Developing a production possibility set of wildlife species persistence and timber harvest value

David E. Calkin, Claire A. Montgomery, Nathan H. Schumaker, Stephen Polasky, Jeffrey L. Arthur, and Darek J. Nalle

Abstract: An integrated model, combining spatial wildlife population and timber harvest and growth models, was developed to explore tradeoffs between the likelihood of persistence of a wildlife species, the northern flying squirrel (Glaucomys sabrinus), and timber production on a landscape on the west side of the Oregon Cascade Range. A simplified wildlife model was developed from the fully parameterized spatial wildlife model, using a habitat neighborhood-weighting scheme, for use in the optimization. Simulated annealing, a heuristic optimization technique, was used to solve for harvest schedules that maximized the net present value of timber harvest subject to a target value for likelihood of species persistence over a 100-year planning period. By solving this problem for a range of species persistence targets, a production possibility frontier was developed that showed tradeoffs between timber harvest value and likelihood of species persistence on this landscape. Although the results are specific to the wildlife species and the landscape analyzed, the approach is general and provides a structure for future models that will help land managers and forest planners to understand tradeoffs among competing resource uses.

Résumé : Un modèle intégré, combinant des modèles à référence spatiale de populations fauniques et de récolte et croissance de matière ligneuse, a été développé pour explorer les compromis entre la probabilité de persistance d’une espèce faunique, le grand polatouche (Glaucomys sabrinus), et la production ligneuse dans un paysage du versant ouest de la chaîne des Cascades en Oregon. Un modèle faunique simplifié a été développé, à des fins d’optimisation, à partir du modèle faunique à référence spatiale paramétrique complet en utilisant un système de pondération des habitats voisins. L’adoucissement simulé, une technique heuristique d’optimisation, a été utilisé pour produire des cédules de récolte qui maximisent la valeur actuelle nette de la récolte ligneuse tout en visant une valeur-cible de probabilité de persistance de l’espèce sur une période de 100 ans. En produisant ces cédules pour une gamme de cibles de persistance de l’espèce, nous avons pu déterminer une frontière des possibilités de production qui montrait les compromis entre la valeur de la récolte ligneuse et la probabilité de persistance de l’espèce dans le paysage. Malgré que les résultats soient spécifiques à l’espèce faunique et au paysage étudiés, l’approche est généralisable et elle fournit un cadre pour de futurs modèles qui aideront les aménagistes du territoire et les planificateurs forestiers à comprendre les compromis entre l’utilisation de ressources concurrentes.

[Traduit par la Rédaction]

Introduction

Public land managers are called upon to meet multiple, and sometimes conflicting, ecological and economic goals. This is illustrated by the debate on how to promote both timber sales and continued survival of species such as the marbled murrelet, northern spotted owl, and various stocks of anadromous salmon in the Pacific Northwest. In a recent report to the U.S. Secretary of Agriculture (Johnson et al. 1999), an interdisciplinary Committee of Scientists recom-
sues (e.g., survival of a key species), there is a growing number of studies that consider both ecological and economic issues in an integrated fashion. Several recent studies (Pressey et al. 1997; Ando et al. 1998; Polasky et al. 2001) have focused on solving the maximal coverage or minimum area problems. Maximal coverage problems attempt to identify the maximum number of different wildlife species that can be represented on a given land base, while the minimum area problem minimizes the amount of area in a reserve system such that a set number of species are represented. Other studies, most notably Hof et al. (1994) and Hof and Rafael (1997), have used optimization techniques to explore the spatial layout of habitat for specific wildlife species. The Hof et al. (1994) study optimized the spatial and temporal layout of management actions for two species with competing habitat requirements on a hypothetical 25-cell grid, while Hof and Rafael (1997) optimized habitat placement for the northern spotted owl (Strix occidentalis) using a spatially explicit wildlife habitat model. A growing number of studies have used production possibility frontier methodology or marginal cost analysis to explore the relationship between biodiversity and timber harvest value. Montgomery et al. (1994) developed the concept of species viability as a marginal choice between the estimated probability of species survival and the value of timber harvest using habitat protection for the northern spotted owl as an example. Haight (1995) compared the economic cost in terms of foregone timber harvest revenue of different viability constraints for a hypothetical sensitive wildlife species. Arthaud and Rose (1996) developed a weighted approach that compared the timber harvest value with a habitat suitability index for the ruffed grouse (Bonasa umbellus). Haight and Travis (1997) and Marshall et al. (2000) explored cost-effective protection strategies for sensitive wildlife species. Kangas and Pukkala (1996) and Pukkala et al. (1997) developed indices to represent biodiversity goals and explored the relationship between timber harvest volume and these indices on two case studies. Rohweder et al. (2000) examined the tradeoffs between timber harvest value and a small set of biological goals in northeastern Oregon.

There are compelling arguments that further integration in resource modeling is needed. Murray and Snyder (2000) stated in the introduction of a special issue of Forest Science dedicated to spatial modeling in forest management and natural resource planning that the special issue was "...brought about by the continued independent development of nature reserve design and spatially constrained harvest scheduling modeling research."

In this study, we integrated models of wildlife population dynamics and timber production, incorporating wildlife habitat and timber harvest scheduling considerations into a single optimization framework. Using a heuristic approach to optimization, specifically a simulated annealing algorithm, we identified the approximate bound on the set of feasible combinations of likelihood of species persistence and timber harvest value, known as the production possibility frontier (Mas-Colell et al. 1995). The production possibility frontier illustrates the tradeoff between these two outputs under efficient land management, showing how much timber harvest must be reduced to increase likelihood of species persistence by some amount (or vice versa). Land management that generates combinations of timber harvest and likelihood of species persistence inside the production possibility frontier is inefficient in the sense that one output could be increased without decreasing the other. The production possibility frontier was identified without regard to landowner objectives or constraints, to estimate the productive capacity of the site for the modeled outputs. A simple policy simulation (a single reserve on a managed landscape) was done to illustrate the potential of the approach for policy analysis.

This work extends previous studies by using a stochastic spatially explicit wildlife population simulation model, PATCH, that is sensitive to habitat quality to track wildlife populations on a changing landscape over time and to estimate likelihood of species persistence on that landscape (Schumaker 1998). The managed landscape contributed to both outputs, rather than being allocated to one or the other as in the reserve site problem. Like Hof and Raphael (1997), we used the simulation model to parameterize a simplified wildlife habitat model, using a neighborhood-weighting scheme, for use in the optimization model. Solutions were passed back through the fully parameterized wildlife simulation model to produce our final estimates of the production possibility frontier.

The problem of optimal landscape management is complex because of both spatial and dynamic components. Heuristic optimization techniques can be applied to problems where complete enumeration of the solution space is unrealistic because of the size of the problem and where traditional integer programming methods are computationally prohibitive (Reeves 1993). Heuristic techniques have been applied to large computationally solvable problems and have been shown to identify “good” (i.e., close to the globally optimal) solutions at low to moderate levels of computational effort. Studies such as Lockwood and Moore (1993), Sessions and Sessions (1993), Murray and Church (1995), and Boston and Bettinger (1999) have used heuristic optimization techniques for timber harvest scheduling applications. Additionally, Pukkala et al. (1995), Kangas and Pukkala (1996), Laroze and Greber (1997), and Bettinger et al. (1996, 1997, 1998) have developed heuristic optimization algorithms to identify solutions for forest management problems with conservation objectives. Several different heuristic optimization techniques have been developed including simulated annealing, tabu search, threshold accepting, and genetic algorithms. We used simulated annealing (SA) in our analysis (Kirkpatrick et al. 1983), because it is relatively simple to implement, computationally efficient, and produces solutions that compare well with those obtained using other heuristics (e.g., Murray and Church 1995; Gendreau et al. 1994; Boston and Bettinger 1999; Sharer 1999).

We developed and applied our methodology to a case study on a forested landscape on the west side of the Oregon Cascade Range in which we examined tradeoffs between net present value of timber harvest and likelihood of persistence of a species approximating the northern flying squirrel (Glaucomys sabrinus) over a 100-year time horizon. In the next section of the paper, we describe the integrated model and give details on each major component. We then report results for the case study. We discuss our results and the direction of future work in the final section. While our case study is specific, the approach itself is general and can be
adapted to accommodate additional or different species, different geographic areas and additional or different land management activities and economic concerns.

**Materials and methods**

**Model formulation**

The purpose of the model was to identify management for efficient combinations of timber and wildlife on a landscape. We constructed an optimization model that maximized the value of timber production, $T$, subject to a wildlife objective, $W$, meeting specified minimum thresholds, $C$:

\[
\text{max } T, \quad \text{subject to } W \geq C
\]

The wildlife objective, $W$, was defined as the probability of persistence of at least one breeding individual on the landscape at the end of the 100-year time horizon. Other possible definitions that would have suited the purpose of this study include population size, length of time to extinction, and probability of the population not falling below some positive threshold (Marcot and Murphy 1996). By solving the model for a range of target values for the probability of persistence, $C$, we identified a set of combinations likely to be close to the production possibility frontier. To obtain spatially and intertemporally explicit solutions to this problem, we took five steps, outlined below and described in detail in the following sections. The integrated model, with all of its components, is illustrated in Fig. 1.

1. **Obtain data describing the landscape and wildlife species.** We used a remotely sensed image to characterize the vegetative cover for a study area on the west side of the Oregon Cascade Range. We parameterized the wildlife population simulation model with life-history parameters for the northern flying squirrel.

2. **Construct $W$ for the optimization model.** Because the wildlife population simulation model was too slow to be used in the optimization, we used logistic regression to construct a simplified wildlife model, using a neighborhood-weighting scheme, to represent probability of persistence as predicted by the simulation model.

3. **Construct the economic or timber production objective, $T$, for the optimization model.** We used net present value (NPV) of timber harvest over a 100-year time horizon as a measure of the benefits of timber production. We allowed three timber-management activities in each decision period: do nothing, wildlife thin, and clear-cut harvest.

4. **Construct a SA optimization algorithm.** We used the algorithm to search for timber management regimes that maximized the NPV of $T$, meeting specified targets, $C$, for $W$. The optimization algorithm was solved several times for a range of $C$ values. Each solution produced a timber-management regime, showing the time and location of management activities, and a time series of maps showing the resulting vegetative cover types and conifer age-classes.

5. **Estimate the production possibility frontier.** Each solution was simulated in the fully parameterized wildlife model to produce our final estimate of the production possibility frontier.

Fig. 1. Model framework.

(1) Obtain data describing the landscape and wildlife species

The study area used in this investigation was a 10 000 ha landscape selected from the $1.2 \times 10^6$ ha portion of the geographic information system (GIS) image developed by Cohen et al. (1995, 2000) of the west side of the Oregon Cascade Range as it appeared in 1988. Each 25-m$^2$ pixel (data unit) was classified into one of six vegetative cover types: semi-closed conifer dominant, semi-closed hardwood dominant, semi-closed mixed species, closed conifer dominant, closed hardwood dominant, and closed mixed species. Closed conifer forests were further classified into 20-year age-classes. In 1988, 76% of the $1.2 \times 10^6$ ha area was classified as forestland, with 42% in a mature or old-growth condition. About half of this area is in federal ownership; the remainder is a mix of nonindustrial private, industrial private, and State of Oregon ownerships. The study area is all in federal ownership. About 80% was classified as forestland, with 53% in a mature or old-growth condition (see Fig. 2 for a breakdown of the cover types).
We selected the northern flying squirrel as our wildlife species for the following reasons:

(1) It prefers older coniferous forests; consequently, timber harvest and squirrel persistence are competing forest uses.

(2) Its maximum dispersal distance is relatively small; thus, the local spatial arrangement of habitat is important for squirrel persistence.

(3) Interest in the squirrel has increased recently, because it is the primary prey species of the northern spotted owl (Verts and Carraway 1998).

Annual survival and fecundity rates, dispersal distances, and home range sizes for the squirrel were based on estimates reported in Bigger and Vesely (2000) and Witt (1992). The probability of survival from one year to the next was set at 50%. Breeding was initiated in the second year at a mean rate of 2.5 surviving female offspring per adult female per year.

The PATCH model organizes the 25-m² pixels into hexagonal territories on the landscape. We specified a territory size of 5.6 ha based on the estimated home range size of the squirrel.3 Squirrels moved using a biased (slightly towards good habitat) random walk, and the maximum dispersal distance was fixed at 4.8 km. Habitat classes used by the squirrel were ranked (see Table 1) based on expert opinion in order of preference with 10 being the most preferred (Adamus 2000). Habitat classes unsuitable for the squirrel were given a zero ranking.

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(2) Construct W for the optimization model

We used a life-history simulator called PATCH (a program to assist in tracking critical habitat) (Schumaker 1998) to simulate the trajectory of a species population over time on a particular landscape. PATCH is a spatially explicit single-species model that tracks individuals as they are born, move, reproduce, and die. The PATCH model has several features that make it particularly appropriate for the methodology developed in this study. First, PATCH is a general model that can simulate a variety of territorial terrestrial vertebrate species. Second, PATCH allows users to easily input time series of GIS vegetative cover maps and conduct species population simulations on the landscape as the vegetation grows or is modified by timber management. Third, PATCH is particularly sensitive to landscape quality and pattern, giving the model the ability to explore the effects of timber management activities that occur over time on species persistence. Finally, PATCH includes several stochastic elements so that multiple simulations yield a distribution of likely outcomes for a landscape. Demographic stochasticity is inherent in PATCH and arises from the use of a random

Table 1. Squirrel habitat preference rankings.

<table>
<thead>
<tr>
<th>Habitat class</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Semi-closed mixed species*</td>
<td>4</td>
</tr>
<tr>
<td>Semi-closed conifer*</td>
<td>4</td>
</tr>
<tr>
<td>Closed mixed species*</td>
<td>4</td>
</tr>
<tr>
<td>0- to 19-year conifer forest</td>
<td>4</td>
</tr>
<tr>
<td>20- to 39-year conifer forest</td>
<td>7</td>
</tr>
<tr>
<td>40- to 59-year conifer forest</td>
<td>7</td>
</tr>
<tr>
<td>60- to 79-year conifer forest</td>
<td>8</td>
</tr>
<tr>
<td>80- to 99-year conifer forest</td>
<td>9</td>
</tr>
<tr>
<td>100- to 119-year conifer forest</td>
<td>9</td>
</tr>
<tr>
<td>120- to 139-year conifer forest</td>
<td>9</td>
</tr>
<tr>
<td>140- to 159-year conifer forest</td>
<td>9</td>
</tr>
<tr>
<td>160- to 179-year conifer forest</td>
<td>9</td>
</tr>
<tr>
<td>180- to 199-year conifer forest</td>
<td>9</td>
</tr>
<tr>
<td>≥200-year conifer forest</td>
<td>10</td>
</tr>
</tbody>
</table>

*The semi-closed mixed, semi-closed conifer, and closed mixed categories were lumped together with the 0–20 year conifer class for the timber growth model.
number generator in its survival, reproduction, and movement decisions.

A number of details concerning the PATCH model (Schumaker 1998) are omitted here for the sake of brevity. However, the model’s use of space must be more fully explained for the following discussion to be clear. PATCH was designed for territorial, terrestrial organisms. The user must supply a mean territory size, and the model breaks a landscape up into an array of hexagonal territories of this size. Each territory is assigned a score that designates its value to the species being modeled. The scores are the arithmetic mean of the ranks (Table 1) assigned to each pixel contained in a hexagon. PATCH’s survival and reproductive rates are supplied by the user as a population projection matrix (Leslie 1945; Lefkovitch 1965; Caswell 1989). To connect territory quality to demographic performance, PATCH assigns different projection matrices to each territory, depending on its score. Once each territory is assigned a projection matrix, it can also be assigned an expected growth rate for the wildlife species. The growth rate used by the model is the dominant eigenvalue of the hexagon’s projection matrix, commonly denoted by lambda, $\lambda$. A value of $\lambda = 1$ corresponds to an exact balance (at steady-state conditions) between the expected mortality and reproductive rates, $\lambda > 1$ corresponds to demographic sources (Pulliam et al. 1992), and $\lambda < 1$ corresponds to demographic sinks (Pulliam et al. 1992). Thus, the map of $\lambda$s that PATCH constructs couples the original landscape to habitat rankings, estimates for territory size, survival rates, and reproductive outputs. The structure of these maps reveals a great deal about how a wildlife species will perform in a landscape.

PATCH’s detailed simulations are too time intensive to use directly in the optimization algorithm. To make the optimization tractable, we used the PATCH-assigned $\lambda$ values to develop a simplified wildlife model to proxy for full PATCH simulations. The proxy was closely correlated with PATCH simulation outcomes and can be calculated quickly.

The optimization algorithm requires a large number of iterations, each of which require a set of 100 PATCH simulations for 100 years on each of sixty 10,000 ha landscapes drawn randomly from the study area; the proportion of the landscape that qualified as suitable for the northern flying squirrel, this is a simple 2 × 2 matrix with juvenile and adult columns and fecundity and mortality rates in the rows.

<table>
<thead>
<tr>
<th></th>
<th>Juveniles</th>
<th>Adults</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fecundity</td>
<td>0.0</td>
<td>2.5</td>
</tr>
<tr>
<td>Mortality</td>
<td>0.5</td>
<td>0.5</td>
</tr>
</tbody>
</table>

This process requires that the input matrix be associated with territories of a specific quality. We assigned our input projection matrix to territories with a score of 9.5. PATCH uses, as a default, a linear interpolation function with zero intercept to assign better matrices to higher quality territories, and poorer ones to lower quality territories.

Hanski and Ovaskainen (2000) provide another example using an eigenvalue approach to analyze the contribution of individual habitat patches to the metapopulation capacity of a network of patches for a spatially realistic model.

The optimization algorithm requires a large number of iterations, each of which require a set of 100 PATCH simulations for 100 years on the altered landscape to assess likelihood of species persistence. A full set of 100 replicate simulations of squirrel population dynamics for 100 years on a series of 10 images takes approximately 3 min on a Pentium 800 with 128 MB of RAM.

Conducting multiple runs of the same landscape may introduce dependent observations. These dependencies may artificially decrease standard errors but the estimates should remain unbiased. The primary objective was to identify a proxy that did a good job predicting the results of simulation runs and this was accomplished.

We expected the long-term persistence of a territorial, dispersal-limited species such as the squirrel to be influenced by the amount, location, and quality of habitat in each of the individual 5.6-ha territories. We, therefore, developed a territory-level habitat index, $x_{rsi}$, for each territory $s$ on landscape $i$ based on the quality of its internal habitat and that of its neighbors. We expected the influence of the habitat quality in neighboring territories to decrease with distance from the focal site. Each territory is surrounded by concentric rings of neighboring territories (Fig. 3) that we index with a parameter $r$. The nearest ring to any given territory is specified by $r = 1$. The next ring considered depends on dispersal distance and is defined by $r = R$. With this in mind, we defined $x_{rsi}$ to be the territory’s own lambda value, $\lambda_{rsi}$, multiplied by a summation term representing the aggregate influence of territories in neighboring rings:

$$x_{rsi} = \lambda_{rsi} \sum_{j=1}^{R} \beta_j M_{rsj}$$

where $\beta_j$ is a weight indicating the influence of habitat in ring $r$ and $M_{rsj}$ is the sum of the powers of the lambda values, $\lambda_{jrsi}$, for the $j = 1, 2, ..., 6r$ territories in ring $r$.

$$M_{rsj} = \sum_{j=1}^{6r} \lambda_{jrsi}^j$$

The power coefficient, $\gamma$, when greater than unity, introduces a nonlinear effect that makes higher quality territories within each ring contribute relatively more than the poorer ones.

We defined a landscape-level habitat index, $z_i$, for landscape $i$ as the sum of the $S$ highest valued territory habitat indices (determined experimentally), $x_{rsi}$, on landscape $i$ plus a constant, $\alpha$.
Additional regression results were reported in Calkin (2001), and the full set can be obtained from the first author.

Increasing the residual deviance is a statistic used in logistic regression for measuring the difference between the observed number of successes or failures and the predicted expected number of successes or failures. It plays the same role as the residual sum of squares in linear regression.

We used only the $S$ highest valued territory habitat indices. Since $z_i$ depends on the sum of the territory indices, this meant that for small $S$, the optimization model would select only the highest quality habitat, while for large $S$ the model might instead select a larger area of moderate quality habitat.

We used logistic regression to estimate the value of the $\beta$ coefficients for the sum, the coefficients were essentially constrained to be equal regardless of habitat quality.

Equation 6 predicts likelihood of species persistence on an unchanged landscape for 100 years. However, timber production requires activities that modify the landscape over time. To capture the effect of a changing landscape, we computed $F(z_i)$ based on habitat conditions existing at the beginning of each 10-year time period, $t$. The subscript $t$ refers to the 10-year time period and replaces subscripts $i$ and $n$ in eq. 4. The PATCH proxy, $W$, used in the optimization was the product of these estimated likelihoods:

$$
\max_{\beta} \log L(\beta) = \sum_{i=1}^{S} \sum_{n=1}^{20} [y_{in} \log[1 - F(-z_i)] + (1 - y_{in}) \log[F(-z_i)]]
$$

using the statistics computer program S-PLUS, version 4.0 (MathSoft Inc. 1997).

Alternative logistic models were estimated for $\gamma = 1, 2, 3$; $S = 50, 100, 150, 250, 500, 1000$, all; and $R = 1, 2, 3$. Alternative models were compared using the residual deviance. The model with the lowest residual deviance was $S = 50$, $R = 2$, and $\gamma = 3$. Although the model with the lowest residual deviance (hence the best fit) was for $S = 50$, we found we needed to use the model for $S = 100$ to obtain high probabilities of species persistence, because that model allowed moderate-quality habitat to be included in the solution. Therefore, we used alternative models for $S = 50$ and $S = 100$, with $R = 2$, and $\gamma = 3$ in the optimization algorithm. Regressions results are shown in Table 2 for the models we used along with values for residual deviance, the correlation coefficient between model predicted value, $\beta_{01}$, and observed likelihood of species persistence (from PATCH simulations) for the 60 landscapes in the sample, root mean square error, and an out-of-sample correlation coefficient for 30 additional randomly drawn landscapes.

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Table 2. Estimation results for landscape-level habitat index, $z_t$, for alternative models with $S = 50, 100, 150, 250$, and 500.

<table>
<thead>
<tr>
<th>$S$</th>
<th>50</th>
<th>100</th>
<th>150</th>
<th>250</th>
<th>500</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>-11.9 (15.2)*</td>
<td>-10.7 (15.2)*</td>
<td>-10.0 (15.4)*</td>
<td>-9.0 (15.7)*</td>
<td>-7.0 (16.1)*</td>
</tr>
<tr>
<td>$\beta_1$</td>
<td>0.0027 (3.5)*</td>
<td>0.0019 (3.9)*</td>
<td>0.0014 (3.5)*</td>
<td>0.00098 (3.5)*</td>
<td>0.00059 (2.5)*</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>0.0026 (5.9)*</td>
<td>0.00096 (3.4)*</td>
<td>0.00060 (2.5)*</td>
<td>0.00031 (1.8)</td>
<td>0.00013 (0.89)</td>
</tr>
<tr>
<td>Residual deviance</td>
<td>641.6</td>
<td>660.3</td>
<td>668.8</td>
<td>692.8</td>
<td>761.3</td>
</tr>
<tr>
<td>Sample correlation</td>
<td>0.956</td>
<td>0.948</td>
<td>0.947</td>
<td>0.932</td>
<td>0.870</td>
</tr>
<tr>
<td>RMS</td>
<td>0.076</td>
<td>0.082</td>
<td>0.085</td>
<td>0.092</td>
<td>0.125</td>
</tr>
<tr>
<td>Out-of-sample correlation</td>
<td>0.940</td>
<td>0.931</td>
<td>0.902</td>
<td>0.834</td>
<td>0.770</td>
</tr>
</tbody>
</table>

*Wald statistics are given in parentheses. Asterisks indicate the coefficient is different from zero at the 5% significance level.

\[ W = \prod_{t=1}^{10} F(z_t) \]

$W$ is not the actual probability of persistence over the 100-year time period because (i) each $F(z_t)$ is an estimated probability of survival on a given landscape for 100 years, rather than the probability of survival over 10 years, and (ii) the probabilities are treated as independent events, rather than allowing dependence across periods. This multiplicative form introduced a small dynamic component to the proxy in the sense that the marginal contribution of habitat in one period depends on the habitat in the remaining periods. It favors an even distribution of habitat over time. That is, for a given $Z = \Sigma z_t$, for $t = 1$–10, $W$ is maximized when $z_1 = z_2 = \ldots = z_{10}$. However, this form does not differentiate between different sequences of good and bad landscapes. For that, we returned to PATCH to simulate the solutions.

(3) Construct the economic or timber production objective, $T$, for the optimization model

Timber-management units were defined to correspond one-to-one with the hexagonal 5.6-ha squirrel territories. One of three timber management prescriptions was assigned to each timber-management unit at the beginning of each 10-year period in the 100-year time horizon:

(1) Clear-cut harvest

A management unit was considered eligible for clear-cut harvest if one-third of its area was conifer forest more than 40 years old. If a unit was selected for clear-cut harvest, every pixel of conifer timber greater than 20 years of age was harvested and regenerated into conifer forest.

(2) Wildlife habitat thin

A management unit was considered eligible for wildlife thin if one-half of its area was conifer forest more than 40 years old. If the unit was selected for wildlife thin, all pixels of conifer timber between 60 and 160 years of age were thinned to remove all but the 40 largest trees that met the age requirement. There is growing evidence that heavy thinning is conducive to the development of stand characteristics associated with historical old-growth stands such as large-diameter trees and the presence of multiple canopy layers (Andrews et al. 2000; Bailey and Tappeiner 1998; Hayes et al. 1997). We assumed that heavy thinning would reduce the time to create the old-growth stand characteristics favored by the squirrel to 30 years from the time of the thin. Thus, the area was assigned a habitat preference ranking of 10 at that time (without the thin it would be either 8 or 9).

(3) No action

Our management units were always eligible for no action. If a unit was selected for no action, any pixel that had been in its current 20-year age-class for 20 years was advanced to the next 20-year age-class.

Timber stand growth and harvest yield tables for clear-cut and thinning harvest volumes were developed using the Oregon growth analysis and projection model ORGANON for northwestern Oregon (Hann et al. 1997).12 ORGANON is an individual tree growth model. The user provides a list of trees with measurements and management activities and ORGANON generates projections for future forest conditions and the timber harvest yields. Conifer stands were assumed to be low site Douglas-fir (Pseudotsuga menziesii (Mirb.) Franco) and were assigned a 50-year site index of 90, a conservative estimate for mid- to high-elevation west side Oregon Cascade Range.13 A higher site index would have increased timber value because of higher harvest yields and potentially shorter rotation times between harvest activities. Because yield data for managed older stands is limited, ORGANON uses interpolating functions to estimate harvest yields for all stands older than 120 years. The yield tables we used were reported in Calkin (2001).

Harvested timber was valued using stumpage price projections for the Pacific Northwest west of the Cascade Mountain range from the USDA Forest Service 2000 Resources Planning Act Timber Assessment (Haynes 2000). Thinned timber was valued at 90% of the clearcut stumpage value to account for higher harvest cost. Site preparation and tree planting costs were mean values for western Oregon of

12See also http://www.cof.orst.edu/cof/frresearch/organon/
13Initial tree lists were based on representative timber inventory plots from the most recent timber inventory compiled by the Forest Inventory and Analysis Program at the USDA Forest Service Pacific Northwest Research Station. The mean 50-year Douglas-fir site index for low site inventory plots in western Cascade Range in Oregon was 91 (D.M. Adams, R.A. Schilling, G. Latta, and A. Van Nalts. Timber harvest projections for private land in western Oregon. Unpublished manuscript on file with D. Adams, Department of Forest Resources, Oregon State University, Corvallis, OR 97331, U.S.A.).
$740/ha (1999 dollars).\textsuperscript{14} Future timber harvest revenues and costs were discounted to the present using a 4% real discount rate, consistent with USDA Forest Service guidelines developed by Row et al. (1981) to represent the real long-term productivity of capital. The value of the land and timber at the end of the 100-year time horizon was computed under the assumption that it would be managed at the NPV-maximizing (or Faustmann) rotation from that point on.

(4) Construct SA optimization algorithm

The production possibility frontier was estimated by maximizing NPV of $T$ subject to $C$ for $W$ as defined by eq. 8. The timber harvest volume in each decade $t$, $t = 1, 2, ..., 10$, is defined as $h_t$, the stumpage price as $v_r$, and the discount rate as $r$. Let $V_{100}$ represent the value of the standing timber at the end of the time horizon. The constrained maximization problem is

$$\begin{align*}
\text{maximize} & \quad T = \sum_{r=1}^{10} v_r h_r (1 + r)^t + V_{100} (1 + r)^{100} \\
\text{subject to} & \quad W = \prod_{r=1}^{10} F(z_r) \geq C
\end{align*}$$

Ideally, we would solve the optimization and identify the production possibility frontier exactly. Because of the size and complexity of this problem, we used a SA heuristic algorithm to find good, but not necessarily optimal, solutions. The size of the decision space grows exponentially with the number of management units (territories) and time periods. In this study, there were 1822 management units and 10 time periods. The influence of neighboring territories on the quality of a site contributed additional complexity to the problem.

A typical SA algorithm begins by selecting an initial solution. It explores a set of possible solutions by swapping one or more elements of the current solution, e.g., reschedule clearcut timber harvest for a unit to a different time period or change a unit from wildlife thin to clearcut harvest or no harvest. The SA re-evaluates each new solution and if one meets the constraint and improves the objective function, it is accepted. If it meets the constraint and does not improve the objective function, it is still accepted if it meets a stochastic acceptance criterion. The control parameter for the SA acceptance criterion is referred to as the “temperature”; the higher the temperature, the more likely a non-improving solution will be accepted.\textsuperscript{15} The temperature is reduced according to what is called a “cooling schedule”. The cooling schedule governs the frequency and amount that the temperature is reduced and serves as a stopping criterion. Cooling schedules are unique to each problem and are generally established through experimentation to achieve fast but high-quality solutions. The algorithm iterates until the stopping criterion is met, at which time the probability of accepting a non-improving solution should be close to zero, and the final solution is saved. SA algorithms, being inherently stochastic, are typically run multiple times to produce a set of solutions for comparison purposes.

The SA algorithm for this problem is shown in Fig. 4 along with the cooling schedule parameters we used. The algorithm was solved for a 10 000 ha study area for a range of values for $C$ using the alternative specifications for the proxy reported in Table 2. The value $C = 0$ was included to provide a solution that yielded maximum NPV of timber production.

Because the PATCH proxy, $W$, is based only on the $S$ highest valued territory indices, it was necessary to sort territory index values, $x_r$, for each 10-year period in descending order. In each iteration of the optimization algorithm, the management prescription for one management unit was swapped, changing the territory index values for that unit and two radii of neighboring territories (a total of 19 territories), and the values were resorted. We used an insertion sort that outperforms other sort methods when only a small proportion of the elements in the list are out of sequence (Sedgewick 1988).\textsuperscript{16}

Finally, the SA solutions for $S = 100$ were compared with solutions obtained using an alternative heuristic algorithm known as threshold accepting (TA) (Dueck and Scheuer 1990; Dueck 1993). We did this only to confirm that the SA solutions were reasonable; it serves as confirmation of our SA algorithm if the threshold accepting solutions are close to the SA solutions. The threshold sequence was taken directly from Dueck and Scheuer (1990), and the number of iterations was such that the TA and SA algorithm examined approximately the same number of harvest schedule switches. Reassuringly, the TA solutions were close to the SA solutions with timber harvest values only 1.2–3% less than the corresponding SA solutions. More fine tuning of the TA algorithm would likely have further reduced or eliminated the difference.\textsuperscript{17}

\textsuperscript{14}Cost data was obtained from a survey of private landowners conducted by the Oregon Department of Forestry and is on file with G. Lettman, Oregon Department of Forestry, Salem, OR 97310, U.S.A.

\textsuperscript{15}SA accepts a nonimproving solution if a pseudorandom number on $(0, 1)$ is less than $e^{-\delta T}$, where $\delta$ is the change in the objective function value and $T$ is the temperature.

\textsuperscript{16}Insertion sort, an elementary sorting method, is often described by the analogy of sorting cards for a bridge hand: consider the elements one at a time, inserting each in its proper place among those elements already sorted. For an unsorted file insertion sort is quadratic in solution time, typically requiring $N^2/2$ comparisons and $N^2/8$ exchanges. However, if the file is almost sorted, insertion sort is linear.

\textsuperscript{17}There are other approaches to evaluating the quality of heuristic solutions, but each has its drawbacks. Many studies apply extreme value theory, where an extreme value distribution (such as the Weibull) is empirically fitted to a random sample of the best solution value found over multiple runs and a confidence interval is found for the location parameter (Bettinger et al. 1998; Boston and Bettinger 1999; Sharer 1999). However, this technique requires that the estimated confidence interval for the location parameter is assumed “a priori” to contain the optima, and this is what was to be inferred in the first place. Other studies have used traditional optimization techniques to identify the true global optimum of the planning problem, and then compared this solution to a set of solutions identified using the heuristic algorithm (Murray and Church 1995; Cutt et al. 1997; Boston and Bettinger 1999). But for this study, traditional algorithms such as branch-and-bound are computationally intractable.
Estimate production possibility frontier

The final step was to replace the proxy values, $W$, with the corresponding estimates of likelihood of species persistence obtained from the PATCH model. Each SA solution consisted of a 10-decade timber management schedule, showing when and where prescriptions were applied, and the corresponding time series of 10 maps, showing post-management habitat conditions at the beginning of each decade. We ran 100 replicate PATCH simulations using the time series of habitat maps for each solution. Likelihood of species persistence was estimated as the proportion of 100 simulations with ending population greater than zero. For comparison, we also ran a set of PATCH simulations for the initial landscape with no timber harvest.

Finally, we compared the solutions on the production possibility frontier to a reasonable real world alternative, a simple habitat reserve system, to illustrate the potential of this approach for policy analysis. A single reserve, consisting of a five-radius hexagonal block of territories (about 90 territories; see Calkin (2001)) with high-valued habitat indices was set aside and the NPV of timber harvest was maximized on the remaining landscape using a simple greedy algorithm. The greedy algorithm assigned the harvest schedule with the highest NPV to each non-reserved unit.

Results

The production possibility frontier

Optimization results are presented in Table 3 and the production possibility frontier is shown in Fig. 5. We found that the alternative proxies for different values of $S$ performed differently in their ability to identify solutions over the full range of likelihood of species persistence. On the study area, a full range of solutions could be identified using $S = 50$ and $S = 100$. The PATCH proxy target values, $C$, are shown in 10th roots, which are roughly comparable with a 100-year
probability value. The solutions are estimates of the production possibility frontier. They show variation, because both the optimization algorithm and the PATCH simulations are stochastic.

Figure 5 shows the physical tradeoffs between the two outputs. It appears to be concave to the origin. In the no timber harvest scenario, the likelihood of species persistence was 100%, and the value of the standing timber at the end of the time horizon, discounted for 100 years, was $14.5 million ($1450/ha) (this point is off the scale in Fig. 5). In the unconstrained maximum NPV of timber harvest solution, which had an NPV of $476 million ($47 600/ha), the likelihood of species persistence was zero. The production possibility frontier shows that relatively high likelihood of species persistence (0.7–0.8) can be achieved with NPV of timber operations less than 10% below the maximum value ($440–$460 million ($44 000–$46 000/ha)).

Table 3. Simulated annealing optimization and PATCH simulation results for the study area showing net present value of timber harvest (NPV) in millions of dollars, 1999, and likelihood of species persistence (LSP) in percent: best optimization results for each target value (C) of the PATCH proxy and number of high-valued territories (S).

<table>
<thead>
<tr>
<th>C</th>
<th>S = 50</th>
<th>S = 100</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NPV  LSP</td>
<td>NPV  LSP</td>
</tr>
<tr>
<td>0.97</td>
<td>427.4   77</td>
<td>408.7   96</td>
</tr>
<tr>
<td>0.75</td>
<td>453.2   55</td>
<td>445.0   78</td>
</tr>
<tr>
<td>0.50</td>
<td>450.7   51</td>
<td>451.6   75</td>
</tr>
<tr>
<td>0.32</td>
<td>462.8   26</td>
<td>455.8   68</td>
</tr>
</tbody>
</table>

*Solutions that are illustrated in Fig. 6.

If values to society were known for both timber and squirrel persistence, a socially optimal combination of the two outputs could be identified. This would be the point at which the slope of the production possibility frontier is equal to the value to society of squirrel persistence relative to timber. Since only timber values are known, this point cannot be identified. However, the concavity of the production possibility frontier indicates that it is probably optimal to manage for both squirrel habitat and timber (multiple use) rather than to manage exclusively for either squirrels or timber (dominant use). Only if the value of one use was very much higher than the other (e.g., if the site was considered critical habitat for a threatened and endangered species), might dominant use be optimal.

The production possibility frontier that we identified can be used to evaluate the efficiency of alternative land management plans with respect to squirrels and timber. A plan is inefficient if one output (e.g., likelihood of squirrel persistence) can be increased without reducing the other output (e.g., NPV of timber production). The simple reserve system...
that we modeled is a case in point. It yielded a NPV of timber production of $446 million ($44 600/ha) and a likelihood of species persistence of 64%. However, the SA algorithm identified two solutions that were superior to the reserve system in both timber production and in squirrel persistence and two solutions that produced almost as much timber value while increasing the likelihood of species persistence by 14%. Analysis of the SA solutions would help land managers search for similarities and then design feasible management plans, such as reserve systems, that were closer to the production possibility frontier.

The production possibility frontier can also be given a marginal opportunity cost interpretation. For example, it would cost approximately $26.9 million in forgone timber harvest to increase the likelihood of species persistence in this study area from 56 to 84%. Conversely, the opportunity cost of increasing the NPV of timber harvest from $427.3 million to $454.2 million would be the value of the 28% of likelihood of squirrel persistence that must be forgone.

Figure 6 shows the trajectory of timber harvest over time for three typical solutions (noted with asterisks in Table 3). Most of the timber harvest occurs in the first decade, with the remaining occurring in the sixth and seventh decades. For example, a solution with $S = 100$ and $C^{0.1} = 0.97$ had 75% of the units scheduled to be clear-cut and an additional 10% of the units scheduled for wildlife thinning in the initial decade. Of the units clear-cut in the first decade, all were scheduled for clear-cutting again in either the sixth or seventh decade. The high NPV of the study landscape comes largely from harvest in the initial decade and was likely due to the following reasons.

1. There is a large amount of valuable mature and old-growth forest in the study area.
2. Only the $S$ highest-ranked territories and their neighbors contributed to the habitat proxy value, $W$. Therefore, there were many management units that could be harvested without reducing the habitat proxy value.
3. Wildlife thins in “middle-aged” forests (60–160 years) increase the NPV of timber harvest while also improving squirrel habitat. As a result, if a management unit can be thinned in the first decade, it will be.
4. Because of discounting, early harvest adds more to the objective function than late harvest.

**Discussion**

We used a heuristic optimization algorithm to identify combinations of two outputs, NPV of timber production and the likelihood of species persistence for the northern flying squirrel, that approximate the production possibility frontier for those two outputs in the study area. This study demonstrated how biological and economic models can be integrated in an optimizing framework to (i) learn more about the productive capacity of a particular site, (ii) explore the compatibility of multiple uses on a forested landscape, and (iii) evaluate the efficiency of alternative land-management plans that might be under consideration for a site.

Because the case study reported in this paper is for a particular species on a particular landscape, there are some aspects of the analysis that are specific to this study. These include the landscape itself and the species we modeled, the wildlife population and the timber growth and yield models, and the proxy for the wildlife simulation model that was used in the optimization model. The method, however, has potential for greater generality. The wildlife population model we used may be parameterized for any terrestrial vertebrate species and can be run on any landscape for which there is sufficient data. The parameters of the proxy were estimated for the northern flying squirrel on the west side of the Oregon Cascades. However, the form of the equation,
particularly the neighborhood-weighting scheme, would be appropriate for any species with limited dispersal capability for which the local spatial arrangement of habitat is an important determinant of local population persistence.

The concepts underlying our approach are general, however, and may be applied more broadly. Possible extensions include the following.

(1) Multiple wildlife species. However, this study and most studies of this nature (with the notable exception of Ho et al. (1994)), focus exclusively on commodity–noncommodity tradeoffs but suppose that an increase in the likelihood of squirrel persistence came at the expense of elk habitat. By modeling species with different habitat requirements we could trace out the production relationships between such competing conservation objectives.

(2) Different kinds of outputs. The approach we demonstrated may just as well be applied to reducing fire hazard, improving aesthetic quality, or increasing recreational use of a site. All that is needed is credible means of predicting and quantifying outputs of interest (see Pukkala et al. (1995) for an example of forest planning with scenic and recreational considerations).

(3) Larger geographic areas. Conservation priorities are rarely set at the scale of our 10 000 ha study area. Although increasing the geographic scale of the problem greatly increases its complexity, it makes the results more valuable to decision makers.

(4) More realistic and detailed models. The more realistic the characterization of the problem to be solved, the more likely it will be possible to implement the solutions. Several significant factors were necessarily omitted in this case study. For example, we did not impose landowner objectives and constraints, because we wanted to estimate the unconstrained productive capacity of the site. In fact, it is unlikely that solutions identified by this method would be implemented because the landowners have insufficient incentives to do so. Private landowners often manage primarily for financial objectives in response to market signals. Public land managers face various regulatory constraints that limit their actions. However, landowner objectives and constraints could be modeled with our approach as well, and the extent of inefficiency that is their legacy could be measured.

It is important to understand the role of uncertainty in modeling for policy analysis. There are two sources of uncertainty to be concerned about. First, uncertainty arises because the true values of the model parameters are unknown. Second, there is demographic and environmental stochasticity. We used PATCH’s model of demographic stochasticity, the random fluctuations in survival, and reproductive rates among individuals. However, little is known about environmental stochasticity, the changes in survival, and reproductive rates for all individuals resulting from fluctuations in environmental conditions, and hence, we chose not to model it. The importance of these different sources of uncertainty could be explored systematically using sensitivity analysis. That would be a substantial undertaking for a model of this complexity, but some attempt to understand the robustness of the results would be essential prior to using this model to prescribe on-the-ground management. In general, the note of caution sounded by many biologists, when faced with conservation policy choices, arises because environmental perturbations are unpredictable, many model parameters are unknown, and the cost of being wrong (extinction) is irreversible.

This study required collaboration across disciplines at all stages: from framing the question to be addressed, parameterizing and using the biological and economic models, and interpreting the results. Such collaboration will become the standard for forestry research in the future as land managers are forced to make the most productive use of increasingly stressed landscapes.

The forest planning literature contains examples of heuristic optimization algorithms, production possibility concepts, integrated resource models, and biodiversity considerations. Murray and Snyder (2000) identified a need for integration between nature reserve design and harvest scheduling and the importance of evaluating both commodity production and conservation considerations in spatial optimization research. The present study reflects increasing efforts within the natural resource modeling community to address this need. Specifically, this study developed a neighborhood-weighting scheme to represent biological simulation results, optimized solutions for timber harvest value subject to neighborhood habitat constraints and applied the full biological simulation model on the optimized solutions. This approach increased the biological reality of existing efforts to incorporate biodiversity considerations in forest planning efforts. We think that this study provides an example of how the relative strengths of wildlife simulation models and harvest scheduling optimization algorithms may be integrated to further understand the tradeoffs between forest commodity production and biodiversity protection.

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References


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