to most environmental modelling techniques, BNs 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, BNs are a particularly appropriate method of dealing with systems were uncertainty is inherent, which tends to be a key issue in ecological systems. Communication of uncertainties is also essential when developing models for management.

The most common sources of uncertainty that a BN will represent is that of a lack of knowledge of complex systems, and the inherent variability within these systems. The other sources of uncertainty that can be represented in a BN include: statistical variation (for example, parameter measurements); the subjectiveness of judgements through from expert elicitation of model structure and estimation of probabilities; the inherent randomness of some complex systems; and also any disagreement that may arise between multiple experts. As with other Bayesian statistical approaches, it is not possible to identify or differentiate between sources of model uncertainty (delineating between lack of knowledge and natural variability). As BNs estimate only exact probabilities, credible intervals or imprecise probabilities are not given. This is a weakness of the BN approach (see Section 4.2 of this workshop report).

BNs have a number of other appealing properties that make them particularly useful for ecological data analysis, as well as management decision-making. As stated, they show cause–effect relations directly through a simple causal graphical structure, but they are also easily constructed, extended and modified; they have a natural way to handle missing data; even though they inherently incorporate uncertainty in relationships, they are able to be understood without much mathematical background; they can show good prediction accuracy even with rather small sample sizes (Kontkanen et al. 1997); the conditional probabilities between variables are able to be constructed using observed data, results from model simulations, or even expert knowledge; they are able to easily integrate different submodels together, even if these submodels are 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 of this workshop report.

BNs can also be used in a number of different ways. They can be used for prediction of the value of a missing piece of data using other data sets; they can be used to forecast the likely values of system states given differing future scenarios; they can aid system managers in making decisions that optimise a certain desired outcome; because they are easily understandable, they can be used to aid in social learning of a system, either of the reasons for certain effects taking place after certain causes, or the reasons for a certain management decision taking place; and they can be used to develop a user's understanding of a system, amongst other uses. This information is summarised in Table 1, which shows the functionality of various integrated modelling approaches, obtained from Letcher and Jakeman (undated). Indeed, because the structure of a BN is that of a conceptual box-and-arrow diagram, the very process of constructing a BN can help the modeller improve their understanding of how the system works.

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		X	X	X		X
	Forecasting		X	X	X		X
	Decision Making	X	X	X	X		X
	System Understanding	X	X		X	X	X
	Social Learning	X	X		X	X	X
Input Data Type	Qualitative and Quantitative		X				X
	Quantitative only	X		X	X	X	
Focal Range	Focused and In-depth				X		
	General and Broad	X					
	Compromise			X			X
	Both		X			X	
Express Uncertainty	Yes		X				X
	No	X		X	X	X	
Model Output	Individual					X	
	Aggregated	X	X	X	X		X

In summary, the two major reasons for using a BN are: 1) to obtain a mathematically optimal decision on the basis of information provided to the network; or 2) to attain an improved understanding of the environmental system, leaving the decision-makers to reach their own conclusions on the basis of that understanding. The latter approach is generally recommended (Cain 2001), as then the network merely supports decision-makers rather than making the decision for them.

2.1 Structure of a Bayesian network

The structure of a BN is a graphical model consisting of nodes, which are connected by unidirectional arrows (arcs). A BN thus has a causal structure, where node A affects node B, which in turn affects 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 1: Causal structure of a Bayesian network

In a BN, the directions of arcs may not form a cycle, and thus the form of the structure is that of a directed acyclic graph. It is this acyclic nature that provides one of the setbacks of BNs for use in ecological modelling: it has trouble in handling feedback in a system. This, as well as potential solutions to this problem, are discussed in more detail in Section 4.1 of this workshop report. However, due to having the simple structure of a directed acyclic graph, BNs are relatively easy to construct via adaptation from a simple conceptual model.

Indeed, a BN that contains only nodes and arcs is simply a conceptual 'box and arrow' model, sometimes referred to in this context as a Bayesian 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 BN (Cain 2001). These probability sets are called conditional probability tables, and they are used to express and calculate the relationships between nodes.

Each node in a BN represents a physical variable of the system. It is treated as a random variable, which can take any one of a finite number of discrete, mutually exclusive states that completely define the states that variable can conceivably take in the real world. Variables may be Boolean (true or false), categorical (high, average, low), discrete (integers) or continuous. If a variable is continuous, it is generally handled by dividing its range into subranges with discrete values. Discretisation of variables is not a requirement of BNs (Pearl 1998), but is used generally since most commercial programming shells require it.

Although the potential loss of information can be a disadvantage of the process of discretisation (discussed in further detail in Section 4.2 of this workshop report), it can prove to be particularly useful in the case of variables with a distinct breakpoint significant to management. For example, if a variable describes the amount of rainfall in a month, but a value of 10 is enough to fill a particular well, the variable may be discretised into two states that might be named '<10' and '≥10', or 'unacceptable' and 'acceptable'. It is important to note that the resolution of discrete states must reflect the nature and quality of the information available, the degree of complexity permitted by computing load, and the comprehensibility of the model.

Nodes in a network can represent information from different scientific disciplines (such as hydrology, ecology, economic, sociological), and can represent processes over different temporal or spatial scales. Thus it is possible to base the structure of a BN on a number of submodels that have been integrated together to form a single BN. These submodels can represent physical or chemical processes or even political or socio-economic influences. The outcomes of these submodels can be integrated into a set of endpoints (representing environmental, social or economic variables) that describe outcomes of the network model as a whole. Thus each submodel can be used to determine how processes change endpoint variables.

2.2 How do Bayesian networks work?

The relationship between a child node and all its parents is described by a conditional probability table (CPT). Each entry in the CPT gives the probability that the child takes a particular one of its discrete values, given a particular combination of values of its parents' states. Thus 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 (that is, 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 BN 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 programming shell Netica (*http://www.norsys.com*).

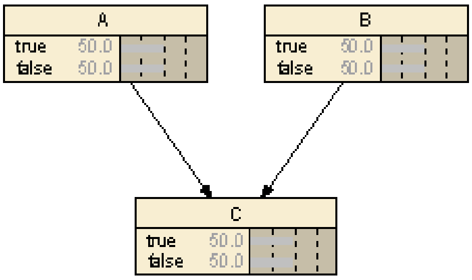
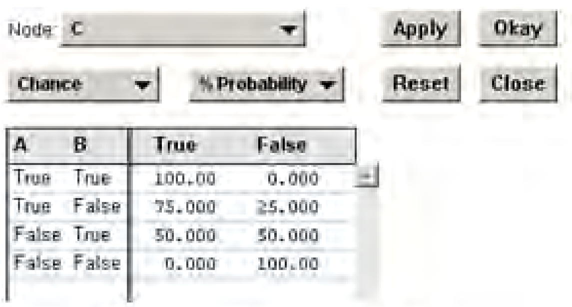


Figure 2: Simple BN example

In this example, all nodes are discretely 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.

In the network shown in Figure 2, 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 this example, direct expert elicitation is used.



A	B	True	False
True	True	100.00	0.000
True	False	75.000	25.000
False	True	50.000	50.000
False	False	0.000	100.00

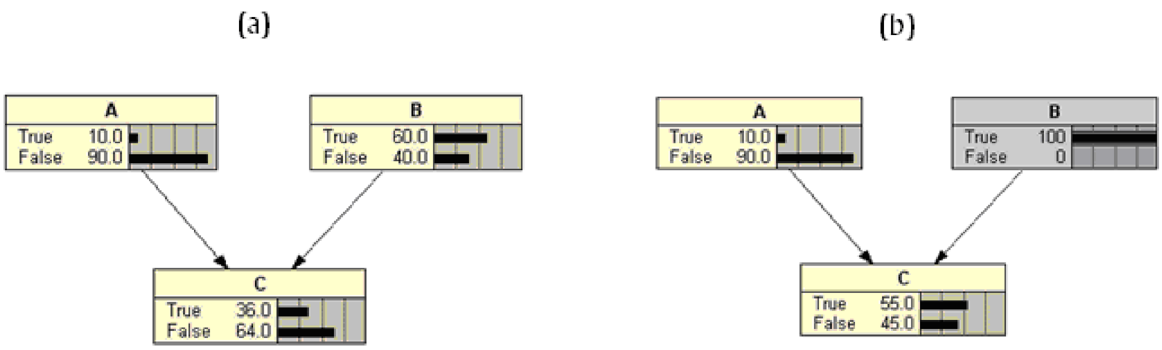
Figure 3: CPT for node C

Elicitation will usually take the form of scenarios as they appear in the table. For example, given A is true and B is true, what is the probability that C is true (here 100%)? The fully parameterised CPT is shown in Figure 3 to the left, seen here in the Netica formatting. It is an important point to note that the method of probability generation must always be rigorously documented, including any assumptions and limitations.

When the probability distributions of each node have been defined, the network is able to be 'solved', as shown in Figure 4(a) below. 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 be examined easily. 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 4.

Figure 4: Bayesian network before and after the propagation of new information



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, which are discussed in greater detail in Section 3.4 of this workshop report. Bayesian decision networks 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 Bayesian decision network, 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.

2.2.1 Parameterisation

There are various methods of obtaining the conditional probabilities of the nodes in a BN. As used in the above example, the probabilities can be obtained through elicitation from experts in the field. The accuracy of information obtained through elicitation can range from a deep understanding of the strength of the relationships, to a more heuristic estimate (such as 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 probabilistic 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; and 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, they are able to use incomplete data sets to calculate conditional probabilities. A further benefit of BNs is that they are able to use any combination of these methods to calculate the conditional probabilities, which allows for greater accuracy should any particular method be unable to give a good estimate of a certain probability (such as an inability of expert elicitation to give accurate probabilities in the case of a particularly rare set of events).

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 is possible for this information to be incomplete or unavailable in parts. 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.

2.2.1.1 Expert elicitation

Methods of elicitation are documented elsewhere (for example, Cooke 1991; 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. 2005). 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 (for example, 'Low', 'Medium' or 'High'), this will limit the potential for future updating of the model with 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 7.1 of this workshop report).

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).

2.2.1.2 Data learning

Many common BN programming shells, such as Netica, can estimate conditional probabilities of the interactions in a model from data using an Expectation-Maximization (EM) or Gradient Descent (GD) algorithm. It requires only the model's causal structure to be defined beforehand, and iteratively calculates maximum likelihood estimates for the states of the parameters given the data and the model structure. This is similar to the way in which neural networks are created, but as the structure of a BN is defined by the user prior to entering the data, it gives far greater control to the user.

Woodberry et al. (2004) discussed the point that, due to the inherent difficulty involved in building a BN directly through elicitation from domain experts, there is growing interest in developing machine learning of BNs from data through techniques such as EM and GD. They developed a knowledge engineering-based spiral method for cyclically structuring, parameterising and evaluating a BN, which could be performed either through data analysis or expert elicitation in cases where data were minimal (which, as previously stated, is often the case for complex systems such as ecological and biological systems). They found that often the best method, which led to the most accurate BNs, was to use a combination of both methods.

Because environmental data often include missing values, since problems in sampling may mean that some unique event or point in time is missed, EM techniques prove to be particularly useful in the process of data learning. Unlike many estimation methods, EM algorithms are able to handle situations with missing observations, whether the data are missing randomly, or their absence is dependent on the states of other variables (Uusitalo 2007). EM approximates the distributions for the incomplete data using Dirichlet distributions. This allows BNs to provide a natural method of dealing with missing data.

As with any modelling technique, it is possible to overfit a BN. Indeed, BNs can be more susceptible to overfitting, due to the relative ease of construction of the nodes and arcs. To avoid overfitting, it is common practice to use sensitivity analyses to measure the effect of one variable on another. Common BN programming shells, such as Netica, have an inbuilt and easily used sensitivity analysis component. This allows for the easy detection of variables that are not contributing to the model. Sensitivity analysis can also suggest any potential areas for further research.

2.2.2 Propagation algorithms

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. 2005). That is, if a1 and a2 describe the variable A taking its first and second states respectively, then, in this example:

$$\begin{aligned} P(c1) = {} & P(c1|a1,b1)\bullet P(a1,b1)+P(c1|a1,b2)\bullet P(a1,b2) \\ & +P(c1|a2,b1)\bullet P(a2,b1)+P(c1|a2,b2)\bullet P(a2,b2) \end{aligned}$$

Upward propagation of evidence through the BN is based on Bayes' rule:

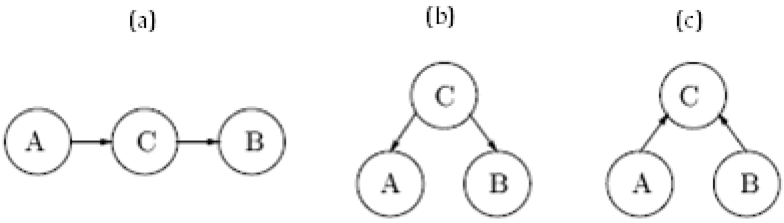
$$P(a1,b1|c1) = \frac{P(c1|a1,b1)\bullet P(a1,b1)}{P(c1)}$$

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 through 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 2007). For example, in Figure 5 (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 artificial intelligence literature.

Figure 5: Common dependence relationships in Bayesian networks



If two nodes have a common cause, such as node C in Figure 5(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 5(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 5(c), A and B in effect compete to explain C (Norton 2007).

2.2.3 Evaluation

Once constructed, a BN must be evaluated before it can be labelled complete, yet this critical element of the BN building process is sometimes overlooked. Testing any detailed model against empirical data is a crucial aspect of the modelling process (Walters 1997), and where possible, models should be tested with datasets that are as independent as possible from the ones used to define the model (Holling and Allen 2002).

In cases where large data sets are not available (especially common in complex systems such as ecological and biological systems), independent examination from a domain expert can also be used. Because of the ability of BNs to incorporate information from various sources, it is possible to evaluate them through a combination of both statistical data and domain expert evaluation (Pollino et al. 2007b; Woodberry et al. 2004). Further, this also means that Bayesian methods can be used to test expert predictions against empirical data, assess expert bias, and provide a framework for the efficient accumulation and use of evidence (Newman and Evans 2002; Pollino et al. 2007b).

Without any empirical data, the benefits of implementing and using BNs cannot be fully realised, as the accuracy of how well the model represents the system cannot be properly assessed. Therefore the acquisition of empirical data, collected through 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.

3. Benefits of Bayesian networks

BNs have become widely used and accepted in ecological applications due to their flexibility in being able to represent complex systems and incorporate and portray uncertainty and variability within a user-friendly environment. Consequently, they are particularly useful for communication and educational purposes.

3.1 Complexity

The greatest challenge today, not just in cell biology and ecology but in all of science, is the accurate and complete description of complex systems. Scientists have broken down many kinds of systems. They think they know most of the elements and forces. The next task is to reassemble them, at least in mathematical models that capture the key properties of the entire ensembles (Wilson 1998, p. 85)

Ecosystems are composed of multiple heterogeneous, complex interactions between components that exhibit nonlinear and transient behaviours (Green et al. 2005). The management of complex ecosystems is being increasingly driven towards the solution of multiple goals, including the sustainability of multiple resources over large areas and long time periods (Kangas and Kangas 2004). Consequently, such complexity requires that any model of an ecosystem must take into account temporal, spatial, topographic and climatic variations, amongst other considerations, as well as any interactions between flora and fauna. In addition to these factors, there may also be socio-economic, political and cultural considerations. Thus understanding and effectively modelling such an ecosystem naturally requires a multidisciplinary approach (McCann et al. 2006).

Up until only recently, ecological models were predominantly deterministic process models that only poorly represented complex systems, representing only relationships that were readily quantifiable, with no attempt to assess uncertainty. Such models also rarely quantified the relationship between physical and biological variables, with only inferences being drawn to assess relationships between these processes. Unlike process models, BNs readily integrate information from a range of disciplines, incorporate both quantitative and qualitative evidence across a range of scales, and do so without losing the uncertainties associated with this evidence. BNs offer a simple yet robust method of effectively modelling the complex nature of an ecosystem.

The simplicity of the links between variables in a BN means that it is possible not only to model very complex systems, but to model them with a large number of state variables, often without too great an increase in complexity or computational power (Jakeman et al., 2007). BNs also enable a modular approach to systems modelling, which enables BNs to be readily adapted. Indeed, Bayesian approaches for modelling complex ecosystems can start to address the need for a better understanding of complex systems, while acknowledging the uncertainties that exist in our understanding of how the system functions, as well as the variability that is inherent within such systems (Pollino et al. 2007a). Reducing uncertainties in decision-making can be addressed using principles of adaptive management. An adaptive management approach explicitly recognises the existence of uncertainty, documents modelled hypotheses about the responses of ecological systems to management interventions, monitors actual responses, and adjusts management actions over time (Failing et al. 2004). BNs provide a framework for iterative updating as more knowledge becomes available, and consequently, the principles of adaptive management can be readily applied within a BN context (Pollino et al. 2007a; Prato 2005; Smith et al. 2007b). The potential use of BNs in AM is discussed further in Section 7.1 of this workshop report.

3.1.1 Uncertainty and variability

Due to the inherent complexity of ecosystems, coupled with our limited understanding of the interactions between certain elements of the system, uncertainty is an essential component of any model attempting to represent ecosystem processes (Pollino et al. 2007a).

Uncertainty is defined as a lack of knowledge about the accuracy of a measurement of a system, and it is an inherent property of the limitations of observing or understanding a system (Finkel 1996). Uncertainty can arise from bias and sampling errors, which are often unavoidable due to imperfect sampling techniques, or from measurement error. It is often possible to reduce uncertainty about parameter estimates and causal relationships through additional research, but for complex systems, uncertainty will generally always be present. Variability, on the other hand, is an inherent property of a system, and it refers to the naturally or anthropogenically induced variation of the states of a system over space or time. In other words, it describes the degree of variation, or the susceptibility to variation, of parameters over the whole system. As a simple example, a pond exhibits variability if bacteria concentrations differ over different depths.

In BNs uncertainties are represented using probabilities; therefore, unlike other modelling approaches, BNs are not limited by the lack of existing information or understanding. As such, BNs are able to aid in informed decision-making about a system even before scientific understanding is complete (Wooldridge 2003). Moreover, when modelling uncertain systems using BNs, conditional probabilities used need not 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 that is discussed further in Section 4.2.3 of this workshop report.

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; however, as with other modelling techniques, if attempting to model a data-poor system, caution is warranted (McCann et al. 2006). But because of this, BNs have proven to be particularly useful for systems where little data exists and a combination of evidence sources are required (for example, Marcot et al. 2006; Pollino et al. 2007a; Ticehurst et al. 2007).

As BNs calculate and display the uncertainties in parameters of a system, the risks associated with any decision can readily be calculated from these uncertainties. For example, when examining model predictions over broad ecological scales, predictions are intrinsically linked with indeterminacy. The longer the timescale and the more dynamic an ecosystem, the greater the uncertainty will be in predictions. Our poor understanding of the workings of ecological systems leads to even greater model uncertainties. Such uncertainties need to be communicated to environmental managers and decision-makers to provide an understanding of the risks associated with management options. The use of BNs within management frameworks is discussed in more detail in Section 6 of this workshop report.

3.2 User-friendliness

BNs are able to show the causal relationships between variables in a system explicitly through the simple format of boxes and arrows. This structure is generally easily understood by most parties that could be involved in the construction and utilisation of a model, even those without any formal scientific training. This is particularly beneficial should a BN being produced be required to explain management decisions to stakeholders in the system.

The simplicity and easily understood structure of BNs is also particularly useful if the process of expert elicitation is to be used in constructing the CPTs of a network. The elicitation will usually require only an estimate of the probability of scenarios as they appear in the table (for example, given that A is true and that B is true, what is the probability that C is true?). This allows for the possibility of eliciting information from stakeholders in the system that might have an imperfect understanding of the mathematics underlying the probability of a scenario, but have a deep understanding of the system itself; rather than being able to elicit information only from an expert who might have only a limited understanding of the exact ecosystem to be modelled.

BNs can be used to readily 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, which can take a long time depending on the size of the model.

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). A decision-maker is able to instantly see the effect of any decision they might make on the system, with the click of a button. This allows the decision-maker to test the effect on the system of a whole range of scenarios, not just a particular intended choice, without the need to wait while the model updates every time. This in turn can give the manager a far greater understanding of how the system works and responds. BNs also allow the user to examine potential or observed outcomes of a system for causes. The rapidity with which BNs update also aids in communicating, for example, the results of simulation-based models, and reasons behind the particular choice made, to any interested parties.

3.2.1 Communication and education

McCann (2006) states, 'resource management is, at its heart, people management, and is mediated through revealing to decision-makers, the public, and others the consequences of competing management policies. The degree to which a proposed resource-use policy is acceptable to decision-makers and stakeholders lies, in part, in the validity of the underlying scientific evidence, consistency with existing social and cultural views, economics, and the degree to which the policy is understandable and commensurate with other existing, accepted policies.'

In general, decision-makers and stakeholders in an ecological system to be modelled will not be trained ecologists, and so they are unlikely to be able to understand the highly technical language used in many complex representations of ecosystems. Thus, a modelling approach that provides a readily understandable representation of complex systems and human influences can be of vast help in communicating with non-specialists (McCann et al. 2006).

Due to the explicit method of showing causal relationships in an easily understood box-and-arrow format, the formation of a BN is a relatively simple process and is also relatively easy to understand. This previously discussed simplicity means the construction of a BN can be performed by almost anyone with knowledge of the system to be modelled. This allows for stakeholders in the system to play a much larger role in the construction of any BN, and it can also mean that communicating the features of the model is a far simpler process, which can sometimes be a very important point. The degree to which the effectiveness of the decision that is made depends on system stakeholders adopting the new management decision.

Indeed, due to thee ease of constructing BNs, Cain (2001) suggests constructing a number of separate BNs, one for every group of interested stakeholders, when faced with the task of modelling an unknown system. This construction is recommended to be performed in close contact with each group, which increases the likelihood of the groups understanding the results and outputs of the final, completed BN, by encouraging their participation in the process of construction, including the production of the CPTs in any elicitation exercises. This in turn increases the chances that any management decisions made using the model will be adopted by the relevant stakeholders (Hart et al. 2006).

3.3 Integration

As stated in Section 3.1 of this workshop report, ecosystems generally tend to comprise a large, complex array of interactions between separate components. These components might be related to a particular scientific discipline—for example chemical, meteorological, biological, geographical, hydrological—and so modelling such a particular component of the system would involve close contact with a specialist in one of these fields. However, when the ecosystem as a whole is to be attempted to be modelled, a far more multidisciplinary method of modelling is needed. BNs comprise one such method.

One of the major benefits of BNs is the degree to which the scales, accuracies of probabilities, and even types (the scientific discipline from which information is sourced) of connected variables can differ. One node, which might describe the microscopic soil quality and density of a piece of farmland, can be the parent of a node describing the extent of the farmer's income. Various factors affecting an ecosystem can thus be brought together and displayed in the one network.

The simple structure of BNs also allows them to comprise simple submodels that feed into one another. The process of combining submodels is simple, as it involves simply extending causal links to and from one submodel to the appropriate places in another submodel. These submodels might describe physical, climatic, or even socio-economic factors that can affect the ecosystem. Thus a BN is able to relatively easily incorporate all, or at least most, of the multiple components that affect the ecosystem, subject to the level of understanding of each component.

Further, because each submodel comprises just nodes and links, with an underlying set of probabilities, each submodel can easily be lifted from one BN for use in another. If this new network is to model a different ecosystem, but will use the same causal graphical structure, all that must be done is to change the underlying probability set. Also, as the simple causal graphical nature of BNs is easily understood, this also simplifies the process of obtaining information from experts in the various fields required. The simple structure of BNs also makes the scientific learning process explicit, which thus makes the assumptions made by the various experts transparent and open to discussion.

3.4 Bayesian decision networks

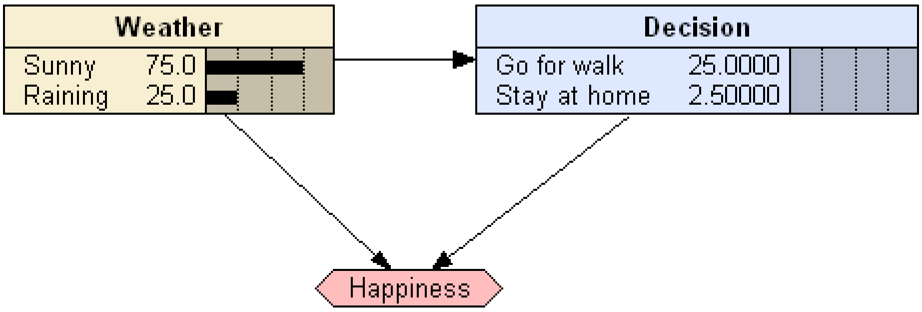
Up to this point, all BNs discussed have been Bayesian belief networks (BBNs), which are constructed solely using 'Nature' nodes. Nature nodes describe the possible empirical or calculated states that separate components of the system to be modelled and the probabilities of these states occurring. There exists a special case of BBNs, however, called Bayesian decision networks (BDNs), for which two other types of nodes can also be used. These are 'Decision' nodes, and 'Utility' nodes.

Decision nodes represent two or more choices that a manager can take, which will 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 with them. Instead, they are able to 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 be used in conjunction with Utility nodes to solve for some desired outcome, such as maximised benefits.

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 CPT 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 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.

A simplified small example BDN incorporating both these types of nodes, so as to better illustrate their use, is shown below in Figure 6. It illustrates the decision process carried out by a person in determining whether to go for a walk, given the chance of rain. Figure 6 also shows the derived expected utility table for the Utility node 'Happiness'. The values displayed in the Decision node 'Decision' reflect the expected utilities for each decision, based upon the input probability distribution of the Nature node 'Weather.'

Figure 6: A simple BDN example, including expected utilities for each Utility node



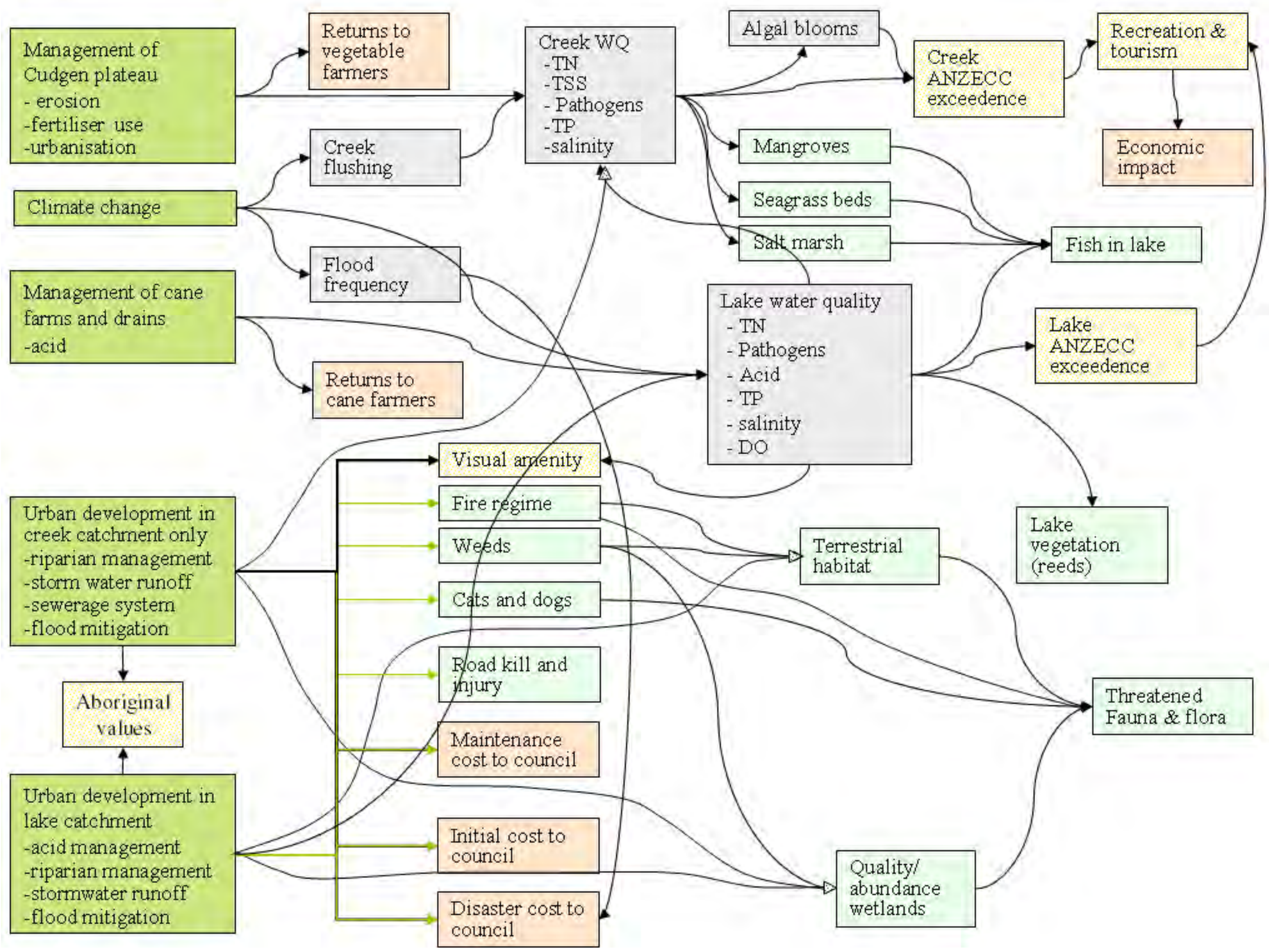
Decision	Weather	Happiness
Go for walk	Sunny	50
Go for walk	Raining	-50
Stay at home	Sunny	-5
Stay at home	Raining	25

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.

An example of a BDN that has incorporated knowledge from a number of sources is the Coastal Lake Assessment and Management (CLAM) network (Ticehurst et al. 2007), a section of which is shown below in Figure 7. The CLAM network is a modelling tool that allows stakeholders to assess the social, economic and environmental trade-offs associated with development, remediation and use options for coastal lakes and estuaries. It describes a number of management decisions that can be put into place, and the expected costs and benefits of these decisions. The network in Figure 7 shows an application of the tool used to model the Cudgen Lake in New South Wales.

In Figure 7, the Decision nodes are coloured green, while the Utility nodes are coloured red. All other nodes in the network are Nature nodes. It can be seen that Utility nodes are thus able to be connected not only to Decision nodes, but outcome Nature nodes as well.

Figure 7: Bayesian network for the CLAM BDN model



Source: Ticehurst et al. 2007

Due to 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 in response to a decision 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 of 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, however, 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 6, one user of the network might prefer walking in the rain, which would drastically change the expected utilities. Sometimes, monetary 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.

4. Limitations of Bayesian networks

In spite of their remarkable power, there are some inherent limitations and liabilities to BNs. The limitations of BNs extend from representation of dynamics (temporal, feedbacks, spatial), poor representation of continuous variables, the size of CPTs in complex networks, the use of exact algorithms for probability propagation, and problems associated with use of subjective expert opinion. These limitations are considered below.

4.1 Dynamics

4.1.1 Temporal variability

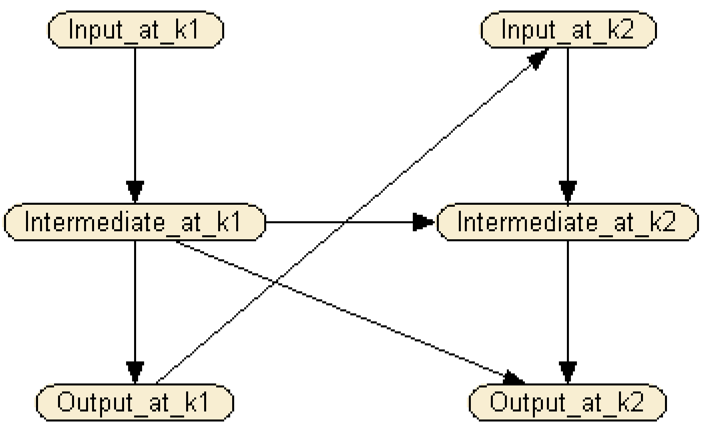
Variability is an inherent component of many ecosystems, as discussed in Section 3.1 of this Appendix. If a model is only being used to investigate and describe the state of the ecosystem on a small enough timescale, it can be acceptable to ignore the effect of time. However, any actions made on an ecosystem will have ramifications that will affect the states the system is in. Thus it is generally desirable that any model attempting to explain an ecosystem should be able to deal with temporal changes.

Not being able to easily deal with time is one of the main limitations of BNs. Their ease of construction and adaptability do allow for quick updating of the network if new information about how the states of the system parameters, or their interactions, have changed unexpectedly after an action becomes available. However, when determining the outcomes of a management decision, it is often important to know this not only for the current time, but for future time points as well. This is particularly so when examining system changes over long time scales, such as climate change. Thus, this limitation represents a major problem in the widespread adoption of BNs.

However, 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*; in other words, 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 BNs (not to be confused with BDNs—Bayesian decision networks) can be used.

Dynamic BNs 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 timesteps, and placing a structurally similar copy of the network within each timestep. A causal relationship between output nodes in timestep *k* and relevant nodes in timestep *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.

Figure 8: Example of a simple Dynamic Bayesian network



In this way, it is possible to model any number of required timesteps. Dynamic BNs are also able to update using the same algorithms as standard BNs. However, the example shown above in Figure 8 has only three nodes per timestep. For networks of reasonable complexity, 20 or more nodes would not be unfeasible, and if only five timesteps 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 dynamic BNs 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 timestep, and the inter-timestep causal probabilities also remain the same between each timestep, 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 timestep, and the inter-timestep causal links between one timestep and the next, in order to create a dynamic BN of a specified number of timesteps. Once this information is input, a large number of timesteps can be run with the same computational power requirements as that of a dynamic BN with only a few.

Naturally, this solution applies only if the intra- and inter-timestep links remain constant over all timesteps to be modelled. This is generally widely applicable, but just like the Markov property, it can be somewhat restrictive. It is for this reason that, as previously stated, dealing with temporal variability within BNs is currently an area of much research.

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 BNs 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. It is done simply: if node A is affected by node B at the same time as affecting node B, incorporating an inter-timestep causal link between node B at timestep *k* and node A at timestep *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 dynamic BN increases, as the size of a CPT within the network will increase. This problem of increasing complexity is discussed further in Section 4.2 of this Appendix.

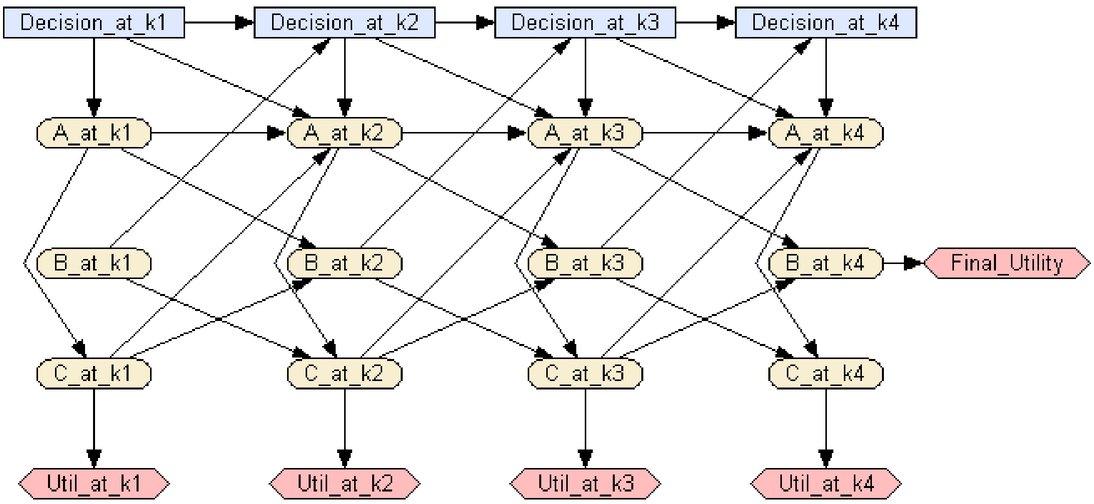
4.1.3 Dynamic decision networks

Just as a static BN can be extended by allowing for temporal variability to create a dynamic BN, 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 timesteps 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 timesteps to be modelled, or a number of utility nodes within each timestep, or perhaps both. This greatly assists the decision maker to find and take the optimum decision at each time step, thereby maximising some desired outcome not only in this time step, but into the future as well.

A simple Bayesian diagram of an example DDN spanning four timesteps is shown below in Figure 9. The intra-timestep causal structure of this DDN is comprised of three 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.

Figure 9: Bayesian diagram of a simple four-timestep DDN



It can also be seen in Figure 9 that the inter-timestep causal links are repeated at each timestep. As previously discussed, this is not necessary in the construction of a DDNif causal links are not constant over time, but the repetition does reduce the required complexity of a dynamical network (Section 4.1 of this paper).

4.1.4 Spatial variability

The states and values of variables in many ecosystems can vary not only with respect to time, but over the length or area of the system as well. For example, water might be of a higher quality upstream of an urban area than it is downstream. Depending on the purposes of the exercise, this variability does not always need to be taken into account, or it can be roughly accounted for through approximation. For example, in the case of the stream, the spatial variability could be represented as some probability, based on the relative areas, of the water quality taking a certain value. However, if the variability does need to be taken into account, any model depicting the system must be able to incorporate spatial variability.

Just as BNs have difficulty in dealing with temporal variability, BNs also suffer from an inability to model spatial variability easily. Just as the inherent difficultly to model temporal variability can be a great setback, the inherent difficulty of modelling spatial variability is similarly a major setback for the widespread adoption of BNs in the realm of ecological modelling. Dealing with temporal variability, though potentially cumbersome, generally does not require too much increased complexity. In contrast, the currently most prevalent method of dealing with spatial variability can become excessively complex, depending on the accuracy required.

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 BN designed to model spatial variability, or a subcomponent thereof, could be set up in a similar fashion to a finite element analysis model, where each node affects only adjacent nodes, incorporating conditional probability tables instead of direct deterministic relations. However, due to the acyclic nature of Bayesian diagrams, feedback cannot occur in a single timestep. This means that, unless the model incorporates temporal variability also (further increasing the complexity), 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. This is the case in the aforementioned example of the flow of a stream, where there is only one spatial direction, and thus only one dimension required to be modelled. If 2- or even 3-dimensional spatial variability is to be modelled to any great detail, for example in modelling bacteria concentration in a pond, the complexity required to construct a BN can quickly become unwieldy. This is especially the case if the conditional probabilities can be obtained through expert elicitation only.

In such situations, different modelling techniques might be better suited to modelling this variability. However, once such a model has been constructed, it is possible to run it a number of times. This can give the modeller enough information to calculate the conditional probabilities of the system, so a BN that incorporates this spatial variability can be created. Then, because of the usefulness of BNs in management decision-making, the BN could be used by a manager to find some optimum solution. In this way, it is possible for BNs to deal even with the high complexity of 3-dimensional spatial variability.

Another factor that can greatly simplify the inclusion of spatial variability into a BN is if the ecosystem varies with respect to space, but the separate components in the ecosystem have little to no interactions with one another. This may be the case in, as an example, the varying topography, soil quality or distance from irrigation of different sections of a farm. If this does apply, a BN could be constructed that might, for example, use each separate component of the farm as a root node, with a subcomponent attached to each one. Decision and utility nodes could then be included to determine the best part of the farm to plant a certain crop. This type of spatial representation has recently been extended to representation of BN outputs in GIS (McNeill et al. 2006; Smith et al. 2007b).

4.2 Imprecise probabilities

4.2.1 Discretisation of variables

Many parameters that would be modelled in BNs often have continuous values. However, most commercial BN programming shells can deal only with these continuous variables through discretisation. Because of this, a BN might be able to capture only 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).

Thus, if particularly high statistical accuracy is required from a model, finding a good discretisation of variables is a task that requires particular attention. 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 number of intervals and the significance of the breakpoints. It should also, preferably, try to guarantee that each of the intervals has a reasonable amount 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.

However, depending on the complexity of the system and the degree of statistical accuracy required, this is often not a major limitation of BNs, particularly since they tend to be fairly robust to imprecise probabilities (Wooldridge 2003). This discretisation can also be particularly useful if the variable were to have a particular breakpoint significant to management, as discussed in Section 2; however, it is also important to ensure that a compromise between model simplicity and accuracy is maintained. Further, by discretising values, it can be possible to capture non-linear relationships between variables in an easier way then would be required for continuous values without requiring too much computational power (Myllmäki et al. 2002). Complex variable distributions can also be easier to model, for example bi- or multimodal distributions, which can be difficult for model types that use parametric distributions to capture. If such a distribution is to be modelled, however, a large number of states will be required for that node. This will, in turn, increase the number of conditional probabilities required between that node and any child nodes it has.

4.2.2 Exponential growth of conditional probability tables (CPTs)

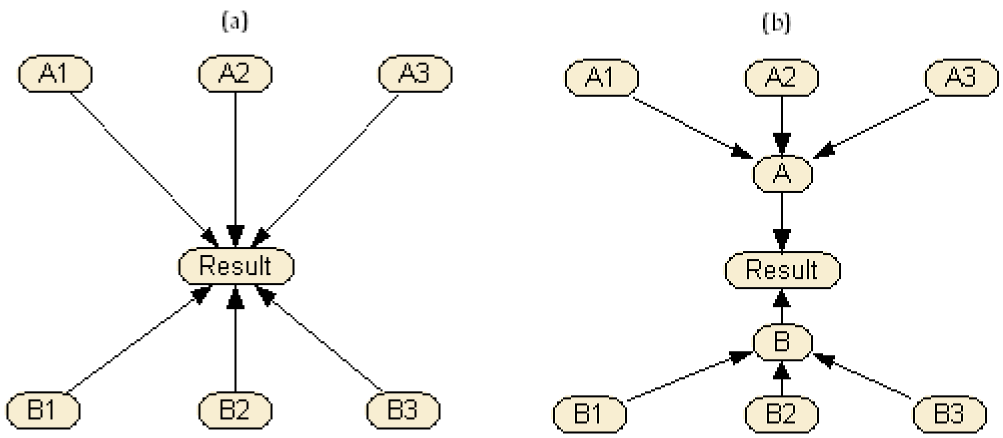
It was stated in Section 2 of this Appendix that BNs are able to greatly simplify the computational power required to run them through the notion of conditional independence. Even so, if a node in a BN has a large number of parent nodes, the CPT defining that node can quickly become overly complex, particularly if the CPT can only be constructed through the process of expert elicitation. As such, it is a general rule-of-thumb of BN modelling that no node in a BN should have more than four parents. However, since there tend to be so many factors defining most environmental systems, this is sometimes not possible to follow.

A couple of techniques do exist, though, which can aid in simplifying overly complex node structures. Probably the best way to simplify an overly complex BN is to be clear about which factors need to be represented in the BN, and which factors do not. It is an important aspect of modelling in general that any model, not just a BN, should only focus on factors that are important to what is being modelled.

For example, if a variable that was thought to be important in the ecosystem is actually unlikely to affect the outcome of a management plan, or to be changed by it, there is generally no need to include it in the network. Similarly, if a node state is not of interest, or is unlikely to be reached, then it can also be left out. The extent to which a node affects or is affected by the rest of the network can be examined through sensitivity analysis. While this may sound obvious, it can be relatively easy to include information in a BN that is not strictly necessary, which can lead to greatly increased, and unwarranted, complexity.

Another useful method of simplifying a BN is a process known as 'divorcing,' an example of which is shown in Figure 10. As seen in Figure 10(a), all nodes in the network feed directly into the one child node, 'Result'. However, if the nodes A1, A2 and A3 are all related to a certain process that does not depend on any of B1, B2 or B3, they can be 'divorced' from the node Result by including an intermediate node 'A', shown in Figure 10(b). 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.

Figure 10: 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)



As can be seen, divorcing actually adds nodes to a network, which might not intuitively seem to be the best way of simplifying it. However, even though nodes are added, 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 10 had three possible states, then in Figure 10(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: which is $3 \times 3 \times 3 \times 3 \times 3 \times 3 \times 3 = 2187$. In Figure 10(b), the size of the CPT for node A is $3 \times 3 \times 3 \times 3 = 81$, likewise for node B. Because nodes A and B only have three states each, the size of the CPT for Result would be $3 \times 3 \times 3 = 27$. 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, because adding the new variables will group the BN into logical subsections. However, this raises an important point: divorcing cannot be done when it results in ignoring important interactions between parents that can influence the child (Cain 2001). For example, in Figure 10, if the node Result can be affected conditionally by different combinations of the nodes A1 and B2, then this effect can be captured by the BN in 10(a). However, depending on the parameterisation of the nodes A and B, the effect will probably not be able to be captured by the divorced BN in 10(b). If this is the case, a different divorcing procedure to that shown in 10(b) would need to be performed.

Divorcing also has a further impact in that it increases the number of nodes between any management interventions and the objectives. This can have the effect of 'diluting' the impact of the interventions on the objectives, particularly if the CPT underlying the divorcing node is specified with uncertainty (Cain 2001).

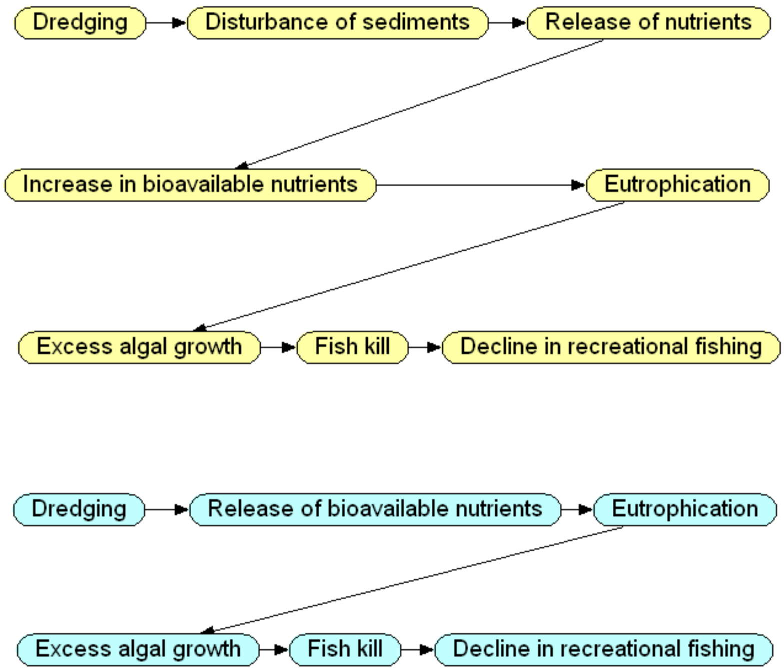
Sometimes it is not possible to simplify a BN. In complex ecosystems, for example, one or more of the CPTs can become overly complex, greatly increasing the required computational power. This can represent a major limitation to the adoption of BNs in such instances. However, it will usually be possible to simplify a network. Indeed, a network that cannot be simplified might indicate that the BN is attempting to model too broad a scope. The process of simplification also provides three advantages: firstly, it helps the BN be more easily understood by those not involved in its construction; secondly, it can allow for the BN's creator to develop a deeper understanding of how the system being modelled works because of the need to perform a more rigorous investigation into which interactions are actually important; and finally, it makes it easier to fill in the CPTs. The fewer entries in a CPT that need to be filled in, the smaller the chances of obtaining erroneous probabilities due to expert elicitation (Cain 2001).

4.2.3 Propagation of imprecise probabilities

It has been stated earlier in this section that BNs are generally fairly robust to imprecise probabilities, due to their inherent use of probability and uncertainty. However, if a network is particularly large, and in particular if it has a large number of intermediate nodes between root and outcome nodes, a significant error in the estimation of a conditional probability towards the start of the chain can propagate through the intermediate nodes until it becomes considerable. This is because of the very nature of Bayes' Theory.

A long chain of nodes will, in general, have a larger degree of sensitivity to error due to propagation than a shorter one. Indeed, long causal chains with little to no branching can sometimes be a sign of a poorly designed BN, as any input evidence will be 'diluted' (Cain 2001). As such, lumping groups of parameters forming a causal chain into one node, where possible, or simply removing variables that are found to be redundant in the process being modelled, can greatly increase the accuracy, and hence usefulness, of a BN. For example, as shown in Figure 11 below, 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 bioavailable 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.

Figure 11: Propagation example showing long (yellow) and short (blue) causal chains describing the same outcome



However, even a well-designed BN can be subject to the propagation of imprecise probabilities. Imprecise probabilities can be particularly prevalent when the conditional probability of a rare event is to be obtained, as few data will generally be available. For this reason, it is important that the method of probability generation used is always rigorously documented, including any assumptions and limitations.

4.2.4 Probability Intervals

Probability intervals provide a more realistic and flexible modelling approach for applications with uncertain and imprecise knowledge (Thone et al. 1997). BNs, although they inherently deal with uncertainties, are often criticised as they rely on exact probabilities. This is a result of using 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, for example, 'between 80 and 90 per cent'. 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 to allow the incorporation of probability intervals.

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

4.3 Subjective input into Bayesian networks

Analyses of historical and comparative empirical data rarely provide the range and resolution of data needed for predictive models (Pollino and Hart 2005b). Often, such data are also situation-specific and scale-dependent, not accommodating the range of influences that can operate in different settings at different 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 2005b; Sobehart et al. 2001).

Even though BNs provide a natural way of dealing with missing data, it is generally preferable to supplement knowledge in such cases (see Section 3.1 of this Appendix). If data are 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 (Pollino et al. 2007b; Sikder et al. 2006). Thus there is no doubt that the use of expert judgement has an important role, particularly in environmental management (Rykiel 1989). Expert judgement can often be one of the few identifiable ways to introduce sound ecological knowledge into environmental management. However, a BN is only as useful as the reliability of this expert knowledge. Use of expert judgement can introduce bias into an assessment, which can have a negative influence on decision-making. Some sources of bias are outlined below.

4.3.1 Expert biases

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).

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

As reviewed in other papers (e.g. Pollino and Hart 2006), 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. This can be done by explaining that an honest assessment is required. It may also be possible to construct incentive structures encouraging 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 because information is sparse.

In making judgements, at least four types of heuristics are commonly employed (Baddeley et al. 2004; Burgman 2005) defined as follows:

1. **Availability** is the heuristic of assessing an event's probability by the ease with which an occurrence of the event is recalled
2. **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
3. **Control** is the tendency of people to act as though they can influence a situation. If it is perceived that a person can control a situation, higher risks tend to be tolerated
4. **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 (that is, 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. In addition to addressing bias, it is best to obtain a diversity of independent judgements because 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). This can result in a 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 does arise where there are substantial differences of opinion amongst experts, it is preferable that these differences be kept explicit in a BN model (Pollino et al. 2007a).

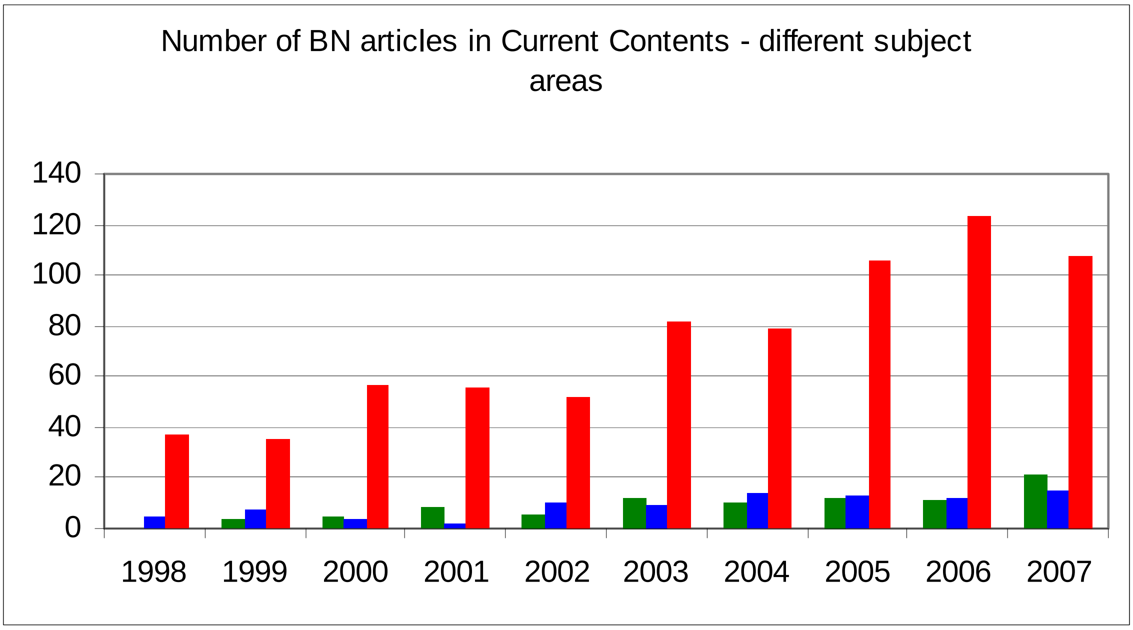
Obviously, given these multiple sources of biases, the question of how best to elicit and incorporate expert input into a BN model is crucial, having implications for the overall model robustness and representativeness of a system (Pollino and Hart 2006). In Bayesian statistical models, where enough 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 (such as probability distribution function with moments). A number of formal methods for eliciting probabilities have been described previously (for example, 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 BN context to limit the sources of bias (Pollino and Hart 2006).

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 their flexibility, BNs 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 (as shown in Figure 12). BNs have been proven to be particularly useful in medicine, due to their ability to be used in aiding diagnosis (for example, probabilistic networks designed to answer the question: which illness do these symptoms indicate). Likewise, BNs are increasingly being used for biological and ecological applications, as can be seen in Figure 12.

Figure 12: The number of articles published about or using BNs by discipline



Notes: red = engineering/IT, blue = medicine, green = biology and ecology
The search engine used was Current Contents (MBNM 2007).

Other areas where BNs have been developed and have found a use include military applications, space shuttle propulsion systems, applications in Microsoft Office (in software troubleshooting, 'the paper clip'), financial market analysis, risk assessments of nuclear power plants and robotics.

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 focused on conservation, assessing risk, or aimed at integrating information across disciplines, complexity, trade-offs, and uncertainty are common features. Within each of these frameworks, BNs have proved particularly useful for focusing issues by clearly structuring the formulation of a problem within a participatory-style and transparent process. Natural resource management BN applications included in this review are listed in Table 2. The select functionality of each of the applications is highlighted.

Table 2: List of BN applications, showing select criteria for the type of application and aspects of the model.

Application	E-Flows	Conservation	Risk	Integration: Sustainability	Integration: Models	System Understanding	Prediction: planning	Adaptive management	Participatory	Temporal	Spatial	Utilities (BDN)
Fish (Rieman et al. 2001)		X				X	X	X				
Land use change (Bacon et al. 2002)				X				X	X			X
Fish (Borsuk et al. 2002)	X	X			X	X		X	X			
Coral (Wooldridge & Done 2003)		X	X			X	X	X				
TDML (Borsuk et al. 2004b)			X		X	X	X	X	X			
Fishery (Little et al. 2004)		X				X	X			X	X	
Fish (Baran et al. 2003)		X			X		X		X	X		
Pollution (Stiber et al. 2004)			X				X					
Water management (Bromley et al. 2005)	X			X	X	X	X	X	X			X
Wimmera (Chee et al. 2005)	X	X	X				X					X
OkTedi (Pollino & Hart 2005a)			X		X	X	X	X		X	X	
Fish (Pollino & Hart 2005b)	X	X			X		X	X				
Pollution (Dorner et al. 2007)			X		X		X			X		X
Water management (Olalla et al. 2006)				X		X	X		X			X
Water management (Varis et al. 2006)				X	X	X	X		X			X
LUIM (McNeill et. 2006)			X				X				X	
Coastal management (Ticehurst et al. 2007)				X	X		X		X			X
Dunnart (Smith et al. 2007b)		X				X	X	X			X	
Fire (Smith et al. 2007a)		X				X	X	X	X		X	
Koalas (Pullar & Phan 2007)		X				X	X	X			X	

Application	E-Flows	Conservation	Risk	Integration: Sustainability	Integration: Models	System Understanding	Prediction: planning	Adaptive management	Participatory	Temporal	Spatial	Utilities (BDN)
River management (Reichert et al. 2007)	X			X	X	X	X	X	X			X
Climate change (Tighe et al. 2007)		X	X		X	X	X	X	X	X	X	
Fish (Pollino et al. 2007b)	X	X	X			X	X	X			X	
Eucalypt A (Pollino et al. 2007b)		X	X			X		X	X		X	
Eucalypt B (Hart et al. 2007)	X	X	X			X	X	X	X	X	X	
Fish (Menke et al. 2007)	X	X	X				X					

5.1.1 Conservation assessments

While conducting further research to collect more data can reduce uncertainty in decision-making, a sense of urgency often surrounds management of ecological systems, where decisions cannot wait until a definitive understanding of ecological processes, species distributions and future change scenarios are obtained. Often we also have data, but the data are patchy, collected such that they do not consider causality or simply have not been applied in a modelling framework. BNs are proving to be particularly useful tools for assisting investments in research and decision-making by structuring knowledge, existing data and data collection.

5.1.1.1 Terrestrial ecology

Compared with aquatic ecology applications, fewer BN applications have been developed for terrestrial ecology purposes. One of the limitations of using BNs for terrestrial applications was representation of outputs spatially, with most BNs being spatially lumped (see Section 4.1.4). Research to overcome this limitation has resulted in methods of linking inputs and outputs to a geographical information system (GIS) (Ames 2002; Pullar & Phan 2007; Smith et al. 2007b).

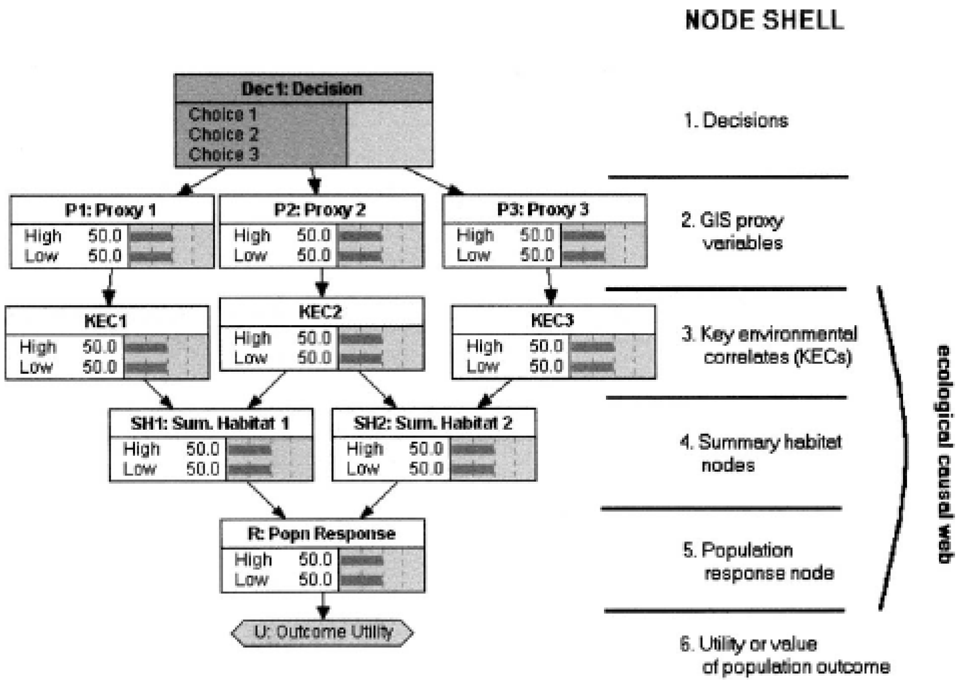
(Smith et al. 2007b) developed a BN to map the habitat suitability of the Julia Creek Dunnart *Sminthopsis douglasi*, an endangered ground-dwelling mammal of the Mitchell grasslands of north-west Queensland that was previously thought to be extinct, and so for which there existed little expert knowledge. Using a similar approach, (Pullar & Phan 2007) constructed a simple GIS-based BN to predict the likelihood of occurrence of koala populations close to urban environments.

In Smith et al. (2007a), a BN for adaptive management of fire in conservation reserves was developed within a participatory setting. This approach provided a mutual learning environment that captured the collective knowledge of the factors influencing planning and implementing, monitoring and reviewing outcomes, thus allowing critical success factors influencing the success of adaptive management to be identified.

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 focused his frameworks based on population viability and habitat suitability. The BN Marcot created is shown below in Figure 13.

Figure 13: General structure of a BN model for evaluation population viability for wildlife species



Source: Marcot et al. (2001)

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 when assessing land management strategies for the Columbia River basin in America. They found that the process of creating the BNs greatly involved collection of information aimed at better understanding the system and documenting assumptions. Marcot further developed these methods for developing and evaluating BNs in (Marcot et al. 2006).

In Borsuk et al. (2002), a BN was constructed to investigate all the possible causes of a decrease in the health status of Brown Trout *Salmo trutta* 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 then 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.

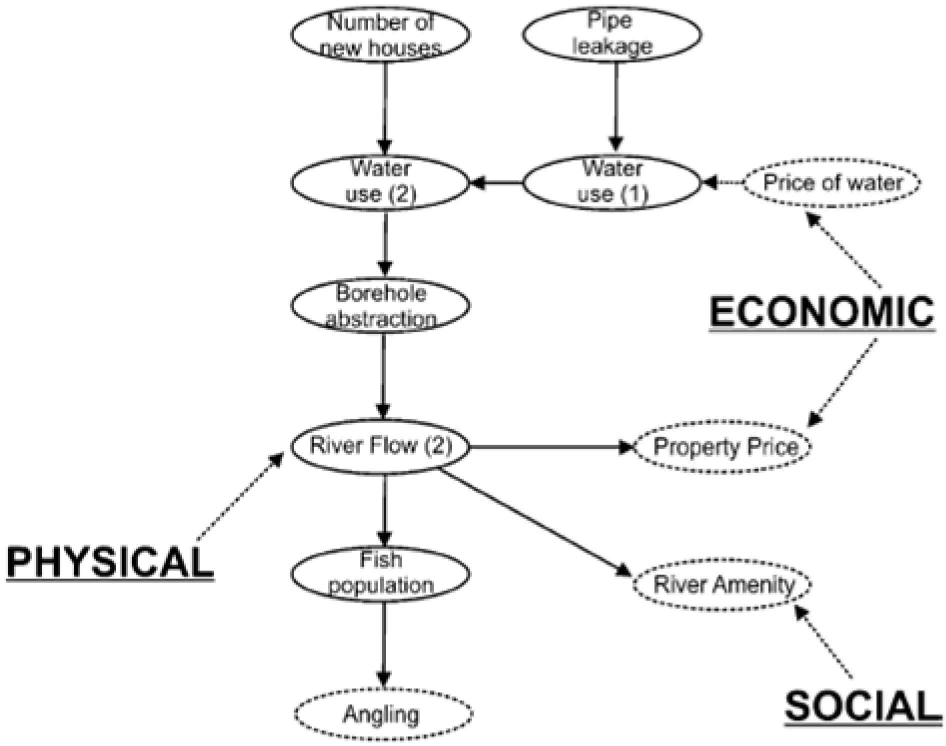
Using a BN, Little et al. (2004) created a hypothetical simulated fishery, based on the coral trout fishery on the Great Barrier Reef, to examine the effect of information flow among fishing vessels. The BN was useful in capturing the reaction of fishers to the implementation of fishery management decisions. Spatial variability was incorporated into this BN, with the model being used to compare 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 under several 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 of this workshop report). Baran et al. (2003) constructed a dynamic BN to model fish populations on a tropical floodplain system; feedback loops were included in the model. 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

BNs were developed for integrated management of four basins across Europe, with the focus being 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 below in Figure 14.

Figure 14: A simple BN examining trade-offs between water use, water price, river amenity and fish population



Source: Bromley et al. (2005)

Likewise, Martin de Santa Olalla et al. (2006) also created a BN with a high level of stakeholder involvement to fulfil legal requirements within the European Union Water Framework Directive (Directive 2000/60/EC). The BN was constructed to model the water resource management in a region faced with the risk of overexploitation of the local aquifer, which had been brought about by a considerable increase in the surface area of irrigated arable land during the past 25 years. The BN was able to show that the current level of aquifer exploitation was not sustainable, and it tested scenarios of future management. Because of the high level of stakeholder involvement, the probability of adoption of proposed solutions was thus increased.

Bacon et al. (2002) constructed a two-stage BN to model the risks of land use change, also incorporating the ideas of adaptive management. The first stage used decision modelling techniques to assess if a manager was currently satisfied with the present situation compared with various potential alternatives. If this indicated dissatisfaction, a BDN was used to estimate, in more detail, both 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 (for example, financial, social and ecological). The approach described in the report was illustrated with a case study of the factors that might influence changes from farming to forestry in a marginal upland area of the United Kingdom.

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. Likewise, Ticehurst et al. (2007) used BNs for integration purposes, modelling sustainability-based management issues and decisions regarding coastal lakes in New South Wales (an example is shown in Figure 7). 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

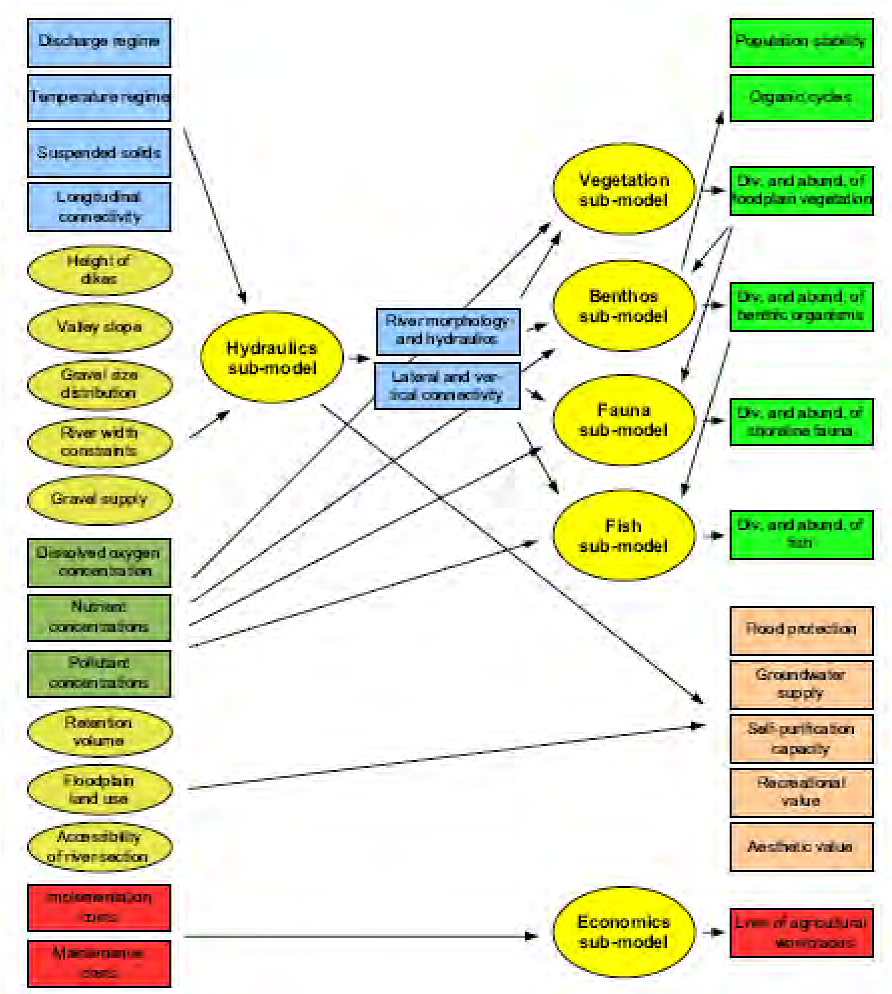
Step 6: Ranking of alternatives

Step 7: Assessment of results

These steps are not unlike existing decision analysis methods. 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) to provide 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 15.

Figure 15: Overview of the integrative model for the prediction of outcomes of decision alternatives for river rehabilitation



Source: Reichert et al. (2007).

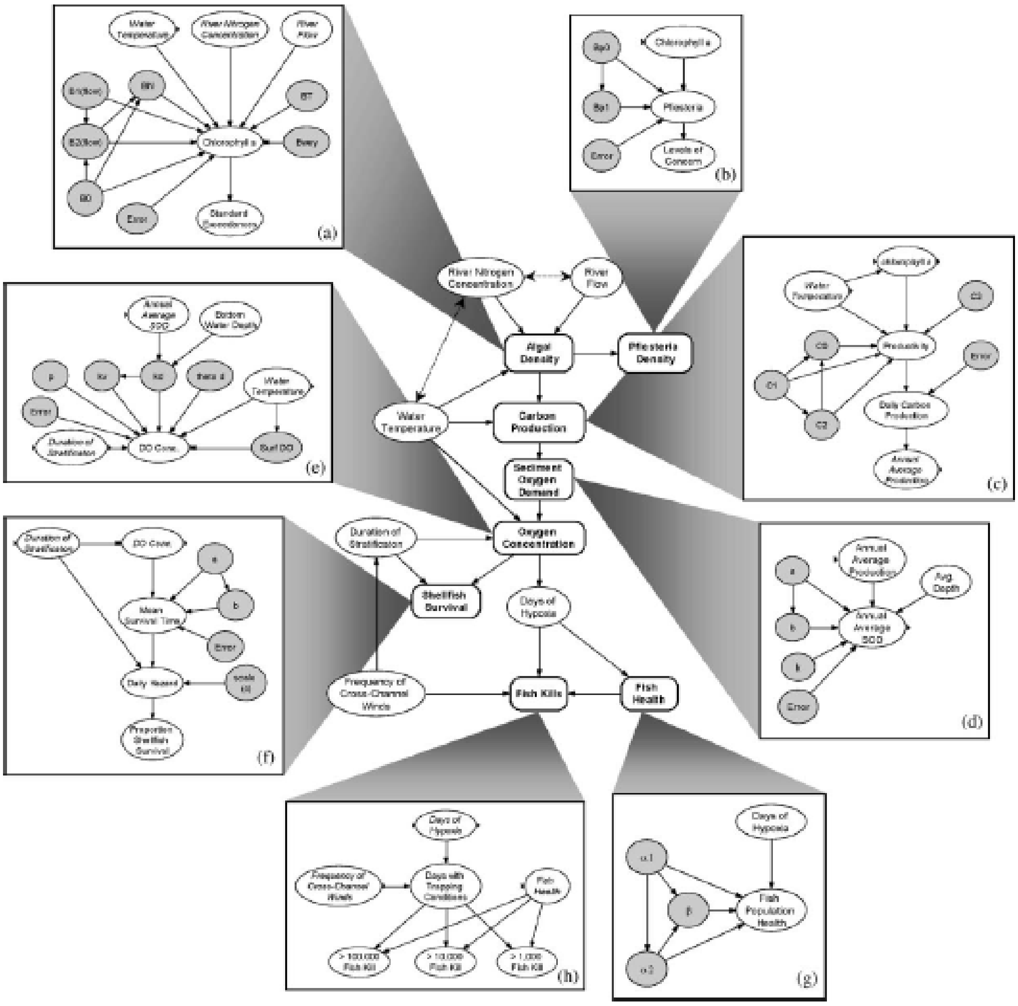
A BN, embedded within a decision support system—EXCLAIM: EXploring CLimAte Impacts on Management—was developed for the Central West Catchment Management Authority (CWCMA) (Tighe et al. 2007). The BN acted as an integration tool, linking a water quality and ecological outcomes to climate model (OzClim—after Page and Jones 2001) to a flow model (IQQM—Jones and Page 2001). The BN model was specific for the Macquarie Catchment (Macquarie River and Macquarie Marshes), and was developed with stakeholders and the CWCMA. EXCLAIM is designed to be able to be broadened in scope (space, time and issues) and can be updated as new data and knowledge become available.

5.1.3 Risk assessment

The risk assessment framework is increasingly being applied to examine both human and non-human stressors on ecological systems. Risk-based decision-making aims to quantify the likelihood of a threat occurring, the consequences of this to an ecological system, process or value, and the associated uncertainty in the predictions. Until recently, the ability to predict changes in dynamic ecosystems due to stressors was limited by both the poor understanding of the drivers of ecological processes and structure, and the lack of modelling tools that could represent such complexity with associated uncertainties. However, the recent growth in the use of BN tools for ecological risk assessments has resulted in major advances in better understanding and managing ecosystems despite their inherent complexity.

Borsuk et al. (2004b) exploited the BN cause-and-effect assumptions to develop a eutrophication model for the Neuse River estuary, North Carolina. When compared to other total maximum daily load (TMDL) models, the BN did not out perform any of the other water quality modelling approaches, but the approach did fit into the context of adaptive management (Stow et al. 2003). The network consisted of a number of interlinking submodels, shown in Figure 14.

Figure 14: Neuse River estuary eutrophication BN



Source: from Borsuk et al. (2004b)

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

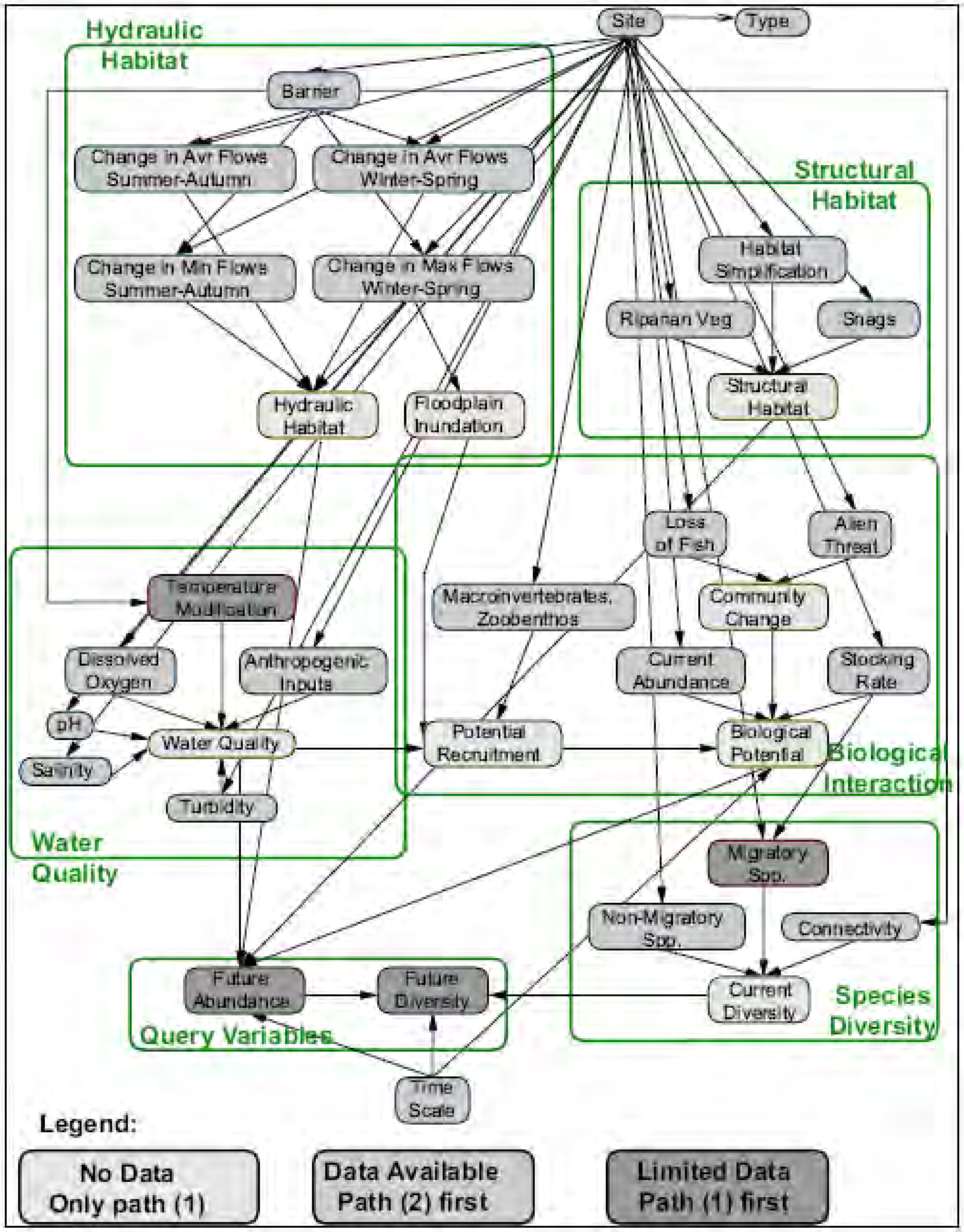
In Stiber et al. (2004), a BN was constructed in order to combine multiple expert opinions on cleaning up hazardous chemicals at a site with contaminated groundwater. Probabilities were obtained for the same BN from a number of experts. The final BN incorporated all of the elicited probabilities, with higher weightings given to those probabilities that proved to be more reflective of actual observed data. Similarly, Dorner et al. (2007) 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 submodel BN based on a simplified crop rotation revenue model. The model can be used for multi-year analysis.

Similarly, a BN was developed for a risk assessment case study, focusing on native fish communities in the Goulburn Catchment (Victoria, Australia) (Pollino et al. 2007b). The BN (shown in Figure 16) considered habitat suitability of native fish communities in a multi-stressor environment, and it was useful for prioritising stressors at different sites and reaches across the catchment at two time scales. In developing the model, information gained through knowledge elicitation and quantitative data was combined to parameterise and evaluate the BN.

In Thomas et al. (2005) a quantitative BN was developed for improving risk-based decision-making for tropical seagrass habitats of the Great Barrier Reef. Seagrass are influenced by a complex suite of parameters, including impacts from land-derived runoff. In Wooldridge and Done (2003), a BN was constructed, based on various sources of data, to predict the probability and extent of coral bleaching in the Great Barrier Reef. The resulting BN was used to identify the relative strengths of dependency of a range of potential causative factors associated with the presence or absence of large-scale coral bleaching.

Similarly, 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, focusing future planning efforts and investments in management and data collection. A BN model constructed for a Black Box *Eucalyptus largiflorens* ecosystem in the NSW Murray floodplain was built with community consultation. The original model was unnecessarily complex. Using evidence from disparate studies, a simpler model was constructed that showed the major factors influencing tree health and recruitment were flooding frequency and grazing pressure (Hart et al. 2007).

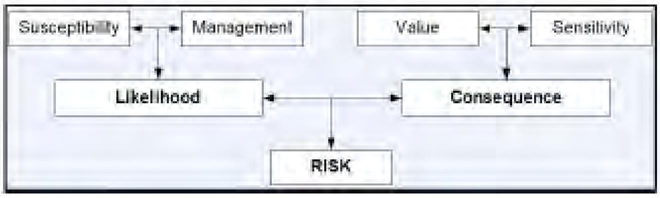
Figure 16: BN for native fish in the Goulburn Catchment (Victoria)



Source: Pollino et al. (2007b)

Another risk assessment application is the Land Use Impact Model (LUIM) developed by McNeill et al. (2006). LUIM is a spatially explicit tool that incorporates aspatial knowledge of relationships between landscape characteristics and land management practices, together with a spatial component that uses a GIS to map where these relationships exist or are likely to exist. These data are then linked in to a risk assessment framework by a BN within LUIM, as shown in Figure 17.

Figure 17: The Land Use Impact Model (LUIM) framework



Source: McNeill et al. (2006)

The LUIM application was used to inform the prioritisation of actions for a soil erosion management plan in West Gippsland. Maps were produced showing the risk of degradation from six soil erosion processes under current and future management regimes. The risk maps were used to identify 'high value' assets to be protected from further degradation as part of the soil erosion management plan.

Risk assessment and management strategies are steadily being adopted by the mining industry to better predict the risks to the environment. Pollino and Hart (2005a) describe the problem formulation and risk analysis methods used to assess the risks of operations of the Ok Tedi copper mine (Papua New Guinea) to the downstream environment. The modelling approach used for risk analysis was a BN that acted as an integration, system exploration, uncertainty, and risk management tool. Four BNs (three aquatic resource models: drinking water, fish and algae, and one terrestrial resource model) were constructed, each undergoing a rigorous evaluation process. Aquatic resource BNs were assessed as being suitable for risk management and were used to assess the impacts of alternative future mine operation scenarios, examining system changes over space and time. The terrestrial model sought to highlight gaps in knowledge and data.

The applications described throughout this section have each examined systems that were complex, highly variable, poorly understood, and either had biased data sets, or no data at all. However, as has been shown, each of the BNs created were able to assist in structuring current knowledge and support future decision-making within an adaptive risk management framework.

6. Environmental flow assessments

Fisheries depend upon natural regimes of river flow for their productivity and full development benefits. Managing rivers to sustain these benefits requires that environmental flow requirements of river fisheries be understood and conveyed effectively into decision-making processes at multiple levels within the river basin (Arthington et al. 2007).

The Arthington et al. (2007) research report reviewed existing environmental flow methods and fisheries production models to determine which combination of existing approaches will provide most potential for development of such decision support tools.

6.1 Bayesian network applications

Chee et al. (2005) explored decision-making in ecosystem management as a process of balancing multiple objectives, constraints, trade-offs and uncertainties against a complex backdrop of socio-economic, cultural and political considerations and limited ecological understanding. In the context of the ecological risk assessment framework, the authors' modelled environmental flows in the Wimmera River in Victoria, a degraded, semi-arid lowland river. Stakeholder engagement and consideration of uncertainties were particularly important aspects of the ecological risk assessment process, and the BN proved to be a particularly good method for modelling the system.

In developing the BN, information and data from a wide range of sources were used, and the BN proved useful in synthesising these diverse information sources. The BN (shown in Figure 18) was constructed to capture current understanding on the potential effects of environmental flow management on Freshwater Catfish *Tandanus tandanus*. The BN model was designed to evaluate alternative environmental flow management strategies, and it supported adaptive management within an ecological risk assessment framework.

Using information contained within the Murray Flow Assessment Tool (Young et al. 2003), a BN was constructed to characterise fish group responses to flow (Figure 19) (Pollino and Hart 2005c). The fish BN has the capacity to integrate model outcomes for individual categories or groups of fish, at one or more locations, and over broad spatial scales. Within a BN, management actions or system changes can be readily tested by calculating how probable events are, and how these probabilities can change given subsequent observations, or they can predict change given external interventions. Flow scenarios or habitat changes can be tested in the model using interventions. Model uncertainties are readily communicated with outcomes presented as probabilistic distributions. As the model is graphical, model transparency is encouraged, augmenting communication and educational processes. Further, using Bayesian statistics encourages the learning process by formalising a sequential approach to probabilistic updating. This property suits the adaptive management process well.

Figure 18: Bayesian decision network for Freshwater Catfish in the Lower Wimmera River,

Notes: The diagram shows the instantiation of a flow release strategy in which the Median Mean Daily Flow (MDF) =10 megalitres per day and the number of 'freshes'=3. The value associated with each decision choice in the Fresh magnitude node indicates the expected utility of making that choice (Chee et al. 2005)

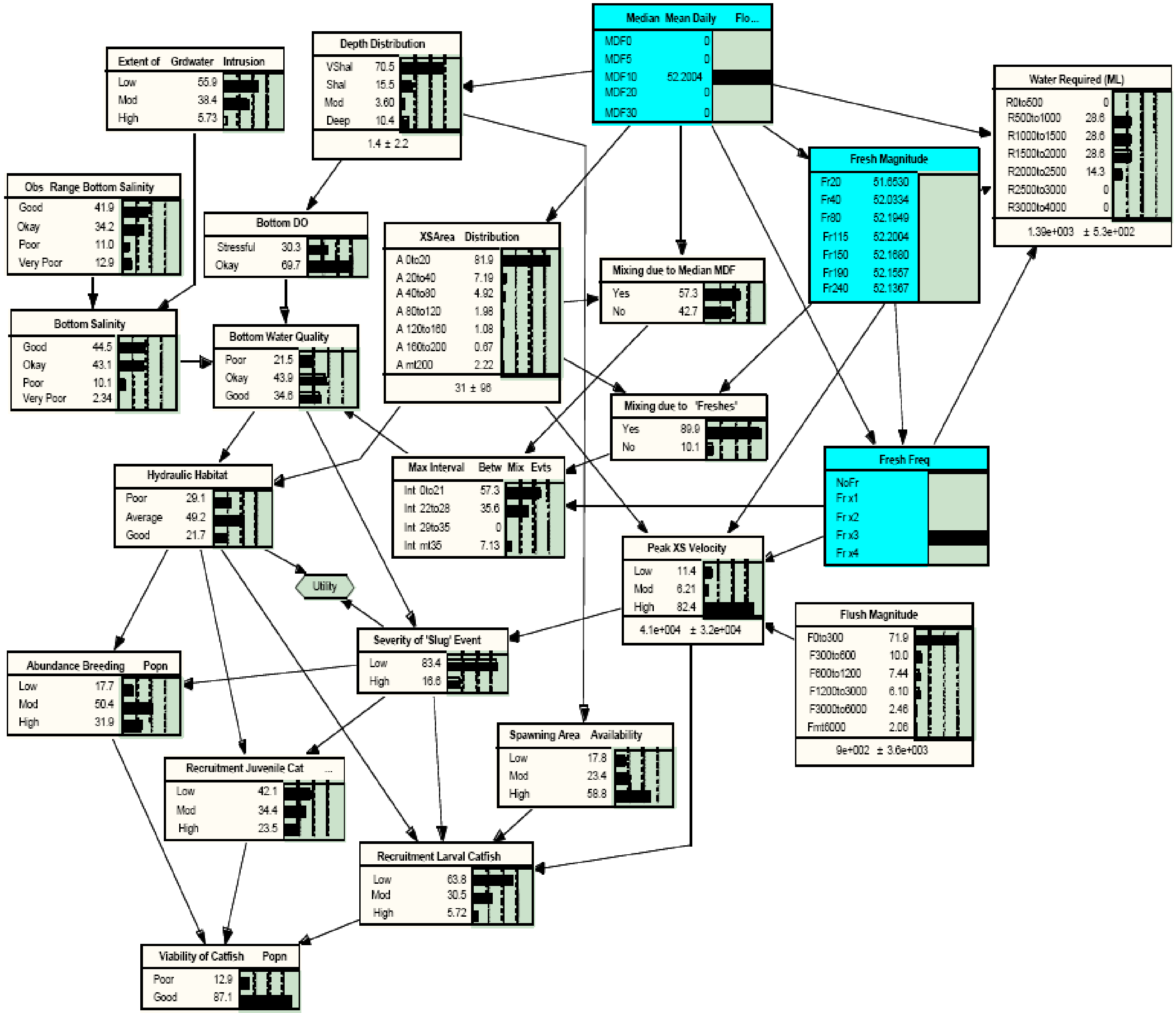
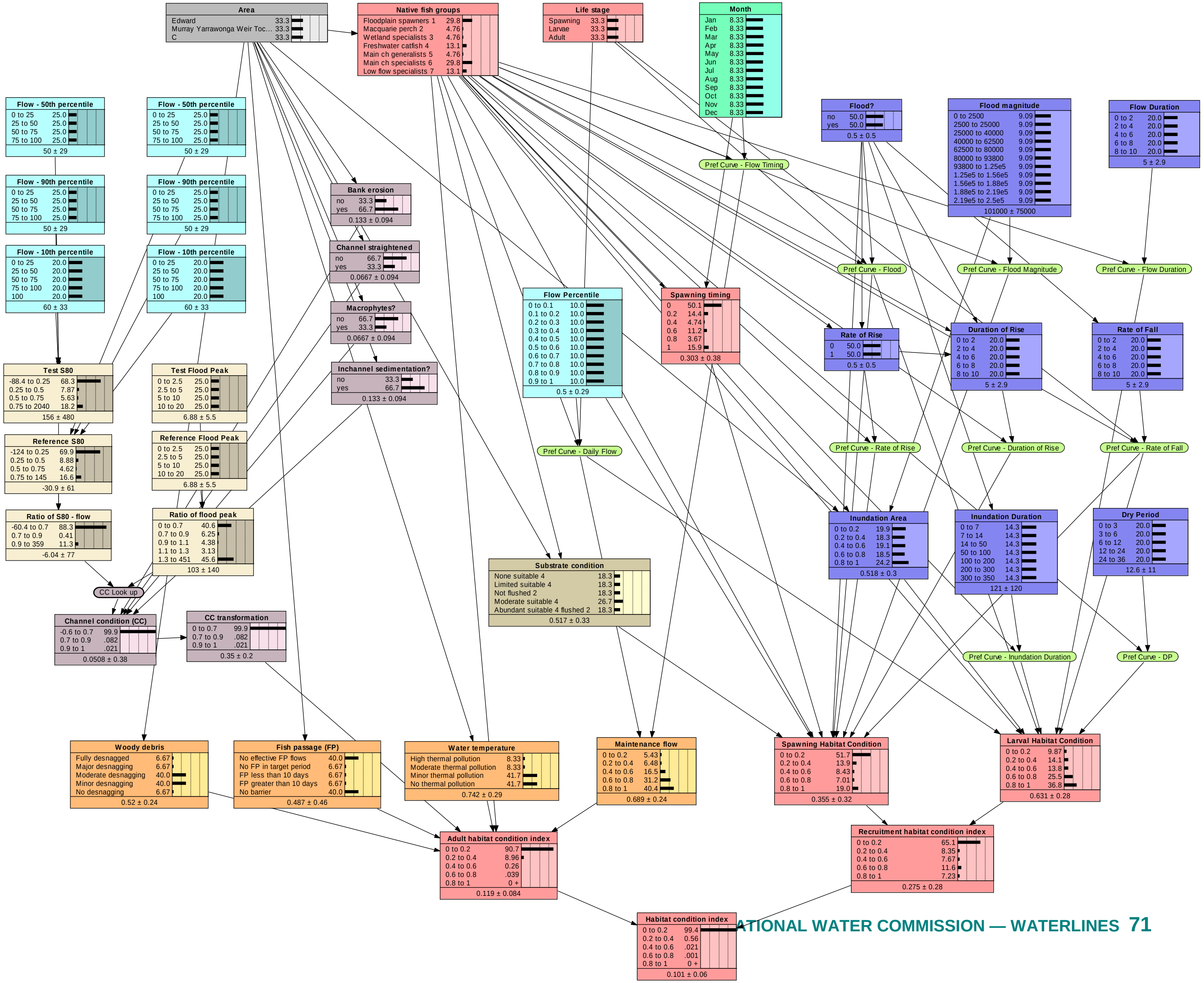


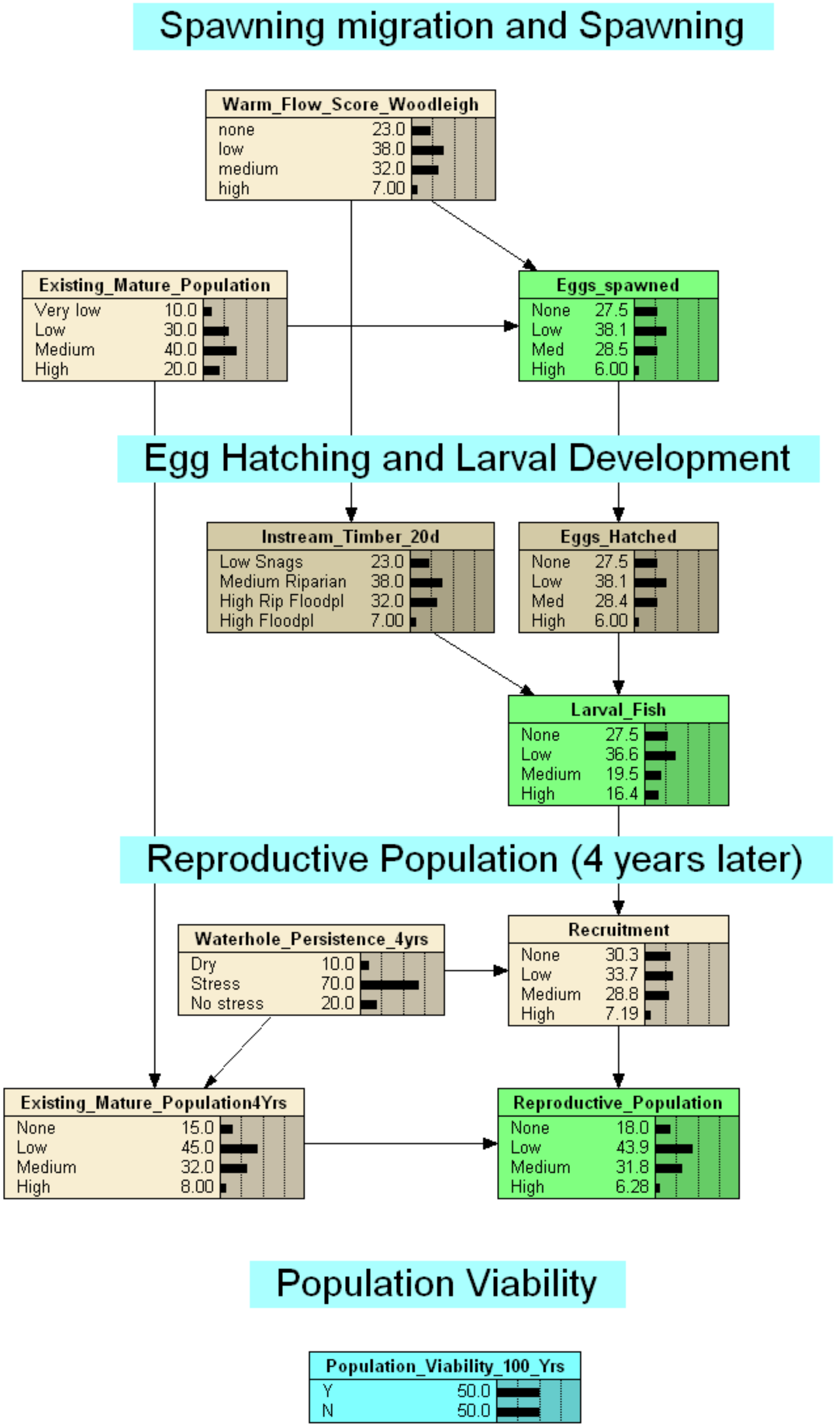
Figure 19: Fish Bayesian network, showing model states

Source: Adapted from the Murray Flow Assessment Tool (Pollino and Hart 2005c).



In Menke et al. (2007), a static BN was developed as a part of Queensland's environmental flow assessment program (Department of Natural Resources and Water, Queensland Government), to model and compare the risk posed from flow management scenarios to the viability of selected representative freshwater fish populations (Figure 20). The initial model was calibrated for Golden Perch *Macquaria ambigua oriens* only.

Figure 20: Bayesian network for Golden Perch

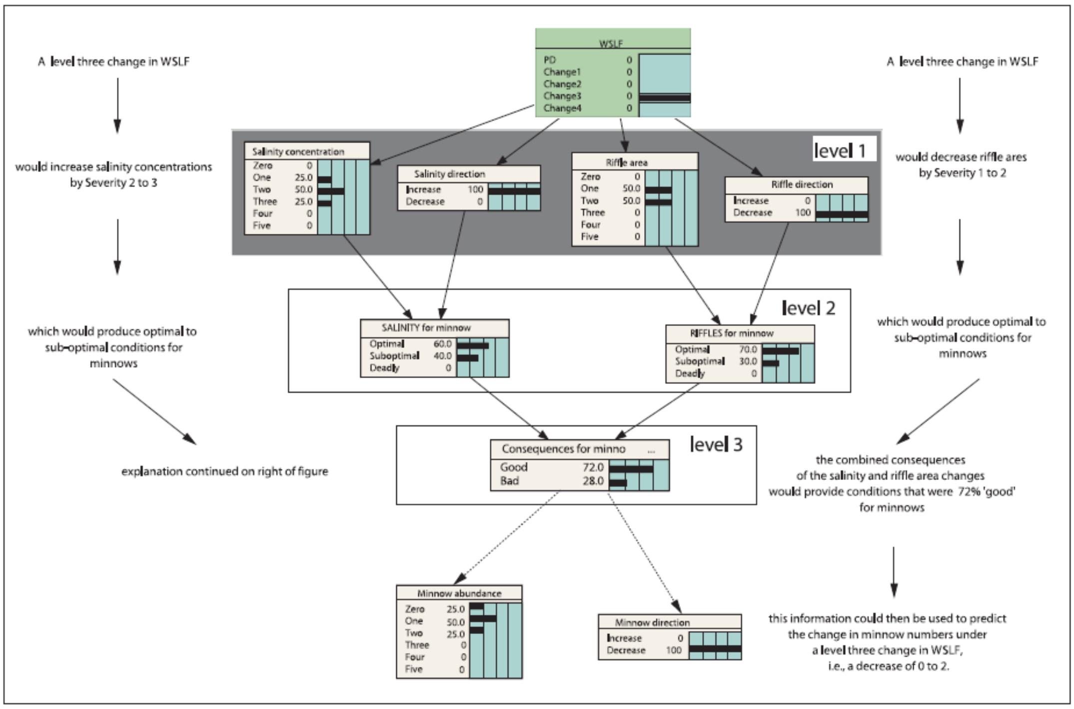


Source: Menke et al. (2007)

The BN's development process was particularly useful for formalising conceptual models, eliciting expert knowledge, and for combining available hydrological data with the scant available biological data. The static BN aims to focus on the water requirements of each major life history phase of the Golden Perch, including spawning, larval development and recruitment, with the model endpoint being defined as the viability of the Golden Perch population over the simulation period. The static BN was also extended to a 100-year simulation dynamic BN model.

Arthington et al. (2007) has undertaken a comprehensive review of environmental flow assessment methodologies for managing large rivers and floodplains for fisheries production. DRIFT (Downstream Response to Imposed Flow Transformation) is described as an interactive, scenario-based environmental flow methodology, which explicitly includes a socio-economic component. A hypothetical BN was constructed for DRIFT, as shown in Figure 21 below.

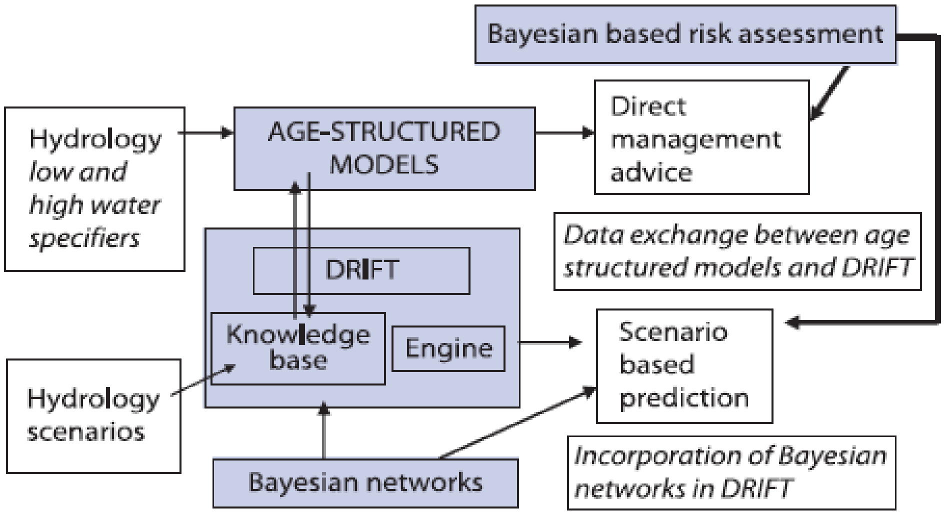
Figure 21: Hypothetical Bayesian network constructed for DRIFT consequences of changes in wet season low flows for the Maloti minnow *Pseudobarbus qualthlambae*



Notes: The BN uses two ‘driving’ variables: salinity and riffle area; WSLF = Wet Season Low Flow
Source: Arthington et al. (2007)

The review concluded that the methodology of DRIFT, when combined with the use of BNs and age-structured fisheries models, will provide the most promising direction for future research. The proposed integration of methodologies would take the form shown in Figure 22. The authors do also recognise that there will be cases where this approach will not work and other environmental flow methodologies and tools will be required.

Figure 22: Proposed integration of DRIFT, Bayesian networks and age-structured models



Source: Arthington et al. (2007)

6.2 Other synergistic approaches

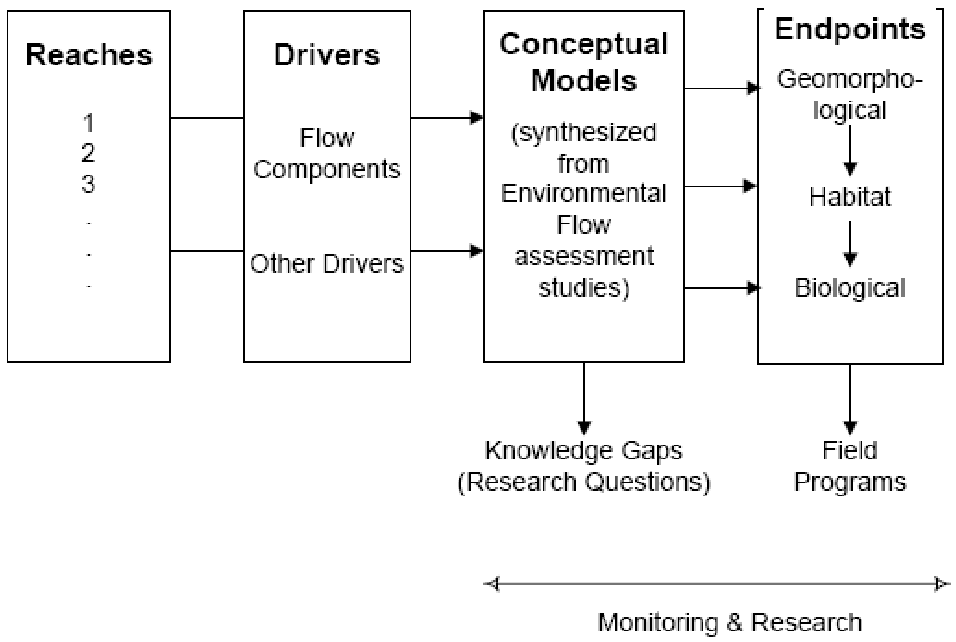
Failing et al. (2004) provided an example of an integration of probabilistic policy analysis and multi-stakeholder decision methods with the focus on a hydroelectric facility in British Columbia, Canada. The decision-making framework utilised probabilistic judgments of experts, a decision tree, and a Monte Carlo simulation to examine alternative decisions for implementing an experimental flow release program to test the response of salmonids to flow. Although a BN was not used, the approach used is highly synergistic. The technical evaluation of the expected costs and benefits of the program were integrated into the multi-stakeholder decision process, assessed the magnitude of uncertainty and its potential to affect water management decisions, and incorporated the preferences of stakeholders for alternative outcomes. The approach applied adaptive management within a broader decision problem, and it demonstrated the utility of combining expert judgment processes and stakeholder values with adaptive management to improve the likelihood that proposed experimental approaches will deliver a nett value to society. The process is further documented in Failing et al. (2007).

In the Victorian Environmental Flow Monitoring, Assessment and Planning (VEMAP) program, the Department of Sustainability and Environment of Victoria has specified that Bayesian models are to be considered for the analysis of monitoring data. In a subsequent report (referred to as VEMAP Stage I), a series of recommendations was made on analysis of data collected for environmental flow assessment purposes (Cottingham et al. 2005). In this report, hierarchical Bayesian statistical models were the form of Bayesian models specified (compared to BNs, Bayesian statistical models have several advantages in the implementation of models, however they are limited by their non-user-friendly environment and ease of testing management scenarios). Cottingham et al. (2005) regarded the key advantage of Bayesian analyses to be their flexibility.

Unlike BNs, which implement mathematical relationships in a graphical framework, relationships in hierarchical Bayesian statistical response models are expressed mathematically by equations. These are used to define the response predicted for any given environmental flow regime, and they can easily fit models of varying complexity using many different distributions for variable values, and effects, such as spatial and temporal autocorrelation, can be readily built into models (Cottingham et al. 2005). Data re-sampling methods (such as Monte-Carlo simulation, including Bayesian Markov-chain Monte-Carlo methods) are then used to characterise uncertainty in model responses and model inferences (Cottingham et al. 2005). As with BNs, site specific covariates (for example, flow-related habitat features such as the availability of pools or riffles) can be included, and alternative models of causality can be retained and revised in light of new data and framework therefore more suited to the continual analysis of data on a regular basis.

Stage II of VEMAP was undertaken for individual rivers using the following process outlined in Figure 23 (Chee et al. 2006):

Figure 23: VEMAP process for defining environmental flow objectives



Source: Chee et al. (2006)

The process was used to define environmental flow objectives across a series of river reaches in a way that is consistent with the FLOWS method (DNRE 2002), which is based on the Natural Flow Paradigm (Poff et al. 1997). Bayesian statistical models were used as the modeling approach, as advised in the VEMAP stage I report.

7. Some considerations for using Bayesian networks for risk-based environmental flow assessments

As discussed below, using BNs for environmental flow assessments confers three major advantages:

1. their ability to be used for adaptive management
2. their use in integration
3. their use within a policy environment.

7.1 Adaptive management

Historically, overconfidence in understanding of ecosystems and the effectiveness of management actions has lead to some unwelcome surprises (Sainsbury et al. 2000). The appeal of adaptive management is driven by three factors: our rudimentary knowledge of natural systems, systems being in a constant state of disequilibrium (due to variability), and community goals and management expectations always being in flux. An adaptive approach to management involves documenting hypotheses, implementing an intervention, monitoring responses, and adjusting management actions over time (Failing et al. 2004). Although many management plans now contain at least a passing reference to the need for an adaptive approach, unfortunately at present there exists little historical management experience in this area. Additionally, policy frameworks promoting adaptive management have suffered from not having the right tools to meet this need. A Bayesian framework of analysis is ideal for adaptive management purposes (Dorazio and Johnson 2003; Prato 2005).

A BN can be used to make the connections between ecological understanding and environmental management explicit, and it ensures that associated uncertainties are communicated. It is hoped that BNs that have been sufficiently tested for 'believability' and robustness will be deployed in real environments, where the assumptions contained in the model can be tested. As a BN model is a continual learning tool, the models have an extended life span. These features facilitate and promote adaptive management and risk assessment or risk management frameworks.

7.2 Integration and participation

Adaptive management should begin with a concerted effort to integrate existing interdisciplinary experience and scientific information into dynamic models that attempt to make predictions about the impacts of alternative policies (Holling 1978; Walters 1986; Walters 1997). The need to undertake integrative assessments in order to enable more holistic planning and decision-making for allocating environmental flows has been widely recognised, but decision support frameworks and modelling technologies that meet these needs have been limited.

Although the principles of integrated decision making are straightforward, linking together all the diverse factors to facilitate decision-making in a quantitative way is highly complex. BDNs are model-based decision support systems that have the potential to meet the needs for water resource managers while explicitly acknowledging the complexities arising from such analyses. Being graphical, results can also be readily communicated and interpreted with relative ease and speed.

As stated, BN models are particularly ideal for model integration, where they can be used to integrate information from other models to represent system processes. This avoids 'reinventing the wheel' and recognises that other models can better represent systems, especially dynamic systems. However, as BNs can also be used within a sustainability context (for example, to examine ecological, social and economic factors), they fit into a decision-making framework. This makes them more relevant for participatory style processes.

BNs have the potential to allow the public to become better engaged in an informed discussion in resolving the trade-offs between water users, such as irrigator and environmental requirements. An effective community consultation process that addresses trade-offs 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.

7.3 Policy environment

BNs offer a pragmatic and scientific approach to modelling complex environments that are able to provide direct answers to environmental management assessment and planning processes using the best information available (quantitative and qualitative). BDNs enable the impacts of environmental and regulatory factors on ecological endpoints to be examined. This can enable the conflicts between policy objectives (for example, 'to protect the needs of the environment' and 'to facilitate water markets') to be examined in a single integrated framework, facilitating integrated decision-making.

BNs seek to promote transparent decision-making, communicate uncertainties associated with decisions, and recommend strategies for reducing uncertainties in an adaptive management context. These attributes are essential for promoting equitable and sustainable water management in Australia today.

Using a BN model, environmental flow changes as a result of alternative river operations scenarios or system changes, such as climate change, can be rapidly investigated to inform decision-making processes. Considering that model endpoints are direct measures of ecological endpoints, the results are easily interpreted by decision-makers. Moreover, being that predictions are likelihoods, they are directly applicable to risk management. Using sensitivity analyses, models also enable threats to environmental values to be prioritised, and for key data and knowledge gaps to be identified. Thus, areas needing further research or more monitoring data are identified.

By using a formal quantitative approach to decision-making, it is anticipated that a greater understanding of decision processes, and how they relate to management, can be achieved, and the decisions made will be more robust, defensible and tractable. Given that BNs are not a difficult tool to construct or use, they are more likely to be adopted into environmental management.

8. Concluding remarks

The benefits and limitations of BNs to assist decision makers in environmental flow assessments, is a topic for further discussion.

BNs have the potential to assist decision-makers by:

- their ability to be easily used and understood
- allowing the assessment of environmental flow scenarios, with associated costs, for maintaining (or restoring) the ecological health of Australian rivers and streams
- integrating hydrological and ecological response models
- integrating assessment of the importance of environmental flow strategies in the context of other investment strategies for managing environmental processes (such as riparian restoration activities)
- linking investments with outcomes in an adaptive management context
- integrating ecological considerations with socio-economic factors
- testing alternative policy options and trade-offs for environmental flow regimes
- prioritising funding resources for future monitoring and research efforts to fill priority knowledge gaps
- encouraging system thinking
- facilitating interdisciplinary and participatory processes.

Limitations of the approach include poor representation of temporal dynamics, spatial dynamics, feedbacks and representation of probability distributions.

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