Chapter 5
Application of Threshold Concepts to Ecological Management Problems: Occupancy of Golden Eagles in Denali National Park, Alaska

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Abstract In this chapter, we demonstrate the application of the various classes of thresholds, detailed in earlier chapters and elsewhere, via an actual but simplified natural resource management case study. We intend our example to provide the reader with the ability to recognize and apply the theoretical concepts of utility, ecological and decision thresholds to management problems through a formalized decision-analytic process. Our case study concerns the management of human recreational activities at Alaska's Denali National Park, USA, and the possible impacts of such activities on nesting Golden Eagles, *Aquila chrysaetos*. Managers desire to allow visitors the greatest amount of access to park lands, provided that eagle nesting-site occupancy is maintained at a level determined to be acceptable by the managers themselves. As these two management objectives are potentially at odds, we treat minimum desired occupancy level as a *utility* threshold which, then, serves to guide the selection of annual management alternatives in the decision process.

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As human disturbance is not the only factor influencing eagle occupancy, we model nesting-site dynamics as a function of both disturbance and prey availability. We incorporate uncertainty in these dynamics by considering several hypotheses, including a hypothesis that site occupancy is affected only at a threshold level of prey abundance (i.e., an *ecological* threshold effect). By considering competing management objectives and accounting for two forms of thresholds in the decision process, we are able to determine the optimal number of annual nesting-site restrictions that will produce the greatest long-term benefits for both eagles and humans. Setting a utility threshold of 75 occupied sites, out of a total of 90 potential nesting sites, the optimization specified a *decision* threshold at approximately 80 occupied sites. At the point that current occupancy falls below 80 sites, the recommended decision is to begin restricting access to humans; above this level, it is recommended that all eagle territories be opened to human recreation. We evaluated the sensitivity of the decision threshold to uncertainty in system dynamics and to management objectives (i.e., to the utility threshold).

Keywords Golden Eagles · *Aquila chrysaetos* · Utility threshold · Ecological threshold · Decision threshold · Occupancy modeling · Structured decision-making · Adaptive management · Uncertainty · Wildlife disturbance

Introduction

Structured Decision-Making and Thresholds

Thresholds, in the context of management decisions, have recently received attention in the conservation and ecological literature (Martin et al. 2009c; Samhouri et al. 2010; Andersen et al. 2009). In this volume, Nichols et al. (Chap. 2) have provided clear guidelines to distinguish among classes of threshold and, at the same time, have offered a logical conceptual framework for considering the role and appropriate application of threshold types in structuring a decision process for management problems. Here, we illustrate this conceptual framework by describing the formal inclusion of thresholds into a process of structured decision-making (SDM). Our example focuses on the management of recreational activities near nesting Golden Eagle (*Aquila chrysaetos*) territories in Alaska's Denali National Park (Denali NP). We used a simplified version of an actual case study (Martin et al. 2011) to illustrate the relationship among different types of thresholds when applying SDM to natural resource management. Our objectives for this chapter are to describe the formulation of the management problem in an SDM framework and explore in detail the process of testing for and incorporating thresholds in the SDM framework.

SDM is an analytic framework that aids decision-makers in coping with complexity and uncertainty by deconstructing the problem into components, identifying the sources of uncertainty and impediments to the decision, and then finding the optimal solution by integrating the components (Clemen and Reilly 2001). Essential elements of the SDM process include a clear statement of objectives that are expressed as quantitative measures and are used to evaluate the success of management decisions, a set of discrete actions that form the basis of the decision, one or more models of the system dynamics that predict the outcome of each potential management action in terms of the measurable objectives, and an optimization method that identifies the action that is most likely to achieve the objectives given the expected outcomes and effects of uncertainty (Clemen 1996). When decisions are made repeatedly over time, SDM can become an adaptive process if it includes a targeted monitoring program that is used to reduce uncertainty in system behavior and feed information back to managers. Monitoring of this form is specifically designed to provide information on the state of the system to (1) allow state-dependent decisions to be made, (2) evaluate progress towards objectives following the implementation of a management action, and (3) improve future management decisions by comparing observations of system response to predictions generated by competing models, thereby reducing the uncertainty of future predictions (Lyons et al. 2008; McCarthy and Possingham 2007; Williams et al. 2002). As natural resource management decisions are often made in the context of thresholds—in the form of triggers that prompt the need for specific actions to be taken or a desire to keep a focal state variable above or below a specified level—clarifying threshold categories and their roles is essential to improving our decision-making abilities.

Three types of thresholds—ecological, utility, and decision—have been identified as being relevant to natural resource management (Nichols et al., Chap. 2; Martin et al. 2009c). Ecological thresholds, arguably the type most commonly encountered in the literature, are considered as boundaries between alternative ecological regimes and represent values of system state where substantial changes in the dynamics of one or more elements of the system are observed (e.g., Fahrig 2001), or where system state variables or rate parameters reach certain levels (Nichols et al., Chap. 2). For example, in the context of a predator species, prey abundance level may be regarded as a relevant state variable, such that attainment of some level (ecological threshold) brings about dramatic increases or decreases in local rates of colonization or extinction. Alternatively, ecological thresholds can be viewed as values of state or other variables at which vital rates attain specified values. For example, the concept of extinction threshold (Lande 1987) concerns the proportion of suitable habitat potentially available to a metapopulation. The extinction threshold is that proportion of patches containing suitable habitat at which the probability of metapopulation extinction is equal to one.

Utility thresholds, in contrast, are formulated from management objectives and defined as the point where small changes in system state or performance level result in significant improvements (or declines) in the return (utility) of decision outcomes (Martin et al. 2009c). Utility thresholds are derived from value judgments of stakeholders and most often pertain to desired ecosystem states or functions. Correspondence between ecological and utility thresholds is possible, but establishment of a utility threshold can be independent of the existence of ecological thresholds. Samhouri et al. (2010) provide an example of how a utility threshold might coincide with an ecological threshold: If the desired system state of a freshwater lake is clear water, then the utility threshold value may correspond naturally with an ecological threshold where small changes in nutrient input result in dramatic changes to water clarity. In the context of Golden Eagles, a utility threshold might be based on the desire of managers to ensure that some minimum number of eagle territories is occupied each year (Martin et al. 2011). Such an objective could arise from the values of the protected area manager, from observations on nesting numbers before significant human disturbance was recorded in the park, or from a population viability analysis (PVA) suggesting that sustained occupancy above this threshold level will maintain the risk of local extinction at a desired low level. The latter possibility represents a utility threshold coinciding with one form of ecological threshold.

Finally, decision thresholds are defined as changes in state variable values that result in changes in the optimal management action recommended to meet management objectives. As such, a decision threshold is the product of the SDM process itself, conditional on any ecological threshold(s) included in the predictive models and on the utility threshold(s) included in the objective function. In the case of managing eagles in Denali NP, a decision threshold would be represented by a change in management policy (e.g., from few to many restrictions imposed on human recreational activities) resulting from predicted changes in the number of occupied nesting territories (a state variable) and the desired occupancy level (utility threshold). Changes in management decisions, therefore, will be a product of the model(s) of system dynamics and the objective function specified by managers. The model(s) of eagle occupancy dynamics predicts the impacts of human activities, accounting for any hypothesized ecological thresholds, while the objective function contains any specified utility thresholds.

Golden Eagles and the Impacts of Recreational Activities on Nesting in Denali National Park

Denali NP, Alaska, contains the highest-reported nesting density of Golden Eagles in North America, with approximately 80 breeding pairs monitored since 1988 (C. McIntyre, personal communication; Kochert et al. 2002). In a 1,800-km^2 study area within the park, eagles nest exclusively on cliffs and rock outcroppings. Denali Golden Eagles are migratory, returning to the park each March to lay 1–3 eggs. Eggs are incubated for approximately 40 days, with hatching occurring in June and young eaglets fledging by early August. Managers in Denali NP are concerned that back-country hiking, airplane tours, and other recreational activities may negatively impact the occupancy of Golden Eagles in potential nesting sites and, therefore, reduce overall breeding success in the study area. Martin et al. (2009a) suggested that Golden Eagle occupancy and breeding success may be influenced by human disturbance and the abundance of snowshoe hares (*Lepus americanus*), a principal prey item of nesting eagles. Human recreational activities have been implicated as a significant factor in wildlife disturbance, including negative effects on raptor nesting success and stress or reduced productivity in other nesting species (McGowan and Simons 2006; Morse et al. 2006; Steidl and Anthony 2000; Swarthout and Steidl 2003). Managers, however, are also mindful of the role of the NP and are mandated to provide as many recreational opportunities to human visitors as possible without threatening or causing undue disturbance to habitat or wildlife. Thus, the management decision in this problem is to what extent the park should restrict human recreation activities in eagle nesting territories. The potential for human disturbance to affect the occupancy of Denali eagles is unknown and represents one source of uncertainty. In our formulation of the decision structure for this management problem, we also recognize that the form of the relationship between prey abundance and eagle occupancy represents additional uncertainty, and therefore consider alternative hypotheses to describe and test this relationship. Martin et al. (2009a) used multistate site occupancy models (unoccupied, occupied, occupied with breeder) to evaluate the effect of disturbance and hare abundance on parameters that govern the occupancy and breeding dynamics of eagles. For our current emphasis on the role of thresholds in decision-making, we simplified the example of Martin et al. (2009a) by using two-state occupancy models (i.e., unoccupied or occupied) described by MacKenzie et al. (2006). We extend a similar two-state occupancy analysis developed by Martin et al. (2009b) to include model covariates of hare abundance and human disturbance. Finally, we describe a monitoring program that could be implemented to reduce uncertainty in model confidence through an adaptive management approach (Williams et al. 2002, 2007).

Methods

Defining an Objective Function with Utility Threshold Constraints

Management objectives embody the fundamental desires of the decision-maker and can, and in most cases should, represent the values of all stakeholders. Objectives, then, become the basis for assessing the success of alternative management decisions. The objective function, a mathematical formulation of management objectives and constraints (Williams et al. 2002), is the formal means to quantify the management outcome (return) of implementing any particular decision at a given time. If the decision-maker must consider several objectives simultaneously, it is often useful to convert one or more objectives into constraints and include them in the objective function as utility thresholds. Management objectives for Denali NP are to maximize recreational opportunities for human visitors, while at the same time minimizing the effects of recreation on site occupancy levels of Golden Eagles in nesting territories. To reconcile these seemingly competing goals, we convert the second objective to a constraint and include it as a utility threshold in the objective function. The utility threshold, like the objective function in general, is a value judgment and is decided on by the decision-maker. In this case, park personnel provided expert opinion and concluded that using the average number of occupied nesting territories observed over the last 20 years was an appropriate minimum threshold for management objectives. This threshold value is incorporated in decision-making by way of a penalty parameter that devalues the current return on a particular management action, given the expected system response (Martin et al. 2011):

$$\alpha = \begin{cases} 0, & E_i\left(N_{t+1}^{\mathrm{O}}\right) < \tau \\ 1, & E_i\left(N_{t+1}^{\mathrm{O}}\right) \geq \tau \end{cases}, \tag{5.1}$$

where α is the penalty factor, $E_i(N_{t+1}^{\mathrm{O}})$ is the expected number of occupied nesting sites in year $t+1$, following management action i, and τ is the utility threshold value. As specified by this equation, if occupancy is expected to fall below τ after the implementation of management action i, the value returned by the objective function is multiplied by the penalty factor and, thus, reduced to 0, i.e., $\alpha = 0$. If expected occupancy is equal to or greater than τ, the return produced by the objective function retains full value, i.e., $\alpha = 1$.

The full utility function can then be defined as

$$U_t\left(N_t^{\mathrm{O}}, r_t\right) = \left(N^{\mathrm{tot}} - r_t\right) \times \alpha, \tag{5.2}$$

where the utility value, U_t, is a function of the number of occupied territories (N^{O}) and the number of territories restricted to human activity (r) at time t. N^{tot} is the total number of nesting sites available. By minimizing the number of restricted territories, we maximize the function ($N_t^{\mathrm{tot}} - r_t$), but only so long as expected nesting-site occupancy remains above τ (i.e., $\alpha \neq 0$).

We then select a sequence of management actions, from the present (t) to some future time (T) that maximizes our objective function with respect to expectations under random environmental variation

$$\max_{r_t} E \sum_t^T [U_t(N_t^{\mathrm{O}}, r_t)]. \tag{5.3}$$

Specifying Alternative Management Actions

The annual decision for Denali NP managers is how many potential nesting sites to restrict to park visitors. The nesting area believed to be affected by human recreation contains 90 potential nesting territories. We have simplified the problem such that the number of sites restricted in any year (r_t) can take an integer value from 0 to 90. We do not consider the spatial location or arrangement of territories in determining the optimal level of restrictions, but recognize that it may not be realistic to restrict access to one territory independently of adjacent territories (i.e., trails might pass through multiple territories and, if closed, would naturally affect access to all territories they cross).

Developing Dynamic Models of System Behavior

We use a two-state occupancy model, simplified from previous analyses of this population (Martin et al. 2009a, 2011), to describe eagle dynamics in their nesting sites. The model links territory transition probabilities (extinction and colonization rates) with hypotheses about the effects of management actions on these dynamics. The number of occupied territories in a given year can be modeled as a Markov process:

$$N_{t+O}^{\mathrm{O}} = (N_t^{\mathrm{U}} \times \gamma) + \left[N_t^{\mathrm{O}} \times (1 - \epsilon)\right], \tag{5.4}$$

where N^{O} is the number of occupied territories, N^{U} is the number of unoccupied territories, γ is the probability that an unoccupied territory will be occupied the next year (colonization), and ϵ is the probability that an occupied territory will be unoccupied in the next year (local extinction). Simply put, this model states that the number of occupied sites in time $t+1$ depends on the number of unoccupied sites in year t that are colonized, plus the number of occupied sites that do not go extinct between year t and $t+1$. We modify the basic occupancy model to link the predicted impacts of our management actions to eagle occupancy dynamics (see Martin et al. (2011) for the three-state version of this model):

$$\begin{aligned} N_t^{\mathrm{O}} = {} & \frac{N_{t-1}^{\mathrm{U}}}{N^{\mathrm{tot}}}\left[r_t \gamma_R + \left(N^{\mathrm{tot}} - r_t\right)\gamma_{NR}\right] \\ & + \frac{N_{t-1}^{\mathrm{O}}}{N^{\mathrm{tot}}}\left[r_t\left(1 - \epsilon_R\right) + \left(N^{\mathrm{tot}} - r_t\right)\left(1 - \epsilon_{NR}\right)\right], \end{aligned} \tag{5.5}$$

where N^{tot} is the total number of available territories, r_t is the number of territories which are restricted to recreation, subscripts R and NR correspond to the anticipated effects of restricting and not restricting territory sites, respectively, on the probabilities of colonization and extinction. As we do not consider the spatial configuration of territories or location of restrictions, Eq. 5.5 makes the assumption that once the number of site restrictions is determined, they are applied without regard to the occupancy status of a territory. This is a simplified but realistic approach because we assume that decisions on the number of site restrictions will often have to be made prior to ascertaining the occupancy status of territories in the study area.

Predicting nesting-site occupancy in Eq. 5.5 is contingent on estimating occupancy transition parameters, γ and ϵ. Martin et al. (2009a) estimated nesting and reproductive transition probabilities for eagles using 20 years of nest survey data. They tested for the expected effects on eagle occupancy dynamics of disturbance and environmental variables such as nesting-site elevation and snowshoe hare (*L. americanus*) abundance. Here, we extend this work by considering the possibility that a specific level of snowshoe hare abundance may constitute an ecological threshold related to patch extinction or colonization probabilities. As system dynamics are not known with certainty, we account for this uncertainty by presenting multiple hypotheses regarding the functional relationship between hare abundance, disturbance to nesting sites, and the parameters that govern eagle occupancy. To simplify the problem for illustrative purposes, we offer four a priori models to represent possible relationships between environmental variables (prey abundance), management alternatives (minimizing disturbance through restricting access), and conservation objectives (maintain site occupancy and recreational opportunities). In this case, our initial model (*Model 1*) hypothesizes a negative relationship between hare abundance and the probability of local patch extinction and a positive, additive effect of both hare abundance and reduced disturbance on patch colonization. *Model 2* represents a no-effect model predicting that neither extinction nor colonization probabilities are influenced by snowshoe hare abundance or restricting access to eagle territories. *Model 3* hypothesizes that hare abundance has no effect on occupancy dynamics, but human disturbance negatively affects the probability of colonization. *Model 4* posits the existence of an ecological threshold, where values of colonization and extinction are predicted to differ above and below a given hare abundance level. While the structure of *Model 4* could take many forms, we offer one hypothetical example where transition parameters are as follows:

$$logit\,(\gamma) = \alpha + \beta_1 \times HareTH + \beta_2 \times Disturb, \qquad \text{and}$$
$$logit(\epsilon) = \alpha + \beta_1 \times HareTH,$$

where α's are intercepts and β's are slope parameters describing the relationship between covariates and probabilities of colonization (γ) and extinction (ϵ). As in *Models 1–3*, γ and ϵ are modeled as linear-logistic functions and converted to linear functions via the logit link (MacKenzie et al. 2006). In *Model 4*, the logit of colonization is modeled as a linear combination of human disturbance (where $Disturb = 0$ when access to a site is restricted, and 1 otherwise) and hare abundance relative to a given threshold, which is modeled as a binomial outcome (*HareTH*). Extinction probability is modeled as a function of threshold hare abundance only. *HareTH* is a dummy variable that takes the form

$$HareTH = \begin{cases} 0, & hare\ index \leq \tau_h \\ 1, & hare\ index > \tau_h \end{cases},$$

where *hare index* is a covariate for hare abundance measured annually and relevant to all sites, and τ_h is an ecological threshold value for the hare abundance index. In our example, we arbitrarily set $\tau_h = 0.07$. We simplify the analysis by modeling *hare index* as a random variable following a distribution based on expert opinion and observed hare fluctuations (mean = 0.12, SD = 0.11), but hare abundance can be modeled in a more realistic manner (see Martin et al. 2011).

We use the 20-year data set collected on nesting-site occupancy to provide initial measures of credibility (weights that sum to 1 for all members of the model set) for the four models. Occupancy modeling is implemented in PRESENCE 2.4 (Hines 2008), and model selection is based on Akaike information criterion (AIC; Burnham and Anderson 2002). AIC weights are then used as relative measures of confidence in each candidate model when determining the optimal management decision for any level of site occupancy (see next section). A directed monitoring program allows us to reduce the structural uncertainty represented by competing models and adjust model weights as empirical evidence supports one or more models over the others (Williams et al. 2002).

Optimal Decision-Making and Simulations

The aim of this analysis is to select the optimal number of nesting sites to restrict each year in order to meet management goals defined through our objective function: maximizing recreational opportunities while achieving a minimum threshold level of site occupancy. We use the general expression for system dynamics (Eq. 5.5) to discriminate among all possible management alternatives at each time step and select the number of nesting sites to restrict each year that is expected to provide the optimal long-term benefit given the current state of the system. We consider this a Markov decision process because annual occupancy state is modeled as dependent on the state in the previous year. Uncertainty in system dynamics must be accounted for in decision-making and is represented here by differences in the predictions of competing models (*Models 1–4*). The optimal, state-dependent decision is then obtained by means of a passive optimization algorithm, which accounts for the uncertainty (weight associated with each model) via weighted model averaging. Initial model weights are based on AIC values from the model selection process and used to average the expected return from each of the four models. In an actual management situation, monitoring would follow the decision at each time step and provides the ability to learn about the system by confronting model predictions with observations. Model weights would then be updated via Bayes' theorem to reflect the new confidence in one or more models, resulting in improved predictions and better management decisions (see Williams et al. 2002). This approach is considered one of passive adaptive management, as the evolution of model weights is not accounted for over the time horizon of the optimization (Williams et al. 2002). We calculated the optimal sequence of state-dependent decisions using stochastic dynamic programming, based on the Principle of Optimality (Bellman 1957) and implemented in ASDP v3.2 (Lubow 2001). Stochastic dynamic programming iterates backwards from some future time and aggregates long-term benefits to the current return obtained by the decision made in the present time step (Williams et al. 2002). We ran the dynamic model for a maximum of 350 iterations, until a stable decision policy was reached and maintained over 15 consecutive iterations.

We simulated annual eagle occupancy levels predicted through implementation of the optimal decision policies under each of the four models as representing the "true" behavior of the system. To assess the value of selecting optimal annual restriction levels, we compared this policy to alternative suboptimal decision scenarios including a fixed policy of no management and that of restricting all sites to recreation. Under the belief that each model, in turn, represents the best hypothesis of system dynamics, we also simulated the evolution in model weights to explore the reduction of uncertainty over time.

Decision Thresholds and Sensitivity

As described earlier, decision thresholds are the products of the SDM process, resulting from interactions between the objective function (including utility thresholds), the predictions of system dynamics models (including identified ecological thresholds), the set of decision alternatives available, and the optimization procedure. Thus, a decision threshold is a location in state space where the optimal management action shifts from one alternative to another. This change occurs as a function of the predicted effects of management decisions on those state variables and the desired outcome as expressed through the objective function. Uncertainty in system dynamics, and therefore, in the response of the system to management, reduces the returns expected to result from optimal decisions because those decisions are made with incomplete understanding of the system. In order to assess the importance of uncertainty to management decisions, we can investigate the sensitivity of the optimal decision to the uncertainty inherent in our models. If the competing models all lead to the same management actions for a point or region of state space, then the decision is said to be "robust" to uncertainty (Regan et al. **?** . In this situation, there is no advantage to try to reduce structural uncertainty. In addition to structural uncertainty related to models and to possible ecological thresholds, we also evaluate the sensitivity of decision thresholds to our selection of utility threshold values.

Results

Occupancy Dynamics of Golden Eagles in Denali National Park

Using the simplified set of four competing models describing the dynamics of eagle occupancy, *Model 3* (no hare effect; human disturbance influences colonization) best explained the process underlying 20 years of nesting-site observations in Denali NP with an AIC weight of 0.74 (Table 5.1). *Models 1* and *4*, hypothesizing that hare abundance influences both colonization and extinction probabilities either linearly or beyond an ecological threshold, both received some support in the model selection process ($w = 0.14$ and 0.11, respectively; Table 5.1) and, therefore, should be considered as plausible models for explaining system dynamics. The no-effect model (*Model 2*) received virtually no support. Parameter estimates for model coefficients were in the expected directions for covariables with disturbed (unmanaged) sites showing reduced colonization probability and increased hare abundance enhancing colonization and reducing extinction probabilities (Table 5.2). Using the coefficient estimates from the best-supported model (*Model 3*), we slightly modified parameter values for the remaining models such that equilibrium occupancy ($\psi^* = \gamma/[\gamma + \epsilon]$) was approximately equal across all models under conditions of an undisturbed site

Table 5.1 Occupancy model selection for Golden Eagles in Denali National Park, USA, using Akaike information criterion

Model		ΔAICc	w	K
Model 3	$\psi(1)\epsilon(.)\gamma(Disturb)p(t,.)$	0	0.74	13
Model 1	$\psi(1)\epsilon(Hare)\gamma(Disturb + Hare)p(t,.)$	3.32	0.14	15
Model 4	$\psi(1)\epsilon(HareTH)\gamma(HareTH + Disturb)p(t,.)$	3.74	0.11	15
Model 2	$\psi(1)\epsilon(.)\gamma(.)p(t,.)$	15.6	0.01	12

Model parameters included probability that a site was occupied in the first study season [$\psi(1)$], the probability of a site becoming unoccupied if occupied in the previous year (extinction, ϵ), the probability of an unoccupied site becoming occupied in the following year (colonization, γ), and the probability of detecting nesting eagles, conditional on the site being occupied (p). We estimated initial occupancy as constant; extinction and colonization probabilities were modeled variously as functions of human recreational activity at the nesting site (*Disturb*), of prey availability as related linearly (*Hare*), of prey availability functioning as an ecological threshold (*HareET*), or as constant (.). Detection probability was modeled as varying among years but constant within a given year *p(t,.)*. *AICc*: Akaike's information criterion corrected for small sample sizes, *ΔAICc*: for the *i*th model is computed as $AICc_i - \min(AICc)$; *w*: AICc weight; *K*: number of parameters

Table 5.2 Coefficient estimates for covariate parameters included in occupancy dynamic models

Parameter	Coefficient	Model 1	Model 2	Model 3	Model 4
γ	α_0	– 0.880	– 0.85	– 0.740	– 0.770
	$\beta_{1(Hare,\ HareTH)}$	1.000	–	–	0.150
	$\beta_{2(Disturb)}$	– 1.390	–	– 1.380	– 1.378
ϵ	α_0	– 2.770	– 2.854	– 2.843	– 2.822
	$\beta_{1(Hare,\ HareTH)}$	– 1.040	–	–	– 0.085
	$\beta_{2(Disturb)}$	–	–	–	–

The structure for the four models is provided in Table 5.1. Coefficients for linear predictors of colonization (γ) and extinction (ϵ) probabilities include an intercept (α_0), prey abundance (β_1), and human disturbance at a nesting site (β_2). Under *Model 4* the beta coefficient for *HareTH* relates to a dummy variable signaling prey abundance above or below a threshold of 0.07

at average hare abundance. Applying coefficient values from Table 5.2, a graphical representation of the four competing models is provided in Fig. 5.1.

Optimization

We set the utility threshold to $\tau = 75$ out of 90 potential nesting sites, based on the objectives (values) of the decision-makers in Denali NP and on historical occupancy levels. Assuming, sequentially, that each of the four models approximates "truth," we determined the optimal decision in a given year for each value of the occupancy state variable (Fig. 5.2a). Differences in the recommended decision at any point in the state space, depicted in Fig. 5.2, demonstrates the relevance of structural uncertainty to the optimal decision. As expected, the optimal decision under the no-effect model (*Model 2*) is to restrict none of the sites at any level of occupancy because limiting human disturbance has no impact on future occupancy. For the remaining models,

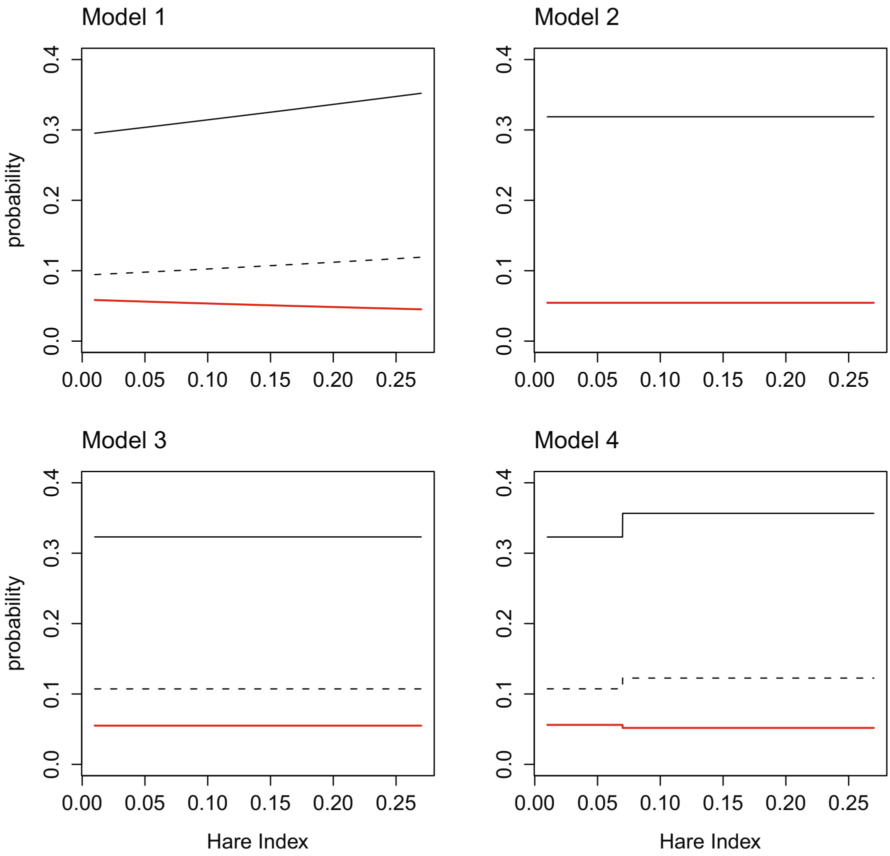

Fig. 5.1 Hypothetical models representing alternative functional relationships between snowshoe hare abundance, management, and occupancy dynamics for Golden Eagles at potential nesting sites. *Black lines* are local colonization probabilities, with *dashed lines* representing unmanaged sites and *solid lines* representing sites at which disturbance is reduced by restricting hiker access to nesting areas. *Red lines* are local extinction probabilities. *Model 1* is considered the global model, predicting that both human disturbance and snowshoe hare abundance influence colonization probability and that hare abundance affects extinction. *Model 2* represents a no-effect model in which neither hare abundance nor disturbance affects site occupancy. *Model 3* hypothesizes that disturbance influences colonization, but that hare abundance has no effect on occupancy dynamics. *Model 4* depicts a hare index value of 0.07 as an ecological threshold, with different colonization and extinction probabilities above and below this hare index. This model also includes a human disturbance effect

restrictions begin at occupancy levels below 80 territories and quickly increase until all sites are restricted to human access as soon as site occupancy falls below the threshold value (Fig. 5.2a). Note that for any level of site occupancy, the optimal management decision under *Model 1* or *Model 4* (both of which incorporated hare abundance as a random variable) is to restrict more sites than under *Model 3* (which included no stochastic component). Management decisions made under models that

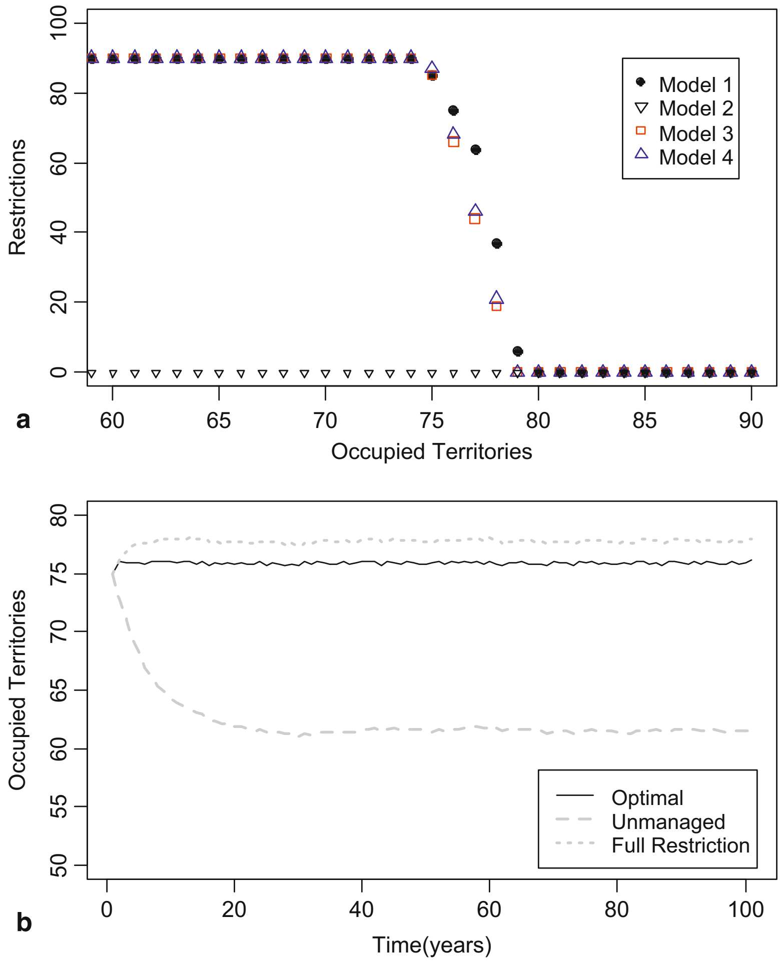

Fig. 5.2 **a** A decision rule depicting the optimal state-dependent management decision at each level of the state variable (nesting-site occupancy) for each of the four models under evaluation. *Model 2* predicts no influence of disturbance on occupancy dynamics and, therefore, recommends no management action taken at any level of occupancy. Decision thresholds are strongly influenced by the utility threshold in this scenario ($\tau = 75$ occupied sites) and occur over the range of 75–79 occupied territories for *Models 1*, *3*, and *4*. **b** Simulations (average of 10 iterations) under *Model 4* of Golden Eagle occupancy levels following optimal (*solid line*) and suboptimal (*dotted* and *dashed lines*) decisions. Suboptimal decisions included restricting hiking in all 90 eagle territories each year and, alternatively, opening all nesting territories for human recreation access

incorporate stochastic elements are expected to be more conservative than if based on deterministic models. The optimization algorithm anticipates the expected loss in return from periodically falling below the utility threshold and, therefore, recommends greater site restrictions in order to maintain average occupancy levels above those predicted by a deterministic model.

Figure 5.2b illustrates simulated levels of occupancy predicted under a single stochastic model (*Model 4*) when following the optimal decision policy as compared to maintaining fixed, suboptimal policies of no management and, alternatively, restricting human access to all eagle nesting territories. Equilibrium occupancy was approximately 0.66 under a policy of no park management; this is compared to average occupancy of 0.84 by following the optimal decision policy. The added benefit to eagles resulting from a policy of restricting all sites to human activities was determined to be minimal under *Model 4*, with the probability of occupancy increasing only 2 %, to 0.86. The costs (i.e., expenditure of resources and denying recreational benefits to park visitors) of such intensive management obviously outweigh the slight gains in eagle occupancy. Indeed, using the current objective function (Eq. 5.2) to quantify the return of implementing each of these management policies, we determined that both of the suboptimal approaches resulted in significantly lower annual utility values ($\bar{U}_t \cong 0$) than the optimal policy under *Model 4* ($\bar{U}_t = 20.7$, $\mathrm{SD} = 8.0$).

Model Uncertainty

We evaluated the relevance of structural uncertainty to system dynamics by simulating the predicted eagle response to optimal decision policies under each of the four models and comparing the outcomes. Although "truth" was represented by a single model in each simulation, optimal decisions at each time step were determined by incorporating structural uncertainty (represented by the distribution of model weights) in the optimization. Beginning with an initial occupancy of 75 out of 90 nesting territories, we simulated the sequence of decisions and predicted consequences over a 100-year period (Fig. 5.3a, b). The variability observed in both occupancy and restriction policy predicted by *Models 1* and *4* is attributable to fluctuating prey populations and illustrates the influence of environmental variation on decision processes (Fig. 5.3a, b). The uncertainty of environmental variation (random variation in hare abundance under *Models 1* and *4*) produces higher average occupancies than deterministic *Model 3*, which is held at the utility threshold value. Put another way, in order to maintain eagle occupancy above the utility threshold in the face of environmental variation, the optimal policy in a stochastic system is to manage for somewhat higher occupancy levels in order to avoid declines below the utility threshold in years of low hare abundance. Occupancy under deterministic *Model 2* is unaffected by hare abundance or management actions and remains at an equilibrium of 0.85 (76.1 sites occupied; Fig. 5.3a).

Management policies (temporal variation in number of sites restricted) were a function of initial model weights, the time required to "learn" which model was most appropriate for the system, and the predicted occupancy state. As annual decisions were a function of predicted occupancy state, the average decision policies under the two stochastic models were slightly less conservative than *Model 3* due to the higher levels of occupancy maintained under stochastic dynamics (Fig. 5.3b). Occupancy under *Model 1* was more variable and observed to fall below the threshold more

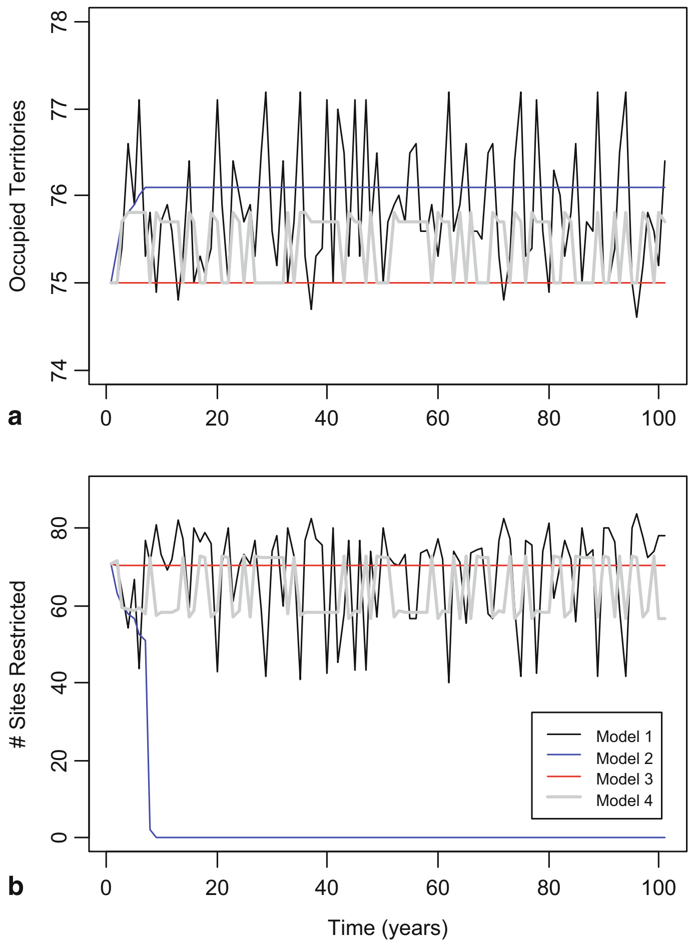

Fig. 5.3 A 100-year simulation (single realization) of **a** predicted system response (occupancy) and **b** the optimal decision policies under each of four competing models. All simulations were performed with model weight based on the AIC model selection (Table 5.1), allowing model weights to evolve over time, but where each model, in turn, represented "truth." *Model 3* is held at the utility threshold because it predicts occupancy dynamics as deterministic and settles on a stable decision policy almost immediately. Stochastic *Models 1* and *4* must maintain occupancy levels above the threshold value to reduce the chances that occupancy falls below the desired level

frequently than under *Model 4*. The decision policy, therefore, under *Model 1* showed greater variability and was more conservative (mean annual restrictions = 68.4 sites) than under *Model 4* (mean annual restrictions = 63.8 sites). The initial weight of *Model 2* was very low (initial $w = 0.01$), and thus updating of model weights required several years before the influence of the other models on the annual decision finally abated and the appropriate action (no restriction) under this model was selected (Fig. 5.3b). We illustrate the evolution of model weights more directly in Fig. 5.4, in which system dynamics were simulated under *Model 4*. We note that the weight

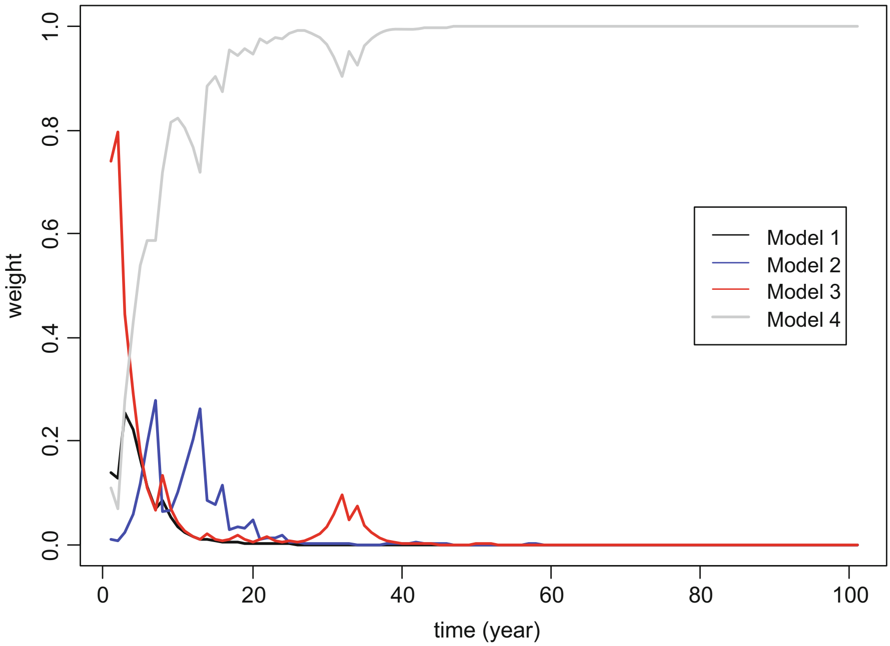

Fig. 5.4 Simulation (single realization using a passive adaptive optimization) of the change in model weights over time for the four models included in the model set, under the assumption that *Model 4* (threshold model) represented "truth."

for the initial highest-ranking model (*Model 3*) rapidly drops and that weights for *Models 1* and *3* share similar evolutions due to their comparable structure (Table 5.1).

Structural Uncertainty and Sensitivity of Decision Thresholds

While the sensitivity of decision thresholds to structural uncertainty under *Models 1*, *3*, and *4* is relatively low (Fig. 5.2a), the magnitude of differences in decisions made under each of these models in the simulation was significant, suggesting that reducing uncertainty in the structural dynamics of eagle occupancy would be valuable for managing the species (Fig. 5.3b). The impact of uncertainty on decision-making is most apparent when considering the potential for differences in optimal management response under the "no-effect" model (i.e., if *Model 2* is determined to be closest to "truth," no sites are restricted) relative to the level of restriction under the other models in our model set (Figs. 5.2a and 5.3b). Although managers will account for uncertainty at any point in time by weighting the consequences predicted under each model by its relative degree of support and selecting that management action determined to be optimal (results not shown), the range of possible decision thresholds under the four

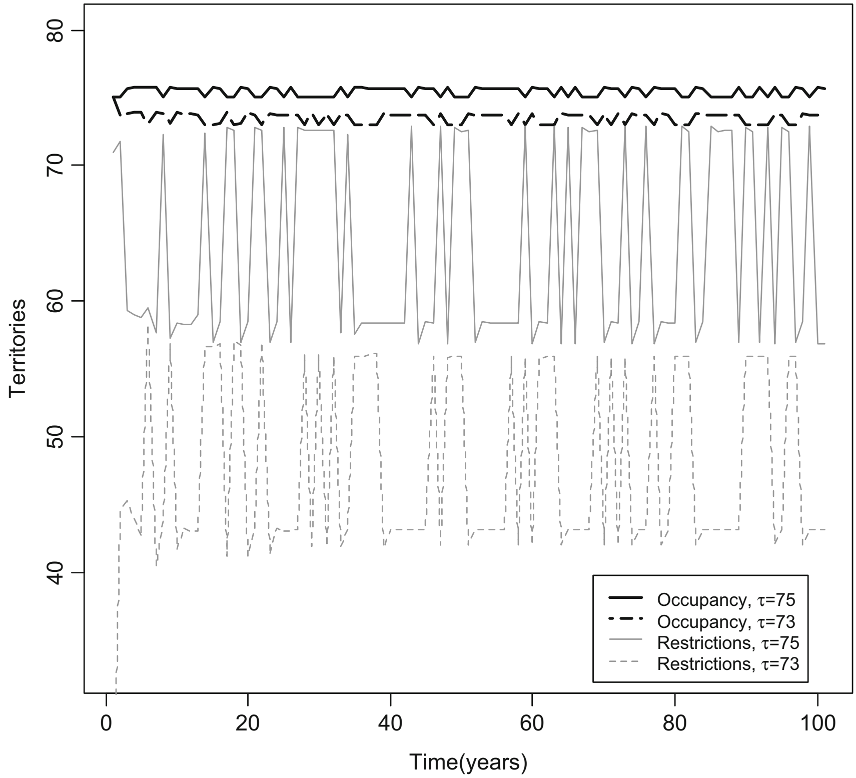

Fig. 5.5 Simulations (single realization) demonstrating the sensitivity of the decision threshold to utility thresholds ($\tau = 75$ and 73). Simulations included all models (weight distribution based on AIC model selection and allowed to evolve over time), but data depict the differences in occupancy and decision policies under *Model 4* as representing "truth." A reduction of the utility threshold from 75 to 73 resulted in a slight decline in average occupancy (*dark lines*) but a much larger reduction in average management actions (*gray lines*)

models in our set demonstrates the degree to which management could be improved by resolving this uncertainty.

In addition to evaluating the sensitivity of decision thresholds to model uncertainty, we can also examine the impact on decisions resulting in changes to the utility threshold. Evaluating changes in optimal management decisions when small changes are made to utility threshold values may be useful if management objectives are expected to change or evolve over time. For example, by reducing the utility threshold of desired occupancy level from 75 to 73 territories, we observe only a slight decline in average occupancy under *Model 4*, whereas the decision threshold was highly sensitive to this change. With this small change in utility threshold, we observed a substantial reduction in the average optimal number of sites to restrict, dropping from 63.9 (SD = 7.3) to 47.4 (SD = 7.1) territories per year (Fig. 5.5).

Discussion

The example we presented here originated from an actual case study, but was simplified to illustrate the three types of thresholds—ecological, utility, and decision—and to demonstrate how such thresholds might be included under an SDM framework in the management of natural resources. Following the operational definitions outlined by Martin et al. (2009c) and Nichols et al. (Chap. 2), utility thresholds were derived from the values of managers or stakeholders and can be incorporated explicitly into the management objectives via an objective function. Utility thresholds specify which values of state variables are viewed as desirable and undesirable and can result in changes to management when the system state approaches undesirable levels. Ecological thresholds, as the name suggests, represent biological phenomena and are the values of system state variables or environmental drivers where small changes result in either substantial changes to system dynamics or cause state variables or other parameters to reach specified levels. As such, ecological thresholds are important when considering the predictions of system response to management actions (or other changes in state variables) and should be included in system models. Decision thresholds are a product of the decision-making process and can formally be derived from the objective function, which may include utility thresholds, and from the models of system dynamics, which may include ecological thresholds.

In our example concerning human disturbance and nesting Golden Eagles in Denali NP, Alaska, we developed an objective function that accommodated two competing objectives: permitting recreational opportunities for human visitors to the Park, while concurrently maintaining what is believed to be an appropriate level of eagle nesting-site occupancy. We treated one objective, eagle occupancy, as a utility threshold which acted as a constraint on the remaining objective of recreational opportunities. Specifically, the objective function sought to maximize the number of potential eagle nesting sites at which hiking was permitted, subject to the constraint that eagle occupancy was maintained above the level specified by the utility threshold.

The concept of an ecological threshold is illustrated in our example by a single hypothesis describing the relationship between nesting-site occupancy dynamics and the abundance of a specific eagle prey item, snowshoe hares. This hypothesis, with its corresponding threshold, is incorporated into our set of potential models and, thus, represents uncertainty in system dynamics that can be confronted with data and reduced over time via an adaptive management strategy (Williams et al. 2002). By incorporating ecological threshold hypotheses into competing models that are relevant to the predicted effects of management actions on system dynamics, we focus our attention on those biological hypotheses that are most applicable to our stated management objectives. We used a model selection process to evaluate whether human disturbance and hare abundance are likely to influence the colonization and extinction probabilities of nesting-site occupancy. After the no-effect model (*Model 2*), which received virtually no support, the threshold model (*Model 4*) received the least amount of support ($w = 0.11$; Table 5.1). In adaptive management, however, optimal decisions are not based solely on the top-ranking model, but instead consider the predictions of all plausible descriptions of system dynamics, weighted by our relative confidence in each model (i.e., multimodel decision-making). In our example, weights were derived from a prior analysis, but they can also be based on "expert opinion," by consensus of stakeholder groups or other means. We then make the best decision recognizing that uncertainty exists. As we select management actions and monitor the response of the system, we learn about system dynamics and update our relative confidence in each model. Such a process leads to the accumulation of knowledge based on science and allows us to concurrently improve decision-making.

The decision thresholds in the Golden Eagle example were found to be highly sensitive to the value of the utility threshold. Lowering the utility threshold by only two sites resulted in a significant reduction in the average number of management restrictions imposed each year. Conducting such a sensitivity analysis provides decision-makers a tool with which to analyze the consequences of value judgments and evaluate the costs and benefits of their decision policies. Except in the case of the no-effect model (*Model 2*), the decision thresholds were moderately insensitive to the uncertainty associated with the remaining system dynamics models although the potential benefit from resolving this uncertainty may be significant. By directing our attention explicitly to those areas of uncertainty that have the greatest impacts on the management decision, our analysis allows us to reduce the complexity of the problem (and unnecessary impediments to decision-making) by choosing to ignore the many additional uncertainties that have little or no influence on decision thresholds. Although the decision thresholds were relatively robust to uncertainty in the three effect-models (*Models 1*, *3*, and *4*), the simulated optimal decision policies anticipated by these models were affected by treating the hare index as a stochastic random variable. Martin et al. (2011) discuss in greater detail the various approaches to handling environmental covariables, such as prey abundance, and possible consequences to the decision optimization.

Misconceptions about, or failure to distinguish among, utility, ecological, and decision thresholds has likely obstructed efforts to understand the roles and impact of thresholds on decision-making in conservation. The SDM framework, as we have outlined here, appears to serve as a natural and appropriate mechanism for clarifying and applying specific threshold concepts in the context of natural resource management. We hope that our example encourages managers to think carefully about their objectives and to be explicit when considering the incorporation of thresholds into their decision-making process.

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