

## AN ABSTRACT OF THE DISSERTATION OF

Darek J. Nalle, for the degree of Doctor of Philosophy in Forest Resources,  
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Title: Optimizing Spatial and Temporal Aspects of Nature Reserve Design under  
Economic and Ecological Objectives

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Alteration of natural areas in attempts to support increasing human populations has been a crucial yet less publicized contributor to the fall of many of the world's greatest civilizations, since healthy ecosystems can help maintain stable societies and economies. Given this unhappy fact and the ancient relationship between people and the natural world, it may be surprising that science has only recently begun to holistically-study the linkages among the social, economic, and ecological aspects of human society. This dissertation seeks to contribute a small piece to the growing body of knowledge about what might be socially, economically, and ecologically sustainable. Tools from ecology and economics are brought together in realistic modeling frameworks to explore interactions, and operations research techniques are employed to find solutions to complex problems that the human mind can only partially comprehend.

In particular, the work builds by designing fixed-site reserve systems with attention to spatial design in Chapter 2. Chapter 3 extends the model by

incorporating a simplistic economic aspect – maximizing combinations of ecological objectives subject to constraints on the total purchase price. However, the permanent restriction of economic activities in some areas might be excessive if accompanied by an ecologically-sensitive set of spatial and temporal management actions. Chapters 4 and 5 generalize the concept of reserve design by simulating the reactions of populations of two vertebrates to timber production on a 1.7 million hectare landscape over a 100 year planning horizon. Theoretical production relationships between ecological and economic outputs were found, and tradeoffs between outputs were identified. Policies relating to timber production and species survival were implemented, and their resultant degree of inefficiency could be directly calculated.

This dissertation demonstrates how combining ecological and economic models with operations research techniques could be used to better manage the natural resource base. By providing a means for identifying tradeoffs, more defensible decisions can be made, approaching alternatives that might be socially sustainable.

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Optimizing Spatial and Temporal Aspects of Nature Reserve Design under  
Economic and Ecological Objectives

By

Darek J. Nalle

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I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

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## **DEDICATION**

I dedicate this work to Laure, for not bothering me, sometimes listening to my ramblings, and smiling through my changing moods. Her love and understanding will always mean far more to me than the degree granted.

# Optimizing Spatial and Temporal Aspects of Nature Reserve Design under Economic and Ecological Objectives

## Chapter 1. Introduction

Operations Research (OR) offers many optimization, simulation, and other quantitative analysis tools that can provide efficient solutions when allocating scarce resources. These methods have been applied with great success in many fields, including finance, economic planning, manufacturing and supply chain management, pharmaceuticals and health care, information systems, transportation, industrial engineering, and telecommunications. Since the inception of the Nobel Prize in economics in 1969, roughly half of all winners were awarded the prize for their work that either used optimization tools or for the development and application of new optimization tools (The Nobel Prize Internet Archive 2001).

The functionality of applied optimization could be attributed to George Dantzig, whose pioneering work during World War II for the United States Air Force and subsequently with The RAND Corporation led to his creation of the Simplex Method, first presented in 1947 (OR/MS Today 1996). The Simplex Method minimizes a continuous linear function subject to a set of continuous linear constraints. Although “the world is nonlinear,” as retorted a colleague when Dantzig finished his presentation (OR/MS Today 1996), Dantzig’s method is still widely used today due to its solution speed, robustness of application, and

the clever problem transformation techniques from many subsequent researchers. In the past five decades, exact solution algorithms for various constrained and unconstrained, continuous nonlinear, combinatorial, and mixed continuous and combinatorial problems have been developed (see Murty 1985; Nemhauser and Wolsey 1988; Bertsekas 1996) to augment the Simplex Method (as well as alternative exact algorithms to solve linear programs (Karmarkar 1984)). These traditional solution methods are deterministic and typically employ gradient searches at some level during solution.

Even though exact methods exist for many common optimization formulations, this alone is no guarantee that they may be successfully implemented. The number of variables under consideration is an essential factor, and solution times on many commonly occurring problem formulations increase exponentially with the number of variables. Despite increases in modern computing power, problem size still determines whether or not it is feasible to implement many exact solution methods. Some researchers hypothesize that problem size will still be a major obstacle even if a photon-based, rather than electron-based, computing system were to be developed (Cerny 1999). This limitation, known as the “curse of dimensionality”, combined with the availability of modern computing power and the inadequacy of gradient searches on highly nonlinear problems and infeasibility on combinatorial problems, has spawned various alternative solution approaches.

Many different heuristic techniques have been proposed and implemented

on common optimization formulations across various fields of study. These approaches are generally quite novel; for example, one approach simulates the development of transportation routes created by ant colonies (Dorigo 1992); another follows Darwin's notion of the survival of the fittest by searching with a population of solutions, mating the more fit individuals and producing genetically similar offspring (Holland 1975; Goldberg 1989); and yet another method mimics the annealing processes from the production of metal alloys and vitrification of glasses (Metropolis et al. 1953; Kirkpatrick et al. 1983). Most heuristics contain some degree of stochasticity that allows the search procedure to possibly extract itself from local optima and explore different portions of the solution space. The inability to do so with gradient techniques is one reason why heuristics have found extensive use, especially because some heuristic solutions on certain problem types have been far better than those found by traditional deterministic methods. However, no one heuristic procedure has been shown to be superior to all others across different optimization formulations, thus adding to their mystic.

Operations Research techniques have also been used in forestry, although appearing later than in many other fields. Some of the earliest and most common forestry-specific applications take the form of linear programs that have come to be referred to as the Model I and Model II formulations (Johnson and Scheurman 1977). Each model schedules harvesting activities over a time horizon but does so in a slightly different manner. The main difference between the formulations lies in the definition of the programming variables. The Model I formulation

defines variables that track the activities applied to each stand over the entire planning horizon. In the Model II formulation, variables track only the lifetime of a stand regardless of the planning horizon. Both formulations have relative advantages and disadvantages (Johnson 1977); these include their ease of solution but general omissions of spatial issues. More recent applications of OR to problems with spatial components in forestry include Hof and Raphael 1997; Hof and Bevers 2000; and Sessions et al. 2000.

The practice of forestry, i.e., silviculture, falls under the heading of applied ecology. Treatment options include clear-cutting, thinning, planting, fertilization, suppression of undesirable vegetation, prescribed burning, pruning, and no action at all. Such actions affect the assemblages, quantity, diversity, and distribution of wildlife, plant composition, soil characteristics, watershed flow, and micro and macroclimates in and around managed forests. Operations Research methods are beginning to be accepted in ecological applications, notably in nature reserve design. Because optimization, stochastic modeling, and simulation are not discipline-specific tools, one aspect of this dissertation is to explore areas where OR techniques might aid applied ecology and thereby broaden both fields of study.

Forestry also falls under the heading of agricultural economics. Demand for wood and wood products will likely increase as human populations increase, as has been the historical trend (UN FAO Report 1999). From an investment standpoint, there is an intimate link between the rate of return and the rate of stand



growth. Because the rate of stand growth decreases with time, a profit maximizer will harvest when market conditions determine that the stand's monetary growth rate has fallen below the current rate of return of the next best investment alternative. Harvesting then, as a silvicultural treatment, affects ecological conditions spatially and temporally, and the magnitude of spatial and temporal effects has caused much debate concerning landowner rights and economic objectives, silvicultural practices, and other issues pertaining to economic and ecological sustainability. Another aspect of this thesis is to employ OR techniques to find solutions that simultaneously identify and highlight tradeoffs between complementary and/or competing economic and ecological objectives.

One means of balancing economic and ecological objectives is to permanently restrict economic production on some lands by establishing fixed-site nature reserves. Operationally, the types and amounts of different habitat that occur within reserved areas and the location of reserves are of great ecological importance. Large contributions to biodiversity can be made by reserving as many distinct types of habitat as possible. Since different species have different habitat area requirements, the amount of habitat reserved directly influences population sizes and long-term survival likelihoods. Conventional wisdom dictates that enough habitat area should be set aside to maintain sufficient genetic diversity in the population. Also, the spatial arrangement of reserved lands is thought to promote long-term species sustainability. A system of reserves located close together can provide a network of safe havens for species to travel to if a

catastrophic event were to occur in one of the smaller reserved areas. Conversely, a system of spatially distant reserves can help decrease the spread of disease and the risk of total loss from a large, concentrated disturbance such as a major fire. Tradeoffs between the survival of different species also arise from spatial design issues. Aviators and plants with air-born seed dispersal would generally benefit from a compact but not necessarily connected spatial design. On the other hand, slow moving terrestrial species would generally benefit from a contiguous design. Many other species, such as the deer, turkey, cougar, bobcat, elk, and black bear, would likely benefit from a combination of reserve compactness and contiguity.

Chapter 2 develops a new spatially explicit optimization model and new heuristic solution method that can find the most compact and/or contiguous spatial arrangement of reserved lands while meeting habitat requirements. Within the model, a parameter is included that allows the user to explore how and where reserve location changes for different levels of compactness and contiguity. Additionally, the model allows for the inclusion of existing reserved areas. By solving the model with and without existing reserves, the effects of existing reserves on compactness and contiguity and on overall reserve location can be determined exactly. The model and solution method were applied using physical habitat data from the 44000 km<sup>2</sup> Klamath-Siskiyou ecoregion of southwestern Oregon and northwestern California. It was found that existing reserves have the greater effect on future reserve contiguity but also affect future reserve compactness. Furthermore, it was observed that as the amount of each habitat to

be reserved increased, the location of the most compact and/or contiguous proposal moved across the landscape. This finding has important implications for land managers because the location of the best spatial design can change as conservation priorities change.

The location of fixed-site reserves is not only a major ecological issue; it also has significant economic considerations. The model in Chapter 2 ignores cost and thereby assumes an unlimited budget for reserve proposals. Scarce resources are typically available for conservation purposes, and so the purchase price of land to be set aside is an essential factor in reserve design. Chapter 3 extends the model in Chapter 2 by requiring that the total reserve purchase price not exceed a fixed budget amount. As the available budget is increased, the marginal return on compactness and contiguity can be viewed as a function of cost. The new model was applied using physical habitat data and land values from Josephine County, Oregon. Within the county are existing reserves that are administered by different federal agencies. The new model was run both with and without the current reservation status under the same incrementally increasing allowable budget. For Josephine County, it was found that for the same budget amount and habitat reservation requirements, an augmented reserve network containing existing reserves could never be made as compact or contiguous as one without existing reserves. Conversely, for the same degree of compactness or contiguity, the purchase price of an augmented network with existing reserves was always more expensive (*at least 25% higher*) than one without existing reserves. These results

suggested that coordinated planning across federal and state agencies and non-governmental organizations can greatly improve the spatial attributes of a reserve design, thus increasing likelihoods of species survival while simultaneously decreasing purchase costs.

The establishment of areas permanently restricted from economic use may not be the only means of balancing economic and ecological objectives. Instead, spatial and temporal alterations of traditional economic management actions might be sufficient to maintain species populations. Although there may indeed be lands that should be permanently set aside, the amount of land that is permanently withdrawn under only a fixed-site reserve system might be excessive if accompanied by a species-sensitive, spatial and temporal set of management actions. Chapter 4 explores this notion by first developing methodology for predicting population responses of species with different vital rates, habitat preferences, and movement behavior from different spatial and temporal harvest patterns. In Chapter 5, the methodology is then embedded within an optimization model, and the estimated population responses of two species are maximized under species-sensitive spatial and temporal harvesting on a 1.7 million hectare landscape in the western-central Cascades of Oregon over a 100-year planning horizon. Unlike Chapters 2 and 3 where spatial and temporal economic impacts on commodity production were ignored, the supply of logs produced over a long planning horizon was explicitly determined under expected market conditions using a newly developed hybrid heuristic optimization search procedure while

maintaining allowable species population sizes through time. By incrementally changing the population size targets of each species, tradeoffs between the maximum expected population sizes of the different species and maximum stumpage production were found. Locating this relationship, known as a production possibility frontier, is useful because it represents the maximum possible combinations of outputs attainable from a landscape – in this case, both biological (e.g., species populations) and economic (e.g., timber). Therefore, for the two species selected, if a fixed-site reserve system is superior to all other alternatives for species conservation, this option would be identified by the optimization routine. Furthermore, the optimization routine will determine the best spatial design under differing levels of efficient economic production for each species as the landscape changes spatially and temporally.

Another important component of the model is to simulate regulatory effects on ecological and economic production. Because roughly one half of the 1.7 million hectare study region is federally owned, current policies pertaining to species and public timber management were imposed on those lands. These additions make the production relationships more realistic, and points along the new production possibility frontier were found. By comparing these point with the unrestricted frontiers, the level of effectiveness of policies intended for species conservation can be measured exactly. In this way, managers and politicians can use the tools and methods provided to make more informed and defensible decisions.

In all of the studies in this dissertation, optimization techniques have been successfully used to show how the most can be had from scarce and possibly competing resources. Arguably, this is extremely important as people put increasing pressure on the land base for products and services such as commodity production, recreation opportunities, species survival, ecosystem functions, and personal values. In sum, although “the world is nonlinear”, the comment exemplifies the potential shortcomings of linear thinking. The use of OR methods, in conjunction with the vast knowledge compiled across disciplines and intelligent planning, can aide in determining what is ecologically and economically sustainable, including the sustainability of our own population.

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## **Chapter 2**

### **Designing Compact and Contiguous Reserve Networks with a Hybrid Heuristic Algorithm**

Darek J. Nalle, Jeffrey L. Arthur, and John Sessions

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## 2.1 Abstract

Conflicting opinions from environmental advocates and economic interests on the best strategy for management of public lands often leaves land managers in a difficult position. Since ecosystem sustainability is in the long-term interest of each group, the establishment of nature reserves could simultaneously address both views. To promote sustainability, fragmentation of existing natural habitats should be avoided, since it is commonly recognized as being disruptive to the species adapted to these habitats. Therefore, when designing an efficient nature reserve, the compactness and contiguity of the land reserved is an essential consideration.

Motivated by the on-going reserve efforts in the large and diverse Klamath-Siskiyou region of southwestern Oregon and northwestern California, common heuristic search techniques are implemented and results compared on various simulated test problems. From these findings a new heuristic is developed that reduces solution time and increases solution quality. When applied to the Klamath-Siskiyou region, results are promising.

**Keywords:** Nature reserve problem, quadratic 0-1 programming, heuristics

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### 2.3 Introduction

Increasing pressure from the public and the scientific community for ecological sustainability is a primary consideration in the formulation of land use policy. This changing of objectives and re-emphasis of others (Committee of Scientists 1999) places added burden on land managers, especially those who oversee public lands, to balance multiple and often conflicting uses. In order to assess tradeoffs under such a management policy, sustainability must somehow be incorporated into the decision process.

Nature reserves are regarded as an efficient tool for ecosystem and species sustainability (Noss and Cooperrider 1994). The conventional wisdom is that by protecting the broader habitat, the individual species, their inter-relatedness, and ecosystem processes will likely be protected as well (ignoring issues pertaining to specific threatened or endangered species).

If managers use reserves to promote sustainability, then the potential locations must be known for multiple use tradeoff assessment. Furthermore, the proposal itself must be biologically and managerially defensible. Since management regions are typically large in size and contain diverse eco-characteristics, and because design issues are complex, optimization methodologies are useful since they can identify the best proposal(s) for a pre-defined set of reserve objectives. Thus, the use of these techniques enables managers to make more informed and defensible decisions.

When designing a reserve or system of reserves, issues include overall compactness and contiguity, representation of all species, maximal inclusion of especially rare and/or threatened species, establishment of wildlife corridors, representation of all habitats, and adherence of the final reserve proposal to management goals. To date, there is much research and debate over how to select areas to include in the final proposal; solution methods range from simple greedy algorithms (Pressey et al. 1997) to complex optimization routines (Arthur et al. 1997; Ando et al. 1998).

The problem addressed here differs from the body of literature that has come to be known as the Reserve Site Selection Problem (RSSP). A typical optimization formulation of the RSSP is represented as an integer program and reserves the minimum number of parcels of land necessary to cover as many species or ecosystems as possible (Cocks and Baird 1989; Possingham et al. 1993; Church et al. 1996; Snyder et al. 1999), sometimes subject to a budget constraint (Ando et al. 1998). Other variants (integer programs as well) seek to select parcels such that the probability of species occurrence is at least as large as some threshold value (Cocks and Baird 1989; Pressey and Logan 1998; Haight et al. 2000). Neither of these formulations explicitly considers spatial placement, so the mathematically optimal reserve proposal under such formulations may be quite fragmented. Furthermore, the presence/absence (or estimated probability of occurrence) data necessary for these formulations must be obtained from intensive

ground surveys and/or estimation techniques that are subject to detection and sampling errors. Such data is costly to generate in terms of both time and money.

According to island biogeography theory, minimum parcel-to-parcel distance is expected to decrease the probability of extinction for any given species (MacArthur and Wilson 1967). In practice, strict adherence to this notion may be shortsighted, since a disjoint reserve system can provide benefits such as reduced risk to fire and disease. However, if fragmentation is thought to be a major threat to many species' survival, it is questionable how ecologically optimal the solutions of the RSSP and its variants are, because any proposal containing numerous disjoint parcels of land would have failed to address the underlying concern of habitat fragmentation. Therefore, reserve compactness and contiguity should be explicitly modeled. Assuming species are dependent upon habitat and that different habitats support unique assemblages of species, habitat representation is a coarse-filter attempt to sustain biodiversity. This approach has its own drawbacks; namely, potentially omitting ecological attributes that could only be observed from intensive ground surveys. However, protecting at least some pre-specified minimum amount of each habitat type attempts to preserve each distinct habitat and helps reduce subjectivity, and the goal of maximal species coverage is then implicitly addressed (Kirkpatrick and Brown 1994; Nantel et al. 1998).

The contribution of this work is to provide a spatially explicit optimization model for selecting parcels of land for reservation in the most compact and/or

contiguous manner possible while satisfying a minimum representation requirement per habitat type. The model is then used to demonstrate how currently reserved lands may affect compactness and contiguity of a future reserve network. While models that include some spatial aspects are not unique (Williams and Reville 1996, 1998; Clemens et al. 1999; Ball 1999; Possingham et al. 2000; Leslie et al. 2000), the model in this paper explicitly addresses both compactness and contiguity objectives.

It is essential to note that solution times for integer programming techniques increase dramatically with the number of decision units under consideration. Except for a few integer program formulations with very special structure (none of which are found in the RSSP literature), the use of branch and bound methods quickly becomes computationally infeasible as problem size increases (Arthur et al. 1997), and despite increasing computing efficiency this will likely be a major limitation for the foreseeable future. Therefore, to solve our formulation on large real world data sets, heuristic techniques are necessary.

The remainder of the paper is organized as follows. Section 2.4 details the optimization formulation. Section 2.5 briefly presents results and comparisons from three common heuristic methods that were implemented on various test problems. From these results a new heuristic is developed, and results using this new algorithm on another simulated landscape are reported. Section 2.6 introduces a real world data set from the Klamath-Siskiyou region of northwestern California and southwestern Oregon that contains many scattered

protected areas. Results are shown under a 10% and 25% minimum reservation requirement per habitat. This is done both with and without the current reservation status of parcels to reflect how current reserves may affect the future compactness and contiguity of a reserve network. Section 2.7 contains conclusions and describes some ongoing extensions of the work presented in this paper.

## 2.4 Optimization model

For the purpose of this paper all habitats are assumed to be of equal ecological value. This ignores habitat-specific species abundance issues that may be important when reserving a large network containing both species rich and species poor habitats. Also, the approach does not account for temporal issues and changing ecological attributes. The model developed assumes that (i) all parcels in the database are immediately available for reservation, and (ii) those parcels comprising the final proposal are ecologically essential forever. In reality, decisions regarding the establishment of permanent reserves are often constrained by private ownership, existing mining claims, timber leases, grazing permits, and encroaching human urbanization. If the study region is threatened by urbanization, then part (ii) of this assumption is more realistic since land once urbanized typically stays that way. In regions where human encroachment is of



lesser concern, there may still be subsets of the region which, for various ecological and/or aesthetic purposes, should be permanently set aside.

If the primary objective is to create or enhance a reserve network in the most compact manner possible, the optimal proposal will have a minimum perimeter to area ratio. Hence, the overall shape of the optimal reserve will be as circular as possible and the distance from any parcel to all other parcels will be as small as possible. Arguably the most accurate way to measure this is to sum the distances between every pair of parcels in the final reserve proposal. A problem with summing all pair-wise distances is that non-circular arrangements of parcels will be deemed less desirable, even if the resulting proposal is a preferred reserve design based on other non-geographic measures. Furthermore, for some regions a compact proposal may not exist due in part to minimum habitat representation requirements; in such cases, the sum of all inter-parcel distances would return a proposal that is, overall, in a circular arrangement but containing possibly many disjoint clusters of parcels. Disjoint areas pose a problem for two reasons: fragmentation not only decreases the likelihood of habitat sustainability, but it increases the management costs of the entire reserve.

On the other hand, if the primary objective is to create or enhance a reserve network in the most contiguous manner possible, then each parcel should share at least some minimum width border with at least one other parcel. The overall shape need not be circular, but a compact and contiguous design should be selected if such a proposal exists. An efficient way to measure reserve contiguity

is to sum the number of parcel adjacencies. There are drawbacks associated with just summing adjacencies, since under such a measure it is possible to select a reserve design that is nowhere compact but completely connected (e.g., a spider web pattern).

When taken separately, minimizing distances and maximizing adjacencies between parcels have different ecological implications for different species. A minimum distance, disjoint reserve would generally benefit aviators and those plants with heavier reliance on wind-borne seed dispersal. On the other hand, a contiguous, non-compact design would generally benefit slow moving terrestrial species and plants with more gradual seed dispersal techniques. Some species, such as many game animals, would benefit from a combination of these two design characteristics. Hence, it is desirable to explore the tradeoff between reserve compactness and contiguity in a given area, and this capability is included in the optimization model.

It is assumed that the geographic region under consideration is divided into a fixed number of uniformly sized *sites*, which are also referred to as *cells*, *units*, or *parcels*. In addition, it is assumed that each site is classified into one and only one type of habitat that does not change with time, and to accommodate situations where some areas of the study region are permanently protected, that each site is either unrestricted (and thus a candidate for protection) or already withdrawn (denoted as Congressionally Withdrawn, or CW). To develop the optimization model, the following notation is used. Let  $m$  be the total number of

distinct habitat classes in the study area, and denote a generic class by  $i$ .

Similarly, let  $n$  represent the total number of cells in the study area,  $j$  denote a generic cell, and  $N = \{1, 2, \dots, n\}$  the set of all cell indices. Also define:

$n_i$  = the number of cells of habitat class  $i$ ;

$N_i$  = the indices of the cells in habitat class  $i$  ( $N_i$  has cardinality of  $n_i$ );

$n_i^{cw}$  = the number of cells in habitat class  $i$  already reserved as CW cells;

$M_i^{cw}$  = the indices of the CW cells in habitat class  $i$  ( $M_i^{cw}$  has cardinality of  $n_i^{cw}$ );

$M_i$  = the indices of the non-CW cells in habitat class  $i$  ( $M_i$  has cardinality of  $n_i - n_i^{cw}$ );

$\alpha_i$  = the minimal percentage of habitat  $i$  to be reserved;

$b_i$  = the minimum number of *additional* parcels of class  $i$  that must be included in the reserve ( $b_i = \max\{0, \alpha_i n_i - n_i^{cw}\}$ );

$b$  = the number of additional parcels of any habitat class to include in the reserve (where  $b \geq 0$ );

$L$  = the total number of additional cells to include in the reserve proposal (note that

$L = b_1 + b_2 + \dots + b_m + b$ );

$d_{jk}$  = the Euclidean distance between the centers of cells  $j$  and  $k$ ;

$A_j$  = the set of cells  $k$  adjacent to  $j$  (restricting  $k > j$ ).

The inclusion of the parameter  $b$  provides a useful analysis tool. By incrementally increasing  $b$  and comparing the respective reserve proposals, the marginal return on reserve compaction and contiguity can be viewed as a function of increased availability of land for conservation. As a consequence of these definitions, the set of cell indices  $N = \{1, 2, \dots, n\}$  is partitioned into  $N_1, N_2, \dots, N_m$  and each  $N_i$  is expressed as  $\{M_i \cup M_i^{cw}\}$ ; that is, cells are clustered by habitat class and further partitioned by their current legal status.

Finally, each raster-type cell is represented by a binary decision variable  $x_j$  such that:

$$x_j = \begin{cases} 1 & \text{if parcel } j \text{ is included in the reserve proposal} \\ 0 & \text{otherwise.} \end{cases}$$

The quadratic 0-1 optimization model is:

$$\text{Minimize} \quad \lambda \sum_{j=1}^{n-1} \sum_{k=j+1}^n x_j d_{jk} x_k - \delta (1-\lambda) \sum_{j=1}^{n-1} \sum_{k \in A_j} x_j x_k \quad (2.1)$$

$$\text{subject to:} \quad \sum_{j \in M_i} x_j \geq b_i \quad \text{for } i = 1, \dots, m \quad (2.2)$$

$$\sum_{j \in N} x_j = L \quad (2.3)$$

$$x_j = 1 \quad \text{for } j \in M_i^{cw} \quad (i = 1, \dots, m) \quad (2.4)$$

$$x_j = 0 \text{ or } 1 \quad \text{for } j \in M_i \quad (i = 1, \dots, m) \quad (2.5)$$

The first summation in equation (2.1) measures the compactness of the cells in the reserve proposal and the second measures contiguity (the use of  $A_j$  avoids double-counting adjacencies). Since the objective is minimization, adjacencies are subtracted rather than added. The parameter  $\lambda \in [0,1]$  explores the tradeoff between compactness and contiguity, and the parameter  $\delta > 0$  weights the sum of adjacencies so that the two measures are more directly comparable; that is, scaling  $\delta$  so that both measures are of roughly the same magnitude gives  $\lambda$  a more intuitive meaning. Constraint (2.2) ensures that the minimum representation is met for each habitat, and constraint (2.3) requires  $L$  cells to be selected. In all subsequent results,  $b = 0$  was used for simplicity of presentation; consequently, the constraints in equation (2.2) held as equalities. Constraint (2.4) pragmatically includes all CW cells, and constraint (2.5) limits each decision variable to the required binary values.

The optimization model in equations (2.1) - (2.5) differs from reserve design formulations that ignore spatial metrics. In particular, if the spatially explicit objective function in equation (2.1) was replaced with the commonly used objective of minimizing the number of parcels included in the reserve (i.e. minimizing  $\sum x_j$  over all  $j \in N$ ), our formulation reduces to a set-covering problem. However, because each cell belongs to a unique habitat class, it can be seen that every feasible solution to the covering problem that consists of exactly  $b_i$

distinct cells from  $M_i$  is necessarily optimal and has minimal objective value of  $\sum b_i$ .

## 2.5 Heuristic comparison and development

The model developed for compaction and connectivity in equations (2.1) - (2.5) is a constrained quadratic 0-1 program. No polynomial time solution methods exist for such problems, although a transformation method can be used that results in a much larger linear integer problem (Klein and Aronson 1991). Using such a transformation causes a quadratic increase in the number of binary variables, and applying this method to equation (2.1) on a small landscape containing just 100 parcels results in a linear integer program with thousands of decision variables. Most real world data sets contain thousands of parcels, so branch and bound integer programming techniques are computationally intractable for such problems due to long solution times.

Heuristic selection in practice is often based on various non-scientific criteria. Certain problem types can make some algorithms more attractive than others, but it is not currently known which heuristic technique consistently finds the best solutions across problem types. Our approach to heuristic design and eventual development was to implement different techniques on various simulated test problems (or grids). The ideal solution method would be robust to landscape characteristics such as size, shape, number of habitat types, and spatial correlation

within habitats, as well as find optimal or near optimal solutions in real time. We applied the three most commonly used heuristics: Simulated Annealing (Metropolis et al. 1953; Kirkpatrick et al. 1983), Tabu Search with short-term memory only (Glover 1989, 1990; Glover and Laguna 1997), and Genetic Algorithms (Holland 1975; Goldberg 1989).

Each technique requires parameter settings that can greatly affect the quality of solution found, regardless of problem formulation. We first varied heuristic parameter settings, grid characteristics, the percent to reserve per habitat, and the values of  $\lambda$  in equation (2.1) *within each heuristic* in factorial designs to see how algorithmic parameter values affected the speed and quality of the best solution found over all grid types. Once the best algorithmic parameter settings had been statistically identified using Multiple Comparisons with the Best (Hsu 1984) for each heuristic across all grid types, comparisons *between heuristics* were then performed using the best settings from each heuristic.

To assess the heuristics in terms of nearness to optimality, one test grid containing 144 cells was solved by complete enumeration using a 10% habitat constraint. This was done for four values of  $\lambda$ : 0 (adjacency measure only), 1/3, 2/3, and 1 (compactness measure only) – a task that took one and a half months on four Sun Sparc 40 stations running in parallel. For brevity, only results when  $\lambda = 1$  are presented, but these are typical of what was found across all values. On average, Simulated Annealing (SA) found the best solutions ( $1.6\% \pm 2.2\%$  above optimality) with Tabu Search (TS) and the Genetic Algorithm (GA) doing

significantly worse ( $10.7\% \pm 5.8\%$  and  $11.5\% \pm 7.2\%$ , respectively). However, the average time until SA found its best solution on a run was about four times slower than TS, and the GA runtime was about five times longer than that of SA.

To improve solution speed while maintaining closeness to optimality, a new method was developed that used relative heuristic strengths to offset their respective weaknesses. First, it was observed that solution quality from a simple greedy algorithm (i.e., using TS but maintaining no history list to decrease CPU time) was statistically no different from TS or GA. Furthermore, when using TS, instead of computing all pair-wise distances for all of the candidate entering cells (a very expensive task computationally, especially on large data sets), a proxy measure was identified. The distance between each candidate cell and the current solution's centroid (without the cell selected for removal) was substituted for the compactness measure. Because the cell with the shortest distance to the current solution's centroid is highly correlated with the cell that has the smallest sum of all pair-wise distances, the proxy dramatically reduces CPU time without degrading solution quality. Incorporating the proxy compactness measure into the simple greedy routine and denoting this algorithm as 'TS0', it was found that solution quality was statistically no different than TS and GA, but the time until the best solution was found with TS0 was 20, 8, and 150 times faster than SA, TS, and GA.

To improve on the nearness to optimality of TS0, the algorithm was augmented with SA. The approach, denoted SA-TS0 and overviewed in Figure



2.1, is as follows. An initial feasible solution is randomly generated and TS0 is applied (an intensification strategy). The best solution found by TS0 is likely a local optimum, so this solution is supplied to SA. Since the degree of overlap with an optimal solution is unknown, SA is used to either fine-tune (intensification) that from TS0 or move away from spatially distant local optima (diversification). The parameter values of SA are set to rather small values so that not too many objective function evaluations are performed (to save CPU time), and SA is terminated sooner than is typical. Upon termination of SA, the *current* SA solution – *not the best found* – is handed back to TS0 and the cycle is repeated. Since SA's current solution is probably not the best one found, this technique adds to the diversification strategy. To obtain quality results with SA-TS0, it was found that SA's initial temperature should be about 2-3% of the best solution found by TS0's first pass, and SA should be terminated when its temperature is about 1-2% of TS0's first pass best solution; with these parameter settings the best solution was typically found within four cycles between SA and TS0.

Applying SA-TS0 to the grid that was solved by complete enumeration, the optimal solution was found on 49 out of 50 runs after about 3 cycles (0.0001%  $\pm$  0.2% above optimal on average). Using a PC with 120 MHz processor and 32 MB of RAM,

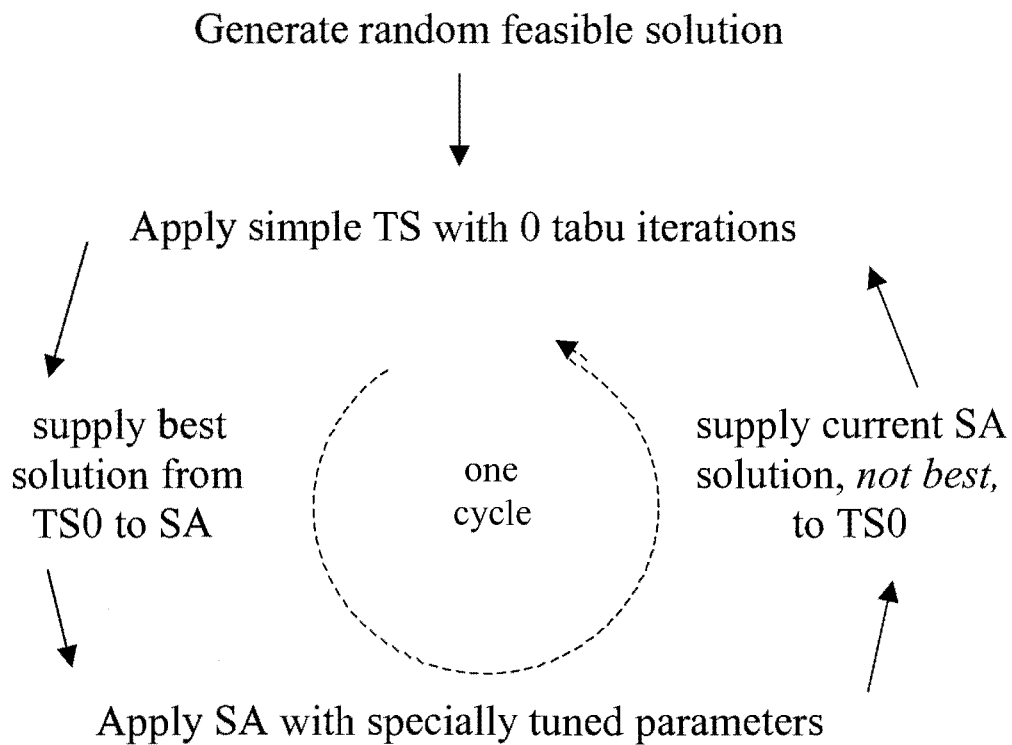


Figure 2.1. Flowchart of the SA-TS0 algorithm. The best global solution is typically found by four cycles.

and performing all runs in the MATLAB v5.0 (The Mathworks 1999) software platform using uncompiled code (which is significantly slower than C-compiled code), the average time until finding the best solution was  $68 \pm 16$  seconds.

These times were about 2 times faster than TS, 8 times faster than SA, and 40 times faster than GA. Hence, on this test problem, SA-TS0 was superior to all other methods implemented in solution quality, and second only to TS0 in speed until finding the best solution.

Finally, before solving a large real world data set, SA-TS0 was applied to another test grid with attributes similar to the area discussed in Section 2.6. A new grid with 144 cells and 6 equally sized habitats was randomly generated. Approximately 13.5% of the area in the real data set is reserved, so 20 cells ( $144 \text{ cells} * .135 \approx 20 \text{ cells}$ ) were randomly selected to be withdrawn in the test problem. This was done by selecting a random spatial pattern whose cells were fairly clumped together.

The algorithm was run fifty times for four values of  $\lambda$ , and every run began with a different random initial solution. Results are given in Table 2.1. With the exception of the contiguity measure (i.e., when  $\lambda = 0$ ), the algorithm identified the best globally found solution on every run. It also identified many alternate best solutions, even within a run. Across all 200 runs, the average computing time until the best solution was found was  $55 \pm 20$  seconds. From these findings, the algorithm is expected to perform similarly on data from the real world study area.

Table 2.1. Results using the SA-TS0 algorithm on a single landscape for various values of the objective function parameter  $\lambda$ .

$\lambda$	Best objective value found <sup>1</sup>	Number of times best value found <sup>2</sup>	Number of alternate solutions
0	-610.0	34	9
1/3	212.8	50	2
2/3	991.9	50	1
1	1765.9	50	2

<sup>1</sup> Across all values of  $\lambda$ , the average CPU time until finding the best solution on a run using a PC with 120 MHz processor and 32 MB of RAM was  $55 \pm 20$  seconds. All simulations were run on the MATLAB v5.0 (The Mathworks 1999) software platform using uncompiled code.

<sup>2</sup> Number shown is out of 50 runs using the given value of  $\lambda$ , where each run was started with a randomly generated initial solution. Runs were performed with  $\delta = 10$ .

## 2.6 Application, results and discussion in the Klamath-Siskiyou ecoregion

The Klamath-Siskiyou region (Figure 2.2) of southwestern Oregon and northwestern California encompasses 43284 km<sup>2</sup> (37% of which is privately owned) and is extremely diverse (Wallace 1992). Elevation ranges from sea level to 3000 m, and annual precipitation from under 50 cm to over 300 cm. Over 3500 plant species have been found, including 75 conifer and hardwood tree species. For these reasons The World Conservation Union has declared the area to be of Global Botanical Significance, one of just seven in North America. The area has been remotely sensed, partitioned by a grid with 2 km resolution (resulting in 10821 cells), and each cell classified as one of 19 distinct physical habitat classes based on climate and soil characteristics. Within the region are existing disjoint nature reserves (primarily Congressionally designated Wilderness Areas) that comprise approximately 13.5% of the total area but collectively do not represent all 19 habitat classes; percent coverage of each habitat ranges from 0% in low-lying, fertile classes to 63% in a high, cool class with poor soil. Hence, the existing reserves alone do not equally address the sustainability of species that depend on each habitat in the region.

For all results that follow, the SA-TS0 algorithm was implemented in

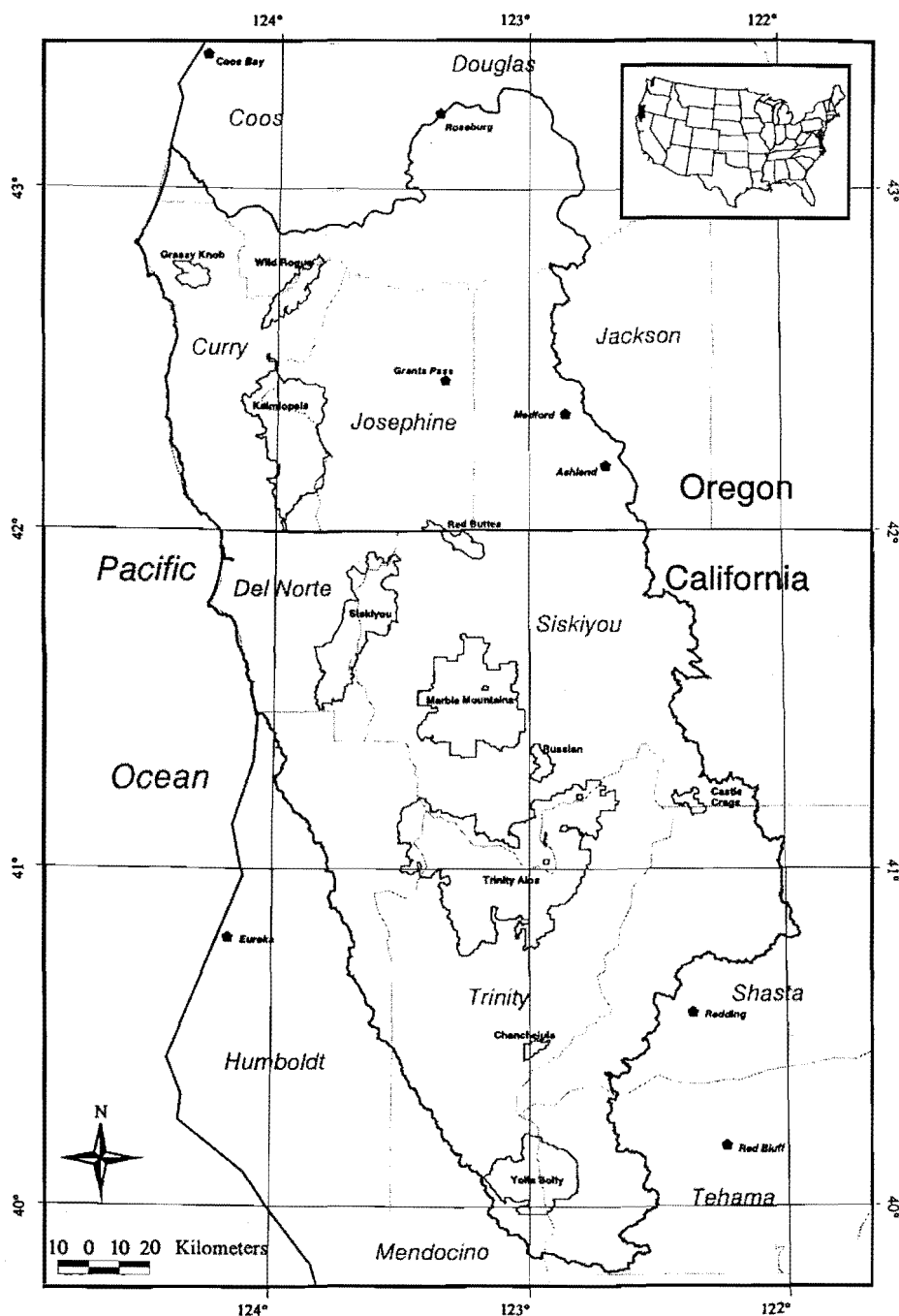


Figure 2.2. Map of the Klamath-Siskiyou study area with current CW areas outlined. Inset shows location of the study area in the continental United States.

C-compiled MATLAB code and run on a PC with a 700 MHz processor and 512 MB of RAM. Ideally, look-up tables containing all pair-wise distances and adjacencies between the 10821 cells would be computed prior to algorithm implementation to further reduce CPU time, but this proved infeasible due to limited RAM storage; hence, look-up tables for just the cells in the current solution could be maintained. This way only the distance and adjacency measures for the entering candidate cell had to be calculated, and this decreased the time until the best solution was found by an average factor of 30.

#### 2.6.1 Minimum Reservation Requirement of 10% and 25% *with* Existing Reserves

To demonstrate the approach on a real world data set, two minimum habitat representation requirements were chosen: 10% and 25% reserved per habitat. The latter percentage falls roughly within the lower end of the range (25% to 75%) suggested by conservation biologists to withdraw (Noss 1996), while the former percent might be viewed as a tradeoff between conflicting interests in a region.

At 10% minimum reservation per habitat, nine of the nineteen habitats are underrepresented and require an additional 487 cells to be reserved. Although there are on the order of  $10^{711}$  ways to select these cells, the time until the best solution found was only about one hour. Figure 2.3 maps the best solutions found

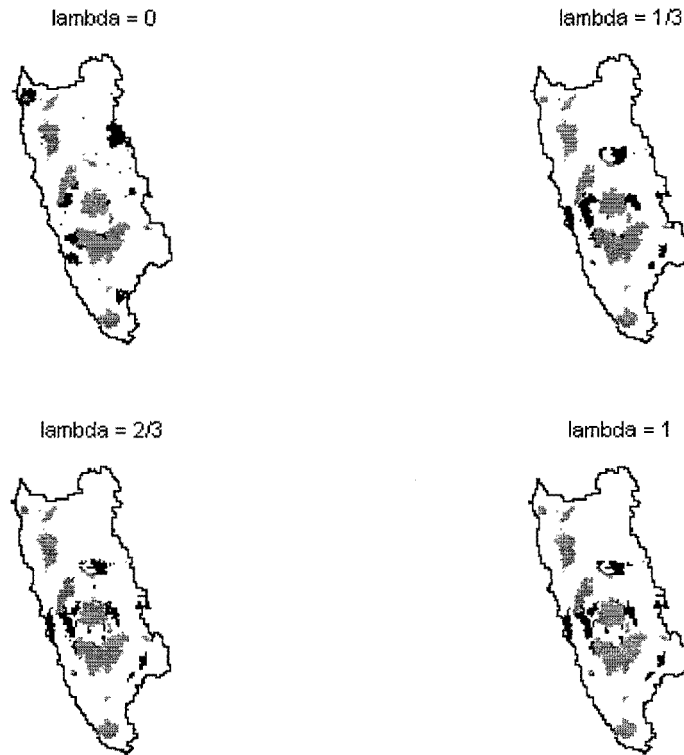


Figure 2.3. Results for the Klamath-Siskiyou study area for 10% minimum reservation requirement per habitat class and various values of the objective function weighting factor  $\lambda$ . The gray shaded areas are the current lands under protection (the CW cells) and the black areas depict the additional cells selected by the SA-TS0 heuristic algorithm.



for the four values of  $\lambda$  of 0, 1/3, 2/3, and 1. When  $\lambda = 0$  (i.e., just adjacencies, where two cells are defined to be adjacent if they share a common edge or vertex), the solution adds cells onto six existing reserves, and identifies four areas where new reserves might be established. There are a handful of unconnected cells, but closer inspection revealed that this was due to the minimum habitat reservation requirement; that is, no cells of these habitat types existed that were adjacent to any of the current or suggested reserve areas. As the value of  $\lambda$  increases, the new reserve areas move closer to the center of the region. It might be expected under the compactness measure that the centroid of the CW cells (1405 cells total) should pull in the additional cells and dominate their placement, but that the adjacency measure should not be affected by this phenomenon because distances beyond bordering cells are not accounted for.

At 25% minimum reservation an additional 1638 cells need to be selected from 15 underrepresented habitats. There are on the order of  $10^{1932}$  ways to select these, and the time until the best solution was found increased to an average of three hours. Figure 2.4 maps the best solutions found over the four values of  $\lambda$ . At  $\lambda = 0$ , cells are added to eight existing reserves, four large areas composed entirely of additional cells are created, and corridors between the three central CW areas are created. Again, as  $\lambda$  increases, new reserve areas are pulled in towards the center of the region. Even though there are more additional cells to reserve than CW cells, the CW areas still appear to control new reserve placement when selecting for compactness, although this might also be a consequence of the

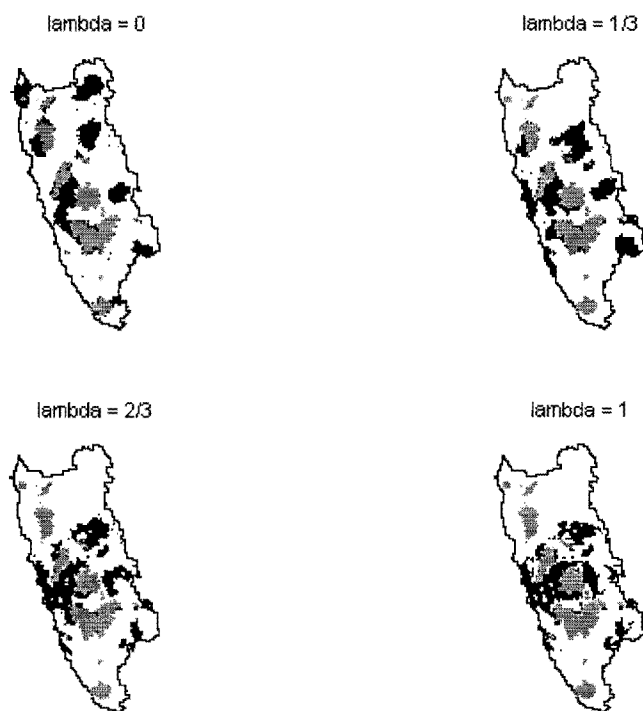


Figure 2.4. Results for the Klamath-Siskiyou study area for 25% minimum reservation requirement per habitat class and various values of the objective function weighting factor  $\lambda$ . The gray shaded areas are the current lands under protection (the CW cells) and the black areas depict the additional cells selected by the SA-TS0 heuristic algorithm.

spatial arrangement of physical habitats within the landscape. When  $\lambda = 1$ , the most compact solution is more fragmented than that when  $\lambda = 2/3$ ; this occurs in part due to the greater emphasis on compactness and because some underrepresented habitats are not located near the overall centroid.

Comparing proposals from the two reservation requirements, cell placement is consistent for the larger values of  $\lambda$  (likely due to pull from existing reserves and spatial arrangement of habitat types); however, it is not entirely consistent for the smaller values. At 25% minimum reservation, six additional habitat classes are underrepresented that were fully represented at the 10% level. Some of the differences in location occur because land near existing reserves is classified as one of these six habitats (e.g., the Kalmiopsis; see Figure 2.2). Other differences are attributed to the greater flexibility in cell placement, since more land must be reserved and more habitat interactions, whether real or not, can be accounted for.

#### 2.6.2 Minimum Reservation Requirement of 10% and 25% *without* Existing Reserves

To explore how existing CW areas in the region might control the placement of additional parcels, CW status was ignored and the algorithm was rerun.

At 10% minimum reservation per habitat, 1090 cells must be selected.

There are now on the order of  $10^{1511}$  feasible solutions, and average solution time was about three hours. Figure 2.5 maps results for the same four values of  $\lambda$ .

With the exception of the pure compactness measure, there is very little overlap with existing CW lands; however, when comparing the locations of additional cells between Figures 2.3 and 2.5 for each value of  $\lambda$ , placement is much more consistent.

At 25% reservation, 2713 cells must be selected; average solution time increased to about five hours since there are now on the order of  $10^{2619}$  feasible solutions. Figure 2.6 plots these results. Again, there is very little overlap with CW lands for the pure contiguity measure, but more overlap occurs for the pure compactness measure. Since the same trend is found at 10% without CW status, this shows, for this data set, with its smaller number of CW cells compared to the total number of cells, that CW areas more strongly influence parcel location when selecting for contiguity, but the spatial arrangement of habitats more strongly influences parcel location when selecting for compactness.

Comparing proposals at 10% and 25% with and without CW status, parcel location differs the most under the pure contiguity measure. This has important operational consequences if managers were to develop a hierarchical plan for land acquisition as the minimum percentage to reserve per habitat increased over time. That is, the most contiguous reserve proposal at one habitat reservation requirement may not be the most contiguous proposal at another reservation

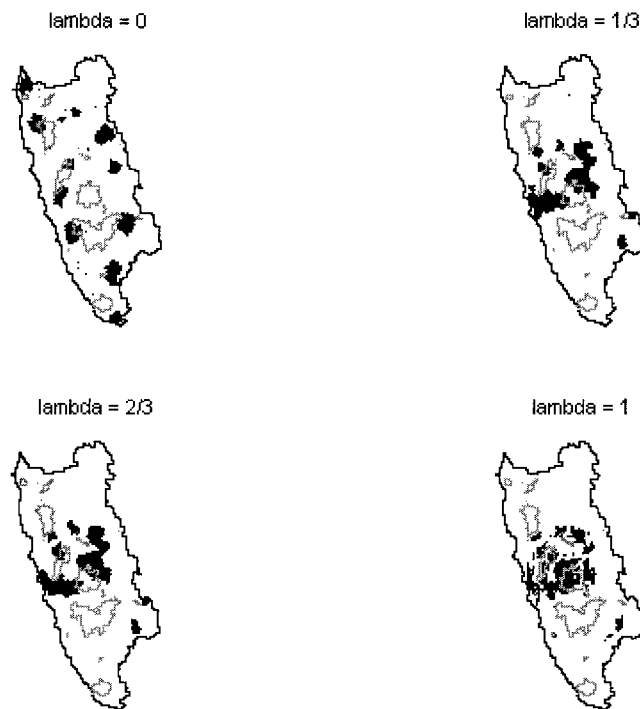


Figure 2.5. Results in the Klamath-Siskiyou study area for 10% minimum reservation requirement per habitat class and various values of the objective function weighting factor ( $\lambda$ ). The gray cells outline lands currently under protection and the black cells are those selected by the SA-TS0 algorithm when CW status is ignored.

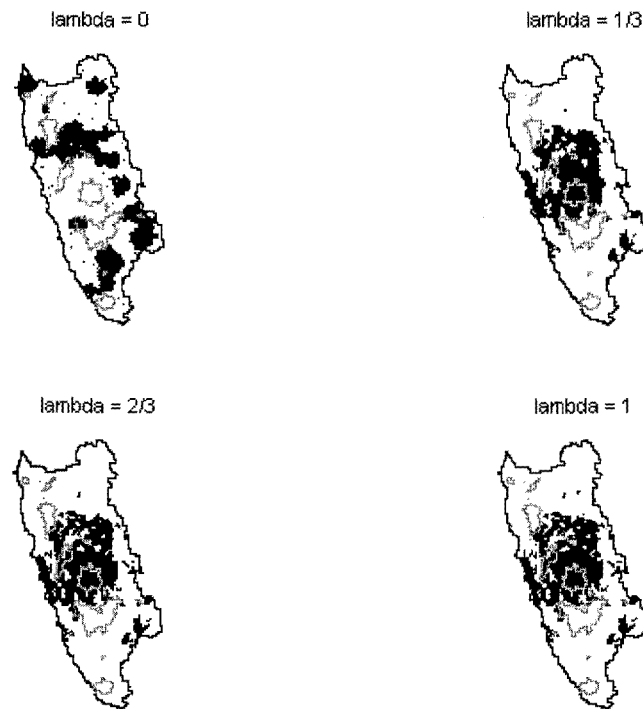


Figure 2.6. Results in the Klamath-Siskiyou study area for 25% minimum reservation requirement per habitat class and various values of the objective function weighting factor ( $\lambda$ ). The gray cells outline lands currently under protection and the black cells are those selected by the SA-TS0 algorithm when CW status is ignored.

requirement. Furthermore, the same might hold for the compactness measure as well, but this was not observed in Klamath-Siskiyou data set.

## 2.7 Conclusions and Future Efforts

This paper has presented an optimization model and various algorithms for developing nature reserve proposals that minimize fragmentation and non-adjacencies while representing at least a minimum percentage of all habitats. The hybrid SA-TS0 algorithm selected additional parcels for reservation such that they: (i) suggested new areas for protection; (ii) connected with existing reserves; and (iii) developed wildlife corridors between reserves. Although the compactness and contiguity measures found different proposals for the Klamath-Siskiyou region, this is a reflection of the nonexistence of a completely compact and connected arrangement of habitat representation requirements. Consequently, each measure selects cells under different objectives, and both measures can be useful to the land manager for trade-off assessment.

It is the ultimate responsibility of decision makers to decide which areas must be included (e.g., areas of particular ecological or geological significance, aesthetic value) and which areas should not be included (e.g., urban habitat, landfills). The model developed in this paper can accommodate such requirements by assuming that the necessary areas are CW and omitting the non-desirable areas from the database. However, the algorithmic solution should

never be taken as the final word, but as a contributing step. Models and algorithms can help to simplify the task, but they cannot replace human judgment and should thus be considered as tools to assist in decision-making.

It was anticipated that the adjacency measure would improve overall connectivity between disjoint individual reserves, but this was not entirely the case. Although the heuristic performed quite well in the minimization of the objective function, it is unclear how well the objective function measured total network contiguity. By summing *all* adjacencies about a cell, the measure was observed to select more rounded, disjoint individual reserves. Future work focuses on four areas: (1) improving connectivity, (2) considering budgetary restrictions, (3) specifically addressing requirements of threatened/endangered species, and (4) reducing algorithmic run time. It is anticipated that algorithm runtime can be decreased to the point where decision makers – when mutually convened in real time – can utilize the spatial intelligence, power, and flexibility of these approaches.

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### **Chapter 3**

## **Economic and Spatial Impacts of an Existing Reserve Network on Future Augmentation**

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### 3.1 Abstract

An optimization model for land reservation was developed that explicitly selects parcels in the most compact or contiguous manner possible while meeting habitat requirements and a budget limitation. The model was used to compare the effects of an existing reserve network on future parcel spatial locations and total cost. Using habitat and land value data from Josephine County, Oregon, it was found that a system of existing reserves created by various policies and overseen by different agencies can decrease future reserve compactness and contiguity, and increase total cost. This work suggests that coordinated planning can result in more efficient conservation efforts for less cost.

**Keywords:** nature reserves, quadratic 0-1 programming, conservation planning.

### 3.2 Acknowledgements

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### 3.3 Introduction

Human population growth has driven the conversion of natural habitats for urban, agricultural, and other uses. Natural habitats have been altered and fragmented worldwide, and this occurrence is thought to have increased the rates of species extinction and extirpation (Wilson 1988). In response to such events, the establishment of fixed-site nature reserves has been proposed as an effective means for species preservation (Noss and Cooperrider 1994).

The problem of selecting plots of land for reservation is complex since often many objectives – possibly complementary or conflicting – must be simultaneously considered. These include the coverage of all species, adequate representation of each habitat, cost, and appropriate spatial arrangements. Optimization techniques are useful as a contributing step to aid in reserve design and selection because they find proposals that best meet objectives given the scarce resources available. Solutions are thus made more defensible through the efficient allocation of resources.

Various optimization models have been proposed for site selection. The most common formulation is known as the Reserve Site Selection Problem (RSSP). These models maximize the number of distinct species included subject to a pre-specified amount of land (Cocks and Baird 1989; Church et al. 1996) or for a given budget for land acquisition (Ando et al. 1998; Polasky et al. 2001). Although the formulation provides a useful upper bound on the total number of

species that may be included for a given amount of land or budget, there are limitations. Species presence/absence data may not be available (thus rendering the approach infeasible), and species abundance is ignored. Other variants address these concerns through the use of probabilistic species occurrence measures (Polasky et al. 2000) and probabilistic population thresholds (Haight et al. 2000), but these also do not consider the spatial arrangement of the selected sites.

To account for habitat depletion *as well as* habitat fragmentation, another class of models has been developed. These differ from the RSSP and its variants in two main ways. First, these models represent habitat types rather than maximize species coverage. This method of species conservation is known as a coarse filter approach since the protection of habitat is thought to facilitate preservation of the assemblages of species adapted to each habitat. Thus habitat representation is used as a proxy measure for species coverage, and the larger the area protected, the larger population sizes are expected to be. The second difference is the incorporation of spatial considerations when selecting parcels of land for reservation (Williams and ReVelle 1996 1998; Hof and Raphael 1997; Clemens et al. 1999; Leslie et al. 2001; Nalle et al. 2001). These models generally attempt to select adjacent parcels for least cost while meeting habitat representation requirements. The model in (Nalle et al. 2001) is unique in that it explicitly selects parcels in the most compact or contiguous manner possible and allows evaluation of tradeoffs between compactness and contiguity. This paper



extends that model by incorporating a budget constraint and illustrating the type of economic analysis that can be performed.

The regulatory framework and landowner behavior on the landscape are major issues in reserve design and selection that have received less attention in the literature. In the United States, various public policies have driven the creation of fixed-site nature reserves. However, most are species-centric in their intent (e.g., Species Protection Act, National Environmental Policy Act, Endangered Species Act). These laws apply to all ownership types, but public lands have largely borne the brunt of conservation efforts. Furthermore, many different public and private ownerships exist, each with different management objectives. These include the USDA Forest Service, USDI Bureau of Land Management, USDI Wildlife Refuge System, USDI National Park Service, and various state agencies (all public owners), in addition to industrial and nonindustrial private owners and nongovernmental organizations such as The Nature Conservancy and Wilderness Society. Little coordination exists between these somewhat autonomous groups for land preservation. Operationally, possible consequences for reserve design include over- or under-representation of important ecological attributes, disproportionate spatial economic impacts on local communities (especially those whose economies depend more directly on the natural resource base), sub-optimal spatial arrangements of reserved areas arising from uncoordinated land withdrawals, and larger than necessary costs.

This paper makes two contributions to reserve selection and design. The first is a demonstration of how to compactly or contiguously select additional parcels of land when augmenting an existing reserve network under a budget constraint. The second contribution is a demonstration of how to directly compare the best compactness, contiguity, and cost between reserve proposals. Using data from Josephine County, Oregon, an existing reserve network was augmented by selecting new parcels of land in the most compact or contiguous manner possible while meeting habitat representation requirements and a set of budget limitations. The model was then rerun with the same habitat requirements and budget amounts but ignored the protection status of existing reserves. From these results, total cost curves were traced out and the marginal return on reserve compactness and contiguity can be seen as a function of cost. In Josephine County, it was found the current reserve design can always be made more compact or contiguous for less cost.

The remainder of this paper is organized as follows. Section 3.4 develops the spatially explicit optimization model and overviews a new solution method used to solve the model. Section 3.5 describes how habitat and land value information from Josephine County was derived. Section 3.6 compares the effect of existing reserves on compactness, contiguity, and cost. The paper concludes with a discussion of key results and suggestions for future research.

### 3.4 Optimization model and solution method

Two scenarios were investigated to compare reserve proposals in terms of compactness, contiguity, and cost. These can be envisioned as depicting two potential managerial situations. The first scenario addresses the concern of representing all habitats at some minimum level in the presence of existing reserves. The second scenario examines the minimum representation of all habitats ignoring the existing reserves. Because the first scenario's reserves constrain the selection of additional parcels, comparing the two scenarios reveals the first's degree of spatial and cost inefficiency.

The model developed below assumes that the study region is partitioned into uniformly sized cells (which are also referred to as parcels or units), and each cell is classified by habitat type that does not change with time. For habitat classes  $i = 1, \dots, m$ , and cells  $j = 1, \dots, n_i$  (where  $n_i$  is the number of cells of habitat class  $i$  in the study area), define binary decision variables:

$$x_{ij} = \begin{cases} 1 & \text{if cell } j \text{ of habitat } i \text{ is included in the reserve proposal} \\ 0 & \text{otherwise} \end{cases}$$

For the scenario when the study region contains some protected lands, each cell is considered to be either unrestricted or *free* (and thus a candidate for reservation), or restricted (already *reserved*). Specifically, each decision variable is classified according to its reservation status, and the free cells are denoted as

$x_{ij}^F$  while the reserved cells are referred to as  $x_{ij}^R$ . For each habitat  $i$ , the free and reserved cells are assumed to be grouped separately so that the first  $n_i^F$  cells are free and the remainder are reserved. Hence:

$$x_{ij}^F = 0 \text{ or } 1 \quad \text{for } i = 1, \dots, m \text{ and } j = 1, 2, \dots, n_i^F \quad (3.1)$$

$$x_{ij}^R = 1 \quad \text{for } i = 1, \dots, m \text{ and } j = n_i^F + 1, n_i^F + 2, \dots, n_i \quad (3.2)$$

For the second scenario, only equation (3.1) is relevant since those cells currently reserved are allowed to be free so that the number of free cells is  $n_i^F = n_i$ .

Let  $\alpha_i$  be the minimum *percentage* to reserve of habitat class  $i$ . Then  $\alpha_i n_i$ , rounded up to the nearest integer, is the minimum number of cells in the study area of habitat  $i$  that have to be reserved. For the first scenario, the required number of cells for habitat  $i$  may be a combination of free and reserved cells (due to equation (3.2)); thus we write:

$$\sum_{j=1}^{n_i^F} x_{ij}^F + \sum_{j=n_i^F+1}^{n_i} x_{ij}^R \geq \alpha_i n_i \quad \text{for } i = 1, \dots, m \quad (3.3)$$

If the existing reserves contain at least  $\alpha_i n_i$  cells of habitat  $i$ , then no free cells of this class must be selected. For the second scenario (where  $n_i^F = n_i$ ), the

second summation in (3.3) does not exist, so at least  $\alpha_i n_i$  cells of habitat  $i$  must be selected.

Because funding for land acquisition is often a major limitation, the total purchase price must not exceed the available budget. Define  $c_{ij}$  as the purchase price of cell  $x_{ij}$  and let  $C$  be the total budget for acquisition. In order to directly compare the total cost between the two scenarios, the cost of the existing reserves is deducted from the total budget amount for the first scenario. The budget amount,  $C$ , thus represents the total amount available for conservation purposes under both scenarios. Thus we require:

$$\sum_{i=1}^m \sum_{j=1}^{n_i^F} c_{ij} x_{ij}^F + \sum_{i=1}^m \sum_{j=n_i^F+1}^{n_i} c_{ij} x_{ij}^R \leq C \quad \text{for } i = 1, \dots, m \quad (3.4)$$

Again, the latter summation in (3.4) does not exist for the second scenario because there are no reserved cells.

To compare proposals spatially, two metrics were introduced. The first, compactness, was defined as the average Euclidean distance between any two parcels in a reserve proposal. To measure this, all pair-wise Euclidean distances between parcels of land in a reserve proposal were summed together (omitting redundancies). The smallest sum has the smallest average distance between parcels when the amount of land in the reserve proposal is held constant. Shorter distances between reserved parcels can benefit species survival because less travel

through unprotected areas is required. The second metric, contiguity, was defined as the average number of reserved parcels that were adjacent to any other reserved parcel, where two parcels were defined to be adjacent if they share a common edge or corner. To measure contiguity, all adjacencies about each parcel were counted and then summed over all parcels (also omitting redundancies). By decreasing unprotected edges around a reserved parcel, the freedom of movement of some species is enhanced. Also, preserving disjoint clumps of reserved areas that are spatially distant on a landscape can decrease the spread of disease and lower the risk of total habitat destruction from disturbances such as fire and wind.

Let  $d_{ijkl}$  be the Euclidean distance between cells  $x_{ij}$  and  $x_{kl}$ , and define  $a_{ijkl} = 1$  if cells  $x_{ij}$  and  $x_{kl}$  are adjacent and  $a_{ijkl} = 0$  otherwise. Because the spatial measures sum distances and adjacencies between *all* cells (both free and reserved) in a proposal, the <sup>F</sup> and <sup>R</sup> superscripts were ignored for clarity of presentation, and combining both spatial measures into one statement yields:

$$\lambda \sum_{i=1}^m \sum_{j=1}^{n_i} \sum_{k=i}^m \sum_{l=j+1}^{n_k} x_{ij} d_{ijkl} x_{kl} - (1-\lambda) \sum_{i=1}^m \sum_{j=1}^{n_i} \sum_{k=i}^m \sum_{l=j+1}^{n_k} x_{ij} a_{ijkl} x_{kl} \quad (3.5)$$

The first summation in (3.5) measures compactness while the second measures contiguity, and the parameter  $\lambda \in [0,1]$  permits tradeoff assessment between the two spatial metrics. Minimizing (3.5) creates a compact and/or contiguous reserve system since distances and adjacencies are defined to be positive in sign.

Finally, in addition to the minimum habitat requirements, the reservation of more land of any habitat class was included here. In this way proposals from the two scenarios could be directly compared under the compactness and contiguity measures since both required the same number of cells to be reserved. Let  $L$  be the total number of cells that are to be included in a proposal. Then for both scenarios the decision variables must satisfy:

$$\sum_{i=1}^m \sum_{j=1}^{n_i^F} x_{ij}^F + \sum_{i=1}^m \sum_{j=n_i^F+1}^{n_i} x_{ij}^R = L \quad \text{for } i = 1, \dots, m \quad (3.6)$$

The first scenario (with existing reserves) was modeled by minimizing (3.5) subject to (3.1), (3.2), (3.3), (3.4), and (3.6). The second scenario (without existing reserves; i.e.,  $n_i^F = n_i$ ) was modeled by minimizing (3.5) subject to (3.1), (3.3), (3.4), and (3.6) where all cells are free. Both optimization formulations are examples of constrained quadratic 0-1 optimization models. No polynomial time solution methods were known that can optimally solve such programs. Quadratic programs can be transformed into 0-1 integer programs (Rosing and ReVelle 1986; Klein and Aronson 1991) and solved with branch and bound techniques. Unfortunately, the transformation increases the number of decision variables quadratically, and even for problems with only a few hundred 0-1 variables, this renders branch and bound computationally infeasible (due to exponentially increasing solution times). Since most real world data sets contain many thousands of cells, an alternative solution method was needed for this model.

From previous work (Nalle et al. 2000 2001), three common heuristic methods were implemented and experimentally compared on various problems. These were Simulated Annealing (Metropolis et al. 1953; Kirkpatrick et al. 1983), Tabu Search (Glover 1989; Glover and Laguna 1997), and Genetic Algorithms (Holland 1975; Goldberg 1989). From these results, a new method was developed that capitalized on their respective strengths. The new approach, denoted as SA-GS, was as follows. First, an initial feasible solution was randomly generated. The solution is an array that contains as many elements as the number of cells needed to satisfy the habitat reservation requirements plus possible additional cells of any habitat (a total of  $L$  entries). Each element in the array is a reference number that referred to a specific cell in the study region. An exploration search strategy was applied where an individual element was randomly chosen and the occupying reference number (a specific cell) was replaced with a different reference number (i.e., a different cell) of the same habitat type. In this way, solution feasibility was always maintained.

A purely greedy search (GS) was applied first. This operated by randomly choosing an individual vector element (cell reference number), and the occupying cell was replaced with the cell that returned a smaller objective function value, if found. The search terminated after no improvement was made in the objective function after a specified number of iterations had elapsed. The best solution found at this stage was rarely the optimal solution, so Simulated Annealing (SA) was applied to the best solution in hopes of improvement.



Because it was not known if a global optimum had been found, or if the GS solution was a local optimum, SA was used to either intensify the search about the best solution found by GS or move away from the GS best solution. The parameters of SA were tuned so that the initial temperature was approximately 2-3% of the best solution value found by GS, and SA terminated when its temperature was approximately 1% of the GS best objective function value found. Fewer iterations were performed by selecting a relatively small initial temperature and relatively large termination value, thus helping reduce solution time. At termination, the *current* solution of SA (which most likely was *not* the best solution found by SA) was supplied as the initial starting solution to GS, and the process was repeated. In this manner, GS would typically begin with a different solution each time (a diversification strategy). Each repetition was referred to as a cycle, and it was observed that the best solution was usually found within four cycles. When tested on a data set whose global optimum had been found by complete enumeration, the method averaged 0.001% above optimality (vs. 11% above optimality on average for the three common heuristics), and found such solutions in a fraction of the times (8 times faster on average) than the next best heuristic procedure.

### 3.5 Data collection

Josephine County, Oregon was selected for analysis for several reasons. First, the county comprises approximately 10% of the Klamath-Siskiyou ecoregion. This region is diverse physically and biologically (Wallace 1992). Elevation ranges from sea level to 3000m, average January (winter) precipitation varies from under 70 mm to over 850 mm, and hundreds of soil types are found here, including sensitive serpentine soils. Biologically, about 3500 plant taxa are known to occur (8% of which are endemic to the region), including 45 hardwood and 30 coniferous species of trees. The region was declared to be of Global Botanical Significance by the International Union for the Conservation of Nature in 1992.

In order to develop solutions, cell locations, habitat delineation per cell, and purchase price per cell were needed. Physical habitat classifications in the region were derived based on soils, temperature, and precipitation (Vance-Borland 1999); thirteen habitat types were delineated in Josephine County. The region was partitioned with a 1 km grid, and each cell was classified as belonging to one and only one physical habitat type. This was the finest habitat resolution available, so the analysis was conducted using 1 km cells as the decision variables.

Ownership in Josephine County is also diverse. Approximately 69% of the county's 4181 km<sup>2</sup> are publicly owned – about half of this is managed by the USDA Forest Service and a little less by the USDI Bureau of Land Management. Portions of two wilderness areas (Kalmiopsis and Rogue River) comprise 6% the

county, the USDI National Park Service manages the Oregon Caves National Monument, the USDI Wildlife Refuge System administers stretches of Wild and Scenic Rivers and Viewpoints along the Rogue and Illinois rivers, and there is a small amount of scattered land owned by the state of Oregon. The local economy is primarily resource based (forestry, mining, farming, and livestock grazing), and land management objectives of the different owners in the county include resource extraction, tourism, and recreation.

Market values on all private and some public lots were obtained from the Josephine County Assessors Office database. It was assumed that the market value accurately estimated the net present value of all future income streams from the land. In cases where no assessed market values were available on public lands, the values were imputed based on the market values of neighboring lands so that all values were measured on a comparable basis. The habitat classification map and land value map were then overlaid to obtain an estimated purchase price per cell.

Some caveats about this land value estimation procedure should be noted. Land is typically less expensive per unit area when purchased in large tracts. Hence, the value of cells contained within larger tracts might be underestimated. Also, price elasticities were ignored since it was unclear how a large reservation of land (i.e., a decrease in the supply of economically viable land) in the county would impact the local economy and thus change land values.

### 3.6 Results

For both scenarios, it was supposed that a minimum of 10% of each habitat must be reserved, although results were consistent for all percentages that were explored (these ranged from 5% to 40% per habitat). Each of the two scenarios was run separately for values of  $\lambda = 0$  (contiguity measure only) and  $\lambda = 1$  (compactness measure only). All optimization runs were performed using MATLAB v5.3 executable code (The Mathworks 1999) on a 700 MHz PC with 512 MB of RAM. Solution times ranged from 3 to 10 minutes per run.

For the first scenario, 266 cells are already reserved, and these completely meet the requirements of three of the thirteen habitat classes. An additional 254 cells from the remaining ten habitats had to be reserved (i.e., in the optimization

model  $\sum_{i=1}^m \sum_{j=1}^{n_i^F} x_{ij}^F = 254$  and  $\sum_{i=1}^m \sum_{j=n_i^F+1}^{n_i} x_{ij}^R = 266$ ) to satisfy the 10% minimum

requirement, thus reserving 520 cells in total. A breakdown of the number of cells per habitat, number of existing reserved cells per habitat, and the number of additional cells needed is found in Table 3.1. For the second scenario, 424 cells had to be selected to meet the habitat requirements in Constraint (3.3). To make the first and second scenarios directly comparable spatially, an additional 96 cells

of any habitat class also had to be reserved (i.e.,  $\sum_{i=1}^m \sum_{j=1}^{n_i^F} x_{ij}^F = 520$  and

$\sum_{i=1}^m \sum_{j=n_i^F+1}^{n_i} x_{ij}^R = 0$ ) so that again 520 cells are reserved in total. Table 3.1 also lists

the number of cells per habitat that must be selected for the second scenario.

To provide benchmark solutions that do not account for spatial design issues, the minimum cost proposal was first found for each scenario. That is, for the first scenario, the total estimated purchase price was minimized subject to constraints (3.1), (3.2), (3.3), and (3.6); for the second scenario, cost was minimized subject to constraints (3.1), (3.3), and (3.6). In order to meet the habitat requirements, the minimum purchase price of the existing reserve system is approximately \$24.1 million, while the minimum cost without the existing reserves is approximately \$19.5 million. To explore how cost affects total reserve compactness and contiguity, the budget amount,  $C$ , was increased incrementally from each scenario's minimum cost value until constraint (3.4) was no longer binding.

Figure 3.1 maps the best solutions found for each scenario when selecting for contiguity ( $\lambda = 0$ ). As the budget amount increases, there is greater flexibility in cell placement and disjoint cells are allowed to clump together to form larger, disjoint reserve areas. For smaller budget amounts, cell placement between the two scenarios is fairly consistent but such overlap dissipates as the budget increases. The divergence is caused by the existing reserves and shows that even though they only cover three habitats at the

Table 3.1. Cells per physical habitat type and number of additional cells to be selected.

Habitat	total #	First Scenario with existing reserves		Second Scenario without existing reserves	
		free	reserved	free	reserved
1	35	4	0	4	0
2	280	14	14	28	0
3	61	7	0	7	0
4	124	13	0	13	0
5	1052	106	0	106	0
6	154	16	0	16	0
7	181	19	0	19	0
8	357	36	0	36	0
9	129	13	0	13	0
10	830	0	130	83	0
11	259	26	0	26	0
12	605	0	93	61	0
13	114	0	29	12	0
total	4181	254	266	424	0
additional cells		0	NA	96	NA
total # of cells in the proposal		520		520	

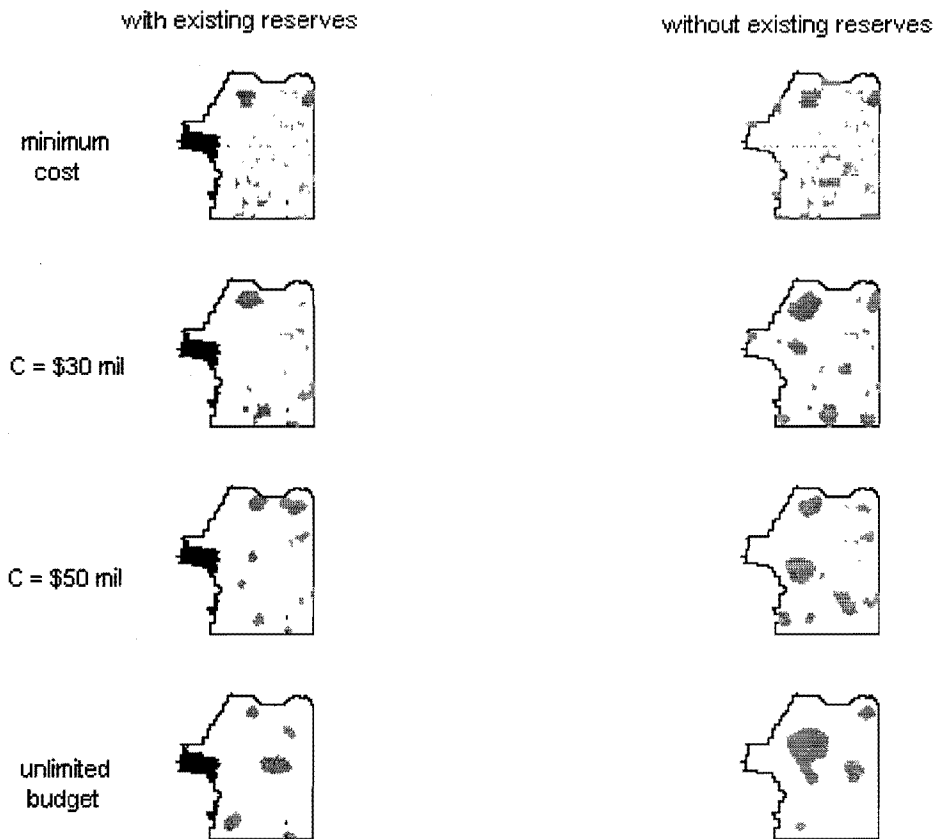


Figure 3.1. Cells are selected under the contiguity measure ( $\lambda = 0$ ). The left-hand column depicts the first scenario where an existing reserve system (266 cells) is augmented with additional cells (254 cells) to meet minimum habitat requirements (520 cells in total). The right-column depicts the second scenario where existing reserves are ignored; 424 cells are needed to meet the minimum habitat requirements and 96 additional cells are selected (520 cells in total) to make the first and second scenarios directly comparable using the contiguity measure. The black cells are the existing reserves, and the gray cells are those selected by the algorithm.

10% level, this coverage is sufficient to skew future placement under the contiguity measure.

Figure 3.2 maps the best solutions found for each scenario when selecting for compactness ( $\lambda = 1$ ). The maps on the top row of Figure 3.2 are the same as those on the top row of Figure 3.1; these are the minimum cost solutions that ignore spatial considerations. As was found with the contiguity measure, cell placement between the two scenarios changes greatly as the budget increases. The second scenario (without existing reserves) pulls inward to form a nearly circular clump, whereas the first scenario remains fragmented. Once again the existing reserves skew future cell placement for compactness and greatly reduce the best compactness attainable.

Direct analytical comparisons of reserve contiguity, compactness, and cost for the two scenarios are found in Figures 3.3 and 3.4. These four graphs depict total cost curves by connecting the spatial measures of the best proposals found over different budget amounts. Subplots 3.3(a) and 3.3(b) examine contiguity, and subplots 3.4(a) and 3.4(b) examine compactness. Both 3.3(b) and 3.4(b) rescale the abscissa of 3.3(a) and 3.4(a), respectively, so that the differences between the two scenarios can be more readily seen. In Figure 3.3(a) large marginal returns on contiguity for both scenarios are initially possible for slight increases in the allowable budget. However, returns decrease rapidly once the budget exceeds approximately \$28 million (Figure 3.3(b)). Large initial returns on compactness also occur for both scenarios (Figure 3.4(a)), but these trail off



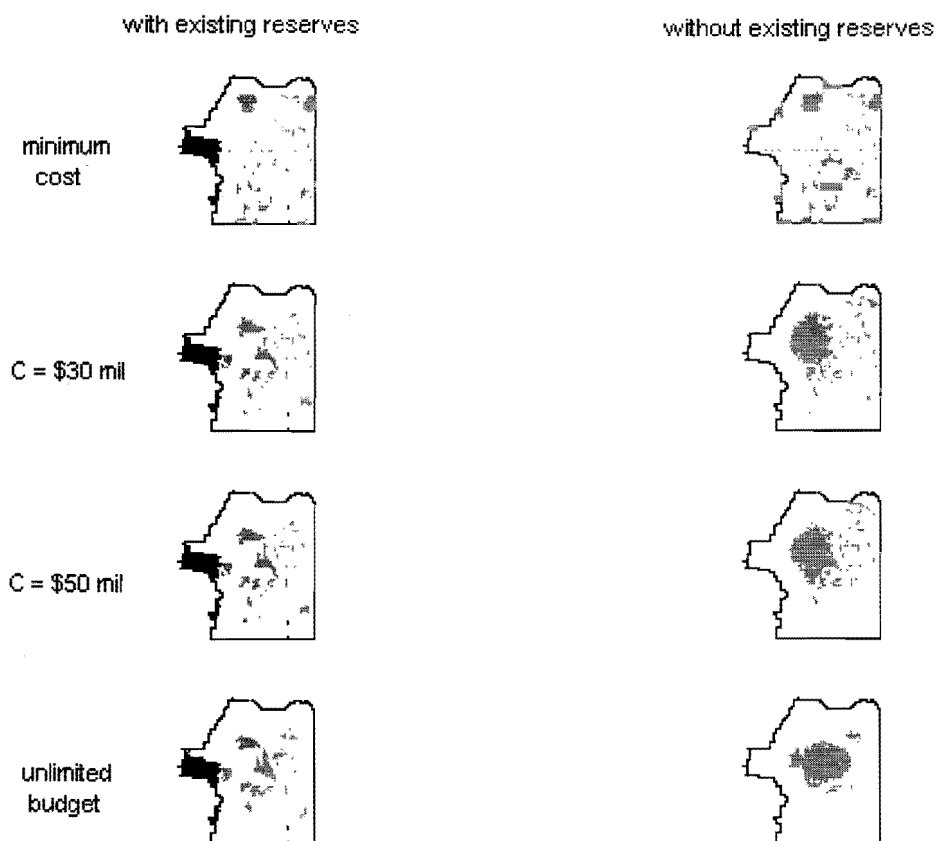


Figure 3.2. Cells are selected under the compactness measure ( $\lambda = 1$ ). The left-hand column depicts the first scenario where an existing reserve system (266 cells) is augmented with additional cells (254 cells) to meet minimum habitat requirements (520 cells in total). The right-column depicts the second scenario where existing reserves are ignored; 424 cells are needed to meet the minimum habitat requirements and 96 additional cells are selected (520 cells in total) to make the first and second scenarios directly comparable using the compactness measure. The black cells are the existing reserves, and the gray cells are those selected by the algorithm.

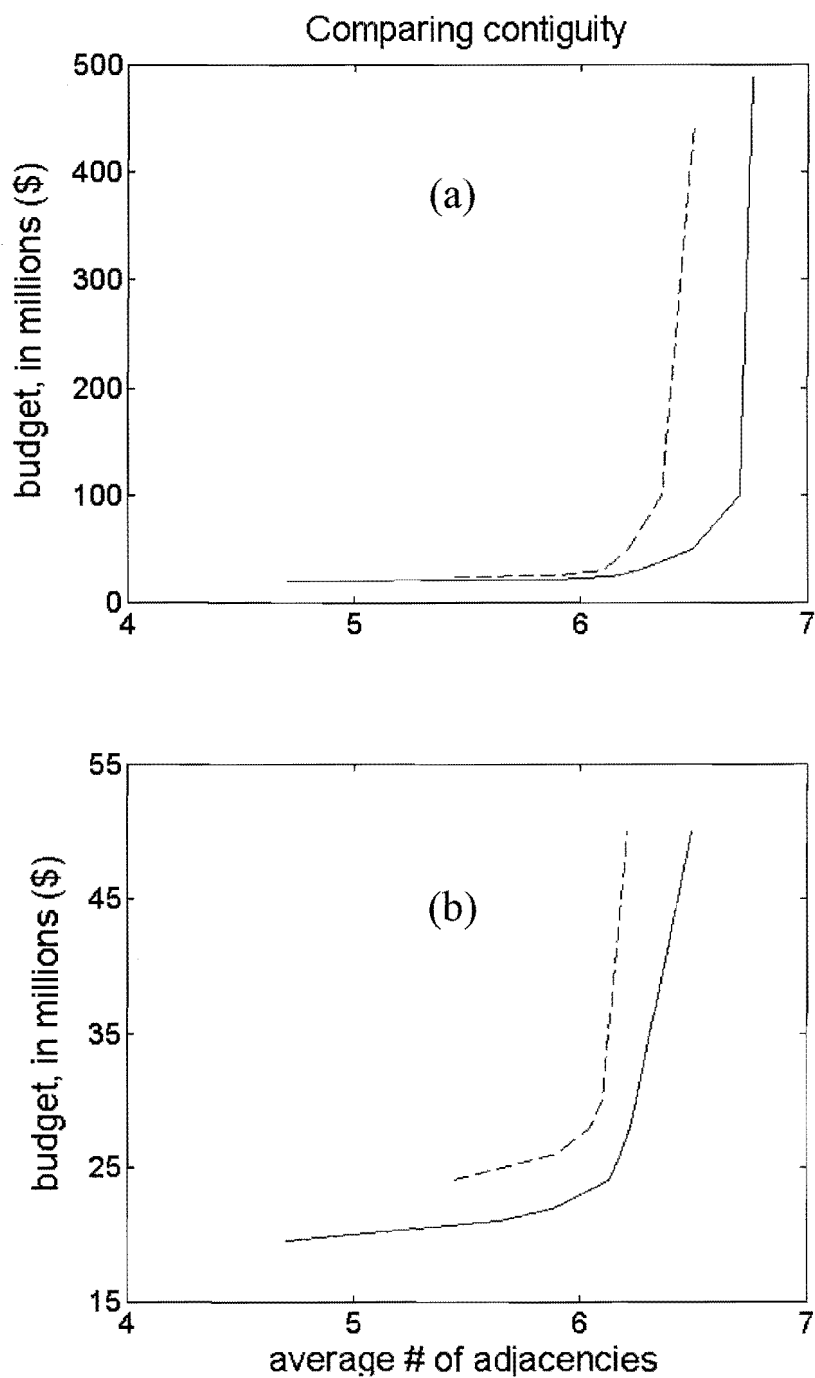


Figure 3.3. Total cost curves for contiguity. Results found from the first scenario when existing reserves are included are plotted with a dashed line. Results when existing reserves are ignored are plotted with a solid line.

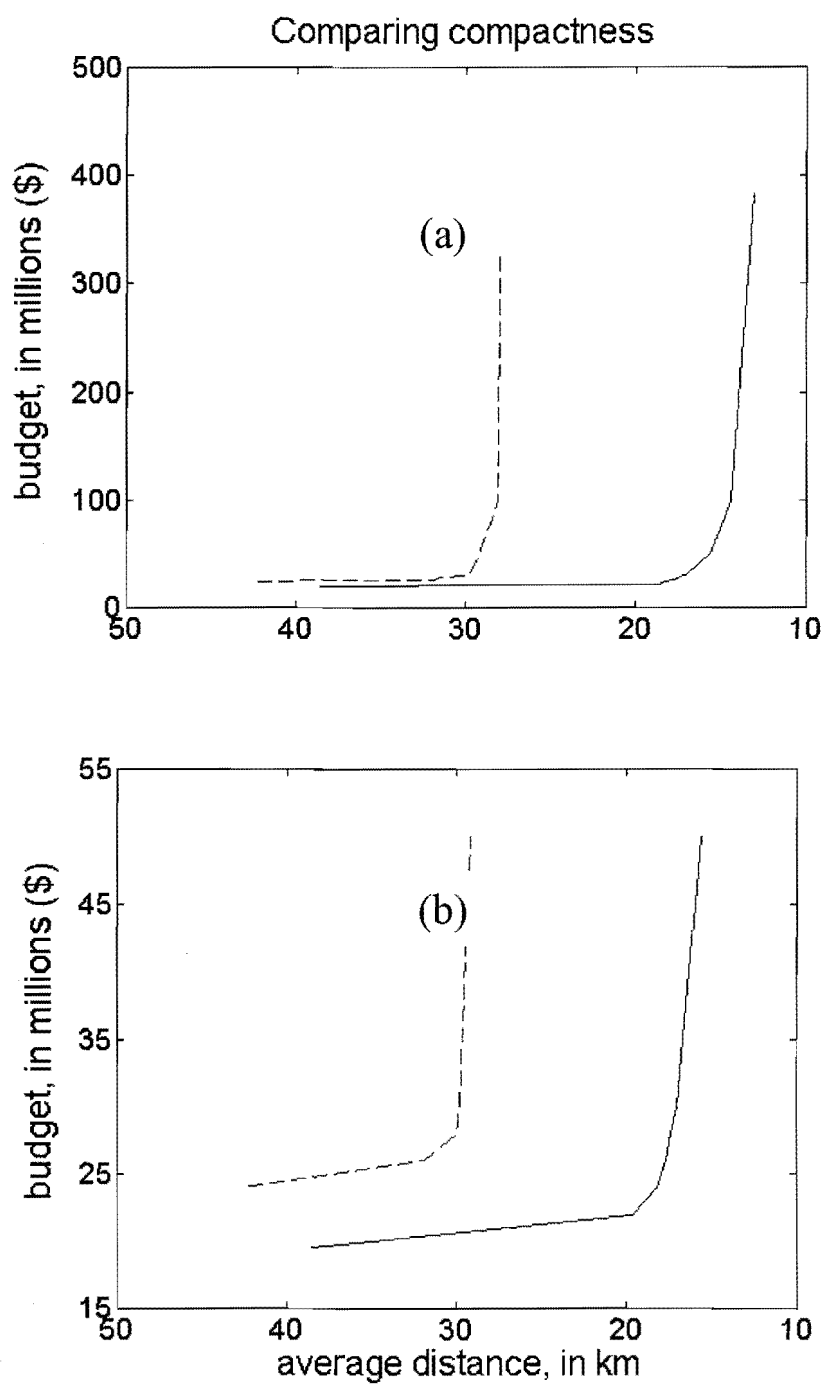


Figure 3.4. Total cost curves for compactness. Results found from the first scenario when existing reserves are included are plotted with a dashed line. Results when existing reserves are ignored are plotted with a solid line.

once the budget exceeds approximately \$26 million (Figure 3.4(b)). The plots show that for the same budget amount, the second scenario always has greater reserve contiguity and compactness; conversely, for a given level of contiguity or compactness, the second scenario always finds a less expensive proposal. Furthermore, when satisfying the minimum habitat requirements at least cost (ignoring spatial measures), the existing reserve system costs \$4.6 million more – an inflation of 24%.

### 3.7 Discussion

The maps are a useful means of presentation because they show where and how reserve location changes for various levels of funding. The cost curves illustrate what levels of financial investment are needed to achieve desired spatial outcomes for a reserve design. They also demonstrate what is spatially attainable if a management decision is made to “trade up” from an augmented design with existing reserves to one that is not bound by existing reserves. With these tools, it has been shown that existing reserves can constrain the best possible contiguity and compactness attainable. Also the cost curves show that the average cost per additional cell is higher for the existing reserve system.

The existing reserve system represents the conservation efforts of different individuals and owners under many objectives. All operate within an institutional framework of landownership rights and regulations that influence and constrain

management behavior. This work indicates that uncoordinated conservation objectives can impact overall design, and that additional effects are associated with these issues. A more efficient allocation of resources might result not only in more effective species preservation, but the potential cost savings could be transferred to other regions for enhanced protection.

We note that the total cost of acquiring land may not be a comprehensive measure of economic impact. Spatial economic effects have so far been ignored. It might be expected that as reserve locations change, so too will the magnitude and locations of regional economic impacts. Future work will incorporate economic input-output models and measures of non-market amenities to better estimate the costs and benefits of land withdrawals at different scales. These estimated effects could be used to spur dialogue between public and private or urban and rural groups concerning subjects such as public compensation to private owners for lost revenues, rural community-level transition assistance, or potentially higher commodity prices resulting from the loss of land for production. Consideration of all of these issues might help society better determine the levels of species conservation it is willing to maintain.

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## **Chapter 4**

### **Estimating Extinction Risk with Spatial and Temporal Measures**

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#### 4.1 Abstract

Ecologists have long recognized that landscape change is the rule rather than the exception. Human induced alterations, however, have greatly increased the rate of change and, consequently, affected species populations to various degrees. To better model the risk of species extinction or extirpation, the impacts of temporal and spatial changes must be included in the estimation procedure. This paper presents methodology for estimating habitat quality and population sizes obtained from a detailed wildlife simulator as a landscape changes through time and space. The estimates are based on the suitability of a territory for occupation as well as the suitability of surrounding territories. As changes to a landscape occur the estimates can be quickly updated, making it possible to interface with other software applications in real time. In particular, embedding the estimators within an optimization model is computationally feasible, whereas direct use of the wildlife simulator often is not. The approach is demonstrated using a wildlife simulator (PATCH) from the U.S. Environmental Protection Agency and species with different vital rates, habitat preferences, and movement behavior.

Key words: extinction risk estimation, wildlife population modeling, PATCH.

## 4.2 Acknowledgements

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### 4.3 Introduction

Human demand for economic-based outputs from the land base has accelerated the rate of landscape change. These changes have in turn affected the populations of different wildlife species (Maurer and Villard 1996; Fagen et al. 2001), and the consequences – both actual and anticipated – have helped drive conservation policy and planning (Dunning et al. 1995; Turner et al. 1995; Murphy 2001). A frequent part of conservation policy and planning is measurement of the risk of species extinction and extirpation (Fahrig 1997; Fagen et al. 2001). Accurate estimation of future population trends requires, in part, simultaneous knowledge of species' vital rates (survival and reproduction), habitat requirements (source/sink characteristics), and movement behavior (site occupation and re-colonization) (Conroy et al. 1995; Brawn and Robinson 1996; Ruckleshaus et al. 1997; Mooij and DeAngelis 1999; Ruckleshaus et al. 1999; South 1999). Because extirpation risk is a measure of uncertainty over time and space, in addition to detailed species-specific knowledge, the incorporation of inter-temporal spatial relationships can lead to more realistic risk estimation.

Timber harvest is used here, in addition to forest growth, as a vehicle for habitat alteration over time. Harvests are one of the most common activities having a major impact on wildlife in the selected study area for this work. To examine the impacts of landscape change on species populations, different management regimes could be implemented on the ground and their effects thus

observed. However, experimental methods cannot be applied because resource requirements are limiting, necessary time frames may be too long, and experiments might result in the extirpation of the species of concern. Simulation provides a useful alternative to real life manipulation and observation on the landscape – especially the study of management scenarios that might lead to extirpation.

Past efforts at simulating population responses have by and large been hampered by computing power and storage space, available species data (Conroy et al. 1995; Brawn and Robinson 1996; Ruckleshaus et al. 1997), and modeling of spatial relationships. To circumvent such limitations, researchers have often been forced to use simplistic modeling procedures, and these concessions generally reduce inferential power and can bring results into question. Recently, enhanced computing power and better knowledge of species vital rates, habitat preferences, and dispersal behavior have accelerated the development of species simulators with increased realism and flexibility. One such wildlife simulator is PATCH (a Program to Assist in Tracking of Critical Habitat). PATCH (Schumaker 1998) is a spatially explicit, stochastic simulator that reads GIS imagery and species life history characteristics to link every attribute of a species' life cycle to the quality and distribution of habitat throughout a landscape. The model tracks an entire population of organisms comprised of individuals that are born, disperse, breed, and die. Landscape change is simulated by loading different maps of habitat quality as time progresses, and the effects on species populations (hence on

extinction or extirpation risk) are directly simulated.

This work is motivated by the increasing pressure on land managers to do more with less. Managers must often make difficult resource allocation decisions that impact regional economic and ecological conditions. Costs are an important aspect in the decision process, and the single largest contributor may be the opportunity cost of foregone economic production. Optimization tools are useful in such situations since they can address questions of economic efficiency and cost-effectiveness on a large landscape over a long planning horizon. However, they also can be used to identify types of management actions that minimally affect important ecological factors that managers must consider, such as the risk of species extirpation.

This paper is one component of a broader study that attempts to maximize the production of sustainable economic and ecological outputs from a large landscape. One obstacle to the combined economic and ecological modeling approach is that direct interfacing with PATCH during dynamic optimization is presently infeasible due to long simulation run times. Although results from PATCH can generally be obtained within seconds or minutes, this is too slow when used in conjunction with optimization procedures that can require millions of iterations (especially if wildlife simulations are needed at each iteration of the optimization procedure). Thus a proxy measure for PATCH simulation results that could be quickly computed and updated was needed, and this is the focus of the current paper. Because wildlife simulation is the preferable alternative to

large-scale, real-world landscape experimentation, and since PATCH and PATCH-like models provide the best predictions for wildlife simulation, the proxy should only be regarded as an approximation to estimated population reactions to different management scenarios.

Results are obtained here using forestry models and one specific wildlife simulator, but the approach is general and can be used for any application seeking to estimate the risk of species extirpation. There are three main contributions of this work: (a) spatial estimation methods for determining habitat quality as a landscape changes through time are developed, (b) a means of quickly updating habitat quality estimates when simulating landscape change is given, and (c) it is demonstrated how a time series of estimated population sizes can be quickly approximated on a large landscape. With these three steps, it is possible to build more realistic ecological estimation into a dynamic optimization procedure.

The remainder of this paper is organized as follows. Section 4.4 describes the study area and the three species that were selected for modeling. Section 4.5 introduces the associated data needed for the wildlife simulator and the methods used in deriving quick, spatially explicit, proxy measures for PATCH results. Section 4.6 presents results from a validation study of these measures. Lastly, Section 4.7 contains discussion.

#### 4.4 Study area and focal species

To realistically model species population sizes and estimate risks of extirpation, a large study area was selected from the map of vegetative cover for the Willamette River Basin in western Oregon in 1990 (Pacific Northwest Ecosystem Research Consortium 2001). The area stretches 108 km from the crest of the Cascade Range westward to the Willamette Valley and is 184 km from north to south (1.7 million hectares in total). The types of habitat that occur are similar on a north-south gradient but generally change uniformly on an east-west gradient due to topography. All farmland and major cities and towns lie near the western border of the study region. The remaining 70% is predominately coniferous forest cover with some mixed hardwood and softwood stands.

Landscape change should affect species differently because each species has evolved its own set of habitat affinities. Hence, conservation planning must take into account potential tradeoffs between species. In this work, three focal species endemic to western Oregon were selected to explore how temporal and spatial harvest schedules affect expected population sizes and to identify tradeoffs among species. These species are the Gray jay (*Perisoreus canadenis*), the Great horned owl (*Bubo virginianus*), and the Common porcupine (*Erethizon dorsatum*). Ecologists have hypothesized these three species to prefer different types of forested habitat (Bigger and Vessely 2000). The Gray jay is expected to have the highest affinity for mature stands, is thought to be sensitive to human development, and is found at elevations of 600m to 1650m. The Great horned owl is thought to be a generalist (as long as larger diameter trees are available for



nesting) with the exception of intermediately-aged, dense stands. Such stands have reached canopy closure, are beginning to experience competition-induced mortality, and have little or no understory vegetation. Not only is navigation in these stands difficult for the large predator, but the absence of an understory can preclude the owl's prey of small mammals and other birds. The Common porcupine is also thought to be a generalist with its stand preference decreasing with stand age. The Great horned owl occasionally preys upon the Common porcupine, but the impact on populations is thought to be negligible (Verts and Carraway 1998). It was expected that the different dispersal distances will lead to different configurations of preferred habitat on the landscape.

Vital rates are conferred with a population projection, or Leslie matrix (Caswell 1989). When life history data is limited, allometric scaling relationships (Brown 1995) that relate vital rates and movement ability to body size can be used instead.

## 4.5 Methods

Since temporal and spatial aspects are essential factors when estimating extinction risk, a two-step procedure was developed for (i) estimating habitat scores and (ii) approximating simulated population sizes as the landscape changed temporally and spatially. The first sub-section describes the different PATCH parameter settings used for all subsequent analyses, while the second sub-section

details how habitat quality was estimated through time and space. The third sub-section overviews the statistical collection of data from smaller landscapes, and that last sub-section describes how the estimated population density prediction equations were derived.

#### 4.5.1 PATCH parameterization

PATCH offers a variety of parameters that can be fine-tuned to better model the species of interest. Each species was selected for its different life history characteristics, expected habitat preferences, minimum predator-prey interactions, and dispersal distances (Table 4.1).

In addition to the territory size of a species, its maximum dispersal distance, and population projection matrix, the type of search a species performs when looking for quality habitat can be controlled. For all simulations and species in this paper, an intelligent search was imposed, meaning that an individual would select the highest quality site (from those that are unoccupied) within its maximum yearly dispersal distance.

Another important setting is the distribution of the initial (simulated) population on the landscape. PATCH allows the user to do one of two things.

Table 4.1. Species life history characteristics, taken from Adamus (2000).

	Gray jay <i>Perisoreus canadensis</i>	Great horned owl <i>Bubo virginianus</i>	Common porcupine <i>Erethizon dorsatum</i>
territory size (ha)	65	50	80
max annual dispersal distance (km)	11	75	3
General habitat rankings (0-10)			
stand age:			
young	1	4	10
intermediate	4	8	8
mature	10	10	7
expected life span (yrs)	3 – 6	15 – 20	4 – 7
Leslie matrix	0.00 0.90	0.00 0.35 0.35	0.00 0.50
	0.32 0.82	0.68 0.00 0.00	0.38 0.74
		0.00 0.76 0.85	

Either the software automatically places one individual on each territory that contains some amount of habitat, or the user can manually specify the set of occupied territories at the outset. If territories at the outset generally contain poor to marginal habitat, population sizes will decline during the first two to three decades when simulations are performed on static landscapes (i.e., simulating populations on a single, non-changing map for a specified number of years), until reaching a more-or-less steady state (due to stochasticity). The converse holds as

well. For this work, the initial population was always automatically specified by PATCH in order to save time when initializing the simulator.

In order to run PATCH, at least one raster-based map must be loaded into memory. Each map represents habitat quality for a single species by assigning integer scores to every pixel on the map. The higher the score of a pixel, the better its expected quality of habitat. Quality may depend on the interaction between many different factors, such as the vegetative structure, type of cover, and forest age-class in the pixel; type and amount of vegetative structure, cover, and age in the surrounding pixels; or the pixel's distance to the nearest stream, road, or urban area. For the purposes of this study, habitat scores ranged from 0 (the poorest) to 10 (the highest). Management actions and habitat change are represented in PATCH by loading a new map for each desired time period. In its current form, the software can only estimate population responses of one species per simulation. Thus, in order to simulate multiple species on a changing landscape over time, multiple habitat maps (one time-series of maps for each species) must be individually generated, loaded, and simulated.

One habitat map for each species was compiled by an expert panel of ecologists (Adamus 2000); these are found in Figure 4.1. The panel used species-specific knowledge and a map of the vegetative cover in 1990 with pixel resolution of 30m by 30m (Pacific Northwest Ecosystem Research Consortium 2001). Hence, to reconstruct the panel's scoring mechanism for each species, the habitat quality of every pixel was a function of the pixel's vegetative cover and

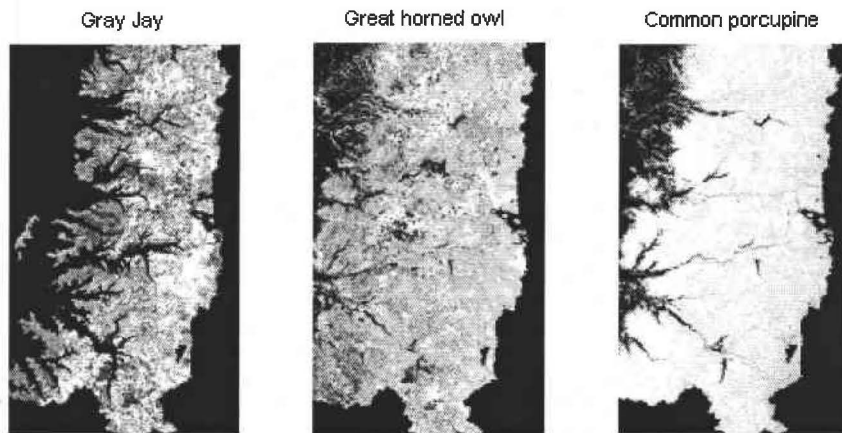


Figure 4.1. Initial habitat maps compiled by expert opinion. The lighter the shade of gray, the higher the quality of habitat for that species on the landscape.

other unknown factors. Furthermore, because the derivation of habitat maps was done only once and was based only on the vegetative cover in 1990, these maps represent the expert panel opinion at a single point in time. Therefore, to evaluate the impact of changes on the landscape, the landscape itself must be re-evaluated.

#### 4.5.2 Estimating habitat quality

The habitat maps are a quantitative measure of the ability of each location on the landscape to support an individual member of a population. However, the maps are also qualitative since they were derived from expert opinion. The first task was to generate a spatial scoring procedure based on the observable landscape attributes in 1990 so that scores could be quickly updated when simulating landscape change (i.e., applying different management actions to different locations through time). It was assumed that the underlying map of vegetative cover in 1990 (from which the experts compiled the habitat map for each species) had sufficient variation to represent the full range of possible spatial habitat arrangements.

The first step towards estimating habitat quality as the landscape changed was to examine how habitat scores for each species were derived. The habitat maps revealed that, for each species, habitat quality of a pixel was not a one-to-one function of its stand age. For example, even though the gray jay is expected to have the strongest preference for mature (old-growth) stands, this vegetation

class was not always rated a 10 and was often scored a 0. Error could account for some of these rankings, but preliminary regression analysis showed that a species-specific habitat score for a pixel could be accurately modeled as a function of the its forest age class and the forest age class distributions of neighboring pixels. Because another component of our work was to contrast species survival with timber production, management units were defined on the landscape. This was done using a uniform grid, and the area of each square management unit (70.5 hectares – or 784 pixels) was chosen to be approximately the average territory size of the three species. So that an altered landscape could be re-scored, it was necessary to re-evaluate the habitat quality of each management unit (as well as those units within some proximity) when landscape attributes were dynamically changed during optimization. The habitat quality of each management unit for each species was measured by summing the habitat scores of all pixels within the management unit (for that species).

Since the quality of habitat within a management unit might be influenced by the surrounding quality of habitat, a ring structure about each unit was devised. This is shown graphically in Figure 4.2. Those units whose geographic centers were within 840m, or a 1 “unit” distance, were defined be in the first ring about a generic management unit. The units whose centers were at least 840m but less than 1680m (a 2 “unit” distance) comprised the second ring, and units centered at least 1680m but less than 2520m (a 3 “unit” distance) defined the third ring. This

was repeated until a list of ten rings about each generic management unit were enumerated.

To model these basic spatial relationships, regressions were performed. Specifically, the following notation is defined for each management unit  $u = 1, \dots, n$  and its associated ring structure  $r = 1, \dots, 10$ :

$c_{u1}$  = number of coniferous pixels aged 0-20 years within generic unit  $u$ ;

$c_{u2}$  = number of coniferous pixels aged 21-40 years within generic unit  $u$ ;

$c_{u3}$  = number of coniferous pixels aged 41-60 years within generic unit  $u$ ;

$c_{u4}$  = number of coniferous pixels aged 61-80 years within generic unit  $u$ ;

$c_{u5}$  = number of coniferous pixels aged 81-200 years within generic unit  $u$ ;

$c_{u6}$  = number of coniferous pixels aged  $> 200$  years within generic unit  $u$ ;



			3			
	3	3	2	3	3	
	3	2	1	2	3	
3	2	1	unit	1	2	3
	3	2	1	2	3	
	3	3	2	3	3	
			3			

Figure 4.2. Ring structure used for estimating a generic harvest unit's habitat score for each species.

$c_{u7}$  = number of mixed hardwood and softwood pixels in generic unit  $u$  (no age classifications were available for mixed forested pixels);

$R_r^u$  = the set of management units in ring  $r$  about generic management unit  $u$ .

All management units were used when estimating habitat quality for the owl and porcupine, but only those units falling within the gray jay's elevation range were used. The total habitat score of a management unit, for each species,  $i = 1, 2, 3$ , was estimated from ordinary least squares with equation (4.1):

$$\begin{aligned}
 \text{(habitat score)} \\
 \text{E} \left| \begin{array}{l} \text{for species } i \\ \text{in unit } u \end{array} \right| &= \beta_{i0} + \sum_{g=1}^7 \beta_{ig} c_{ug} + \sum_{w \in R_1^u} \sum_{g=1}^7 \beta_{i(g+7)} c_{wg} \\
 &+ \dots + \sum_{w \in R_{10}^u} \sum_{g=1}^7 \beta_{i(g+93)} c_{wg}
 \end{aligned} \tag{4.1}$$

The estimated regression coefficients (assuming unbiased, independently distributed normal errors for each species) are given in Table 4.2. It was found that only the first three rings were statistically significant for the three focal species, and that a large proportion of variation for the owl and porcupine was explained by the regression results. Even though these species have different dispersal characteristics, the three-ring sphere of influence likely represents the dampening effect of distance within PATCH. These relationships were assumed

to be constant through time since they were based on only the initial habitat map of each species.

It was decided to drop the Gray jay from the study due to low predictive power and seemingly nonsensical results. The estimated coefficients for stands aged 61 to 80 years are always negative and are generally the largest in magnitude among the other coefficients within a ring. There is no reason for this to have occurred (Ernst 2001) and it could not be adequately explained. Possible contributors could be (i) an underlying error in the initial habitat maps compiled from expert opinion; (ii) the jay's restricted elevation range; (iii) an invalid assumption that the 1990 map contained sufficient variation; or (iv) interaction between (ii) and (iii). Although the cause is unknown, this demonstrates how dependent the habitat scoring procedure for each species is on just the one initial habitat map.

The residuals from fitting the equations in Table 4.2 represent unobservable factors influencing a unit's habitat score (such as distance to a stream or road). These were recorded for each management unit. As forest cover changed through time and through harvesting (it was assumed that all harvested stands were regenerated into coniferous forest), the habitat score for each management unit and each species was computed with the equations in Table 4.2, and then adjusted by adding the residual to this value. This way, the predicted habitat scores for every management unit were calibrated to be the same as those from the initial habitat maps. By adding the residual value to each unit, it is

Table 4.2. Estimated regression coefficients for predicting a unit's habitat score. A '\*' represents those coefficients that are statistically significant at the 0.05 level, while a '\*\*' represents significance at the 0.01 level.

Coefficient for variable	Gray jay	Owl	Porcupine
Intercept	3847.672**	364.621**	282.539 **
# of pixels in the unit aged 0-20	-0.031	0.180 *	0.189 *
# of pixels in the unit aged 21-40	-0.071	0.042	0.376
# of pixels in the unit aged 41-60	0.161	0.224	0.395
# of pixels in the unit aged 61-80	-0.025	-0.365	-0.403
# of pixels in the unit aged 81-200	-0.042	0.048	0.056
# of pixels in the unit aged 200+	-0.074	0.197 *	0.337 **
# of pixels of mixed forest cover	-0.060	0.162 *	0.297 **
# of pixels in 1 <sup>st</sup> ring aged 0-20	-0.110	0.253 **	-0.340 **
# of pixels in 1 <sup>st</sup> ring aged 21-40	-0.488	0.011	-0.131
# of pixels in 1 <sup>st</sup> ring aged 41-60	0.150	0.381 **	-0.302 *
# of pixels in 1 <sup>st</sup> ring aged 61-80	-1.429 **	0.050	-0.484 *
# of pixels in 1 <sup>st</sup> ring aged 81-200	-0.385 **	-0.025	-0.345 **
# of pixels in 1 <sup>st</sup> ring aged 200+	-0.398 **	0.065	-0.127 *
# of pixels in 1 <sup>st</sup> ring of mixed forest	-0.147*	0.042	-0.184 *
# of pixels in 2 <sup>nd</sup> ring aged 0-20	-0.080	-0.238 **	0.825 **
# of pixels in 2 <sup>nd</sup> ring aged 21-40	-0.259	-0.065	0.894 **
# of pixels in 2 <sup>nd</sup> ring aged 41-60	0.378 **	-0.374 **	0.643 **
# of pixels in 2 <sup>nd</sup> ring aged 61-80	-0.360	0.033	1.007 **
# of pixels in 2 <sup>nd</sup> ring aged 81-200	0.523 **	0.132 **	0.526 **
# of pixels in 2 <sup>nd</sup> ring aged 200+	0.740 **	0.155 **	0.473 **
# of pixels in 2 <sup>nd</sup> ring of mixed forest	0.187 **	0.326 **	0.725 **
# of pixels in 3 <sup>rd</sup> ring aged 0-20	-0.109 **	0.173 **	0.368 **
# of pixels in 3 <sup>rd</sup> ring aged 21-40	-0.119	0.245 **	0.408 **
# of pixels in 3 <sup>rd</sup> ring aged 41-60	-0.020	-0.048	0.222 **
# of pixels in 3 <sup>rd</sup> ring aged 61-80	-0.265	0.435 **	0.257 **
# of pixels in 3 <sup>rd</sup> ring aged 81-200	0.072 **	0.214 **	0.288 **
# of pixels in 3 <sup>rd</sup> ring aged 200+	0.074 **	0.219 **	0.252 **
# of pixels in 3 <sup>rd</sup> ring of mixed forest	-0.065 **	0.282 **	0.306 **
R <sup>2</sup>	0.35	0.76	0.88

implicitly assumed that the unobservable factors do not change with time. In reality this may not be true, but the assumption is necessary since only one habitat map per species was available that had been compiled by expert opinion.

From the equations in Table 4.2, the habitat score for each unit and each species could be quickly computed as the forest cover within each pixel either aged or was changed by timber management activities. In order to simulate the effect of harvesting on habitat quality, if a unit was scheduled to be harvested, then its habitat score could be quickly changed by subtracting off the contribution of its current forest cover and then adding the effect of the new forest cover.

Also, because habitat scores were found to change based on the distribution of forest type and age classes from all units in the three surrounding rings, harvest of a single unit would cause changes to all habitat scores in the 3-ring sphere of influence from the first period of harvest until the end of the planning horizon.

The linearity of the equations in Table 4.2 allows scores to be quickly updated. This is important for two reasons. The first is because additivity does not require the entire habitat scoring measure for a unit and those units in the three surrounding rings to be recomputed every time a management action is altered. Only the change in forest cover type and coniferous forest age class within a single unit must be addressed. Second, linear functions require far less computation time than more complex operations such as SQRT, LN, or EXP. To better integrate a realistic species simulator in an optimization routine that might

require millions of iterations, any decrease in CPU time per iteration will magnify returns in speed over the course of solution.

#### 4.5.3 Population data generation

With a means for predicting habitat score through time and space having been established, the next step was to generate data from which to estimate species population sizes as the landscape changed through time. Ideally, various management regimes would be simulated on the entire study landscape (1.7 million hectares) with dynamically changing, spatially-linked habitat scores. However, the habitat maps needed for one simulation run in PATCH on the entire study area required approximately 1.5 GB of storage space and about 3 hours of CPU time to generate on a PC with two 700 MHz processors in parallel. Consequently, forty smaller sub-landscapes were randomly selected from the study area. These ranged in size from approximately 2% to 20% of the larger region, and varied in shape (e.g., square, rectangular).

Simulated management activities were performed on each sub-landscape. The intent was not to generate likely or even feasible timber management, but to provide a broad range of series of landscapes on which to simulate species survival and, from these results, to develop dynamic linkages of population responses. The activities fell into four broad categories: “high” harvesting, “medium”, “low”, and “no” harvesting over the 100-year periods. Each unit was

deemed to be available for harvest if at least 25% of its pixels were classified as coniferous forest. If a unit was selected for harvest within the 100-year planning horizon, a prescription was randomly assigned. Each prescription consisted of a series of actions in each decade which were to either clear-cut or do nothing. Harvest activities could occur in any decade, but a 20-year minimum rotation age was imposed to contain the number of possible prescriptions. For the “high” harvest category, all harvestable units were felled at least once during the 100-year horizon. In the “medium” category, at least half but not all of the harvestable units were felled at least once during the horizon. For the “low” category, at least one harvestable unit but less than half were felled, and for the “no” category, no harvesting ever occurred (i.e., the entire sub-landscape was allowed to grow for 100 years).

Twenty harvest schedules were randomly generated for each sub-landscape. For each schedule, a series of ten habitat maps was generated for each species; each map thus represented decadal landscape change over 100 years. Each series of maps was loaded into PATCH and each species was simulated for the 100-year horizon. This was repeated 50 times per time-series; resulting in 50 PATCH simulations per harvest schedule on each sub-landscape or in  $50 \times 20 \times 40 = 40000$  population time-series per species. For each of the 20 harvest schedules on each of the 40 sub-landscapes, the 50 PATCH replications of population sizes were averaged on a year-by-year basis. The resulting

observations thus consisted of 20 time-series of mean population sizes for each species, on each of the 40 sub-landscapes.

#### 4.5.4 Estimating population sizes

From initial work with PATCH using static landscapes, it was observed that species population sizes were highly correlated with the amount of habitat available on a landscape (the number of pixels with coniferous forest vegetative cover), the quality of the habitat (the sum of all pixel's habitat scores), the habitat's area to edge ratio, and population sizes in previous time periods. All of the landscape characteristics are straightforward to measure from GIS imagery, and population sizes in previous time periods can be obtained explicitly from PATCH simulation runs.

Since the variable of interest was the mean species population size through time, and because the sub-landscapes were of different areas, a normalization was applied to make the variable of interest directly comparable across sub-landscapes. This was to divide the mean population size time-series by the area of the sub-landscape. The resulting dependent variable was therefore one of population density through time rather than size. It was assumed that the amount and location of all forests did not change over time. Therefore, if a pixel was classified as coniferous or mixed forest cover on the initial vegetative coverage



map, it would always remain classified as forested, regardless of the age class present (including recent clear-cuts).

Each sub-landscape could be envisioned as a block effect, since population densities arising from different harvest schedules on the same sub-landscape might be correlated. Potential within-sub-landscape dependencies will not influence estimated regression coefficients (i.e., the estimates are still unbiased); however, if positive correlations are present, they will reduce estimated standard errors and thus artificially reduce associated p-values. Since the interest of this work was to merely estimate PATCH population sizes – not to do hypothesis testing to identify those covariates that influence PATCH population sizes – all mean population time-series were aggregated together during analysis. Regressions were performed for each species using the 800 observations, but the amount of forested area was included as a regressor to account for one difference between the 40 sub-landscapes.

For each harvest schedule on each sub-landscape (i.e., each observation), habitat scores in the ten decades and the total amount of coniferous forest were normalized by dividing each by the area of the sub-landscape (to account for differences in sub-landscape area). Mean population densities were regressed on past population densities, present and past normalized habitat scores, and the normalized amount of coniferous and mixed cover on each sub-landscape. Because PATCH was programmed to place one individual on every territory with habitat at the outset of all simulations, and because the initial population size

might artificially be too high or too low, regressions were performed on a decade-by-decade basis.

The following model (equation (4.2)) was fit for species  $j = 1, 2$ , decade  $t = 1, 2, \dots, 10$ , and sub-landscape  $k = 1, 2, \dots, 40$ :

$$\begin{aligned}
 E(\text{population density}_{jt}) = & \beta_{jt0} + \beta_{jt1} (\text{population density}_{j(t-1)}) \\
 & + \beta_{jt2} (\text{population density}_{j(t-1)})^2 \\
 & + \beta_{jt3} (\text{population density}_{j(t-2)}) \\
 & + \beta_{jt4} (\text{normalized habitat score}_{jt}) \\
 & + \beta_{jt5} (\text{normalized habitat score}_{j(t-1)}) \\
 & + \beta_{jt6} (\text{normalized coniferous forest cover}_k)
 \end{aligned} \tag{4.2}$$

Results are provided in Table 4.3. The amount of variation explained by these equations for both species is lower when predicting the initial population in the first year, but by the ninth year and all decades thereafter, the equations always explain at least 90% of the variation. For each species, the coefficients tend towards similar values as the decades progress, suggesting that the effects of the PATCH-supplied initial populations have dissipated.

The question may arise as to why habitat edge was not significant when predicting population densities. One explanation is that the spatially-embedded habitat scoring procedure has already accounted for it. Edge can be an important

Table 4.3. Estimated population density prediction equations for the owl and porcupine. A '\*' denotes those coefficients significant at the 0.05 level, while a '\*\*' denotes those significant at the 0.01 level. All measures are normalized by dividing each by the area of coniferous forest on the initial landscape.

### Population density in year 1

	owl	porcupine
intercept	-0.4808	0.4508
cover	0.0021	-0.0007142
habitat score in decade 1	0.000021	0.0003354 **
R <sup>2</sup>	0.36	0.75

### Population density in year 9

	owl		porcupine	
intercept	8.2758	**	1.8593	**
cover	-0.00265	*	-0.0021500	**
habitat score in decade 1	0.0000192	*	0.0000855	*
population in year 1	-12.7215	**	-1.3921	**
(population in year 1) <sup>2</sup>	6.7793	**	1.1219	**
R <sup>2</sup>	0.93		0.96	

### Population density in year 19

	owl		porcupine	
intercept	0.5144		1.0125	**
cover	-0.0007104		-0.0004635	
habitat score in decade 1	-0.0000431		-0.0004947	
habitat score in decade 2	0.0000342		0.005170	**
population in year 1	-0.907	**	-0.2851	
population in year 9	2.0883		0.3196	
(population in year 9) <sup>2</sup>	-0.2537		0.2089	**
R <sup>2</sup>	0.90		0.97	

### Population density in year 29

	owl	porcupine	
intercept	-0.0667	-0.3822	
cover	0.0000403	0.0006361	
habitat score in decade 2	0.0000990	-0.0004032	**
habitat score in decade 3	-0.0000894	0.0003618	**
population in year 9	-0.5848	0.0000021	*
population in year 19	1.5352	1.0332	**
(population in year 19) <sup>2</sup>	0.176	0.0475	
R <sup>2</sup>	0.93	0.98	

### Population density in year 39

	owl	porcupine	
intercept	-0.0431	-0.8895	*
cover	0.0002620	0.0008713	
habitat score in decade 3	0.0000334	-0.0001793	*
habitat score in decade 4	-0.0000552	0.0001729	*
population in year 19	-0.1638	0.0000001	
population in year 29	0.8738	2.5651	**
(population in year 29) <sup>2</sup>	0.1569	-0.4383	**
R <sup>2</sup>	0.98	0.97	

### Population density in year 49

	owl	porcupine	
intercept	0.0064	-0.3462	
cover	0.0000628	-0.0009334	
habitat score in decade 4	-0.0000016	-0.0002209	**
habitat score in decade 5	0.0000003	0.0004079	**
population in year 29	-0.3652	0.0000010	**
population in year 39	1.0776	1.5695	**
(population in year 39) <sup>2</sup>	0.1170	-0.1841	**
R <sup>2</sup>	0.99	0.97	

**Population density in year 59**

	owl		porcupine	
intercept	0.1095		0.3037	
cover	-0.0002500	*	-0.0003360	
habitat score in decade 5	0.0000119	*	-0.0001003	**
habitat score in decade 6	-0.0000051		0.0003209	**
population in year 39	-0.26003		0.0000000	
population in year 49	1.1656	**	1.8541	
(population in year 49) <sup>2</sup>	0.1505		-0.2104	
R <sup>2</sup>	0.99		0.94	

**Population density in year 69**

	owl		porcupine	
intercept	-0.0467		-1.1164	
cover	0.0000736		0.0008051	
habitat score in decade 6	-0.0000038		0.0000568	
habitat score in decade 7	0.0000017		0.0001565	**
population in year 49	-0.71884	**	0.0000001	
population in year 59	1.7139	**	1.2657	
(population in year 59) <sup>2</sup>	0.1208		-0.2597	
R <sup>2</sup>	0.99		0.93	

**Population density in year 79**

	owl		porcupine	
intercept	0.0429		-0.2367	
cover	0.0000039		-0.0001253	
habitat score in decade 7	0.0000061		-0.0001022	
habitat score in decade 8	-0.0000116		0.0001549	
population in year 59	-0.2996		0.0000031	
population in year 69	1.1133	**	2.2810	**

(population in year 69) <sup>2</sup>	0.0834	-0.3743	**
R <sup>2</sup>	0.99	0.94	

### Population density in year 89

	owl		porcupine	
intercept	-0.0213		-0.3567	
cover	-0.0000358		-0.0000322	
habitat score in decade 8	0.0000031		0.0000047	
habitat score in decade 9	0.0000033		0.0000816	
population in year 69	-0.8004	**	-0.0000033	
population in year 79	1.8912	**	2.3586	**
(population in year 79) <sup>2</sup>	-0.2269	*	-0.3698	**
R <sup>2</sup>	0.99		0.95	

### Population density in year 100

	owl		porcupine	
intercept	-0.4154	**	-0.3382	
cover	0.0006526	**	-0.0000258	
habitat score in decade 9	0.0001606	**	-0.0004518	
habitat score in decade 10	-0.0001667		0.0005297	
population in year 79	0.02033	**	-0.0000004	
population in year 89	0.8270	**	1.8783	**
(population in year 89) <sup>2</sup>	-0.0294		-0.2309	**
R <sup>2</sup>	0.99		0.98	

factor, but this effect was contained in the habitat score function since habitat close to or bordering an edge would be scored according to species preferences.

#### 4.6 Validation study

The accuracy of the spatially-embedded habitat scoring procedure could not be verified since it was based on expert opinion. However, the accuracy of the population density prediction equations needed to be tested on the landscape of interest. To do so, more PATCH simulations were performed using the complete 1.7 million hectare study area (thus using out-of-sample data). Specifically, six random harvest schedules from the “high” class were generated, as well as six from the “medium”, six from the “low”, and one from the “no” (there is only one way to grow out the landscape). For each of the nineteen sets of management actions and for each species, a time-series of ten habitat maps was generated using the habitat scoring measures. Each time-series was run in PATCH 50 times, and the mean population size (averaging the 50 runs within time period) was recorded.

For each species  $j = 1, 2$ , and each decade  $t = 1, 2, \dots, 10$ , observed population densities were then regressed on the predicted population densities using equation (4.3):

$$E\left(\begin{matrix} \text{observed} \\ \text{population} \\ \text{density}_{jt} \end{matrix}\right) = \beta_{jt0} + \beta_{jt1} (\text{predicted population density}_{jt}) + \beta_{jt2} (\text{predicted population density}_{jt})^2 \quad (4.3)$$

Assuming normal errors, significance testing was performed to test first for curvature (i.e.,  $H_0: \beta_{jt2} = 0$ ); if p-value  $> 0.05$ , then  $\beta_{jt2}$  was dropped and the model rerun to test for a slope of unity (i.e.,  $H_0: \beta_{jt1} = 1$ ). In all cases (i.e., for each species  $j$  and decade  $t$ ),  $\beta_{jt2}$  was found to be statistically no different from zero and  $\beta_{jt1}$  was found to be statistically no different from one. A total of forty t-tests were performed, and with a significance level of 0.05, two tests would be expected to be falsely significant under the null; however, this was not observed. Finally, the proportion of variation explained by each prediction equation was high (the smallest  $R^2$  observed was 0.97).

#### 4.7 Discussion

The integration of ecological simulation and optimization techniques to identify economic efficiencies and effective conservation policy and planning strategies is a powerful tool for management. Other researchers have recognized this capability, stating that “resource economists and management scientists probably need to pay more attention to simulation methodologies and ecologists probably need to pay more attention to optimization methodologies” (Hof and



Bever, 1998). The work in this paper develops procedures to quickly estimate habitat quality through space and time, rapidly update habitat quality as landscape change is simulated, and instantaneously estimate the resultant population sizes one could obtain from a wildlife simulator. Because the intent of this work was to predict population sizes obtained from PATCH on a specific landscape using data observed on smaller landscapes (thus saving time), no attempt was made to develop a general set of prediction equations that could be applied to *any* landscape. However, the methods outlined provide a means of data collection that could be used to fit a random coefficients model for inference to any landscape.

The purpose of the estimation procedures outlined in this work is not to replace the wildlife simulator; rather to bridge the gap between optimization technology and species simulation. As is the current trend, the amount of spatial information gathered and its associated attributes continues to increase while its resolution becomes more refined. Furthermore, knowledge of species vital rates, habitat preferences, and movement behavior is also increasing. However, such detailed information can be of little use for addressing some kinds of questions when simulating landscape change under realistic, spatially-dependent economic behavior, because embedding a detailed wildlife simulation model within an optimization application is infeasible due to long solution times. This paper presents methods to overcome such difficulty, thus making the powerful combined modeling approach feasible and operational.

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## **Chapter 5**

### **Locating Production Possibility Frontiers of Economic and Ecological Outputs Over Long Horizons**

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and Steve Polasky

## 5.1 Abstract

The scheduling and allocation of fixed resources for efficient levels of production is a common economic activity that obtains the most from that which is available. This concept is useful for natural resource management, especially as society places increasing pressure on the natural land base for multiple and possibly competing outputs. In this paper, a three-dimensional production possibilities frontier of timber production and two focal species with different habitat preferences, life history characteristics, and movement behavior is located for a 1.7 million hectare forested region in central Oregon over a 100 year planning horizon. Economic and ecological theory are brought together within the unified modeling framework of Operations Research to explicitly identify spatial and temporal sets of management actions that maximize the efficient production of timber subject to constraints on the population sizes of the two focal species. Relevant policy scenarios are then implemented, and their degrees of inefficiency can be determined. It was found that each species benefited from different management strategies, but neither would be extirpated from the landscape when maximizing economic return alone.

**Keywords:** production possibilities frontier, resource economics, optimization, conservation planning, policy simulation.

## 5.2 Acknowledgements

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### 5.3 Introduction

Much fruitful interaction between the traditionally disjoint disciplines of economics and ecology has occurred in recent decades. With hindsight, it might not be a surprise this has taken place because healthy economies often arise from healthy ecosystems and the maintenance of ecosystems is thought to sustain healthy economies. Neither economic- nor ecological-based decisions exist in a vacuum, but determining socially optimal levels of economic and biological production is yet an unresolved issue. There are many reasons for this, such as the inherent difficulty in valuing non-market goods and services, changes in public opinion, inefficient government policy and non-uniform enforcement of regulations, and incomplete scientific understanding of economic and biological linkages.

Despite these shortcomings, a variety of methods have been proposed that attempt to better address society's desire for economic and ecological production. One approach seeks to permanently withdraw areas from economic production by creating nature reserves. Such models typically focus on representing as many species as possible for the least amount of land or cost. Variants of this approach exchange species for habitat representation, but spatial and temporal economic affects are most often ignored. The appropriateness of withdrawing areas from resource production is usually not in question; however, the concerns regarding the permanency of reserving lands could be minimized if accompanied by



ecologically less disruptive sets of management actions. Another general approach seeks to maximize the economically efficient production of marketable goods where the type and intensity of management actions are altered through time to address ecological concerns. Constraints can take the form of disallowing management actions in adjacent areas for a certain period of time following disturbance, leaving buffer zones around ecologically sensitive areas, or imposing maximum harvest amounts on the stock of species. Such ecological considerations are usually single-species-centric and therefore can be ecologically unsatisfactory.

Social welfare economics provides a theoretical foundation for determining the socially efficient allocation of fixed resources. It can be shown there exist three necessary and sufficient conditions for achieving maximum social well-being. The first condition is that the marginal rate of substitution (i.e., a consumer's relative preference for one or more goods in terms of one or more other goods) must be equal across consumers. In other words, each individual consumes the mix of goods that maximizes their utility; if this did not occur, the solution would not be optimal to this individual and additional trading would take place. The second condition requires that the marginal rates of technical substitution (i.e., the ratios of shadow prices on inputs among all goods in production) must be equivalent. If the ratios were not equivalent, then it is assumed capital would be re-allocated for increased return on production. The third condition states that the marginal rate of transformation (i.e., the tradeoff in

production among goods – the slope of the production possibility frontier) must be the same as the marginal rate of substitution. This last condition is the cornerstone of social efficiency, since it dictates that social utility is best met by maximally producing the relative combination of goods that are most preferred by society.

Social efficiency is a theoretical construct and therefore can be extremely difficult, if not impossible, to attain in practice. Many obstacles exist. However, the better the information is pertaining to any one of the three conditions, the closer society can come to social efficiency through improved public policy making. Some researchers argue that the marginal rate of substitution for non-market goods and services, such as species survival and ecosystem services, can never be truly known (this is an area of on-going study). Even if relative preference functions were known, a means of determining the set of combinations of outputs that are maximally obtainable from fixed resources (i.e., the production possibilities frontier) would have to be developed. This is the focus of the current paper.

Information describing the production possibility frontier is useful for various reasons. The frontier determines inefficient combinations of goods (interior points), and the degree of inefficiency of these points can be explicitly measured. The slope of the frontier relates how much of one good must be traded in order to increase the amount of another good (i.e., the marginal rate of transformation). The change in the slope can highlight (i) decreasing returns

between competing goods if the shape of the frontier is concave with the origin; (ii) show which goods are rivals if convex to the origin; or (iii) determine which goods are incompatible if the slope is always zero or infinite. Perhaps most useful, the frontier provides a means of relating outputs without placing monetary value on non-market goods.

The work in this paper is applied in nature and draws on economic and ecological theory to develop a more detailed and realistic combined modeling approach. The supply of one output (timber extraction) was maximized under a time-series of stumpage demand equations subject to thresholds on the expected population sizes of two species with different vital rates, habitat preferences, and movement abilities. Population sizes were estimated from a realistic and flexible wildlife model that simulates and tracks individuals on a changing landscape through time. Spatial and temporal harvest schedules were found using a hybrid heuristic optimization procedure. The combined modeling approach was used to estimate a production possibility frontier of efficient economic production and species survival. Once the frontier was located, different land-use regulations were imposed and points along the policy-restricted frontiers were located to directly estimate their degrees of inefficiency. Although no preference functions were found, this work provides a basis for better estimating social optimality. The application presented is specific to forestry, but the methodology is general enough for use in other natural resource applications with economic and ecological components.

The paper is organized as follows. Section 5.4 describes the ecological data needed and methods used, while Section 5.5 does the same for the economic component. Section 5.6 brings both aspects together within a single optimization model, and the new hybrid heuristic solution method is overviewed. Estimated production possibility frontiers are presented in Section 5.7, as well as the effects of three relevant policy scenarios on timber production and species survival. Finally, Section 5.8 contains discussion and suggests areas of future research.

#### 5.4 Ecological data and methods used

This study focused on a 1.7 million hectare tract of land located in the foothills and mountains of the central Cascade mountain range in Oregon, contained within the Willamette River Basin (Figure 5.1). The area was remotely sensed in 1990 and partitioned into 30 m by 30 m pixels (Institute for a Sustainable Environment 1999). Each pixel was classified as one of 35 dominant cover types, such as high-density urban, seasonal wetland, or oak savanna. Because the major economic output of interest for this study is softwood timber production, only coniferous and mixed hardwood and coniferous forested pixels were considered available for harvest (these classifications comprised 70% of the region). Pixels containing coniferous forest cover were further partitioned into 10-year age classes, whereas the mixed forest cover types were not since no classification routine was available.

Two focal species were selected from available data to explore how different spatial and temporal resource extraction patterns affect their expected population sizes and to find tradeoffs between species. These species were the Great horned owl (*Bubo virginianus*) and the Common porcupine (*Erethizon dorsatum*). Both are native to the study region. In addition to different life spans, reproductive capability, and maximum dispersal distances, each species is expected to prefer differently aged forest stands. The Great horned owl is a forest generalist as long as some larger diameter trees are available for nesting, but it is not found in intermediate-aged dense stands. The Common porcupine is also a forest generalist but prefers younger stands. The owl very infrequently preys upon the porcupine, making negligible issues relating to predatory-prey interactions for the current work (Verts and Carraway 1998).

To more realistically estimate population sizes through time, a detailed wildlife simulator from the U.S. Environmental Protection Agency was employed. PATCH (Schumaker 1998) stochastically simulates individuals as they move about a landscape,

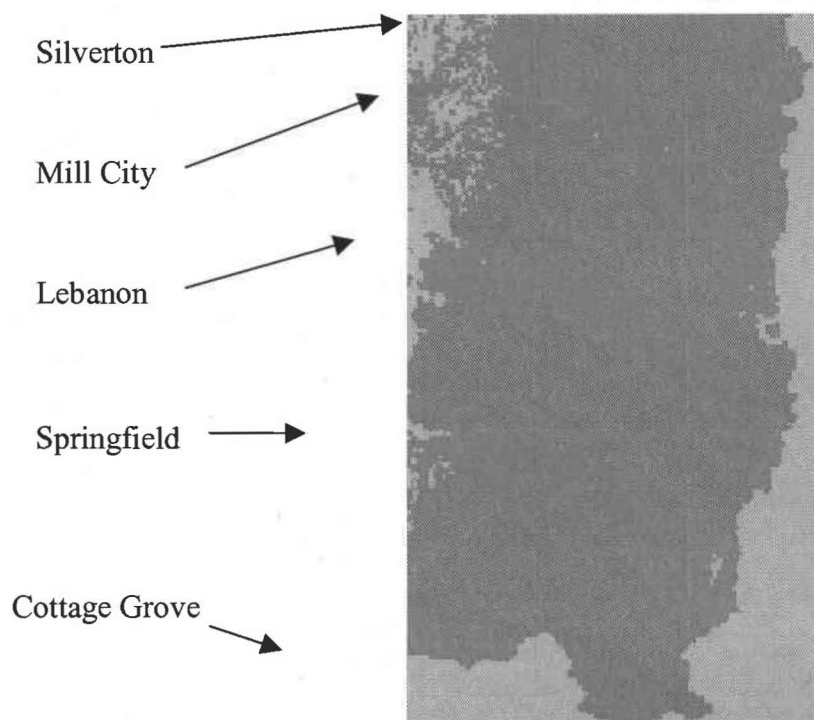


Figure 5.1. Map of study area and location of depots. Silverton is farthest north and Cottage Grove is farthest south. Forested areas are in darker gray.

breed, and die. Required inputs are species vital rates (survival and reproduction), habitat preference (source/sink characteristics), and movement behavior. Vital rates are entered with a population projection matrix (Caswell 1998), and movement behavior is specified by entering a maximum dispersal distance and territory search procedure. Habitat quality is represented by loading new maps periodically during the simulation. Each map is a matrix of pixels with assigned integer scores – the higher the score of a pixel, the better the quality of habitat in that particular pixel.

Because the harvest of timber will affect the amount, quality, and location of habitat, harvesting was expected to influence population sizes through time and space. It was initially hoped that the wildlife simulator could be dynamically linked to the optimization procedure discussed in Section 5.4. In this way, as management actions were altered, the effects on population sizes could be estimated directly using PATCH. However, although PATCH can simulate population responses in a matter of seconds, the simulator was still too slow to be used interactively with optimization procedures that can require many millions of iterations to find just a single solution. Since many solutions were needed to trace out the 3-dimensional frontier, another approach was required.

In order to find solutions in real time, a two-step procedure was applied to estimate PATCH results. The first step developed a method of assigning habitat quality (i.e., pixel scores) based on the forest age class in the pixel, as well the forest age class of the pixels within a certain radius. Hence, as management

actions were altered – changing which locations were harvested and when – in the search for economically efficient solutions, habitat quality could be quickly updated. The second step involved estimating population sizes on the landscape through time. These were found by simulating thousands of different harvest schedules on the landscape in PATCH and then regressing population responses on metrics of habitat structure and quality. Further details may be found in Nalle<sup>a</sup> et al. (2001).

Lastly, forest stand volume in the western Cascades was predicted using average growth and yield estimates of a typical dominant Douglas-fir stand developed by Adams et al. (2001). The group obtained site indices (a measure of forest productivity) from a U.S.D.A. Forest Service inventory of western Oregon from 1995 to 1997; the average site index was found to be 117 feet at a base age of 50 years. Douglas-fir dominant stand volumes were predicted onward from an age of 15 years using the growth and yield simulator ORGANON (Hann et al. 1997), while regenerated stand volumes were predicted up to 15 years using SYSTM1 (Richie 1993). All estimated yields were subject to peer review. No information on the locations of sampled forest stands used to estimate site indices could be discerned, so the estimated average site index in the western Cascades was assumed for all coniferous forest pixels in the study region. Furthermore, because ORGANON does not predict stand volume beyond 150 years, volumes for stands aged 150 to 200+ years were predicted by regressing volume quadratically on stand age and then extrapolating to 200 years. Because softwood



production is usually measured in board feet and ORGANON only measures stand growth in cubic feet, stand cubic foot volumes were transformed to board feet with standard conversion factors from northwest Oregon. Estimated board foot yields are found in Table 5.1.

Table 5.1. Yield estimates from ORGANON using a typical stand from Forest Inventory Analysis database (site index 117' at 50 years), and estimated skyline harvest and haul costs for an average stand in the western Cascades of Oregon.

age	bf per pixel (in 1000's)	harvest costs per 1000 bf (\$)	haul costs per 1000 bf (\$), distance in km	
			< 80	80-200
20	0.434	140	50	60
30	1.819	125	40	48
40	3.529	115	40	48
50	6.440	100	35	42
60	8.851	90	35	42
70	10.069	80	30	36
80	12.233	75	30	36
90	14.188	75	30	36
100	15.907	75	25	30
110	16.773	75	25	30
120	18.442	70	25	30
130	19.789	70	25	30
140	20.329	65	20	24
150	21.283	65	20	24
160	21.722	65	20	24
170	22.217	65	20	24
180	22.310	65	20	24
190	23.218	65	20	24
200	23.218	65	20	24
200+	23.218	65	20	24

## 5.5 Economic data and methods used

A total of 28251 management units were delineated with a uniform grid that was 28 pixels on a side (resulting in an area of  $0.70 \text{ km}^2$ ). This area was chosen to approximate the average territory size of the two species. If at least 25% of the unit's area was classified as coniferous forest at the outset, then the unit was deemed to be available for harvest (resulting in a total of 19622 harvestable units, referred to as management units). Harvests were only allowed to occur in 10-year periods because this was the resolution of the coniferous forest age class data, and the planning horizon was set at 100 years to better capture the effects of harvesting on the two species through time. Only two harvest prescriptions could be applied in each decade; these were to either clear-cut and replant in the following year or take no action. It was assumed that the forested land base did not change through time. No thinning alternatives were used because no specific information on forest composition and structure that the two species might prefer was available. Such alternatives could provide a means of generating revenue while speeding the development of habitat quality. This is a topic of on-going silvicultural effort that could be used in the future to improve estimates of the production frontier.

Stumpage prices were defined as log prices less harvest and haul costs. Log prices were determined explicitly under downward sloping aggregate demand for logs in western Oregon. This provides added realism to the economic

component since the study area is large and contains productive stands (thus avoiding large harvest amounts in a period that could severely depress prices). Demand equations were adapted from Adams et al. (2001) and are found in Table 5.2. As time progresses, the price intercept was linearly increased to reflect the assumption of increasing demand for softwood in the future.

Harvest costs depend on the method used (i.e., ground-based skidding, skyline systems, helicopter, etc.) and the type of management action performed. In this study, only skyline harvesting was considered. Although it is somewhat more expensive than ground-based skidding, less soil compaction and erosion occurs, and this better fosters future stand growth (and economic value). Skyline harvest costs decrease with stand age; estimates are also found in Table 5.1. These include the cost of capital and labor and contain a profit, risk, and overhead allowance of 20% (Kellogg et al. 1996). Site preparation and replanting costs were assumed to be \$740 per hectare using 8' by 8' planting density of Douglas-fir. (Lettman 1997).

Haul costs were determined based on four factors: transportation distance, stand age, truck rental, and time of commute. Straight-line distances from each management unit to the nearest of five pre-selected depots on the landscape were computed. The location of depots was based on historical occurrence (influenced by topography), and logs could only be brought to these sites during the planning horizon. Depot locations are found in Figure 5.1. More board feet can be taken from larger trees, so older stands are cheaper to transport on average per unit area.

Table 5.2. Estimated stumpage demand equations adapted from (Adams et al. 2001).

Decade	price intercept ( $\alpha_i$ ), in \$/billion bf	slope ( $\beta_i$ )	quantity intercept, in billions of bf
1	10.694	-0.6147	17.40
2	10.944	-0.6147	17.61
3	11.194	-0.6147	18.01
4	11.444	-0.6147	18.42
5	11.694	-0.6147	18.82
6	11.944	-0.6147	19.22
7	12.194	-0.6147	19.62
8	12.444	-0.6147	20.03
9	12.694	-0.6147	20.43
10	12.944	-0.6147	20.83

Estimated haul costs per stand age and distance traveled are found in Table 5.1. It was assumed that 30 minutes was needed to either load or unload a truck and that average speed in transit is 40 km/hour regardless of load. Finally, trucks and drivers were estimated to rent for \$50 per hour and can haul 5 thousand board feet per load (Kellogg 2001). No limit was imposed on the number of available trucks and drivers or the total amount of timber brought to any particular depot.

All harvest activities were assumed to occur immediately during a harvest period. If a unit was selected for harvest, its replanting, harvest, and haul costs were summed together and discounted to the first period with a rate of 4% (Row et al. 1981).

## 5.6 Optimization model and methods used

To explore tradeoffs between timber production and the two focal species, the three-dimensional production possibility frontier was found empirically by maximizing the economically efficient production of timber subject to a series of thresholds on estimated population sizes. Instead, population sizes could have been maximized subject to a series of thresholds on economic efficiency, but the results obtained under either approach would be the same regardless of the choice of objective.

It is assumed for modeling purposes that maximizing consumer and producer surpluses will simulate competitive market equilibrium outcomes. This equates to maximizing the discounted area under each decadal demand equation, up to the quantity harvested, less all discounted harvest and haul costs in each period. The summation of discounted areas and costs is expected to generate a smoother although not necessarily even-flow of timber. Also, because the slope of the demand equations is negative and because a stand not harvested in one period will grow in volume to the next period, a greater incremental gain in consumer and producer surpluses can be obtained by holding some timber for harvest in future periods.

To develop the optimization model, the following notation is needed. Let  $j = 1, \dots, n$  refer to a specific management unit,  $t = 1, \dots, T$  represent each decade in the planning horizon, and  $i = 1, 2$  denote each species. Let  $k = 1, \dots, K$  refer to each possible prescription (a prescription is defined as a set of management actions assigned to each management unit taken over the entire planning horizon

– either clearcut or do nothing in each period), and let  $k = 1$  refer to taking no management actions at all in perpetuity. For each unit  $j$  and each prescription  $k$  define binary decision variables:

$$y_{jk} = \begin{cases} 1 & \text{if unit } j \text{ is assigned prescription } k \\ 0 & \text{otherwise} \end{cases}$$

Because the age class distribution within each management unit determines the quantity extracted as well as harvest and haul costs, the inventory of each unit in each decade must be accounted for and dynamically changed depending on the particular set of management actions, or prescription, assigned. To save time during optimization runs, some pre-processing measures were taken. First, a 20-year minimum rotation age was imposed to reduce the number of possible actions that could be taken. This resulted in a total of  $K = 127$  sets of prescriptions, which included allowing the stand to grow over the entire horizon ( $k = 1$ ). Next, for each management unit and each prescription, the amount of timber removed and discounted cost of harvest and haul was computed for every decade in which harvests occurred (as specified by the particular prescription applied). These values were stored in matrices specific to each unit whose row numbers corresponded to the number of the unique prescription ( $k$ ). To address the economic and ecological sustainability of management actions taken in the first 100 years, it was assumed that each stand would be managed under the same

prescription in perpetuity. This is important when determining the value in the first 100 years for those units containing mostly older stands at the outset that might be harvested both early and late during the horizon. For each unit and each prescription, the net present value of all future income streams (using the average decadal price over the first 100 years found when maximizing consumer and producer surplus without regard to species populations) was calculated at year 100 and discounted to the present. These values were stored in vectors whose positions corresponded to each unique prescription ( $k$ ).

Furthermore, define additional notation and binary decision variables:

$a_t$  = discounted area under the linear demand equation for decade  $t$

$h_{jkt}$  = quantity harvested from unit  $j$  under prescription  $k$  in decade  $t$ ,  
in thousands of board feet

$c_{jkt}$  = discounted harvest and haul cost of extracting timber from unit  $j$   
under prescription  $k$  in decade  $t$ , in dollars

$f_{jk}$  = net present value of managing unit  $j$  as prescription  $k$  in perpetuity,  
in dollars

$\alpha_t$  = price intercept of the linear demand equation in decade  $t$ , in dollars  
per thousand board feet

$\beta_t$  = slope of the linear demand equation in decade  $t$

$r_t$  = stumpage price from linear demand equation in decade  $t$ , in dollars per  
thousand board feet

$p_t$  = adjusted stumpage price in decade  $t$ , in dollars per thousand board feet

$s_{it}$  = estimated population size of species  $i$  in decade  $t$ , a complex spatial and temporal function arising from each harvest schedule on the landscape

$g_{it}$  = threshold on the population size of species  $i$  in decade  $t$

$$z_t = \begin{cases} 1 & \text{if } r_t \text{ is } > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$w_t = \begin{cases} 1 & \text{if } r_t \text{ is } < 0 \\ 0 & \text{otherwise} \end{cases}$$

The optimization model is:

$$\text{Maximize} \quad \sum_{t=1}^T \alpha_t - \sum_{j=1}^n \sum_{k=1}^K \sum_{t=1}^T c_{jkt} y_{jk} + \sum_{j=1}^n \sum_{k=1}^K f_{jk} y_{jk} \quad (5.1)$$

subject to:

$$\alpha_t + \beta_t \sum_{j=1}^n \sum_{k=1}^K h_{jkt} y_{jk} = r_t \quad \text{for } t = 1, \dots, T \quad (5.2)$$

$$r_t z_t \geq 0 \quad \text{for } t = 1, \dots, T \quad (5.3)$$

$$r_t w_t \leq 0 \quad \text{for } t = 1, \dots, T \quad (5.4)$$

$$z_t + w_t = 1 \quad \text{for } t = 1, \dots, T \quad (5.5)$$



$$\frac{1}{2} r_t z_t + \frac{1}{2} r_t (1 - w_t) = p_t \quad \text{for } t = 1, \dots, T \quad (5.6)$$

$$\frac{1}{2} (\alpha_t - p_t) \sum_{j=1}^n \sum_{k=1}^K h_{jkt} y_{jk} + p_t \sum_{j=1}^n \sum_{k=1}^K h_{jkt} y_{jk} = a_t \quad \text{for } t = 1, \dots, T \quad (5.7)$$

$$\left[ \begin{array}{c} T \\ \prod s_{1t} \\ t=1 \end{array} \right]^{(1/T)} \geq g_{1t} \quad \text{for } t = 1, \dots, T \quad (5.8a)$$

$$\left[ \begin{array}{c} T \\ \prod s_{2t} \\ t=1 \end{array} \right]^{(1/T)} \geq g_{2t} \quad \text{for } t = 1, \dots, T \quad (5.8b)$$

$$\sum_{k=1}^{127} y_{jk} = 1 \quad \text{for } j = 1, \dots, n \quad (5.9)$$

$$z_t = 0 \text{ or } 1 \quad \text{for } t = 1, \dots, T \quad (5.10)$$

$$w_t = 0 \text{ or } 1 \quad \text{for } t = 1, \dots, T \quad (5.11)$$

$$y_{jk} = 0 \text{ or } 1 \quad \text{for } j = 1, \dots, n \text{ and } k = 1, \dots, K \quad (5.12)$$

The first summation in equation (5.1) sums the areas beneath the decadal linear demand equations down to the quantity axis. The second summation in equation (5.1) subtracts off all discounted costs associated with harvesting, and the third summation adds the sum of the net present values of managing each unit

in perpetuity under the assigned the set of prescriptions. Consumer and producer surpluses are thus maximized by subtracting all costs from the sum of the areas beneath the demand curves.

Constraint (5.2) computes the decadal price of timber from the linear demand equations based on the total quantity harvested in each decade. From this constraint, it is possible for  $r_t$  to be negative in sign if large harvest amounts were to occur. To avoid this, constraints (5.3), (5.4), (5.5), (5.10), and (5.11) ensure that the price is set equal to zero in a decade if harvests amounts exceed the quantity intercept. To see why this is, if  $r_t < 0$  then (5.3) forces  $z_t = 0$ , (5.5) sets  $w_t = 1$ , and  $p_t = 0$  from (5.6). On the other hand, if  $r_t > 0$  then (5.4) sets  $w_t = 0$ , (5.5) sets  $z_t = 1$ , and so  $p_t = r_t$  in (5.6). If it so happened that  $r_t = 0$ , then (5.6) forces  $p_t = 0$  in which case the values of  $z_t$  and  $w_t$  and would be irrelevant. For some applications, it might be desirable to allow prices to become negative to reflect costs that would need to be incurred, but in this paper it is assumed for simplicity that prices never drop below zero. The first set of terms on the left-hand side of constraint (5.7) computes consumer surplus in each period (the area of a triangle), while the second set on the left-hand side computes the total revenue received by land owners in each decade (the area of a rectangle). Constraint (5.8) is nonlinear and requires that the geometric mean of the estimated time-series of population sizes for each species exceed the pre-specified thresholds (see Nalle<sup>a</sup> et al. 2001 for the derivation of  $s_{it}$ ). The geometric mean is used to capture temporal swings in population sizes since larger deviations from the threshold within each decade

will have a greater effect on the geometric mean value. This implicitly assumes that relatively stable population sizes through time are more desirable, but it still allows sizes to fluctuate. The geometric mean also reflects the fact that extinction is forever. Allowing populations to fluctuate about an aggregate value is important for this work since harsh restrictions on population sizes could artificially influence the location of the frontier, whereas light restrictions might not apply enough pressure on the algorithm to find solutions with sufficiently large population sizes. The geometric mean was selected over additive measures (such as a variance) since, from previous work, such additive measures allowed substantial declines in population sizes during the final decade. Finally, constraint (5.9) ensures that one and only one prescription set is assigned to each management unit, and constraints (5.10), (5.11), and (5.12) restrict  $z_t$ ,  $w_t$  and  $y_{jk}$  to binary values.

In this basic model structure, no regulatory constraints are imposed. However, since one objective of the study was to examine the effect of different policy scenarios, these are later modeled as separate scenarios. Because 55% (935 thousand hectares) of the study area is owned by the U.S. government, three relevant policies pertaining to management actions on federal lands were also explored. These were:

- (1) to require a “non-declining even-flow” of timber (National Forest Management Act 1976) on public lands;

- (2) to require non-declining even-flow on public lands, *and* that no federally owned stands can be harvested that have an average age of at least 200 years at the outset of the planning horizon (U.S. Forest Service Directive 2001);
- (3) to disallow all harvests on all public lands.

The first policy intends to provide sustained yields that address matters of inter-generational equity and national security. The second policy at present is somewhat vague because no common definition of an old-growth stand has been formally accepted, and, as stated in the Directive, certain management actions might be allowable on old-growth tracts for protection against disease and destruction by fire. Finally, the third policy prohibits all timber production and seeks to manage public forests for species associated with old-growth. For the purpose of this work, a management unit was defined to be federally owned if at least half of its pixels were in public ownership. An old-growth stand was defined as a management unit where at least half of the pixels comprising the unit were at least 200 years old. This resulted in a total of 12374 management units that were classified as federally owned (out of the 19622 harvest units on the landscape), and of these, 1218 (or 4.4% of the study region) were classified as both federally owned and old-growth.

To incorporate each policy within the optimization model, some additional notation and constraints are required. Define:

$L$  = the set of management units  $j$  in federal ownership

$D$  = the set of management units  $j$  classified as both federally owned and as old-growth

$$\sum_{j \in L} \sum_{k=1}^K h_{jkt} y_{jk} \leq \sum_{j \in L} \sum_{k=1}^K h_{jk(t+1)} y_{jk} \quad \text{for } t = 1, \dots, (T-1) \quad (5.13)$$

$$y_{j1} = 1 \quad \text{for } j \in \{L \cap D\} \quad (5.14)$$

$$y_{j1} = 1 \quad \text{for } j \in L \quad (5.15)$$

Constraint (5.13) imposes a non-declining even-flow of timber on federal lands, constraint (5.14) disallows harvest activities on all federally owned old-growth management units, and constraint (5.15) disallows harvesting on any federally owned management unit.

Solution times of the combinatorial model specified above increase exponentially with the number of management units and prescriptions, making traditional branch and bound techniques infeasible for the application presented in this paper. To solve the model, a hybrid heuristic approach was developed based on concepts from Simulated Annealing (Metropolis et al. 1953; Kirkpatrick 1983) and Tabu Search (Glover 1989<sup>a,b</sup>; Glover and Laguna 1997). When each was separately implemented, solution quality was comparable statistically, but solution times were measurable in days. This was an obstacle because, in order to locate a three-dimensional frontier, many different optimization runs were needed to trace out the boundaries. To maintain solution quality while increasing the

speed of solution, a hybrid procedure was developed that combined the relative strengths of each technique.

Simulated Annealing (SA) is a variant of Monte Carlo sampling methods where a perturbed solution inferior to the current solution is accepted with probability proportional to the difference between objective function values weighted by a temperature parameter. A perturbed solution superior to the current solution is always accepted, but the stochastic element can allow the search to extract itself from local optima. One perturbation and resulting decision comprise one iteration of the algorithm. The initial temperature is slowly decreased (or “cooled”) while the algorithm runs – thus accepting inferior solutions with decreasing probability as the search progresses – and the search terminates once the temperature is near 0. Three parameters are specific to SA: the initial temperature (a positive constant), the rate of cooling (a constant greater than 0 but less than 1), and the number of iterations that pass before decreasing the temperature (the temperature is typically decreased by multiplying the current temperature by the rate of cooling). In practice, the determination of parameters for SA is generally done by trial and error. Smaller values of the initial temperature at first admit solutions nearer to the current best solution (in terms of objective function values), but by allowing a large number of iterations to pass before cooling the temperature (or by setting the rate of cooling to be almost equal to 1), more of these inferior solutions will be accepted on average (note that

setting the initial temperature to 0 results in a purely random, greedy search through the solution space).

Tabu Search (TS) is a greedy algorithm that, in its basic form, evaluates all solutions in a neighborhood of the current solution. The neighborhood does not need to have any spatial component and is completely user-defined. If the best solution in the neighborhood is the best solution found globally, this solution is always accepted. However, if the best solution in the neighborhood is not the best globally found solution and is not tabu, it is still accepted. Once accepted, the move is placed on a tabu list for a user-defined number of iterations. The use of the tabu list forces the search into new areas of the search space (a diversification strategy) and helps prevent cycling of the algorithm. Generally, TS has only one parameter: the number of iterations a previously accepted move remains tabu. The larger the number of tabu iterations, the more diverse the search is expected to be. If the tabu iteration is 0, then the search is similar to SA when its initial temperature is 0 (TS accepts the *best* candidate solution in the neighborhood whereas SA accepts *any* randomly selected candidate that betters the current solution). For the application in this paper, simple TS was implemented, meaning that once a large, pre-specified number of iterations had elapsed, no additional diversification strategies were employed and the search terminated.

The main drawback of TS is that for problems with large neighborhoods, generally only small gains in the objective function are achieved for large

amounts of computation time. For this application, even when the neighborhood was restricted to just a few dozen management units, SA found solutions with statistically comparable objective function values, but TS required two days more on average to find such solutions. A potential drawback with the general form of SA is that no model-specific information is utilized in the random selection of a solution to perturb. Because the problem in this work has spatial components, a spatial neighborhood was defined for each harvest unit. When embedding methodology from TS in SA, thus creating a hybrid algorithm, solution times decreased from days to about one hour while maintaining a quality of solution that was statistically no different from either SA or TS. This reflects similar results found when implementing other hybrid heuristics on nature reserve problems (Nalle<sup>b,c</sup> et al. 2001)

A flowchart of the approach is found in Figure 5.2. First, for each management unit a neighborhood of other management units was enumerated. From previous work developing a fast proxy for the wildlife simulator, the type and amount of forest covers in units in the 3 surrounding rings was found to statistically influence the habitat quality of each management unit, as well as the type and amount of forest cover within the particular unit. Not coincidentally this was how the neighborhood about each management unit was defined (it included all units in the 3 surrounding rings as well as the management unit itself). Second, a randomized list of  $n$  numbers from  $j = 1, \dots, n$  was created ( $n$  is the total number of management units in the study area), and a random harvest



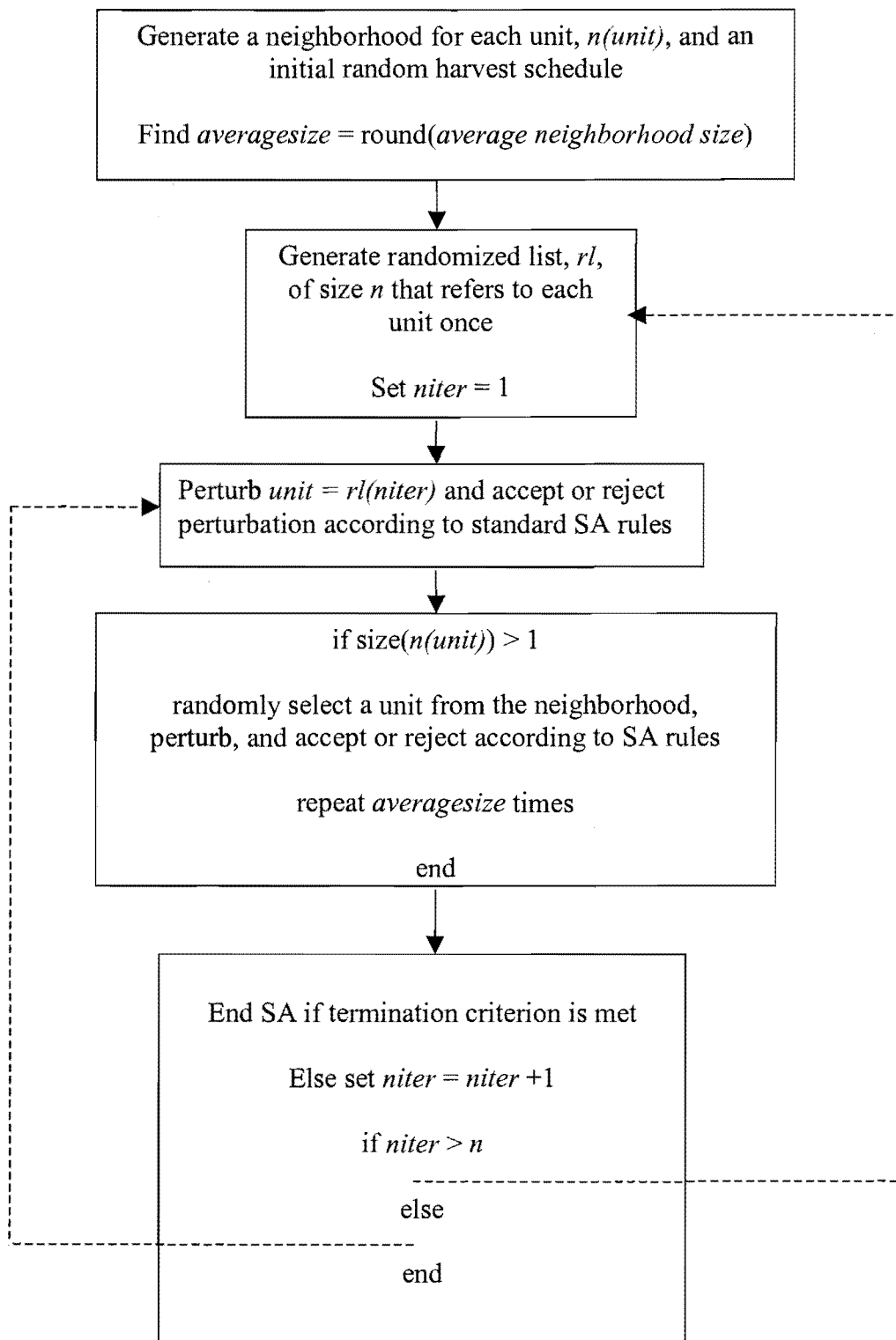


Figure 5.2. Flowchart of the hybrid algorithm to solve the optimization model.

the randomized list was perturbed, and the next selected from this unit's neighborhood. In cases where the number of units comprising a neighborhood was less than the pre-specified number of iterations (because not all management units were spatially connected to other management units), no subsequent units in the neighborhood were perturbed and the next unit on the randomized list was perturbed. Once each unit on the list had been selected, a new randomized list was generated and the process repeated until the termination criterion of SA was met.

It was observed from empirical testing that solutions of comparable quality were found in the least time when the number of iterations from which management units in a neighborhood were selected was set to the average size of all neighborhoods. This is an intensification strategy, and it is the main reason for improved solution times over both simple TS and standard SA. Fewer objective function evaluations occur than in simple TS, and the spatially-defined neighborhoods on this spatial problem improve the objective function faster than completely random selections about the landscape (as is the case for standard SA). The use of the randomized list is a diversification strategy that forces and ensures the search will sample more areas on the landscape, while the use of standard SA during the sampling procedure serves as both an intensification and diversification strategy.

## 5.7 Results

Due to the quantity of information generated while optimizing, general trends are presented first via the estimated production possibilities frontier. Constraints (5.13), (5.14) and (5.15) were initially ignored since policies can only constrain the location of the frontier. The non-policy constrained frontier thus provides a benchmark of efficiency against which all others solutions can be compared. Because each point on the frontier is the culmination of many spatial and temporal details, a number of specific solutions obtained from the optimization model are then examined to provide more insight into their distinct characteristics.

All results were obtained using MATLAB v5.3 executable code (The Mathworks 1999). Solution run-times that were found using the hybrid solution method ranged from approximately 30 to 90 minutes on a PC with two 700 MHz processors and 512 MB of RAM. To satisfy the nonlinear species constraints (5.8), these were represented in the objective function through the use of penalty terms. Penalties were only incurred if a threshold was not met.

#### 5.7.1 Non-policy constrained analysis

The non-policy constrained, three-dimensional frontier was found by maximizing timber production over a lattice of points representing thresholds on the geometric means of population size time-series for the two species. To

identify the lattice, the timber objective (equation (5.1)) was first maximized subject to a set of thresholds on each species individually, without regard to the other species, and the unconstrained population sizes of the other species were recorded. This located the range of geometric mean values that could be obtained under the timber objective for each species individually, and it provided values for thresholds from which to start when locating tradeoffs among species. Then, for a fixed target value on the owl, the timber objective was maximized subject to the fixed bound on the owl and an incrementally increasing bound on the porcupine. A boundary of the frontier was located once the iteratively increasing threshold on the porcupine could no longer be met for each fixed bound on the owl. This process was repeated by moving to the next fixed threshold on the owl and increasing the threshold on the porcupine until a new frontier boundary was located.

There are many different spatial and temporal aspects in this problem, so it is not possible to simultaneously present all results in only one graphic. Each solution obtained from optimization contains one time-series over the ten decades of estimated population sizes for each species, a time-series of discounted consumer and producer surpluses, a time-series of board feet harvested, the objective function value, and the geometric mean values for both species population time-series. In addition to these, the solutions display different spatial attributes through time, such as patterns and locations of habitat quality for each species, and the locations and frequencies of management activities on the

landscape. General trends are presented first by summarizing the timber objective with the sum of discounted consumer and producer surpluses and representing the estimated population size time-series with their geometric mean values. These are the basic units of measurement when displaying the production possibility frontier.

The three-dimensional production possibility frontier is presented via the projections in Figures 5.3 (a), (b), and (c). Figure 5.3 (a) projects the frontier onto the porcupine-timber value plane. Geometric mean target values for porcupines are plotted on the x-axis and the discounted sum of consumer and producer surpluses on the y-axis. The relationship between porcupines and timber values is complementary from approximately 4000 to 19500 porcupines, until the point of maximum timber value (occurring at approximately 19500 porcupines). The reason for this relationship is because porcupines have the highest affinity for younger stands. Thus, harvesting more frequently on the landscape decreases the average age of a stand, which in turn increases the quality and amount of porcupine habitat and porcupine population sizes. However, after the point of maximum timber value, the relationship between porcupines and timber values changes from complementary to one of substitutes. The reason for this is because, in order to increase the quality and quantity of porcupine habitat, the average age of a stand must decrease even further. The only way to do so is to harvest more stands at an earlier age than otherwise would be profitable (harvest and haul costs exceed the revenue from the stand), thus decreasing the aggregate

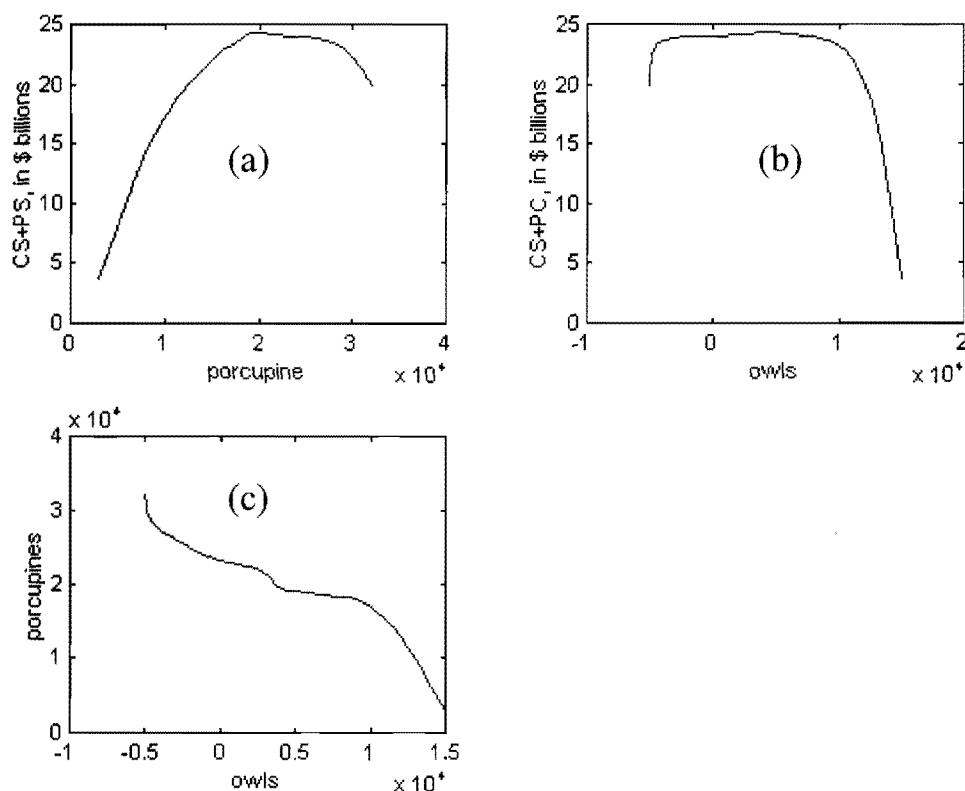


Figure 5.3. Projections of the non-policy constrained production possibilities frontier. Targets for the owl and porcupine are the geometric means of estimated population sizes. The timber objective value is the sum of discounted consumer and producer surpluses.

timber value. From the graph, it can be seen that estimated porcupine sizes can be increased from approximately 19500 to 32000 individuals (a 64% increase) for a corresponding decrease in the timber value from \$24 billion to \$16 billion (a 30% decrease from the maximum value).

Figure 5.3 (b) projects the three-dimensional frontier onto the owl-timber value plane. Geometric mean target values for the owl are plotted on the x-axis and the discounted sum of consumer and producer surpluses on the y-axis. It can be seen that owl populations range from 0 to about 15000 individuals. Although population sizes cannot drop below 0 in practicality, there is a range of timber production over which owl populations are estimated to be less than zero. Rather than represent negative population size estimates with the value of 0 (thus converting interval-type data into ordinal-type data), “negative” sizes are instead used to better relay information about the quality of owl habitat on the landscape at the corresponding levels of timber value and porcupine population size. In general, such information is useful since it more precisely measures the tradeoffs between economic and biological outputs. For the special cases where the owl population size is predicted to be less than zero, the ending estimated population size in the last decade is substituted for the geometric mean value of the population time-series to avoid reporting imaginary numbers. From the plot, it can be seen that owls and timber values are substitutes when owl sizes range from about 3800 to 15000 individuals. Initially, owls decline from 15000 to about 9000 individuals (a 40% decrease), while timber values increase sharply over this

range (a 475% increase). Then from about 9000 owls to 3800 owls, timber values increase slightly (by about 5%), but owls continue to decline (by about 58%).

Once owls drop below 3800 individuals, the relationship between timber values and owls reverses; that is, they become complements (although only slightly so). The reason for this, as noted above, stems from the ability to further increase porcupine sizes. Since porcupines have the highest preference for young stands, harvesting both (i) more frequently and (ii) more area than is economically profitable not only decreases the timber objective (since costs are excessive), but more and more owl nesting sites are converted into high quality porcupine habitat (i.e., young stands).

Lastly, Figure 5.3 (c) projects the frontier onto the owl-porcupine plane. Geometric mean target values for the owl are found on the x-axis and geometric mean target values for the porcupine are on the y-axis. As in Figure 5.3 (b), negative owl values are plotted to better measure the tradeoff between the two species at different population sizes. The relationship between owls and porcupines is always one of substitutes. Although owls were predicted to be extirpated from the landscape when there are approximately 22000 porcupines, porcupines can still be increased by about 45%. A point of inflection occurs very near the point of maximum timber value (at about 3800 owls and 19500 porcupines). What is happening in this region is that in order to increase porcupines while minimally decreasing the timber value and owls, intermediate-aged stands are harvested. Owls have the lowest affinity for such stands (those



aged from 40-60 years), so harvesting these has little to no negative affect on owl sizes (as witnessed by the increased slope of the frontier). Eventually, however, to further increase porcupine sizes, more and more older stands (preferable owl habitat) must be harvested, and this eventually causes the extirpation of the owl.

Many items of interest can be construed from Figure 5.3. When the timber value was maximized without regard to either species, it was not possible to extirpate the owl or porcupine from the landscape. Both species are present on the actual landscape, thus providing limited validation to the models of economic production used in this paper. A distinct trade-off between population sizes of the owl and porcupine is present. There is also a distinct relationship between the timber objective and the owl, as is the case for the timber objective and the porcupine. These relationships are so strong that, according to the economic and ecological models, it is not possible to increase the value of one output without simultaneously decreasing (or increasing) the value of another output. This is the reason why the frontier appears as a line in three-space rather than a three-dimensional sliver.

To view the general spatial and temporal trends that occur along the frontier, four representative points were selected. Their geometric mean target values are found in Table 5.3. One important aspect of the heuristic optimization procedure is its stochastic nature of solution. It is very likely that different solutions with similar objective function values will be found for the same set of geometric targets on population sizes. This occurrence is due in part to the

algorithm's stochasticity, but it also can be attributed to the shape of the objective function. A smoother surface will contain fewer local optima, but less well-behaved functions will contain more areas in which the search procedure can become trapped. Each point on the frontier is the best solution found by the optimization procedure for the same set of geometric mean targets. These were found by

Table 5.3. Location of four representative points along the non-policy constrained production possibilities frontier.

Point	Target for owl	Target for porcupine	CS+PS surplus, in \$ billions
A	13000	9808	17.136
B	7500	18619	24.010
C	2424	22000	24.095
D	-4386	28000	23.561

re-running the solution procedure 10 times, starting each run at a different initial solution. It is important to examine the characteristics of multiple solutions found by the stochastic optimization algorithm for the same set of population targets. This sheds light on solution reproducibility and whether or not there are multiple global optima. For each of the four representative points, graphs are displayed that plot different temporal aspects of the solutions found for each point's unique set of geometric mean target values.

Figure 5.4 plots the number of board feet harvested in each decade for the four points. For each set of targets, results from a random sample of five different

optimization runs are plotted on the same graph. Although only five solutions are shown for each of points A, B, C, and D, the results are the same regardless of the sample chosen. It can be seen that the amount harvested through time is nearly identical in each situation. This suggests that in order to maximize efficient economic output, there is only one board-foot pattern that simultaneously manages for each set of species targets. The actual harvest locations from each optimization run are different, but the cumulative board-foot trajectory is nearly the same for a given set of species targets under the timber objective. When the owl target is 13000, the trajectory of the amount harvested generally decreases, and the amount harvested in the initial period is the largest because the algorithm selected a subset of stands to intensively manage, while allowing the remaining stands to age. However, as fewer owls are required on the landscape, the trajectory generally increases since fewer older stands are needed to provide owl habitat (and due to the linearly increasing price intercept from the stumpage demand equations (see Table 5.2)).

Thus far, species time-series have been represented solely by their geometric means. However, it is important to know how this measure mirrors the predicted sizes through time since trajectories that crash in the final decade are not ecologically sustainable. Figures 5.5 (a), (b), (c), and (d) plot the predicted population sizes for each species over time. Figure 5.5 (a) shows the population

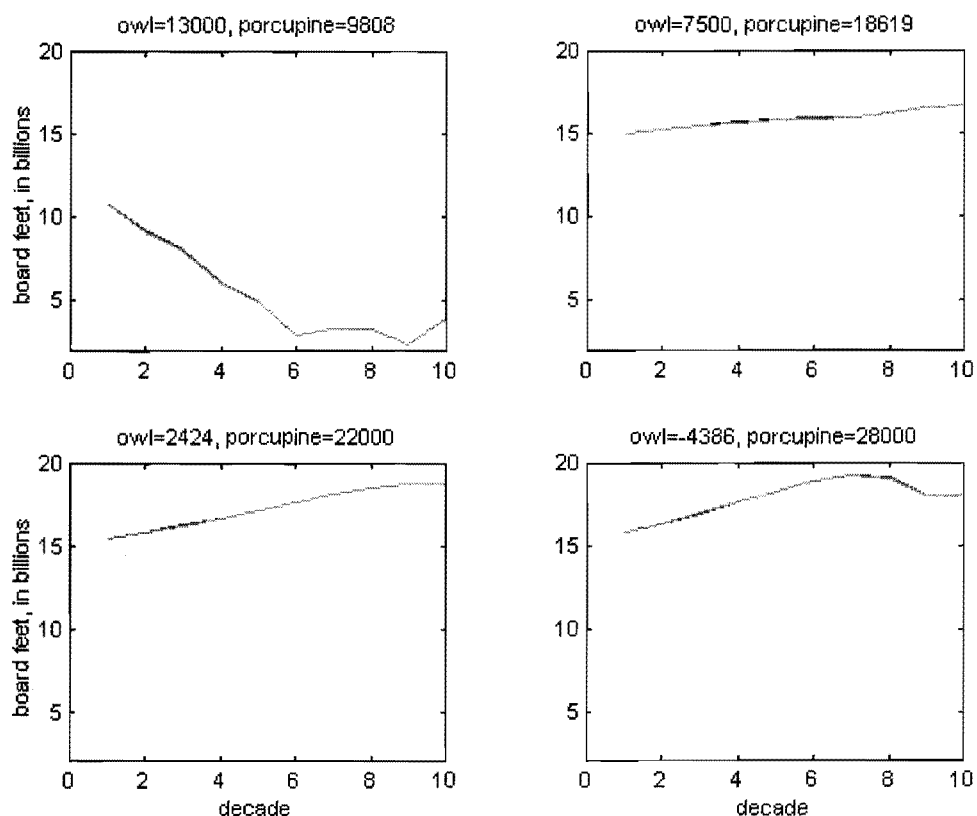


Figure 5.4. Board feet harvested per decade for the four representative points along the frontier. Each subplot is for a different set of species targets and contains the board feet time-series for five separate optimization runs. Due to scaling within each plot, all five trajectories fall more or less atop each other.

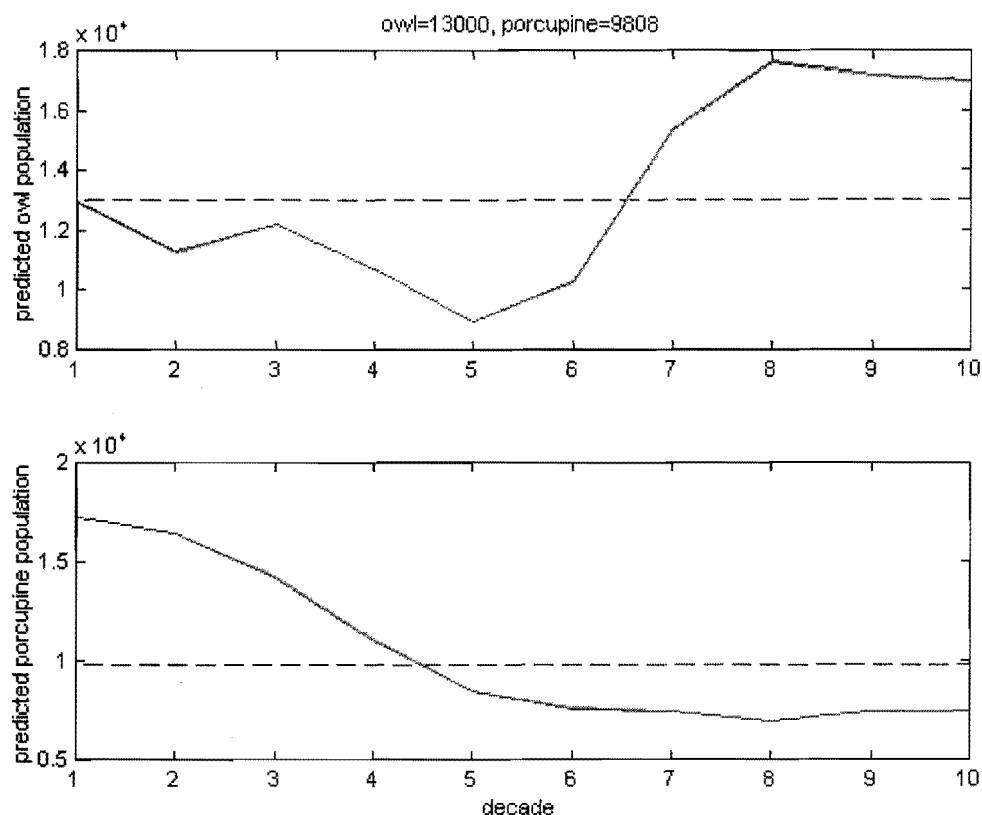


Figure 5.5 (a). Comparing predicted population sizes with their targeted geometric mean values. The geometric mean is the dashed line, while the five population time-series are the colored lines. Each set of subplots is for one of the four representative points on the frontier. This plot depicts the scenario when the owl target is 13000 and the porcupine target is 9808.

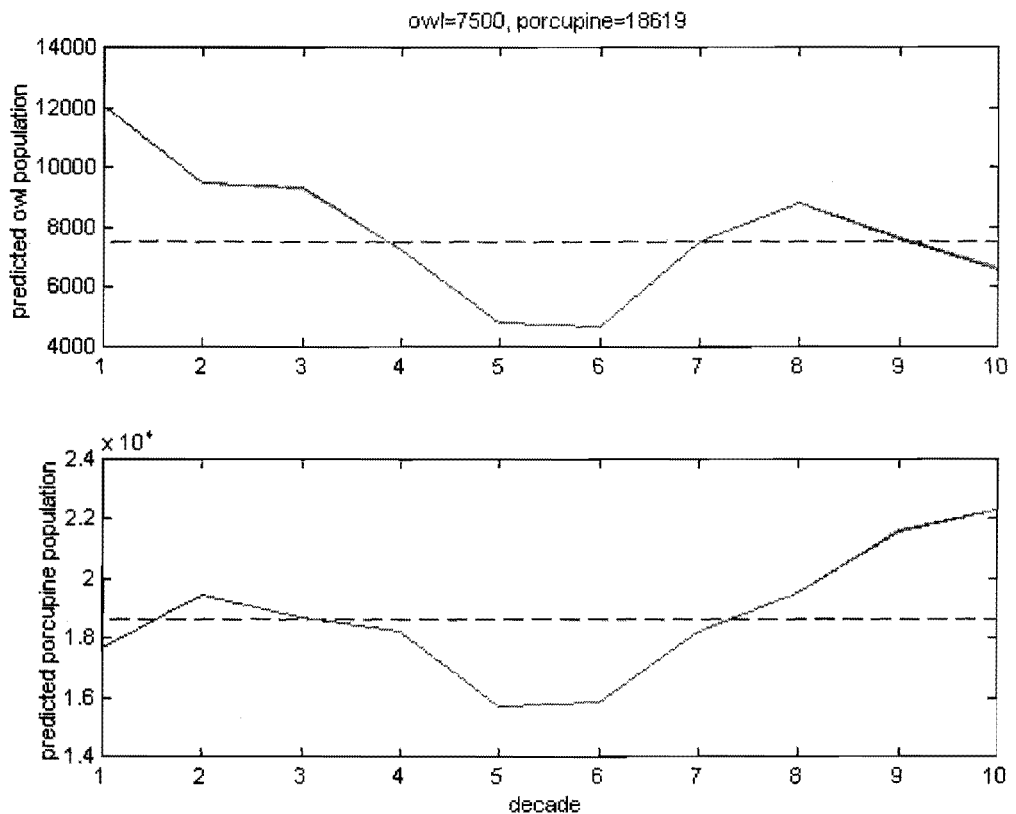


Figure 5.5 (b). Comparing predicted population sizes with their targeted geometric mean values. The geometric mean is the dashed line, while the five population time-series are the colored lines. Each set of subplots is for one of the four representative points on the frontier. This plot depicts the scenario when the owl target is 7500 and the porcupine target is 18619.

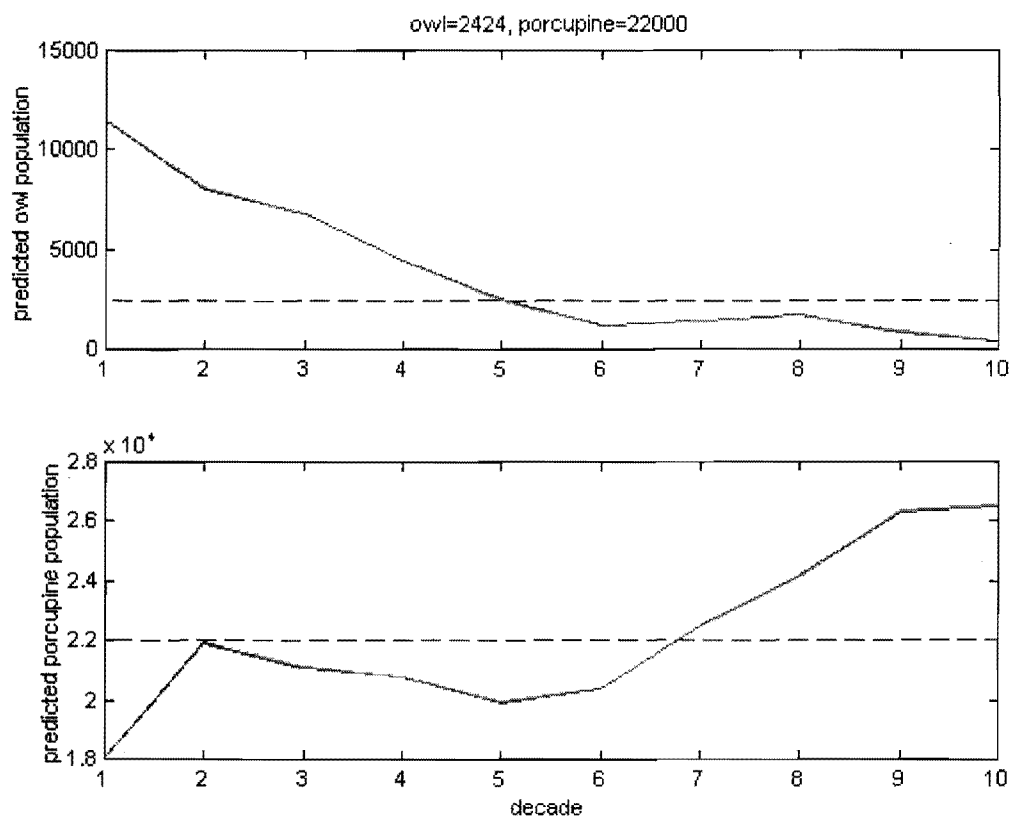


Figure 5.5 (c). Comparing predicted population sizes with their targeted geometric mean values. The geometric mean is the dashed line, while the five population time-series are the colored lines. Each set of subplots is for one of the four representative points on the frontier. This plot depicts the scenario when the owl target is 2424 and the porcupine target is 22000.

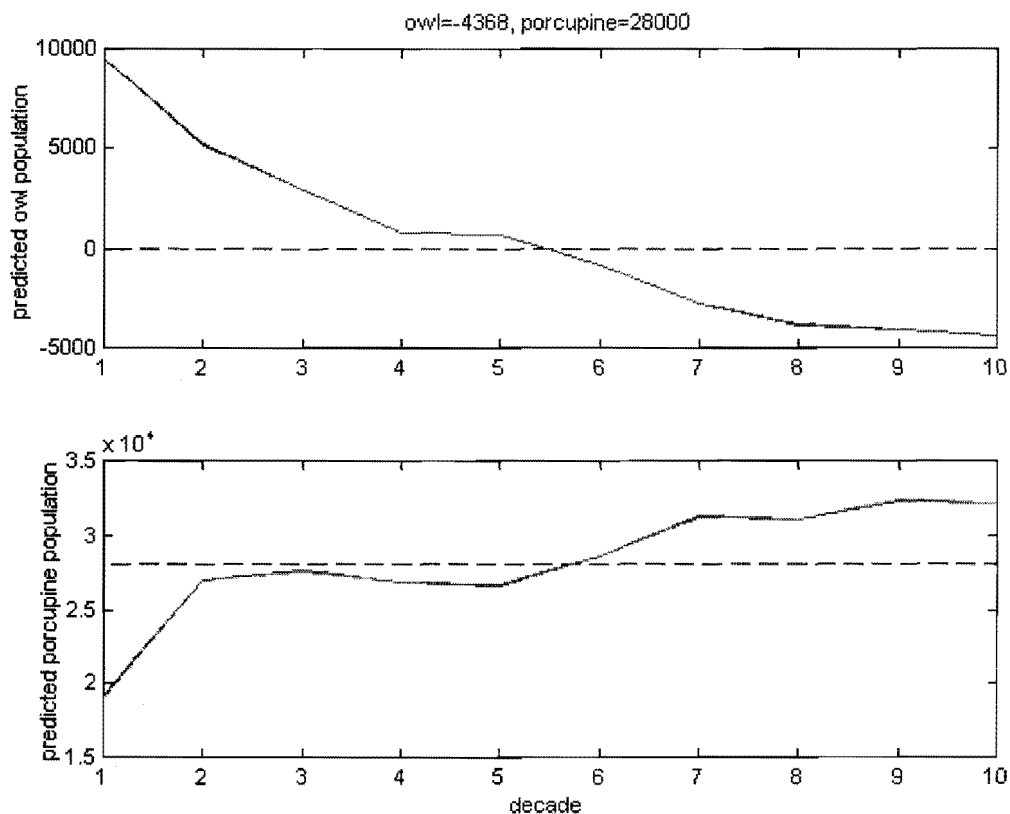


Figure 5.5 (d). Comparing predicted population sizes with their targeted geometric mean values. The geometric mean is the dashed line, while the five population time-series are the colored lines. Each set of subplots is for one of the four representative points on the frontier. This plot depicts the scenario when the owl's ending population size is -4386 and the porcupine target is 28000.



time-series for point A. The owl trajectory is at the top and the porcupine trajectory is at the bottom. The dashed line on each subplot is the specified geometric mean target, and the time-series from the five optimization runs are plotted with differently colored lines. Even though the five solutions were found from different starting points, they all have very similar trajectories for both species. The owl trajectories start near the target value (13000 owls), decline for the first five decades, but eventually increase and come to a more or less steady-state by the 8<sup>th</sup> decade. The ending size is higher than the specified geometric mean target to adjust for the smaller earlier population sizes. The porcupine populations start much higher than the target, but decline below the target and also reach a somewhat steady state.

Figure 5.5 (b), plots population time-series for point B. The ending population size of the owl is much closer to the target, but the porcupine exceeds its target at the end to compensate for the outcomes in the 1<sup>st</sup>, 5<sup>th</sup>, and 6<sup>th</sup> decades when the population sizes were below the target. Figures 5.5 (c) and (d) show analogous time-series for points C and D, respectively. In all eight plots, the trajectories found from multiple optimization runs are very similar. This provides further evidence that on this landscape there is only one way to manage for specified species population sizes while maximizing efficient economic production. Finally, it is observed that as targets are increased, ending population sizes generally exceed the targets, but for lower targets, populations generally fall below the targets. It was anticipated that an extra constraint would be necessary

during optimization to prevent population sizes from dropping dramatically in the final decade, but this situation never occurred across all optimization runs.

The species population size time-series presented thus far have been estimates of what might be expected from the wildlife simulator, PATCH (see Section 5.2). The estimated production possibilities frontier could be flawed if the estimates of PATCH outcomes used in the optimization were inaccurate. To examine how well estimated population size time-series matched PATCH simulation results, the five solutions for each of the four representative points were loaded into PATCH, and the effects of the management regimes were simulated for both species. Results that compare the estimated (or predicted) population sizes with the observed PATCH outcomes on the landscape are found in Figures 5.6 (a) and (b). Figure 5.6 (a) compares observed and predicted population sizes for the owl at each of the representative points. Time is plotted on the x-axis and the difference between observed and predicted is on the y-axis. Each colored line on a subplot represents the time-series of differences for one of the five different optimization solutions. In general, the larger the population size target, the larger the variability was between observed and predicted sizes. However, the differences are generally off by no more than 1% of each target value depicted, and all colored lines generally bounce about the zero line, demonstrating apparent unbiasedness. When the porcupine target was 28000, both the predictive wildlife proxy and actual PATCH results showed that owls were extirpated by the 6<sup>th</sup> decade. For this reason, the difference between

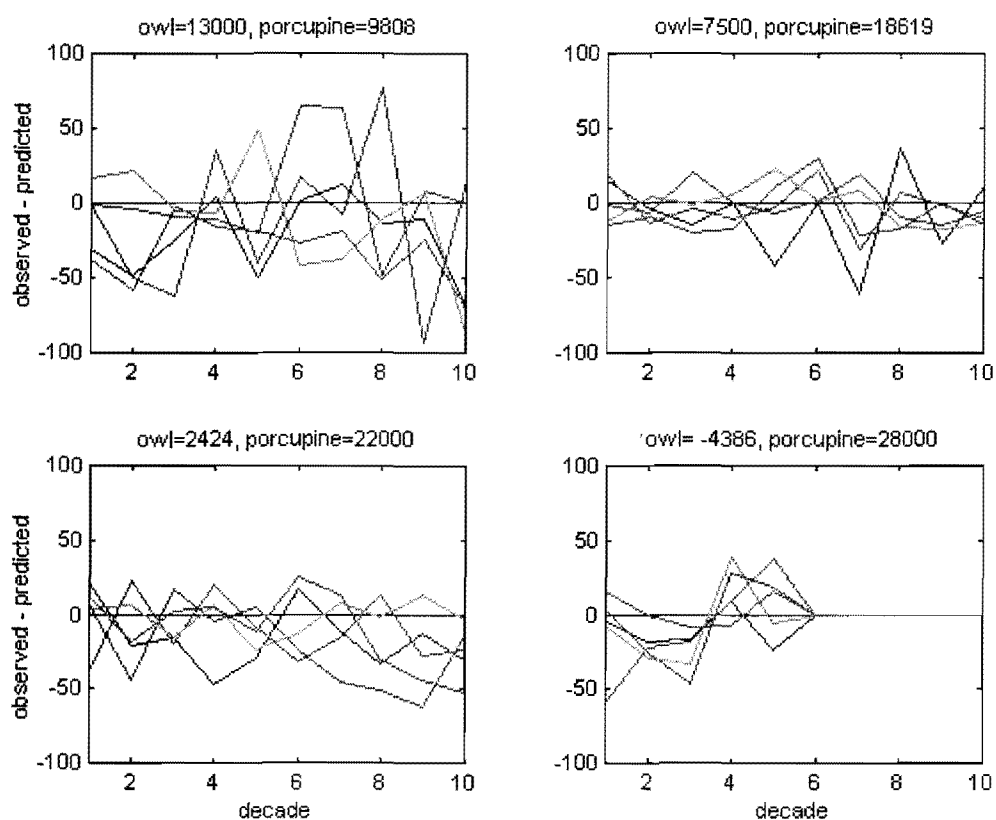


Figure 5.6 (a). Comparing observed owl population sizes from PATCH simulations with predicted sizes from optimization runs over the four representative points. Each colored line is from a separate optimization run.

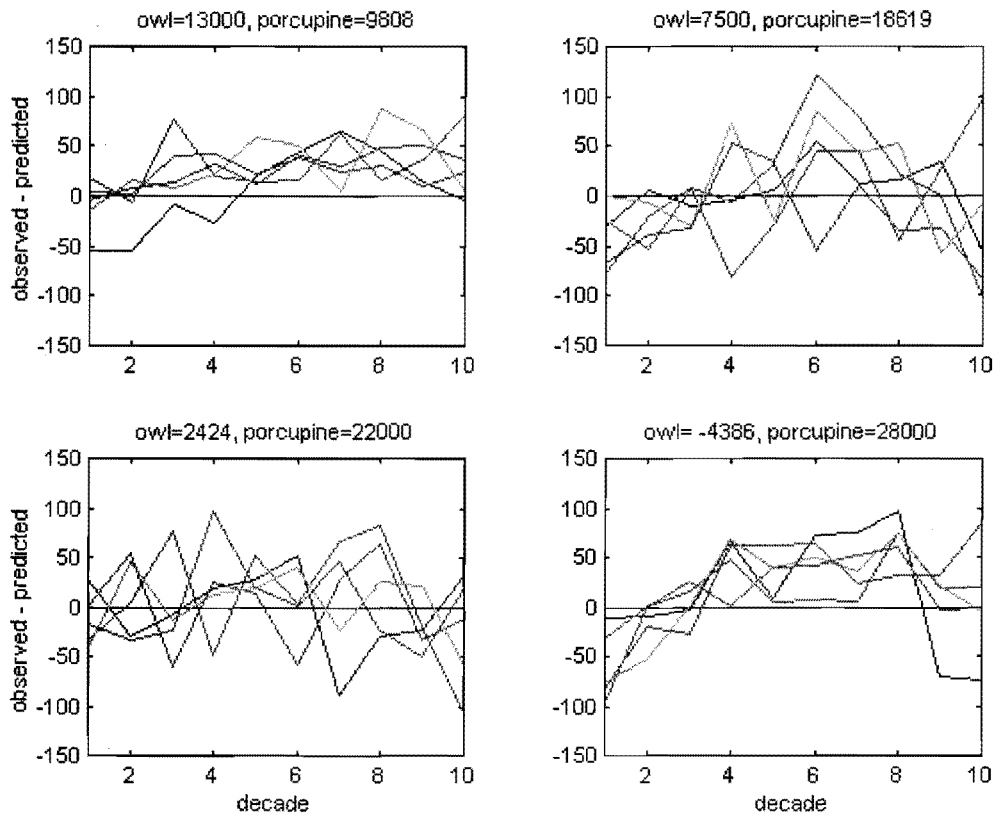


Figure 5.6 (b). Comparing observed porcupine population sizes from PATCH simulations with predicted sizes from optimization runs over the four representative points. Each colored line is from a separate optimization run.

observed and predicted owl population sizes was not plotted beyond the 6<sup>th</sup> decade. Figure 5.6 (b) plots the same variables but does so for the observed and predicted porcupine populations. The trends are similar to those for the owl – variability is somewhat higher for larger porcupine targets but it was never different than 1% of the target, and the differences generally appear unbiased (although some curvature is present when the porcupine target was 28000).

To examine spatial attributes of the four representative points, maps of harvest activities and habitat quality through time were developed. Only one time-series of maps per species for each representative point are shown. This is because the maps developed for the multiple solutions are very similar in terms of habitat pattern, but only the exact locations of the habitat structures created by the optimization model were different. Figures 5.7 (a), (b), (c), and (d) map harvests in each period for representative points A, B, C, and D, respectively. Those stands that are harvested in a period are colored yellow, and those that are not are colored green. Figures 5.8 (a), (b), (c), and (d) map owl habitat, and Figures 5.9 (a), (b), (c), and (d) map porcupine habitat, for points A, B, C, and D, respectively. Habitat quality is represented with color. The closer the color is to red on the spectrum, the better the quality of habitat for that particular species.

Figures 5.7 (a), (b), (c), and (d) shows that stands closer to the depots are generally more intensively managed in the first decade, creating a large block of young forest, but the economic objective generally makes the harvest of stands along the crest of the Cascades less attractive. Thereafter, harvest areas spread

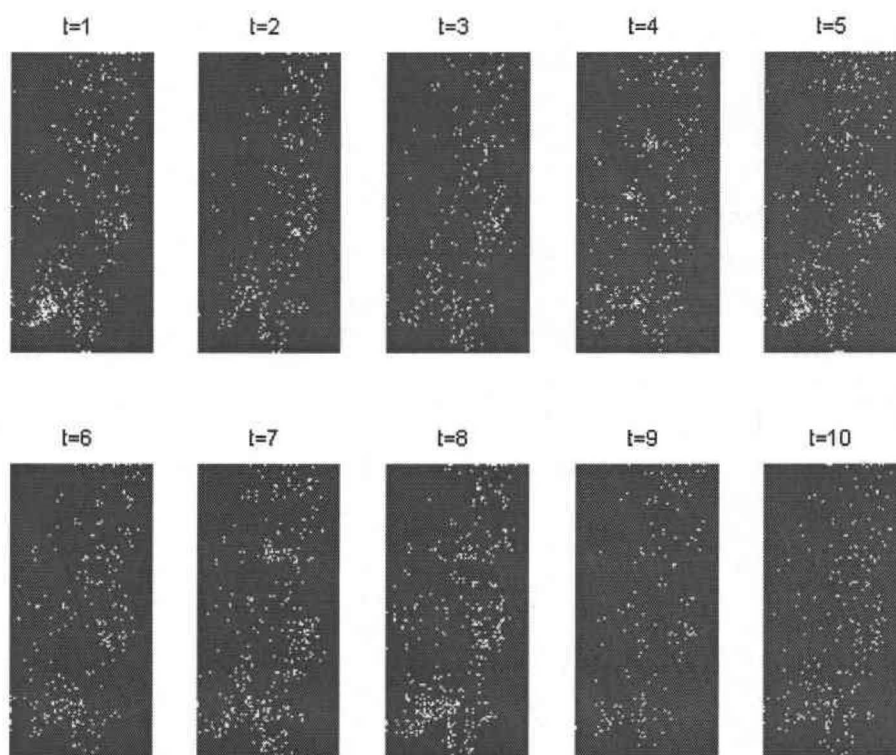


Figure 5.7 (a). Maps displaying harvest locations in each decade for representative point A (owl = 13000, porcupine = 9808). Harvested areas appear in yellow.

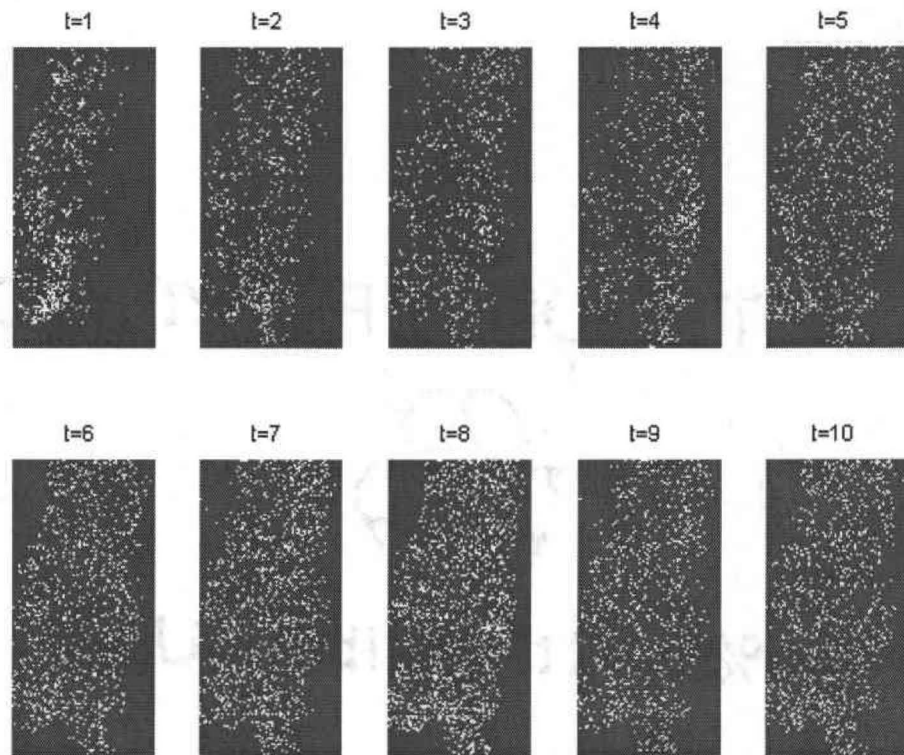


Figure 5.7 (b). Maps displaying harvest locations in each decade for representative point B (owl = 7500, porcupine = 18619). Harvested areas appear in yellow.

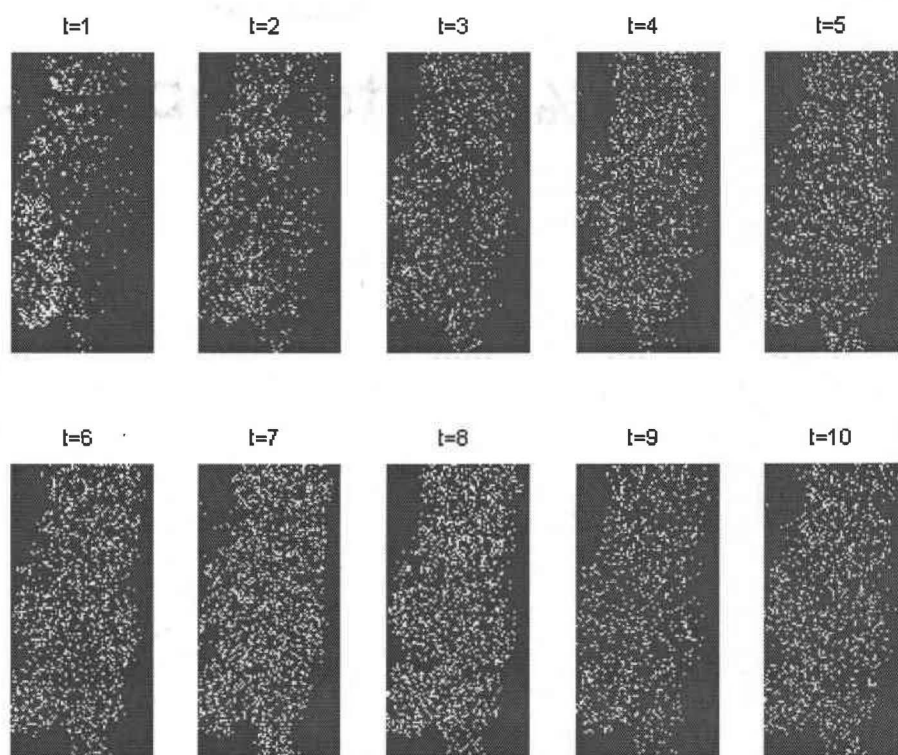


Figure 5.7 (c). Maps displaying harvest locations in each decade for representative point C (owl = 2424, porcupine = 22000). Harvested areas appear in yellow.



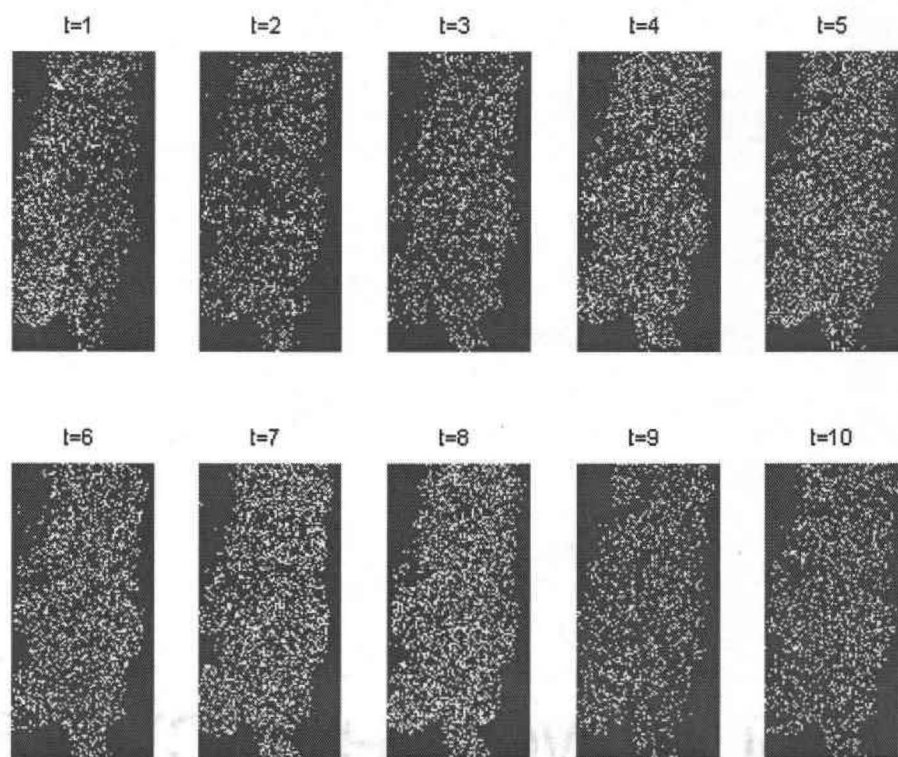


Figure 5.7 (d). Maps displaying harvest locations in each decade for representative point D (owl = -4386, porcupine = 28000). Harvested areas appear in yellow.

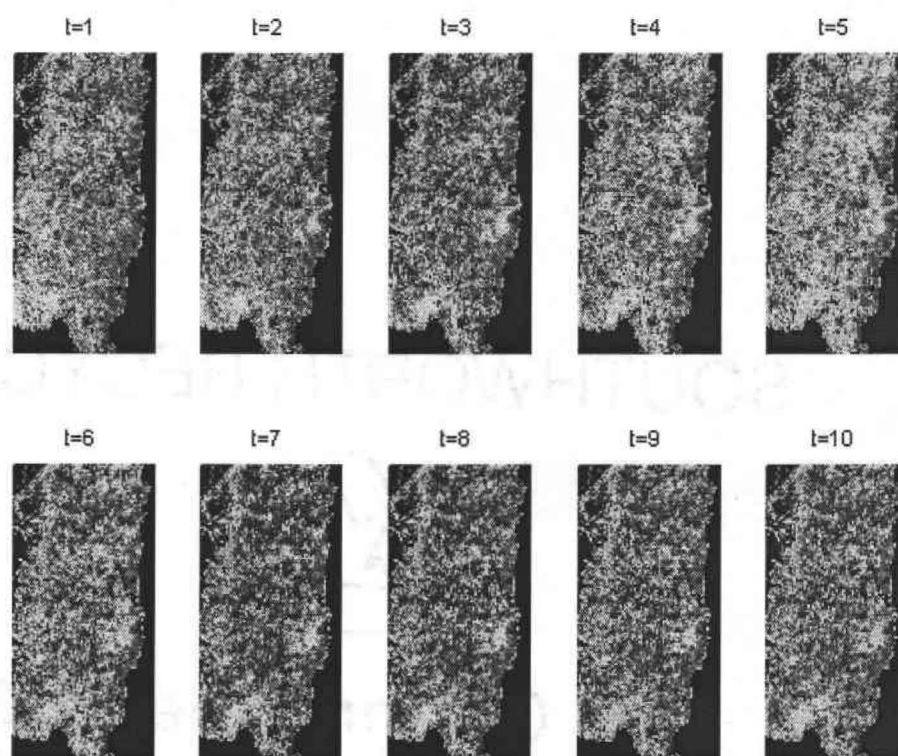


Figure 5.8 (a). Time-series of owl habitat maps for representative point A (owl = 13000, porcupine = 9808). The closer to red the color of an area is, the better its habitat quality for the owl.



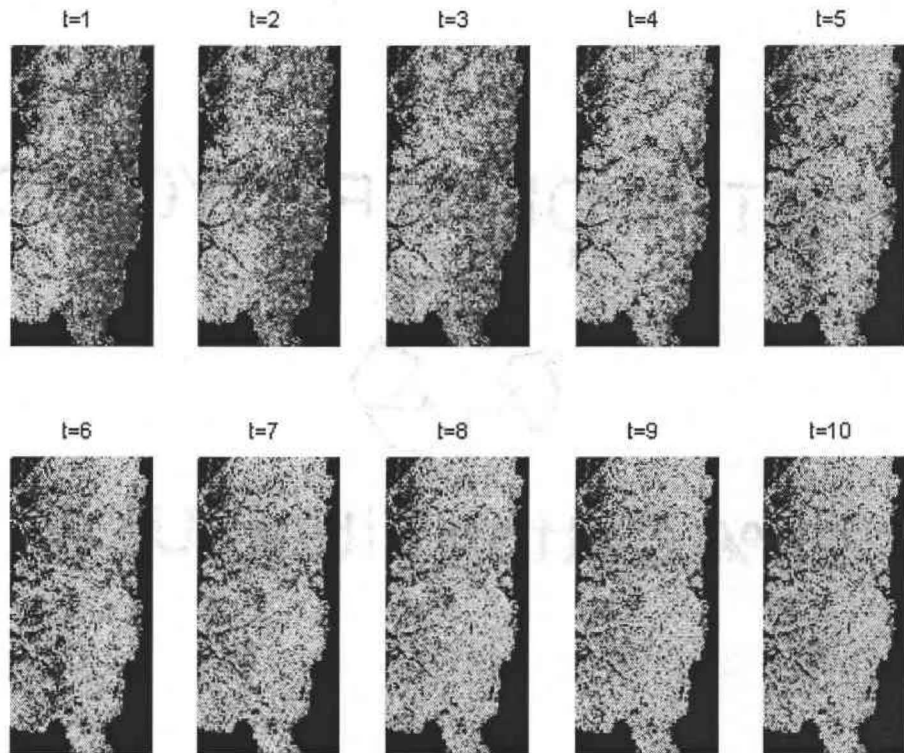


Figure 5.8 (c). Time-series of owl habitat maps for representative point C (owl = 2424, porcupine = 22000). The closer to red the color of an area is, the better its habitat quality for the owl.

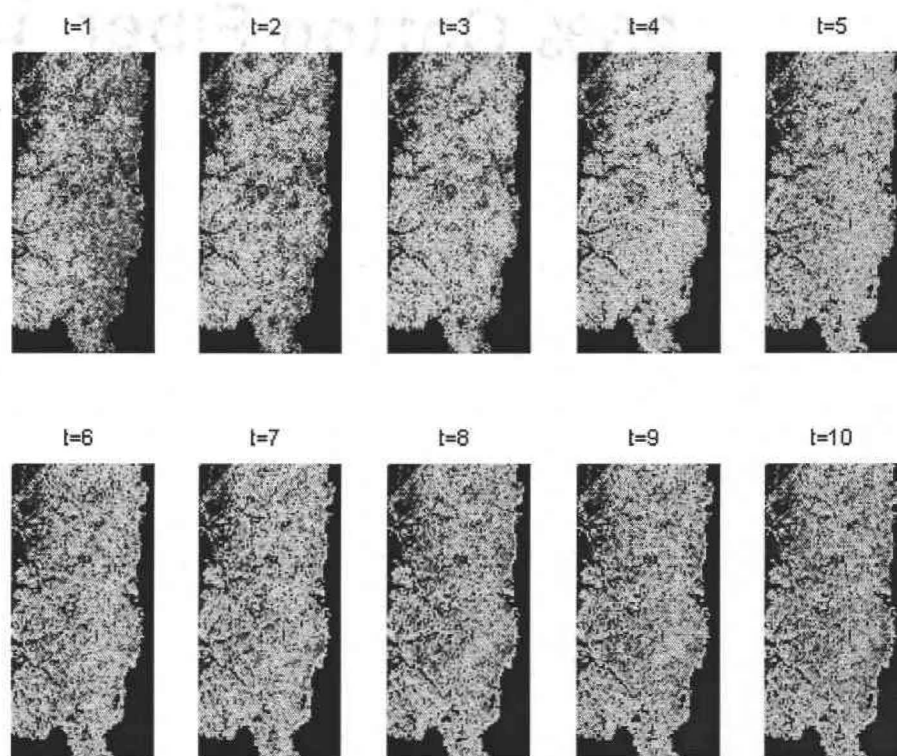


Figure 5.8 (d). Time-series of owl habitat maps for representative point D (owl = -4386, porcupine = 28000). The closer to red the color of an area is, the better its habitat quality for the owl.

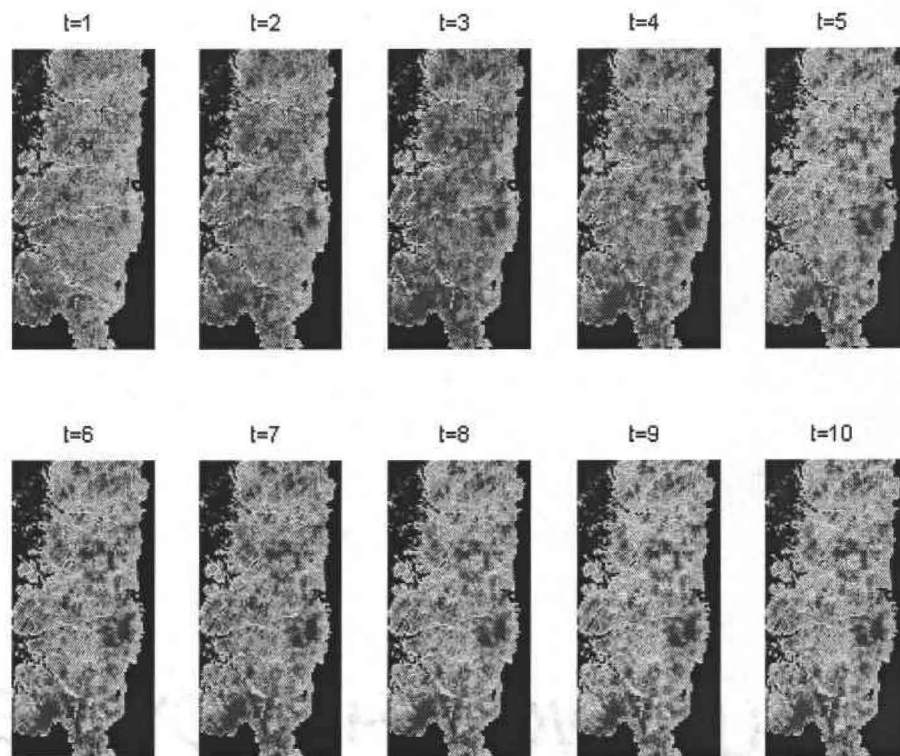


Figure 5.9 (a). Time-series of porcupine habitat maps for representative point A (owl = 13000, porcupine = 9808). The closer to red the color of an area is, the better its habitat quality for the porcupine.

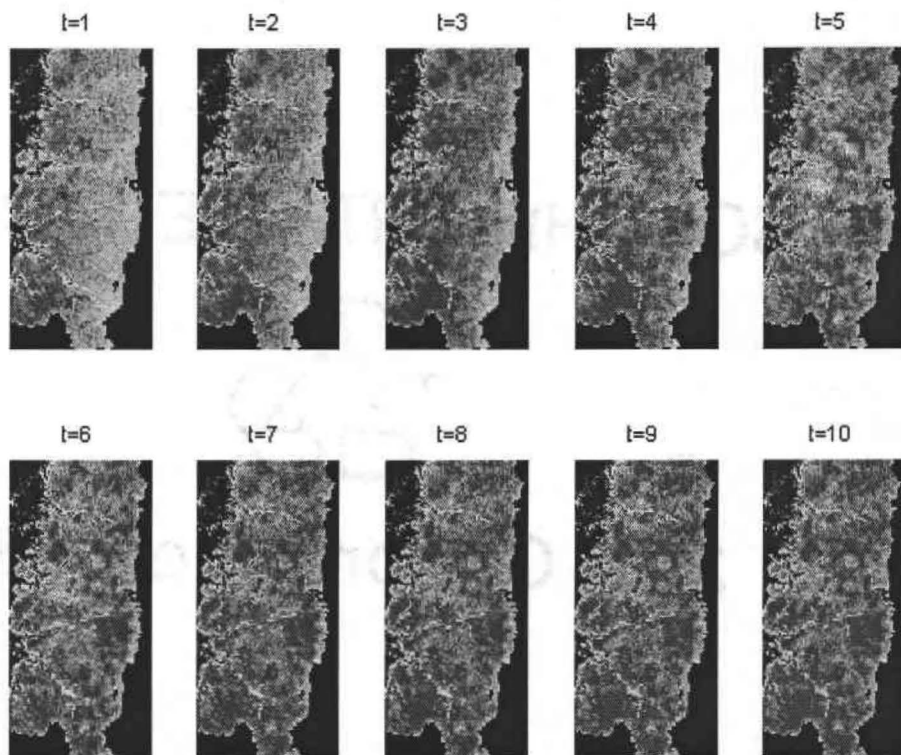


Figure 5.9 (b). Time-series of porcupine habitat maps for representative point B (owl = 7500, porcupine = 18619). The closer to red the color of an area is, the better its habitat quality for the porcupine.

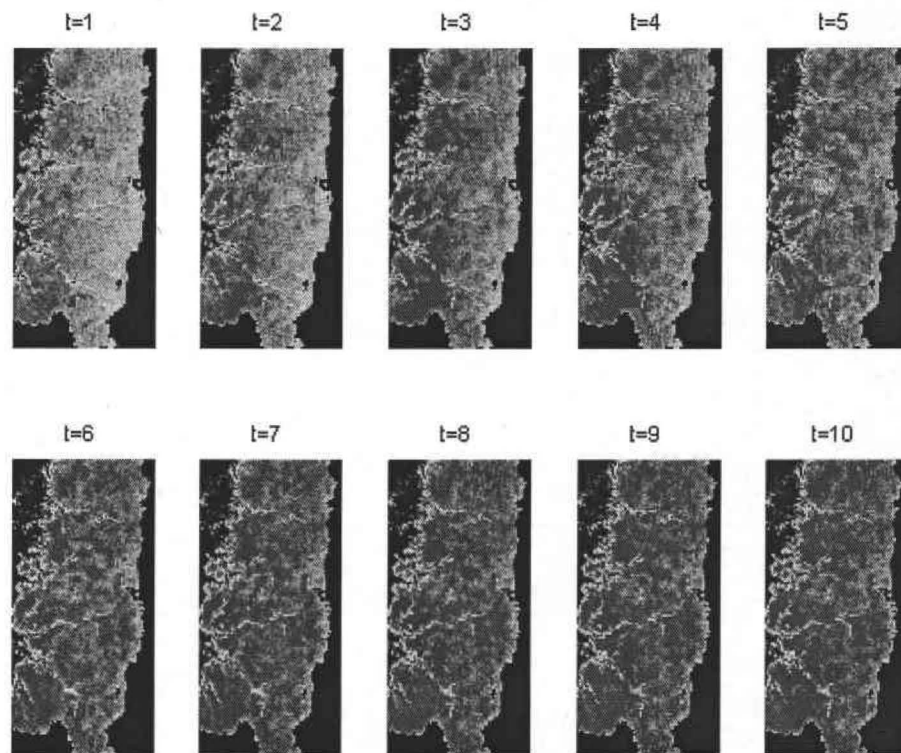


Figure 5.9 (c). Time-series of porcupine habitat maps for representative point C (owl = 2424, porcupine = 22000). The closer to red the color of an area is, the better its habitat quality for the porcupine.



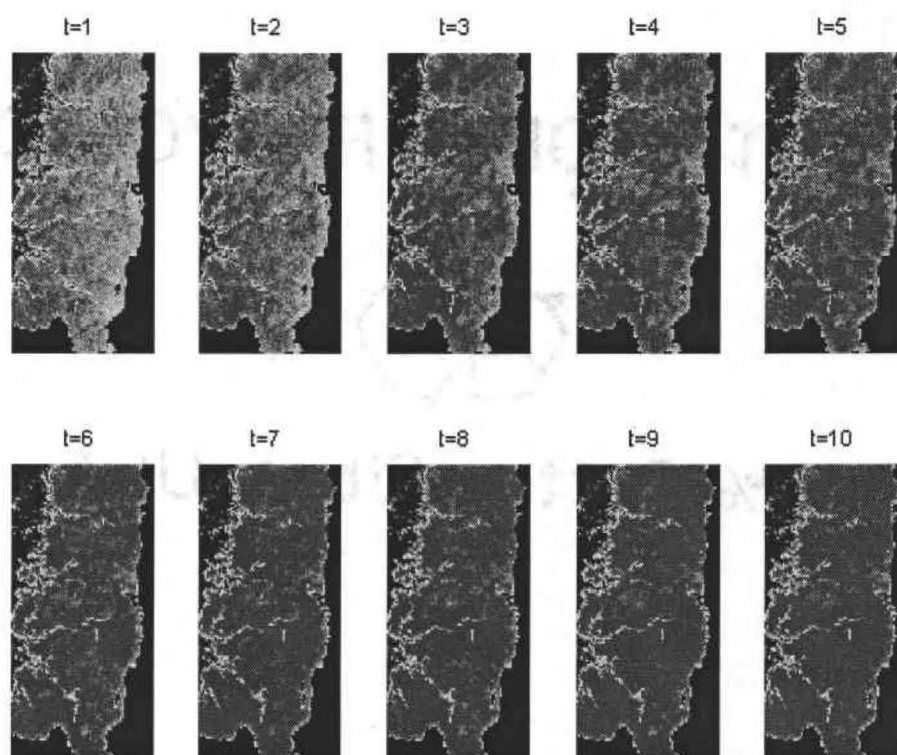


Figure 5.9 (d). Time-series of porcupine habitat maps for representative point D (owl = -4386, porcupine = 28000). The closer to red the color of an area is, the better its habitat quality for the porcupine.

out across the landscape in a more-or-less random fashion. Harvest frequency becomes more intense as the owl target declines and porcupine target increases. It is important to note that if the objective was instead to simply maximize the quantity of board feet harvested over the 100-horizon, the owl will be extirpated from the landscape (from PATCH simulations). As the owl target is decreased, the high quality habitat across the entire landscape in Figure 5.8 (a) is first transformed into pockets of higher quality habitat surrounded by marginal habitat (b), then fewer pockets of high quality habitat appear while the surrounding habitat is further marginalized (those stands closest to the depots are generally of the least quality) (c), and finally nearly all of the landscape is of low quality habitat (d). In (d), it is important to note that the population drops to 0 by the 6<sup>th</sup> decade. A handful of scattered quality habitat areas remain, but these are not estimated to be sufficient to support a viable owl population. What is occurring in the four owl habitat maps is that spatially, the owl can tolerate fragmentation on the landscape since it can travel great distances in search of food and habitat (see Nalle<sup>a</sup> et al. 2001). However, it can only tolerate the marginalization of habitat until most of the older stands are harvested. No distinct, large, contiguous areas of solid red appear in the same location on all the maps, suggesting that the owl is not as affected as some species by forest age-class fragmentation as long as a sufficient amount of older stands are left.

As for the porcupine, its habitat maps are mostly red because the porcupine is more of a forest generalist than the owl. Due to the trade-off

between timber production and owl populations, the deep red areas (younger stands) increase with the decreasing owl targets. Unlike the owl habitat development, the location of a few deep red areas persists, suggesting that larger, contiguous fixed-site reserves might better suit the porcupine.

### 5.7.2 Policy-constrained analysis

Once the frontier was located, relevant policy scenarios could then be examined. To see how well the three different policies described in equations (5.13), (5.14), and (5.15) related to the frontier, the optimization model was re-run to obtain three additional points for comparison. Species population targets (constraints (5.8)) were ignored to see how each policy might impact the owl and porcupine. The optimization model imposed the first policy by maximizing the objective function subject to constraints (5.2) through (5.13) (except for (5.8)). This scenario merely constrains timber production on public lands by requiring a non-declining even-flow. The model was next used to maximize the objective function subject to constraints (5.2) through (5.14) (except for (5.8)). This simulated the second policy of interest – that of requiring non-declining even-flow on public lands and disallowing all harvests on publicly owned old-growth stands. Finally, the third policy scenario was implemented by maximizing the objective function subject to constraints (5.2) through (5.12), and constraint (5.15) (except for (5.8)). This last scenario disallows all harvests on public lands. The

results from the three scenarios are found in Table 5.4, as well as the result previously obtained when the timber objective was maximized while disregarding species populations. As should occur, objective function values decreased as harvest activities on public lands were more constrained. In all cases, as timber production was restricted, populations of the owl increased while populations of the porcupine decreased.

Table 5.4. Species geometric mean population sizes for different policy-constrained and non-policy scenarios.

CS+PS	Discounted		
	owl	porcupine	in \$ billions
Maximum timber value	3851	19562	24.340
Even-flow on public	3914	18806	24.053
Even-flow on public and no harvest of publicly- owned old-growth	3943	18695	23.976
No public harvests	8503	14121	21.057

Graphs similar to those above are shown in Figures 5.10 to 5.15. Figure 5.10 plots board feet harvested in each decade for the four scenarios listed in Table 5.4. Amounts regularly increase and are nearly identical, except for the case when no timber is extracted from public lands. Because half of the forested tracts in the study area are owned by the U.S. Government, disallowing harvests on public lands essentially creates price incentives for other (i.e., private) owners to harvest more frequently. However, there is not sufficient private timber supply

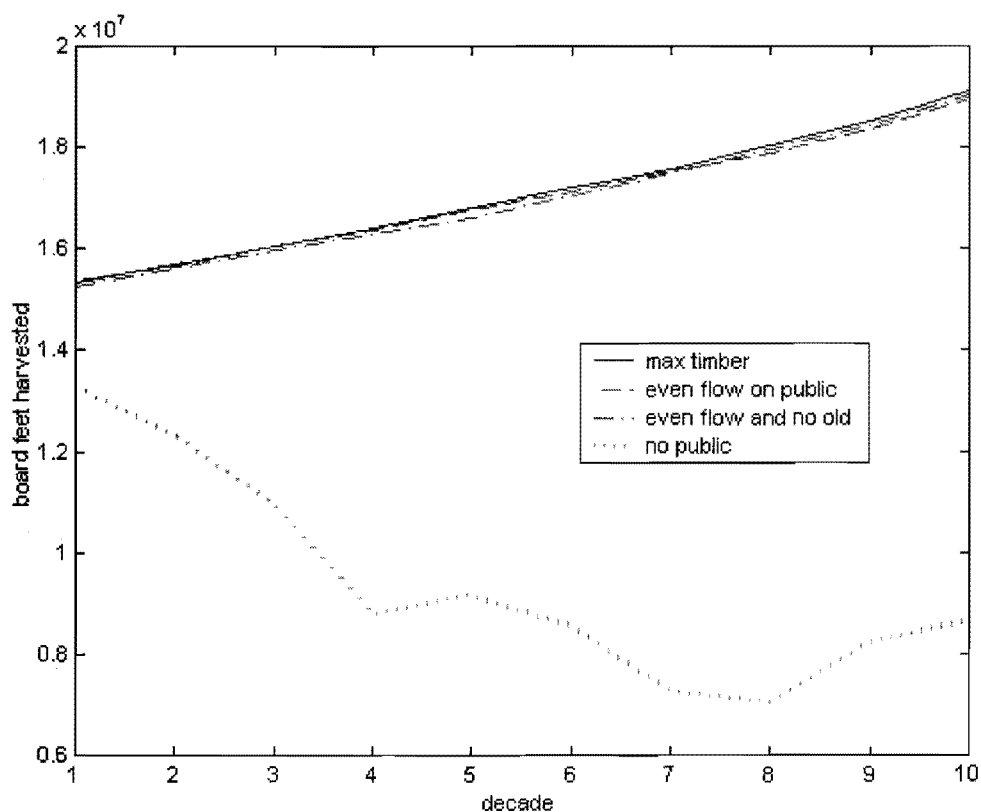


Figure 5.10. Plot of the amount of board feet, in billions, harvested in each decade for the four scenarios listed in Table 5.4.

in the region to force production at the margin, and this is the reason for the non-smooth flow of stumpage in the last policy scenario.

Figure 5.11 (a) plots the time-series of owl populations for the four scenarios. Populations decline until the fifth decade where they level off, except for the fourth scenario where populations rebound. Only when public harvests are disallowed is the ending owl population approximately the same as its beginning population. This results from allowing a portion of the landscape to age, thus creating more owl habitat in later periods. For the other three scenarios, the ending owl population is just 20% of its initial size. Figure 5.11 (b) plots porcupine time-series. In terms of stability, porcupine sizes are the least affected species for the different scenarios. However, their densities are most affected by the last policy scenario since they have less affinity for older stands.

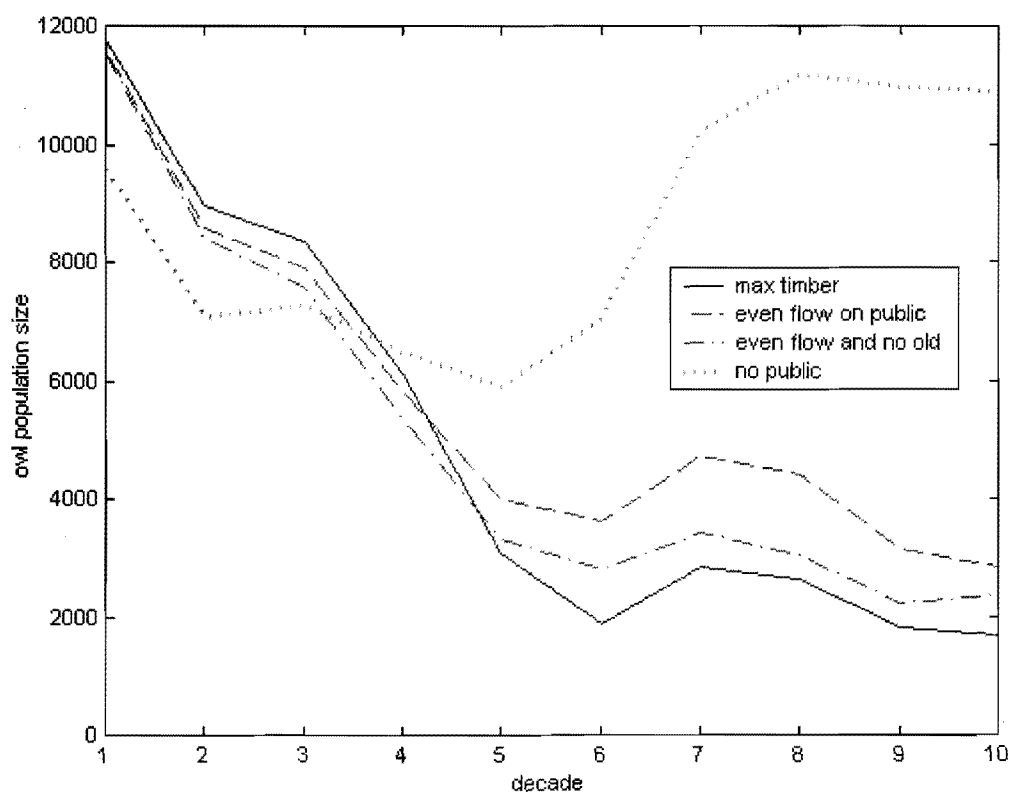


Figure 5.11 (a). Plot of owl time-series for the four scenarios listed in Table 5.4.

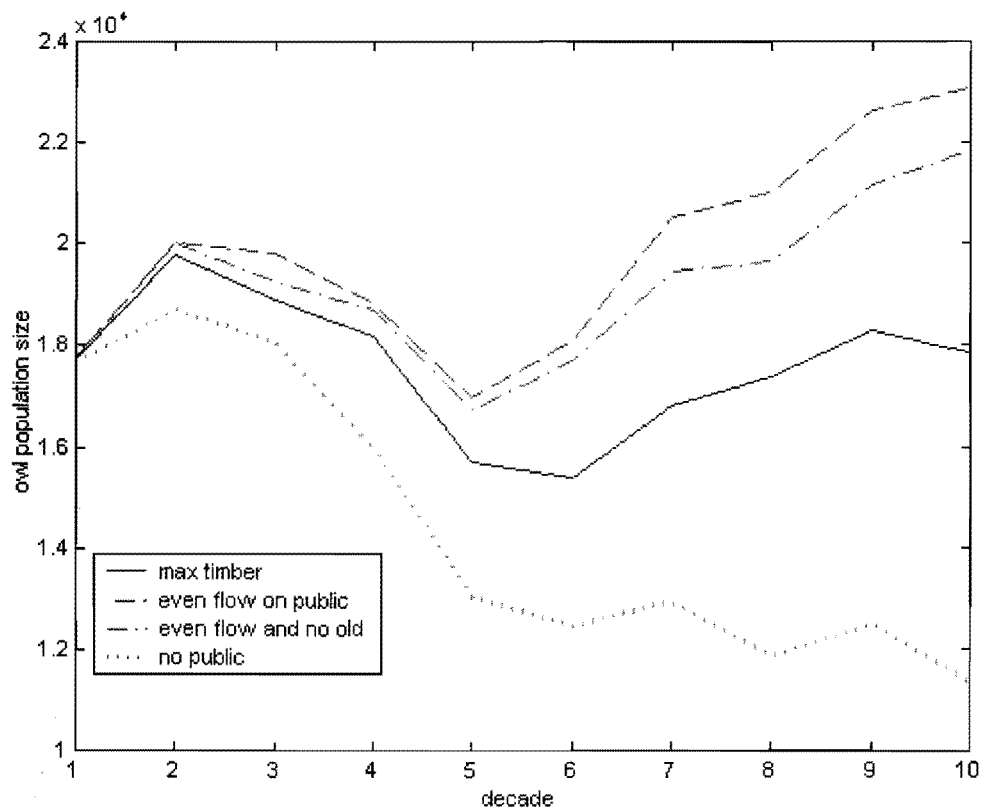


Figure 5.11 (b). Plot of porcupine time-series for the four scenarios listed in Table 5.4.



Finally, maps for the four scenarios are displayed. Figures 5.12 (a) and (b) show owl and porcupine habitat maps at the point where the timber objective is maximized with no restrictions. Owl habitat quality is worse nearest the depots (haul costs are the least there; thus, stands closer to the depots can be harvested more frequently) but improves with distance. This trend holds as time progresses, but the total amount of owl habitat declines until the sixth or seventh decade, at which point the location of quality habitat becomes more or less fixed. The change in porcupine habitat (Figure 5.12 (b)) progresses in nearly the opposite direction of owl habitat, with larger, contiguous blocks of deep red appearing at unchanging locations.

Figures 5.13 (a) and (b), 5.14 (a) and (b), and 5.15 (a) and (b) show similar maps for the first, second, and third policies, respectively. In Figure 5.13 (a), when non-declining even-flow is required on public lands (all areas on the right half of the map), the higher quality owl habitat in Figure 5.12 (a) is converted into marginal owl habitat, but a greater area of marginal owl habitat exists in Figure 5.13 (a). From Figure 5.13 (b), the requirement of non-declining even-flow improves porcupine habitat over that when no harvest restrictions were placed on public lands (Figure 5.12 (b)). When non-declining even-flow *and* the harvest of “old-growth” stands on public land are disallowed, the corridor of high quality owl habitat reappears along the crest of the Cascades (Figure 5.14 (a)) and more marginal owl habitat areas are available (as opposed to Figure 5.12 (a) when no

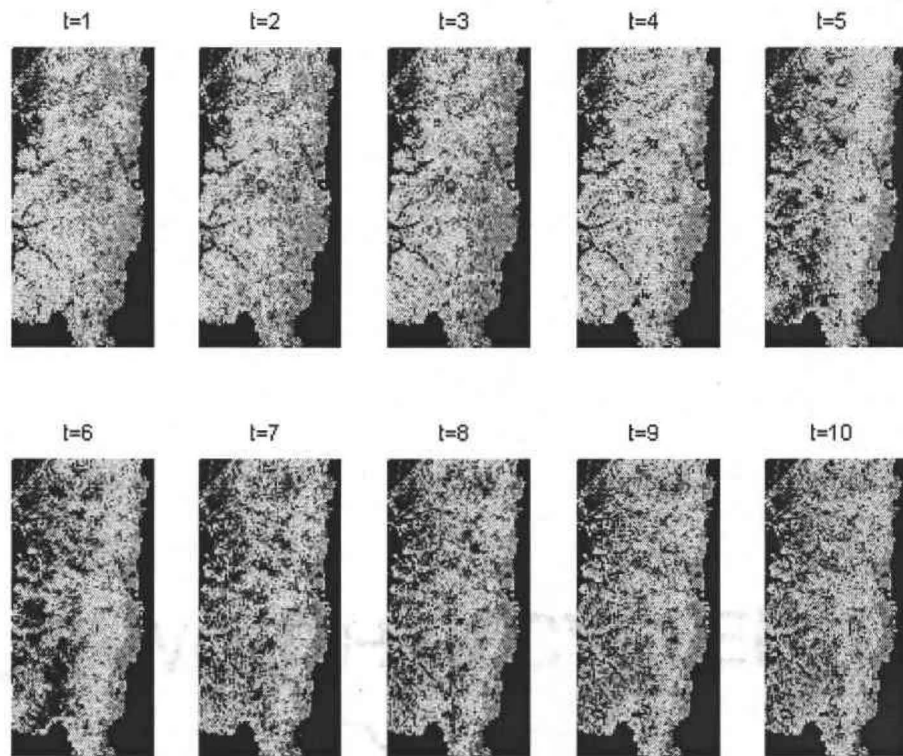


Figure 5.12 (a). Time-series of owl habitat maps at the point where the timber objective is maximized. The closer to red the color of an area is, the better its habitat quality for the owl.

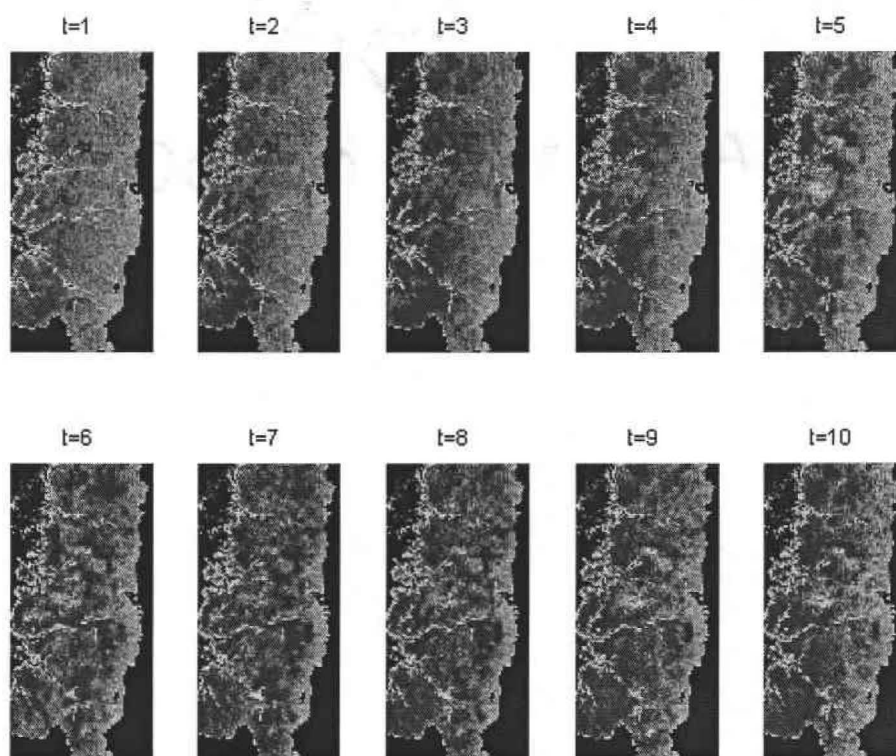


Figure 5.12 (b). Time-series of porcupine habitat maps at the point where the timber objective is maximized. The closer to red the color of an area is, the better its habitat quality for the owl.

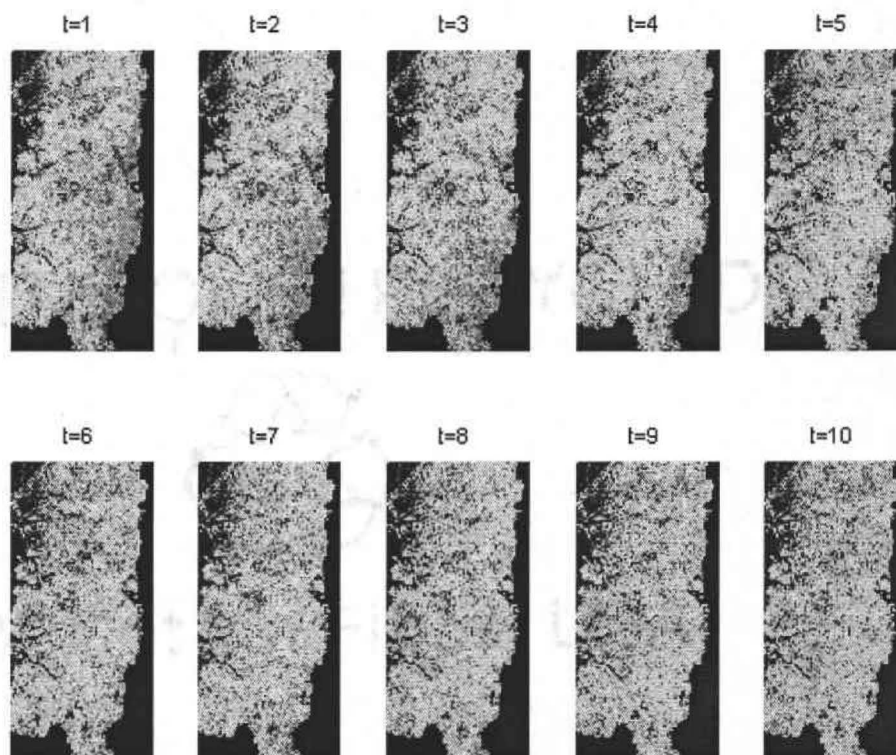


Figure 5.13 (a). Time-series of owl habitat maps under the first policy scenario where a non-declining even-flow of timber occurs on public lands. The redder the area, the better the quality of habitat for the owl.

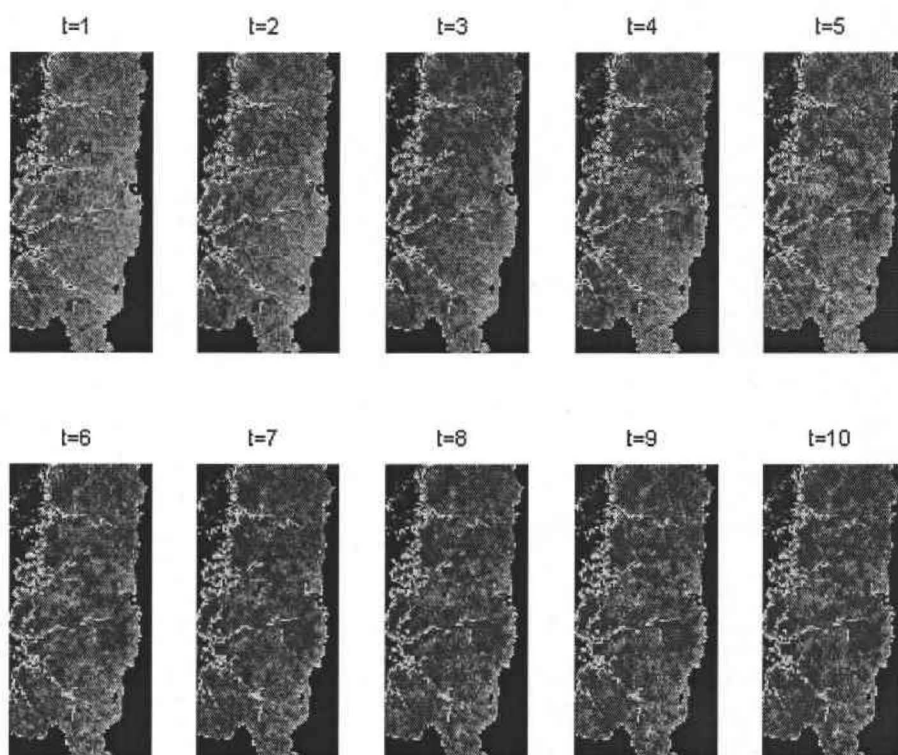


Figure 5.13 (b). Time-series of porcupine habitat maps under the first policy scenario where a non-declining even-flow of timber occurs on public lands. The redder the area, the better the quality of habitat for the porcupine.

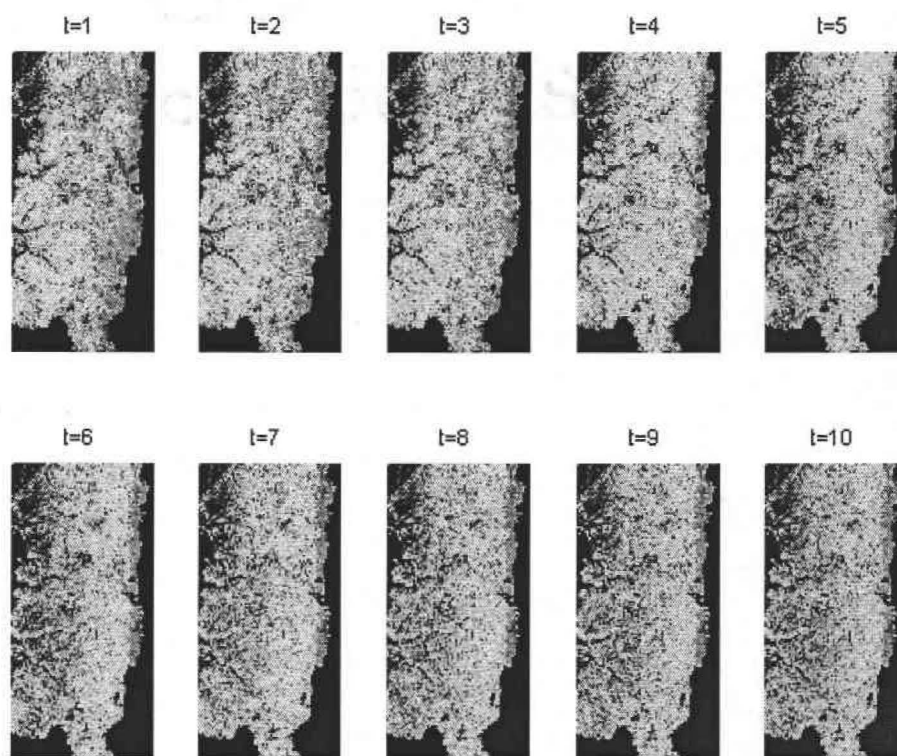


Figure 5.14 (a). Time-series of owl habitat maps under the second policy scenario where a non-declining even-flow of timber occurs on public lands and no publicly-owned stands that are at least 200 years old at the outset can ever be harvested. The redder the area, the better the quality of habitat for the owl.

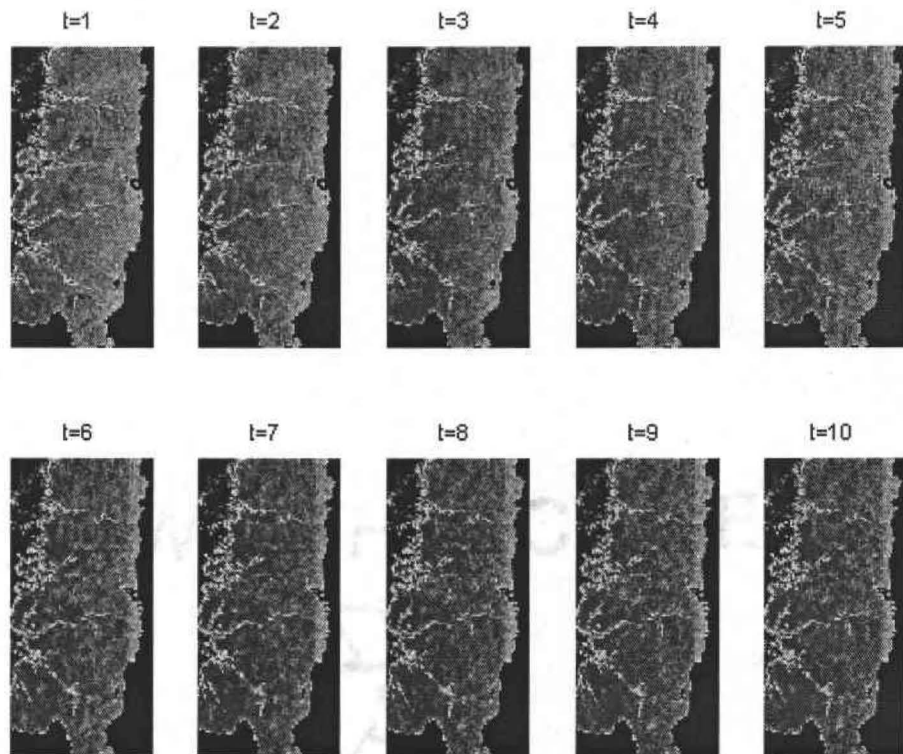


Figure 5.14 (b). Time-series of porcupine habitat maps under the second policy scenario where a non-declining even-flow of timber occurs on public lands and no publicly-owned stands that are at least 200 years old at the outset can ever be harvested. The redder the area, the better the quality of habitat for the porcupine.

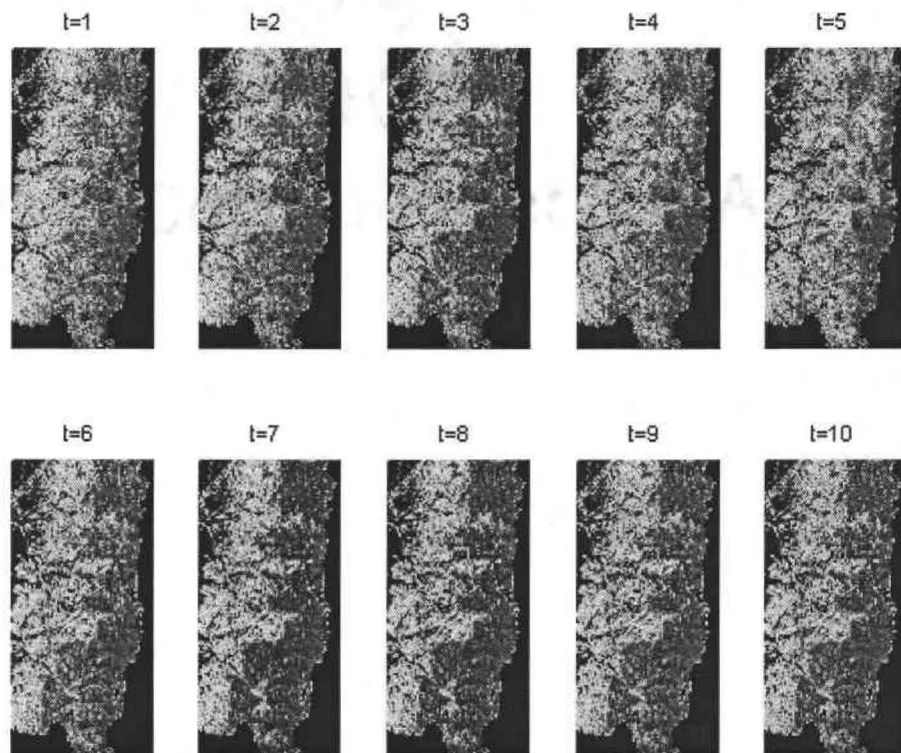


Figure 5.15 (a). Time-series of owl habitat maps under the third policy scenario where no timber harvests are ever allowed on public lands. The redder the area, the better the quality of habitat for the owl.



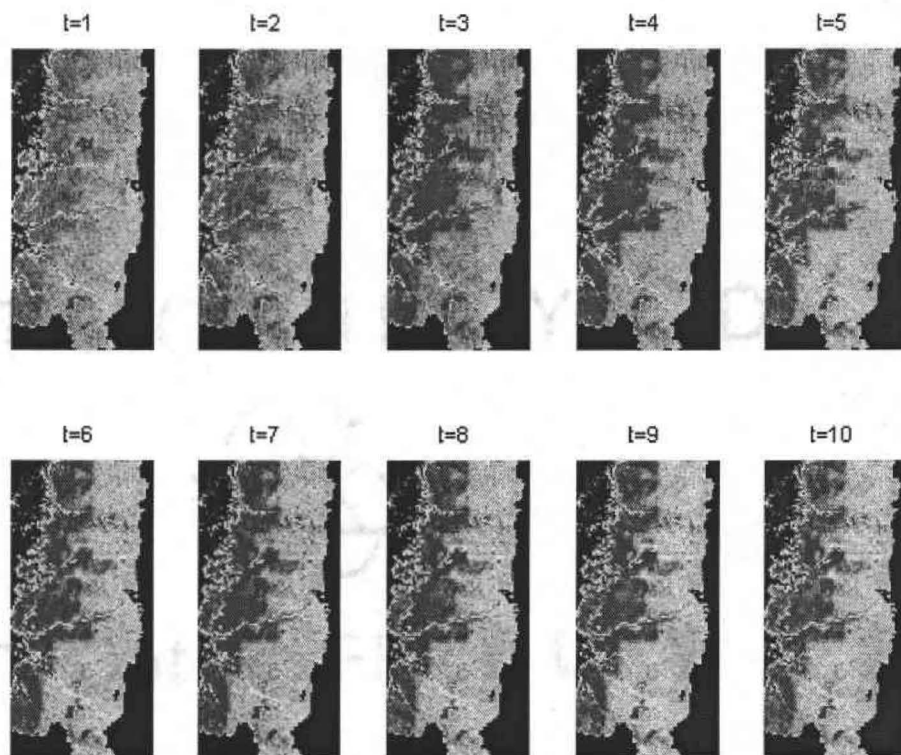


Figure 5.15 (b). Time-series of porcupine habitat maps under the third policy scenario where no timber harvests are ever allowed on public lands. The redder the area, the better the quality of habitat for the porcupine.

harvest constraints are required). Finally, when no harvests are allowed on public land, it is clear from Figures 5.15 (a) and (b) that managing all public lands for species with affinities for older stands, e.g., the owl, under efficient economic timber production will create a large block of young stands (ideal porcupine habitat) in the private sector (those areas located nearest the depots) since haul costs are smaller.

## 5.8 Discussion

The results obtained in Section 5.7 covering just three of the many outputs from the large study landscape are a small sample of the information generated when searching for the production possibilities frontier of lands managed for multiple objectives. However, to better understand economic and ecological linkages in the region, more factors could be included, such as: additional endemic species (to aid in reserve design); invasive species (for more efficient use of resources in Integrated Pest Management); risk of losses by natural disturbances (to better address uncertainty in species protection and flow of timber through time); water quality and flow (for riparian habitat restoration and maintenance); enhanced modeling of timber demand between regions (for added realism); and models of land cover type conversion (to estimate changes in the location and amount of forested habitat). Each component adds another layer of complexity to the model, and this can make understanding, visualization and

communication of tradeoffs difficult. Such difficulty is no reason to abandon the approach, but it is nonetheless a legitimate concern to keep in mind when attempting to relate findings to decision-makers and the public. Certain outputs might serve as proxy measures for other outputs, such as the porcupine for the timber objective in this study, thereby reducing the dimensionality of the problem. However, caution should be taken if reduction is used since other important links could be lost. For example, by substituting the timber objective for the porcupine, the link to the threatened Pacific fisher – thought to be sensitive to forest fragmentation and a major predator of the porcupine – would not be accounted for.

The work presented in this paper is an important step in the continued integration of Operations Research, Ecology, Economics, and Statistics to model real world actions and associated consequences on the landscape. Numerous results have come from this cross-disciplinary effort. Although the original intent was to use the wildlife simulator directly to model the effects of management actions through time and space, it was found that it is possible to accurately estimate population sizes based on summary measures such as the amount of forested area, the quality of habitat in present and past time periods, and past population sizes. The use of a simple economic measure of output that included estimated demand for stumpage and travel costs resulted in realistic land management behavior and showed where and when on the landscape sub-populations of species were expected to occur. By combining the economic and

ecological outputs within an optimization framework, the timing and location of management activities could be arranged to simultaneously manage for different amounts of owls and porcupines. In other words, the optimization routine identified the type and spatial configurations of habitat that best supported both species while maintaining efficient economic production. This showed that optimization tools can be very beneficial to managers who must manage for and justify the locations of multiple and possibly competing usages. Lastly, it has been demonstrated that the consequences of relevant policy scenarios can be obtained using optimization tools. Results can then be used to determine policy adherence to objectives, and uncover institutional shortcomings that can be corrected with more effective, defensible, and responsible policy-making.

There are many possible avenues of further research. The inter-play of additional ecological outputs needs to be studied, as well as the effectiveness of proposed fixed-site reserves on these species. But before doing so, different spatial and non-spatial measures of habitat quality as it relates to the amount and distribution of forest cover must be examined to provide benchmarks against which alternative forest management plans can be compared. More points along the frontier must be studied in greater detail to see how well the proxy measure models the wildlife simulator, and the uncertainty of not meeting specified management goals needs to be addressed by modeling the probability of reaching different species target levels as a function of economic production, initial landscape conditions, habitat spatial layout, and other factors. It is hoped that this

work will provide decision-makers and the public with sufficient science-based information to better achieve long-term goals as measured by both economic and ecological objectives.

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## Chapter 6. Summary

Ecologists have long hypothesized that species will benefit by varying degrees from different spatial arrangements of habitat. Whether all species native to a region could be sustained from a series of scattered, fixed-site nature reserves or one large, contiguous fixed-site reserve is still an open question. It is also not currently known if permanent reserves are a necessity for species survival. Such large-scale problems with spatial and temporal components are generally difficult to solve, and this is one reason why OR techniques have been used throughout the body of this dissertation.

Chapter 2 developed a new solution heuristic and new spatial model to develop maximally compact and contiguous reserve proposals while meeting habitat requirements. The new model extended existing spatial optimization models for reserve design, and the new search technique improved upon existing optimization procedures to solve constrained quadratic zero-one formulations. When applied on a 44000 km<sup>2</sup> tract, it was found that the percentage to reserve of each habitat changes the location of the best possible spatial arrangement, that spatial designs differ under a compactness or contiguity objective, and that existing reserves can constrain the location and quality of the best possible spatial arrangement.

A shortcoming of Chapter 2 is that economic factors were completely ignored. All solutions were found under the assumption of an unlimited budget



for land acquisition. Funding for conservation purposes is usually a major restriction, so the total estimated purchase price of land in a reserve proposal is an important consideration. Chapter 3 extended the spatial optimization model by incorporating a budget constraint. When applied on a 4200 km<sup>2</sup> tract, it was found that large gains in terms of reserve compactness and contiguity could be had for very slight increases in the allowable budget. This trend continued until reserve proposals neared what was maximally possible spatially; at which point the trend sharply reversed and only small gains in spatial design could be had for very large increases in the allowable budget. Furthermore, when the same analysis was done in the presence of existing reserves, it was found that the spatial design could always be improved for the same or lesser cost when existing reserves were ignored. The contributions of these findings were threefold. They suggested that conservation planning can be improved through more coordinated efforts between different federal, state, and private organizations; they identified what was maximally obtainable for the same amount of resources; and they provided a means of measuring the efficiency of an existing reserve design.

Chapters 2 and 3 noted that species are expected to respond differently as spatial arrangements change, but no species were simulated to verify how spatial designs might promote or adversely impact species survival. The models also did not account for temporal change on the landscape. Because habitat can change through time and because the assurance of species survival is a major driving force behind conservation planning, it is questionable how well these solutions

address species sustainability. Economic treatment was also lacking. Although the estimated purchase price of land is a measure of all future incomes streams under its *current* management, withdrawing land from economic production has other economic and social ramifications that were not accounted for. Regional impacts on resource-based production were ignored, and the assumption that permanent, fixed-site reserves are the best and only means of species sustainability was never examined.

Chapters 4 and 5 sought to develop a more realistic modeling framework to identify tradeoffs between conservation purposes and economic production as well as between different species. To accomplish these goals, an advanced, realistic wildlife simulator, PATCH, from the U.S. Environmental Protection Agency, was employed to estimate spatial and temporal impacts on species populations from spatial and temporal timber extraction and temporal habitat change in forest growth. Optimization was used to determine the timings and locations of management actions under the objective of economic efficiency while maintaining predefined population thresholds. However, direct interfacing with PATCH during dynamic optimization was not possible due to long simulation run times.

Chapter 4 developed spatial and temporal methodology to quickly estimate population responses to landscape change. Three species were simulated: the Gray jay; Great horned owl; and Common porcupine. Each has different vital rates (survival and reproduction), habitat requirements (source/sink

characteristics), and movement behavior (site occupation and re-colonization). From direct observation in PATCH, regression equations were found that provided a means of spatial estimation that quickly determined habitat quality as a landscape changes through time. These also allowed for the rapid update of the habitat quality estimates when landscape change occurred, and with these equations a time-series of population sizes could be instantaneously determined on a large landscape. Since optimization procedures can require many iterations, the speed of estimating population responses is an essential factor for real-time solution. Chapter 4 makes economic tradeoff assessment possible by embedding the estimated behavior of a realistic species simulator within an optimization model.

Chapter 5 sought a more unified modeling approach that could directly answer questions relating to tradeoffs between economically efficient resource production and species survival, reserve design, and policy effectiveness. A new heuristic optimization procedure was used to explicitly identify spatial and temporal sets of management actions that were maximally efficient under both economic and ecological objectives. This relationship, known as the production possibilities frontier, is useful since it shows which combinations of economic and ecological outputs are maximally obtainable on any given landscape, but, perhaps most importantly, the frontier provides a means for comparing the levels of different outputs without attaching economic value to non-market goods and services. When efficient timber production and the population sizes of two

species were compared on a 1.7 million hectare forested landscape, the focal species benefited from different types of reserve designs arising from different management actions over a 100 year planning horizon. The Common porcupine tended to prefer large, compact, and contiguous blocks of habitat, whereas the Great horned owl could tolerate a certain degree of forest age-class fragmentation as long as enough older stands were available on the landscape in any given time period. This showed that it was not possible to simultaneously maximize population sizes of both species, but it was possible to maintain viable populations of each for near maximal amounts of economically efficient timber production on this particular landscape.

The work in this dissertation attempts to bring together economic and ecological perspectives within the unified modeling framework of OR. It has been shown that OR can aid in decision-making, identify tradeoffs between competing uses, and improve efficiency when simultaneously addressing economic and ecological concerns. The lessons highlighted here show that purely economic-based decisions do not exist in a vacuum – they have short- and long-term ecological impacts. This issue has been a legitimate criticism from the environmental lobby. However, the same criticism can be made of purely ecological-based decisions – these also have short- and long-term economic impacts. The results found by optimization procedures in this work are not sets of management actions that should be taken, rather they are sets of actions that could be taken. Determining the levels of biological and economic production that

society is willing to manage for is no easy task, but it is nonetheless necessary as more information is gathered (through OR techniques or otherwise) about the interactions people have with the land, air, and water.

The OR community is continually discovering new ways in which it might contribute to natural resource management. Despite its limited name recognition in other fields, OR practices have become staples in many industries, due in part to the trillions of dollars in gains from cost efficiencies and revolutionary pricing structures, as well as institutional backing. Acceptance arises from a track record of results. This has occurred in economics, but it is still needed for ecological applications. It is hoped this dissertation will help construct a portion of a bridge between economics and ecology towards more efficient natural resource utilization.

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