Integrating info-gap decision theory with robust population management: a case study using the Mountain Plover

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Abstract. Wildlife managers often make decisions under considerable uncertainty. In the most extreme case, a complete lack of data leads to uncertainty that is unquantifiable. Information-gap decision theory deals with assessing management decisions under extreme uncertainty, but it is not widely used in wildlife management. So too, robust population management methods were developed to deal with uncertainties in multiple-model parameters. However, the two methods have not, as yet, been used in tandem to assess population management decisions. We provide a novel combination of the robust population management approach for matrix models with the information-gap decision theory framework for making conservation decisions under extreme uncertainty. We applied our model to the problem of nest survival management in an endangered bird species, the Mountain Plover (*Charadrius montanus*). Our results showed that matrix sensitivities suggest that nest management is unlikely to have a strong effect on population growth rate, confirming previous analyses. However, given the amount of uncertainty about adult and juvenile survival, our analysis suggested that maximizing nest marking effort was a more robust decision to maintain a stable population. Focusing on the twin concepts of opportunity and robustness in an information-gap model provides a useful method of assessing conservation decisions under extreme uncertainty.

Key words: Charadrius montanus; info-gap; information-gap analysis; matrix models; Mountain Plovers; robust population management; sensitivity analyses.

INTRODUCTION

Wildlife managers and conservation professionals often have to make timely decisions in the face of considerable linguistic and epistemic uncertainty (Regan et al. 2002). The former type of uncertainty usually arises when language is imprecise and leads to the use of terms that are vague or ambiguous. The later, and perhaps more familiar, type of uncertainty manifests itself as measurement or process error, and is often expressed with a probabilistic model. The type of uncertainty where a probability can be assigned to an outcome is referred to as risk in the economics literature (Hummel et al. 2009).

In some cases, though, epistemic uncertainty may be so extreme and pernicious that it cannot be dealt with through commonly used probabilistic methods. This often happens when data are so poor (or are entirely lacking) that the associated uncertainty is immeasurable. By immeasurable we mean that it would not be possible to sell insurance against the event, because the expected cost cannot be computed. This type of uncertainty is sometimes referred to as *Knightian uncertainty* (Knight 1921, Ben-Haim 2006). Unfortunately, one cannot always wait for new and better data before making a management decision. This disconnect between the rate at which new information accrues and the need to take action makes reliance on models imperative in making defensible decisions (Starfield 1997).

Building a matrix population model is one method that biologists may use to capture the dynamics of a wildlife population (Caswell 2001). Formal analysis of matrix models provides a way to examine the impact of certain management decisions on the life-history parameters of a species. Biologists often analyze the sensitivity of model parameters to determine which life stages should be the focus of management (e.g., Silvertown et al. 1996). However, sensitivity analyses are limited in terms of their usefulness in population management. Hodgson and Townley (2004), for example, point out that the results of sensitivity analyses often point to impractical management options (e.g., improving adult survival in birds). Traditional sensitivity analyses also do not allow for multiple perturbations at the same time (Baxter et al. 2006, Hodgson et al. 2006, Lubben et al. 2008), unless we assume responses to perturbations are linear and lack interactions (Caswell 2001). For "at-risk" species, these problems are amplified because biologists often lack necessary life-history information. This can make the parameterization of models partic-

ularly difficult, weakening conclusions, and opening decisions to challenges.

One common method for dealing with a lack of information about the vital parameters of a species is to borrow estimates from other studies or related systems (so called "placeholder values"; Starfield 1997). The same lack of knowledge that requires borrowing parameters poses additional difficulties in making management decisions. One does not know how wrong the borrowed values are relative to the system under study. Placing some measure of uncertainty on placeholders is difficult, if not impossible, because these estimates are not derived from the system to which they are being applied. For example, suppose a biologist estimates the survival rate for an organism (complete with standard errors or confidence intervals) in a part of the species' range that contains much of its original high quality habitat. Now, suppose a biologist working at the edge of the species' range lacks these estimates, but wishes to predict the viability of this population. The biologist could borrow the previous survival estimate, but would not know how biased survival at the edge is from survival in other portions of the range. Thus, making any type of management recommendation based on borrowed information could be highly suspect.

Ben-Haim (2006) proposed a solution for these situations and called it "information-gap decision theory." Typically, an information-gap (info-gap) decision analysis has three components: (1) a system model, (2) an uncertainty model, and (3) a criterion or performance requirement. The system model is what describes the behavior of the system under different decision scenarios. Because we often have little data, we cannot describe the parameters of the system with probability distributions. As a result, we cannot perform a formal risk analysis. We can, however, represent the uncertainty in the system using an info-gap uncertainty model. This model specifies the levels of uncertainty around each of the parameters in the system model. We treat the system model parameters as nominal points, and using the uncertainty model, we can specify a region or "horizon" of uncertainty around each nominal point (Ben-Haim 2006). We then assess the level of uncertainty around each parameter (or decision) relative to a performance criterion. We often specify the minimum acceptable state, or threshold, as the criterion.

Ben-Haim (2006) further developed the concept of immunity functions for quantitatively measuring the desirability of certain decisions relative to the performance criterion. In an info-gap analysis immunity takes on two forms: robustness and opportunity. For decisions that shift the nominal points above the performance criterion one can tolerate more system uncertainty before reaching the state of failure. Decisions that cause the system to exceed the performance criterion over a wide range of uncertainty are said to be more "robust" or "immune to failure" (Ben-Haim 2006). The other type of immunity deals with decisions that shift the nominal points of the system model below the performance criterion. These decisions are not desirable in general. But because there is uncertainty in the system and, thus, the efficacy of the decision, there is always the possibility that the outcome of the decision is wrong. There is a possibility under this scenario that we could meet the performance criterion. Therefore, we would like to know what the smallest amount of uncertainty is that one needs to be able to assume the possibility, but not a guarantee, of a desirable outcome. Decisions that do not require large amounts of uncertainty to meet this possibility are said to be more "opportune" or "less immune to success" (Ben-Haim 2006).

Assessing management decisions in an info-gap context is not done frequently in natural resource management, although some examples do exist. Hipel and Ben-Haim (1999) provide good examples of the concept of robustness and uncertainty in hydrologic models used in watershed management problems. A common outcome for info-gap applications in natural resources is that tradeoffs typically occur between the amount of system uncertainty that one is willing to tolerate and the amount of investment one is willing to make in management (e.g., McCarthy and Lindenmayer 2007). Likewise, others have shown that there is often a tradeoff between decisions that are optimal (i.e., maximize the criterion) and those that are robust to uncertainty (Moilanen and Wintle 2006, Moilanen et al. 2006). In that regard, Regan et al. (2005) has shown that decisions in endangered species management could change as uncertainty increases or as management criteria change.

In the above examples, information-gap theory has been used to help understand decision making in fairly "large" management problems (e.g., watersheds, habitat restoration, threatened species lists). Here, we take the approach of applying info-gap theory to a "small" local management problem. Our case study involves the efficacy of protecting the nests of an endangered bird (the Mountain Plover, *Charadrius montanus*) from being destroyed by agricultural cultivation. The goal of this analysis was to answer two questions: (1) Is protecting nests from cultivation an effective management strategy for maintaining Mountain Plover populations? (2) If it is, how much effort should be expended in terms of searching agricultural fields for Mountain Plover nests? Like many endangered population management programs, we started with very little information and tried to make defensible recommendations about the management of this population.

METHODS

Case study: Mountain Plover and nest protection

The Mountain Plover is a shortgrass prairie bird species whose breeding range primarily occupies the states of Montana, Colorado, and Wyoming in the USA. A small portion of the eastern edge of this range

PLATE 1. Mountain Plover nest in an agricultural field in western Nebraska, USA. Photo credit: Bart Bly.

extends into the state of Nebraska, where this bird is listed as a species of concern (Schneider et al. 2005). Knopf (1996) has documented widespread population declines for this species since the late 1960s. Researchers have suggested that one possible reason for the observed decline could be related to the fact that this species often nests in agricultural fields subject to mechanical tillage (Knopf and Rupert 1999; B. Bly, *personal observation*). Thus, nest failure has the potential to be high in largely agricultural portions of the shortgrass prairie, such as western Nebraska.

Little is currently known about the Nebraska population of Mountain Plovers. Recent monitoring programs have shown that Mountain Plover relative abundance in Nebraska is fairly low, and that they frequently nest in dryland agricultural fields (B. Bly, M. Post van der Burg, A. Tyre, L. Snyder, J. Jorgenson, and T. Vercauteren, *unpublished data*). The Nebraska Prairie Partners, a conservation partnership between the Rocky Mountain Bird Observatory and the Nebraska Game and Parks Commission, has been managing plover nest survival in Kimball County, Nebraska, in an effort to improve population persistence in the state. Their strategy is to search for nests in agricultural fields and then protect the nests by marking them so that producers can easily avoid nesting areas and thereby

alleviate a potential cause of nest failure (Bly et al., *unpublished data*).

Recent research by Dreitz and Knopf (2007) in Colorado showed that the success of unprotected nests in agricultural fields was similar to the success of unprotected nests in native grassland sites. They suggested that nest marking would provide little in the way of benefit for Mountain Plover population growth, but could be used to establish partnerships with private landowners. However, the value of nest marking might be higher for regions such as western Nebraska, which are almost entirely dominated by agricultural fields. Bly et al. (*unpublished data*) found that protected plover nests in Nebraska farm fields had remarkably high success rates (see Plate 1). They also found that artificial nests were at fairly high risk of failing due to mechanical cultivation, and suggested that managing nest survival would have some benefit in improving plover population growth. Claims about the potential drawbacks and benefits of nest marking, however, must be evaluated in the context of the Mountain Plover's entire life history.

System model

For our system model we assumed that the dynamics of Mountain Plover populations followed a simple matrix formulation:

Table 1. Results of a sensitivity and elasticity analysis for a Mountain Plover (*Charadrius montanus*) population projection matrix.

Parameter	Estimate	Sensitivity	Elasticity
Fecundity (f)	2.7	0.14	0.45
Nest success (NS)	0.79	0.70	0.45
Juvenile survival (S_0)	0.35	1.58	0.45
Adult survival (S_1)	0.68	1.00	0.55

Note: The value of each parameter in the model corresponds to the estimate of the parameter in the table.

$$\mathbf{N}_{t+1} = \mathbf{A}\mathbf{N}_t \qquad (1)$$

where $\mathbf{A}$ is a 2×2 Leslie matrix, $\mathbf{N}_t$ is a 2×1 vector of population sizes in each age class at time t, and $\mathbf{N}_{t+1}$ is a 2×1 vector of population sizes in the next time step. We borrowed the matrix $\mathbf{A}$ from Dinsmore (2003), which was based on Mountain Plover populations in Montana.

We defined $\mathbf{A}$ as a post-breeding matrix:

$$\mathbf{A} = \begin{pmatrix} F_0 & F_1 \\ S_0 & S_1 \end{pmatrix} \qquad (2)$$

where F_0 and S_0 are the juvenile fertility and survival rates, respectively. Likewise, F_1 and S_1 are the adult fertility and survival parameters, respectively. We calculated the fecundity for Nebraska Mountain Plovers assuming that each female laid two nests per season, each nest contained an average of 2.7 eggs, and the probability of a marked nest surviving to fledge at least one offspring was 0.79, whereas unmarked nests survived with a rate of 0.19 (Bly et al., *unpublished data*). Thus, we calculated the fertilities as follows:

$$F_i = 2 \times 2.7 \times \text{NS} \times S_i \times 0.5 \qquad (3)$$

where NS is the nest success estimate, and S_i is the survival estimate for the ith age class.

We did not have survival estimates for the Nebraska population of plovers, so we used the juvenile and adult survival estimates provided in Dinsmore (2003). These estimates were 0.35 for juveniles and 0.68 for adults.

Sensitivity, parameter perturbations, and info-gap analysis

As a point of comparison, we conducted a traditional sensitivity and elasticity analysis that considered only the instantaneous change in population growth rate (λ) given a small perturbation in a single parameter. We considered three parameters in our analysis: adult survival, juvenile survival, and nest success. We perturbed one parameter at a time leaving the others at their nominal values.

This classical analysis is fairly limited in what it says about the efficacy of a certain management decision (Hodgson and Townley 2004). Similarly, it does not account for uncertainties in multiple parameters (Hodgson et al. 2006). Other methods such as Monte Carlo simulations or life table response experiments (LTRE) can incorporate multiparameter variation (Caswell 2001), but these approaches often require enough information to be able compare effects of management or construct distributions around model parameters. In our case we did not know how to structure this uncertainty and we wanted to know the desirability of different management decisions.

Using the robust population management methodology of Deines et al. (2007), we assessed the impact of this unknown uncertainty on our ability to meet a performance criterion. Specifically, this method involved specifying the full set of possible parameter combinations and then determining which combinations of this set met a prespecified value of population growth rate, λ. We began with a nominal matrix $\tilde{\mathbf{A}}$ and perturbed it to obtain a new set of parameters in a new matrix $\mathbf{A}$; thus $\mathbf{A} = \tilde{\mathbf{A}} + \mathbf{P}$, where $\mathbf{P}$ is a perturbation matrix with nonzero entries. We were only interested in perturbations that met our performance criterion $\lambda = 1$. Following Deines et al. (2007), λ is an eigenvalue of $\mathbf{A}$ if and only if

$$\det(\lambda \mathbf{I} - \mathbf{A}) = 0. \qquad (4)$$

We solved Eq. 4 for the parameter combinations of adult survival, juvenile survival, and nest success that lead to an eigenvalue of $\lambda = 1$. The nominal points for our matrix parameters can be found in Table 1. Setting $\lambda = 1$ divides the parameter space into two regions; perturbations that lead to population growth above λ and perturbations that lead to growth below λ. Deines et al. (2007) provides a more in depth description of this method in two dimensions as well as a theoretical justification for using Eq. 4.

Interestingly, it turns out that the methodology of Deines et al. (2007) is a solution to the ellipsoid-bound info-gap model (Ben-Haim 2006):

$$U(\alpha, \tilde{\mathbf{u}}) = \left\{ \mathbf{u} : [\mathbf{u} - \tilde{\mathbf{u}}]^T \mathbf{V}[\mathbf{u} - \tilde{\mathbf{u}}] \le \alpha^2 \right\}, \quad \alpha \ge 0 \quad (5)$$

where $\tilde{\mathbf{u}}$ is a vector of nominal matrix parameters, $\mathbf{u}$ is a vector of parameter values to be compared to the nominal value, $\mathbf{V}$ is a positive definite real symmetric matrix, and α is the unknown level of uncertainty in $\tilde{\mathbf{u}}$ (i.e., the horizon of uncertainty). The matrix $\mathbf{V}$ can be used to transform (e.g., stretch) the ellipsoid bound. Stretching the bound would only be necessary if one could expect some of the parameters of the model to respond differently to the same amount of uncertainty. In our case, we did not have enough information to be able to know whether this is the case. Therefore, we assumed that $\mathbf{V}$ is the identity matrix.

The ellipsoid-bound model effectively measures the distance between a nominal point and some point that represents a given level of performance. Normally, this bound would be found by evaluating the set under a proposed value of α. The methodology of Deines et al. (2007) can be used to solve for α directly. Using info-gap terminology, the values that we solved for using Eq. 4 are equivalent to $\mathbf{u}$ and the nominal points for our matrix model are equivalent to $\tilde{\mathbf{u}}$. The difference

between these values is the α needed to draw a line that connects the performance criterion and the nominal points of the model (Ben-Haim 2006). We used immunity functions to measure the desirability of decisions in terms of α. Our immunity functions were relatively simple:

$$\hat{\alpha}(\mathbf{u}, \lambda) = \max[\alpha: \lambda[\mathbf{u}] \geq \lambda_c] \qquad (6)$$

$$\hat{\beta}(\mathbf{u}, \lambda) = \max[\alpha: \lambda[\mathbf{u}] \leq \lambda_c]. \qquad (7)$$

Here, Eq. 5 is the robustness function and determines the maximum level of uncertainty that still meets the criterion. On the other hand, Eq. 6 is the opportunity function and provides a measure of the minimum level of uncertainty that leads to the potential of meeting the criterion. Recall that we are interested in the maximum and minimum levels of uncertainty in all three parameters. The easiest way to find this level of uncertainty is to imagine a vector drawn between the nominal values, which occupy a point in three-dimensional space, and the performance criterion. The shortest vector for nominal points below the criterion gives us a measure of the minimum amount of uncertainty (immunity) needed for the possibility of success. If the nominal point is above the criterion, then the shortest vector gives us a measure of the maximum amount of uncertainty we can tolerate before failing.

Performance criteria and decision algorithm

The main purpose of this analysis is to assess the efficacy of the nest protection strategy in maintaining Mountain Plover populations. As in most cases where a decision is to be made, we do not have direct evidence of the impact of protecting or not protecting a nest. But we do have evidence from an artificial nest study (Bly et al., *unpublished data*), which suggests that unprotected nests are at greater risk of destruction than protected nests. We used the point estimates for the nest success of protected and unprotected nests as nominal points in our matrix model. We then perturbed the nominal points for survival and nest success so that we considered the entire range of possible values that gave us $\lambda = 1$.

Because the efficacy of nest marking is in doubt with regard to population management, we considered a range of decisions in which the amount of effort invested in nest protection varied. We assumed that most of the available nesting habitat in our study area was identified and that our decision was to invest some amount of effort in searching for nests. We then assumed that no effort (0% of area searched) shifted our nominal nest success estimate to our estimate for unprotected nests (0.19); searching 100% of the available area shifted our nominal nest success estimate toward our estimate for marked nests (0.79):

$$NS = 0.79 \times (E) + 0.19 \times (1 - E) \qquad (8)$$

where NS is nest success and E is the level of effort

between 0 and 1. Thus, nest success at intermediate levels of effort was simply a weighted sum between the two extremes. However, there is still uncertainty in the efficacy of this decision about effort. That is, we are not sure whether the decision to invest 60% effort really leads to nest success of 55%. This uncertainty in the efficacy is included in the info-gap analysis, because if we are wrong about the difference between marked and unmarked nests this would change the weighted average. Thus, the robustness and opportunity calculated for each level of effort includes errors due to misestimation of the difference in nest success.

The result of Eq. 7 simply shows how the nominal point for nest success was calculated for nests in agricultural fields. It is likely that Mountain Plovers also nest in rangeland sites, where nest protection would not have an impact. However, no data currently exist on the fates of these nests as they have not been found in Nebraska. If we can assume that there is an additional source of nest failure that nest marking cannot impact (i.e., predation of nests in rangelands) than that could reduce any impact that nest marking in agricultural fields does have on the persistence of Mountain Plovers. To examine the effect of nest marking in concert with rangeland nests, we performed this analysis again by adding an additional nest success estimate to our weighted sum. We used the nest success estimate from Dreitz and Knopf (2007), who studied plover nest success in rangeland sites in Colorado. We computed the nominal point for our new nest success estimate as

$$NS = [0.79(E) + 0.19(1 - E)] \times 0.41 + 0.37 \times (0.59) \qquad (9)$$

where 0.37 is the success rate for rangeland nests estimated by Dreitz and Knopf (2007), 0.59 was the estimated percentage of rangeland in our study area, and 0.41 was the estimated percentage of agricultural land.

We conducted our analysis in MATLAB (version 7.8.0; Mathworks 2006) and used the following decision algorithm: (1) We selected a value of effort that varied uniformly between zero and one in increments of 0.01. Based on this value we computed a value for NS using equation 8 or 9. (2) We used this value of NS as a new nominal point in our matrix model. We kept the adult and juvenile survival estimates at 0.68 and 0.35, respectively. We then perturbed the matrix using Eq. 4 and solved for all values of our three parameters, in increments of 0.01, that gave us stable population growth. (3) We then computed opportunity and robustness using the current nominal points. The immunity values were computed as the minimum linear distance between the nominal point and the boundary where population growth was stable. We then went back to the first step and chose another value for effort.

RESULTS

The results of our sensitivity analysis showed that the absolute change in Mountain Plover growth rate was
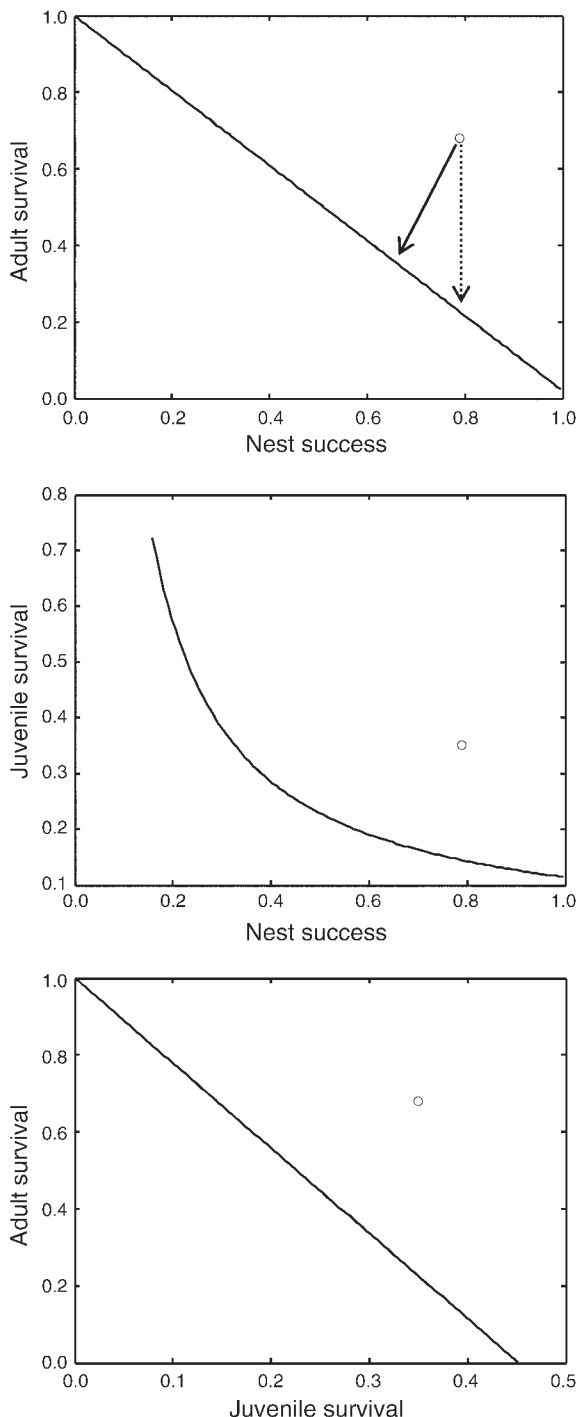
most sensitive to juvenile survival (Table 1). When the matrix perturbations were rescaled we found that λ was most elastic to proportional changes in adult survival.

When we performed our info-gap analysis we found that increasing nest success could have an appreciable positive effect on population growth (Fig. 1). We also found that by increasing nominal nest success we could tolerate more uncertainty in our survival parameters. For instance, if we assumed that our nest success estimate was perfect (i.e., exactly 0.79), then we could afford to underestimate our adult survival parameter by ~56% before we started to lose positive or stable population growth (i.e., adult survival ~0.30). Likewise, if we assumed that the lower bound of nest success was 0.68, we could then draw a vector from the nominal point (0.79) to the boundary (where nest success equals 0.68; Fig. 1). Doing this shows that we can tolerate slightly less uncertainty in adult survival. In this case, we could only afford for adult survival to be about 41% lower (i.e., adult survival ~0.40).

We formulated our model so that as we increased searching effort our nominal point for nest success also increased. Of course, each level of effort had its own measurement of the amount of immunity to failure or possibility of gain. The amount of immunity for each level of effort is plotted in Fig. 2. This figure allowed us to compare the relative amount of opportunity or robustness of decisions about effort under a single criterion (λ = 1). Under the scenario with no rangeland nests the amount of uncertainty needed to increase the possibility of a success (i.e., meet the performance criterion) decreased up to 23% of the area searched. Note that decreasing this uncertainty is good because it increases the possibility of meeting the criterion. At about the 23% level of effort, we switched from measuring opportunity to measuring robustness. In this case, we would like to increase the amount of uncertainty in order to reduce the possibility of failure. Decisions that increased searching effort also increased nest success and tended to be more robust.

When we included rangeland survival the qualitative result remained the same, but the quantitative result changed. Under this scenario it took less searching effort to increase our nominal nest success estimate to the point of exceeding the performance criterion. But, we

FIG. 1. Two-dimensional projections of the three-dimensional space of possible parameter values (adult survival, juvenile survival, nest survival) in a matrix model for Mountain Plovers, *Charadrius montanus* (effort = 100%). These parameter values were found by perturbing a set of nominal values (open circles) and then solving the characteristic equation of the matrix assuming a leading eigenvalue of 1. Points on the curved lines represent parameter combinations that produce a stable population growth rate (λ = 1). The curves in all figures represent the boundary between population decline (left of the line) and population growth (right of the line), which

←

is a two-dimensional slice through a surface in the three-dimensional parameter space. The solid arrow in the top panel is the shortest vector between the nominal point and the curve. This vector represents the maximum amount of uncertainty that can be tolerated in both parameters before reaching the performance criterion. The dotted arrow represents the case where we have perfect certainty in one parameter (*x*-axis), but uncertainty in the other parameter (*y*-axis). Note that reducing uncertainty in one parameter means we can tolerate more uncertainty in another parameter.
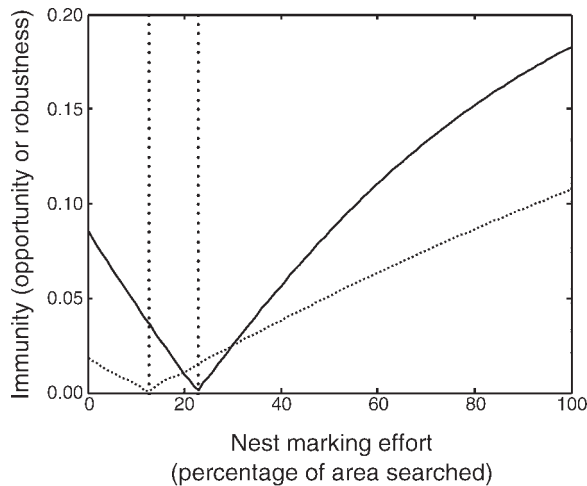
Fig. 2. The robustness and opportunity curves for various levels of nest searching for Mountain Plover nests in western Nebraska, USA. Both curved lines represent the minimum linear distance from nominal matrix model parameters to a performance criterion ($\lambda = 1$). For each level of effort, the nominal point shifted, and the minimum linear distance was calculated. The vertical dotted lines represent the point where the solid and dashed lines stop measuring opportunity (to the left) and start measuring robustness (to the right). The curved solid line represents the scenario where rangeland nest success was not included; the curved dashed line represents the scenario where rangeland nest success was included.

could not afford to be as wrong as under the scenario where we did not include rangeland nest success. This is because rangeland nests have higher nest success than unmarked nests, but lower nest success than marked nests. As a result, including rangeland nests improves performance (reducing immunity to windfall success) at low levels of nest marking effort, but reduces performance at high levels of nest marking effort (decreasing immunity to failure).

Another way to compare the relative robustness of decisions is to compare how the robustness of a single decision changes relative to different performance criteria. In Fig. 3, lines further to the right represent more robust decisions for a given performance criterion. Here, we compared three decisions about effort. We found that the ability to tolerate uncertainty decreased as the performance criterion increased. When the performance criterion was 1 or above, the robust decision was to invest maximum effort. However, if the desired level of performance dropped to ~0.5, then the decisions change and the more robust decision was to invest 50% effort. If the desired level of performance is extremely low (i.e., ~0.2), then the most robust decision is to invest no effort. This demonstrates a property of robustness: Demanding higher performance from a system typically means one can expect less robustness for a given decision. Similarly, Fig. 3 also shows how different decisions trade-off against each other depending on the desired level of performance and robustness.

DISCUSSION

Our results suggested that nest protection provides a potentially useful management strategy for maintaining Mountain Plover populations in a highly agricultural landscape. Furthermore, our results showed that spending more effort in nest marking provides an insurance policy against uncertainty in vital rates for this population. Our analytical approach is not meant to replace the need to gather more precise estimates of these vital rates; there can be no substitute for good data. But many management strategies proceed regardless of whether data exist. Our analysis provides an example of how defensible decisions could be made in the context of a conservation program for which little current data exist.

Our analysis also reinforces the notion that there are limitations to standard matrix sensitivity analyses in assessing management options (Hodgson and Townley 2004). Others have shown that the last parameter in a matrix (oldest age survival) is often most sensitive mathematically, but may be the least practical in a wildlife management context (Hodgson et al. 2006, Deines et al. 2007). The last parameter can also be constrained by biological limits, such as senescence (Lubben et al. 2008), which we did not consider in our analysis. Senescence is likely to be a problem for matrix models if the last age class essentially functions as an "immortal" class. Lubben et al. (2008) showed that when one includes the possibility that some age classes may be absorbing states, or non-reproductive, management should shift toward increasing fecundity in younger age classes because older age classes (and dead individuals) do not contribute to the population. In our analysis, one can see that maximizing adult survival to near 100% survivorship means we can reduce nest survival to near zero.
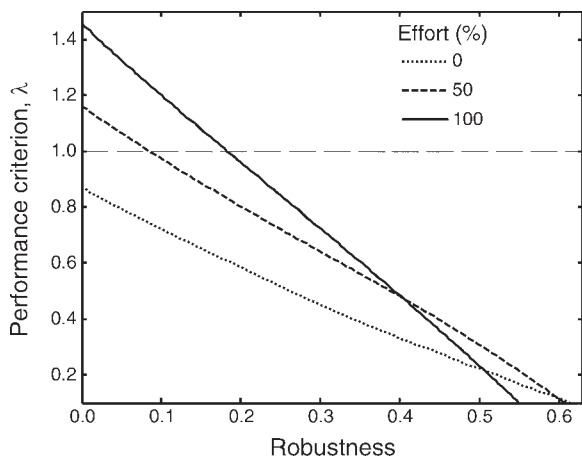

Fig. 3. Relationship between a desired level of performance in Mountain Plover population growth rate (λ) and robustness. The dotted, dashed, and solid lines represent different decisions: investing effort at the 0%, 50%, and 100% levels of nest searching effort, respectively.

If we had stopped at the sensitivity analysis, we would have reached two possible conclusions. The first is that we need more information about adult and juvenile survival. But in terms of assessing nest management strategies today, we cannot wait for new information to be gathered tomorrow. The second is that if we wanted to have the greatest affect on Mountain Plover populations, we should focus on increasing adult survival because it had the largest elasticity in our analysis assuming the costs of management are equal (Baxter et al. 2006). Caswell (2001) provides methods of analyzing more practical management scenarios using simulations or LTREs, which consider changes in multiple parameters. We adopted a different approach because we did not have enough information to be able to compare the fixed effects of different management strategies and because we could not reliably place distributional assumptions on our matrix model parameters. Thus, we focused on the concepts of robustness and opportunity.

Again, we know nothing about Mountain Plover vital rates in Nebraska, with the exception of nest success. But based on our guesses at adult and juvenile survival, we could afford to be wrong about these parameters if we could control some of the uncertainty in nest success. Our results also suggested that if we could raise nest success we could simultaneously tolerate greater uncertainty in the other parameters. In our model, the only way to increase nest survival was by increasing searching effort. But the relative utility of effort seemed to vary depending on whether the estimate of nominal nest success was below $\lambda = 1$ or above it. When comparing the relative utility of different decisions, it would make sense to choose those decisions that are more robust. But if some other factor limited the amount of effort we could expend, then it could make sense to compare the relative opportunity of different decisions. Note that our treatment of opportunity and robustness is specific to our case and is somewhat unusual compared to other info-gap analyses in conservation biology (e.g., Regan et al. 2005, Moilanen et al. 2006). With regard to comparing decisions, increasing nest searching effort had the effect of decreasing the amount of uncertainty need for the possibility of success slightly faster than it did on increasing the uncertainty needed to avoid failure. If we think about the space within which the matrix parameters were perturbed and then place the surface within that space, then we would see that nominal points below surface have more distance to travel before reaching the surface, but they appear to close the information gap faster because they start out closer to the performance criterion. As the nominal points move away from the performance criterion they begin to run out of room sooner because of the placement of the surface within that space.

Our analysis suggests that the placement of this surface depends on whether the component of nests that one has some management effect on makes up the majority of nests. If most nests in Nebraska were found in agricultural fields, then we would need comparatively more uncertainty in order to ensure the possibility of a success when effort was low, but we could tolerate much more uncertainty in the efficacy of our management when effort was high. By adding additional sources of failure over which we have no management control we changed our results. Under this scenario we needed much less uncertainty to ensure a possible success, but we needed more effort to begin making robust decisions. This happened because the additional source of failure (i.e., predation on rangeland) reduced the range of possible nominal points of nest success.

Our formulation of this case study differs from others who have adopted similar robust population management approaches (Hodgson et al. 2006, Deines et al. 2007, Lubben et al. 2008), because we explicitly integrated the concept of robust population management with info-gap decision theory. We feel that this integration provides a powerful framework for decision-making in management by using the mathematically flexible methods of matrix analysis with the assessment of decision outcomes relative to a performance criterion. Because we adopted a formal info-gap approach to decision analysis, we were thus able to measure the robustness and opportuneness of decisions under extreme uncertainty. This is the critical difference between our approach and previous robust management approaches.

It is comparatively easy for most biologists to understand the concept of robustness. In our case, we referred to decisions as robust when they exceeded our performance criterion (stable population growth) over a large range of uncertainty. In conservation programs, it may often be necessary to focus on situations that at least lead to stable population growth because negative growth puts a species at risk of extinction. However, our approach also addresses situations when decisions do not necessarily meet the performance criterion, but could lead to success considering the level of uncertainty in the model parameters. This potential for "windfall gain" (Ben-Haim 2006) is a unique perspective in assessing conservation decision making. In light of this perspective, our results suggest that some level of nest protection effort is good because it either increases the possibility of success (opportunity) or because it reduces the potential for failure (robustness).

One potential criticism of our analysis is that we assumed Mountain Plovers were distributed evenly across Kimball County. That is, we assumed that birds were equally likely to be found in either rangeland or agricultural fields. While this assumption certainly works for comparing agricultural fields with and without protected nests, this assumption may not be valid for comparing rangeland and agricultural fields. We do have some evidence from analyses of point count data that this assumption might not be entirely valid for Mountain Plovers in Nebraska (M. Post van der Burg,

unpublished data). In our analysis, this potential source of bias in our nest success estimate is incorporated into the information gap around the nominal value of nest success that is calculated under the assumption of a uniform distribution. We also think that an additional unanswered question is whether our set of decisions would be applicable to the entire range of Mountain Plovers. At such a large scale, it may not make as much sense to consider decisions relating to the amount of effort one invests in protecting nests. Instead, one would need to refocus the decision set to be whether to protect some percentage of high-quality nesting locations within this species' range. This is not meant as statement to undermine local conservation programs, but rather to illustrate that that goals and decision sets may change based on the scale at which decisions are made.

Another thing to keep in mind is that our analysis only focuses on the choice of how much effort to invest in nest searching effort. Again, the main goal of our approach was only to assess the claims made by others (positive or negative) about the utility of nest protection efforts in the context of vital rate parameters. In reality, conservation decisions would be more nuanced. Managers most likely face more complicated sets of decisions such as whether to invest in nest protection, habitat restoration, or continued monitoring. As long as the performance of all decisions can be measured using the population growth rate, the combination of matrix methods and info-gap we have used here can also be used to evaluate the robustness and opportuneness of larger sets of decisions.

One difficulty faced by all decision analyses is choosing an appropriate criterion for comparing decisions. Population growth rate (λ) provides a potentially powerful index of population performance, largely because exponential growth is so pervasive in natural populations and because it incorporates numerous life history parameters (Caswell 2001). Likewise, Caswell (2001) argues that prescribing management based on other indices would not be very different from those based on λ. Thus, management recommendations should be fairly robust if the assumption is that management affects vital rates.

Setting the criterion to a population growth rate of one is a natural choice for problems of robust population control for at least two reasons. First, it provides the lower bound of a set of criteria that are likely acceptable to the conservation community. Of course, it would be best to strive for management that increases a population's growth rate, but in order to properly assess the uncertainty in the efficacy of our management decisions we had to set a lower bound on what we could accept as an outcome from management. Furthermore, as we found, there is an inherent tradeoff between criteria and the robustness of a decision (e.g., Regan et al. 2005). Setting the bar too high might increase the possibility of failure, which could impact the perception of the utility of various management

strategies. Second, setting the population growth goal to some value greater than one may prove problematic if the population has saturated the available habitat. At this point, density-dependent mechanisms are likely to kick in and reduce the growth rate to near one. This could give the illusion of failing to reach a management goal if the criterion is greater than one.

Of course, we should also regard the management goals set forth in this paper in the larger context of Mountain Plover management, specifically. Here, we are only concerned with how decisions affect an index of persistence (λ). Elsewhere in the Mountain Plover's range, biologists have identified a close association between Mountain Plovers and black-tailed prairie dogs (*Cynomys ludovicianus*), which are thought to maintain preferred nesting sites (Dinsmore 2003, Dinsmore et al. 2005, Tipton et al. 2009). These studies suggest that management of prairie dog colonies is necessary for maintaining Mountain Plover populations. Certainly, increasing preferred nesting habitat within the state of Nebraska should be a priority, especially if the long-term management goals are to increase Mountain Plover population size and reverse population declines (Schneider et al. 2005). However, the majority of Mountain Plovers in Nebraska are found in agricultural fields, and prairie dog colonies are fairly rare in the southwest corner of the state. Nest protection may, therefore, serve as a useful short-term management strategy in the state until preferred nesting habitats can be restored.

Carefully deciding which management goals to focus on and what decisions are to be evaluated, in light of management effort, is just as important as how one evaluates management decisions. In this paper we have demonstrated an approach that deals with the problem assessing the relative utility of management decisions when uncertainty in the efficacy of those decisions is unstructured or pernicious. Considering the limitations on available data, it becomes increasingly important to rely on modeling in order to assess the relative value of management decisions. Therefore, explicitly accounting for uncertainty in the efficacy of management strategies will also need to become an integral part of conservation planning and decision making.

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SUPPLEMENT

MATLAB code for info-gap analysis of Mountain Plover matrix population model (*Ecological Archives* A021-015-S1).