

BAYESIAN APPROACHES CAN HELP MAKE BETTER SENSE OF ECOTOXICOLOGICAL INFORMATION IN RISK ASSESSMENTS

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Ecological risk assessment is an increasingly used process for estimating and characterising the likelihood and the effects of human actions on ecosystems. The process is aimed at improving decision-making, particularly in quantifying the expected magnitude of effects and the uncertainty in these predictions (Suter 1993; Burgman 2005; Hart et al. 2005). Sources of uncertainty in a risk assessment include our poor understanding of complex ecosystems and the general paucity of available data on these systems. Until recently there have been few methods available that enable us to quantify risk, while explicitly acknowledging these uncertainties. Because of this, little progress has been made in developing ways to assess the effects of multiple hazards within ecosystems, with most risk assessments being primarily focussed on single hazards or stressors (Hart et al. in press).

This is particularly so in the case of toxic contaminants, the domain of ecotoxicologists. Methodologies for characterising risk due to toxicants range from the use of fixed safety factors (e.g. application factors) to species sensitivity distributions (SSDs). This latter approach is recommended in the ANZECC & ARMICANZ (2000) water quality guidelines. Both the fixed factor and SSD methods are primarily focussed on analysing the risks due to single toxic stressors, and typically use lethal or sublethal (e.g. growth, reproduction) endpoints for single species and single toxicants generated in strictly controlled laboratory settings and under specified conditions. Such datasets are often limited and sparse, and consequently they need to be manipulated in order to represent the complex biological communities making up natural ecosystems.

Some of the extrapolations applied to toxicity datasets include the use of acute data to predict chronic toxicity effects (i.e. the acute to chronic ratio), toxicity data from non-indigenous species used to represent resident biota, and data with different endpoints (i.e. mortality, growth, reproduction) aggregated with little regard to how this may impact on findings. Unfortunately, it is common that the assumptions behind these manipulations are left implicit and poorly documented. The deficiencies of SSDs due to assumptions made during analyses and as a consequence of restricted datasets have been well documented in the scientific literature (e.g. Calow and Forbes 2003; Pennington 2003; Verdonck et al. 2003; Duboudin et al. 2004).

There are now no excuses for not accounting for the uncertainties associated with the data and the estimates of protection levels, since there are a range of statistical approaches available to estimate the uncertainty intervals around SSDs (Verdonck et al. 2003; Duboudin et al. 2004; Bossuyt et al. 2005). Estimates of uncertainty associated with SSDs are currently not a requirement of the ANZECC

& ARMICANZ water quality guidelines, despite estimation of uncertainty being an essential component for assessing risk. Indeed, the recognition and quantification of uncertainty is critical for ecosystem managers faced with making decisions to minimise risks (Marks et al. 2003). It is vital that estimation of uncertainty is incorporated into future revision of the water quality guidelines. Despite their limitations, SSDs are potentially powerful tools in setting water quality guidelines for new chemicals.

As noted above, there are few real situations in catchment management where the risks to ecosystems are dominated by a single toxicant – the most common situation is that there are multiple stressors or hazards that impact on the ecosystem. There are few studies where SSDs have been applied in such situations. We are also concerned that field-derived data are rarely used in Australia to produce SSDs, probably because this is not clearly recommended in the ANZECC & ARMICANZ water quality guidelines. Field survey records, such as pre-impact versus post-impact data, or across a gradient of the stressor(s), are particularly relevant for assessing contaminants such as increased salinity due to irrigation, or increased metal concentrations due to mining. Often field census data can also be used for anthropogenic chemicals, such as pesticides. Use of field data can enable a more integrative analysis of environmental degradation, acknowledging that contaminants rarely occur in isolation. Field data have been used previously to derive SSDs for salinity (Hart et al. 2003), but few studies have investigated combining laboratory and field datasets (Hose and Van den Brink 2004). However, it should be noted that sufficient field datasets are often unavailable, or have associated uncertainties.

Bayesian statistics is one of a number of methods for explicitly analysing uncertainties. In particular, Bayesian Networks (BNs) have emerged as a flexible and pragmatic approach for applying Bayesian statistical analysis to complex systems. They are increasingly being used as an integrative tool, enabling the quantification of risk where multiple hazards exist (Cain 2001). BNs, unlike SSDs, can combine field and laboratory data and expert knowledge from a combination of sources (including that generated from SSDs), while explicitly acknowledging the uncertainty in that data and knowledge, and the inherent variability of the target ecosystem. A very important characteristic of BNs is that they can be readily updated as new data and knowledge are gained, a fundamental component of the risk assessment cycle.

Bayesian Networks look like cause-effect conceptual models, with boxes (nodes) representing the important system variables, and a series of arrows connect these variables

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and representing the direct causal linkages based on process understanding or statistical associations (Cain 2001). Conditional probabilities are used to represent the strength of the relationship between nodes, considering every possible combination of values of parent nodes. Prior information distributions are assigned to each variable, which can be determined using data or expert opinion, or a combination of both. Uncertainty is embodied in these distributions, thus the flatter the distribution, the higher the uncertainty. Upon updating a BN, a posterior probability distribution is calculated. Prior distributions are updated to represent a new set of observations (e.g. data or knowledge). BNs can be used to calculate how probable events are, and how these probabilities can change given subsequent observations or system changes (Korb and Nicholson 2004).

For complex systems, the magnitude of the uncertainty can be particularly high, and result in the probability distributions for the predicted endpoints being too broad for reliable decisions to be made (Brand and Small 1995). In these cases, improved model predictions and enhanced decision reliability can only be achieved if the uncertainties are reduced by further data collection or other research efforts. The BN allows this data collection to be much better targeted at addressing specific questions.

We are currently running a project to assess the impacts of a copper mine operating in Papua New Guinea. A Bayesian Network is being constructed to quantify the likelihood of exposure and the impacts of increased bioavailable metals in the water column and loss of structural habitat to indigenous fish communities. Both laboratory-derived toxicity data and long-term field data are being used in the assessment. Fisheries monitoring data are being used to examine changes in abundance and biomass of fish communities over time, given changing environmental condition. Previously defined toxicity data thresholds (including thresholds generated from SSDs) for each metal type and loss of structural habitat thresholds are also defined as individual outputs of the network, and changes in biomass can be examined in relation to threshold data to examine synergies (or otherwise). The Bayesian network is specifically designed to fit in with existing monitoring programs, facilitating the iterative and learning process. Subsequently, the model will be used to represent new situations as they arise, and uncertainties in model predictions can be reduced as model relationships are tested and refined. The model can also be used to identify potential gaps in knowledge and data (research and monitoring).

In conclusion, we have argued that a number of changes are needed if ecotoxicological information is to contribute more meaningfully in ecological risk management. In particular, there must be increased effort in determining the uncertainty associated with SSDs, and field data need to be used together with laboratory-derived ecotoxicological data. Additionally, ecotoxicologists need to adopt integrative methods, such as Bayesian Networks, to allow their data to be combined with other available datasets and knowledge to more fully address natural resource management issues.

REFERENCES

- ANZECC & ARMCANZ. 2000. *Australian and New Zealand Water Quality Guidelines*. Australia and New Zealand Environment and Conservation Council & Agriculture and Resource Management Council of Australia and New Zealand, Canberra.
- Bossuyt BTA, Muysen BTA and Janssen CR. 2005. Relevance of generic and site-specific species sensitivity distributions in the current risk assessment procedures for copper and zinc. *Environmental Toxicology and Chemistry* **24**, 470-478.
- Brand KP and Small MJ. 1995. Updating uncertainty in an integrated risk assessment: Conceptual framework and methods. *Risk Analysis* **15**, 719-731.
- Burgman MA. 2005. *Risks and Decisions for Conservation and Environmental Management*. Cambridge University Press, Cambridge, UK.
- Calow P and Forbes VE. 2003. Does ecotoxicology inform Ecological Risk Assessment? *Environmental Science and Technology* **37**, 147A-151A.
- Cain J. 2001. *Planning Improvements in Natural Resources Management*. Centre for Ecology & Hydrology, Wallingford, UK.
- Duboudin C, Ciffroy P and Magaud H. 2004. Effects of data manipulation and statistical methods on species sensitivity distributions. *Environmental Toxicology and Chemistry* **23**, 489-499.
- Hart BT, Lake PS, Webb A and Grace M. 2003. Use of risk assessment to assess the ecological impacts of salinity on aquatic systems. *Australian Journal of Botany* **51**, 689-702.
- Hart BT, Burgman M, Grace M, Pollino C, Thomas C, Webb JA, Allison GA, 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.
- Hart BT, Burgman M, Grace M, Pollino C, Thomas C and Webb JA. (in press). Risk-based approaches to managing contaminants in catchments. *Human and Ecological Risk Assessment*.
- Hose GC and Van den Brink PJ. 2004. Combining the species sensitivity distribution concept for endosulfan using laboratory, mesocosm and field data. *Archives of Environmental Contamination and Toxicology* **47**, 511-520.
- Korb KB and Nicholson AE. 2004. *Bayesian Artificial Intelligence*. Chapman and Hall / CRC Press, London.
- Marks H, Coleman M and Michael M. 2003. Further deliberations on uncertainty in risk assessment. *Human and Ecological Risk Assessment* **9**, 1399-1410.
- Pennington DW. 2003. Extrapolating ecotoxicological measures from small data sets. *Ecotoxicology and Environmental Safety* **56**, 238-250.
- Suter GW. 1993. *Ecological Risk Assessment*. Lewis Publishers, Chelsea MI.
- Verdonck FAM, Aldenberg T, Jaworska J and Vanrolleghem PA. 2003. Limitations of current risk characterization methods in probabilistic environmental risk assessment. *Environmental Toxicology and Chemistry* **22**, 2209-2213.