Development Of Criteria For Simplifying Ecological Risk Models

[1]**Thomas, C.**, [1]**B. Hart**, [2]**A. Nicholson**, [1]**M. Grace**, [3]**J. Brodie and** [1]**C. Pollino**

[1]Monash University WSC, [2]Monash University CSSE, [3]James Cook University ACTFR, E-mail: Colette.Thomas@sci.monash.edu.au

Keywords*: model simplification; risk prioritization; Bayesian Network; decision support; seagrass*

EXTENDED ABSTRACT

Tropical seagrass habitats of the Great Barrier Reef are influenced by a complex suite of parameters. Recently there has been particular interest in the impact of land-derived runoff to the long-term viability of tropical seagrass habitats. Seagrass ecosystems are highly variable and poorly understood. A decision support tool that copes sufficiently with knowledge gaps and uncertainty was required to support the management of this complex stochastic system. We chose to develop a quantitative Bayesian Network (BN) as the risk management decision support tool for tropical seagrass. The objective of the decision support tool was to improve understanding of the current state of the seagrass ecosystem at risk, the impact of multiple threats to seagrass, and/or the impact of multiple management choices on seagrass health. A Bayesian Network was preferred for decision support tool development because BNs can summarize small-scale, unpredictable, and unmanageable processes via probabilistic expressions which can be updated as new information comes to hand. The capacity of BNs to summarize system processes encourages analytic focus to be directed toward the most critical factors.

A significant issue that arises during the development of such BN applications is the large number of possible cause-effect linkages that can be modeled. Quantitative modeling of every possible threat to the ecological receptor of interest (which in this case is seagrass) will create a very complex model. This is a significant issue because complex models are difficult and time-consuming to parameterize and populate. The paucity of ecological data available for parameterization further complicates modeling tasks. Expert judgment can be used to fill these gaps, but the elicitation required to access this knowledge is notoriously costly and time-consuming. More complex models are also more difficult to explain and communicate to stakeholders and decision makers. This is a critical aspect of decision support tools, which are designed to be used by decision makers (i.e. managers) rather than technical experts. Inability to foster adequate understanding and acceptance of the tool among users will compromise decision support tool uptake and utilization.

Clearly there is a need to simplify and focus BN modeling tasks. The best way to simplify the BN is to minimize the number of factors (representing threats) requiring parameterization. Within the context of the domain, this becomes a question of determining which system components are likely to be insignificant for achieving decision makers' objectives. The inclusion of these low-priority factors from subsequent phases of BN modeling should be prevented. However the process used to make such modeling decisions can strongly influence the final ranking of each factor. The decision making process can thus affect the credibility of both the ranking and of the decision support tool itself. Prioritization processes for models have been developed elsewhere, however they commonly approach the task from a broad, top-down perspective directed towards ranking risk issues. We found this perspective unhelpful for prioritization of ecological factors within the issue we are modeling.

Here we present a new bottom-up prioritization approach for BN model simplification. We found that a qualitative five-phased system kept the process simple, structured and focused. Mandatory documentation of evidence used (or not) to support prioritization decisions increased the rigor and consistency of the process, bolstered credibility of the outcomes among experts, and provided an audit trail. Application of the process significantly reduced the size and complexity of the seagrass conceptual model and simplified BN model construction. Comprehensive expert input was vital in the conceptual model simplification process.

1. INTRODUCTION

Our knowledge of the complex mechanisms that impact on ecological health is poor, and our ability to predict the impacts of anthropogenic and other threats is limited. Few predictive tools are available to accommodate both the complexity and uncertainty of these relationships. Bayesian Networks (BNs) are able to address these issues better than most modeling approaches (Stow & Borsuk 2003), and were therefore chosen to provide the technological basis of a decision support tool for seagrass management.

Seagrasses of the Great Barrier Reef are considered at risk from a range of threats, including river-borne land-derived contaminants such as suspended particulate material, nutrients and pesticides (Brodie 2001). To develop a BN, Hart et al. (2005) and Pollino et al. (2005) recommend that a conceptual model of the issue be developed prior to quantitative BN modeling. Typically, however, conceptual models of ecological risk issues are too complex to be easily converted into a meaningful and tractable BN.

The state of health for an ecosystem is determined by a set of physiological, ecological and anthropogenic factors. These factors interact, but do not exert equal influence over the health of the ecosystem. Some will dominate the system, others will mediate dominant influences and the role of others will be almost imperceptible. Clearly, the most influential factors in a system have the highest priority for inclusion in predictive models. Thus the model builder is faced with a set of modeling decisions even before the quantitative modeling has begun: Which factors should be included for further modeling, and which excluded? Here we discuss a robust process for prioritizing factors to be included in BN models for risk management.

1.1. Why is a prioritization method needed?

The need to prioritize factors for inclusion in a quantitative BN is clear. However, the simplification process can present a difficult problem. The relative rankings of factors is complicated by uncertainty; evidence available for decision making can be incomplete, subjective or conflicting; and no single 'correct' result exists. In such cases the process of decision making becomes particularly important (Vlek 1984).

The dependence of risk prioritization outcomes on the methods (decisions) used to perform the rankings has been demonstrated previously in conservation ecology (Burgman et al. 1999). Such decision-making processes will ultimately involve human judgment and are therefore prone to the cognitive error and bias of the decision-maker (Burgman 2005). However, most of the previous ranking efforts have not been undertaken systematically; this compromises their credibility and reduces their chances of implementation (Florig et al. 2001).

If the credibility of the foundation is compromised, then the credibility of the model is also compromised. Procedures for improving the credibility of prioritization processes have been covered well in the top-down risk prioritization literature. Criteria developed for risk prioritization processes (Fischhoff 1995, Kadvany 1995, Florig et al. 2001) relevant to the current study can be summarized:

- Systematically consider best available knowledge,
- Reflect uncertainties of the knowledge,
- Identify the connections between facts and value judgments,
- Internally consistent,
- Procedurally transparent,
- Acceptable to stakeholders in terms of the process used and the outcome,
- Describe the level of agreement & the sources of disagreement among stakeholders.

Consideration of human health issues and social and economic impacts were excluded from this list as they were beyond the scope of the study.

1.2. The risk context, and case study

Determination of low-priority factors is always dependant upon the context of the particular problem in question. Case studies are a useful way to provide this context. We used the Herbert River catchment, located in the monsoonal tropics of north Queensland, as the case study for development of the decision support tool. Land use in the Herbert River catchment is dominated by beef and sugar production but World Heritage rainforest and urban areas are also present. The Herbert River flows into Hinchinbrook Channel and the Great Barrier Reef World Heritage Area, which contains extensive coral reefs and seagrass meadows. Seagrasses support commercial prawn and fin-fishery industries as well as populations of threatened species including dugong (*Dugong dugon*) and green sea turtles (*Chelonia mydas*). The long-term viability of the meadows is therefore considered a conservation priority (Haynes et al. 1998, Brodie et al. 2001). However many features of the Herbert catchment threaten seagrass health (Haynes et al. 1998, Brodie et al. 2001). The prioritization of risk factors dealt with here is the first phase of a larger project involving the development of a quantitative BN decision support tool for risk management of seagrass.

2. THE PRIORITIZATION PROCESS

Powerful machine learning techniques such as CaMML can be used to simplify existing BNs (Korb & Nicholson 2004). Although these are excellent tools for small, data-rich models with relatively low uncertainty, more complex BN contexts require some simplification prior to quantitative model construction. Approaches for simplification of BN model structure have been poorly documented. Here we formalize a methodology for prioritizing factors for inclusion into a BN structure.

2.1. Top-down vs. bottom-up prioritization

Early in this study it was found that existing approaches for ecological threat prioritization and modeling were inappropriate. Most risk prioritizations are undertaken top-down, with the objective of determining which issue (e.g. water quality) requires priority regulatory attention (U.S. EPA 1990, Feldman et al. 1999, Haimes et al. 2002, Pollard et al. 2004).

However ecological risk assessment can be approached from a different perspective, using bottom-up approaches, particularly when the objective of the assessment is protection of an iconic species. The issue can be considered in terms of the viability of the threatened species i.e. a value-based, bottom-up perspective. In instances such as these, where a single ecological endpoint (i.e. value) has been identified to be of significance, judgment about the relative importance of different ecological values is no longer required. This approach can be adopted where a focal endpoint is identified, for example native fish abundance (Pollino et al. 2004) or wetland species richness (Hart et al. 2003).

Other risk ranking approaches have also addressed the importance of ecological value (e.g. Pollard et al. 2004, Willis et al. 2004); however these were still concerned with ranking risks, where risks may involve a range of ecological values. Here our focus is the identification of factors (e.g. threats, stressors), influential to a given ecological value, for priority management attention.

Decision support tools are required when decision problems are complex or uncertain. A decision problem exists when the present state (e.g. of the ecosystem) does not match the state we desire (Figure 1a) or when the present state is feared to worsen (Figure 1b; Bartee 1973). Working from the knowledge of the desired state (e.g. sufficient seagrass) allows inference about ways to prevent or reverse negative change.

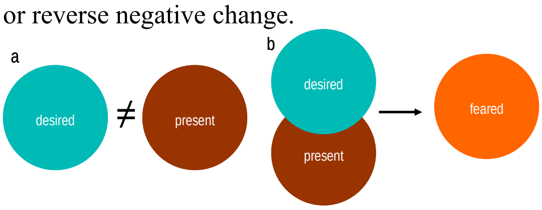

Figure 1. Problem states and trajectories.

A problem is solved when there is no difference between the present state and the desired state, or when a feared state is prevented from occurring (Bartee 1973). Logically then, a good decision support tool will also identify our understanding of how to achieve the desired state in order to identify the factors causing negative change. Existing environmental management objectives (Haynes et al. 1998, Brodie et al. 2001) were used as the basis for excluding low-priority factors.

Value judgments are unavoidable during risk and threat ranking (Fischhoff 1995, Kadvany 1995, Hart et al. 2005). Application of a 'value-focused approach' (Keeney 1992) immediately constrains the scope of the risk analysis to only those factors relevant to the ecological endpoint(s). This perspective leads decision makers to work 'backwards' from an ecological value to risk factors and their management.

3. A BOTTOM-UP PRIORITIZATION APPROACH

A five-tiered process for factor prioritization was created to work through a rough hierarchy of system specificity, described in terms of primary, secondary and tertiary factors controlling seagrass ecology (Figure 2). All biological organisms are unavoidably exposed to, or rely on, a set of fundamental factors for survival (e.g. light, nutrients). Excess or insufficient supply of these factors detrimentally affects organism viability, and all beneficial and adverse impacts are mediated or expressed through these factors.

Secondary factors are those that directly influence primary factors and/or the endpoint, and are loosely classified as either ecological (i.e. biological, geographical, or meteorological) or anthropogenic (i.e. human activity). Secondary factors are more specific to the context of any particular risk than primary factors. Tertiary factors do not directly influence the endpoint or the primary factors. Tertiary factors are determined by the temporal and spatial location of the risk assessment, and likely to be the most context-specific factors in the system.

The three factor levels and their interrelationships were graphically modeled. This was followed by a phase of explicit simplification (Phase Four), then a phase of critical review and verification (Phase Five).

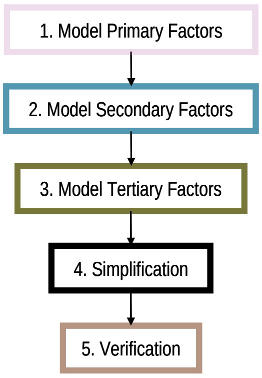

Figure 2. Five-phased prioritization approach.

The approach was simple but evidence-based, and provided an audit trail. Data and observations, background information, expert judgment and local knowledge (Scheiner 2004) were all counted as evidence. All evidence types were considered equally valid; if some factors were better known or studied than others this did not influence their treatment during prioritization. The purpose of the five phases was to generate a simple conceptual model of the issue, from which a quantitative BN could later be developed.

The process ensured obscure or poorly-understood threats were not overlooked or dismissed without due scrutiny. Development of the conceptual model was undertaken using the software (i.e. Netica; Norsys Inc. 2000) planned for BN development. This reduced duplication of effort into the next phase, and provided an intuitive graphical interface for communication of the process in the expert workshop (Phase 5). Netica represents cause-effect relationships with a directed arrow pointing from the 'cause' variable to the 'effect' variable. Because the software only deals with acyclic relationships, feedback loops were excluded from the conceptual model.

Phase One: Represent primary factors.

The basic (primary) factors required for seagrass survival and their interrelationships were identified in Phase One. Identification of these most critical system components was therefore undertaken first. These factors do not operate in isolation but interact. Interactions believed to exist among the listed factors were also graphically represented (Figure 3). The relevance of each factor, its interactions with other factors, and details of the information source(s) were documented.

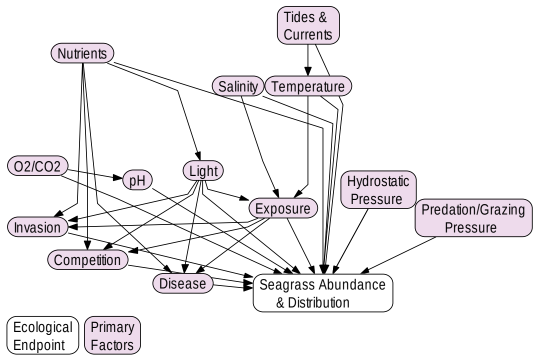

Figure 3. BN structure for seagrass case study after undertaking Phase One.

Phase Two: Represent secondary factors.

Factors that could affect seagrass directly or that could directly modify any physiological factor were identified in Phase Two. These secondary factors were added to the model derived in Phase One (Figure 4).

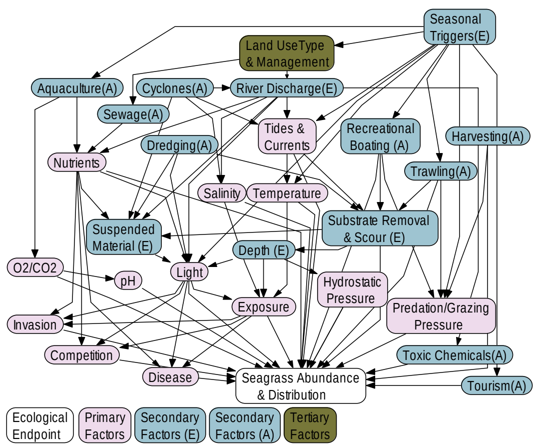

Figure 4. BN structure after Phases Two and Three for the seagrass case study.

Interactions believed to exist among and between the primary and secondary factors were indicated on the graph. The graphing task was simplified by formulating each secondary factor as either an ecological (Figure 4, nodes marked (E)) or anthropogenic (Figure 4, nodes marked (A)) cause. The relevance, interactions and information source(s) for each factor were documented as described for Phase One.

During Phase Two the number of factors in the model roughly doubled, from the initial 13 factors to a total of 27 factors (Figure 4, Table 1). As expected for an ecological model, it was the links between factors that contributed the most to the complexity of the model, which increased from 28 to 67 links in total (Table 1).

Phase Three: Represent tertiary factors.

Causal pathways were identified for each factor, and where necessary tertiary factors were added to the model. This phase was equivalent to asking, "What other general processes, events or factors can change the influence that (say) 'River Discharge' has upon 'Seagrass Abundance & Distribution'?". Evidence to support the inclusion of each of these factors and interrelationships were documented as described in Phase One. Only one tertiary factor was added and linked with three secondary factors, i.e. 'Land Use Type & Management' (Figure 4). At the conclusion of Phase Three causal pathways to 'Seagrass Abundance and Distribution' were dominated either by uncontrollable ecological factors, which represent the system's residual (background) risk, or anthropogenic factors.

Phase Four. Simplify the model.

The evidence was reviewed and the relevance of each factor at the study site was rated 'low' or 'high'. A factor was considered relevant if it had been associated with significant negative impacts in the study area or neighboring systems (within 400 km), or if data existed to show that impact conditions were likely to occur in the study area, or if a factor was likely to mediate (amplify or diminish) the influence of other factors upon the seagrass. Significant negative impacts to seagrass include reversible loss of seagrass abundance or distribution in the medium term (5-10 years), or worse.

Completion of Phases One to Three resulted in a descriptive model containing 28 factors and many more relationships between factors. Application of the simplification process described in Phase Four drastically reduced model complexity. Sixteen low-priority factors were removed, which eliminated 45 links (Figure 5, Table 1).

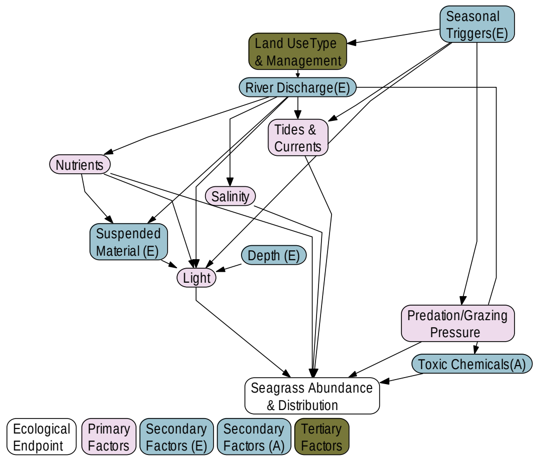

Figure 5. Simplified BN structure after Phase Four.

Phase Five: Verification.

In Phases One to Three a conceptual model of the key factors in the system was constructed. In Phase Four, factors least relevant to the seagrass endpoint were filtered from the model (Figure 6). Evidence collected to support culling decisions were collated and presented with the simplified model at an expert workshop in Phase Five.

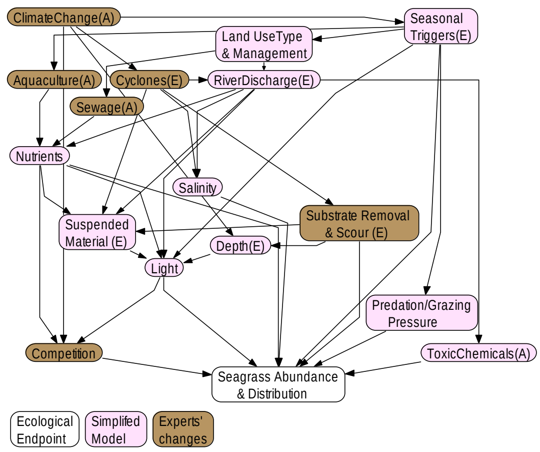

Figure 6. Simplified BN structure after workshop consultation in Phase Five.

Eight experts in seagrass ecology and management critically reviewed the culled model and the evidence used for its development. Provision of evidence supporting the modeler's prioritization decisions increased the acceptability of the model to experts. Omissions or additions of factors were discussed and when agreed upon were reflected by making appropriate changes to the model. Irresoluble points of conflict between experts were represented by separate models when required.

Table 1. Total numbers of factors and links in the conceptual model per phase.

Number of links	Phase 1	Phase 2	Phase 3	Phase 4	Phase 5
primary → endpoint	13	13	13	5	5
primary → primary	15	15	15	1	2
secondary → endpoint	-	6	6	1	3
secondary → primary	-	21	21	14	11
primary → secondary	-	2	2	1	1
secondary → second'y	-	12	12	1	11
tertiary → primary	-	-	0	0	0
tertiary → secondary	-	-	2	1	2
primary → tertiary	-	-	0	0	0
secondary → tertiary	-	-	1	1	1
Total no. factors[1]	13	27	28	12	16
Total no. links	28	67	70	25	36

[1] excluding the endpoint

Some prioritizations were modified by experts during workshop discussions. No factors were removed but five factors ('Cyclones', 'Sewage', 'Aquaculture', 'Substrate Removal & Scour', and 'Competition') were reinstated and one new secondary factor ('Climate Change') was inserted. The final model (Figure 6) contained 16 factors and 36 links, but still contained 57% of the factors and 51% of the links identified in Phase Three (Figure 4). We found that the bottom-up approach and audit trail facilitated reprioritization during the expert workshop.

3.1. Model summary

A five-phased bottom-up approach was used to simplify a complex descriptive model to a smaller, more focused model of roughly half the size. The simplified model was required as a starting point for the next stage in the construction of a quantitative BN decision support tool. Therefore factors that were qualitatively modeled here as high priorities for seagrass may, during iterative quantitative modeling and analysis tasks in the following stage of BN development, prove to be relatively insignificant. Priority factors may also change as the understanding of the risk issue grows or if new factors are discovered.

The hierarchical level of a factor could be roughly correlated with its distance from the endpoint. Expert input was found to be critical to the prioritization process. Ideally the prioritization process should include a broader stakeholder consultation process (i.e. public, fisheries, tourism etc). If full stakeholder consultation had been feasible, the model could better account for local knowledge. Future applications will need to address this to improve BN acceptance and implementation among non-expert stakeholders.

4. CONCLUSION

The development of a Bayesian Network had been planned to support risk management decisions for the protection of coastal seagrasses. However, the complexity of the issue made the task of modeling all the factors in the system intractable. To overcome this problem and provide strategic focus to the modeling, factors needed to be prioritized prior to their inclusion in a quantitative BN. A five-phased qualitative system was developed to distinguish between likely significant and inconsequential factors to seagrass. We did not use traditional risk-ranking methods, but approached the task from the receiving end of the issue (i.e. bottom-up). This forced a re-think that helped focus factor prioritization decisions to only those that were specific to the endpoint of interest. Although the prioritization process was qualitative, collection and collation of evidence used for prioritization lent transparency and credibility to the process. Documentation of evidence facilitated expert elicitation and increased expert acceptance of the final model.

The process outlined here was developed to prioritize biophysical factors to an ecological endpoint. Within the constraints of the research, the new approach met the requirements of risk prioritization criteria. Future applications would however, benefit from broad stakeholder involvement, and inclusion of social and economic factors. The model will be quantified and further refined in the next phase.

5. ACKNOWLEDGEMENTS

This work was conducted with a scholarship from the Monash University Water Studies Centre, and supported by the Great Barrier Reef Marine Park Authority (GBRMPA) and the Australian Centre for Tropical Freshwater Research (ACTFR), James Cook University. The authors would like to thank the reviewers for their valuable comments.

7. BIBLIOGRAPHY

Bartee, E.M. (1973), A holistic view of problem solving, *Management Science*, 20(4), 439-448.

Brodie, J., M. Furnas, S. Ghonim, D. Haynes, A. Mitchell, S. Morris, J. Waterhouse, Yorkston H., D. Andas, D. Lowe, and M. Ryan (2001), *Great*

Barrier Reef Catchment Water Quality Action Plan, Townsville, Great Barrier Reef Marine Park Authority.

Burgman, M. (2005), *Risks and Decisions for Conservation and Environmental Management*, Cambridge, Cambridge University Press.

Burgman, M.A., D.A. Keith, and T.V. Walshe (1999), Uncertainty in comparative risk analysis for threatened Australian plant species, *Risk Analysis*, 19(4), 585-598.

Feldman, D.L., R.A. Hanahan, and R. Perhac (1999), Research: Environmental priority-setting through comparative risk assessment, *Environmental Management*, 23(4), 483-493.

Fischhoff, B. (1995), Ranking risks, *Risk: Health, Safety and Environment*, 6, 191-203.

Florig, H.K., M.G. Morgan, K.M. Morgan, K.E. Jenni, B. Fischhoff, P.S. Fischbeck, and M.L. DeKay (2001), A deliberative method for ranking risks (i): Overview and test bed development. *Risk Analysis*, 21(5), 913-921.

Haimes, Y.Y., S. Kaplan, and J.H. Lambert (2002), Risk filtering, ranking, and management framework using hierarchical holographic modeling, *Risk Analysis*, 22(2), 383-397.

Hart, B.T., P.S. Lake, J.A. Webb, and M.R. Grace (2003), Ecological risk to aquatic systems from salinity increases, *Australian Journal of Botany*, 51, 689-702.

Hart, B.T., M. Burgman, M. Grace, C. Pollino, C. Thomas, and J.A. Webb (2005), Risk-based approaches to managing contaminants in catchments, *Human and Ecological Risk Assessment*, **in press**.

Haynes, D., D. Kellaway and K. Davies (1998), Protection of wetlands adjacent to the Great Barrier Reef, Great Barrier Reef Marine Park Authority, Workshop Series No. 24, pp. 128.

Kadvany, J. (1995), From comparative risk to decision analysis: Ranking solutions to multiple-value environmental problems, *Risk: Health, Safety and Environment*, 6, 333-358.

Keeney R.L. (1992), *Value-focused thinking: A path to creative decision-making*, Harvard University Press, 416 pp., Cambridge.

Korb, K.B. & A.E. Nicholson 2004, *Bayesian Artificial Intelligence*, Chapman & Hall/CRC, 364 pp., Boca Raton.

Norsys Inc. (2000), *Netica*, http://norsys.com.

Pollard S.J.T., R.V. Kemp, M. Crawford, R. Duarte-Davidson, J.G. Irwin, and R. Yearsley 2004, Characterizing environmental harm: Developments in an approach to strategic risk assessment and risk management, *Risk Analysis*, 24(6), 1551-1560.

Pollino, C.A., P. Feehan, M.R. Grace, and B.T. Hart (2004), Fish communities and habitat changes in the highly modified Goulburn catchment, Victoria, Australia. *Marine and Freshwater Research*, 55, 769-780.

Pollino, C.A., O. Woodberry, A.E. Nicholson, and K.B. Korb (2005), Parameterising Bayesian Networks: A case study in ecological risk assessment, *Proceedings of the 2005 International Conference on Simulation and Modelling (SIMMOD05)*, Thailand.

Scheiner, S.M. (2004), Experiments, observations, and other kinds of evidence, *The nature of scientific evidence: Statistical, philosophical and empirical considerations*, (Eds) M. Taper & S.R. Lele, University of Chicago Press, pp. 51-69, Chicago,

Stow, C.A. & M.E. Borsuk (2003), Enhancing causal assessment of estuarine fishkills using graphical models, *Ecosystems*, 6, 11-19.

U.S. EPA (1990), *Reducing Risk: Setting Priorities and Strategies for Environmental Protection*, Washington, D.C., EPA Science Advisory Board, SAB-EC-90-021.

Vlek, C. (1984), What constitutes 'a good decision'?: A panel discussion among Ward Edwards, Istvan Kiss, Giandomenico Majone and Masanao Toda., *Acta Psychologica*, 56(1-3), 5-27.

Willis, H.H., M.L. DeKay, M.G. Morgan, H.K. Florig, and P.S. Fischbeck (2004), Ecological risk ranking: Development and evaluation of a method for improving public participation in environmental decision making. *Risk Analysis*, 24(2), 363-378.