Ecological risk assessment and Bayesian modelling

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The short document summarises recent research by the Water Studies Centre and partners in the application of ecological risk assessment techniques and Bayesian modelling to the management of natural resources.

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Ecological Risk Assessment

Why needed?

The objective of Ecological Risk Assessment (ERA) is to provide a robust process that incorporates a transparent, scientific, precautionary and ecologically sustainable approach to the management of environmental risks.

The Water Studies Centre and partners have developed an *ERA Framework* that is catchment-based and focuses on the difficult task of assessing the risks to multiple ecological assets from multiple hazards (Hart et al., 2005)[2]. The framework synthesises the methods required to achieve successful adaptive management of natural resources.

This framework is primarily focused on the risks to aquatic ecosystems (e.g. rivers, wetlands, estuaries), but is robust enough to be used to assess the ecological risks to other natural resource assets in catchments (e.g. land, soil, vegetation, biodiversity), as is illustrated in the Case Study section below.

What is involved?

The ecological risk assessment framework involves a number of key steps (Figure 1), including:

- *Defining the problem* – this involves careful scoping of the problem, agreement on how it is to be assessed, and how the acceptability of actions will be judged.
- *Deciding on the important ecological assets, and identifying hazards to these assets* - hazards are prioritised by evaluating their effects on valued elements of ecosystems and ecosystem services.
- *Analysing the risks to the ecological values* – the analysis process used needs to be appropriate for the situation in order to provide adequate information for decision-making. Guidance is provided on both qualitative and quantitative methods.
- *Characterising the risks* - the technical details of risk analyses needs to be made accessible to decision-makers and broader stakeholders. In particular, the uncertainties and assumptions associated with analyses require careful and transparent documentation.
- *Making decisions* – selection of the best management option or strategy will be the one that results in the effective minimisation of the ecological risks, while also being cost-effective and acceptable to the stakeholders. Guidance is provided on a number of multi-criteria methods for assisting this process.
- *Managing the risks* – a risk management plan provides recommendations on managing or mitigating all high or unacceptable risks. The risk management plan should include a robust program to *monitor progress* to ensure the strategies are working, and a *review and feedback process* for making changes if needed.

Benefits

ERA is a robust process for:

- Clearly defining the environmental assets that need to be protected, managed or rehabilitated,
- Identifying the threats and hazards to the assets,
- Defining the linkages and relationships between the threats and values, normally starting with the development of conceptual models,
- Prioritising the risks (consequences x likelihood) to these assets,
- Identifying existing knowledge and major knowledge gaps.

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[2] Hart, B. T., Burgman, M., Grace, M., Pollino, C., Thomas, C., Webb, J. A., Allison, G. A., Chapman, M., Duivenvoorden, L., Feehan, P., Lund, L., Carey, J. and McCrea, A. (2005). *Ecological Risk Management Framework for the Irrigation Industry*, Technical Report, Land & Water Australia, Canberra, Australia (available www.sci.monash.edu.au/wsc).

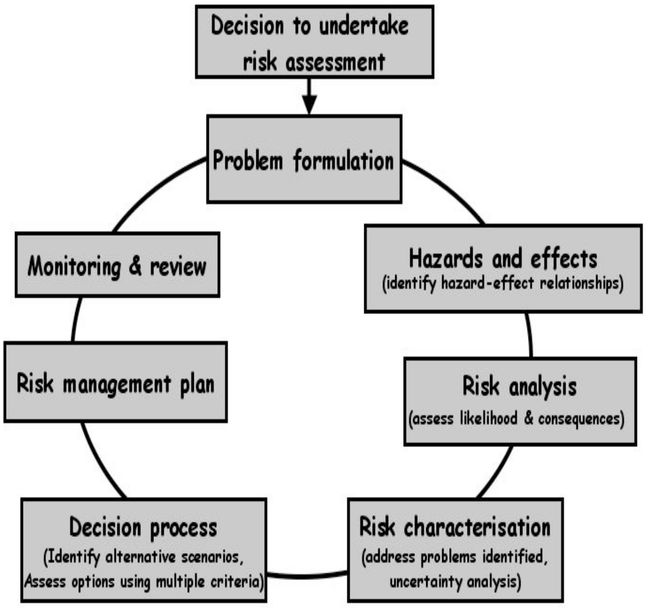

Figure 1: Overall risk assessment and management framework (Hart et al. 2005)

Bayesian modelling

Why use them?

A major difficulty faced by many (most) managers of aquatic and terrestrial resources is the 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.

For these reasons Bayesian models are increasingly being used as decision support tools to aid in the management of ecological systems, and particularly in those situations where the risks are such that quantitative methods are warranted.

A particular advantage of Bayesian decision network (BDN) 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.

What are they?

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, with uncertainties being reflected in model outputs. 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.

How do they work?

A Bayesian decision network is made up of a collection of nodes that represent important environmental variables. Arrows represent the causal relationships between the nodes (variables). Bayesian networks use the network structure to calculate the probability certain events will occur, and how these probabilities will change given subsequent observations or a set of external (management) interventions. A *prior probability* represents the likelihood that an input parameter will be in a particular state. The *conditional probability* calculates the likelihood of the state of a variable given the states of input variables affecting it. And the *posterior probability* is the likelihood that a variable will be in a particular state, given the input variables, the conditional probabilities, and the rules governing how the probabilities combine.

A number of commercially available modelling shells are now available (e.g. Netica - www.norsys.com).

What is involved in building a Bayesian network model?

Model structure

The first step in constructing a Bayesian decision network is to develop a causal structure (often based on a conceptual model), with relevant variables (nodes) and dependencies. Important criteria for inclusion of variables in Bayesian networks are that the variable is either:

(a) manageable, (b) predictable, or (c) observable at the scale of the management problem. Any processes or factors not included become part of the uncertainty of the network, forming the predictive uncertainty described in probability distributions.

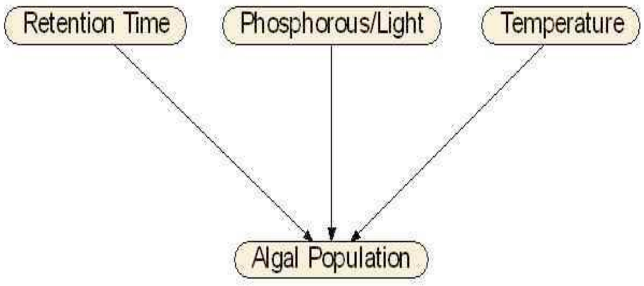

Figure 2: Simplified version of an algal network

One of the strengths of Bayesian decision networks is their ability to integrate existing models or processes and to integrate existing datasets. Figure 3 shows the conceptual structure of a model for predicting the impact of riverbed aggradation and water quality, particularly increased Cu concentrations produced by acid rock drainage (ARD), on fish abundance and contamination. The Bayesian model integrated information from two sub-models (HEC-6 and OkARD/OkChem) into a single predictive framework.

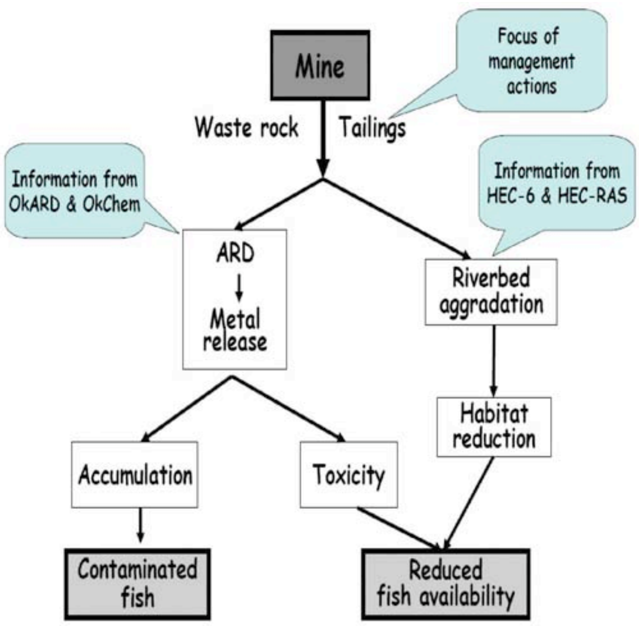

Figure 3: Schematic of a fish BDN model developed for OkTedi Mining Limited

Building a model

1. Structure of a Bayesian network

As discussed earlier, developing a causal structure, with relevant variables and dependencies, is the first step in constructing a Bayesian network.

2. Discretisation of nodes (assigning states)

States or condition of the variables can be categorical, continuous or discrete. In order to represent continuous relationships in a Bayesian network, a continuous variable must be divided or discretised into states. The states of a variable can be numerical ranges (≤ 3, >3) or expressions (that can also represent data if appropriate, e.g. acceptable ≤ 3, unacceptable >3). If relevant, these states can represent targets, guidelines, existing classifications or percentiles of data.

3. Specification of prior probabilities

After defining node states, the linkages between nodes need to be described. Parent nodes lead into child nodes, the outcome of child nodes are conditional on how the parent variables combine. This is relationship is defined using conditional probability tables (CPTs).

In the networks, sub-networks describe physical or chemical processes relevant to the spatial scale specified. The impacts of these on the final outcome node, which often represent a biological/ecological process, are combined in the CPTs. For this reason, Bayesian networks are often described as being integrative models.

CPTs can be derived via one or a combination of methods:

- Direct elicitation of scenarios from expert;
- Parameterisation from datasets;
- Equations that describe relationships between variables.

It should be noted that for Bayesian networks, the more complex the interactions the more conditional probabilities there are to specify.

4. Calculating posterior probabilities

Data or new knowledge can be incorporated into BNs and used to calculate posterior probabilities. Data sources can be entered into the network as a series of 'cases'. Cases can represent data collected during a monitoring exercise, undertaken as part of a research study, and so on.

5. *Model evaluation*

A range of validation tools can be used for BNs. Evaluation can involve data or technical experts, or both. Quantitative evaluation with data is preferable. Such measures include predictive accuracy and sensitivity analyses.

Predictive accuracy tests are used to determine model error rates, which are quantified using data (although not the same data used for model parameterisation). This method measures the frequency with which the predicted node state (that with the highest probability) is observed, relative to the actual value. Outcomes can be used to identify weaknesses in the model, and where more effort can be targeted in order to improve model accuracy.

Sensitivity analysis is used to identify the key drivers in the model and major knowledge gaps in our understanding. Sensitivity analysis of mathematical models can be used to investigate the uncertainties and inaccuracies in model structure, relationships and outputs, and subsequently identify where priority knowledge and data gaps exist. Thus, based on these results, recommendations for targeted monitoring and research studies can be made.

Sensitivity analyses provide a ranking of importance of variables, relative to the variable of interest (usually the endpoint). These variables indicate where better quantification in the network should be investigated and identify the most influential variables on model endpoints. Subsequently, these are the variables that should be given greater attention. In a management context, it is these variables that may represent key management actions or knowledge gaps. As sensitivity findings can differ for different spatial areas of interest or scenarios tested, key knowledge gaps and priority risks can also differ.

6. *Knowledge gaps and priority risks*

Having established the structure of the model, and the relationships used to drive the model, the key knowledge gaps in our understanding and priority risks can be identified. To do this, sensitivity analysis is used.

Testing management scenarios

Management scenarios can be tested by entering new information into the network as evidence, directly changing the distribution of probabilities on the node itself.

How can Bayesian network models help?

- Make predictions (probabilistic output),
- Test management options,
- Identify data/knowledge gaps and prioritise needs.

Case studies

A summary of the following case studies will be provided. The WSC has been involved in developing Bayesian network models to assist decision-making in all these cases.

- Risks from mine-derived contaminants (Ok Tedi and Fly Rivers, PNG)
- Irrigation ERA framework
- Black Box (*Eucalyptus largiflorens*) wetlands (Murray-Darling Basin)
- Condition of *Eucalyptus camphora* wetlands (Worri Yallock creek catchment)
- Native fish communities (Goulburn R)
- Environmental flows (Wimmera R)
- River health – macroinvertebrates (Loddon R)
- Lyngbya research (Morton Bay, Qld)
- Seagrass health (Great Barrier Reef)

Some reports are available at:

www.sci.monash.edu.au/wsc

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