Risk Analysis: An International Journal, 2010, vol.30, #2, pp.277-284

Reconciling uncertain costs and benefits in Bayes nets for invasive species management

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Abstract

Bayes nets are used increasingly to characterize environmental systems and formalize probabilistic reasoning to support decision-making. These networks treat probabilities as exact quantities. Sensitivity analysis can be used to evaluate the importance of assumptions and parameter estimates. Here, we outline an application of info-gap theory to Bayes nets that evaluates the sensitivity of decisions to possibly large errors in the underlying probability estimates and utilities. We apply it to an example of management and eradication of Red Imported Fire Ants in southern Queensland, Australia and show how changes in management decisions can be justified when uncertainty is considered.

Introduction

Decision tables and trees are simple frameworks for formal decision-making that involve acts, states, and outcomes (Resnik 1987). Bayes nets are directed acyclic graphs (decision trees) of probabilistic relationships among variables, in which links imply causal relationships (Cartwright 2003). Bayes nets are used mostly to assist decision-makers synthesize data and other information with the beliefs of experts and stakeholders. The graphic format of Bayes nets is useful for communication, providing a platform for integrating opinions (Sagrado and Moral 2003).

A variety of algorithms exist to infer probabilistic, causal relations from independent (marginal) distributions and update expectations with new data (Pearl 2000, Korb and Nicholson 2003). They have been applied widely in engineering and artificial intelligence research (e.g., Sigurdsson et al. 2001, Korb and Nicholson 2003, Sagrado and Moral 2003) and their use is growing in ecology and natural resource management (Reckhow 1999, Borsuk et al. 2001, 2003, Hart et al. 2006). In ecological applications, some data may be available from the system under study, from other, similar systems or extrapolated from theoretical expectations. However, in many circumstances, parameters and causal structures are based on subjective estimates. Whether based on data, prior studies or subjective belief, parameters and relationships in Bayes nets are uncertain. Thus, it is important to evaluate the sensitivity of decisions to these uncertainties.

Information-gap (henceforth termed 'info-gap') theory was invented to assist decision-making when there are substantial knowledge gaps and when probabilistic models of uncertainty are unreliable (Ben-Haim 2006). In general terms, info-gap theory finds decisions that achieve a minimally acceptable (satisfactory) outcome in the face of non-statistical uncertainty, given a nominal estimate of the system. It provides a platform for comprehensive sensitivity analysis relevant to a decision. In ecology, info-gap analysis has been used to evaluate threatened species management actions with uncertainty in utilities and probabilities (Regan et al. 2005), to design reserves that account for uncertainty in the spatial distribution of wildlife habitat (Moilanen and Wintle 2006, Moilanen et al. 2006a, b), to determine the power of a sampling strategy for a hypothesis test when the moments of the distribution are uncertain (Fox et al. 2007), and to decide between forest management options when there are substantial uncertainties related to occurrence of fire (McCarthy and Lindenmayer 2007). Walshe and Massenbauer (2008) used info-gap analysis together with a Bayes net to evaluate the sensitivity of wetland management options to uncertainties in a decision table.

Info-gap methodology requires three main elements: a process model, a performance measure, and a model for uncertainty. The process model is a mathematical representation of the components of a system, their interactions and influence on the variables of interest, for which management aspirations (performance criteria) are set. In a Bayes net, this model is the usual causal network and associated probabilities. A performance measure is an outcome, a measure of utility, for which different stakeholders may hold different aspirations. The model for uncertainty is a mathematical representation of the way in which the value of a parameter, the form of a function or the structure of a model varies from a nominal value (best estimate) under increasing levels of uncertainty (Ben-Haim 2006).

The purpose of this paper is to implement info-gap theory to account for uncertainty in the probabilities underlying a Bayes nets. We demonstrate how info-gap theory can be used to analyse trade-offs in attempts to eradicate the Red Imported Fire Ant (RIFA, *Solenopsis invicta* Buren) in eastern Australia. While the Fire Ant Control Program has been successful in eradicating the species from most of the area infested initially, patches of infestation remain. Managers have several strategies at their disposal, including developing improved methods for detecting the species, investing in better spatial predictions, and enhancing the skills of field staff (DPIF 2006). In this study, we explore the sensitivity of management decisions based on a specified model to uncertainty about probabilities and social preferences (utilities).

Methods

Red Imported Fire Ant habitat and eradication

Moloney and Vanderwoude (2002) gave a detailed account of the history and ecology of Red Imported Fire Ants in Australia. They noted the species was detected in Brisbane, Australia early in 2001, although it was probably present for several years prior to its detection. The species is an important pest in North America, where it damages agricultural crops, animal production, farm infrastructure, and human health and environment. Evidence from the USA suggests that the species will occupy any land with mean annual rainfall exceeding about 500 mm, excepting areas that experience extreme cold. It has the potential to occupy millions of square kilometers of the Australian environment (Scanlan and Vanderwoude 2006) where, as well as damaging urban and agricultural systems, it is likely to severely affect many species of ants and other arthropod communities, snails, amphibians, reptiles, birds and mammals.

RIFA are currently restricted mainly to urban and suburban areas around Brisbane, Queensland. There, they occur primarily in association with open and disturbed ecosystems including cleared or partially cleared areas, farm paddocks, parks, industrial sites, residential areas, open forests and sites adjacent to waterways (DPIF 2006). They are less likely to occur in undisturbed habitat. Eradication efforts use predictive maps of the species' distribution to guide eradication efforts. Several eradication techniques are available, including aerial spraying, and laying baits or injecting nests with poison, using teams operating on foot in the field. The success of ground-based treatment depends on training and on the ease with which people can move through the terrain and its vegetation.

A workshop was held in Canberra on February 19, 2007. Participants involved in the eradication of RIFA, or who were experts in the ecology of the species, developed models for eradication of the species and discussed available data. The workshop outlined a Bayes net that reflects the logic underlying attempts to find and eliminate nests.

Info-gap methods

When Bayes nets are used for decisions, they may include a model for expected utility,

$$EU_j = \sum_{i=1}^{n} p_i v_{ij} \,, \tag{1}$$

where EU_j is expected utility of the j^{th} act, p_1 to p_n are the probabilities of the n possible states and v_{ij} are the utilities associated with the act-state pairs. Performance is assessed, in this case, by the expected utility of the decision.

An info-gap model for expected utility is represented by the sets $U_p(\alpha, \tilde{p})$ and $U_v(\alpha, \tilde{v})$, where the subscripts p and v indicate the info-gap models for uncertain probability and utility, respectively, α is the uncertainty parameter, and $\tilde{p}$ and $\tilde{v}$ are vectors of the best estimates of the probabilities and utilities for all the possible system states. The sets $U_p(\alpha, \tilde{p})$ and $U_v(\alpha, \tilde{v})$ become more inclusive, expressing greater uncertainty, as α rises. Hence α is referred to as the horizon of uncertainty. The utilities are the values associated with alternative outcomes, including the ecological, human health and social benefits (here, termed environmental values) of eradication success and the dollar costs of searching potentially infested areas. Utility is maximized when environmental benefits are high and search costs are low. It is minimized when there is little chance of success and search costs are high.

We identify $\tilde{p}_i$ as the nominal estimate of the probability that the system is in state i, p_i as the actual probability, $\tilde{v}_{ij}$ as the nominal estimate of the true utility (v_{ij}) of the outcome associated with act j if the system is in state i.

In this application, we assume that uncertainty in the probabilities and utilities is represented by intervals about whose size we are uncertain (*c.f.*, Burgman, 2005). An interval info-gap model of uncertainty is expressed as a set of values v_{ij} (for utilities) or p_i (for probabilities) whose fractional deviation from the respective nominal values $\tilde{v}_{ij}$ and $\tilde{p}_i$ is no greater than α, however, the value of α is unknown. The info-gap model for uncertainty about the state probability (p_i) is the family of nested intervals (and noting, because they are probabilities, p_i and $\tilde{p}_i$ *are* constrained to lie in the interval [0,1]):

$$\frac{|p_i - \tilde{p}_i|}{\tilde{p}_i} \le \alpha . \tag{2}$$

This implies that, at the horizon of uncertainty α, p_i is in the interval

$$(1-\alpha)\tilde{p}_i \le p_i \le (1+\alpha)\tilde{p}_i . \tag{3}$$

In this model of uncertainty, p_i varies from its nominal value, $\tilde{p}_i$, by no more than a fraction α. The horizon of uncertainty, α, is unknown. As α increases, the set $U(\alpha, \tilde{p})$ becomes more inclusive. Hence info-gap models are summarized as a family of nested sets, rather than a single set, of possible values of the uncertain entity (Ben-Haim 2006).

The info-gap model for the set of probabilities is the following family of nested sets of probabilities:

$$U_p(\alpha, \tilde{p}) = \left\{ p : 1 = \sum_{i=1}^{n} p_i, \max[0, (1-\alpha)\tilde{p}_i] \le p_i \le \min[1, (1+\alpha)\tilde{p}_i], i = 1..., n \right\}, \alpha \ge 0 . \tag{4}$$

It is instructive to note that a standard Bayesian treatment of uncertainty for this set of probabilities could take the form of a Dirichlet distribution. The info-gap model U_p describes possible sets of p_i that add to 1, and has a nominal set of values (analogous to the mean or median) but unlike the Dirichlet distribution, the info-gap model does not specify a fixed measure of variance, nor is it a distribution. The set of admissible probabilities at scale α is simply a set of admissible values.

The analogous details for the characterization of info-gap uncertainty in utilities are (see Regan et al. 2005),

$$U_v(\alpha, \tilde{v}) = \{ v : \max[0, (1-\alpha)\tilde{v}_{ij}] \le v_{ij} \le \min[100, (1+\alpha)\tilde{v}_{ij}], i = 1...n, j = 1...m \} \quad \alpha \ge 0. \tag{5}$$

This function restricts utilities to the interval [0,100] for the purpose of this example.

Info-gap analysis addresses the basic question of robustness: how far from the nominal values can the models and data be, without jeopardizing the quality of the outcome? A policy that is highly immune to errors in the models and data is preferred over a policy that is vulnerable to error. Info-gap decision analysis can be used in this context to maximize robustness of a given model for a specified performance threshold, rather than to maximize expected performance.

The process model, performance requirement, and uncertainty models ((4) and (5)) provide a system of equations that may be solved for estimates of robustness. We use this system to find the strategy among the set available to us that maximises robustness for achieving an outcome that is good enough (above some minimally satisfactory critical performance threshold, EU_C). The robustness function for action j is (Regan et al. 2005):

$$\hat{\alpha}(j, EU_C) = \max\left[\alpha : \left(\min_{\substack{v \in U_v(\alpha,\tilde{v}) \\ p \in U_p(\alpha,\tilde{p})}} EU_j\right) \geq EU_C\right], \qquad (6)$$

which states that the robustness of action j is the maximum level of uncertainty α that guarantees an expected utility EU no less than EU_C. Regan et al. (2005) discuss the process for analyzing probabilities as the horizon of uncertainty expands. In our models, we employ discrete distributions.

Results

The analysis begins with a tree that represents causal links in a program to detect and eradicate the pest. States of the systems at each node in the tree are estimated from data or expert judgement. The probability of successful eradication is calculated as a function of these values. Then, the info-gap analysis is applied, wherein the fractional errors are applied to the probabilities and utilities, and utilities are evaluated at the boundary of the envelope defined by the increasing horizon of uncertainty, α.

Figure 1 shows a Bayes net representing a site in Brisbane at which it is suspected there has been a new infestation by RIFA. The net shows the likelihood of eradication as a function of the treatment used and whether or not the infestation is found ('located'). Successful location of the new nest requires that the field crew searches the right area, and that it finds the pest, when it is in fact present. The quality of the map is represented by the likelihood that the team will be guided to the correct location (nominally 90%; Figure 1, 'Map_Locations' node). That is, the model assumes the habitat map is of sufficient quality that there is an 90% chance that the infested site will be visited by a surveillance team (for 'Map_Locations', $\tilde{p}$ =[0.90,0.10]).The probability of detection is a function of search effort, itself a function of cost. The costs may be incurred in the time spent in the field, the labour cost of recruiting and retaining experienced and effective personnel, or by developing technical tools and quantitative support to guide detection effort.

The nominal values represent best guesses regarding the species biology and the effectiveness of interventions. In this model, they assume that the species prefers disturbed landscapes, some of the landscapes will be relatively difficult to search, and others will not allow broadcast spraying from a helicopter. Thus, the node for the 'Treatment' assumes 70% of sites will be amenable to helicopter spraying (the most effective eradication method) whereas 20% of the landscape is readily accessible by foot, and 10% is difficult terrain in which the chances of successful eradication are reduced (for 'Treatment', $\tilde{p}$ =[0.70,0.20,0.10]).

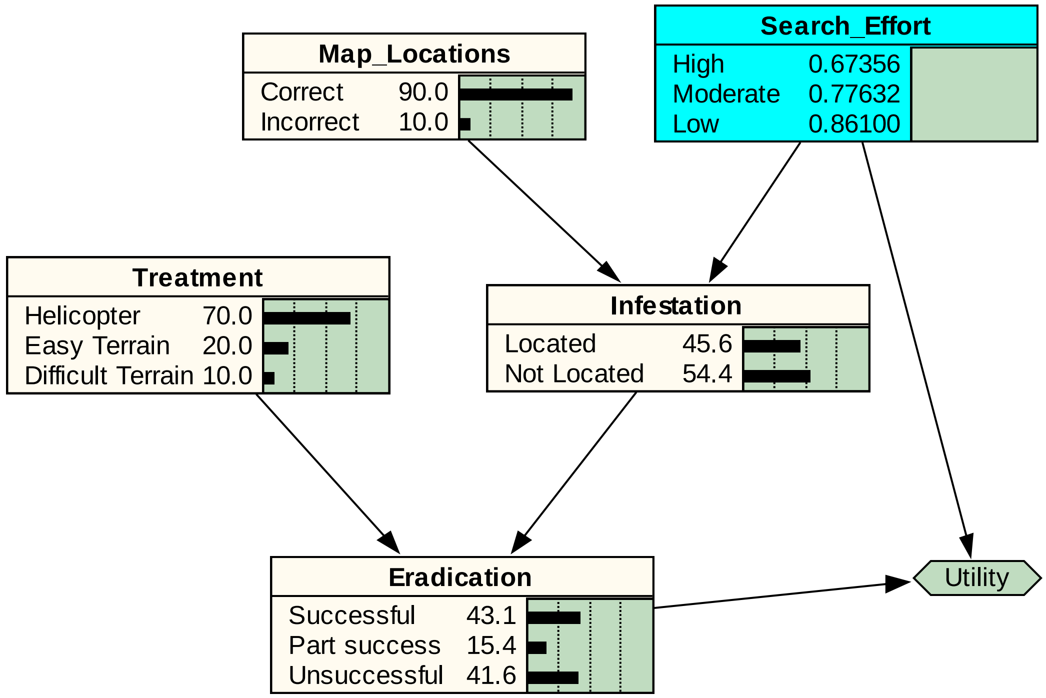

Figure 1. Bayes net for the eradication of Red Imported Fire Ants. The numbers in the nodes for Map_Locations, Treatment, Infestation and Eradication are estimated probabilities, $\tilde{p}_i$ (expressed as %). The Search_Effort node shows the solution using a traditional analysis; the values 0.674, 0.776 and 0.861 represent the expected values that result from decisions to search with varying intensities. In this example, the utilities consider both the environmental benefits of success and the costs of searching (see text). Values in the Infestation and Eradication nodes are calculated from tables of conditional probabilities (see Tables below).

All of the marginal and conditional probabilities and utilities in this network involve expert judgments and are highly uncertain. The parent nodes (‘Treatment’ and ‘Map_Locations’) in Figure 1 are vectors of marginal probabilities.

The values that appear in the nodes for Infestation and Eradication are not transparent in Figure 1. They involve conditional probabilities (Table 1). If the habitat map leads the eradication team to the correct general location and search intensity is high, there is an estimated 80% chance the nest will be found. Even if the map leads to a ‘wrong’ location, high search effort may still locate a nest, by chance, with a probability of 10% (Table 1a). If the eradication team uses helicopter application of a spray at the correct location, the chance of successful eradication is estimated to be 90% and the chance of partial success (eliminating most of the individuals at the site) is 10% (Table 1b).

Table 1. Conditional probability tables for locating an infestation (a function of map location and search effort) and eradication (a function of correctly locating the infestation and the treatment applied)

1a. Infestation

Map Location	*Search Effort*	*Located*	*Not Located*
Correct	High	80	20
Correct	Moderate	50	50
Correct	Low	20	80
Incorrect	High	10	90
Incorrect	Moderate	5	95
Incorrect	Low	2	98

1b. Eradication

Treatment	*Infestation*	*Success*	*Partial success*	*Unsuccessful*
Helicopter	Located	90	10	0
Helicopter	Not located	10	20	70
Easy Terrain	Located	80	20	0
Easy Terrain	Not located	5	10	85
Difficult Terrain	Located	60	30	10
Difficult Terrain	Not located	0	5	95

This analysis evaluates two utility functions (Table 2). Social and ecological (environmental) values accrue from partially and completely successful operations. In the current context, these values result from people in this urban landscape having access to open space for recreation and social interaction, and from avoiding human health costs and substantial ecological damage. It is difficult to quantify these values in dollar terms, although multicriteria decision analysis may be used for approximation (Chee 2004). Irrespective of the valuation, greater search effort is attractive because it improves the chances of eradication. Managers, however, are forced to consider costs. 'High' intensity search effort is roughly 3.3 times more expensive than 'Low' search effort.

Expected utility at zero robustness represents the expectations under standard Bayes net analysis. Robustness analyses were implemented on the Bayes net for expected utility and for the ratio of utility to cost. We used the envelope-bound info-gap models, eqs. (4) and (5). Three different management strategies are studied: high, moderate, and low search intensity. The results are shown in Figs. 2a and 2b.

The first thing to note is the negative slopes of all the robustness curves. This expresses the irrevocable trade-off between robustness-to-uncertainty and quality of the outcome (expected utility or utility-to-cost ratio). Aspiring to better (higher) outcome entails worse (lower) robustness to uncertainty.

Table 2. Utilities associated with eradication success (ignoring costs) and including costs.

2a. Utilities resulting from different levels of success of eradication efforts (ignoring search costs)

Eradication	*Utility*
Success	100
Partial success	20
Unsuccessful	1

2b. Utilities resulting from consideration of both environmental benefits and economic costs of alternative search strategies.

Eradication	*Search_Effort*	*Utility*
Successful	High	1.00
Successful	Moderate	1.67
Successful	Low	3.33
Partial-success	High	.20
Partial-success	Moderate	.33
Partial-success	Low	.67
Unsuccessful	High	0.01
Unsuccessful	Moderate	0.0167
Unsuccessful	Low	0.033

The second point to note is that the robustness becomes zero at the value of the outcome which is predicted by the best-estimated values of the uncertain parameters. For instance, the expected utilities of high, moderate, and low search intensity are predicted, based on the best-estimates of the parameters, to be 67, 46 and 27, respectively. However, the robustness to uncertainty of these outcomes is zero: infinitesimal errors can lead to short-fall. Based on the best-estimate predictions of expected utility, high search intensity is preferred over moderate, which in turn is preferred over low intensity.

These preferences agree with preferences based on robustness. Since more robustness is better than less, the robust-satisficing decision rule indicates that high intensity is again preferred over moderate, which is preferred over low intensity. In short, when considering expected utility, the best-estimate (zero-robustness) preferences agree with the robust-satisficing estimates.

The situation is different when considering the utility-to-cost ratio (UCR, Fig. 2b). The best-estimates of the UCR are 0.86, 0.78 and 0.67 for low, moderate and high search intensity respectively. In other words, the best-estimate preferences based on the UCR are precisely the reverse of those based on expected utility.

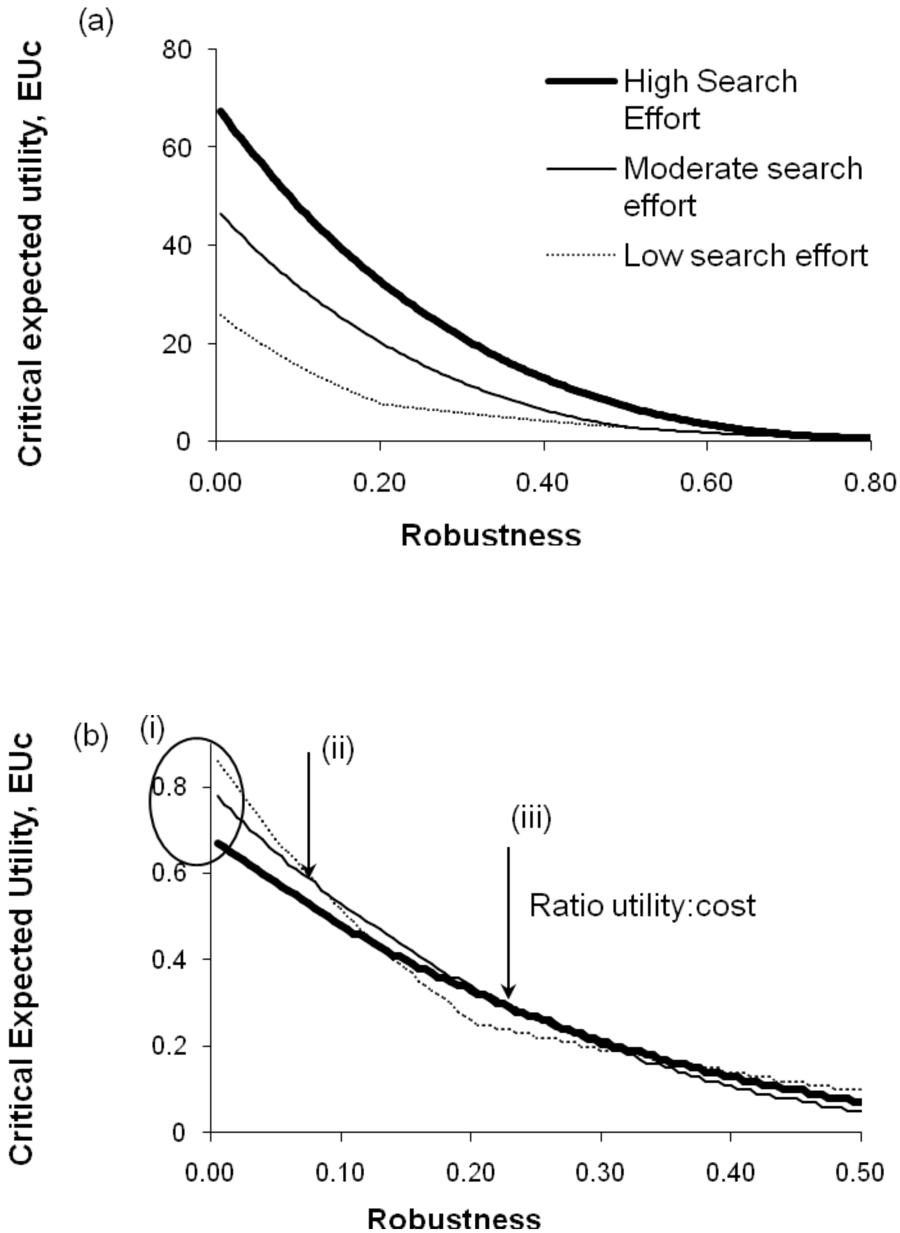

Figure 2. Curves for Critical Expected Utility versus Robustness (the horizon of uncertainty, α) (a) guaranteed utility based on the Bayes net and the envelope bound model for uncertainties in probabilities and utilities, i.e., when search costs are ignored, (b) the utility to search cost ratio (UCR) for each of three search intensities, i.e., when search costs are included. Low search intensity has lowest expected utility over the full range of parameter uncertainty (a) but it has the highest of utility to cost ratio (i) in (b) when α=0. At levels of α of about 0.08 in (b), the robustness curves for low and moderate search effort cross (ii). At levels of α of about 0.22, the robustness curves for moderate and high search effort

cross (iii). The three search strategies are essentially equivalent for robustness above about 10%.

The robust-satisficing preferences based on the UCR are more complicated because the robustness curves cross. The low- and moderate-intensity robustness curves cross at about 8% robustness. Thus low intensity is preferred over moderate intensity below 8% robustness, while moderate is preferred over low at greater robustness. Even moderate errors in the estimated parameters will exceed 8%. We see that the low, moderate and high intensity robustness curves are quite close together over the entire range, above about 10% robustness. This indicates that, in terms of the UCR, the analyst is indifferent between these options.

A subjective judgment has been made once in this analysis: judging the potential for error to exceed 8 to 10%, and thereby rejecting low-intensity search in the UCR case, and judging the moderate and high options to be equivalent for UCR. In the present example this judgment is probably not controversial: while one is unable to identify a largest-possible error in the estimated probabilities and utilities, it is not difficult to believe that only 10% error is wishful thinking.

In general, however, it may be necessary to make more difficult judgments in choosing between strategies based on the robustness criterion. If the robustness curves of alternative options cross at mid-range values of either robustness or performance, the analyst may need to choose which side of the crossing values are more plausible (for robustness) or more essential (for performance).

Discussion

Sensitivity analysis of the Bayes net allows managers to evaluate the importance of assumptions underlying alternative management strategies. One question that arises is, what is the importance of good quality maps of potential habitat for efficient search strategies. The Bayes net suggests that if map accuracy (expressed as the likelihood that the area of a new infestation is visited) is 50%, rather than 90%, then the chance of successful eradication given high search effort efforts falls from 65% to 52%. Furthermore, the sensitivity of eradication success to this parameter will increase as the species becomes rarer in the landscape. That is, as the eradication program improves its success, remaining nests will become harder to locate and the importance of the quality of the predictive map will increase.

The robustness curves in Figure 2 illustrate an important feature of info-gap analysis. Managers may trade robustness for quality of outcome (either expected utility or utility-to-cost ratio), as expressed by the negative slopes of the curves. One may take a position of supporting a strategy that has lower expected utility, but greater robustness to uncertainty in delivering a specified benefit. Environmental managers often are most concerned with avoiding catastrophic outcomes, preferring options with acceptable outcomes that are robust to uncertainty. Info-gap analysis provides an explicit means of quantifying the robustness of alternatives, providing an additional dimension for negotiation.

We have shown that, in the present example, the analyst is able to select a strategy essentially without making value judgments regarding critical performance requirements or plausible levels of uncertainty. In general, however, this is not the case, and the analyst will have to deal with the issue of ‘sufficient’ utility. What is the “required performance threshold”? What value is important to achieve? Then, which strategy can achieve that critical expected utility with the greatest robustness? These are social judgements, not scientific ones. They involve trade-offs between competing social values. The info-gap analysis makes the trade-off explicit and provides an added dimension for discussions about social preferences. For instance, one may forgo some aspirations for utility (i.e., negotiate towards a strategy with lower expected value) in return for greater surety of returning at least a given amount. Bayes nets that ignore these uncertainties run the risk of leading decision-makers to conclusions that are blind to the uncertainties in the model and their consequences for expected outcomes.

This paper does not address the issue of how to implement methods for finding info-gap solutions for the general case of large Bayes-net problems. Exhaustive search of all possible combinations of probability and utility are suitable for low-dimensional problems. However, larger-dimensional problems require analytical solution of the robustness function.

When considering invasive species, there may be legal or social obligations to reduce a species distribution below a specified level. In these circumstances, the objective function would be simpler. Management would be constrained to options that result in an acceptable level of success.

The values in the utility table reflect social preferences and may have been specified to reflect other objectives. For instance, alternatives may be to keep the budget within specified bounds, and then to maximize the chance of eradication, or to maintain a minimum (acceptable) level of RIFA infestation in the landscape, and then to optimize surveillance effort. These represent different performance measures and could lead to different info-gap solutions.

In most natural resource applications, as in the example above, one can identify both positive and negative outcomes in the objective function. In this instance, there is a desire to eliminate the species, while keeping the budget within some bounds. The focus is on ‘value’, and the value of greater chances of eradication success needs to be expressed on an equivalent scale to that representing the costs of management. We achieved this in this example though the utility-to-cost ratio. In applications, subjective values weigh economic costs against environmental and social aspects of a decision. Different stakeholders will have different opinions. Other tools such as multicriteria decision analysis may be used to explore differences of opinion and achieve consensus (Chee 2004). Info-gap theory may then be used to explore the robustness of options to uncertainty in these social preferences.

Acknowledgements

This study was supported by funds from the Australian Centre of Excellence for Risk Analysis, an output of ACERA Projects 0601 and 0611, and by the Commonwealth Environmental Research Facility for Applied Environmental Decision Analysis.

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