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Application of decision theory to conservation management: recovery of Hector's dolphin

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Abstract. Decision theory provides an organised approach to decision making in natural resource conservation. The theory requires clearly stated objectives, decision alternatives and decision-outcome utilities, and thus allows for the separation of values (conservation and other societal objectives) from beliefs. Models express belief in the likely response of the system to conservation actions, and can range from simple, graphical representations to complex computer models. Models can be used to make predictions about likely decision-outcomes, and hence guide decision making. Decision making must account for uncertainty, which can be reduced but never eliminated. Uncertainty can be described via probabilities, which in turn can be used to compute the expected value of alternative decisions, averaging over all relevant sources of uncertainty. Reduction of uncertainty, where possible, improves decision making. Adaptive management involves the reduction of uncertainty via prediction under two or more alternative, structural models, comparison of model predictions to monitoring, and feedback via Bayes' Theorem into revising model weights, which in turn influences decision making. As part of a 3-day workshop on structured decision making (SDM) and adaptive resource management (ARM), we constructed a prototypical decision model for the recovery for Hector's dolphin (*Cephalorynchus hectori*), an endangered dolphin endemic to New Zealand coastal waters. Our model captures several steps in the process of building an SDM/ARM framework, and should be useful for managers wishing to apply these principles to dolphin conservation or other resources problems.

Introduction

Conservation biologists are frequently called upon to assist policy makers and others with decision making to achieve conservation and other goals. Often, they are confronted with problems for which there is profound uncertainty about the current state and dynamics of the system under consideration, and hence the response following any chosen conservation decision is also uncertain. In addition, decisions in conservation biology commonly involve conflicts over objectives. Often, the action that is optimal for a purely conservation objective would impinge upon some economic or other societal value. Even in those, arguably few, cases where non-conservation objectives are irrelevant, conservation actions ordinarily involve non-trivial costs or other tradeoffs. For example, the allocation of all available resources to the recovery of a single endangered species precludes the use of these resources for other initiatives. This type of 'opportunity cost' becomes particularly stark when there is a high likelihood of failure.

Here we describe a structured approach to decision making in conservation, following the principles of SDM (structured decision making) and ARM (adaptive resource management). Readers may refer to works such as Lindley (1985) and Clemen (1996) for a general coverage of SDM; applications in conservation are provided in Possingham (1997), Maunder *et al*. (2000), Dorazio and Johnson (2003), and Regan *et al*. (2005), among others. Similarly, Walters (1986), Ludwig *et al*. (1993), and McLain and Lee (1996) provide general coverage of ARM, with examples works such as Johnson and Williams (1999), Conroy *et al*. (2002), Johnson *et al*. (2002), Williams *et al*. (2002), Moore and Conroy (2006), and Nichols and Williams (2006). First, we describe the basic elements of a decision-making problem, including delineation of objectives, identification of decision alternatives, and the construction of simple predictive models of decision outcomes. We describe how virtually all conservation decisions are subject to uncertainty, much of it uncontrollable, and why it is critical that uncertainty be quantified and incorporated into decision making. We then describe how some forms of uncertainty can be reduced via information feedback under adaptive management. We illustrate these principles via an example relevant to New Zealand conservation: efforts to recover the endangered Hector's dolphin (*Cephalorynchus hectori*) via limitations on fishing activities.

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Elements of SDM

All conservation decisions have several elements in common, whether or not these are explicitly recognised. First, each has an *objective*, or some outcome that the decision maker is trying to achieve (or, in some cases, avoid). We will discuss objectives in more detail, below, but examples of conservation objectives include, as appropriate, minimising extinction risk, avoidance of biodiversity loss, or maximising harvest opportunity. Second, in all but trivial cases, there is a choice among two or more actions or *decision alternatives*, even if the alternative is simply to take no action. Third, following any decision are *consequences*, outcomes that occur once the decision is made. The consequences of a decision may be influenced by the actions taken (or not taken) by the decision maker, and by other factors beyond the control of the decision maker, such as random environmental effects. Note that consequences can lead towards or away from the objective.

We have not yet said anything about how to select a decision so that the consequences tend to fulfil, and not depart from, our objective. To do this we need at least one *model* of how we think the decision will influence outcomes, which will then guide our choice of the decision most likely to fulfil the objective. This model need not be complex, or even mathematical, but we argue that every decision maker has in mind a model before he or she makes a decision.

The distinction among objectives, decision alternatives, consequences, and models is fundamental to coherent decision making (Lindley 1985), and becomes especially important, as we deal with complex and contentious decision problems. In particular, a clear separation between *objectives*, which represent one's values, and the model, which represents one's beliefs about processes, is necessary before coherent decision making can proceed.

Complicating decision making is the reality that decisions are affected by multiple sources of uncertainty, and conservation decision making is no exception. *Environmental stochasticity* involves environmental factors beyond the control of the decision maker, so that outcomes following decisions are not completely predictable. For example, managers might attempt to increase carrying capacity via prescribed fire, but other factors are beyond management control, such as a disease outbreak. *Partial controllability* occurs when the decision itself turns out to be manifested in an uncertain manner. For example, a prescribed fire is intended to encompass 100 ha, but instead covers 50 (or 150). Decision makers must also take into account the fact that, rather than observing the true state of the system, we are generally forced to rely on sample data and statistical inferences. This leads to *statistical uncertainty*, which, by inducing bias, imprecision, or both in parameter estimates, degrades both our ability to determine our present conditions, as well as to evaluate the effectiveness of conservation actions. Finally, we have thus far assumed that the basic decision-outcome model is correct, so that our predicted response to management is indeed the most likely one. However, in most cases other responses are possible, and may even be supported by data. These alternative possible responses constitute, in a sense, competing hypotheses that can be empirically evaluated, and form the basis of *structural uncertainty* (Williams *et al.* 2002). All of these sources of uncertainty should be taken into account in decision making; the last, structural uncertainty, potentially can be reduced via an integrated program of management under prediction and information updating from monitoring, known as *adaptive management* (Walters 1986; Williams *et al*. 2002).

In the next section, we illustrate principles of SDM and ARM, and key steps in developing a SDM/ARM process, using as our example the conservation of Hector's dolphin, an endangered species endemic to New Zealand. We considered this example as part of a 3-day workshop on decision analysis and adaptive management held at University of Otago in February 2007.

Example: conservation of Hector's dolphin

Hector's dolphin is the world's smallest dolphin, and the only dolphin endemic to New Zealand (Baker 1978; Slooten and Dawson 1994). The species inhabits coastal water where it is vulnerable to anthropogenic impacts, including pollution, disturbance by boating, and entanglement in gill-nets used in commercial and recreational fishing (Slooten and Dawson 1994; Cameron *et al*. 1999; Slooten *et al*. 2000). The species is classified as endangered under IUCN criteria (Klinowska 1991). Subsequent survival estimates and population projections (viability analyses) have affirmed this status, suggesting a high probability of continuing population declines (Slooten *et al*. 1992, 2000; Burkhart and Slooten 2003), with concern focussing on apparently low adult survival rates (Cameron *et al*. 1999; but see Fletcher *et al*. 2002).

We suggest that conservation of Hector's dolphin contains all the classical ingredients for application of structured decision making and adaptive management as outlined above. First, there are both clear conservation goals, and other societal goals that potentially conflict with or constrain the conservation goals. For example, under some scenarios, conservation objectives for Hector's dolphin potentially are achievable by means of restrictions on gill-netting or other fishing activity. However, such restrictions clearly conflict with the objectives of other stakeholders, namely those benefiting economically or otherwise from the absence of restrictions. Second, profound uncertainty exists as to the causes for declines in Hector's dolphin populations, and, specifically, the extent to which reductions in specific mortality sources such as gill-net entanglement would actually remediate these declines. This interaction between conflicting stakeholder values and disagreements over scientific issues potentially results in a gridlock situation, in which disagreements over scientific uncertainty become a rationale for delaying decision making (Slooten *et al*. 2000). As illustrated below, it is possible (and desirable) to disentangle 'values' from science, endeavouring to compromise on the former, and quantify (and where possible reduce) uncertainty in the latter through adaptive management.

A large number of stakeholder groups have an interest in Hector's dolphin management, including conservationists, agency representatives, fishers (commercial, recreational, customary, and subsistence), tour operators, representatives of the aquaculture industry, Maori, and the general public. We focussed our decision modelling on the competing stakeholder groups, conservationist and fishers, and the principal government agencies responsible for setting environmental and

Table 1. Fundamental objectives of stakeholder groups/representatives for Hector's dolphin conservation problem

Stakeholders	Objectives	Avoid
Conservation	(1) Hector's dolphins delisted from IUCN list as a consequence of population growth. (2) Maintain tourism access.	(1) Continued population declines. (2) Excessive human-induced mortality.
Fishers	(1) Maximise long-term profit from fishery. (2) Maintain fishing access.	(1) Additional fishing restrictions. (2) Loss of fishing access.
DOC	Non-threatened Hector's dolphins throughout natural range.	Continued population declines.
MFish	Human-induced mortality does not result in decline in the four subpopulations of Hector's dolphins.	Continued population declines due to human-induced mortality.

fisheries regulations, and to varying degrees representing the stakeholders' interests: the New Zealand Department of Conservation (DOC) and Ministry of Fisheries (MFish). Our working group included staff from DOC and MFish, as well as academics and representatives of conservation non-government organisations, but no representatives of fishing interests except by proxy through MFish. We approached the development of a decision model by first engaging in a role-playing exercise in which participants were asked to assume the role of one of the two broad stakeholder areas, with a spokesperson for each (PWD and DF for fishers/MFish; RJB, AMG, and Susan Waugh for conservationists/DOC).

Formulating objectives

A first step in formulating objectives is the separation of fundamental and means objectives (Clemen 1996). By *fundamental objectives* we mean objectives that are important because they represent the fundamental values of the decision maker, where 'decision maker' often is a proxy for several stakeholders. In contrast, *means objectives* are important because they help to provide the means by which we can achieve the fundamental objectives. The distinction between fundamental and means objectives is not always clear, but can be facilitated by asking two questions: 'why is the objective important', and 'how do we get there'. Objectives that are important, in their own right, without respect to how they are achieved, are fundamental objectives. Objectives that help one to achieve fundamental objectives are means objectives.

Each subgroup developed by consensus objectives that were relevant to their respective stakeholders, along with outcomes they wished to achieve and/or avoid (Table 1). We then organised these into an objective network, in an effort to distinguish between truly fundamental objectives, and means objectives or decisions alternatives (Fig. 1). This effort was illustrative for at least four reasons. First, we discovered that there exist 2–3 truly fundamental objectives; in contrast, it is not clear that 'maintaining tourism' is a distinct, fundamental objective, as much as a desirable by-product of the maintenance of robust dolphin populations (although the two may occasionally conflict, e.g. if tourism activities disturb dolphins). Second, several stated objectives are apparently important principally as means objectives, and thus presumably would be less important, were the fundamental objectives achievable by other means. For example, it may be possible to achieve the fundamental objective 'maintain the fishery' with some loss of profit or access, or increase in regulations, whilst not achieving the means objective 'minimise new regulations' (Fig. 1). Third, some linked goals may be in conflict, as would be the case if 'reduction of human-induced mortality' involved restrictions on tourists' access to Hector's dolphins via motorboats. Finally, we observed that

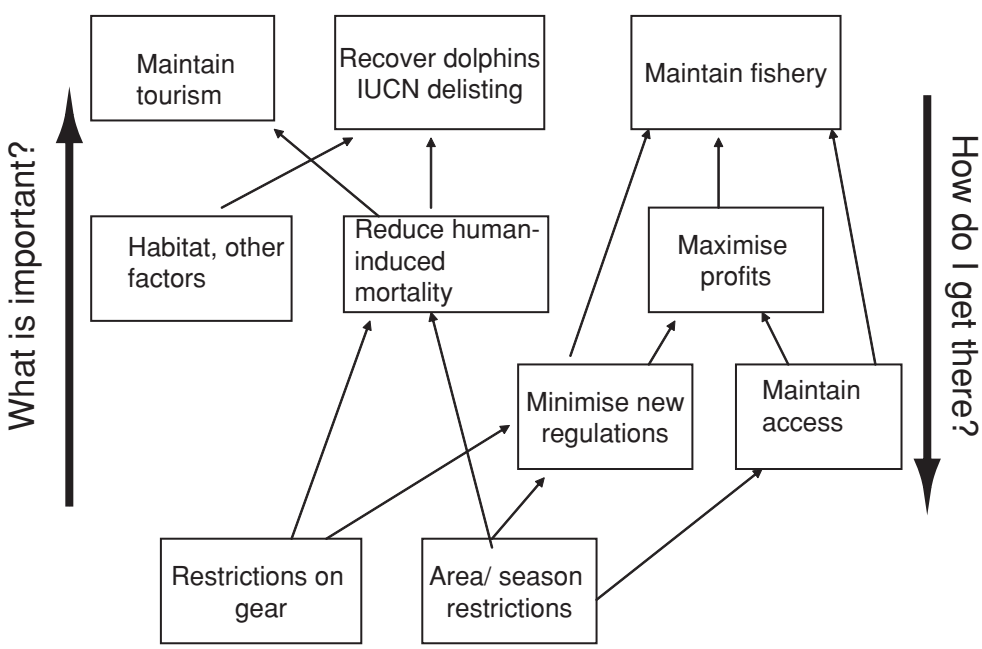

Fig. 1. Objective network showing the relationship between fundamental and means objectives for Hector's dolphins. Fundamental objectives of delisting of Hector's dolphin and maintenance of fishery, with several mean objectives. Arrows indicate connection of means objective (middle levels) and methods (bottom level) to fundamental objectives (top level).

some fairly obvious means objectives were not listed by the group, whether by oversight or by recognition of limited means by which to achieve these objectives. One that was mentioned is 'improve habitat conditions and reduce other mortality factors', which includes mitigating trophic and other effects due to intensive commercial fishing, pollution, and climate change. While recognising that such factors may potentially overwhelm other efforts, the groups felt constrained to focus on objectives and decisions related to the reduction of human-induced mortality, as discussed below.

Decision alternatives

The set of decision alternatives must be feasible, mutually exclusive, and exhaustive (Lindley 1985; Clemen 1996). By feasible, we mean that each decision must be an action that could be implemented if selected; decisions that are impracticable, illegal, or otherwise impermissible, should not be included in the decision model. For instance, a total ban on fishing or other human activities in areas frequented by Hector's dolphin might be effective in reducing human-induced mortality but, if implemented, would be extremely unpopular, unenforceable, and likely to be overruled politically, were it to be selected as the optimal conservation action. By the same token, the decision set must include *all* feasible decisions (that is, it must be exhaustive). Decision alternatives, including 'no action' alternatives, should not be excluded on the basis of preconceptions about efficacy, cost or other concerns, if the alternative is otherwise feasible. Preselection of decision alternatives prejudices the decision process towards predetermined outcomes, particularly when costs or other conflicting values occur. Finally, optimal decision making ordinarily involves the selection of a single, unique decision from among mutually exclusive alternatives (although instances can be accommodated involving multiple, equivalent decisions). To that end, the decision set should involve mutually exclusive choices, so that if 'Alternative C' is selected 'Alternatives A, B, and D' cannot be. Although this sounds restrictive, even complex decisions involving combinations of actions can be rendered as mutually exclusive choices, as seen below. In other cases, the choice of one decision alternative depends on results following another decision. For example, a decision as to appropriate harvest levels to achieve sustainable harvest objectives will generally depend on previous harvest decisions. In these cases, which are common in conservation, decision making is best considered as a sequential process. We discuss sequential decision making in the next section.

On the basis of these guiding principles, our workshop group developed several decision alternatives for conservation of Hector's dolphin. Most previous discussion of means for arresting the decline of Hector's dolphin has focussed on the impacts of gill-net entanglement, specifically controls on fishing methods that are assumed to have direct impact on mortality of Hector's dolphin (Dawson and Slooten 1993). In 1988 the Banks Peninsula Marine Mammal Sanctuary (BPMMS) was established by DOC to protect the local population from entanglement in recreational and commercial gill-nets (Dawson and Slooten 1993). The sanctuary bans the use of gill-nets/set-nets within 4 nautical miles from the coast around Banks Peninsula for the period November–February, inclusive. For the other eight months of the year, gill-nets are permitted but their use is subject to several conditions, such as length restrictions, allowing only one net per boat, and not leaving the net unattended. Effectively, these rules prohibit commercial gill-netting in the sanctuary.

We also discussed controls on volume of harvested fish, thought to potentially have an indirect effect on dolphins (e.g. through food competition), potentially in a two-tiered approach. However, for the purposes of this workshop, we decided to consider a single mechanism for action (control on overall fishing activity). After further simplification, we decided on three decision alternatives representing different levels of controls on fishing:

- Current – i.e. existing controls on fishing (e.g. current gill-net restrictions, overall catch limits, voluntary controls, marine mammal sanctuary)
- Medium – i.e. some additional controls (such as use of pingers, seasonal controls, some additional method controls)
- High – i.e. a large number of additional controls on fishing activity (extensive area closures; other methods such as trawling also addressed)

Actual implementation of any of these alternatives would, of course, require more detailed specification of controls, including timing and spatial restrictions. We note that none of our stakeholders/proxies thought that either the removal of all fishing restrictions, or a total ban on all fishing and boating activity, would be feasible alternatives; thus we have not included these as alternatives. Given the highly endangered status of Hector's dolphin, the exclusion of a 'no action' alternative is probably consistent with current legal and political realities, so that 'current regulations' effectively constitute a baseline.

Objective value (utility)

As noted above, objectives relate to the values of the decision maker, where again 'decision maker' may be a proxy for a group of stakeholders whose values may or may not be in agreement. For some conservation problems, statement of the objective can be relatively straightforward, if there are no competing objective values. Examples of simple, unconstrained objectives could include minimisation of the risk of extinction of a species, where costs or other impacts are of no concern, or maximisation of profit from a fishery, without regard to environmental or other impacts. In these cases, the best decision is that which minimises risk or maximises profit (but notwithstanding issues of uncertainty, discussed later). More commonly, conservation decisions must deal with multiple, and often conflicting, objectives. For example, conservation actions often have direct (e.g. the expenses of control or restoration programs) and indirect (impact of burdensome regulations, opportunity costs of foregoing other conservation actions) costs that must be taken into account in selecting a decision. In other cases, we may be concerned with jointly conserving two or more species with different requirements (e.g. Moore and Conroy 2006).

As suggested above, it often can be difficult to quantify our objective values in common units. However, we do need a way to express the fact that some decision-outcomes are more desirable than others. One approach is based on establishing relative scores or values for decision-outcomes, also called *utilities*. Utility can be measured in many ways, including monetary units, but in many settings it suffices to represent utility with scores that describe the relative value of different decision out-

comes. For instance, we might arrange our decision-outcomes on a scale of 0 to 1 (or 0 to 100%), with 0 and 1 the lowest and highest values, respectively and 0.5 halfway between these two extremes (Lindley 1985). Note that in cases where the decision outcomes have other units of value (e.g. monetary), we could convert these to utility scores readily (and *vice versa*); for example, if the four mutually exclusive and exhaustive outcomes have values of –$100, $0, $50, and $100, we could represent these as 0–1 utility scores by adding $100 and dividing the result by $200 for each value, yielding 0, 0.5, 0.75, and 1.0.

For conservation of Hector's dolphin, we would expect *a priori* that the utilities of different decision-outcomes would differ among stakeholder groups. That is, each group would, if operating in the absence of other stakeholders, presumably assign most, if not all, value to outcomes achieving their fundamental goals, and little, if any, value to competing goals. Formulating a decision model requires us to identify these differing utilities and, to the extent possible, develop a common set of utilities that still satisfies the fundamental objectives of the respective groups, whilst operating within the range of feasible decision alternatives. We approached this by first eliciting utilities for the separate groups, and comparing between groups. For some decision-outcomes there was little disagreement as to utility, and a common value was quickly achieved. For instance, there was agreement that the ideal outcome would be no additional controls *and* populations increase. Likewise, the worst outcome would be high costs to fishers (i.e. substantial additional controls) and population decrease.

Other outcomes required more thought and compromise. For instance, under the initial utility values assigned, there was no situation in which a 'high' level of additional fisheries controls would be favoured. This was largely because the utility values did not sufficiently allow for the high value society would likely assign to dolphin survival (even at high or medium costs to fishers). We revisited this issue and modified the utilities accordingly. There were other substantial disagreements between groups about desirable and undesirable outcomes, which we ultimately had to resolve by taking the mean value of the respective group utilities (Table 2*a*). Even so, we recognised that, in spite of our attempts to 'role play', our 'consensus' utilities (Table 2*a*) do not capture the negative economic consequences that would occur to the fishing industry of increased restrictions on fishing activity. Therefore, we added a second set of utilities that perhaps better captures these economic costs (Table 2*b*). We make no claim that either set of utilities fully captures the range of economic and social values among stakeholders; to do so adequately would require a formal process of goal setting (McLain and Lee 1996), and likely weeks if not months or years of negotiation and compromise. Nevertheless, we think that we have sufficiently captured the key elements of the process, for the purposes of this illustration, and will move on to how we dealt with the biological aspects of the model.

First, though, it is critically important to recognise that these utilities (regardless of the process by which they are derived) have nothing to do with relative belief in the outcome following a particular decision, and *only* concern the value that would accrue, were the specified decision-outcome to occur. This is particularly true if some stakeholders have strong prior beliefs; for instance, some might assert that the pairing 'High controls – population declines' is impossible. A statement of belief such as this, ideally, supported empirically, is properly a part of the decision-outcome probability model as a competing model (below), not the objective function. If a decision alternative will be considered, *all* outcomes that could occur (however likely their occurrence) following the decision, *must* be considered and assigned a utility.

Modelling decision outcomes

As suggested earlier, all decision makers operate under a model, even if implicit, of the decision process. We now formalise the modelling process, initially with simple, graphical models, which eventually can be codified mathematically (e.g. as computer code). To describe the model we employ here a simple, graphical device known as an influence diagram (Clemen 1996) to illustrate the relationship between decisions, outcomes, and objective reward. In many cases, the decision and its value will also depend on the current system state or condition (e.g. abundance, age distribution, diversity, habitat conditions, or other attributes that describe the population, community, or ecosystem of interest). In the case of Hector's dolphin, the influence diagram relates the current status of Hector's dolphin populations to proposed alternative actions, leading to possible outcomes in terms of future status, together with the resulting gain (or loss) in utility thereby achieved.

Our next step was to quantify the relationship between prospective decisions and possible outcomes, explicitly dealing with uncertainty. Ignoring uncertainty virtually guarantees suboptimal outcomes, and may produce results that are indeed quite bad. Considering uncertainty, on the other hand, is a form of 'bet hedging'. When we 'bet' (i.e. make a decision about which the outcome is uncertain), we are concerned not just about the chance that a favourable (or unfavourable) outcome will occur, but also about what its value (utility) is. Our 'conservation' group used a combination of published analyses of demographic data (population viability analyses) and 'expert opinion' to develop alternative models relating our decision alternatives to the probability that the population of Hector's dolphin would decrease, remain constant, or increase over the next 20 years (a time horizon corresponding to projections in Slooten *et al*. 2000). Slooten *et al*. (2000) and Burkhart and Slooten (2003) provided projections for distinct subpopulations of Hector's dolphin, with most subpopulations projected to decline with high probability, but a few to stabilise or increase. For the pur-

Table 2. Decision alternatives, outcomes, and utilities for Hector's dolphin decision problem

(a) Consensus utilities. Values in bold indicate strong agreement between conflicting stakeholder groups. (b) Utility value strongly discounted under the 'high increase' option, reflecting industry economic objectives

Stakeholder	Decision alternative	Utility of outcome		
		Decrease	Stable	Increase
(a) Consensus	Current regulations	0.25	0.50	**1.00**
	Medium increase	0.15	0.45	0.60
	High increase	**0.00**	0.40	0.60
(b) Industry	Current regulations	0.25	0.50	1.00
	Medium increase	0.15	0.45	0.60
	High increase	0.00	0.20	0.30

poses of this exercise, both groups considered a single population of Hector's dolphin and therefore used a slightly more optimistic probability of decline over 20 years of 0.90 (Table 3) versus 0.92–0.94 (Slooten *et al*. 2000). Most of the remaining 0.10 probability we assigned to 'stabilise' but did allow for a small chance (0.025) that the population would increase, even given current regulations. By contrast, the 'Fishery' group had more optimistic assessment of outcomes under this scenario, although the 0.70 probability of decline is consistent with some projections of Slooten *et al*. (2000) (i.e. those assuming a maximum age of 30 rather than 20 years) (Table 3).

Statements about the probability of the three outcomes under alternative conservation decisions require assumptions about the relationship between reductions in gill-net entanglement, and corresponding reductions in adult survival rates and, ultimately, population growth rates. To date, the evidence for mortality reduction via restrictions on gill-netting remains equivocal. Restrictions of gill-netting around Banks Peninsula resulted in no apparent change in survival; however, the comparison was statistically weak (Cameron *et al*. 1999). Much of the evidence that has been marshalled is based on the apparent sensitivity of population growth rates to adult survival rates, a phenomenon common in long-lived marine mammals; by implication, the prediction is that increasing the latter should have a strong effect on the former. However, we have seen no published projections of probability of outcomes (decreasing, stables, or increasing) under specific alternatives. Therefore, the 'conservation' group assumed that a large proportion of mortality in excess of recruitment is due to gill-net entanglement. This assumption, in turn, resulted in the prediction that scenarios of increased regulations would result in corresponding decreases in the probability of short-term population decline and increases in the probability of short-term population growth. (Table 3). By comparison, the 'fishery' group, while initially more pessimistic, were more sceptical that increased regulations would translate to increased growth rates, consistent with a general belief that causes other than fishery activities are primarily to blame for the imperilled status of Hector's dolphin.

Further analyses and data, ideally involving controls, might improve upon these estimated probabilities; also, we recognise the loss of realism incurred by simplification to a single population. Nevertheless, our two models capture the essential dispute about the facts between conservation and fishery interests, which turn on (1) the relative roles of mortality from gill-net entanglement and other sources, and (2) the likelihood that restrictions on fishery activities reducing mortality from gill-nets would substantially improve the population outlook for Hector's dolphin. Note that this device distinguishes between uncertainty in outcomes *given* an underlying model, due to environmental stochasticity or partial controllability, and uncertainty about which underlying model (hypothesis) best represents this system. Finally, the modelling exercise served our main purpose: to separate statements of objective value (utilities, Table 2) from statements about scientific 'fact' (the probability model, Table 3). With this distinction in hand, we could then proceed to comparing decisions, taking into account both environmental (probabilities from population viability analyses and other sources) and structural uncertainty (relative belief in the alternative models).

Table 3. Decision-outcome probabilities for Hector's dolphin decision problem

Model	Decision alternative	Probability of outcome		
		Decrease	Stable	Increase
1. 'Conservation model'	Current regulations	0.90	0.075	0.025
	Medium increase	0.40	0.35	0.25
	High increase	0.05	0.20	0.75
2. 'Fishery model'	Current regulations	0.70	0.20	0.10
	Medium increase	0.60	0.28	0.12
	High increase	0.50	0.35	0.15

Selecting the optimal decisions

Having elaborated the decision alternatives, a mathematical statement of the objectives (i.e. our utilities), and a decision-outcome model, it is possible to examine candidate decisions in order to evaluate which best fulfil the objective. In simple, non-recurring decisions problems, involving a finite list of decision alternatives, the selection of the best decision can sometime be obtained simply by graphing or ranking the objective outcomes under the alternative decisions, and selecting the one corresponding to the highest (or lowest) objective value. The usual approach is to choose the decision that gives us the best average or *expected value* (Lindley 1985). This is accomplished simply by computing the weighted average of the utilities across all the possible outcomes following a decision, with the weights being the probabilities of each outcome. The procedure is then to select the decision that provides the highest expected utility value. More complicated problems, such as those involving recurring decisions, conflicting objectives, or mathematically complex decision-outcome models, generally require specialised computer algorithms to find a solution. For the moment, we treat Hector's dolphin as a non-recurring (static) decision problem; later we will consider how this problem might more appropriately be viewed in a sequential, dynamic fashion.

We used the above utilities (Table 2) and model-specific outcome probabilities (Table 3) to compute expected values for each decision alternative and select an optimal decision, under a range of prior model weights. To perform our calculations we used Netica (www.norsys.com), a graphically oriented program for the analysis of Bayesian Belief Networks (e.g. Marcot *et al*. 2001), of which our decision models are a special case. Although computations for a simple problem like ours are readily performed by other means (e.g. in a spreadsheet), Netica provides a convenient graphical representation of decision problems, and is readily generalised to more complex problems. Further, because of the implicit Bayes operators employed by Netica, the program readily allows for Bayesian updating, as illustrated later. We illustrate how these calculations are made under the 'conservation' model (Table 3). Under this model, the probabilities of decreasing, stable, or increasing populations of Hector's dolphin are respectively 0.90, 0.075 and 0.025 under 'current regulations'. The respective consensus utilities of these outcomes are 0.25, 0.5 and 1.00. Therefore, the expected value of this decision (again, under the chosen model) is

$$E(Current) = 0.90 \times 0.25 + 0.075 \times 0.50 + 0.025 \times 1.00 = 0.2875.$$

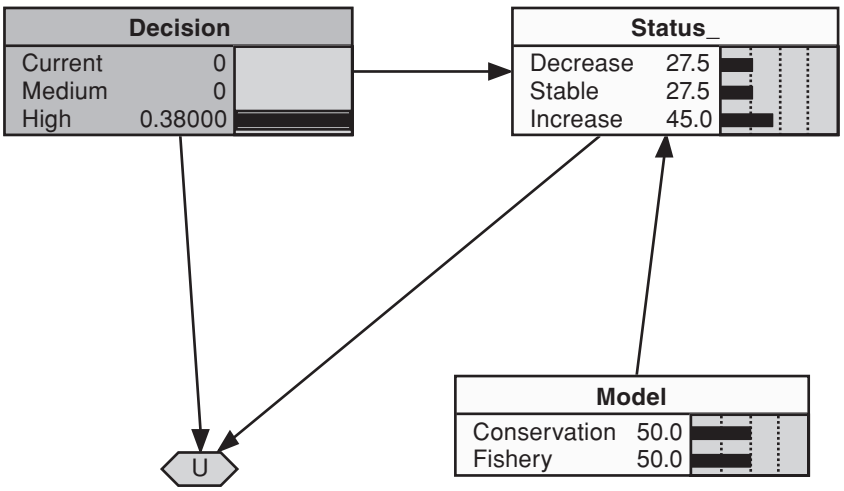

Fig. 2. Bayesian belief network used to illustrate Hector's dolphin decision problem. Decision (high controls) predicted (under equal weight of alternative models) to result in decrease, stability, or increase of Hector's dolphin with probabilities 0.275, 0.275 and 0.45, respectively, resulting in expected value of decision of 0.380 given consensus utitilies (Table 2; see text for full details).

Similar calculations for the other two alternative actions provide *E(Medium)* = 0.3675 and *E(High)* = 0.53, suggesting that the 'high increase' alternative is optimal. By contrast, given the same utilities but the probabilities under the 'fishery' model, we have expected utilities under the current regulations, medium increase in controls and high increase in controls of 0.375, 0.288 and 0.23, suggesting that current regulations are optimal.

We used Netica to provide these calculations under both the consensus and industry utilities (Table 2), as well as to compute expected values under ranges of model weights for the two models (Fig. 2, Table 4). Not surprisingly, when all weight was assigned to the 'conservation' model, either the 'high increase' or 'medium increase' option was clearly favoured over other alternatives, depending on the utitilies employed. However, these options were also favoured under profound structural uncertainty (0.50 weight for each model); in fact, the 'high increase' option remained favoured under the consensus utilities up to weights on the 'fishery' model of nearly 0.75, beyond which the 'current regulations' alternative was favoured for both utility sets. Under these model-specific utilities and outcome probabilities, therefore, relatively weak support would be required of the 'conservation' model, in order to favour fairly aggressive conservation action. Interestingly, the intermediate alternative of 'medium increase' in regulations was found to be optimal only when the 'industry' utilities were employed, reflecting the stronger influence of economic values. Thus, incorporation of economic value, in this instance, may actually help to avoid 'all or nothing' regulations that might otherwise be selected.

We caution that these results are highly dependent on our assumed model and utility values, both of which were obtained via great simplification, and under a degree of subjectivity. They cannot, therefore, be taken to support any particular conservation decisions, but instead are intended to illustrate a process for arriving at conservation decisions that (1) are directed at stated objectives, and (2) take into account uncertainty.

The value of information

This example makes the very important point that information has value, as measured in the currency of our decision problem (i.e. our utility units). In other words, if we had additional information, we could reduce uncertainty and make a better decision – one that provides us with a better objective outcome (higher utility). This happens because whenever we have uncertainty, we have to average over the uncertain outcomes in order to deter-

Table 4. Expected utilities and optimal decisions for Hectors' dolphin conservation decision problem
Optimal decision alternatives (providing highest expected utility) are shown in bold

Model weight		Decision alternative	Expected utility[A]	
Conservation model	Fishery model		Consensus utitilies[A]	Industry utilities[A]
1.00	0.00	Current regulations	0.288	0.288
		Medium increase	0.368	**0.368**
		High increase	**0.530**	0.265
0.50	0.50	Current regulations	0.331	0.331
		Medium increase	0.328	**0.328**
		High increase	**0.380**	0.190
0.25	0.75	Current regulations	**0.353**	**0.353**
		Medium increase	0.308	0.308
		High increase	0.305	0.152
0.00	1.00	Current regulations	**0.375**	**0.375**
		Medium increase	0.288	0.288
		High increase	0.230	0.115

[A]See Table 2.

mine the optimal decision. Decisions made under uncertainty will always lead to a decision whose value is less than or equal to the value that could be obtained by eliminating this uncertainty. This leads to the idea of the *expected value of perfect information* (EVPI), which is the difference between 'the best we could do under perfect knowledge' and 'the value of the best decision, given imperfect knowledge'. We can illustrate this for the Hector's dolphin example, by considering the potential value of completely eliminating structural (but not other) uncertainty in our model. In that case, we would 'know' which model was operating, and would presumably act in accord: under the conservation model, we would elect the 'High' option (with expected utility 0.530); whereas under the 'fishery' model we would elect the 'Current' option (expected utility 0.375). The expected value of our decision is the average of these (0.4525), since we do not presently know which model is true. By contrast, the optimal decision under uncertainty about which model is true is the 'High' option, with expected utility 0.405. The difference (0.451 – 0.405 = 0.0475) is the amount, in utility units, that would be gained by reducing structural uncertainty to zero.

Although largely a theoretical concept, EVPI can be useful. First, it casts the need for information directly in terms of decision making, and in the currency of our objective utilities, as opposed to arbitrary statistical measures. From the standpoint of decision making we ought to be willing to pay up to EVPI (but not more) to reduce uncertainty, via additional research and monitoring. In practice, the actual value of data is less than EVPI, due to statistical uncertainty, partial controllability, and other 'noise'. More importantly, thinking of information in this way focuses monitoring and research programs on improving decision making, rather than achieving arbitrary standards of precision or statistical power.

Reducing uncertainty

Clearly, the relative belief in these two alternative models potentially has a large effect on decision making, and the assignment of apparently arbitrary weights to these models would therefore seem unsatisfactory. In some cases, a formal, information-theoretic approach can be used to provide an information-based weight of evidence for each model (Burnham and Anderson 2002). This approach is very similar to that used by Conroy *et al*. (2002) in the development of adaptive harvest management models for American black ducks (*Anas rubripes*). This approach is not without problems; for instance, it tends to rely heavily on retrospective data, rather than controlled, prospective studies (Conroy *et al*. 2002).

However, often there is little or no empirical support for the initial model weights, but decisions must still be made. Even when there is strong evidence favouring one model, structural uncertainty still exists, and therefore decision making would be improved if that uncertainty were reduced. In either case, it may be necessary to start with initial, subjective model weights based, for instance, on expert opinion. Regardless of the origin of the initial weights (objective or subjective), there is the potential for adaptive updating, when sequential decision making is coupled with monitoring to assess outcomes following decisions. Here, we sketch how an adaptive process might work for the conservation of Hector's dolphin, providing a hypothetical scenario programmed in Netica. Suppose that we assume initial weights of 0.5 for each model (either because of lack of discriminatory evidence or because of stakeholders' inability to agree on the appropriate evidentiary basis). The optimal decision, given these weights and the model-specific utilities and outcome probabilities (Tables 2, 3), is the 'high' alternative (Table 4, Fig. 2). Once this option is selected and implemented, our model-averaged predictions provide probabilities of 0.275, 0.275 and 0.45 that the population will decrease, remain stable or increase, respectively (Fig. 2). Suppose that we monitor the population following this decision and observe that the population decreases. Because this event has now occurred, it is no longer a prediction, and by setting this quantity to a 'known', Netica automatically recalculates the probability of the remaining 'unknown', the model weights, under Bayes' Theorem. When structural uncertainty about the system exists, monitoring takes on a new role, because it allows us to gauge how well each of our competing models predicts system changes following a decision. A standard measure for this comparison is the likelihood under each model, which provides a measure of agreement of the outcome predicted under the model and the observed outcome. In turn, the likelihoods are used with Bayes' Theorem to modify our relative belief in alternative models with new observations (Williams *et al*. 2002). A general expression for the sequential updating of model weights via Bayes' Theorem is

$$w_i(t+1) = \frac{w_i(t)L_i(t)}{\sum_{j=1}^{n} w_j(t)L_j(t)},$$

where $w_i(t)$ and $w_i(t+1)$ are the probability weights of model i before and after updating, respectively, and $L_i(t)$ is the likelihood of the monitoring data collected at time t under model i. The denominator of this expression is the sum of the weighted likelihoods for all of the n competing models.

In our example, the likelihoods that the population is observed to decrease following the 'High' option are 0.05 under the 'conservation model' and 0.5 under the 'fishery model'. Taking these values, and assuming initial model probabilities of 0.5 each, we have an updated weight for the 'fishery' model of

$$\begin{aligned} w_F(t+1) &= \frac{w_F(t)\,L_F(t)}{w_F(t)\,L_F(t) + w_C(t)\,L_C(t)} \\ &= \frac{0.5 \times 0.5}{0.5 \times 0.5 + 0.5 \times 0.05} \\ &= 0.91 \end{aligned}$$

with the updated weight for the 'conservation' model obtained similarly (or simply by subtraction from 1.0 since there are only two models) as 0.09 (Fig. 3). The new model weights would then be the new basis for subsequent decisions, resulting in a new optimal decision of 'current regulations'. This is an example of adaptive resource management (ARM) under sequential decision making at a single location. The approach could readily be extended to sequential decision making involving several sites, perhaps more suited to the Hector's dolphin problem, in that regulatory actions could be taken in some areas, with feedback from monitoring applied to areas where actions have not yet been taken (or which are maintained as controls). In general, ARM comprises four elements (Williams *et al*. 2002):

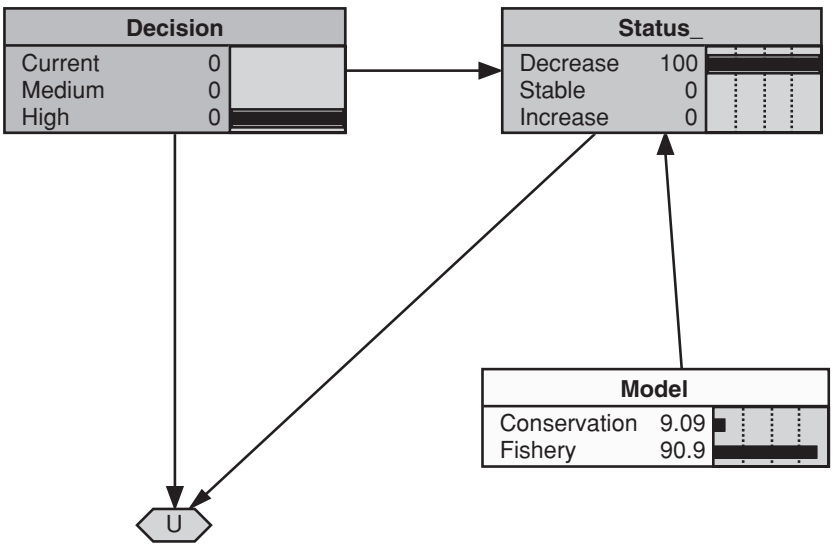

Fig. 3. Hypothetical scenario involving adaptive updating for sequential Hector's dolphin decision problem. Selection of 'high' decision alternative results in decrease of Hector's dolphin, consistent with new model weights of 0.09 and 0.91, respectively (see text for details).

(1) Decisions are made based on predictions under two or more alternative models, and lead towards some defined objective. (2) Decision making is repeated sequentially, either through time or space. The combination of (1) and (2) combined with (3), a monitoring program, allow comparison of model predictions to observations, and the incorporation of this predictive feedback into the revision of information weights. Finally, (4) the new information weights are used to inform decision making, leading us to new predictions and management choices, and returning to Step (1).

In this example, we have glossed over two technical issues that would need to be addressed in an actual implementation of ARM. First, the model predictions, as cast in Table 3, are over 20-year periods. In all likelihood managers would desire empirical feedback to decision making much sooner (perhaps over periods of 1–5 years). For instance, it might be more appropriate to predict annual population growth (Burkhart and Slooten 2003), for comparison to annual estimates of population change through aerial surveys (Slooten *et al*. 2004) or capture–recapture (Gormley *et al*. 2005). Second, in our simplification of the Bayesian updating procedure, the outcome probabilities are used directly to compute the likelihoods under each model, without reference to sampling error. In practise, the likelihoods would also need to account for statistical uncertainty induced because sample data are being used to estimate abundance and demographic parameters.

Although we have emphasised a Bayesian decision theoretic context for conservation decision making, we recognise that other approaches may be more appropriate for given problems, particularly when large amounts of data or other knowledge exist. Formal optimisation procedures, such non-linear and dynamic programming, simulation, and heuristic methods such as genetic algorithms (Goldberg 1989) can be very useful tools for decision analysis. The key is the proper incorporation of uncertainty into decision making and, ideally, provisions for its reduction via some type of adaptive feedback, both of which can be provided by Bayesian approaches. Also, our Hector's dolphin example is largely reliant on subjective information (i.e. expert opinion), which can be controversial. We point out, however, that Bayesian updating of knowledge proceeds rigorously under the likelihood principle and thus that strong experimental evidence will inevitably dominate weak, subjective prior information (Berger 1980). The reality is that much knowledge in conservation is weak and is often subjective; Bayesian approaches provide a way to utilise this knowledge in decision making, while seeking to improve it empirically (e.g. Maunder *et al*. 2000; Breen *et al*. 2003; McCarthy *et al*. 2004; Martin *et al*. 2005).

Finally, this approach complements, rather than supplants, previous efforts to quantify and incorporate uncertainty into decision making (e.g. Slooten *et al*. 2000). Rather than focussing on the issue of uncertainty *per se*, we have shown how uncertainty interacts with decision-outcome utility in important and sometimes unpredictable ways. However, reduction of uncertainty addresses only one aspect of the problem, because decision making also must deal with fundamental values that may be in conflict. The approach we have outlined allows separation of the issues of 'values' from that of uncertainty. We have made specific suggestions as to how the latter can be reduced, via monitoring and adaptive updating. When common stakeholder utilities are not obvious, as is likely for Hector's dolphin, resolution will require the skills of experts in the areas of human dimensions and conflict resolution, important areas that are beyond our expertise (see however McLain and Lee 1996). Finally, once objective values and a biological model are incorporated into a decision model, and uncertainties quantified, the decision model can be used to assess the future value of information.

Summary

We suggest that most conservation decision problems can, and probably should, be cast in a decision-theoretic framework, for several reasons. First, as already noted, this allows clear separations of objectives from scientific issues, all too frequently entangled when decisions are contentious. Second, it allows coherent, objective-driven decision making to proceed, even in the face of profound uncertainties about data or likely outcomes following decisions. Third, it provides, via adaptive management, a synthetic way to incorporate existing knowledge, moni-

toring data, and improvements in scientific understanding, into a common framework that is directed at making the best possible decision, given current information. Our Hector's dolphin example, involving a contentious decision issue with conflicting stakeholder goals and beliefs, illustrates this approach.

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