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# **Sequential Land Acquisition Decisions for Nature Reserves under Acquisition and Population Uncertainty**

**Scott A. Malcolm**

**Food and Resource Economics/Operations Research**

**University of Delaware**

## **Abstract**

Nature reserve planning models to maximize species protection are typically formulated for a single period using certain data. In practice, however, parcels must be acquired over time. The status of a parcel may change due to conversion to alternate land use. Populations of species to be protected may change, as well. A two-stage stochastic program that maximizes expected species protection with annual budget constraints is proposed where parcels available for set aside have associated probabilities of being available for acquisition and species coverage. Runs on hypothetical data show that solutions differ from the single period model and depend strongly on the probability of acquisition in future periods.

## 1 Introduction

Mathematical decision models to identify optimal parcels to select for species protection are typically static models that assume all land acquisition decisions are made at once. However, decisions to acquire land for species protection are made on a periodic basis. Planning models that account only for current conditions and are meant to be applied as the need arises will not necessarily result in the highest level of species protection in the long term. There are several reasons for this.

First, land available for purchase today may not be available at a later date. Budgetary considerations restrict unlimited acquisition of desired land, so acquisitions must be made sequentially as funds become available. Pressure to purchase what appears to be the “best” parcel of land may not lead to optimal species protection. This fact has been demonstrated by numerous examples that show that “greedy” algorithms to select parcels do not necessarily lead to optimal solutions.

Secondly, species population viability on a given parcel may change with time. A plant or animal species may be present to a sustainable degree today, but conditions over time (such as the state of being unprotected) may shift populations, reduce their numbers below sustainable levels, or even eliminate them from a particular locale. The opportunity to preserve rare or threatened species may be a one shot deal.

Some investigators have addressed the value of having an optimal reserve network, versus one that is “good enough” (Pressey 1996). They conclude that optimality is worthwhile only if there are real benefits for conservation planning, and only if the concept of optimality is sufficiently broad to encompass other important

ecological concerns. One might add important economic concerns to this caveat. There are several models that have been developed to examine many specific reserve planning issues. However, no single model has been developed to handle all reserve planning situations (Prendergast 1999). Few reserve selection models have addressed the dynamic aspect of the problem. There have been a few models that address incomplete knowledge of species presence. Haight and Travis (1997) use a chance constrained programming model to determine the minimum cost level of habitat protection that satisfies a population requirement. Polasky, et al., (2000) build a model to account for uncertainty surrounding the presence of species at the sites. Species occurrence at a given site is categorized as confident, probable, possible and not present, with probability values assigned to each category. Haight, et al. (2000) build an integer programming model with a probabilistic constraint to maximize species coverage, given that probability of coverage exceeds some predefined threshold.

This paper extends the literature of nature reserve planning models by addressing two different types of uncertainty with a multi-stage model. One type is the uncertainty surrounding the future availability of a parcel of land, with the second being the uncertainty surrounding the future presence of a species in a parcel of land. The objective in each case is to make decisions today so that expected species coverage over the planning horizon is maximized.

Such models require an assessment of future conditions. Duever and Noss (1990) address the issue of future availability to a degree in their method for developing a prioritized ranking of potential sites for preservation. One of the criteria they specify is vulnerability, which is specifically defined as “the likelihood that of events that might degrade or destroy the site within the next few years.”

Stochastic selection models will allow testing of several ideas surrounding land acquisition behavior. For example, what are the characteristics of parcels for which purchase decisions are postponed? What levels of uncertainty will bring parcels into (or remove them) from the solution?

## 2 Modeling Reserve Selection

The problem of reserve selection can be approached from several viewpoints. One is to select the fewest number of reserves that will cover all species. This approach is of limited value when resources limit the implementation of the solution. The problem of can also be addressed from a complementary perspective. Given a fixed number of parcels that can be selected (limited by budget, for example), make the selection so that the greatest number of species is covered. This problem is referred to as the Maximal Covering Problem (MCP) (Church 1996). This formulation requires two types of decision variables. Define a decision variable  $x_i$  that takes a value of one if location  $i$  is selected, and zero if it is left unselected. Also, define a decision variable  $y_j$  that takes a value of one if species  $j$  is represented in one or more parcels, and zero if the species is not represented in any of the parcels chosen. A set  $I(j)$  is defined that contains all sites in  $I$  that cover species  $j$ . The MCP is written as follows.

[MCP]

$$\begin{aligned}
& \max \sum_{j \in J} y_j \\
& \text{s.t.} \\
& \sum_{i \in I(j)} x_i \geq y_j, \forall j \\
& \sum_{i \in I} c_i x_i \leq b \\
& x_i \in \{0,1\}, y_j \in \{0,1\}
\end{aligned}$$

The objective specified by equation 1 is to maximize the number of species covered. Equation 2 requires that for a species  $j$  to be covered, at least one site in the species coverage set must be selected. Equation 3 Implicit in this formulation is the assumption that the solution can be implemented immediately, or at least before any of the data underlying the solution can appreciably change. All sites are assumed to be available, and the membership of the sets  $I(j)$  are assumed to be known with certainty.

## 2.1 Descriptive Example

In general the problem of land acquisition is multi-stage. What is of primary interest is\ to identify the first stage solution; that is, the part of the overall solution that corresponds to the decision that needs to be made today. To simplify the exposition, only two-stages are modeled. To illustrate the two-stage decision process, consider the following example. Three sites are available for selection over two periods, but only one site can be selected in each period. There are seven species, labeled A to G. Site 1 covers species A and B, site 2 covers species B, C and D, and site 3 covers sites D, E, F and G. Moreover, there is uncertainty in the availability of each site in the second period. Site 1 has a probability of  $p_1 = 0.5$  of being available in period 2, with sites 2 and 3 having availability probabilities of  $p_2 = 0.5$  and  $p_3 = 0.5$ . If

one could select both sites at the same time, then choosing site 3 and either site 1 or site 2 will lead to coverage of 6 species. Since site 3 covers the most species, it seems reasonable that it should be selected first. If either site 1 or site 2 is available in the second period, then either can be selected, adding 2 species to the total coverage. However, there is a non-zero probability that neither site will be available, leaving total coverage at 4 species. The expected number of species covered assuming site 3 is selected first is given by:

$$E\left(\sum_i y_i \mid \text{site 3 chosen in first period}\right) = 4 + 2 * p_1(1 - p_2) + 2 * (1 - p_1)p_2 + 0 * p_1p_2 =$$

5.5

The optimal first stage decision is the one that corresponds to the greatest expected species coverage. The expected species coverage given each of the other sites are selected in the first period are:

$$E\left(\sum_i y_i \mid \text{site 1 chosen in first period}\right) = 2 + 4 * p_1(1 - p_2) + 2 * (1 - p_1)p_2 = 5.36$$

$$E\left(\sum_i y_i \mid \text{site 2 chosen in first period}\right) = 3 + 3 * p_1(1 - p_2) + 1 * (1 - p_1)p_2 = 5.5$$

Selecting site 2 in the first period yields the greatest expected coverage, and thus is the optimal choice. Of course, this result depends on the probabilities. It is reasonable to assume that the value of selecting site 3 in the first period will increase if its probability of availability is lower. Figure 1 shows how the optimal first stage decision is affected by the availability probabilities of sites 2 and 3.

## 2.2 Two-stage decision model

It remains to express this decision model formally. We make two modifications to the MCP. First, we introduce a set of scenarios  $S$ . These scenarios

represent possible alternative realizations of future knowledge about species coverage and land availability. Each individual scenario is represented by the identifier  $s$  and occurs with probability  $p_s$ . Species coverage indicator variables now depend on the realization of the scenario and are modified accordingly. Consider breaking the species coverage set into two components. The first component,  $I^1(j)$ , is identical to the  $I(j)$  defined previously. This component contains all the known information about species coverage, and is assumed to be known with certainty. The second component,  $I^{2s}(j)$ , represents the coverage set of species  $j$  if scenario  $s$  is realized at the time the second stage decision needs to be made.

To illustrate the meaning of  $I^{2s}(j)$ , consider a species A that is covered by site 1 in  $I^1(j)$ . If there is a 50% probability that species A is covered by site 1 in the second stage, then the roughly half of the sets  $I^{2s}(A)$  will contain site 1, whereas half will not contain site 1.

The two-stage Maximal Covering Problem has the following mathematical representation.

[MCP 2-stage]

$$\begin{aligned}
& \max \sum_{s \in S} p_s \sum_{j \in J} y_j \\
& \text{s.t.} \\
& \sum_{i \in I^1(j)} x_i^1 + \sum_{i \in I^{2s}(j)} x_i^{2s} \geq y_j, \forall j, s \\
& \sum_{i \in I^1(j)} c_i x_i^1 \leq b_1 \\
& \sum_{i \in I^{2s}(j)} c_i x_i^{2s} \leq b_2, \forall s \\
& x_i^1 \in \{0,1\}, x_i^{2s} \in \{0,1\}, y_j \in \{0,1\}
\end{aligned}$$

The objective defined by equation 4 is to maximize the expected value of species coverage over the range of scenarios. The species coverage obtained for each scenario depends on the locations chosen in the first stage and those chosen in the second stage. The first stage decision is fixed for all scenarios. The second stage decision depends on the realization of the scenario. Equation 5 states that a species can be covered in scenario  $s$  only if a site is selected in either the first or second stage. Equations 6 and 7 are the budget constraints that limit the number of sites selected in each stage.

It so happens that the same model can be used to account for uncertainty in species coverage as for land availability. The interpretation of second stage coverage set changes slightly. To handle uncertainty in species coverage, the realization of each scenario will determine whether or not a particular species is to be found in any coverage set for a site  $i$ . For instance, if a site covers species A, B and C in period 1, if there is uncertainty in the presence of species C, the site may cover only species A and B in period 2 for some scenarios.

### 2.3 Numerical Experience

To test this model, a small hypothetical data set was used. Each of twenty sites randomly covers from one to four of fifteen species. The probability of availability in period two ranged from 0.2 to 1.0. Figure 2 shows the species covered and probability of acquisition for each site. For clarity, all “costs” were set equal to one, and “budgets”  $b_1$  and  $b_2$  were set equal to one. While ignoring costs reduces some of the generality of the problem, it serves to focus the model on the relationship between the acquisition probability and species coverage. With 20 sites, at total of  $2^{20-b_1}$  sets of

sites are possible. To keep the problem manageable, two hundred scenarios were used.

The unique optimal two-site MCP solution is Site L1 and Site L3. The optimal first stage decision is Site L3. Because it is not known which of the possible futures will occur, the exact site to be chosen in the second stage is unknown. Four sites appear as possible stage two solutions. These are shown in Table 1. Notably, Site L1 is not the stage-two site that is the most likely to be chosen. If the probability of availability of Site L3 is varied from its base value of 0.2, the solution changes somewhat. The second stage site selections, with the likelihood of selection, are shown in Figure 3. Site L1 becomes the optimal first stage decision if the availability probability of Site L3 is greater than or equal to 0.3. When its probability is low, it will not be available for some scenarios, so its likelihood of being selected as a second stage site is fairly low. As its probability of availability is increased, it becomes more and more likely to be chosen in the second-stage.

Figure 4 shows how the expected number of species protected changes as uncertainty in site L3 is reduced. As the availability of the “best” site in the second period becomes more certain, the expected number of species preserved increases. This conforms to a general principal that reducing uncertainty will improve solutions, although this proposition remains to be shown in general for this problem.

### 3 Discussion and Further Research

The two-stage stochastic described here will allow further testing of several ideas surrounding land acquisition behavior. For example, what are the characteristics of those parcels for which purchase decisions are imminent or those that should be

postponed? What levels of uncertainty will bring parcels into (or remove them) from the solution? Perhaps the most important implication of consideration of the dynamic elements of the planning problem is to inform the decision maker of the relative value of possible land acquisition. While the emphasis of the decision model is on the first stage decision (which land should be acquired now that maximizes future expected species protection), the potential second stage decisions also yield worthwhile information. As illustrated by the example, some sites do not appear all in the second stage, whereas some parcels are required with a fairly high probability. Efforts leading to future acquisition of these high probability sites could be initiated at an early stage, thus concentrating resources in an effective manner.

Uncertainty in the model is limited to land availability and species coverage. Other uncertainties can crop up. There may also be uncertainty in future costs; land prices may increase or decrease over time. New species may become rare or endangered, and thus need to be considered.

While the objective function used here was to maximize expected species protection, a number of alternative objectives could also be considered. For example, overall habitat value that accounts for a broad range of environmental factors is one possible objective, with inclusion of value to tourism and other social purposes. Results will be strongly dependent on the specific data used. As a result, efficient and accurate solution methods are needed to solve the model. For large, realistic problems, methods will likely be based on heuristic as opposed to exact techniques. Further investigation into the value of information and other economic considerations needs to be undertaken.

This paper has introduced the notion of uncertainty over time into nature reserve selection optimization models. While the value of optimization models as direct planning tools is open to debate, such models can serve a useful role in supporting and clarifying rational wildlife management decisions by policy makers.

## References

Church, R.L., D.M. Stoms, and F.W. Davis, "Reserve Selection as a Maximal Covering Problem," *Biological Conservation*, Vol. 76, pp. 105--112, 1996

Duever, L.C. and R.F. Noss, "A computerized method of priority ranking for natural areas," in *Ecosystem Management: Rare Species and Significant Habitats*, R.S. Mitchell (ed.). New York: New York State Museum Bulletin 471, pp.22-33, 1990

Haight, R.G. and L.E. Travis, "Wildlife conservation planning using stochastic optimization and importance sampling," *Forest Science*, Vol. 43, pp. 129--139, 1997

Haight, R.G., C.S. ReVelle and S.A. Snyder, "An Integer Optimization Approach to A Probabilistic Reserve Site Selection Problem," *Operations Research*, Vol. 48, pp. 697--708, 2000

Hof, J., M. Bevers, L. Joyce and B. Kent, "An integer programming approach for spatially and temporally optimizing wildlife populations," *Forest Science*, Vol. 40, pp. 177--191, 1994

Miller, J.R., "Irreversible land use and the preservation of endangered species," *Journal of Environmental Economics and Management*, Vol. 8, pp. 19--26, 1981

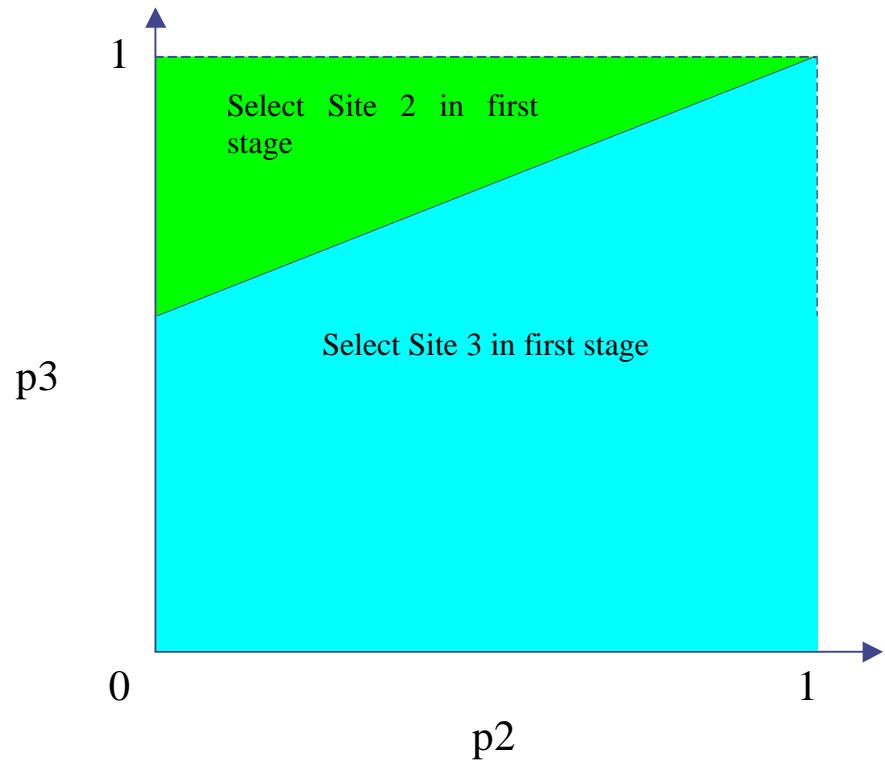
Poiani, K.A., J.V. Baumgartner, S.C. Buttrick, S.L. Green, E. Hopkins, G.D. Ivey, K.P. Seaton, R.D. Sutter, "A scale-independent, site conservation planning framework

in the Nature Conservancy," *Landscape and Urban Planning*, Vol. 43, pp. 143--156, 1998

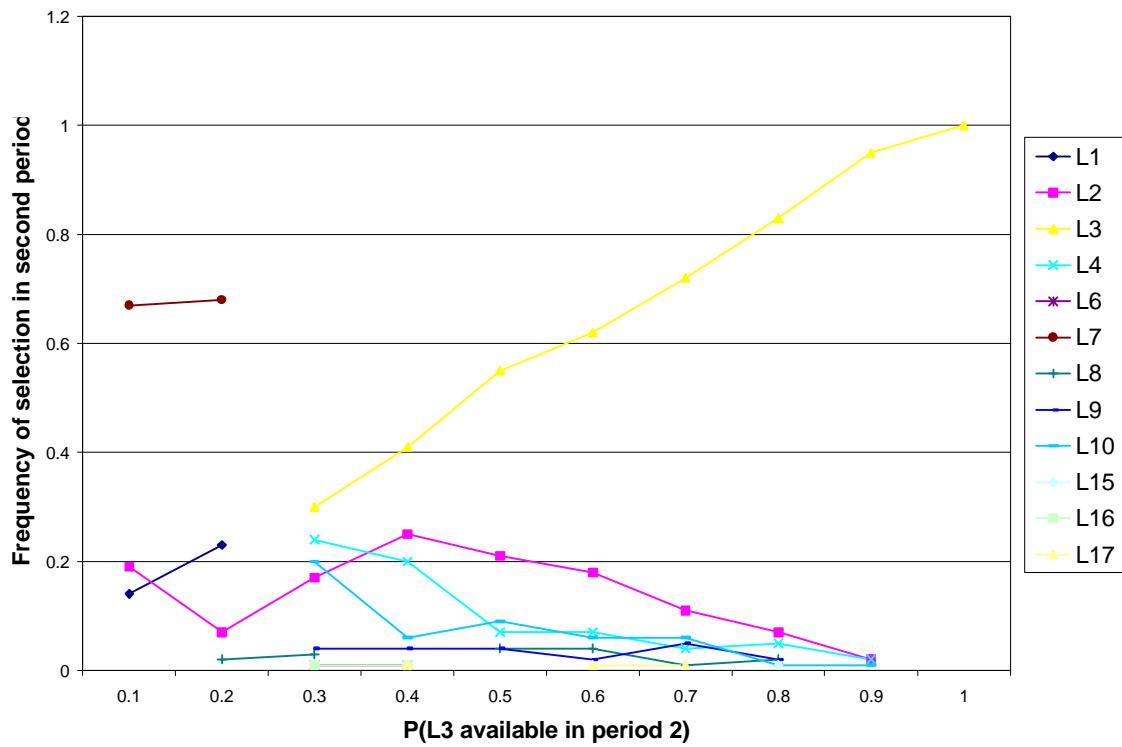
Polasky, S., J.D. Camm, A.R. Solow, B. Csuti, D. White and R. Ding, "Choosing reserve networks with incomplete species information," *Biological Conservation*, Vol. 94, pp. 1--10, 2000

Prendergast, J.R., R.M. Quinn, and J.H. Lawton, "The Gaps between Theory and Practice in Selecting Nature Reserves," *Conservation Biology*, Vol. 13, No. 3, pp. 484--492, 1999

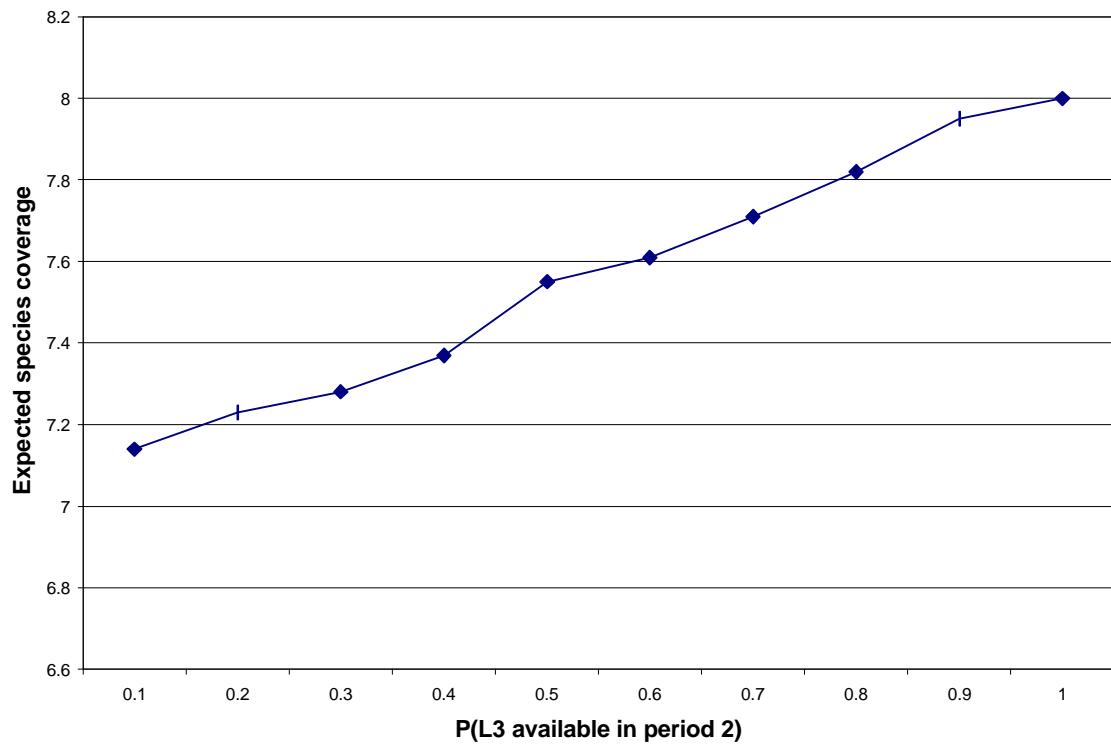
Pressey, R.L., H.P. Possingham, and C.R. Margules, "Optimality in Reserve Selection Algorithms: When does it Matter and How Much?," *Biological Conservation*, Vol. 76, pp. 259-267, 1996



**Figure 1: Decision space for different  $p_2$  and  $p_3$  ( $p_1 = 0.5$ )**



**Figure 2: Selection frequency of sites in second stage**



**Figure 3: Expected species coverage as a function of availability of site L3**

Sites	Species															Species covered	Prob
	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15		
L1	X	X	X	X												4	0.2
L2				X	X	X	X									4	0.2
L3					X	X	X	X								4	0.2
L4							X	X	X							3	0.2
L5								X	X	X						3	0.4
L6									X	X	X					3	0.4
L7										X	X	X				3	0.4
L8		X						X	X							3	0.4
L9	X				X		X									3	0.6
L10			X		X		X									3	0.6
L11		X								X						2	0.6
L12		X					X									2	0.6
L13		X	X													2	0.8
L14					X			X								2	0.8
L15									X	X	X					2	0.8
L16									X	X						2	0.8
L17									X			X				2	1
L18				X												1	1
L19										X						1	1
L20											X					1	1

**Table 1: Sites, coverage and probability**

Site	Probability of second stage selection
L1	0.23
L2	0.07
L8	0.68
L9	0.02

**Table 2: Likelihood of selection in second stage**