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Chapter 17
Mathematical Methods for Identifying Representative Reserve Networks

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Introduction

Many countries have committed to conserving significant amounts of their native biodiversity (McNeely et al. 1990). Biodiversity includes the diversity of ecosystems and the diversity between and within species. Establishing reserve systems dedicated to nature conservation is the cornerstone of most national, regional and state conservation strategies (Soulé 1991).

In this chapter, we explore the question of which parcels of land, henceforth termed sites, should be selected for reservation. Implicit in our analysis is a limit on the total size of the reserve system. From the perspective of nature conservation alone, one would attempt to have the largest reserve system possible; however, in reality, the extent of any reserve system will be limited by social and economic constraints. Thus, building a reserve network that will conserve biodiversity effectively is not a process of accumulating as much land as possible, but, rather, necessitates doing so as efficiently as possible within a constrained area.

We focus on a particular class of reserve design problem where the goal is to achieve some minimum representation of biodiversity features for the smallest possible cost. In these problems the objective is to minimize costs and biodiversity enters as a constraint. For example, governments have agreed to conserve 15% of the pre-European extent of Australia's regional forest types. This sets a constraint, creating an imperative to provide algorithms to minimize opportunity costs to the timber industry or maintenance costs of reserve management, while still satisfying the representation constraint. It is worth noting that there is no guarantee that such a reserve system is adequate – an issue that can only be assessed using explicit population models (see Chapters 7 to 13, this volume). To provide some perspective, we briefly review how reserves have been selected in the past before proceeding with specific examples.

How have we selected reserves in the past?

Most areas now thought of as reserves for "conservation" were not chosen to meet specific biodiversity objectives. Many existing reserves are found in places that are unsuitable for other purposes (such as agriculture or urban development), were chosen for cultural or scenic reasons, or as favored holiday destinations (Pressey et al. 1993). Other areas have been selected to protect a few charismatic flagship or umbrella species (Simberloff 1998, Andelman and Fagan in press) without any guarantee that they will adequately conserve regional biota. Consequently most existing reserve systems have an excess of high mountains, rocky infertile soil, salt lakes and inaccessible swamps. Flat well-drained fertile land is rarely conserved. While a few charismatic species, such as the Northern Spotted Owl, may be well represented within reserves, in general, existing reserve systems provide a poor representation of biodiversity.

What does "classical" conservation biology theory tell us about reserve design? Unfortunately, not much. Early efforts at reserve design were derived from island biogeography theory (MacArthur and Wilson 1963) where the emphasis was on size, shape and number of reserves. Many conservation biology texts still begin their discussion of reserve design with diagrams of good and bad reserve design. For example: long thin reserves with a high edge-to-area ratio are considered poor in comparison to compact reserves; well-

connected reserve networks are considered better than systems made up of isolated reserves; big reserves are considered better than small reserves; and so on. But these prescriptions offer little explicit guidance for decision-makers who are faced with specific choices about how many, which sites, or which configuration to include in a reserve network. The SLOSS debate – should we have a single large reserve or several small reserves – was a product of the island-biogeographic foundation for reserve design theory, and ended in the inconclusive answer, "it depends." In particular, close and well connected patches may be a disadvantage if the arrangement increases correlations among reserves in environmental variation, by inviting disease, exotic species and/or disturbance events to pass from one patch to another. The disadvantages of such processes may outweigh any advantage to be gained from elevated dispersal rates and increased recolonisation probabilities, at least for some species.

For single, well-studied species, it is possible to use population viability analysis to find the best arrangement of habitat patches. It may even be possible to plan a reserve system that will give a particular species an acceptably low extinction probability. This was the aim of intense debate and planning for the Northern Spotted Owl. However, the single species approach avoids the issue that a reserve system designed to be optimal and adequate for a single species is not likely to satisfy the requirements of all species. Rather than blindly trying to maximise the number of species based on the very simple ecological abstractions of island biogeography, the principle of efficiency argues that effective reserve design will seek a reserve system that achieves defined objectives at minimum expense to other land-uses, based on empirical information on species distributions.

The minimum representation problem

An important criterion for a reserve system is that it represents as much of the available biodiversity as possible (Pressey et al. 1993, Morton et al., 1995). By this criterion a reserve system should contain at least one example of every vegetation type and/or one population of every species present within the region of interest. Since there are constraints on the amount of land that can be set aside for nature conservation, it would seem prudent to choose a set of sites that achieves comprehensive representation for the minimum cost (Pressey *et al*., 1993). This is called the minimum representation problem, and if the cost is a linear function of the number of sites in the system, it can be expressed as an integer linear programming problem (Cocks and Baird 1989, Possingham et al. 1993, Underhill 1994, Willis et al. 1996). When only a single occurrence of each species is required and there is a finite number of discrete sites from which to choose, this is termed a set-covering problem.

Table 1. Species by site data for the Columbia Plateau ecoregion. Species Range is the number of sites in which a species is found. Sources of data: California Natural Diversity Data System; Idaho Conservation Data Center, Idaho Fish and Game; Oregon Natural Heritage Program; Nevada Natural Heritage Program; Northwest Lepidopterist Society; The Nature Conservancy; Utah Natural Heritage Program; Washington Natural Heritage Program; and Washington Department of Fish and Wildlife.

				Site number					
Species	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**Species Range**
Loggerhead Shrike	1	1	1	1	1	1	0	1	7
Western Burrowing Owl	1	1	1	1	0	0	0	1	5
Grasshopper Sparrow	1	1	0	1	1	1	0	0	5
Ferruginous Hawk	1	1	1	0	0	0	1	1	5
Sage Thrasher	1	1	1	1	0	0	1	0	5
Western Sage Grouse	1	0	0	0	1	1	1	0	4
Sage Sparrow	1	0	1	1	0	0	0	0	3
American White Pelican	1	1	1	0	0	0	0	0	3
Bald Eagle	0	1	0	0	1	0	0	0	2
Forster's Tern	0	0	1	0	0	0	0	0	1
Site Species Richness	8	7	7	5	4	3	3	3	40

Consider the following example for the Columbia Plateau, a five-state region in the western U.S., that has been the focus of several major conservation planning initiatives (e.g., Davis et. al. 1999). For a sample of 10 bird species of conservation concern, the objective is to conserve at least one population of every species. The presence or absence of each of the 10 species is known for 8 sites, numbered 1-8 in Table 1. A "1" in the species by site matrix (Table 1) denotes a presence while a "0" denotes an absence. The minimum set problem is to find the smallest number of sites that will represent every species once. In this case the minimum set reserve system is sites 3 and 5 – something that can be determined by eye. No other set of two sites conserves all species, although there are plenty of three site reserve systems that conserve all the species. In the language of mathematical programming, the optimal solution is sites 3 and 5, the optimal value is two.

Table 2. Expanded Columbia Plateau data set. The presence or absence of each of eighteen threatened species is known for twelve sites, numbered 1-12. A 1 in the species by site matrix below denotes a presence while a 0 denotes an absence. Range is the total number of sites in which a species is found, Rarity is 1/Range, Site Richness is the number of species in each site, and Rarity Score is the sum of rarity values for the species in the site. Data sources are listed in Table 1.

Species	Site number 1	2	3	4	5	6	7	8	9	10	11	12	Species Range	Rarity
Pallid Bat	1	0	1	1	0	1	1	1	0	1	1	1	9	0.11
Loggerhead Shrike	1	0	0	1	1	1	1	1	1	0	1	1	9	0.11
Western Burrowing Owl	1	1	1	1	1	0	0	1	1	0	0	1	8	0.13
Grasshopper Sparrow	1	1	0	1	1	1	1	0	1	0	0	0	7	0.14
Ferruginous Hawk	1	0	1	1	0	0	0	0	0	0	1	1	5	0.20
Sage Thrasher	0	0	1	1	0	0	1	1	0	0	1	0	5	0.20
Peregrine Falcon	0	1	0	1	1	1	0	0	0	1	0	0	5	0.20
Black-Throated Sparrow	1	1	0	0	1	0	1	0	1	0	0	0	5	0.20
Western Sage Grouse	1	0	0	0	0	0	1	0	0	1	1	0	4	0.25
Sage Sparrow	1	0	1	1	0	0	0	1	0	0	0	0	4	0.25
American White Pelican	1	1	1	0	0	1	0	0	0	0	0	0	4	0.25
Bald Eagle	1	0	1	0	0	1	0	0	0	0	0	0	3	0.33
Forster's Tern	0	1	0	0	1	0	0	0	1	0	0	0	3	0.33
Black Tern	0	1	0	0	0	1	0	0	0	1	0	0	3	0.33
Long-billed Curlew	0	1	0	0	0	0	0	0	0	1	0	0	2	0.50
Pygmy Rabbit	0	0	1	0	1	0	0	0	0	0	0	0	2	0.50
Northern Goshawk	0	0	0	0	0	0	0	1	1	0	0	0	2	0.50
Columbian Sharp-tailed Grouse	0	1	0	0	0	0	0	0	0	1	0	0	2	0.50
Site Richness	10	9	8	8	7	7	6	6	6	6	5	4	82	
Rarity score	2	2.6	2	1.3	1.6	1.5	1	1.3	1.4	1.9	0.9	0.5		

There are some interesting lessons from this Columbia Plateau example. First, note that the optimal solution, select sites 3 and 5, and its associated value, two sites, can be obtained by inspection. For bigger data sets it is not hard to imagine that a solution by inspection will be difficult to find. Given this problem, early workers in the field devised algorithms for finding the minimum set. These algorithms involve selecting complementary sites sequentially, until the objective of representing all species is attained. The most obvious approach to representing every species is to sequentially add sites to the reserve system by selecting the site that adds the most unprotected species to the set that has already been selected. This algorithm is often called the "greedy" algorithm because it greedily attempts to maximize the rate of progress towards the objective at each step. Assuming that initially there are no sites in the reserve system, this algorithm would first select site 1, because it would protect eight species. Once site 1 has selected, we see that each of sites 2,3 and 5 will add a single additional species. Regardless of which of the three is chosen first, two more sites are needed to cover every species. The solution is sub-optimal because it has three sites. This simple algorithm fails because the final reserve system is inefficient, when compared against the optimal reserve system.

Notice that one of the species in Table 1 is only represented in one site. The only place to find Forster's Tern is in site 3. This means site 3 is essential. So, an alternative approach is to first select any sites that are essential and then select sites that add the most unprotected species to the reserve system. This approach, sometimes termed the rarity approach, targets rare species first, and then builds a complementary set from there. In this case, once site 3 is selected, the site that adds the most species to site 3 is site 5, which then completes a reserve system of just two sites.

It is interesting to try to devise different sorts of algorithms to solve these types of problems, and many have been tried (Margules et al. 1988, Nicholls and Margules 1993, Rebelo and Siegfried 1992, Pressey et al. 1997). All the algorithms that choose sites sequentially are, however, inefficient in that they are not guaranteed to find the optimal solution.

Consider a second example from the Columbia Plateau, with an expanded data set containing more species and sites (Table 2). Again, the minimum set problem is to find the smallest number of sites that will represent every species. The first point is that now it is no longer possible to see the optimal solution by inspection, as it was in Table 1. In this case, the minimum set reserve system is sites 3, 9 and 10. No other set of three sites conserves all species, although there are plenty of four site reserve systems that conserve all the species.

Some insight into why sequential algorithms are inefficient can be gained by considering the number of possible reserve systems for any problem. For example, in Table 1 there are eight sites, each of which could be in or out of the reserve system. Hence there are $2^8 = 256$ possible systems, ranging from every site in the system to no sites. Now imagine a more realistic problem, such as the entire Columbia Plateau ecoregion, with nearly 5000 sites. The number of possible reserve systems is 2^{5000}, a number so big that the problem is intractable, even for the fastest computers.

Formulating the minimum representation problem

The best reserve design for a small problem, such as the example in Table 1, can be obtained by inspection. But even moderately sized problems quickly defy solution by inspection. Before considering different methods for solving this problem, we need to formulate the problem within a decision-theory framework – in this case the formalism of mathematical programming.

Let the total number of sites be m and the number of different species (or other attributes such as vegetation types) to be represented be n. The information about whether or not a species is found in a site is contained in a site-by-species (m x n) matrix **A** whose elements a_{ij}, are

$$a_{ij} = \begin{cases} 1 \text{ if species } j \text{ occurs in site } i \\ 0 \text{ otherwise} \end{cases}$$

for $i = 1, \ldots, m$ and $j = 1, \ldots, n$.

Next, define a control variable, that determines whether or not a site is included in the reserve, as the vector **X** with dimension m and elements x_i, given by

$$x_i = \begin{cases} 1 \text{ if site } i \text{ is included in the reserve} \\ 0 \text{ otherwise} \end{cases}$$

for $i = 1, \ldots, m$.

With these definitions, the minimum representation problem is

$$\text{minimise} \sum_{i=1}^{m} x_i \quad \{\text{minimise the number of sites in the reserve system}\}$$

$$\text{subject to} \sum_{i=1}^{m} a_{ij} x_i \geq 1, \text{ for } j = 1, \ldots, n \quad \{\text{subject to each species being represented at least once}\}$$

$$\text{where } a_{ij}, x_i \in \{0,1\}.$$

This is the integer linear programming formulation of the set-covering problem. It is NP-Complete so that the difficulty of guaranteeing an optimum solution increases exponentially with the number of constraints n (Garey and Johnson 1979).

Solving the minimum representation problem – traditional methods

In the context of nature reserve design, the minimum representation problem has been tackled by several authors, in a number of different ways. Kirkpatrick (1983) was first to define the problem, and used a heuristic method to find a solution. Such methods rank each potential reserve site according to a set of criteria, and then reserve the highest-ranking site. The remaining sites are ranked again and the process continued until all species are represented. Originally, the criterion used in ranking was the number of species in a site not yet represented in the reserve system. Other criteria, such as the location of rare species, or combinations of criteria have since been used (e.g., Nicholls and Margules 1993, Rebelo and Siegfried 1992).

As shown above, this approach guarantees a quick answer, but it does not ensure an optimal one (Possingham et al. 1993, Underhill 1994). Another approach to the problem has been to express it in the form of an Integer Linear Program (ILP) and then to use standard mathematical programming techniques like the branch and bound method to find the optimal solution (Cocks and Baird 1989; Church et. al. 1996). Pressey et. al. (1997) compared a variety of heuristic methods (variations of rarity and greedy algorithms) with the optimal solution found by Integer Linear Programming. The ILP package used a branch-and-bound method and found optimal solutions for a reduced version of Pressey et al.'s original data set. The comparison showed that, while solutions obtained with heuristics can be as much as 20% worse than the optimal solution, if a variety of methods are tried, one can probably guarantee being within 5% of the optimum for problems of moderate size. However, ILP fails when the number of reserves is moderately large (more than about 20 or 30), because the problem becomes too big for a solution to be found in reasonable time. Thus, heuristics are fast and easy to understand, but may deliver inefficient solutions, while integer linear programming methods are likely to fail on large problems. ILPs also have the disadvantage of producing a single optimal solution, whereas in a conservation context, flexibility may be advantageous. It might be useful to identify not one, but a range of possible solutions that could meet a particular reservation goal. In the following section, we describe an alternative approach to some of these problems.

Simulated annealing solutions – a comparison

Simulated annealing is a minimization method based on the process of annealing metals and glass (Metropolis et. al. 1953; Kirkpatrick et. al. 1983). It begins by generating a completely random reserve system. Next, it iteratively explores trial solutions by making sequential random changes to this system. Either a randomly selected site, not yet included in the reserve system, is selected, or a site already in the system is deleted. At each step, the new solution is compared with the previous solution, and the best one is accepted. The advantage of this approach is that it potentially can avoid getting trapped in local optima. It allows the reserve system to move temporarily through sub-optimal solution space, and thus increases the number of routes by which the global minimum might be reached. Initially, any change to the system is accepted, whether it increases or decreases the value of the system. As time progresses, the algorithm is more and more choosy about which changes it accepts, rejecting those changes that would increase the value of the system by too large an amount. By the end of a simulated annealing run, only changes that improve (i.e., decrease) the value of the system are accepted. At this point, the system soon reaches a local minimum. To reiterate, the central idea behind simulated annealing is that, by allowing bad changes as well as good, local minima are avoided. The simulated annealing method works as follows:

1. Set input parameters and the maximum number of iterations.
2. Generate an initial reserve system consisting of sites selected at random, and compute objective function.
3. Randomly select a site to add to or delete from the system.
4. Evaluate the resulting change in the objective function: If $e^{\left(\frac{-\text{change}}{\text{Acceptance Level}}\right)} < \text{Random Number}$, then accept the change, otherwise reject it.
5. Decrease the acceptance level, and repeat steps 3 - 5 for the given number of iterations.

The acceptance level determines what size change will be accepted. Negative changes (decreasing the value of the system) will always be accepted. When the acceptance level approaches 0, then the only acceptable changes are those which reduce the value of the system. The use of the exponential term means

that the system spends proportionally little time accepting very bad changes, and much more time resolving small differences.

The relative ability of this method is demonstrated in an example using data from the western region of New South Wales, Australia (Ball et. al. in press). In this region there are 1,885 sites and 248 species of conservation concern. The results are displayed in Table 3. For the same data set, simple greedy and rarity based selection algorithms have achieved results as low as 57 sites (Pressey et al. 1997). This example demonstrates that simulated annealing will generally do better than the simpler heuristics, although it does so at the cost of a slower running time. An additional advantage of simulated annealing is that it will tend to produce a number of solutions rather than a single solution. When using the simple selection algorithms, it is necessary to use a number of different algorithms to generate alternative solutions.

Spatial reserve design

One limitation of the minimum set approach is that it does not account explicitly for the spatial relationships among the sites selected for the reserve system. Without some modification or additional constraints, the final reserve system will almost always be highly fragmented and clearly inappropriate. This is a major problem as there are both ecological and economic reasons why reserves should be spatially contagious with low edge to area ratios. Long thin reserves with a high edge to area ratio will be vulnerable to weed and pest invasions, as well as to "edge effects," caused by biotic interactions like predation (Fagan et. al. 1999) or abiotic factors like humidity or wind. This can mean that for edge-sensitive species that can only persist in a small core area, the effective area of the reserve may be substantially reduced. The size of the core decreases rapidly as the edge to area ratio increases. From an economic perspective, the cost of management often scales more closely with the boundary length of a reserve than with reserve area. From the perspective of logistics, boundaries need to be maintained, and longer boundaries usually mean more neighbours.

Generally, we would like to cluster sites in a reserve system, however, there can be compelling reasons to avoid clustering. Where catastrophes can impact large areas and cause local extinctions, it may be less risky to conserve each species in at least two or three separate places, rather than clustering those sites. Issues such as boundary length, spatial constraints, and costs make the problem significantly more complex. Mathematically, the problem becomes non-linear, because the cost of adding a site to the reserve system depends on which other sites are already protected, and on the spatial relationships between candidate sites and those already reserved. One formulation of a spatial reserve design problem is shown in the following example for section 342I of the Columbia Plateau ecoregion (Bailey 1994). There are 821 sites (subwatersheds) of different sizes. The elements of biodiversity to be conserved in this problem are 113 species, rare plant communities, and common coarse-scale vegetation types. The rare species and plant community data are in the form of presence-absence data, while occurrences of vegetation types are measured in the number of hectares of that type found in each site. Thus, in this problem, there are two types of target representation levels, each for different "types" of biodiversity, expressed as ones and zeros for presence-absence, or as area.

Table 3. Adapted from Ball *et al* (in press). Data set is from the western division of New South Wales, Australia. The optimum value for this problem is known to be 54 sites.

New South Wales Comparison		
Algorithm	**Sites in solution**	**Run Time**
Greedy	61	1 min
Rarity Based	70	2-3 mins
Simulated Annealing	54	40 mins

When using greedy and rarity based algorithms, clustering of reserve sites is often achieved by including an adjacency constraint (Nicholls and Margules 1993). Another approach, used here, is to try to minimize the boundary length of the reserve system. For a given area, a smaller boundary length gives a more compact area. In order to minimize both boundary length and area in this problem, we introduce a boundary length modifier (BLM). The objective to be minimized is now Area + Boundary Length x BLM. By varying the BLM, the relative importance of compactness and size can be balanced. If the BLM is set to zero, the algorithm will ignore boundary length.

A simple measure of the degree of clustering among reserves in the network is the boundary length of the reserve system divided by the area. This is a measure of length per unit area and is quite intuitive. A more advanced measure is the ratio of the boundary length of the reserve system to the circumference of a circle with the same area as the reserve. A circle is the most compact shape possible, so this is the ratio of the boundary length to the theoretical minimum. As such, it is a dimensionless measure. The formula for this measure is:

$$\text{Ratio} = \frac{\text{Boundary Length}}{2\sqrt{\pi \times \text{Area}}}$$

As shown in Figure 1, as the boundary length modifier is increased, both the boundary length and boundary length/area measures decrease. This occurs at the expense of area. Table 4 indicates that when the largest boundary length modifier is used, two thirds of the area is reserved, and the boundary length is minimized. The best balance between total area and clustering seems to be achieved with a boundary length modifier between 0.5 and 1. Here the area is increasing, but the boundary length is decreasing at a greater rate.
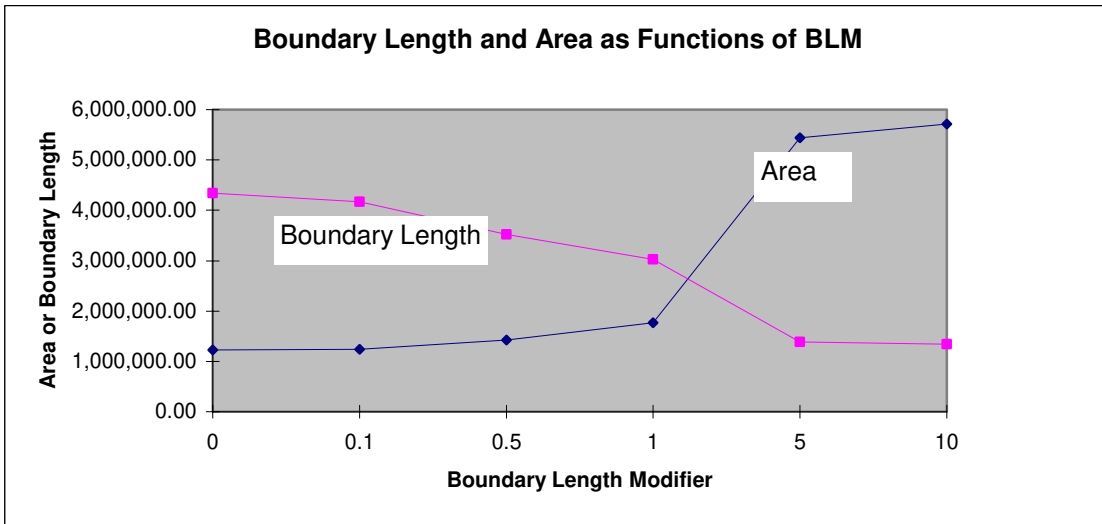

Figure 1. Boundary Length of reserve system (in kilometres) and area (in hectares) of the reserve system as the boundary length modifier is changed. Note Boundary Length is always decreasing while total area increases. The best reserve system will depend on the relative costs of boundary length and area.

Table 4. A reserve network for one section of the Columbia Plateau, designed with simulated annealing, using a variable boundary length modifier. Area is in hectares and boundary length in metres. BL/Ideal is the ratio of the boundary of the reserve to the boundary of a circle of the same size. Data sources are listed in Table 1.

Columbia plateau reserves

BLM	Sites	Area	Boundary Length	BL/A	BL/Ideal
0	124	1,229,570.51	4,337,428	3.53	11.03
0.1	127	1,242,524.27	4,167,834	3.35	10.55
0.5	160	1,427,321.72	3,519,799	2.47	8.31
1	196	1,771,721.86	3,027.734	1.71	6.42
5	598	5,439,757.03	1,386.868	0.25	1.68
10	643	5,712,270.51	1,344.774	0.24	1.59

Possingham et. al.

Figures 2 and 3 illustrate the results of applying the BLM clustering method. In Fig. 2, no boundary length multiplier was used, and the resulting reserve system is very fragmented. In Fig. 3, it is immediately obvious that the reserved sites are well clustered, and there are areas where core sites from Fig. 2 have been transformed into larger contiguous blocks. The number of outlying sites in the reserve network has been reduced. Those that remain represent the only options for capturing some of the rare species.

Boundary Length Modifier 0

Columbia Plateau

Figure 2. Reserve system selected for section 342I of the Columbia Plateau ecoregion, using simulated annealing, with Boundary Length Modifier set to 0. There are 821 sites (i.e., potential reserves), and the conservation goal is to conserve at least one occurrence of each of 113 species, rare plant communities, and common coarse-scale vegetation types. For species and rare plant communities, occurrences are measured by presence-absence data; for coarse-scale vegetation, occurrences are measured as area in hectares. Data sources are listed in Table 1.

Boundary Length Modifier 1

Columbia Plateau

Figure 3. Reserve system selected for section 342I of the Columbia Plateau, using simulated annealing, with Boundary Length Modifier set to 1. All other details as in legend for Figure 2.

The simulated annealing method can be extended beyond the examples here, to incorporate more elaborate spatial requirements for species. For example, if several sites could be affected by the same catastrophe (e.g., a fire or hurricane), we might want to minimize the chances that all reserves for a given species are simultaneously impacted. This can be done by introducing a requirement that species occur in two or three sites, each separated by some minimum distance, while still attempting to minimize total area and boundary length.

Reserve network design in an uncertain world
Despite these kinds of efforts to incorporate spatial considerations into reserve network design, a major limitation of existing approaches is that they remain essentially static (e.g., they are based on a snap

shot in time of species incidence or vegetation distribution). They do not deal explicitly with temporal dynamics or uncertainty. Robust and feasible approaches for incorporating temporal dynamics and various types of uncertainty represent one of the greatest challenges to theories and methods for reserve network design.

Data uncertainty

While mathematical algorithms for reserve network siting continue to improve, data on the distribution and abundance of biodiversity to feed into these algorithms remain quite poor. Systematic reserve planning efforts may employ explicit mathematical expressions, but they are still opportunistic in that they tend to use whatever data are available. Systematically gathered data on the distribution and abundance of biodiversity are scarce. Available data on species abundance and distribution typically are biased in a number of ways: towards charismatic species, such as mammals, birds and butterflies; towards easily accessible sites; or towards favorite study sites such as field stations or areas close to major universities or museums. For example, in the Columbia Plateau, the density of surveyed sites is inversely correlated with distance from major interstate highways (Andelman and Hansen, unpublished). In addition, both the amount of data available, and the extent of areas surveyed vary widely across different parts of the globe. Sometimes, in the absence of consistent empirical data for a particular region, predicted species or vegetation distributions derived from habitat suitability models or interpretation of satellite imagery are used (e.g., Cocks and Baird 1989, Margules and Nichols 1991). Thus, it becomes critical to understand how sensitive reserve siting algorithms are to variations in data type, quantity and quality.

Depending on the amount and types of data available, more complex algorithms may not always provide better solutions. For example, simulated annealing approaches can be very sensitive to the choice of input parameters (e.g., Golden and Skiscim 1986; Murray and Church 1996), but these limitations have not been systematically examined in the context of reserve network siting problems. In contrast, the simpler greedy or rarity based algorithms seem to be relatively robust to the amount of survey effort and to spatial biases in sampling when applied to binary (i.e., presence-absence) data (Andelman and Meir 1999). Moreover, for any particular set of species or ecosystems, determining the optimal balance of reserve clustering and separation to parameterize a simulated annealing algorithm requires detailed empirical data on species life history and/or the spatial distribution of catastrophes, which often do not exist.

Species/Biological dynamics

The basic data used with reserve siting algorithms usually consist of presence-absence data (or more often, simply presence data) for particular species and/or vegetation types. The former (and to a lesser extent the latter) can change. Species appear and disappear from sites independently of whether sites are in, or not in, reserve systems (e.g., Margules & Nicholls 1994), and the frequency with which this happens depends on numerous factors. This means that static approaches may yield reserve networks that may not protect as much biodiversity as one might think. The future of these sorts of problems lies in integrating spatial population modeling with reserve network siting approaches, a significant challenge, both in terms of data acquisition, and model complexity (see Andelman et. al. 2000 for a recent review).

Landscape change, economic and social uncertainty

In most cases it is not possible to both design and implement reserve networks instantly. Even if an optimal set of sites has been identified, it will take decades of negotiation and land purchases to translate that design into a set of reserves on the ground. In the mean time, degrading processes will continue to operate at various spatial scales. If sites are lost before implementation is complete, then efforts to find the optimal reserve system will probably fail. This means, as time passes, not only will the species composition of a site change, the carrying capacity of the site for particular species (i.e., site quality) may be modified, and some sites may be destroyed entirely. Key sites may be lost before they become available for conservation action, and if these key sites are integral to the overall reserve network goals, then the final system may be quite poor when measured against the initial goals. Ideally, then, we seek a dynamic theory of reserve design. Such a theory must explicitly consider many stochastic events: the chance of site destruction and degradation, the chance a site becomes available for sale, the dynamics of the financial system providing capital to buy and manage reserves, and the strength of public interest in conservation relative to other land uses. Combining all these factors in a single model would be almost impossible. Nevertheless, incorporating some of these factors in a model is essential. For example, given temporal

variation in site availability, for small problem sets, Possingham et. al. (1993) used stochastic dynamic programming and found it was possible to determine which sites should be acquired, if and when they become available.

Here we have merely attempted to introduce some of the complexities that will enter into practical reserve design problems, along with some of the mathematical tools for dealing with those complexities. To integrate all these issues in one problem, let alone solve that problem, is very difficult. In practice, the best approach will be to build and solve specific problems for specific organizations and localities. For example, where we have some notion of the particular objectives and financial dynamics of an agency or organization, we might attempt to build a dynamic decision support tool. The most common type of problem will be to determine, when an organisation has some existing capital, and a variety of sites are available for purchase, which, if any, should be acquired at any given point in time. The problem-solving tool should be tailored to the problem at hand.

Discussion

In this chapter we have considered the problem of reserve design from the simplest possible formulation - the minimum set, presence-absence problem - to more complex formulations, including explicit spatial constraints. There are many variations and complexities that we have not discussed. For example, in all cases we set biodiversity as a constraint and tried to minimize economic and other costs. An alternative is to set an economic constraint. In this case, if there is fixed capital available for reserve acquisition, or reserves can cover no more than a fixed proportion of the region, the problem is to maximize long-term biodiversity benefits. This problem has rarely been considered.

Regardless of how the problem is formulated, or the type of algorithm employed, there are additional considerations. In practice, solving the reserve network design problem requires more than just finding the very best solution. Flexibility to explore alternative solutions is one important criterion, because optimality may not be achievable, or its importance may diminish in practical problems (Cocklin 1989a, Andelman et. al. 2000). Generally, conservation planners need to be able to evaluate a range of reasonably good solutions (i.e., from an ecological perspective), in the context of other considerations, such as economics or political expediency. Speed of execution also is important, because it facilitates a much greater level of interaction between the planner and the potential solution space. Solutions can be examined and additional constraints added - such as the forced inclusion or exclusion of some sites - before running the algorithm again. This can give planners and decision-makers a range of good solutions to use in a broader decision making or negotiation context (Pressey et al. 1996, Cocklin 1989b).

With respect to these criteria, the simple methods are very useful. They are quick, which makes it relatively easy for the user to change either the data set (as new information becomes available, or to account for uncertainty) or the selection criteria (to reflect different levels of risk tolerance, or different political or economic considerations), and then quickly reapply the method. For better answers, simulated annealing is an appropriate method. Its use of an objective function with penalties instead of constraints, offers both flexibility and efficiency, although we need to know more about how robust it is to variation in types of data or uncertainty. Integer Linear Programming methods, or optimization methods that work in a dynamic framework, such as stochastic dynamic programming, may be harder to justify for potential users, because their computational complexity gives them a "black box" nature.

There are a wide variety of extensions to these problems, which are only now being studied. Complex spatial requirements and reserve design under uncertainty are only two such avenues. Other areas of interest include problems in which species or other objectives have different weights (values), and there is a fixed amount of land to be set aside; and problems that attempt to simultaneously optimize multiple services (e.g., where a species has one value, say for ecotourism, when it is in a reserve, and a different value, say for trophy hunting, when it is outside a reserve). Solutions to these problems - even approximate solutions - will improve the design of effective reserve networks and, ultimately, will contribute to better protection for biodiversity.

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