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Published in:
Ecological Applications

DOI:
10.1890/03-5419

2005

Ecological Applications, 15(4), 2005, pp. 1471–1477

ROBUST DECISION-MAKING UNDER SEVERE UNCERTAINTY FOR CONSERVATION MANAGEMENT

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Abstract. In conservation biology it is necessary to make management decisions for endangered and threatened species under severe uncertainty. Failure to acknowledge and treat uncertainty can lead to poor decisions. To illustrate the importance of considering uncertainty, we reanalyze a decision problem for the Sumatran rhino, *Dicerorhinus sumatrensis*, using information-gap theory to propagate uncertainties and to rank management options. Rather than requiring information about the extent of parameter uncertainty at the outset, information-gap theory addresses the question of how much uncertainty can be tolerated before our decision would change. It assesses the robustness of decisions in the face of severe uncertainty. We show that different management decisions may result when uncertainty in utilities and probabilities are considered in decision-making problems. We highlight the importance of a full assessment of uncertainty in conservation management decisions to avoid, as much as possible, undesirable outcomes.

Key words: conservation management; decision theory; Dicerorhinus sumatrensis; *information gap; robustness of decisions; Sumatran rhino; uncertainty.*

Introduction

Conservation biologists make management decisions for endangered and threatened species under severe uncertainty. Although frameworks for formal decision-making (Jeffrey 1983, 1992, Resnik 1987, Simon 1959) have been applied in conservation contexts (e.g., Maguire 1986, Maguire and Boiney 1994, Ralls and Starfield 1995, Possingham 1996, 1997), the full suite of uncertainty is rarely considered (Regan et al. 2002). Failure to acknowledge and treat the sources of uncertainty can lead to poor management decisions.

Decision tables and trees are simple frameworks for formal decision-making that involve identifying three main components: acts, states, and outcomes (Resnik 1987). The acts refer to the decision alternatives, the states refer to the relevant possible states of the system, and the outcomes refer to what will occur if an act is implemented in a given state (usually represented in terms of a utility, or value). This framework applies to static problems, where it is assumed that the state of the system does not change substantially through time.

For decision-making under uncertainty, the usual procedure is to assign probabilities to each of the relevant states and utilities to each of the outcomes. The approach usually taken is to maximize expected utility.

Probabilities can be interpreted in different ways. Probabilities assigned to the states may represent the chance that the system is in that state. Although the state in which a system exists is uncertain, the probability that the system is in that state is assumed to be known with certainty. Alternatively, probabilities may be estimates of the degree to which each factor contributes to an effect.

It is extremely difficult, if not impossible, to assign state probabilities and utilities with any degree of certainty in conservation applications. A management decision that assumes that probabilities and utilities are exact, when in fact they are uncertain, can result in management outcomes with unexpected or undesirable results. For example, Maguire et al. (1987) used a decision tree to choose between management actions to conserve the Sumatran rhino, *Dicerorhinus sumatrensis*. Captive breeding gave the maximum expected utility. When implemented, it failed to increase population numbers. The capture of wild animals was substantially detrimental to at least some populations (Rabinowitz 1995). This management action may have failed because (1) not all the relevant states of the system were specified; (2) the relevant states were not mutually exclusive; (3) the states were not static; (4) the probabilities and utilities were incorrect; and/or (5) the prob-

Manuscript received 22 December 2003; revised 18 August 2004; accepted 27 October 2004; final version received 17 November 2004. Corresponding Editor: N. T. Hobbs.
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abilities and utilities were correct, but the system turned out to be in a state with a relatively low utility. To rule out (4), a treatment of uncertainty in the input parameters (probabilities and utilities) is necessary.

The purpose of this paper is to demonstrate the insights that arise when uncertainty in utilities and probabilities are considered explicitly in decision-making problems using information-gap theory. To illustrate the importance of considering uncertainty, we reanalyze the decision problem explored by Maguire et al. (1987), using the theory to propagate uncertainties and to rank management options. Rather than requiring information about the extent of parameter uncertainty at the outset, information-gap theory addresses the question of how much uncertainty is permissible in the system before our decision would change. It assesses the robustness of decisions in the face of severe uncertainty.

General Information-gap Methodology

Information-gap theory was invented by Ben-Haim (2001) to assist decision-making when there are severe knowledge gaps and when probabilistic models of uncertainty are unreliable, inappropriate, or unavailable. Information-gap (henceforth referred to as info-gap) methodology requires three main elements: a mathematical process model, a performance requirement, and a model for uncertainty.

A process model is a mathematical representation of a system or concept. It summarizes what the analyst believes to be true and important about the system. Process models may describe population dynamics, economic utility, groundwater plumes, stream flows, or the transport and fate of toxic substances. For instance, a process model here could be the expected utility

$$\mathrm{EV}[a_j] = \sum_{i=1}^{n} p_i v_{ij} \tag{1}$$

where EV refers to the expected utility of the jth act, a_1 to a_m represent the m acts under consideration, p_1 to p_n represent the probabilities of the n possible states of the system, and v_{ij} represent the utilities associated with the outcome of the state–act pairs. Eq. 1 is the model that we assume best describes the decision-making process.

The performance requirement of a decision is assessed by the measure of performance. A measure of performance may be the chance of population decline, the concentration of a contaminant, the density of algal cells in a freshwater stream, or the size of a managed fish population. The performance measure is usually a value (or values) computed using the process model. The objective may be to reduce the measure, as in the case of extinction risk, or to increase it, as in the case of population size in fisheries management. Performance measures may include multiple attributes. For instance, we may want to reduce the exposure of humans to a contaminant in a stream and increase the expected population sizes of game fish caught from the stream. Here, the performance measure is

$$\mathrm{EV} \geq \mathrm{EV}_\mathrm{C}. \tag{2}$$

That is, we require the expected utility (from Eq. 1) to be no less than a critical threshold EV_C.

The model for uncertainty describes what is unknown about the parameters in the process model. An info-gap model is an unbounded family of nested sets of possibilities. In the case of the process models under consideration here, the corresponding info-gap models are denoted as the sets $U_p(\alpha, \tilde{p})$ and $U_v(\alpha, \tilde{v})$, where the subscripts p and v refer to the info-gap models for probability and utility, respectively, α is the uncertainty parameter, and $\tilde{p}$ and $\tilde{v}$ are vectors of the best estimates $\tilde{p}_i$, $i = 1, \ldots, n$ and $\tilde{v}_{ij}$, $i = 1, \ldots, n$; $j = 1, \ldots, m$. We identify $\tilde{p}_i$ as the nominal model of the probability that the system is in state i. Likewise, we can identify $\tilde{v}_{ij}$ as the nominal model of the utility of the outcome associated with act j if the system is in state i, and v_{ij} as the actual utility (however, see the *Discussion* for issues with the notion of actual utilities). In general, elements of the set $U_v(\alpha, \tilde{v})$ can be scalar, functions, or vectors (as in the current example).

For the sake of simplicity, we will assume that uncertainty in the probabilities and utilities may be represented by intervals of unknown size around each (alternative models of uncertainty are available; see Ben-Haim [2001] for details). An interval 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. Note however that the value of α, the horizon of uncertainty, is not known. The information-gap model for utility uncertainty, then, is the family of nested intervals:

$$\frac{|v_{ij} - \tilde{v}_{ij}|}{\tilde{v}_{ij}} \leq \alpha.$$

This implies that, at the horizon of uncertainty α, the v_{ij} is in the interval

$$(1 - \alpha)\tilde{v}_{ij} \leq v_{ij} \leq (1 + \alpha)\tilde{v}_{ij}.$$

In this model of uncertainty, v_{ij} varies from its nominal value, $\tilde{v}_{ij}$, by no more than a fraction α. The horizon of uncertainty, α, is unknown and unbounded.

For any given value of α, $U(\alpha, \tilde{v})$ is a set of possible values or models of the actual v. As α increases, the set $U(\alpha, \tilde{v})$ becomes more inclusive. This imbues α with the notion of an ‘‘horizon of uncertainty.’’ Hence info-gap models are summarized as a family of nested sets, $U(\alpha, \tilde{v})$, $\alpha \geq 0$, rather than a single set, of possible values of the uncertain entity (Ben-Haim 2001). When $\alpha = 0$, then $\tilde{v}$ is the only possible value in the absence of uncertainty and $U(0, \tilde{v}) = \{\tilde{v}\}$. It follows that if there is no uncertainty, the nominal model is the actual model. These cases are rare, and many would argue that they are nonexistent (e.g., Box 1976).

The model for uncertainty in the probabilities, p, is similar. There are additional constraints that the p's must be positive and normalized to sum to 1. To bound the p values, we may express them as fractions of the nominal value in a manner similar to the bounds on the utilities:

$$\frac{|p_i - \tilde{p}_i|}{\tilde{p}_i} \leq \alpha$$

which implies that, at the horizon of uncertainty α, the ith probability is in the interval

$$(1 - \alpha)\tilde{p}_i \leq p_i \leq (1 + \alpha)\tilde{p}_i.$$

Uncertainties for both utilities and probabilities are defined to have identical relative uncertainties. To keep the p values nonnegative and their sum normalized, we define the info-gap model for probabilities as

$$\begin{aligned} U_p(\alpha, \tilde{p}) &= \Bigg\{p\colon 1 = \sum_{i=1}^{n} p_i; \\ &\qquad \max[0, (1 - \alpha)\tilde{p}_i] \leq p_i \leq \min[1, (1 + \alpha)\tilde{p}_i], \\ &\qquad i = 1, \ldots, n\Bigg\} \qquad \alpha \geq 0. \end{aligned} \tag{3}$$

Similarly, the info-gap model for uncertain utilities is defined as

$$\begin{aligned} U_v(\alpha, \tilde{v}) &= \{v\colon \max[0, (1 - \alpha)\tilde{v}_{ij}] \leq v_{ij} \leq \min[1, (1 + \alpha)\tilde{v}_{ij}], \\ &\qquad i = 1, \ldots, n, j = 1, \ldots, m\} \qquad \alpha \geq 0. \end{aligned} \tag{4}$$

Here the constraint of a normalized sum is not necessary. As we will discuss, we restrict ourselves to utilities between 0 and 1 in this example because they are defined as probabilities of persistence, although in theory they can take any value.

There are many forms of info-gap models, each suited to a different type of prior information about uncertainty (Ben-Haim 2001). For instance, the info-gap model used in this paper can be modified to represent prior information about correlations between the uncertain parameters, or to reflect asymmetric intervals of variation. Different info-gap model structures can represent uncertain, transiently varying functions, or uncertain functions that vary monotonically, but with unknown slope, and so on.

In all cases, the info-gap model helps the decision-maker to address the basic question of robustness: how wrong 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.

Although this phrasing of uncertainty looks similar to standard sensitivity analysis, there are critical differences. Most important among them is that the horizon of uncertainty, α, is unknown and unbounded. In the types of sensitivity analyses that are usually performed in ecological and conservation applications, parameters are perturbed and the corresponding change in model outputs is noted. These types of sensitivity analyses amount to a *stability analysis*, i.e., they tell us how stable the model results are around the input parameter values, and are uninformative about the extent of uncertainty in the results or the input parameters. Furthermore, they are only valid for the range of parameter values that the perturbation encompasses. Other methods address these problems by assigning intervals to values to incorporate the full suite of possible values that these parameters might take (Walley 1991, Moore 1966), but they too require knowledge of bounds on parameters, within which the true value *must* lie. Info-gap modeling approaches the issue of uncertainty from the opposite direction. The power and novelty of the info-gap approach is in the ability to explore the sensitivity of the decision to a wide range of different types of parameter, functional, and structural errors and uncertainties simultaneously, given that we do not know the extent of uncertainty in the system at the outset. We illustrate this approach in the current paper with a specific conservation decision problem.

With a process model, a performance requirement, and an info-gap model, information-gap theory now allows us to evaluate robustness (immunity from error, avoiding unacceptably bad outcomes) and opportunity (chances of windfall, gains that exceed our expectations). The decision-maker can trade robustness for performance. Thus, it recognizes implicitly that uncertainty can be pernicious or propitious (Ben-Haim 2001), although in this application, we explore only the former.

Info-gap theory takes the position that the best strategy is the one that satisfies us with an outcome that is both ''good enough'' and that makes us as immune as possible from an unacceptable outcome. That is, we choose a strategy that maximizes the reliability of an adequate outcome. Let EV_C be a critical value of the expected utility below which we regard performance as unacceptable. We would like the value of the expected utility to be as large as possible, but it must be no less than EV_C. EV_C thus represents a minimum aspiration, and for greater generality, there is no need to choose it a priori; we will return to it.

The process model, performance requirement, and uncertainty model provide a system of equations that may be solved for estimates of robustness. The robustness function for action a_j is formulated as follows:

$$\hat{\alpha}(a_j, EV_C) = \max\left[\alpha\colon \min_{\substack{v \in U_v(\alpha, \tilde{v}) \\ p \in U_p(\alpha, \tilde{p})}} EV[a_j] \geq EV_C\right]. \tag{5}$$

Eq. 5 states that the robustness function $\hat{\alpha}$ for act a_j

TABLE 1. Decision table (utilities and probabilities) for three management options and four states. Utilities are the probabilities that the population will persist for 30 years under the alternative management scenarios and in the relevant states.

		Utilities		
States, S_i (cause of decline)	Probability of each state, p_i	Option 1 (a_1) (translocation), ν_{i1}	Option 2 (a_2) (new reserve), ν_{i2}	Option 3 (a_3) (captive breeding), ν_{i3}
Poaching	0.1	0.3	0.25	0.9
Loss of habitat (timber, dams)	0.3	0.1	0.2	0.2
Demographic accidents	0.5	0.05	0.09	0.01
Disease	0.1	0.1	0.1	0.4
Expected utilities		$\sum_i p_i\nu_{i1} = 0.095$	$\sum_i p_i\nu_{i2} = 0.14$	$\sum_i p_i\nu_{i3} = 0.195$

and critical threshold EV_C, is equal to the maximum value of α, such that the minimum expected value $EV[a_j]$, given uncertainty in the utilities v_{ij} and probabilities p_i, is greater than or equal to the critical threshold. For general EV_C, this will result in a function with variable EV_C. The robustness function $\hat{\alpha}$ is the maximum level of uncertainty α that guarantees an expected utility, EV, no less than the critical threshold EV_C. The robustness of action a_j is the greatest horizon of uncertainty α up to which all probabilities and utilities result in expected utility no worse than EV_C.

The goal is not to maximize expected utility, but to maximize the reliability of an acceptable outcome. This is an important distinction between info-gap analysis and standard decision theory. Because the robustness decreases as the demanded value of EV_C increases, it is necessary to trade one off against the other. Consequently, the action that is recommended by the info-gap analysis, for specified demanded utility EV_C, is that which maximizes the robustness at that value of EV_C. We will see this explicitly in the example.

APPLICATION TO SUMATRAN RHINO CASE STUDY

The Sumatran rhinoceros (*Dicerorhinus sumatrensis*) is listed as "critically endangered" by the IUCN (2004). In the mid-1980s, the species was reduced to a few small subpopulations in Sabah, Sumatra, Kalimantan, Thailand, Malaysia, Burma, and Java. Unprotected habitat was threatened by several human activities, including timber harvesting and dam development. Maguire et al. (1987) evaluated management options with a decision tree in which alternatives were ranked according to maximum expected utility. Utilities were defined in terms of

$$v_{ij} = 1 - P_{ij}(\mathrm{Ext}) \qquad (6)$$

where $P_{ij}(\mathrm{Ext})$ is the probability of extinction of populations within a 30-year time frame under each management alternative a_j and state S_i with probability p_i. This is a convenient choice of utility in the conservation of threatened and endangered populations because it can be calculated using stochastic population models, thereby infusing some biological basis and objectivity into the value of outcomes. Maguire et al. (1987) also estimated the costs (in dollars) of implementing each alternative in a separate decision analysis, which we will not follow here.

For the sake of illustration, we outline a sub-tree based loosely on the analysis of Maguire et al. (1987). It considers four potential causes of the loss of the population: poaching, loss of habitat, demographic accidents, and disease (Table 1). These are the relevant states of the world. Note that here we are assuming that no other relevant states of the world exist and that all states are mutually exclusive. In fact, the Sumatran rhino is most likely affected by all of these processes simultaneously. For illustration, we assume that only single threats are important.

The three management options that we consider from the original suite of alternatives in Maguire et al. (1987) are: captive breeding, translocation, and a new reserve. The utilities resulting from each option are selected as the probabilities that the population will persist for the next 30 years, i.e., the values resulting from Eq. 4. The Maguire et al. (1987) decision analysis differs in a number of respects; for instance, they reported probabilities of extinction for a range of scenarios not included here, and they did not consider demographic accidents explicitly as a potential cause of loss. We stress that we are not attempting to replace or supercede their decision analysis. We merely wish to use it as an illustration of how info-gap decision theory can be applied to conservation contexts.

Table 1 displays the decision table for the reduced decision problem. The values p_i in the second column of Table 1 are the probabilities that the population is threatened by the process specified. We assigned values for these probabilities based on our interpretation of the literature. In many conservation applications, this is not too far from the norm. Subjective judgment is used extensively to assess threats and their likely impacts on populations (Andelman et al. 2001). The utilities in Table 1 have been assigned subjectively for the purpose of illustration. In practice, the utilities could be generated using stochastic population models, historical records, experience with other related species, or by using the subjective judgment of experts (Maguire et al. 1987).

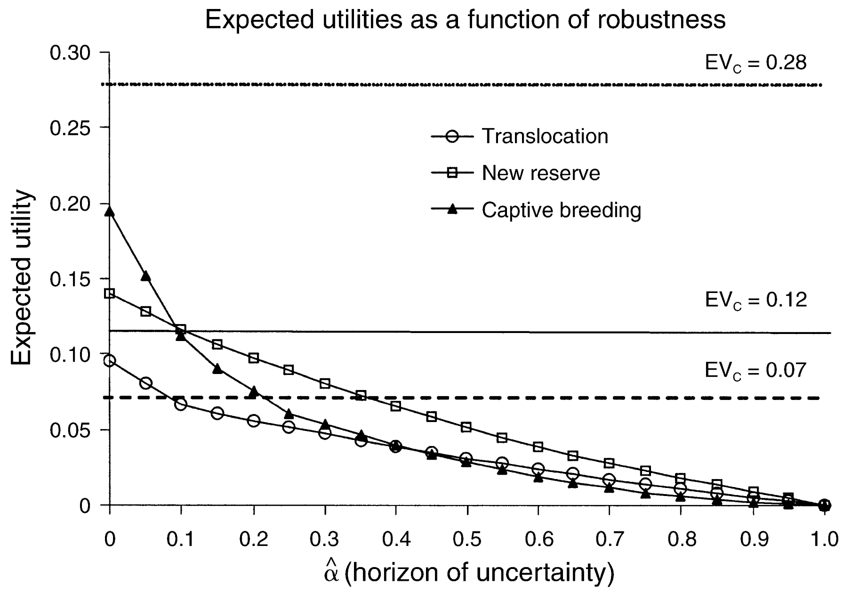

FIG. 1. Robustness curves $\hat{\alpha}(a_j, \mathrm{EV_C})$ vs. expected utility, for the three management options in Table 1. The graph shows the expected utility gained per action, for each horizon of uncertainty $\hat{\alpha}$. The horizontal axis denotes the maximum uncertainty allowed to guarantee the given expected utility. The greater the uncertainty tolerated in the system, the lower the expected utility becomes. Three alternative aspirations, $\mathrm{EV_C} = 0.28$, 0.12, and 0.07, are emphasized.

The main objective of conservation management of endangered species is to minimize the probability of population decline or extinction, or conversely, to maximize the probability of population persistence. Table 1 provides estimates of the response of a Sumatran rhino population to the range of management options considered here. According to standard decision theory, the best action is the one that maximizes expected utility, in this case option 3 (captive breeding). In all cases, substantial uncertainty is associated with these assessments, which motivates the info-gap analysis.

Incorporating uncertainty using the info-gap model

Using the info-gap models of uncertainty in the probabilities and utilities (Eqs. 3 and 4), we wish to determine the greatest horizon of uncertainty, $\hat{\alpha}$, within which all of the outcomes of a given action result in an adequate performance (that is, they result in expected utilities greater than a critical threshold $\mathrm{EV_C}$). As previously discussed, we express the robustness of an action as the maximum uncertainty up to which we always reach the performance aspiration. Combining Eqs. 2 and 5, the robustness of action a_j, given performance aspiration $\mathrm{EV_C}$, is

$$\hat{\alpha}(a_j, \mathrm{EV_C}) = \max\left[\alpha: \min_{\substack{v \in U_v(\alpha, \tilde{v}) \\ p \in U_p(\alpha, \tilde{p})}} \sum_{i=1}^{n} v_{ij} p_i \geq \mathrm{EV_C}\right]. \quad (7)$$

The robustness $\hat{\alpha}(a_j, \mathrm{EV_C})$ of action a_j, with aspiration $\mathrm{EV_C}$, is the greatest horizon of uncertainty α up to which all utilities v (in $U_v(\hat{\alpha}, \tilde{v})$) and all probabilities p (in $U_p(\alpha, \tilde{p})$) result in expected utilities no worse than $\mathrm{EV_C}$. Large robustness implies that attainment of the required expected utility, $\mathrm{EV_C}$, can be depended on, whereas low robustness means that reaching $\mathrm{EV_C}$ cannot be relied upon. Hence the robustness function determines a preference ranking for the management alternatives. The action that maximizes robustness, for a given critical threshold $\mathrm{EV_C}$, is defined as the best action, in contrast to a strategy that simply maximizes the outcome.

RESULTS

We used the data in Table 1 and the info-gap model previously outlined (Eqs. 5 and 6) to evaluate the robustness formula (Eq. 7). Fig. 1 displays robustness curves for the three alternatives under consideration. They show the expected utilities corresponding to each alternative for all values of $\hat{\alpha}(a_j, \mathrm{EV_C})$ between 0 and 1.0. We see that at $\hat{\alpha}(a_j, \mathrm{EV_C}) = 0$ (i.e., when it is assumed that there is no uncertainty in the utilities or probabilities), the original expected utilities are obtained and captive breeding gives the maximum expected utility. However, as $\hat{\alpha}$ increases, the expected utilities for all alternatives decrease and their ranking alters. We see that although captive breeding would be chosen as the alternative with the maximum expected utility for very low values of $\hat{\alpha}$, as $\hat{\alpha}$ increases to $\sim$0.15, it is overtaken by the act ''new reserve'' as the alternative with the greatest expected utility. As $\hat{\alpha}$ increases even further, beyond 0.4, captive breeding becomes the alternative with the lowest expected utility of the three considered. This indicates that the act ''captive breeding'' is not as robust to uncertainty in the parameters

p and v as the other two alternatives. The act ''new reserve'' has the greatest robustness to uncertainty, because it consistently has the greatest expected utility for values $\hat{\alpha} > 0.15$.

The values of $\hat{\alpha}$ in Fig. 1 and Eq. 7 have a specific interpretation. For instance, a value of $\hat{\alpha} = 0.5$ means that all of the parameters (utilities v_{ij} and probabilities p_i) can vary from their nominal values ($\tilde{v}_{ij}$ and $\tilde{p}_i$) fractionally by as much as 0.5, without causing the expected utility to fall below the critical value EV_C.

Fig. 1 also emphasizes three values of the critical value EV_C. If we are prepared to accept only expected utility values no less than $EV_C = 0.07$, then we should choose the act ''new reserve'' as the one with the greatest robustness to uncertainty, with an approximate value of $\hat{\alpha} = 0.34$. Option 2 (new reserve) is preferable over most of the range of uncertainty. If our aspirations are less modest and the critical threshold is set to $EV_C = 0.12$, then we should accept the act ''captive breeding.'' In fact, the acts ''captive breeding'' and ''new reserve'' are the only options that have any chance of delivering an outcome that we can live with. However, we must recognize that our robustness to uncertainty is rather low. Finally, if the critical threshold is set to values $EV_C \geq 0.2$, then none of the alternatives is acceptable because they do not invoke an expected utility that meets or exceeds the aspiration. In this case, we may decide to lower our aspirations and choose the alternative with the maximum expected utility, i.e., captive breeding, with a very low tolerance to uncertainty, or introduce other management actions. Decisions based on maximum expected utilities at $\hat{\alpha} = 0$ are only reliable if we can ensure that there is no uncertainty associated with the probabilities of the states or the utilities of the outcomes.

Thus we see that the higher the aspiration, the lower the immunity to uncertainty. This is a general property of info-gap decision theory: robustness to uncertainty decreases as aspirations increase.

Discussion

Decision-making usually involves trade-offs. In this analysis, we highlight the trade-off between immunity to uncertainty and aspirations. Very demanding aspirations become more vulnerable to uncertainty. In the extreme, decisions based on maximum expected utility (the default in most applications of standard decision theory) are maximally vulnerable to uncertainty. Standard decision theory is not realistically risk averse because it ignores uncertainty in the utilities and probabilities. This is a consequence of assuming that there exists no uncertainty in the constituent parameters, when no such guarantees can be made.

In conservation applications, where a precautionary approach to uncertainty is usually advised, it is crucial to represent uncertainty in all parameters because this can have a substantial effect on the outcomes, as seen in the example presented here. Two distinct issues arise. First, whose utilities do we wish to enhance? The utilities of the agency charged with financing the recovery action may be very different from those of the conservation manager, from those of the political party in power, and from those of broader society. The second issue is that even once it is agreed whose utilities we wish to promote, how are they to be measured? Do we measure them in terms of probability of persistence, expected minimum population size, or financial loss or gain? These two issues do not have obvious resolutions (Colyvan et al. 2001). Info-gap decision-making goes some way toward recognizing and assessing the impacts of uncertainty on the anticipated outcomes of decisions. For instance, once a utility measure has been chosen, info-gap decision theory can provide the range of utility values reliably achievable with a selected action.

Info-gap decision theory provides a platform extending decision theory into a broad range of conservation decision problems. For instance, it may be applied to decisions related to translocation strategies (Haight et al. 2000), probabilistic risk assessments of invasive species (Johnson et al. 2001), species management (Peterman and Anderson 1999), reserve design, and habitat management (Haight et al. 2002). In all of these contexts, it will inform us of the action that gives a satisfactory outcome, and that provides the greatest immunity against parameter and model uncertainty. This will improve flexibility in decision-making under severe uncertainty and will foster more reliable conservation management decisions.

Acknowledgments

We thank Dan Berleant, Mark Colyvan, Martin Drechsler, John Harwood, Tom Hobbs, and an anonymous reviewer for useful discussions and comments that assisted in the preparation of this paper. This work was conducted as part of the *Setting priorities and making decisions for conservation risk management* Working Group supported by the National Center for Ecological Analysis and Synthesis, a Center funded by NSF (Grant #DEB-0072909), the University of California, and the Santa Barbara campus.

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