Chapter 21

OPTIMIZATION OF FOREST WILDLIFE OBJECTIVES

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Abstract This chapter presents an overview of methods for optimizing wildlife-related objectives. These objectives hinge on landscape pattern, so we refer to these methods as "spatial optimization." It is currently possible to directly capture deterministic characterizations of the most basic spatial relationships: proximity relationships (including those that lead to edge effects), habitat connectivity/fragmentation relationships, population growth and dispersal, and patch size/habitat amount thresholds. More complex spatial relationships and stochastic relationships are currently best captured through heuristic manipulation of simulation models. General treatment of stochastic variables in spatial optimization is in its infancy.

Keywords: Habitat connectivity, landscape pattern, reaction-diffusion model, response-surface analysis, search heuristics, simulation optimization, spatial optimization, stochastic population model

1 INTRODUCTION

The objective of this chapter is to review emerging methods that allow analysts to make explicit recommendations (prescriptions) concerning the placement of different features in managed landscapes, so as to optimize wildlife-related objectives. We refer to this general set of methods as "spatial optimization." As used here, spatial optimization refers to methods that capture spatial relationships between different land areas in the process of maximizing or minimizing an objective function subject to resource constraints (we draw a distinction between this set of methods and "spatially-explicit optimization," which simply involves choice variables that are spatially defined and includes no spatial relationships).

2 STATE OF THE SCIENCE IN SPATIAL OPTIMIZATION

In our view, two basic approaches can be used to describe our current capabilities in spatial optimization of landscape pattern: direct spatial optimization approaches and heuristic manipulation of simulation models. We review each of these in turn.

2.1 Direct Approaches

The approach here is to directly include the spatial relationships of concern in a formulation that is focused on the optimization of landscape pattern, per se. We would characterize the approach as having a closed-form formulation with a formal solution method. We would include in this category recent augmentations of the basic "adjacency" formulation (discussed elsewhere in this book) to addressing ecological problems (see, e.g., Bettinger *et al.*, 1997; Barrett *et al.*, 1998; Falcao and Borges, 2001). We would also include recent contributions that have endeavored to add spatial relationships to the set-covering reserve selection model (some examples are Possingham *et al.*, 2000; Nalle *et al.*, 2002; Onal and Briers 2002, 2003; Fischer and Church, 2003). Other authors who have taken relatively direct approaches include Nevo and Garcia (1996), Farmer and Wiens (1999), and Loehle (1999).

Hof and Bevers (1998, 2002) explore a large number of direct spatial optimization formulations, including static models, dynamic models, models of spatial autocorrelation, and models of sustainability. As an example, wildlife habitat fragmentation (spatial division into disaggregated patches) is a common concern with regard to placement of timber harvests. The approach is to directly model the wildlife population growth and dispersal patterns that make habitat connectivity (nonfragmentation) important. This is a dynamic problem where management activities must be scheduled over time, wildlife habitat (determined by forest age) must be tracked as forest stands age and grow, and different wildlife species respond differently to those habitats. The method is related to the classic "reaction-diffusion models" (Skellum, 1951; Kierstead and Slobodkin, 1953; Allen, 1983).

First, the land is divided into cells, where the cell could be scaled to the ecology of the species (e.g., average home range or territory size) or could be scaled simply to provide adequate spatial resolution for the optimization problem. Then, a set of choice variables is defined for each cell, each of which represents a complete scheduled management prescription. For example, each prescription could define the time periods for harvesting the given cell,

including a no-harvest option. Any harvest would reset the forest age class to 0 and would change the habitat for each wildlife species accordingly. Initial forest age classes are assigned to each cell, as well as initial population numbers for each wildlife species included.

The following definitions will be used:

i indexes species

k indexes the management prescription

h indexes the cells, as does n

t indexes the time period

qh = the number of potential management prescriptions for cell h

T = the number of time periods

X_{kh}= the area in cell h that is allocated to management prescription k

K_h= the total area in cell h

S_{iht}= the expected population of species i in cell h at time period t

a_{ihtk}= a coefficient set that gives the expected carrying capacity of animal species i in cell h at time period t, if management prescription k is implemented (based on forest age class)

N_{ih}= the initial population numbers for species i in cell h

g_{inh} = the probability that an animal of species i will disperse from cell n in any time period to cell h in the subsequent time period. This includes a probability for $n=h$, so that the g_{inh} sum to 1 for each combination of h and i

r_i = the "r value" population growth rate (net of mortality not related to dispersal) for species i, and

F_{it} = the total population for species i in time period t.

The simplest objective function would be to maximize a given species' expected total population:

Maximize $\sum_t F_{it}$ for a given i.

The minimum population over all time periods *(m),* for a given species could be maximized as follows:

Maximize m
Subject to $m \le F_{it}$, $t = 1,...,T$ for a given i.

Or, a weighted (V_i) sum of multiple species' populations could be maximized:

Maximize $\sum_i V_i \left(\sum_t F_{it} \right)$.

Many other objective functions are also possible.

The basic constraint set for such a model is

$$\sum_{k=1}^{q_k} X_{kh} = K_h, \forall h \tag{1}$$

$$S_{ih0} = N_{ih}, \begin{matrix} \forall i \\ \forall h \end{matrix} \tag{2}$$

$$S_{iht} \le \sum_k a_{ihtk} X_{kh}, \begin{matrix} \forall i \\ \forall h \end{matrix} \quad t=1,\ldots,T \tag{3}$$

$$S_{iht} \le \sum_n g_{inh} \left[(1+r) S_{in(t-1)} \right], \begin{matrix} \forall i \\ \forall h \end{matrix} \quad t=1,\ldots,T \tag{4}$$

$$F_{it} = \sum_h S_{iht}, \begin{matrix} \forall i \\ \forall t \end{matrix} \tag{5}$$

$$0 \le X_{kh} \le K_h, \begin{matrix} \forall k \\ \forall h \end{matrix}. \tag{6}$$

This model is linear, with continuous variables, and can be solved with the simplex algorithm. Equation 1 limits the total management prescription allocation to the area in each cell. The management prescriptions are defined with no action in the first time period (t=0), which is used simply to set initial conditions. Equation 2 sets the initial population numbers for each species, by cell. The S_{iht} (expected population by species by cell, for each time period) is determined by whichever of (3) or (4) is binding. Constraint set (3) limits each cell's population to the carrying capacity of the habitat in that cell, determined by forest age classes. Constraint set (4) limits each cell's population according to the growth and dispersal from other cells and

itself in the previous time period. The growth and dispersal characteristics of each species are reflected by the parameters in constraint set (4). Constraint set (4) adds up the expected value of the population dispersing from all cells in the previous time period to the given cell in the given time period. It is important to note that whenever (3) is binding for a cell, some of the animals assumed to disperse into that cell are lost because of limited carrying capacity. Reaction-diffusion models assume that organisms dispersing into unsuitable regions will perish. This mechanism provides a probabilistic basis for the expectation that mortality (beyond the nondispersal-related mortality accounted for in the r value) occurs in proportion to the usage of inhospitable surroundings. Thus, actual population growth is determined by a combination of potential growth, dispersal, and spatially located carrying capacities determined by the management prescription allocations. Constraint set (5) defines the total population of each species, in each time period. And finally, constraint set (6) limits the choice variables to be between 0 and the area in each cell.

Hof and Bevers (1998, 2002) applied this basic type of model structure to problems of habitat placement for the black-footed ferret, which also accounted for release schedules of captive-born animals. As a follow-up, it was applied to the black-tailed prairie dog, accounting for population-dependent dispersal behavior. Hof and Bevers also modified this structure to account for water-borne seed dispersal and for habitat edge effects; converted the model to optimize the location of control measures in managing exotic pests; and applied these basic ideas to problems other than organism management (especially stormflow management and fire management).

The primary criticism that can be leveled at this type of approach is that there are limits to the complexity of ecological relationships that can be captured in a closed-form optimization formulation. An alternative explored in the next section is to start with a more complex ecological simulation model and use heuristic procedures to direct repeated predictions with different management regimes, hopefully converging on a near-optimum.

3 HEURISTIC MANIPULATION OF SIMULATION MODELS

The fields of wildlife management and conservation biology contain a long history in developing stochastic models of population viability, which are commonly used to inform wildlife management decisions (Boyce, 1992; Beissinger and Westphal, 1998). Demographic models predict the birth, death,

and migration of individuals in one or more localized populations (e.g., Liu *et al.,* 1995). Incidence function models predict the extinction of local populations and colonization of empty habitat patches (Hanski, 1994). Both types of models incorporate uncertainty in one or more demographic parameters, and Monte Carlo methods are used to sample from the underlying distributions and simulate populations many times for different combinations of parameter values. Thus, stochastic population models yield probabilistic results, which are typically summarized by performance measures for the ending population such as mean patch occupancy or probability that population size exceeds a threshold. Stochastic population models are routinely used to determine the relative effects of habitat management options (e.g., Armbruster and Lande, 1993; Liu *et al.,* 1995). In addition, results of population models, such as relative growth rates of populations in potential reserve sites, are used in formulations of reserve selection models (e.g., Carroll *et al.,* 2003). Only a few studies combine optimization with stochastic population models to determine cost-effective habitat protection. Here we describe some of the basic ideas and approaches.

3.1 Stochastic Optimization with Heuristics

Stochastic population models can be optimized using search heuristics. Moilanen and Cabeza (2002) addressed the problem of selecting a subset of potential reserve sites to maximize the long-term persistence of a species living in a metapopulation given a limited budget for site protection. They formulated an incidence function model for the false heath fritillary butterfly, an endangered species in Finland, and applied the model with 125 potential reserve sites of varying size and isolation. Their site selection problem can be described with the following notation:

i, I = indices for individual sites and total number of sites,

b = upper bound on budget,

c_i = cost of protecting site i,

x_i = 0–1 variable for protecting site i; 1 if site i is protected, 0 otherwise,
$p(x_1,..., x_I)$ = the probability of extinction of the metapopulation in period T.

The optimization problem was formulated as follows:

$$\text{Maximize} \quad 1 - p(x_1,\ldots,x_I) \tag{7}$$

Subject to:

$$\sum_{i=1}^{I} c_i x_i \le b \tag{8}$$

$$x_i \in [0,1], \quad \forall\, i \tag{9}$$

The objective of the optimization problem (Eq. 7) was to maximize the persistence of the metapopulation (one minus the probability of extinction) subject to a budget constraint (Eq. 8) and binary restrictions on the decision variables (Eq. 9). This is not a trivial optimization problem because the objective function value associated with each subset of sites must be estimated using a stochastic population model and the number of different subsets of sites (2^I) increases rapidly with I.

One way to estimate $p(x_1,\ldots,x_I)$ for a given subset of sites is to make N replicate simulations of the population and compute the proportion of simulations that go extinct before time T. The problem with this estimator is that N must be large to get a high level of precision if the probability of extinction is low, which will slow down the optimization considerably. Variance reduction techniques such as importance sampling can be used to increase precision of the estimator for a given sample size N (Haight and Travis, 1997). Importance sampling forces a larger number of rare events from the underlying distribution of the stochastic demographic parameter into the sample that is used for Monte Carlo simulation. Inference from the simulation results is done in a way to correct for sampling bias.

Another option is to define an objective function with properties similar to the probability of extinction $p(x_1,\ldots,x_I)$ and which requires a smaller sample size to obtain a given level of precision. Moilanen and Cabeza (2002) used the average one-step extinction probability of the meta-population calculated over time horizon T and N simulations:

$$\frac{1}{NT}\sum_{n=1}^{N}\sum_{t=1}^{T}\phi_{n,t+1}(x_1,\ldots,x_I;y_{n,t};E_{n,t}) \tag{10}$$

where the function $\phi_{n,t+1}$ is the probability of extinction in period t+1 given the subset of sites protected ($x_1,\ldots, x_I$), the patch occupancy in period t ($y_{n,t}$), and a random environmental variable ($E_{n,t}$). Because their incidence function model provided a closed-form expression for the one-step extinction probability $\phi_{n,t+1}$, computation of the average (Eq. 10) was fast. Further, Moilanen and Cabeza (2002) found that the average one-step extinction

probability was closely related to, but not always identical to, the extinction risk of the metapopulation during horizon T, and it does not require a large sample size to obtain a precise estimate.

Once an objective function is defined, a heuristic is needed to search for the best set of sites. The operations research community has developed a number of heuristics for optimizing stochastic systems using simulation (Andradottir, 1998; Goldsman and Nelson, 1998; Pichitlamken and Nelson, 2001). Moilanen and Cabeza (2002) used a genetic algorithm combined with a local search to optimize their incidence function model. A genetic algorithm operates on a set of alternative solutions, which are called individuals. Each individual is assigned a fitness value equal to the value of the objective function (e.g., Eq. 10). The fitness of an individual determines its probability of taking part in reproduction. Individuals with high fitness reproduce on average more often than those with low fitness. A genetic algorithm proceeds generation by generation with individuals in one generation combining and producing individuals in the next. Moilanen and Cabeza (2002) used 50 replicate simulations to estimate the fitness of each individual in a population. They found that problems with 125 candidate sites converged within 25 generations to almost identical site selections and objective function values.

Optimization of stochastic population models using search heuristics is in its infancy. Commercial simulation packages are beginning to incorporate heuristic optimization tools (e.g., April *et al.*, 2001), and it would be worthwhile to explore their value in optimizing stochastic population models.

3.1.1 Response-surface analysis

Another approach to simulator optimization involves response-surface analysis. Monte Carlo experiments with a stochastic population model can be used to create response surfaces of the relationships between measures of population performance and reserve design features. Then, regression equations representing those relationships can be included in an optimization model to determine the best reserve design features.

Haight *et al.* (2004) used elements of response-surface analysis to address a problem of allocating a fixed budget for habitat protection among disjunct populations of the endangered San Joaquin kit fox in California to maximize the expected number of surviving populations. A demographic model of population viability was used to quantify the risk of extinction of each population under different amounts of protected habitat. The predictions of

the demographic model, in turn, were used to estimate risk-area curves for the populations. The risk-area curves and costs of habitat protection were incorporated into an optimization model to determine how best to allocate limited funds among the populations. The problem set up is as follows.

Suppose we have a set of disjunct populations of an endangered species and a limited budget to protect habitat. By disjunct we mean that each population is isolated enough that migration between populations is inconsequential. Further, assume that we have information for each population about the relationship between risk of population extinction and amount of habitat. Using these risk-area curves, we can formulate an optimization model for determining the amount of habitat to protect for each population that maximizes the expected number of populations that survive over the management horizon. The model has the following notation:

i, I = indices for individual populations and total number of populations,

a_i = amount of already-protected habitat for population i,

b = upper bound on budget,

c_i = unit cost of protecting additional habitat for population i,

d_i = upper bound on the amount of habitat available for protection for population i,

x_i = amount of habitat that is selected for protection for population i,

$p_i(a_i + x_i)$= function for the probability of extinction, population i.

The optimization problem is formulated as follows:

$$\text{Maximize} \sum_{i=1}^{I} 1 - p_i(a_i + x_i) \tag{11}$$

Subject to:

$$\sum_{i=1}^{I} c_i x_i \le b \tag{12}$$

$$0 \le x_i \le d_i \quad i = 1,\ldots,I \tag{13}$$

The objective (Eq. 11) is to maximize the expected number of populations that survive over the management horizon. The probability of extinction of each population depends on the total amount of habitat protected, which is the sum of the already-protected habitat and the newly protected habitat. The risk function can be estimated using predictions from a demographic model of population viability under different amounts of protected habitat as described below. The first constraint (Eq. 12) requires that spending for habitat protection does not exceed the budget. The second set of constraints (Eq. 13) bounds the amount of habitat available for protection.

Haight *et al.* (2004) used a stochastic demographic model of a disjunct kit fox population to predict extinction risk in 100 years in habitat patches of increasing size. For each patch, the estimator of extinction risk was the percentage of 1,000 independent simulations in which population size was <10 individuals in 100 years. The predictions were used to estimate a relationship between extinction risk and patch area. The risk-area relationship was a logistic function estimated using a form of logistic regression called the minimum logit chi-squared method (Maddala, 1983). Logistic regression describes a binary response as a function of one or more explanatory variables. In this case, the binary response was extinction or persistence of a population in a habitat patch, and the explanatory variable was patch area. The minimum logit chi-squared method of estimation is appropriate when there are multiple observations of the binary response for each level of the explanatory variable. Let P_i be the proportion of the 1,000 observations in which the population became extinct in patch i and $P_i/(1-P_i)$ be the estimated odds of extinction. With the logistic model, the log of the odds of extinction is assumed to be a linear function of patch area. The model for San Joaquin kit fox was

$$\log \frac{\hat{P}_i}{1-\hat{P}_i} = b_0 + b_1 \frac{1}{y_i} + b_2 \log(y_i) + \mu_i, \tag{14}$$

where y_i is the area of patch i, b_0, b_1, and b_2 are the regression coefficients, and μ_i is the regression error. Because the log of the odds of extinction is a continuous variable without limit, ordinary or weighted least squares regression can be used to estimate the parameters of Eq. 14. Once the parameters of Eq. 14 were estimated, the equation was transformed into a risk-area relationship by solving for p_i on the left-hand-side. The risk-area curve for each of eight populations was incorporated into the optimization model (Eqs. 11–13) and solved using commercial nonlinear programming software. The results included priorities for reserve expansion under increasing upper bounds on funding and a cost curve showing funding required for incremental increases in population viability.

Hof and Raphael (1997) used elements of response-surface methodology to address a problem of locating habitat reserves for Northern Spotted Owl in the Olympic Peninsula, Washington State (USA), to maximize the overall size of the owl population (rather than the expected number of surviving populations in Eq. 7). They subdivided the landscape into 1681 cells and defined variables for the amount of habitat to be protected in each cell. The owl population in each cell depended on the amount of protected habitat in the cell and the total number of owls in adjacent cells. These functions were estimated using predictions of a stochastic model of spotted owl population viability. Although their equations for population size were nonlinear, Hof and Raphael (1997) approximated them as a series of linear line segments, which allowed them to formulate a linear programming model for habitat protection. Although their formulation had over 20,000 variables and 12,000 equations, it was easy to solve with off-the-shelf commercial software. Results of the optimization model were used to identify potential improvements in a proposed spotted owl habitat protection plan.

4 DISCUSSION AND CONCLUSION

The primary shortcoming of the direct approach is that the amount of ecological detail that can be captured is limited. The primary shortcoming of the Simulation Manipulation approach is, of course, that the outcome is only "the best" alternative from among the landscape layouts investigated. Even with a large number of layouts, near-optimality is not assured. To demonstrate the point, suppose we have 100l and units (e.g., in a 10 x 10 grid). Even if we must consider only one action (v. none), with no scheduling component, there are still 2^{100} or 1.2676×10^{30} possible spatial layouts. Even if 99.9999999% (all but a trillionth) of the layouts can be eliminated as undesirable, we still have 1.2676×10^{21} options. Even if there are a trillion layouts that are acceptable, we only have a $7.886\times10^{-13}(1\times10^{9}\div1.2676\times10^{21}$ chance of hitting an acceptable solution if we randomly arrange our management actions. This suggests the need for optimization procedures in all but the simplest spatial problems. In addition, the implicit response surface may or may not be convex, such that a solution that appears to be near-optimal may actually not be at all.

Thus, the choice is between a precise optimum to a simplified model and an approximate optimum to a more precise model. In a given planning application, the answer may depend on the questions being asked and the circumstances surrounding the planning problem. For example, habitat placement choices may be limited because the pattern of land development

has reduced the configuration possibilities (Saunders *et al.*, 1991). When habitat-placement options are restricted to a small set, simulation modeling may offer a very useful approach for ranking alternative configurations. If, however, placement choices are numerous, then formal spatial optimization may be more useful in determining a layout that really is "the best" given the objectives and constraints of the planning problem. Joint use of both strategies as in Hof and Raphael (1997) or Haight *et al.* (2002) might offer planners the opportunity to take advantage of both the ecological detail captured by simulation models and the analytical power of formal spatial optimization to select the best solution.

It should be fairly clear from this chapter that the state of the science in optimization of landscape pattern borrows heavily from the operations research or management sciences field. Thus, ecology in general and landscape ecology in particular could probably benefit from more utilization of management science methodology. It might be worth pointing out that the flow of knowledge also goes the other way. The study of natural processes has inspired several heuristic procedures in optimization. In particular, a class of heuristic solution algorithms called "genetic algorithms" solves mathematical programming problems by emulating evolutionary processes. In the heuristic search, new trial solutions are created by "mating" previous solutions so as to emphasize positive traits much like natural selection promotes evolution in natural systems. Another example is "simulated annealing" which was originally developed to simulate the annealing process of cooling metals, but which is now commonly used as an optimization search routine.

The most fundamental research need in optimizing landscape pattern is the ability to better capture the relevant ecological relationships in an optimization analysis. A natural reaction to the idea of optimizing spatial pattern across a landscape is that we simply do not know enough about ecological systems to actually optimize them. Indeed, we will probably never know as much about ecology as we would like to. Our reaction is that it is important to apply spatial optimization in the context of an adaptive learning process (as we have noted previously). We will probably never have a level of knowledge that is adequate to find a permanent optimal strategy for a managed ecosystem in a one-time optimization analysis. On the other hand, an adaptive management process that does not take advantage of optimization methods is much less likely to make progress either in learning about the ecological system or in managing it. Applied in a careful, learning process, spatial optimization of landscape pattern has the potential to illuminate new hypotheses for landscape ecology research as well as providing a mechanism to apply landscape ecology research in landscape management.

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