At What Level Will Decision-Makers Be Able to Use Uncertainty Information?

Lowell, K.E.[1,2]

[1] Department of Primary Industries, PIRVic, Victoria
[2] Cooperative Research Centre for Spatial Information, University of Melbourne, Victoria

Email: kim.lowell @dpi.vic.gov.au, klowell@crcsi.com.au

Keywords: *landscape models, risk, spatial uncertainty, hydrology, dryland salinity*

EXTENDED ABSTRACT

As models are increasingly used in land management decision-making, the reliability of model outputs is increasingly scrutinised. Understandably, decision-makers believe that having access to information about model reliability will allow them to make better decisions. This paper argues that this is not necessarily true. Moreover, model developers may be ill-equipped to provide information about model uncertainty because they do not necessarily understand all of the potential sources of uncertainty.

In this paper, concepts related to risk analysis and the use of uncertainty in decision making are presented. In particular, seminal risk analysis work focussed on decision-making in the face of uncertainty is discussed. The literature cited demonstrates clearly that most decision are made using an assumption of information certainty, and there are no widely accepted paradigms or tools for making decisions using uncertain information.

These issues are discussed relative to a fictitious hydrological model applied to a fictitious catchment to identify areas that will be affected by dryland salinity. Shortcomings in conventional goodness-of-fit statistics to describe model uncertainty are discussed. In particular, if one is using spatial data, one must also contend with uncertainty in map construction, and natural variability around variables measured for each cartographic taxon. The large impact of data uncertainty on the precision of model outputs imply that, in using a well-conceived and calibrated model, one can improve the certainty of model outputs considerably by improving the quality of data inputs rather than revising or refining the model.

Aside from the difficulty of producing estimates of model uncertainty that address all types of uncertainty, it is doubtful that decision-makers would be able to use such information to make decisions. Because the information produced is excessively complex, ways must be found to analyse and summarise it if it is ever to be used by decision-makers. For example, suppose that one knows that alternative scenarios A, B, and C produce benefits of 20±3, 30±15, or 15±20 – which is the best? The answer to this question changes with the evaluation criteria – i.e., to maximise the likelihood of benefits or to minimise the likelihood of negative outcomes. This is made even more difficult if one is working with spatial data and one must implement scenarios based on a spatially optimal arrangement of scenarios.

Four major conclusions are presented:

- If a policy decision is obvious without considering uncertainty, consideration of uncertainty will probably not change the decision made.
- Model developers are not necessarily aware of many individual uncertainties and how their interactions impact model calibration and use.
- The magnitude of the impact of many sources of uncertainty is largely unknown.
- Even if uncertainty information were available, the magnitude and complexity of such information would limit its utility for decision-making unless new ways to analyze it and summarize it are developed.

This article makes it clear that one priority in modeling is for the development of improved models and minimal techniques for estimating uncertainty associated with those models. Less obvious is the central point of this paper – even with the development of techniques that provide useful estimates of model uncertainty, there is a considerable amount of work that must be done before those estimates become useful for decision-makers.

1. INTRODUCTION

Models are increasingly used to formulate public policy and plan on-ground activities. As familiarisation with models increases, policy makers are becoming savvier about the benefits and limitations of models. As a consequence, they are increasingly asking for information about the reliability of model outputs. This knowledge is desired in part to further improve their understanding of model abilities and limitations, but also to enable them to make better decisions.

But will knowledge of the uncertainty surrounding model outputs really improve their ability to make decisions? It is argued herein that this question does not, in fact, have a simple answer. Among the numerous reasons for this are:

- Sources of modelling uncertainty are poorly understood even by model developers.
- Knowledge of interactions among the myriad sources of model uncertainty is limited.
- Model uncertainty may be relatively large.
- The way model developers characterise model uncertainty is not useful for decision-makers.
- Model uncertainty may be the same for all options considered and therefore irrelevant in choosing among alternatives.

Despite these factors, it remains seductively simple to think that knowledge of model uncertainty will improve decisions. The purpose of this paper is to explore this idea in the context of models that rely on spatial data to describe landscape dynamics. Through this exploration, readers will become more aware of various sources of uncertainty, and gain insight into why the use of uncertainty may not in reality improve decisions made.

2. RISK AND DECISION-MAKING

Essentially, there is a desire to have information on uncertainty in order to better control decision risk. Modern risk analysis has its roots in the 1950s and the early 1960s when D. Ellsberg completed his Harvard doctoral dissertation ("Risk, Ambiguity and Decision" 1962, published as Ellsberg (2001)) and the seminal paper "Risk, ambiguity, and the Savage axioms" (Ellsberg 1961). These works demonstrated that personal circumstances, language, knowledge of uncertainty and other factors affect decision-making. Perhaps surprisingly, people generally choose the option for which the certainty is the highest *rather than the one that has the greatest likelihood of a positive outcome*.

This has been illustrated by the now-classic example of rewarding a subject for blindly drawing a yellow ball out of an urn containing yellow and red balls. In the example, participants are offered a choice of drawing a single ball from one of two urns. One is known to contain 50 yellow balls and 50 red balls. The only information about the second urn is that it contains *at least* 10 yellow balls. The probability of drawing a yellow ball from the first urn is 0.50 and 0.55 for the second. Most participants, however, choose to draw a ball from the first urn.

Since the late 1980s, the risk analysis community has been grappling with making decisions using what has been termed by some "imprecise probabilities" (e.g., Caselton and Luo 1992). Since that time, risk analysts have explored emerging tools such as belief theory (Caselton and Luo 1992), Bayesian networks (Borsuk *et al*. 2002) and fuzzy set theory (Cameron and Peloso 2005). Other tools for making decisions using imprecise probabilities have also been explored – e.g., decision trees (including classification and regression trees – CART) (Burgman 2005), bounding (Greenland 2004), and ranking (Paté-Cornell 1998).

This has led to further work in a number of disciplines. In the realm of cognitive decision-making, a difference between ambiguity and uncertainty has been noted (Frisch and Baron 1988) as has their effects on decision-making. Others have classified imperfect knowledge as uncertainty and imprecision (Borsuk 2005), or variability and uncertainty (Kelly and Campbell 2000). Application domains include Economics, Human Health, Environmental Contamination, and Climate Change (Van Dijk and Zeelenberg 2003, Mayer 2005, Simon *et al*. 2004, Borsuk and Tomassini 2005, respectively). Regardless of how it is characterised, the need to consider imperfect knowledge in decision-making has been recognised (Reckhow 1994).

3. MODELLING, UNCERTAINTY, AND DECISION-MAKING

The future amount of dryland salinity (DS) in a single catchment – "Catchment A" – is the context for discussing the use of uncertainty in decision-making. DS occurs in Australia as the result of the post-European conversion of woody vegetation to agricultural land. This causes the water table to rise, and soluble salts stored in the soil are brought to the surface thereby rendering the affected land unproductive.

Hydrological models with links to ground-water, topography, soil structure, landcover, and other factors are used to identify areas that will be affected by DS. Policy makers use such information to assess the severity of the problem, determine an appropriate level of response, and plan on-ground activities to mitigate the affects of DS.

For Catchment A, therefore, the first question for a policy maker is “How much land will be affected by dryland salinity?” To answer this, an appropriate hydrological model would be calibrated and run to determine the amount of land that is expected to have the water table rise to within 1.8 m of the surface. (Depth to water table is a common surrogate variable for DS.)

Suppose that an appropriate model returns the answer “100 ha.” If 100 ha is an amount considered “inconsequential” or “irreversibly catastrophic,” then there is little need to consider model uncertainty in formulating a policy response. At most, the policy maker might ask how confident the modeler is that the true value is below or above some critical threshold. In such a case, a verbal (ordinal) response of “very confident” would suffice. The key point is that in either case, the policy response might be the same – do nothing since there is little point in expending a large amount of resources.

The greatest need for uncertainty information occurs if 100 ha of DS is an amount considered to be between “inconsequential” and “irreversibly catastrophic.” If so, the decision-maker will want better information. One source of uncertainty information would be goodness-of-fit statistics for a model – e.g., R^2, the root-mean-square-error (RMSE). But consider what their use implies. A modeler might in good faith use borehole information to validate the model to produce a graph such as Figure 1. Statistical analysis indicates that the root-mean-square error of the model is 0.2 m for Depth to Watertable. Because this value is considered low in a modeling context, the modeler could conscientiously tell the policy maker that the 100 ha is “highly reliable” or “very good.” In fact, this may not be true if all sources of uncertainty are considered. Moreover, the modeler’s way of assessing “highly reliable” may have little meaning for the policy maker.

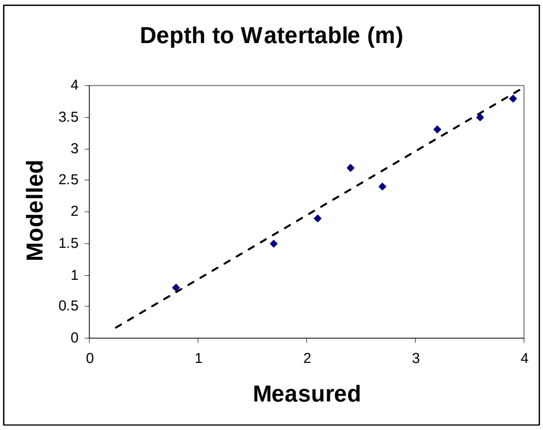


Figure 1. Comparison of model estimates with measured values to estimate model uncertainty.

One reason for this is the fact that a surrogate variable and associated threshold are used to estimate dryland salinity. Though the threshold of “1.8 m” may represent the best scientific information available about areas that will be affected by DS, this threshold may be overly conservative/liberal/generic. Hence the modeller is basing the “100 ha affected by DS” estimate not just on a model, but a threshold value that also has some uncertainty associated with it.

Related to this is the possibility that stating uncertainty as “highly reliable”, or even as an interval – e.g. “within 20%” – may not be useful for a decision-maker. Policy makers have little interest in quantitative assessments and are more likely to want to know the risk or likelihood of something being a “serious problem.” Making such an assessment requires the modeler and the policy maker to work together. The policy maker must provide a definition of what constitutes a “serious problem” – e.g. “more than 125 ha of DS.” The model developer must then convert this to risk by, for example, assuming a normal distribution of uncertainty values and referring to statistical tables that describe the normal distribution. The result would be a statement from the modeller such as “there is a 0.25 chance that there is more than 125 ha of DS in Catchment A.” Policy makers must then consider their tolerance to risk in order to arrive at an appropriate policy decision.

Yet another issue is the general nature of the model-associated uncertainty. Suppose that the uncertainty of the model used is highly sensitive to topography with the amount of error known to increase greatly on hilltops (Fig. 2). Further suppose that none of the boreholes represented on Figure 1 are located on hilltops. In such a case, it is possible that the 100 ha estimate of DS is an underestimate (Fig. 2).

Figure 2. Underestimate of dryland salinity (DS) due to sensitivity of model uncertainty to slope position.

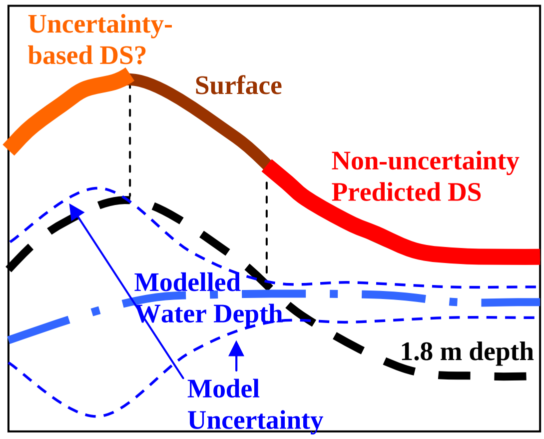
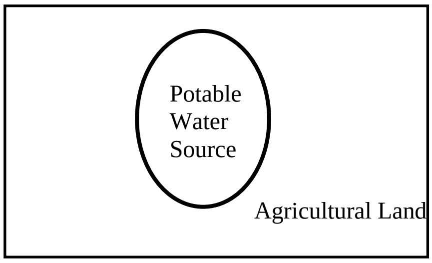


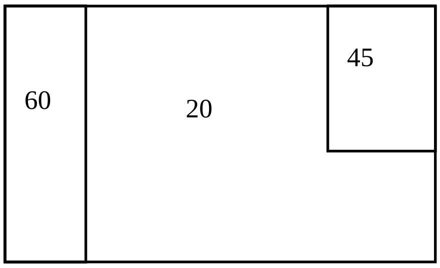
Fig. 2. Underestimate of dryland salinity (DS) due to sensitivity of model uncertainty to slope position.

Yet another set of difficulties arises if the model being employed is spatially explicit, and the policy maker is not asking "*How much* DS will occur?" but instead is asking "*Where* will the DS occur?" Suppose that Catchment A is completely covered by agricultural land with the sole exception being a source of potable water in the centre (Fig. 3a). Public funds are available for DS Protection, and it is necessary to determine where those funds will be spent. A hydrological model identifies three distinct hydrologic zones that coincide with different soil types (Fig. 3b) and is able to estimate the risk that each will be affected by DS given the uncertainties already discussed. Based on this information, it seems apparent that the western rectangle with a DS risk of 0.60 should be targeted. However, using a spatially explicit model introduces uncertainties that have not yet been considered.

Suppose that the model bases its outputs on soil permeability as represented on a soils map and associated database. In real-world procedures, soil attributes such as permeability are obtained for mapped soil types by developing a sampling scheme for each soil type, and then taking measurements from on-ground soil pits. Each soil type is sampled by more than one soil pit meaning that estimates of soil permeability for each type have natural variability. Yet for modeling purposes, the permeability of each soil type is represented using a single value – the mean of all samples – that is generally the only one used in a hydrological model. Given the natural variability in soils and other components of natural systems, the likelihood of DS should not be represented as a single value as in Fig. 3b, but should be represented to reflect the uncertainty (natural variability) around soil permeability (Fig. 4).



Community Assets



Likelihood of DS

Figure 3a) Community assets of Catchment A.
Figure 3b) Model estimate risk of dryland salinity (DS).

Construction of the soils map itself is subject to considerable uncertainty. In some taxonomies, soil taxa overlap – e.g., "Soil C is at least 70% Soil A with inclusions of Soil B of no more than 20%." Even if taxa definitions do not overlap, there is nonetheless considerable uncertainty in a soils map because in reality soil types do not change abruptly as one moves across a landscape, but instead gradually grade into each other. This means that not only are the attributes of each soil type best represented by a numerical range, but the locations of the boundary of each soil type polygon are uncertain (Fig. 4).

Modelling aside, the boundaries of the assets to protect are not always definite. Assets such as "source of potable water" do not necessarily have definitive boundaries and should be represented accordingly (Fig. 5).

Figure 4. Representations of uncertainty in model estimates of likelihood of DS that reflect soil attribute uncertainty and soil type location uncertainty.

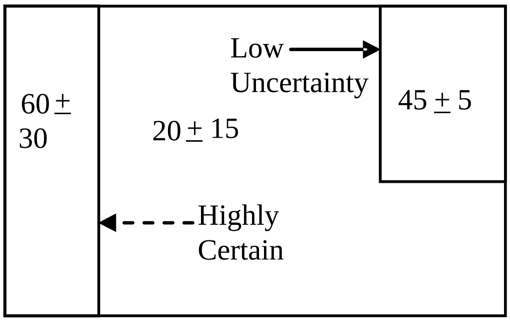
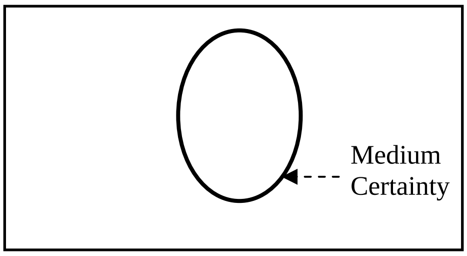


Figure 5. Uncertainty on boundary of community asset to be protected.



So given all of this uncertainty information in our fictitious example, where should DS Protection money be invested? Without consideration of uncertainty (Fig. 3b), it seems apparent that the western rectangle should be protected because it has the highest likelihood of being affected. However, consideration of uncertainty requires that information in Figures 3a, 4, and 5 be combined and the "optimal" plan for spending the DS Protection money determined from that combination of information. However, in seeking to consider uncertainty, even in this highly simplistic example, there is considerable complexity. This makes it apparent that even if uncertainty information were available, without assistance, analysis, or summarization the uncertainty information will not help a policy maker or anyone else make a better decision.

At the same time, this example was contrived to demonstrate how uncertainty information may be required to ensure that the right decision is made. A key to doing this is assessing the value of the assets to be protected – i.e., the source of potable water would be considered much more valuable than several hectares of agricultural land. Fortunately, this source of potable water is in the general area that has the lowest estimated risk of being affected by DS – 0.05 to 0.35 as opposed to 0.30 to 0.90 for the western rectangle and 0.40 to 0.50 for the northeastern rectangle. However, it is known that the boundary of the potable water source may extend beyond its mapped boundary. To the west this is not likely to be an issue because the potable water source is a long distance from a high-risk DS area, and that high-risk area has fairly definite boundaries. To the northeast, however, there exists an area having moderate DS risk but whose boundaries might extend southwest much further than mapped (or might be much further to the east). After assessing this information, it becomes apparent that DS Protection money should be spent to treat the area between the potable water source and the moderate risk northeastern rectangle (Fig. 6).

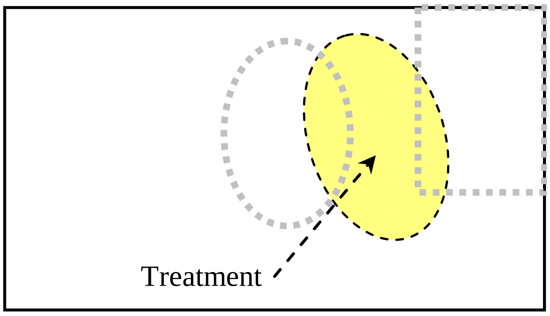


Figure 6. Proposed area to be treated to protect against DS.

4. DISCUSSION AND CONCLUSIONS

The example used herein, despite being highly contrived is nonetheless representative of issues associated with providing model users information about uncertainty. Some general conclusions can be drawn.

- If a policy decision is obvious without considering uncertainty, consideration of uncertainty will probably not change the decision made.
- Model developers are not necessarily aware of many individual uncertainties and how their interactions impact model calibration and use.
- The magnitude of the impact of many sources of uncertainty is largely unknown.

- Even if such information were available, the magnitude and complexity of uncertainty information would limit its utility for decision-making.

Given these difficulties, must policy makers resign themselves to never being able to base their decisions on the uncertainty associated with model outputs? It is argued that the answer to this question is “No.” At the very least, modelers should be able to tell users whether or not model outputs are of high or low uncertainty. Even such simplistic information would assist decision-makers by indicating if a policy decision should tend towards optimism or pessimism. This knowledge about model outputs would have to be balanced by the decision-maker’s assessment of the stakes or the consequences of a decision being wrong.

If more sophisticated uncertainty information such as that described herein eventually becomes available, analytical, optimization, or summarization algorithms and techniques will have to be developed. In a complex real-world situation, without such numerical assistance, it is doubtful that decision-makers will be able to use uncertainty information of any greater complexity than the likelihood of DS information that was presented in Figure 3.

In conclusion, decision-makers may believe they want information about the uncertainty of model outputs to improve their decision-making. Such information is in all likelihood more complex than imagined and therefore currently would be of little use to them. And modelers for their part are not always aware of the uncertainties inherent in their models and the data used to calibrate and run them. Hence, model developers may be limited in their ability to provide uncertainty information. There is considerable work to do before complex uncertainty information is available and before it can be provided to policy makers in a useful format.

5. REFERENCES

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

Borsuk, M., Stow, C. and Reckhow, K. (2002), Integrative environmental prediction using Bayesian networks: a synthesis of models describing estuarine eutrophication, Integrated Assessment and Decision Support, Lugano, Switzerland.

Borsuk, M. and Tomassini, L. (2005), Uncertainty, imprecision, and the precautionary principle in climate change assessment, *Water Science & Technology,* 52(6), 213-225.

Cameron, E. and Peloso, G.F. (2005), Risk management and the precautionary priniciple: a fuzzy logical model, *Risk Analysis,* 25(4), 901-911.

Caselton, W. and Luo, W. (1992), Decision making with imprecise probabilities: Dempster-Shafer theory and application, *Water Resources Research,* 28(12), 3071-3083.

Ellsberg, D. (1961), Risk, ambiguity, and the Savage axioms, Quarterly *Journal of Economics,* 75, 643-669.

Ellsberg, D. (2001), Risk, Ambiguity and Decision, New York, New York, Garland Publishing, Inc.

Frisch, D. and Baron, J. (1988), Ambiguity and rationality, *Journal of Behavioural Decision Making,* 1(3), 149-157.

Greenland, S. (2004), Bounding analysis as an inadequately specified methodology, *Risk Analysis*, 24(5), 1085-1095.

Kelly, E. and Campbell, K. (2000), Separating variability and uncertainty in environmental risk assessment -- making choices, *Human Ecology Risk Assessment,* 6(1), 1-13.

Mayer, H. (2005), Using integrated geospatial mapping and conceptual site models to guide risk-based environmental clean-up decisions, *Risk Analysis: An International Journal*, 25(2), 429-446.

Paté-Cornell, M. (1998), Risk comparison: uncertainties and ranking, in Probabilistic Safety and Assessment and Management, PSAM4 1991-1996 (A. Mosleh and Bari, R., eds.), New York: Springer.

Reckhow, K. (1994), Importance of scientific uncertainty in decision making, *Environmental Management*, 18(2), 161-166.

Reichert, P. and Borsuk, M. (2005), Does high forecast uncertainty preclude effective decision support?, *Environmental Modelling and Software*, 20(8), 991-1001.

Simon, P., Kemp, R., Crawford, M., Duarte-Davidson, R., Irwin, J. and Yearsley, R. (2004), Characterizing environmental harm: developments in an approach to strategic risk assessment and risk management, *Risk Analysis: An International Journal*, 24(6), 1551-1560.

Van Dijk, E. and Zeelenberg, M. (2003), The discounting of ambiguous informatin in econoic decisión making, *Journal of Behavioral Decision Making*, 16(5), 341-352.