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Management and Conservation

On the Role of Budget Sufficiency, Cost Efficiency, and Uncertainty in Species Management

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ABSTRACT Many conservation planning frameworks rely on the assumption that one should prioritize locations for management actions based on the highest predicted conservation value (i.e., abundance, occupancy). This strategy may underperform relative to the expected outcome if one is working with a limited budget or the predicted responses are uncertain. Yet, cost and tolerance to uncertainty rarely become part of species management plans. We used field data and predictive models to simulate a decision problem involving western burrowing owls (*Athene cunicularia hypugaea*) using prairie dog colonies (*Cynomys ludovicianus*) in western Nebraska. We considered 2 species management strategies: one maximized abundance and the other maximized abundance in a cost-efficient way. We then used heuristic decision algorithms to compare the 2 strategies in terms of how well they met a hypothetical conservation objective. Finally, we performed an info-gap decision analysis to determine how these strategies performed under different budget constraints and uncertainty about owl response. Our results suggested that when budgets were sufficient to manage all sites, the maximizing strategy was optimal and suggested investing more in expensive actions. This pattern persisted for restricted budgets up to approximately 50% of the sufficient budget. Below this budget, the cost-efficient strategy was optimal and suggested investing in cheaper actions. When uncertainty in the expected responses was introduced, the strategy that maximized abundance remained robust under a sufficient budget. Reducing the budget induced a slight trade-off between expected performance and robustness, which suggested that the most robust strategy depended both on one's budget and tolerance to uncertainty. Our results suggest that wildlife managers should explicitly account for budget limitations and be realistic about their expected levels of performance. © 2013 The Wildlife Society.

KEY WORDS Bayesian analysis, burrowing owl (*Athene cunicularia hypugaea*), conservation budgets, decision analysis, info-gap decision theory, prairie dog (*Cynomys ludovicianus*).

Many conservation organizations develop management plans to set conservation goals and guide the implementation of strategies to meet those goals (e.g., Schneider et al. 2005). Typically, such plans discuss the need for monitoring to better elucidate the relationship between species and habitats or identify priority areas for conservation. As a starting point, spatially explicit modeling approaches have been developed for predicting the value of habitat patches or sites in terms of metrics such as abundance or occupancy (Royle et al. 2007, Post van der Burg et al. 2011). These approaches rely on the assumption that indices such as abundance reflect habitat quality (Fretwell and Lucas 1970, Johnson 2007), but

situations may occur in which these indices do not reflect the intrinsic quality of a location (Van Horne 1983). Regardless, using index-based predictive models as the basis for prioritizing locations on the landscape appears to be one of the dominant tools in conservation planning (Moilanen et al. 2005). Of course, choosing the best predictive model requires a full understanding of the decision context in which priority areas are chosen. Understanding this context requires a clear statement of the scope of decisions to be made, intended objectives, and an assessment of the trade-offs between articulated conservation objectives (Keeney and Gregory 2002).

Many landscape planning models seem to rely on selecting locations with the highest predicted value (e.g., Niemuth et al. 2009). But in situations where budgets are limited, this approach might underperform in terms of meeting conservation objectives. Constrained budgets are exceedingly

common in conservation and wildlife management. Yet, budget constraints typically do not get articulated in management plans. Rather, the emphasis tends to be on getting better biological information. Plenty of recent literature on conservation planning methodologies has pointed to the need to account for cost explicitly when trying to choose from among various conservation strategies (Moilanen et al. 2005, Moilanen and Cabeza 2007, Schapaugh and Tyre 2012). For example, some strategies may be very effective in meeting some objectives but may be very expensive, whereas another strategy may be less effective but more affordable (Baxter et al. 2006). The problem of cost not only influences the efficiency of such strategies but also determines whether a given budget is sufficient to meet conservation objectives.

This is not to say that focusing on the quality of information used to inform conservation decisions is not a worthwhile problem to address. A decision analysis that relies on model predictions can help a manager determine the best performing (i.e., optimal) conservation strategy. However, as the amount of uncertainty in the model predictions increases, the strategy may no longer perform as expected. In other words, optimal strategies may not be robust to uncertainty (Ben-Haim 2006). A robust strategy would be one that exceeds a performance criterion over a wide range of uncertainty. In this context, we refer to uncertainty as the situation where one cannot assign an objective probability to a particular outcome. This is contrasted with the term risk, which describes the case where an objective probability can be assigned to that outcome (Knight 1921, Tyre and Michaels 2011). The idea of distinguishing between optimal and robust decisions in population management has received little attention in the management literature (but see Regan et al. 2005, Post van der Burg and Tyre 2011). Even less attention has been given to assess how budgetary limits and robustness interact in conservation planning.

Because many conservation planning efforts focus on the relative value of sites, without discussion of cost, we considered 2 species management strategies: one maximized abundance and the other maximized abundance in a cost-efficient way. We used a case study concerned with western burrowing owls (*Athene cunicularia hypugaea*) using black-tailed prairie dog colonies (*Cynomys ludovicianus*) in western Nebraska. Burrowing owls typically nest in burrows that are excavated and maintained by prairie dogs (Poulin et al. 2011). Burrowing owl abundance has been shown to be considerably greater on prairie dog colonies compared with other habitats (Tipton et al. 2008) and declines in owl numbers have been partially attributed to systematic removal of prairie dogs (Desmond et al. 2000). For our case study, we simulated a management problem where the objective was to maintain a population of owls in western Nebraska by choosing a portfolio of sites to manage. We used a spatially explicit Bayesian hierarchical modeling approach to predict how owl abundance would respond to management at prairie dog colonies and used a heuristic optimization algorithm to build a near optimal portfolio of colonies and actions to meet

the owl population objective. We then conducted an info-gap decision analysis to compare the near optimal strategy to suboptimal strategies in terms of how robust they were to errors in the predicted effects of management (Ben-Haim 2006). We then explored how the trade-off between optimal and robust strategies changed under different budget constraints.

STUDY AREA

Our case study focused on a population of western burrowing owls in the panhandle of western Nebraska, which included the following counties: Banner, Box Butte, Cheyenne, Dawes, Deuel, Garden, Keith, Kimball, Morrill, Scotts Bluff, Sheridan, and Sioux. Privately owned lands made up roughly 90% of this 37,000-km^2 region, and consisted of agricultural production in the form of cattle ranching, dryland, and irrigated agriculture (Hiller et al. 2009). Dryland fields mainly produced small grains (wheat and millet), whereas irrigated fields produced corn, soybeans, and sugar beets. We identified 297 prairie dog colonies from 2003 and 2004 from United States Department of Agriculture Farm Service Agency (FSA) aerial photographs taken in the region. The majority of colonies we used in our analysis resided on privately owned rangelands.

METHODS

Case Study and Decision Context

For this case study, we used a simulated decision problem and assessed 2 different strategies. We assumed that a conservation organization established a management objective of maintaining burrowing owls at some target level based on abundance estimates from a set of surveys (described below). The problem for the organization centered on choosing a management strategy that helped them achieve this target in the year following the last survey. For one strategy, we ignored the cost of management and in the other context, we focused on the cost-efficiency of management. In terms of building the optimal strategy, we considered 3 different types of actions for improving owl abundance: using incentive payments to protect active prairie dog colonies, translocation of prairie dogs to inactive colonies, or using grazing at inactive colonies to make inactive prairie dog colonies suitable for burrowing owls. These actions are consistent with recommended strategies for maintaining burrowing owls (Dechant et al. 2003). Below we describe our analysis of observed data from owl surveys to set a conservation target and to predict how owls might respond to management actions.

Burrowing Owl Abundance

We used owl count data collected during 3 years of surveys (2005, 2006, 2007). The number of sample points visited in the surveys varied between years. We conducted repeated counts at some of those sites in every year, but the number of visits also varied between years. We visited 162 points in 2005: 81 points 1 time, 59 twice, 18 points 3 times, and 4 points 4 times. We visited 267 points in 2006: 171 once, 5 twice, and 91 points 3 times. Finally, we sampled 240 points in 2007: 34 once and 206 twice. During each visit to a colony,

we conducted 2 sequential 3-minute surveys: one prior to playing a burrowing owl alarm call and one immediately following the call. We counted adult and juvenile owls between sunrise and 1000 or between 1700 and sunset, when owls emerged from their burrows. We conducted our surveys during a window from late June through late July. More details on these surveys can be found in Post van der Burg (2008).

We estimated burrowing owl abundance and detection error with a Bayesian hierarchical model. We fit models composed of explanatory variables and used Bayesian model averaging to estimate model probabilities and make model-averaged predictions. We based much of our modeling approach on the work of Royle et al. (2002, 2007) and a more detailed explanation of this model can be found in Post van der Burg et al. (2011). In short, we assumed the following model for our count process:

$$p(y_{ij}|\lambda_{ij},p) = \prod_{i=1}^{I} \left(\left(\prod_{j=1}^{J} \text{Bin}(y_{ij}; N_i, p) \right) \text{Pois}(N_i; \lambda_i) \right) \quad (1)$$

where y_{ij} were observations from site i and visit j, which arose from a binomial distribution with an unobservable abundance (N) and a detection probability (p). We further assumed that the unobserved abundance (N) was Poisson distributed with a mean rate (λ). We modeled detection probability as a function of explanatory variables using a logistic regression. We modeled λ as a function of spatially indexed explanatory variables using a Poisson regression. Because we were interested in making spatially explicit predictions of burrowing owl abundance, we included a spatial random effect in the Poisson regression model: $\log(\lambda_i) = \beta_i X_i + s_i + \varepsilon_i$ where β represents a set of model parameters, X_i is a vector of spatially indexed covariates for each of the i points, s represents a spatial random effect, and ε represents uncorrelated error between points. We assumed s arose from a multivariate normal distribution $MVN(0, \sigma^2 K)$, where the covariance term was the product of a spatial variance and an underlying exponential correlation function: $K = e^{-d/\theta}$ where d represents the distance between colonies and θ represents the range parameter, which measured the degree of spatial dependence between points. In our analysis, we assumed a reference prior for the range parameter, which functions as an uninformative prior that yields a proper posterior distribution (Berger et al. 2001). We parameterized the variance terms for the random effects σ_s^2 and σ_ε^2 as precision terms $\tau_s = 1/\sigma_s^2$ and $\tau_\varepsilon = 1/\sigma_\varepsilon^2$, which arose from an inverse-gamma distribution. We assumed inverse-gamma priors on the precision terms for the random effects with a mean of 1 and a variance of 10. We assumed non-informative priors on all abundance and detection model parameters in 2005, normal priors with a mean of 0 and a variance of 10. We used our posterior estimates of the covariate parameters, precision terms, and range parameter in 2005 as priors in our 2006 analysis and likewise used the 2006 posteriors as priors in 2007.

For the detection process, we considered 3 candidate models (Table 1). These models were composed of effects of

playing a call (0 = no call, 1 = call), whether the survey was conducted in the morning or the evening (0 = morning, 1 = evening), and the ordinal day in the season when we conducted the survey. Calls and timing of surveys are all known to affect owl observations (Conway and Simon 2003, Tipton et al. 2008, Crowe and Longshore 2010). With regard to abundance, we considered 18 models. These included effects of prairie dog colony area (ha; Desmond et al. 2000), the effect of dryland agriculture (0 = <50% non-dryland, 1 = >50% dryland) or irrigated agriculture (0 = <50% non-irrigated, 1 = >50% irrigated) within 1 km of each colony (Moulton et al. 2006, Restani et al. 2008), whether the prairie dog colony had been grazed (0 = no grazing, 1 = grazing) during the survey (Faanes and Lingle 1995, Dechant et al. 2003), whether the colony was active with prairie dogs (0 = inactive, 1 = active; Tipton et al. 2008), and finally, effects of elevation (m) and slope (%) on owl abundance (e.g., Wedgewood 1976). We included the spatial random effect in these predictions to account for intrinsic spatial variation that we could not attribute to our other explanatory variables (Wintle and Bardos 2006, Post van der Burg et al. 2011).

We fit these models using Markov Chain Monte Carlo (MCMC) simulation in the R programming language. We employed a Bayesian model averaging approach to estimate our model parameters for both average abundance and detection probability (Link and Barker 2006). We assumed that each detection and abundance model could be sampled independently from a uniform distribution (a total of 54 possible models) and evaluated the models using a Metropolis-Hastings step in our MCMC algorithm (Link and Barker 2006). Further details on our model fitting approach can be found in Post van der Burg et al. (2011). For each of the 3 years (2005–2007), we used our estimated parameters to interpolate predicted abundance to all 297 known prairie dog colonies in the panhandle of Nebraska. All results from these analyses are presented as means and 95% Bayesian confidence intervals (BCI).

Decision Model and Uncertainty Analysis
We developed cost functions for each action; these functions were not intended to represent all of the potential costs but were simply meant to provide realistic estimates of the relative costs of management. We assumed incentive payments would encourage private grazers to keep active colonies on their property. The cost of this action reflected compensating grazers for the loss of economic value due to the presence of active colonies.

Derner et al. (2006) estimated $40/ha as the value of livestock weight gain in rangelands not occupied by prairie dogs. We used this dollar value multiplied by the area of the colony as the cost of the incentive payment. For the translocation action, we assumed that to make inactive colonies active, managers needed to establish prairie dog densities consistent with the average density for our study area (3 dogs/ha). We assumed that the organization incurred costs for this action in terms of personnel time, in this case, 0.90 hours of trapping per prairie dog (Shier 2006). If we

further assumed a single staff biologist to do this work, earning \$20 per hour, this would make the cost \$18 per prairie dog. Thus, multiplying the average density of prairie dogs by the area of the colony by the per prairie dog cost gave the expected cost of translocation. We further assumed that managers would need to provide incentive payments post-translocation, so we added this additional cost to the total cost of translocation. Finally, we considered the possibility of grazing inactive colonies to make them suitable for owls. We assumed that the cost of grazing would be represented by the cost of a grazing lease plus additional costs associated with moving or maintaining animals. We assumed a grazing lease cost of \$38/ha, which was based on the average cost of a grazing lease for Nebraska for 2008 (National Agricultural Statistics Service 2009), and an additional \$20/ha to account for other expenses, based on unpublished agricultural extension literature.

We forecasted burrowing owl populations for each prairie dog colony into 2008 based on our population estimates from our surveys. We used the predicted distributions of abundance for each colony over 2005–2007 to estimate a growth rate for each colony: $(\lambda_{2007,i}/\lambda_{2005,i})^{1/2} = R_i$, where λ was a value sampled from the posterior distribution of estimated abundance for 2005 and 2007 at colony i and R was the distribution of the finite growth rate for colony i. Assuming a discrete exponential growth model, we then stochastically forecasted owl populations on each colony 1 time step into the future: $\lambda_{2008,i} = \lambda_{2007,i} \times R_i$. Because λ_{2008} was stochastically forecasted, we were able to estimate both a mean and variance for the growth rate of each colony. We then predicted what the expected population response would be under each management treatment for each colony: $\lambda_{2008,i} + \beta_{management,i}$, where $\beta_{management}$ is the parameter from our hierarchical model representing the effect of management. Thus, we simulated the effects of management assuming that $\lambda_{2008,i}$ represents the effect of incentive payments, $\lambda_{2008,i} + \beta_{active,i}$ represents the effect of translocations, and $\lambda_{2008,i} + \beta_{grazing,i}$ represents the effect of grazing. We were uncertain what the effect of the actions would be if they were applied to active or inactive colonies. To account for this uncertainty, we estimated the response of a management action as the weighted mean and variance of the expected number of owls, where the weights were the estimated proportion of active and inactive colonies. Note, this assumes that only the current state of the colony, rather than past states, matter in predicting management effects.

Using the estimated posterior means of the predicted responses, we then used a heuristic optimization approach to build the near optimal portfolio of colonies and management actions. We used a heuristic approach because our problem formulation relied on a nonlinear objective function and used discrete integer variables, rendering nonlinear programming infeasible (Loehle 2000). We used a greedy algorithm that used a marignal gain heuristic, which iteratively searched through all possible colony and action combinations. Our algorithm made the determination of the best action and colony by choosing a colony-action pair and evaluating a

Table 1. Posterior support for models describing average detection probability (p) and abundance (λ) of burrowing owls on prairie dog colonies in the western portion of Nebraska over 3 years (2005–2007). For the detection models, the effects included whether a call was played during the survey (call), the ordinal day of the season (day), and whether the survey was done early or late in the day (time). Abundance models included the effects of prairie dog colony area in hectares (area), whether the colony was near irrigated (irrigated) or dryland (dry) agricultural fields, whether the colony was grazed by cattle (grazed), whether the colony was active with prairie dogs (active), and the average percent slope (slope) and elevation (elevation) of each colony in meters. All quadratic effects included a main effect.

	Posterior model support		
Models	2005	2006	2007
Detection			
p	1.00	0.00	0.00
p_{call}	0.00	0.38	0.62
$p_{call+day+time}$	0.00	0.62	0.32
Abundance			
λ	0.02	0.00	0.00
λ_{area}	0.02	0.00	0.00
λ_{area^2}	0.04	0.00	0.00
$\lambda_{irrigated+dry}$	0.03	0.00	0.00
λ_{grazed}	0.03	0.00	0.00
λ_{active}		0.74	0.85
$\lambda_{slope+elevation}$	0.02	0.00	0.00
$\lambda_{area+slope+elevation}$	0.01	0.00	0.00
$\lambda_{area^2+slope+elevation}$	0.04	0.00	0.00
$\lambda_{irrigated+dry+slope+elevation}$	0.02	0.00	0.00
$\lambda_{grazed+slope+elevation}$	0.02	0.00	0.00
$\lambda_{active+slope+elevation}$		0.18	0.11
$\lambda_{area^2+elevation^2}$	0.11	0.00	0.00
$\lambda_{area+slope^2+elevation^2}$	0.08	0.00	0.00
$\lambda_{area^2+slope^2+elevation^2}$	0.26	0.00	0.00
$\lambda_{irrigated+dry+slope^2+elevation^2}$	0.19	0.00	0.00
$\lambda_{grazed+slope^2+elevation^2}$	0.11	0.00	0.00
$\lambda_{active+slope^2+elevation^2}$		0.08	0.04

value function to determine the best change in value. After each iteration, the algorithm selected the best colony and action combination and then removed that colony (and all other associated actions) from further consideration. The algorithm then iteratively searched through the remaining combinations until it exhausted a simulated conservation budget. A detailed description of this approach can be found in van Teeffelen and Moilanen (2008) and van Teeffelen et al. (2008). For each of the k colonies and l actions, we predicted a unique expected response, x_{kl}. We evaluated the response using a sigmoid value function because previous work by Arponen et al. (2005) suggested these functions worked well for landscape planning problems with species exhibiting metapopulation dynamics. In our analysis, we used a value function to map the expected responses onto a 0–1 scale, where 1 is the most value and 0 is the least value. Value functions can be thought of as being analogous to utility functions in the sense that they represent how a decision-maker values changes in performance. Such functions can be especially useful in situations where performance in more than 1 objective is being considered, because they put all the objectives on the same scale. Specifically, our function was $1/(1 + \exp(-b \times (x - T \times 0.5)))$, where b was a constant set arbitrarily to 0.005, T was a desired target value, and x was the vector of responses. For this function, a response that sums to T has a value of 1.0 and a response that sums to $T/2$ has a value of 0.5. For our analysis, we used 2 different objective functions to reflect 2 different strategies for investing in conservation actions.

Our first objective function simply maximized the cumulative value (V) of a particular set of managed sites. That is, given all of the sites already being managed ($x_{k,l}$), choose the action ($x_{k,l}^*$) that results in the greatest increase in value: $\max_{k,l} V(\Sigma x_{k,l} + x_{k,l}^*) - V(\Sigma x_{k,l})$. We refer to this as our maximize strategy. The second objective function considered the cost-efficiency of an action by dividing the change in value by the cost of taking that action: $\max_{k,l}((V(\Sigma x_{kl} + x^*) - V(\Sigma x_{kl}))/(\cos t_{k,l}))$. We called this our cost-efficient strategy. As a point of comparison, we considered how both strategies would perform if the available actions were restricted to a single action (e.g., translocation only or incentive only versions of the maximize or cost-efficient strategies). We analyzed how each of these strategies performed under various budget constraints. These constraints varied from \$0 to \$800,000 in steps of \$20,000. Because all of the strategies rely on mean estimates of management responses, this optimization model can be regarded as a deterministic model.

We next analyzed how robust each of these strategies was to uncertainty in our forecasted predictions of expected owl response. In essence, such an analysis is focused on analyzing the implications of overestimating the expected performance of a management strategy. We assessed this robustness using an envelope-bound uncertainty model (Ben-Haim 2006): $\hat{N}_{total} = \sum e^{(\log(\hat{N}_{k,l}) - SE_{k,l} \times \alpha)}$ where $\hat{N}_{total}$ was the estimate of total abundance from managed sites, $\hat{N}_{k,l}$ was an abundance estimate for colony k under management action l, $SE_{k,l}$ was

the standard error associated with that estimate, and α is the horizon of uncertainty or level of robustness. Note that expected performance does not include non-managed sites. To conduct our info-gap analysis, we simply subtracted a fraction of those standard errors, which was represented by α, from the log-transformed expected performance, which we then back transformed to the response scale and summed into an overall abundance estimate. We used our value function to evaluate this new abundance estimate. We conducted this analysis assuming α ranged from 0 to 1 in steps of 0.1. We performed this analysis on all of the proposed strategies.

RESULTS

Burrowing Owl Abundance Models
Our models suggested that observations contained some bias from imperfect detectability. The support for the best model to explain the pattern of detection error appeared to vary over the course of our survey (Table 1). But, by the last year of our study, the effect of playing a call had the strongest effect on our predictions of detection rate: 0.50 (95% BCI: 0.40–0.56) pre-call and 0.58 (95% BCI: 0.48–0.63) post-call. For our abundance models, we found comparably weak support for any single model for 2005. We should note that this could be because the activity status of the colonies was not collected in 2005. However, in 2006 and 2007 the model distribution shifted in favor of models including the effect of whether a prairie dog colony was active or not (Table 1). We found weak support for models with physiographic effects in 2006 and 2007, and posterior parameter estimates for our physiographic covariates showed very weak effects on average owl abundance. In contrast, we predicted a relatively large effect of active versus inactive prairie dog colonies on owl abundance (Fig. 1).

The underlying spatial patterns in our abundance data suggested that counts were more correlated in 2006 and 2007
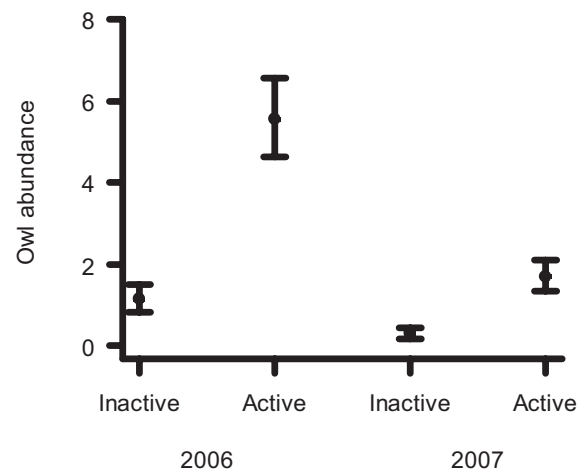

Figure 1. Effect of prairie dog colony status (inactive, active) on burrowing owl abundance in western Nebraska, 2006–2007. Closed points represent posterior mean estimates and error bars represent 95% Bayesian credible intervals.

compared with 2005 (Table 2). In the first year of our study, the estimate for the range parameter (θ) was approximately 1,620 m, whereas in the last 2 years it was 10,097 m. On the other hand, the amount of spatial variability increased, as shown by the smaller estimates of our precision parameters (Table 2). Using this information on spatial variability, we interpolated predictions of owl abundance at each of the 297 colonies within the Nebraska panhandle. In 2005, we predicted an abundance of 2,180 (95% BCI: 1,610–3,090), in 2006, 2,432 (95% BCI: 1,787–3,412) owls and in 2007, we predicted 1,114 (95% BCI: 709–1,941) owls.

Decision and Robustness Analysis

Based on our modeling results, we did not consider grazing as an action because it was not supported in any of our models. Instead we focused on incentive payments and prairie dog translocations. We used the total abundance estimate (i.e., abundance summed across all sites) for 2006 as our desired population target, because it was our greatest estimate, but we could have chosen any value to be the target. Results from the optimization analysis showed that, for the cost-efficient objective function, the total investment should be split between incentive payments and translocations, but more should be invested in incentive payments (Fig. 2A). Using the maximizing objective function, the best decision was to split the investment with a greater proportion of the budget invested in translocations, and for the largest budget, one should invest only in translocations. Perhaps not surprisingly, if one could invest in all of the colonies, the cost-efficient strategy was more than $350,000 cheaper than the maximize strategy (Fig. 2B). The cost efficient strategy outperformed the maximize strategy in terms of the expected population of burrowing owls for budgets of about $450,000 or less. But above this amount, the maximize strategy out performed the cost-efficient one, with almost 135 more owls under the maximum budget.

Under no uncertainty and a budget sufficient to manage all sites for maximum abundance, all strategies performed
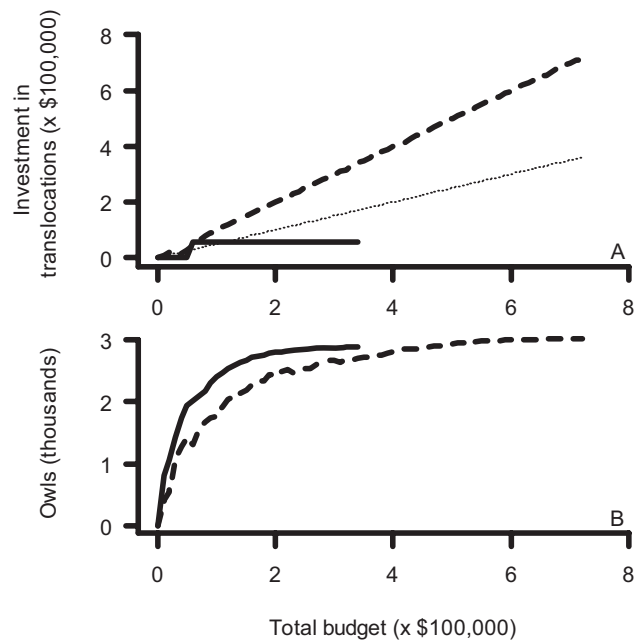

Figure 2. (A) Relationship between total conservation budget and how the budget was invested in prairie dog translocations using a maximize (dashed line) or cost-efficient (solid line) strategy. The remainder of the budget not allocated to translocations was allocated to incentive payments. The thin dotted line represents an equal allocation of the budget to each action. (B) Expected owl abundance for a given budget using the optimal combination of incentive payments and translocations under a maximize (dashed line) or cost-efficient (solid line) strategy. These lines terminate at different total budget values because of the different budget amounts required to manage all sites.

equally well in terms of meeting the abundance target (Fig. 3A). However, when uncertainty was introduced, the performance of each strategy began to decline. The maximize and cost-efficient translocation only strategies, which are identical under a large budget, remain robust over a wide range of uncertainty. If the budget is reduced, this pattern

Table 2. Posterior model averaged mean parameter estimates (SE) of average detection probability ($logit(p)$) and abundance ($log(\lambda)$) of burrowing owls on prairie dog colonies in the western portion of Nebraska over 3 years (2005–2007). Only effects with estimates >0.00 were included. For detection models, the effects included whether a call was played during the survey (call; 0 = no call, 1 = call) and the ordinal day of the season (day) when the count was conducted (time; 0 = morning, 1 = evening). Abundance models included the effects of whether the colony was near dryland agricultural fields (dry; 0 = no, 1 = yes), whether the colony was near irrigated fields (irrigated; 0 = no, 1 = yes), whether the colony was grazed by cattle (grazed; 0 = not grazed, 1 = grazed), whether the colony was active with prairie dogs (active; 0 = inactive, 1 = active), and the average percent slope (slope) and elevation (elevation) of each colony in meters. Additional parameters included the range of autocorrelation in abundance estimates ($log(\theta)$), spatial precision of abundance estimates (τ_s), and the residual error of abundance estimates (τ_ε).

| Parameter	2005	2006	2007
$logit(p)$	−1.98 (0.36)	−0.33 (0.36)	−0.35 (0.19)
Call	−1.278 (0.11)	0.21 (0.04)	0.30 (0.04)
Day	0.07 (0.01)	0.01 (0.01)	0.02 (0.01)
$log(\lambda)$	−4.70 (5.84)	−1.21 (4.35)	−2.41 (5.87)
Dry	0.04 (0.09)	0.00 (0.00)	0.00 (0.00)
Irrigated	0.03 (0.07)	0.00 (0.00)	0.00 (0.00)
Grazed	−0.01 (0.04)	0.00 (0.00)	0.00 (0.00)
Active		1.58 (0.16)	1.76 (0.25)
Elevation	0.01 (0.01)	0.00 (0.01)	0.00 (0.01)
Slope	0.07 (0.06)	0.01 (0.01)	−0.02 (0.03)
$log(\theta)$	7.39 (0.80)	9.22 (0.59)	9.22 (0.39)
τ_s	2.97 (3.96)	1.63 (0.59)	0.89 (0.41)
τ_ε	4.71 (5.35)	1.07 (0.81)	0.87 (0.42)
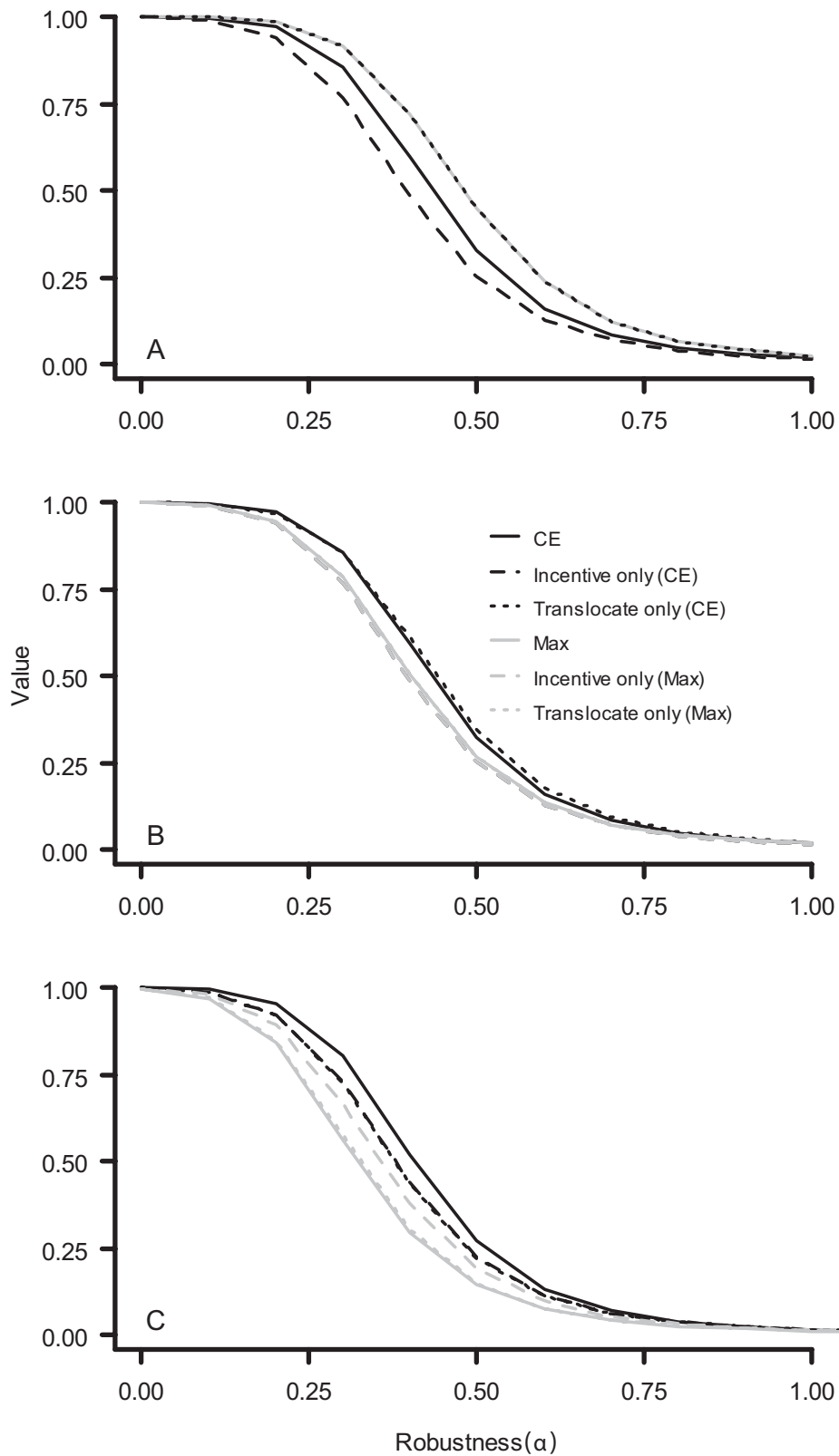
Figure 3. Relationship between the percent deviation from the nominal expected performance (i.e., robustness) and the expected performance outcome (i.e., value) assuming a given conservation strategy. Value was measured on a scale from 0 to 1, where 1.0 means a population target was reached and 0.5 means that half of the target was reached. The 2 main strategies consist of 1 that mixes translocations and incentive payments using a cost-efficient strategy (CE) and 1 that mixes the same actions but uses a maximizing strategy (Max). The other strategies are translocation only or incentive only versions of the maximize or cost-efficient strategies. Each set of curves was generated assuming a budget sufficient to manage all colonies (A), half of the sufficient budget (B) and a quarter of the sufficient budget (C).

changes. Under uncertainty, the cost-efficient strategy is most robust, but only up to a point. As uncertainty increases, a very slight trade-off occurs between the cost-efficient and cost-efficient version of the translocation only strategy (Fig. 3B). With an even smaller budget, the cost-effective strategy is most robust (Fig. 3C).

DISCUSSION

Using rigorous predictive tools to identify areas of high and low conservation value provides an important step in deciding where to implement conservation strategies. But although such tools form a necessary basis for supporting conservation decisions, they do not allow for sufficient guidance in the development of a useful conservation strategy. The ability of a tool to support a decision should be driven by the objectives of the decision maker and the actions they can take to meet those objectives. This ensures that the information collected, as well as the choice of predictive model, informs the specific decision context for the strategy under development. Because limited budgets often constrain conservation, collecting only the information needed to inform decisions should help to improve the cost-efficiency of conservation. But as our analysis suggests, the benefit of a cost-efficient strategy seems to depend on the amount of uncertainty in the model predictions and the degree to which budgets are constrained.

Burrowing Owl Predictions
Some uncertainty in model predictions appears to be driven by detection error. Aside from accounting for this error directly, our results suggest that some steps can be taken to improve surveys. For instance, calls were somewhat effective in increasing the odds of detection in the field. This was consistent with other studies that have found positive effects of playing calls for burrowing owl surveys (Conway and Simon 2003, Crowe and Longshore 2010). However, calls only improved detection rate and did not completely remove false negative error from our model predictions (Tyre et al. 2003). Nonetheless, our results suggested that prairie dog colony area, land use, grazing, and physiographic variables were not good predictors of burrowing owl abundance. This was surprising given that other studies have shown effects of some or all of these factors (Faanes and Lingle 1995, Desmond and Savidge 1996, Villarreal et al. 2005, Moulton et al. 2006, Restani et al. 2008). There are a number of reasons why our study may have had different results. With regard to colony area, we looked at a slightly wider range of colony sizes and surveyed a larger number of colonies than some other studies. We also treated land use, including grazing, as a discrete variable, which may have precluded our ability to find more subtle relationships. Finally, the physiography of our study area is relatively uniform and thus may not be variable enough to establish any relationship with abundance. Instead, we found that the activity status of a prairie dog colony strongly predicted average owl abundance, which is consistent with general findings elsewhere (Desmond et al. 2000, Sidle et al. 2001).

Our results were very similar to the patterns in occupancy found by Tipton et al. (2008), which showed that active colonies were much more likely to be occupied by owls than inactive colonies. This is perhaps not surprising in light of the strong association between prairie dogs and burrowing owls (VerCauteren et al. 2001, Poulin et al. 2011).

Although the presence of active colonies helps to explain much of the variation in burrowing owl abundance, we found that the spatial autocorrelation of these colonies very weakly explained some of this variation. Other studies have investigated the spatial arrangement of owl nests within colonies (Desmond et al. 1995, Fisher et al. 2007), but not how the spatial arrangement of colonies affects owl abundance. The estimates for our range parameter suggest that the spatial process in our data had influence over a very short distance (about 3% of colonies were separated by distances ≤ 10 km). Under this assumption, spatial structure as measured by our random effect could be caused by intrinsic processes like short-range dispersal behavior (Wintle and Bardos 2006). However, we should note that there is also the possibility that the random effect is estimating variation from a missing covariate. As our results suggest, the amount of autocorrelation between colonies is fairly low, which means that intrinsic spatial structuring is fairly limited. Nonetheless, strategically clustering management at colonies near one another may have benefits, but we did not explicitly consider this clustering effect in our decision algorithm.

Burrowing Owl Conservation Strategies
Owl distributions in our study area appear to be driven more by the presence of prairie dogs, which maintain nesting habitat for owls. Numerous recent studies have suggested that management of burrowing owls could be mediated through management of prairie dogs (Lantz et al. 2007; Tipton et al. 2008, 2009). In this decision context, management of prairie dogs would be regarded as a means of improving owl abundance (Keeney and Gregory 2002). If the objective is simply to maximize owl abundance, then the best decision is to invest in expensive actions that have a large affect on owls. This strategy, of course, requires that an organization have a budget sufficient to implement that strategy, which is rarely the case. More realistically, conservation organizations have constrained budgets and look for ways to minimize the cost of actions. If this constraint is made explicit in an analysis, then the best decision may change. Our analysis suggested that an organization's investment strategy should be to use the maximize strategy for budgets up to about 50% of the cost of the most expensive strategy (furthest right in Fig. 2). For budgets less than $450,000, the cost-effective strategy is preferred and managers should invest in decisions that can still meet the conservation target. This pattern occurs because the maximize objective function is directing the algorithm to choose colonies with the greatest abundance, whereas the cost efficiency function is directing it towards colonies with highest cost-benefit value. A cost-efficient strategy can often do more with less money, but only up to a point.

Interestingly, this trend does not necessarily hold true if we are also concerned with how well our model predicts the

expected outcome of an action. Because this model is used to make predictions about the future, those predictions could be wrong. Therefore, each strategy has some associated worst-case outcome for a given level of robustness and we are interested in choosing a strategy that will produce at least the worst-case outcome over a wide range of possible error (i.e., robustness). As our analysis shows, tolerance to uncertainty has the potential to change which strategy should be chosen. As budgets become more constrained, tolerance to uncertainty introduces a slight trade-off between the various alternative strategies. For a given level of performance, we would then want to choose the strategy that maximized robustness; this is a satisficing strategy, rather than an optimal strategy (Ben-Haim 2006). Here, the term satisficing refers to making a decision that meets an acceptability requirement, and is not necessarily concerned with the best (i.e., optimal) outcome. Work by McDonald-Madden et al. (2008) showed that large conservation budgets generally allow for more robustness under moderate levels of uncertainty. Likewise, Wintle et al. (2011) showed that when comparing multiple cost-efficient management strategies, the size of the operating budget had an influence on which strategy was most robust. These results suggest that the cost-effective strategy, given some performance criterion, becomes more robust in cases where budgets are seriously limited. In situations where the budgets are moderately to weakly limited, our results suggest that the maximize strategy may be a more robust option. Additionally, if our budget was insufficient to manage every colony under the maximize strategy, one might be able to acquire additional funding, effectively funding their way out of having to make the robustness-performance trade-off.

These patterns make sense when one considers that budgets restrict what is possible under each strategy. When budgets are large, managers should invest in the strategy that increases abundance the most (i.e., translocations). The predicted responses for the translocation strategy are also slightly less uncertain than those of the next best strategy, which explains why the translocation strategy remains robust. However, when the budget is reduced, managers should spend money on translocations until they can no longer afford that strategy and then spend the remaining funds on incentive payments. However, the predicted responses of incentives are slightly more uncertain than those for translocations. Thus, one can achieve a slightly more robust outcome by investing only in translocations under a wide range of uncertainty. Finally, if the budget is reduced even further, meeting the population target using translocations becomes very difficult because one cannot afford to do as many. Thus, being cost efficient becomes even more important.

Admittedly, these results should be tempered by the amount of reality in our models. All planning and conservation efforts require some sort of modeling, whether implicit or explicit. The degree of complexity of the modeling, of course, creates degrees of cost (i.e., effort, time, etc.), but the more important issue is whether the modeling is adequate to solve the problem. Our case study used a relatively simple problem formulation, which assumed that the solution was static and could be implemented immediately. In actuality, though, this solution would probably be implemented over time, which could mean that the static solution would no longer be optimal. Additionally, land in western Nebraska is largely privately owned and managers may need to overcome substantial political hurdles when implementing conservation strategies focused on prairie dog colonies (Fisher et al. 2007). This raises the possibility that a strategy would have to be implemented in an opportunistic way and trade-offs would have to be made in terms of whether to take implementation opportunities or wait for new opportunities that arise stochastically. Likewise, our model lacks stochastic colony dynamics that may affect owl distributions. For example, the local extinction process for owls may be indirectly related to prairie dog dynamics. Prairie dog extinctions are most often caused by a combination of control measures (i.e., poisoning) and natural processes (i.e., plague; Miller et al. 2007). The risk of prairie dog extinction could be linked to extinction risk for burrowing owls, but if a lag in burrowing owl response occurs after prairie dog extinctions, this relationship may be weak or nonlinear (Desmond et al. 2000). All of these complexities suggest that more dynamic modeling would be required to more accurately represent this decision problem. Because of the size of this problem, typical dynamic optimization approaches are probably not feasible (Moilanen 2008). However, development of new heuristic optimization techniques that allow for very large state spaces and dynamic system models may provide a solution to this problem (Moilanen and Cabeza 2007, Glovin and Krause 2011, Nicol and Chades 2011).

Other considerations should also eventually be addressed in framing this problem. We did not assess trade-offs among multiple objectives; for instance, the trade-off between maximizing revenue for private grazers against maximizing owl abundance or the abundance of other species. Our model also does not incorporate the decision to monitor burrowing owl populations instead of engaging in management. We assumed that management and monitoring were separate and that monitoring was used to inform management. This may be a naive assumption. Many conservation agencies face trade-offs in terms of whether they should invest in reducing their epistemic uncertainty through monitoring or engage in management to meet targets (Probert et al. 2011). This could have the effect of making the cost-effective strategy in our analysis more appealing under larger budgets. Again, our analysis did not consider these additional dimensions, but the general framework we used could easily be modified to incorporate them.

MANAGEMENT IMPLICATIONS

Despite its limitations, our study provides some insight into the issue of population management effectiveness. We demonstrated how models developed to make distributional predictions of species can be leveraged using decision analysis to guide more strategic conservation planning. Such strategic analyses should be considered by planners and managers. By

examining how sensitive management performance is to budget limitations, one can develop a more defensible rationale for trying to acquire a larger conservation budget. In situations where this is not achievable, simply assessing the cost of actions relative to the available budget may lead to the development of strategies that will provide the best outcome, given the limitations. On the other hand, predictions of most likely outcomes could actually overpredict performance. Thus, one ought to be somewhat realistic about their preferred worst-case outcome and choose a strategy that guarantees some lower level of performance should the model predictions be wrong. Although our presentation here was focused on a single species and used a comparatively simple optimization approach, we should note that these methods are useful and ought to be considered by conservation organizations that are tasked with designing complex multispecies management plans.

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