Bayesian decision networks - going beyond expert elicitation for parameterisation and evaluation of ecological endpoints.

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Abstract: Ecological and integrative analyses routinely involve the synthesis of a range of information sources into a single model. Bayesian decision networks (BDN) are increasingly being used for this purpose because they are flexible, transparent and relatively easy to use. Indeed, BDNs offer a scientific and pragmatic approach to improve decision-making in environmental management, directly addressing management needs, while promoting stakeholder participatory processes. However, despite their advantages, many BDNs developed to meet such needs are not being developed or applied to their full potential. The majority of BDNs published to date rely only on expert opinion to parameterise and evaluate ecologically relevant endpoints. In contrast, environmental processes in BDNs, such as water quality, are optimised using quantitative data. In this paper we discuss the need to better exploit the Bayesian aspect of BDNs. We use examples to discussed the contrast between probability networks and BDNs, the need to use existing data where possible for parameterisation and evaluation (in conjunction with knowledge and weighting information sources), and the need to incorporate BDNs into an iterative cycle of updating. We argue that the alleged advantages of BDNs in improving the robustness and scientific credibility of ecological decision-making are questionable if ecological data is not better used in sustainability and risk assessments.

***Keywords**:* Ecology; Bayesian Decision Network; Elicitation; Expert bias

1. SCIENTIFIC UNCERTAINTY AND ENVIRONMENTAL MANAGEMENT

Science is defined as a process of acquiring knowledge aimed at finding the truth. Accordingly, science can bring about differences of opinion and uncomfortable levels of uncertainty (Bradshaw and Borchers 2000). In the study of natural systems, such outcomes are not uncommon. Ecosystems are the products of complex interactions that, for the most part, are poorly understood. Given this, there will always be uncertain and unpredictable aspects in our understanding of ecosystems, and evolving hypotheses of how ecosystems function.

Clearly, an intrinsic feature of ecology is uncertainty. This uncertainty can be classified into two types: *epistemic uncertainty*, which is analytical, being due to limited information and defined as observation error; and *aleatory uncertainty*, which is due to randomness in a system (via process stochasticity or natural variability) (Burgman 2005). Epistemic sources of uncertainty can be reduced by further observations, but aleatory uncertainty is irreducible, representing the inherent properties of a system (Halpern *et al.* 2006; Schreiber *et al.* 2004).

Such uncertainties present a challenge to environmental policymakers and managers who are charged with making decisions about how our natural systems are to be exploited and protected. Previously, one of the most serious challenges to rational decision-making in environmental management was the criticism that individual managers face if they admit uncertainty (Walters 1997). Consequently, many past management strategies were inappropriately designed, leading to decisions that resulted in population crashes or ecosystem failures, causing profound ecological and economic impacts (Halpern *et al.* 2006). Today, the importance of quantifying uncertainty in decision-making is increasingly being recognised as providing a mechanism for describing realistic outcomes and adding flexibility to the decision process.

Two approaches that are widely promoted as sound processes for environmental management are risk assessments and sustainability assessments (Hart *et al.* 2005; Jakeman *et al.* 2003). Both are iteratively structured processes centred on defining a problem, evaluating the problem, and making recommendations on how best to manage the problem. Both also explicitly consider uncertainty, although the degree to which it is represented in an assessment varies considerably. Embodied in each approach are the principles of adaptive management.

Adaptive management is a process that explicitly accounts for uncertainty in ecological systems. It requires the documentation of hypotheses about responses of ecological systems to management interventions, monitoring of ecological responses before and after management interventions, and adjustment of management actions to account for observations (Failing *et al.* 2004). Ecological models are a key component of the adaptive management process. According to Walters (1997), the use of modelling in adaptive management allows one to replace management learning by trial and error with learning by directed experimentation.

1.1 Ecological Models in Environmental Management

In ecology, models serve a variety of purposes, ranging from illustrating an idea, to characterising a complex real-world situation (Neuhauser 2001). In decision making, ecological models are used to explicitly describe components of management and their relationships to the environment, to articulate assumptions and test hypotheses, to integrate different levels and types of knowledge, and to aid in the identification of salient, necessary and sufficient features of a system (Hilborn and Mangel 1997; Schreiber *et al.* 2004). The science of management of large systems is less than exact, and models can provide a powerful way for informing decision makers. Modelling exercises can reveal substantial gaps in knowledge about key processes and functional relationships (Walters 1997).

Many past ecological models were restricted to mathematical equations that represented those parts of the system for which relationships were known (Rykiel 1989; Salles *et al.* 2006). This severely limited the type of knowledge that could be represented in models (Salles *et al.* 2006). Given that much of our ecological knowledge is incomplete, qualitative, fuzzy, or expressed verbally and diagrammatically, ecologists have only limited approaches in modelling for using this information in a meaningful way (Salles *et al.* 2006). These past models also did little to promote the value of iterative updating using new data and knowledge, which is a key component of the adaptive management process.

Recently, advances have been made in using Bayesian methods in ecological modelling. Bayesian approaches have the potential to meet the modelling needs of ecologists and environmental managers alike.

1.2 Bayesian Methods

Assessment of causality is at the core of all models for environmental management (Newman and Evans 2002). A major advantage of using Bayesian methods in environmental management is their ability to aid causality assessments. Bayesian analyses have the ability to guide what is predictable, what is inherently unpredictable, and where additional data can provide the most benefit in understanding and managing a system (Clark 2005). They have the potential to reduce conflicts emerging from less formal integration of available evidence and can be used to direct the better use of limited resources in management (Newman and Evans 2002).

In Bayesian reasoning, it is important to start with an appropriate ‘prior’, which is an assumption of how a particular system works. This *prior* probability is often derived using the subjective belief an expert has in a distribution before an analysis. Using Bayes’s Theorem (Equation 1), this prior probability is then combined with new data resulting in a *posterior* probability. The posterior probability of a hypothesis is given by the product of the prior probability, and the relative likelihood of the data having been recorded if the hypothesis were true:

$$P(B \mid A) = \frac{P(A \mid B)P(B)}{P(A)} \qquad (1)$$

Where P(B|A) is the posterior probability of B given A, P(A|B) represents the conditional probability of A given B (likelihood), P(B) is the prior probability of B, and P(A) is the marginal distribution of A.

According to Dorazio and Johnson (2003), there are virtually no limits to the complexity of Bayesian models. Indeed, the Bayesian process can be used to address the need to better understand and model complex systems (Pollino *et al.* accepted). Bayesian models have the ability to drive research to start answering fundamental questions in ecology, addressing the big questions on how systems work (Pollino *et al.* accepted). They are also a central component in the implementation of adaptive management (Dorazio and Johnson 2003; Pollino *et al.* in press).

2. BDNS: ASSESSMENT OF CAUSALITY

Bayesian Decision Networks (BDNs) offer a modelling framework that has the capacity to explore causality in ecological systems (Pollino *et al.* accepted; Pollino *et al.* in press). A BDN is similar to a hierarchical model in conventional Bayesian statistical models (i.e. models in WinBUGS), but they are graphical representations of probability. BDNs are made up of nodes (variables) connected by arcs (arrows) that represent dependencies. Nodes are random variables that can be continuous, discrete, or categorical. A full description of BDNs can be found elsewhere (e.g. (Korb and Nicholson 2004)). The power of network models, such as BDNs, lies in their simplicity (Green and Sadedin 2005). They have the potential to capture the patterns of connections and interactions within an ecosystem (Green and Sadedin 2005) in a parsimonious style.

BDNs are effective frameworks for (Dorner *et al.* 2006):

1. capturing the structural aspects of the decision problem and serving as a framework for an efficient quantitative analysis of a problem;
2. enabling an efficient representation and exploitation of the conditional independence in a decision model;
3. expressing linkages in probabilistic terms, enabling management strategies to be identified with explicit certainty, despite imperfect knowledge;
4. communicating decision models among decision makers.

Bayesian approaches, including BDNs, allow scientists to combine new data with existing knowledge or expertise, thus providing a systematic procedure for pooling and combining knowledge in order to make decisions (Pollino *et al.* in press; Reckhow 2002). Sensitivity analyses can be used as a tool to identify sensitive variables in a BDN (Pollino *et al.* in press).

2.1 BDN Information Sources

According to Popper, scientific methods producing quantitative information are superior to qualitative methods (Popper 1972). Quantitative measures allow for more explicit statement of models, more rigorous testing of models, and clearer statements of confidence in models (Newman and Evans 2002). However, in complex ecological models, such as for river systems, often there is only limited data available. Analyses of historical and comparative empirical data rarely provide the range and resolution of data needed for predictive models (Pollino and Hart 2005). Often, such data is also situation-specific and scale-dependent, not accommodating the range of influences that can operate in different settings at different scales (Clark 2005). Unfortunately, available empirical data can also be of variable quality, and relying on limited or suspect data alone can have implications for the accuracy and reliability of models (Pollino and Hart 2005; Sobehart *et al.* 2001). Nonetheless, that does not mean that we should forgo the use of such data entirely. Historical data have an important role in model parameterisation and validation, adding to the rigor of ecological models (Pollino *et al.* in press).

If data are inadequate or lacking, the development and evaluation of a BDN model can continue using heuristic methods and domain experts. Bayesian models offer a process where quantitative knowledge or data can be integrated with expert knowledge, as has been demonstrated previously (Pollino *et al.* in press; Sikder *et al.* 2006). There is no doubt that the use of expert judgement has a particularly important role in environmental management (Rykiel 1989). Expert judgement can often be one of the few identifiable ways to introduce sound ecological knowledge into environmental management.

Unfortunately, the way in which expert judgement is introduced into a BDN can lack transparency and rigour. This has been observed in many existing BDNs, with ecological variables often only being defined qualitatively. The justification for this is either to simplify an assessment or due to the lack of robust data. When inherently quantitative variables (such as ecological variables) of BDNs are kept qualitative, they cannot be used in adaptive management processes, and arguably add little rigour to environmental management processes.

A key virtue of the Bayesian approach is the iterative aspect of model development. The reliance on purely qualitative assessments in BDN models can introduce bias into an assessment, which can have a negative influence on decision making. Sources of bias are explored in the next section. We argue that by defining ecological variables qualitatively and encouraging little capacity for model updating, many existing BDNs are really only probabilistic propagation models.

3. EXPERT BIAS

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

In establishing a prior, 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). 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.

The two main types of individual bias are motivational bias and cognitive bias (Baddeley *et al.* 2004; Burgman 2005):

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

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

- *Availability* is the heuristic of assessing an event's probability by the ease with which an occurrence of the event is recalled.
- *Anchoring and adjustment* involves making an initial estimate of a probability using an anchor, and then revising or adjusting it up or down in the light of new information. This typically results in assessments that are biased towards the anchor value.
- *Control* is the tendency of people to 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.
- R*epresentativeness* 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 often *overconfident* about their knowledge (Anderson 1998; Baddeley *et al.* 2004; Burgman 2005). Biases are believed to be amplified when probabilities are extreme (i.e. at the tails of a distribution - close to 0 or 1) (Baddeley *et al.* 2004).

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

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

Obviously, given these multiple sources of biases, the question of how best to elicit and incorporate expert input into a BDN model is crucial, having implications for the overall model robustness and representativeness of a system.

In Bayesian statistical models, where enough information is known about a problem to define an appropriate probability distribution, then formal methods of elicitation are considered appropriate (Bier *et al.* 1999). Expert judgements are used to define parameters quantitatively (e.g. probability distribution function with moments). A number of formal methods for eliciting probabilities have been described previously (e.g. (Baddeley *et al.* 2004; Cooke 1991; Morgan and Henrion 1990; Savage 1971; Wang *et al.* 2002)). The use of formal elicitation methods can also help shift judgements from positional to performance-based debates (Failing *et al.* 2004). Although these methods can reduce expert bias, a method to estimate the uncertainties in expert judgements remains elusive (Baddeley *et al.* 2004).

3.1 Expert Input into BDNs

Unlike classical Bayesian models, in BDNs variables are often defined qualitatively. In this section, we seek to identify the problems that can arise in BDN models when variables are only defined qualitatively (if such variables are inherently quantitative).

In BDN software platforms, variables have the capacity to (and often need to be) discretised. A discrete variable can take on one of several values, and these values are called states. These states can be defined qualitatively or quantitatively. Conditional probabilities describe how a set of states of parent variables combine in a child variable. Consequently both the states of the variable and the conditional probabilities need to be elicited (Pollino *et al.* in press). For the sake of simplicity or using lack of data as a justification, published BDNs often define the states of an ecological variable as qualitative ratings (e.g. Low, Medium, High), despite the inherently quantitative nature of the measure (e.g. success of fish recruitment or algal biomass). This can introduce ambiguity and bias into the assessment.

Using ratings to describes risks associated with animal anti-microbials, Cox *et al.* (2006) found that qualitative risk ratings did not provide sufficient information to discriminate accurately between quantitatively small and qualitatively large risks. The use of qualitative rankings is also likely to result in linguistic ambiguities, value judgements and expert biases (Burgman 2005). Likewise, in a study by Failing *et al.* (2004), quantitative estimates of biomass response were considered to be vastly superior to qualitative biomass estimates as the latter placed no bounds on the range of benefits possible given for alternative scenarios (Failing *et al.* 2004).

We argue that BDN models for environmental management purposes should strive not to fall into the qualitative criterion. States of ecological variables that are defined qualitatively (e.g. Low, Medium, High), limit the potential for future updating of models with empirical data so that the 'Bayesian' aspect of the BDNs is lost. Although qualitative/expert models are often considered to be complementary to quantitative model-based assessments, these latter models rarely have the capacity to accommodate, or be informed by, rapidly growing data sets (Clark 2005). Comparison of expert and data derived parameters against existing (and future) data is also limited (Pollino *et al.* in press).

In BDNs, expert judgment should not been seen as a substitute for data or research, rather it can assist decision-making before all the necessary science is known (Morgan and Henrion 1990). We argue that all ecological models for environmental management should fit into a cycle of adaptive management, exploiting the Bayesian method of model parameterisation (and evaluation).

3.2 Imprecise Probabilities

We recognise that often precise estimates of probability cannot be elicited due to considerable knowledge gaps and inherent uncertainties. To address this, Failing *et al.* (2004) elicited quantitative estimates of fish biomass responses to flow regimes, but bounded these estimates within a confidence interval. This promoted the assessment of the benefits of management alternatives, given considerable uncertainties. Although this was done for a decision tree, a similar approach could be used for BDNs. A similar approach to elicitation was used in Pollino *et al.* (in press).

Sikder *et al.* (2006) developed a formal approach to combining expert information with empirical data. They used elicited quantitative information on the risk of species invasions from experts using rough set and evidence theory (via imprecise probabilities and Bayesian reasoning). Other elicitation and analysis methods that may be useful in such situations are imprecise probabilities, interval analysis, fuzzy set theory and Dempster-Shafer theory (Bier *et al.* 1999).

In complex BDNs models, it may be feasible to focus elicitation efforts on defining quantitative thresholds of importance, concentrating on the important parts of a probability curve (e.g. the tails in a risk assessment) (Bier *et al.* 1999). This can be particularly relevant for ecological parameters, such as setting thresholds of toxicity to fish in a mine-impacted stream.

4. MODEL EVALUATION

Model evaluation is another critical element often overlooked in building BDNs. Testing a detailed model against empirical data is a crucial aspect of the modelling process (Walters 1997). 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; Pollino *et al.* in press). 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.* in press).

Unfortunately, large data sets are not always available (often the case for ecological/biological assessments), but some testing is better than none. Indeed, without empirical data, the benefits of implementing and using quantitative models cannot be fully realised, particularly as the accuracy of how well a model represents a system cannot be assessed. The acquisition of empirical data, collected via adaptive management processes, should be seen as crucial for model evaluation (Sobehart *et al.* 2001). Indeed, the use of Bayesian statistical inference demands that not only are models confronted with empirical data, but also their assumption on how systems are structured is also challenged.

Although peer review of models by independent experts is another form of model evaluation (Morgan and Henrion 1990; Pollino *et al.* in press), complex models that have not or cannot be tested with data should not be relied on for their management implications.

4. CONCLUSION

Expert elicitation is a useful process for revealing weaknesses in existing knowledge and serving as an indication of the quality of decision-making that is possible based on existing knowledge (Rykiel 1989). In contrast to conventional Bayesian models, many BDNs used or promoted for use in decision-making incorporate unbounded subjective and qualitative endpoints.

In BDNs, an often-perceived advantage of qualitative over quantitative systems is that their inputs (e.g. ratings of Low, Medium, High) better reflect the rough, imprecise, but useful knowledge available in practice than do overly precise numerical inputs (Cox *et al.* 2005). However, expert knowledge and judgements that are represented in value-laden terms can lead to bias, logical inconsistencies or paradoxical inference (Burgman 2005; Sikder *et al.* 2006), which can lead to conclusions that are extreme or false. For this reason we emphasise the importance of being aware of such bias.

Expert judgements in BDNs should provide an explicit and quantitative estimates about the probability and magnitude of an ecological variable (Failing *et al.* 2004). We recommend defining quantitative bounds for nodes, resulting in less ambiguity in the model, and facilitating the Bayesian updating process when new knowledge, such as empirical data, is acquired. Model evaluation should be a crucial and mandatory process in building a BDN.

To improve decision making in environmental management, expert judgment should not be regarded as a substitute for empirical data. We believe that the challenge for developers of BDNs is to: (a) produce BDN models that have the ability to combine expert knowledge with existing and future datasets (including monitoring data) and system models, and (b) to exploit the 'Bayesian' feature of BDNs by ensuring models promote adaptive management processes, along with the need for investments in directed and improved monitoring and research (Morgan and Henrion 1990; Pollino *et al.* accepted).

5.0 REFERENCES

Anderson J.L. 1998. Embracing uncertainty: The interface of bayesian statistics and cognitive pschology. *Conservation Ecology* 2, 2.

Baddeley M., Curtis A., Wood R. 2004. *An introduction to prior information derived from probabilistic judgements: Elicitation of knowledge, cognitive bias and herding*. In: Curtis A, Wood R, editors. Geological Prior Information: Geol. Soc. Lond. Special Publication 239. p 1 - 14.

Bier V.M., Haimes Y.Y., Lambert J.H., Matalas N.C., Zimmermann R. 1999. A survey of approaches for assessing and managing the risk of extremes. *Risk Analysis* 19, 83-94.

Bradshaw G.A., Borchers J.G. 2000. Uncertainty as information: Narrowing the science-policy gap. *Conservation Ecology* 4, 7.

Burgman M. 2005. *Risks and decisions for conservation and environmental management*. Melbourne: Cambridge University Press.

Clark J.S. 2005. Why environmental scientists are becoming Bayesians. *Ecology Letters* 8, 2-14.

Cooke R.M. 1991. *Experts in uncertainty: opinion and subjective probability in science*.

New York: Oxford University Press. 321p.

Cox L.A., Babayev D., Huber W. 2005. Some limitations of qualitative risk rating systems. *Risk Analysis* 25, 651-662.

Dorazio R.M., Johnson F.A. 2003. Bayesian Inference and Decision Theory - A Framework for Decision Making in Natural Resource Management. *Ecological Applications* 13, 556-563.

Dorner S., Shi J., Swayne D. 2006. Multi-objective modelling and decision support using a Bayesian network approximation to a non-point source pollution model. *Environmental Modelling & Software* in press.

Failing L., Horn G., Higgins P. 2004. Using Expert Judgement and Stakeholder Values to Evaluate Adaptive Management Options. *Ecology and Society* 9, 13.

Green D.G., Sadedin S. 2005. Interactions matter - complexity in landscapes and ecosystems. *Ecological Complexity* 2, 117-130.

Halpern B.S., Regan H.M., Possingham H.P., McCarthy M.A. 2006. Accounting for uncertainty in marine reserve design. *Ecology Letters* 9, 2-11.

Hart B.T., Burgman M., Grace M., Pollino C., Thomas C., Webb J.A., Allison G.A., Chapman M., Duivenvoorden L., Feehan P. and others. 2005. Ecological Risk Management Framework for the Irrigation Industry. Canberra: Technical Report, Land and Water Australia.

Hilborn R., Mangel M. 1997. *The Ecological Detective*. NJ: Princeton University Press.

Holling C.S., Allen C.R. 2002. Adaptive inference for distinguishing credible from incredible patterns in nature. *Ecosystems* 5, 319-328.

Jakeman A.J., Letcher R.A., Cuddy S.M. 2003. Linking science and social science for sustainable catchment management: A modelling perspective. *Development Bulletin* 63, 24-27.

Korb K.B., Nicholson A.E. 2004. *Bayesian Artificial Intelligence*. London: Chapman and Hall / CRC Press. 364 p.

Morgan M.G., Henrion M. 1990. *Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis.* Cambridge, UK: Cambridge University Press. 332 p.

Neuhauser C. 2001. Mathematical challenges in spatial ecology. *Notices of the AMS* 48, 1304-1314.

Newman M.C., Evans D.A. 2002. *Enhancing Belief during Causality Assessments: Cognitive Idols or Bayes's Theorem*. In: M.H. Roberts J, Newman MC, Hale RC, editors. Overview of Ecological Risk Assessment in Coastal and Estuarine Environments. New York, New York, USA: Lewis Publishers. p 73 - 96.

Piattelli-Palmarini M. 1994. *Inevitable Illusions. How Mistakes of Reason Rule Our Minds.* New York: John Wiley & Sons.

Pollino C.A., Hart B.T. 2005. Bayesian approaches can help make better sense of ecotoxicological information in risk assessments. *Aust. J. Ecotox.* 11, 57-58.

Pollino C.A., White A.K., Hart B.T. accepted. Examination of conflicts and improved strategies for the management of an endangered Eucalypt species using Bayesian networks. *Ecological Modelling*.

Pollino C.A., Woodberry O., Nicholson A.E., Korb K.B., Hart B.T. in press. Parameterisation and evaluation of a Bayesian network for use in an ecological risk assessment. *Environmental Modelling & Software*.

Popper K. 1972. *Objective knowledge. An evolutionary approach.* Oxford: Claredon Press.

Reckhow K. 2002. Bayesian Approaches in Ecological Analysis and Modeling. http://www2.ncsu.edu/ncsu/CIL/WRRI/about/reckhow/Bayesapproach.pdf.

Rykiel E.J. 1989. Artificial intelligence and expert systems in ecology and natural resource management. *Ecological Modelling* 46, 3-8.

Salles P., Bredeweg B., Araujo S. 2006. Qualitative models about stream ecosystem recovery: Exploratory studies. *Ecological Modelling* 194, 80-89.

Savage L.J. 1971. Elicitation of personal probabilities and expectations. *Journal of the American Statistical Association* 66, 783-801.

Schreiber E.S.G., Bearlin A.R., Nicol S.J., Todd C.R. 2004. Adaptive management: a synthesis of current understanding and effective application. *Ecological Management and Restoration* 5, 177-182.

Sikder I.U., Mar-Sarkar S., Mal T.K. 2006. Knowledge-based risk assessment under uncertainty for species invasion. *Risk Analysis* 26, 239-252.

Sobehart J., Keenan S., Stein R. 2001. Benchmarking quantitative default risk models: A validation methodology. *ALGO Research Quarterly* 4, 57-71.

Walters C. 1997. Challenges in adaptive management of riparian and coastal ecosystems. *Conservation Ecology* 2, URL: http://www.consecol.org/vol/iss2/art1/.

Wang H., Dash D., Druzdel M.J. 2002. A Method for Evaluating Elicitation Schemes for Probabilistic Models. *IEEE Transactions on Systems, Man, and Cybernetics - Part B: Cybernetics* 32, 38-43.