

Modeling the Compatibility of Biological and Economic Objectives on a Forested Landscape

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Abstract: An integrated model combining a wildlife population simulation model and timber harvest and growth models was developed to explore the tradeoffs between the likelihood of persistence of a hypothetical wildlife species and timber harvest volumes on a landscape in the Central Oregon Cascades. Simulated annealing, a heuristic optimization technique, was used to solve for harvest schedules that maximized the likelihood of species persistence relative to a given timber harvest volume constraint over a 100 year planning period. By solving this problem for a range of different harvest volumes a production possibility frontier is developed that shows the relative tradeoffs between timber harvest volumes 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 may provide a structure for future models that will allow land managers and forest planners to become more informed about the tradeoffs among competing resources.

Key words (forest management, tradeoff analysis, wildlife population modeling, simulated annealing)

Introduction

Public land managers are often called upon to meet multiple, and sometimes conflicting, ecological and economics goals. For example, in a recent report to the Secretary of Agriculture (Johnson et al. 1999), an interdisciplinary Committee of Scientists recommended that "ecological sustainability provide the foundation upon which the management for national forests and grasslands can contribute to economic and social sustainability." Specifically the report states that the Forest Service needs to provide the ecological conditions necessary to protect the viability of selected focal species and of threatened, endangered and sensitive species. In addition to the emphasis on ecological sustainability, the committee emphasized the importance of traditional resource production such as timber harvest to the economic, social and cultural sustenance of many local communities.

While much of the existing research on land management has focused exclusively on economic issues (e.g., timber production or profitability) or exclusively on ecological issues (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 (see for example, Ando et al. 1998, Haight 1995, Haight and Travis 1997, Holland et al. 1993, Hyde 1989, Montgomery et al. 1994, 1999, Polasky et al. forthcoming).

In this study, we integrate models of wildlife population dynamics and timber production to search for land management regimes that achieve both ecological and economic objectives. Land management decisions

determine the habitat conditions that in turn influence species persistence as well as determine timber harvests. We are in the process of developing our approach and applying it to a case study using GIS data for a forested landscape in the Central Cascades of Oregon. We are examining the trade-off between accumulated timber harvest and likely persistence of a hypothetical species on the landscape. While we report a specific case study, 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.

Using the model in its current form, we examined the production relationships between likelihood of species persistence for a hypothetical species and timber harvest on a landscape. We attempted to trace out the production possibility frontier, which describes the maximum feasible combinations of species persistence likelihood and timber harvest, illustrating the trade-offs between these goals under efficient land management. Land management that generates results inside this production possibility frontier is inefficient and the degree of inefficiency can be calculated. However, because the problem of optimal landscape management is complex (it involves spatial as well as dynamic interactions), we used a heuristic approach, specifically a simulated annealing algorithm, to generate a solution. A heuristic approach generates a good solution without imposing overwhelming computational burdens but does not guarantee an optimal solution.

In this paper, we describe the model in its current form and expected developments as we continue to refine and extend it. In the next section of the paper, we describe how the integrated model fits together. The following sections include details on each major component of the model and the application to the case study landscape. We then report results for the case study. We discuss our results and the direction of future work in the final section.

The Integrated Model

The general framework of the integrated model involves the following steps:

1. Select a set of landscapes from a GIS image of the study area that represent a range of habitat attributes: amount, quality, and configuration of suitable habitat for the subject species.
2. Use a species population simulation model to predict persistence or failure to persist for the subject species on the landscapes at the end of some time period.
3. Develop a proxy to represent likelihood of species persistence in the objective function for the optimization using the results from (2).
4. Define set of potential timber harvest management regimes.
5. Run heuristic optimizations to identify a set of timber harvest schedules (the timing and location of timber harvest) that have the highest value for the proxy for species persistence for a range of timber harvest volume targets on a particular landscape.
6. Use the species population simulation model to predict the probability that the subject species will persist on the landscape as it is modified over time for each of the timber harvest schedules identified in (5). Plot timber harvest volume target against highest probability of species persistence. This is the production possibility frontier estimated by the model.

While the analytical framework is general, some elements of the analysis are necessarily specific to the landscape and species that are the subject of the study. In the next sections, we describe each step of our preliminary analysis for a hypothetical species on a specific landscape and our current efforts to extend and refine the analysis.

The Landscape (Step 1)

The study area we used is a 1.2 million-hectare area in the central Cascade region in Oregon that includes the Willamette National Forest and privately owned forest and agricultural land. A GIS image was developed by Cohen (2000) in which vegetative cover is mapped, including 20-year age classes for the coniferous forest area. We randomly

selected 50 different 62,500-hectare landscapes from the GIS image to use in the development of the proxy in step (3).

The subject species for this paper was a hypothetical wildlife species that is characterized by long life and low fecundity with a preference for older coniferous forests. In our ongoing analysis, we will use the same study area. Our subject species will be the flying squirrel (*glaucomys sabrinus*). This species also characterized by a preference for older coniferous forests. Its search behavior is such that it is more likely to inhabit an available site if it is near its "birth site." We plan to select a stratified random sample of landscapes from the GIS image, stratified on two dimensions: amount of suitable habitat (older coniferous forest), and degree of fragmentation of that habitat on the landscape.

The Species Population Simulation Model (Step 2)

We used a spatially explicit 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 reads GIS imagery describing the landscape directly and uses the data to link species' life history attributes and habitat preferences to the quality and distribution of habitats throughout the landscape. The PATCH model breaks species' life histories into three distinct components. Vital rates (survival and reproduction) determine the growth rate of a species, and are entered into the model using a population projection matrix (Caswell 1989). Habitat preferences describe an organism's use of habitat. Lastly, movement behavior governs a species' ability to navigate a landscape in search of high quality habitat. This approach allows PATCH to link its projections of population persistence to changes in landscape pattern, habitat quality, and habitat connectivity. Landscape pattern strongly controls the distribution of suitable breeding sites (and those ill suited for breeding), while habitat quality determines what survival and reproduction rate the individuals occupying these sites will experience. Habitat connectivity influences the ability of individuals to locate high quality habitat, which influences an individual's fitness as well as the ability of the species to re-colonize parts of the landscape that have experienced local extinctions.

PATCH includes probabilistic demographic and environmental elements so that it is a probabilistic rather than a deterministic simulation model. Multiple simulations may be run to generate a distribution of likely outcomes for a landscape. Altering the time series of landscapes to reflect the changes resulting from timber management activities allows PATCH to simulate the effects of various timber management regimes on the species populations.

To parameterize PATCH for the hypothetical species, we used vital rates, habitat preferences, and movement behavior

that very roughly similar to the marmot and the lynx. We used PATCH defaults for the probabilistic elements of the model. The PATCH parameters for the flying squirrel will be based on Bigger and Vesely (2000). We will still use PATCH defaults for the probability density functions for those parameters, but hope, in the future, to perform sensitivity analysis of model results to the degrees of demographic and environmental stochasticity.

For this study, we defined species persistence as a nonzero population at the end of 100-year PATCH simulation. One hundred PATCH simulations were run on each of the 50 landscapes to give the probability of species persistence on each landscape.

The Proxy (Step 3)

We hope, in the future, to develop an optimization module that will use PATCH (or a similar wildlife population simulation model) simulations directly in the optimization algorithm. At this time, however, that's not feasible. PATCH is a very detailed model that takes too long to run in an optimization routine that might require hundreds of thousands of iterations. Consequently, we developed a proxy for PATCH that can be quickly computed directly from the landscape and that has a high correlation with species persistence as predicted by PATCH for the subject species. The proxy is necessarily specific to the species and the landscape, but we hope to understand which aspects of the proxy are general and can be applied to other species.

Landscape metrics were calculated for each of the 50 landscapes. The set of landscape metrics includes indices that have been identified as important for wildlife dispersal and survival success in the existing literature on landscape patterns: habitat patch area, habitat edge, habitat core area, fractal dimension and shape (Turner et al. 1989, Schumaker 1996). It also includes PATCH specific output such as the number of source breeding sites, the sum of habitat weights, and the number of expected source sites. Source breeding sites are defined within PATCH as sites with an expected dominant eigenvalue greater than 1.0, indicating that birth and out-migration is expected to exceed mortality and in-migration for the site. For this application, the determination of source breeding status was dependent solely on the amount and quality of habitat within a given territory.

We used the grouped logit regression model to relate combinations of these indices to PATCH predictions of species persistence. In the grouped logit model, success occurs if the value of an unobservable index variable that is a linear function of exogenous variables exceeds some threshold value. If the probability of that occurrence, p_i , follows a logistic cumulative density function, the natural log of the odds, Y_i , is equal to the index:

$$Y_i = \ln \left(\frac{p_i}{1 - p_i} \right) = \alpha + X_i' \beta + u_i \tag{1}$$

where p_i is the proportion of 100 PATCH simulations for landscape i in which the ending species population size was nonzero, X_i is a set of landscape metrics corresponding to that landscape, and u_i is an additive error term.

A brief description of the landscape metrics used in this analysis is given in Table 1 with the correlation coefficient between each metric and the log of the odds as defined in Equation (1).

Metric	Description	r
Bs	Number of breeding sites identified by 0.75 PATCH.	
Sbs	Number of expected source breeding sites (PATCH).	0.90
λ Bs	(Sum of expected dominant eigenvalues of all breeding sites) /Bs	0.64
λ Sbs	Sum of expected dominant eigenvalues for all source breeding sites.	0.91
λ /s	λ Sbs / Sbs	0.33
Area	Area of all pixels qualifying as wildlife habitat.	0.38
Wt	Number of habitat pixels weighted by their habitat preference rankings.	0.55
Edge	Length of habitat area edge.	0.00
Core	Habitat core area at least 1 pixel from non-habitat.	0.51
Frac	Fractal dimension	0.38
Shape	Landscape shape index	-0.35

Table 1. Description of landscape metrics and r = correlation coefficient between Y_i and metric.

The variance of the error term in Equation (1) is $100*(1 - p_i) * p_i$ (Maddala 1983). The variables were transformed to correct for this known heteroskedasticity and the coefficients α and β were estimated using ordinary least squares. Small constants (.005) were added (subtracted) when $p_i=0$ ($p_i=1$) (Greene 1997). The results of selected regressions are shown in Table 2.

The relative importance of various landscape metrics in predicting PATCH results depends on the particular species that is being modeled. We found the number of source breeding sites, Sbs , and the sum of the dominant eigenvalues for all source sites, λSbs , to be equivalently powerful predictors of species persistence in PATCH for the hypothetical species. Both had correlation coefficients with Y_i that exceeded 0.90. The correlation coefficient of Sbs with λSbs was nearly perfect. The regression analysis showed that, while there were sets of metrics that explained more of the variation in Y_i than either variable did alone, the gain appeared to be small when compared to the additional computational cost. The adjusted R^2 for the regression of Y_i on the number of source breeding sites was 0.72. For the

regression of Y_i on the sum of the dominant eigenvalues for all breeding sites, it was also 0.72. For the regression of Y_i on all of the variables in Table 1, the adjusted R^2 was 0.81. And for the regression of Y_i on the set of traditional landscape indices (habitat area, sum of habitat weight, habitat edge, core area, fractal dimension, and shape index), it was only 0.29. Regression results for these and other specifications that we tried can be obtained from the authors.

Based on this analysis we chose to use the number of source breeding sites as a predictor of the likelihood of species persistence in a PATCH simulation on a static landscape, unmodified by timber harvest, for this hypothetical species.

The resulting species persistence component, F^S , of the objective function to be maximized took the following form:

$$F^S = \sum_{t=1}^{10} Sbs_t - \sum_{t=1}^{10} \delta_t (S^* - Sbs_t)^2 \quad (2)$$

where $\delta_t = 1$ if $Sbs_t \leq S^*$, else $\delta_t = 0$

The first term is the sum of the source breeding sites for the landscape in each period after it has been modified by any timber harvest activity and by timber stand growth. We used this as a measure of the quality of the landscape for the hypothetical species over the entire time horizon. The second term represents our attempt to incorporate a dynamic element -- that a stable time path of source breeding sites would be better for the species than a volatile one. It acts to smooth the time path of the number of source sites. It is a penalty function that reduces the value of the objective function for negative deviations below a threshold number of breeding sites, S^* . We chose $S^*=40$ for the hypothetical species for this landscape because, in simulations, there was very little risk of species extirpation as long as the number of breeding sites exceeded 40. The quadratic form penalizes large deviations more heavily than small ones, placing a premium on landscapes that are relatively stable over time.

For the flying squirrel, we expect to develop a proxy for PATCH simulations that will represent more complex population dynamics. The number of source breeding sites will surely be an important predictor of PATCH success for the squirrel, but the quality of habitat in neighboring sites will also matter. This will add a spatial component to the analysis that is missing for the hypothetical species that is the subject of this paper.

Timber Harvest (Step 4)

PATCH can simulate species performance on a changing landscape if it is provided with landscape images over time. In this GIS image, coniferous forests are divided into 20-year age classes (Cohen 2000). For simplicity, we defined management units so that they correspond to spatial units used in the species population simulation module, which is a

17-hectare hexagon. In the study, timber management activities occurred once each decade in the 100-year simulation period. Every decade, each hexagon was evaluated for availability for timber harvest; 50 percent of the area must be conifer forest at least 60 years of age. If available, it was either clear-cut harvested or not. Every second decade, unharvested hexagons were aged by one age class. Timber stand growth and harvest yield were governed by relationships developed for Douglas fir and western hemlock stands in western Oregon (Curtis et al. 1981).

Given the existing public attitudes concerning forest practices and the range of silvicultural alternatives available to forest managers, it is unrealistic to limit our management prescriptions to simple clear-cut harvest. We intend to include different alternatives such as pre-commercial and commercial thinning as well as partial cuttings may allow us to increase overall timber harvest and reduce the time it takes to produce high quality wildlife habitat.

The timber harvest component, F^T , of the objective function to be maximized is a simple penalty function:

$$F^T = -\mu \quad (3)$$

where $\mu = 0$ if $\left(V^* - \sum_{t=1}^{10} V_t \right) \leq 0$, else $\mu = \mu^0$

The timber harvest volume in period t is V_t and the timber harvest volume target for the 100-year simulation period is V^* . Solutions that did not meet the timber harvest volume target were rejected for the final solution. But the solution algorithm was able to identify superior solutions when this mechanism was used to allow it to search in neighborhoods of the solution space where the target was nearly met. We set the value of the penalty, μ^0 , at different levels to control how widely the search algorithm would range away from the feasible set.¹

Optimization Module (Step 5)

The objective of our study was to trace out the production possibility frontier showing the maximum feasible combinations of species persistence likelihood and timber harvest. Because the decision space grows exponentially with the number of land units and the time periods included in the analysis, we used heuristic algorithms to find good, though not necessarily optimal, solutions to the problem. Therefore, the results that we found are expected to be close to, but not necessarily on, the production possibility frontier.

¹ We found that relatively large penalties were required to obtain feasible solutions when the timber harvest target volume was high, while relatively low penalties encouraged a wider search of the solution space and improved the ending solutions when the timber harvest target volume was low.

Heuristic optimization techniques have been applied to problems where complete enumeration of the solution space is unrealistic due to the size of the problem and where traditional integer programming methods such as branch and bound are computationally prohibitive. Heuristic algorithms typically use intelligent programming or randomness to establish rules to accept inferior solutions that allow the algorithm to extract itself from local optima and to explore a larger subset of the entire solution space. 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. Several different heuristics optimization techniques have been developed including simulated annealing, tabu search, and genetic algorithms. Heuristic optimization techniques have been gaining favor in forest management applications, most notably Lockwood and Moore (1992), Sessions and Sessions (1993), Murray and Church (1995), Lazore and Greber (1997), Bettinger et al. (1997, 1998), and Boston and Bettinger (1999).

We used simulated annealing (SA) in our analysis (Kirkpatrick et al. 1983). SA is relatively simple to implement, computationally efficient, and produces solutions that compare well with those obtained using other heuristics (Murray and Church (1995) and Gendreau et al. (1994)). Boston and Bettinger (1999) showed SA outperformed tabu search in 3 out of 4 forest planning problems in less computing time (approximately 2 minutes vs. 6 minutes) and outperformed Monte Carlo Integer Programming in all 4 problems with comparable computing time. Sharer (1999) found that SA outperformed simple tabu search in a forest planning problem in significantly less time (12 minutes versus 303 minutes).

SA begins with an initial solution. It moves through the decision space by swapping some elements of the solution with elements selected from the neighboring solution space. SA uses a random acceptance criterion to allow the algorithm to accept inferior solutions to the optimization procedure. In doing so, SA is able to explore a larger set of the solution space than traditional hill climbing techniques that would be likely to converge to local (non-global) optimum. The random acceptance criterion has a control parameter referred as the temperature.² The higher the temperature, the more likely an inferior solution will be accepted. The algorithm begins the search using a high temperature and then gradually cools it so it becomes increasingly less likely that inferior solutions are selected until the probability of accepting inferior solutions is reduced to zero. The quality of the SA solutions depends on the parameterization of the SA algorithm: the initial and

² SA accepts an inferior solution if a random variable selected from a uniform distribution on (0,1) is less than $\exp(-\delta/t)$ where δ is the amount of the change in the objective function value and t is the temperature.

ending temperature, the rate of cooling, the stopping criterion, and the neighborhood structure. Parameters are unique for each problem and their selection generally requires some experimentation by the modeler.

In this problem, the full objective function to be maximized, F , was:

$$F = F^S + F^T = \sum_{t=1}^{10} S_t - \sum_{t=1}^{10} \delta_t (S^* - S_t)^2 - \mu \quad (4)$$

where:

$$\delta_t = 0 \text{ if } (S^* - S_t) \leq 0, \text{ else } \delta_t = 1$$

$$\mu = 0 \text{ if } (V^* - \sum_{t=1}^{10} V_t) \leq 0, \text{ else } \mu = \mu^0$$

Infeasible solutions ($\mu \neq 0$) were not accepted for the final solutions. Our SA algorithm is described in Table 2.

Select an initial solution, a 10-decade harvest schedule for the landscape, by randomly assigning harvest regimes to management units until the timber harvest volume target is met.

Set initial temperature This ranged from 750 for the lowest timber harvest volume target to 1500 for the highest timber harvest volume target.

Repeat

Repeat

Swap. Randomly choose a management unit. Randomly choose an alternative timber harvest schedule to assign to that unit.

If the swap improves that value of the objective function, accept it as new solution.

Else if swap reduces the value of the objective function and meets acceptance criterion, accept it as new solution.

Until 15,000 iterations, then cool temperature to 0.95 times its previous value.

Until stopping criterion is met -- ending temperature of 20 for the lowest timber harvest volume target and 40 for the highest timber harvest volume target has been reached.

Table 2. Simulated annealing algorithm for this problem.

Simulation Results (Step 6)

We reported our results for a single 62,500-hectare landscape. This landscape consisted of 3800 17-hectare

hexagons (some hexagons were truncated by the landscape boundary), of which approximately 700 were available for harvest. There were 72 initial breeding sites on this landscape, of which 23 served as source sites. There were 97 potential source breeding sites during the 100-year simulation as the landscape evolved over time.

We ran four sets of five heuristic optimizations for each of five timber harvest volume targets. The timber harvest volume targets range from 2.25 billion board feet to 2.45 billion board feet. In this range, trade-offs between the likelihood of species persistence and timber harvest were most pronounced for this species and landscape. Outside this range, variations in the timber harvest target had limited effect on the likelihood of species persistence. Specifically, at harvest levels below 2.25 billion board feet, the likelihood of species persistence was constrained primarily by the initial number of breeding sites on the landscape; at harvest levels greater than 2.45 billion board feet, most source breeding sites were eliminated by timber harvest and population persistence was highly unlikely.

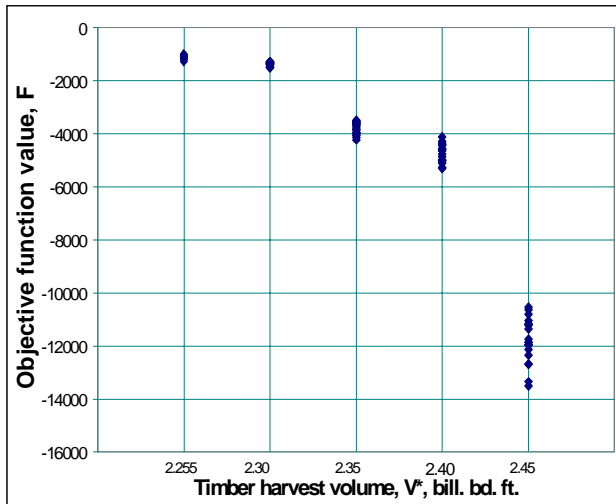


Figure 1: The value of the objective function for 20 solutions for each of five timber harvest volume targets.

The solutions were characterized by a set of ten landscape maps, one for each decade, showing the evolution of the original landscape over time as the forest on each hexagon either grows or is harvested. PATCH simulations on this changing landscape yielded estimates of the likelihood of species persistence for each of the 100 solutions. The correlation between the objective function value, F , and the probability of species persistence as predicted by PATCH was 0.94.

The relationship between the objective function value, F , and the timber harvest volume constraint, V^* , is shown in Figure 1. All 20 solutions per volume are shown in order to illustrate the increasing variation in the solutions as V^*

increases. This is due to the quadratic penalty for less than the threshold number of source breeding sites, which tends to dominate the solutions with very high harvest volumes. Figure 2 is a graph of the production possibility frontier between the likelihood of species persistence and V^* for the four best solutions for each V^* . The concave (to the origin) shape show that likelihood of species persistence for the subject species and timber harvest are competing uses on this landscape – that is, the landscape would be optimally managed for some combination of the two uses. The optimal combination would depend on the relative values society places on them.

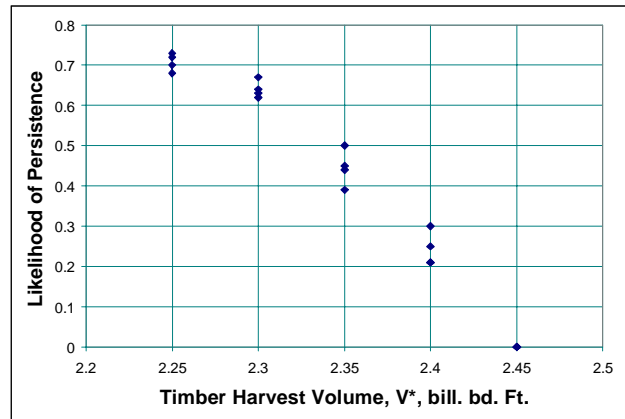


Figure 2: Likelihood of species persistence for subject species on landscape as predicted by PATCH for four best solutions for each timber harvest volume target.

Figures 3 and 4 show trajectories for timber harvest volume and number of breeding sites for selected solutions: one at $V^*=2.25$ billion board feet and one at $V^*=2.40$ billion board feet. Figure 3 shows that a majority of the timber harvest occurs in the first two and last two decades with limited harvest in the middle decades of the planning horizon. Many studies eliminate harvest volume fluctuations by including some type of even flow harvest constraint in the optimization algorithm. However, we decided not to impose an even-flow constraint due to the relatively small size of this landscape and our desire to not impose any “a priori” constraints on the optimization algorithm. However, it should be noted that as we have formulated this problem, timber harvest contributes just as much to the satisfaction of the timber harvest volume target in the last period as it does in the first, so there is no penalty for postponing harvest. In contrast, because source breeding sites contribute to the objective function in every period in which they are present, eliminating them in the first periods is more costly than in the last periods. Hence, sites that are available for harvest and are not suitable habitat are harvested in the early periods so they can become available for harvest again in the 100-year simulation period, while sites that are eligible for harvest and also provide suitable habitat are held until the

last periods and then harvested. Some of these results are artifacts of the problem formulation that will be eliminated when we specify the timber harvest constraint as an economic objective of meeting a present value of timber harvest target for the planning period and also when we impose ending conditions on the landscape that are consistent with sustaining the achieved level of likelihood of species persistence on the landscape.

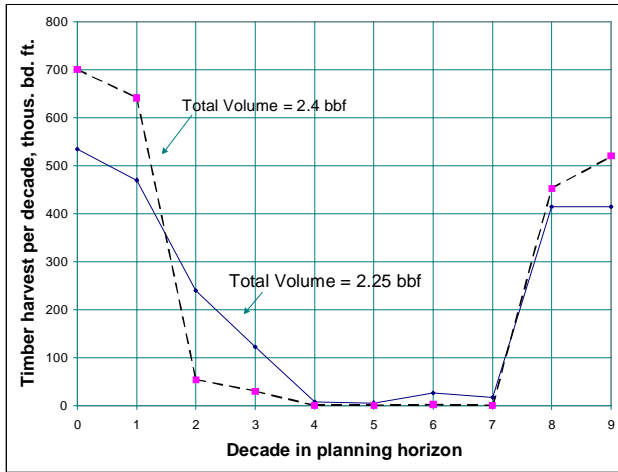


Figure 3: Timber harvest volume per decade over the simulation period.

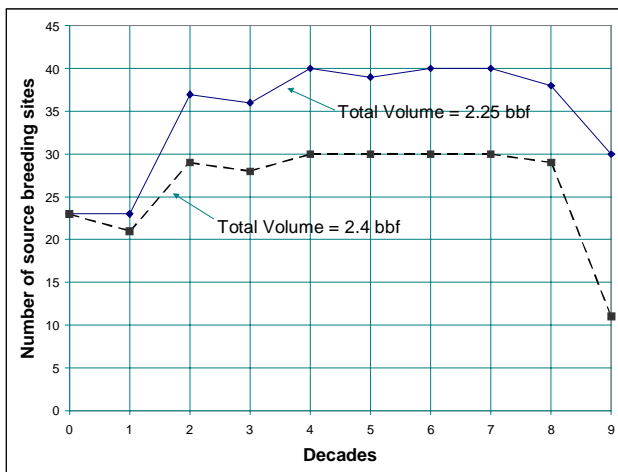


Figure 4: Number of source breeding sites per decade over the simulation period.

The primary shortcoming of heuristic algorithms is that the quality of the best solution found is difficult to assess. Many studies apply extreme value theory where an extreme value distribution (such as the Weibull) is empirically fit 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, and Sharer 1999). A shortcoming of this technique is 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 compare this solution to a set of solutions identified using the heuristic algorithm (Murray and Church 1995, Csuti et al. 1997, Boston and Bettinger 1999). However, because the integer program in this paper contains thousands of decision variables, traditional algorithms such as branch-and-bound are computationally intractable.

We did not attempt to evaluate our solutions with respect to a hypothetical true optimum. Instead, we compared the quality of our solutions with a set of randomly generated harvest solutions. The random harvest algorithm starts with a zero harvest volume and randomly chooses a harvest unit and a management prescription. If the prescription increases the total harvest volume, it is accepted and a new unit and prescription are chosen until the target harvest volume is reached. We created landscape maps from the resulting harvest schedules and these maps were entered into the PATCH model for full wildlife population simulations. Five harvest schedules were simulated for each of two different harvest volumes. At the 2.0 billion board feet level, all five schedules resulted in extirpation of the species from this landscape. At the 1.8 billion board feet level, the estimated likelihood of species persistence ranged from .05 to .29. With the simulated annealing algorithm we were able to identify solutions with non-zero ending populations up to 2.4 billion board feet. Therefore, our solutions are considerably better than those found by a random algorithm.

We intend to simulate some possible outcomes that might actually occur on this landscape, given the pattern of land ownership that occurs on it. This will provide a more realistic comparison for our solutions. The comparison can be interpreted either as a measure of the quality of our solution algorithm or, conversely, as a measure of the efficiency loss associated with imperfect markets face by private landowners and regulatory management on public land.

Conclusion

The simulation results, illustrated in Figure 2, show the physical trade-offs between likelihood of species persistence and timber harvest on this landscape. The solutions are estimates of the bounds on the feasible set of production combinations. Figure 2 can also be given a marginal opportunity cost interpretation. The opportunity cost (the value of output forgone) of increasing the likelihood of species persistence in this case study from 30 to 50 percent is the present value of fifty 50 billion board feet of timber harvest that must be forgone. This can, as well, be couched in terms of the opportunity cost of timber harvest; the opportunity cost of increasing the total timber harvest from this landscape over 100 years from 2.3 to 2.35 billion board

feet is the value of lost certainty of population persistence from 67 to 50 percent.

There are several logical next steps for this research, some of which we have identified in the main body of the paper and are in the process of pursuing. Others include:

1. Simulation of additional species with different habitat needs, body size, life span, fecundity, and dispersal characteristics. This will allow us to explore production relations between different species that may compete on the landscape. This study focused exclusively on commodity/non-commodity trade-offs, representing the cost of species persistence likelihood in terms of the value of commodity production forgone (e.g., pitting loggers against conservationists). But conservation programs may have objectives that conflict, so that the opportunity costs of each may be expressed in forgone accomplishment of the other. For example, managing a stream basin to enhance forage for elk may result in deterioration of the quality of the stream as salmon habitat.
2. As we increase the scale of the analysis to a larger landscape, we will have the opportunity to model more interesting economic interactions. For example, timber harvest and haul cost may vary spatially because it depends on terrain and proximity to a processing facility. The demand for logs at local processing facilities will depend on processing capacity constraints in each period, so that stumpage price in any period may depend on accumulated harvest volume in that period.
3. The model that we developed traces out the production possibilities for species persistence and timber harvest for the study area in the absence of institutional or regulatory constraints. But private landowners make timber management decisions based only on their own private objectives such as maximizing wealth as a function of the value of marketable commodities on their land (e.g., timber). And public land management agencies must meet an array of regulatory constraints. We can measure efficiency loss associated with such constraints by redefining production possibility frontiers using constrained optimization in which the constraints represent various landowner objectives.
4. There is an element of uncertainty in the analysis in its current form, in that one of the outputs is expressed in the likelihood of an outcome. That uncertainty arises in part from uncertainty about PATCH model parameters such as habitat preferences and life history xxx. It also arises from environmental stochasticity. It would be useful to explore the sensitivity of the model solutions to variation in the level of various kinds of uncertainty.

In this study, we developed a framework for analyzing production trade-offs between an ecological objective and an economic objective on a particular landscape. This

required integration of a model to simulate wildlife populations on a landscape and a model for manipulation of that landscape via timber harvest in the context of a heuristic algorithm that guided the search for “best” combinations the two objectives. Such integration and the collaboration across disciplines that is necessary to accomplish it, is absolutely essential as land managers face increasingly complex demands from increasingly stressed landscapes.

This study differs from many previous efforts because it was an attempt to identify the full range of efficient management options for a landscape – those that form the bound on the set of feasible combinations of desired outcomes. Once the efficient set is identified, actual management alternatives that may result from regulatory environments or land ownership patterns can be evaluated with respect to efficiency.

Finally, this study made some progress in the understanding of trade-offs between biodiversity protection and forest commodity production. Most previous studies examined specific conservation strategies for particular high profile species, such as the northern spotted owl or the red cockaded woodpecker (e.g. Montgomery et al. 1994, Hyde 1989). Because the wildlife population simulation model we used can be parameterized for any species for which wildlife preferences and life history parameters are understood, our methodology can be used to evaluate trade-offs associated with a variety of species or even sets or classes of species. This adds depth and generality to the search for efficiency in conservation. At the same time, this study brings far more biological reality and detail to the analysis than did earlier studies that examined trade-offs associated with protection for biodiversity itself or larger groups of species (e.g., Ando et al. 1998, Montgomery et al. 1999).

References

- Ando, A., J. Camm, S. Polaksy, and A.R. Solow. 1998. Species distributions, land values, and efficient conservation. *Science* 279:2126-2128.
- Bettinger, P., J. Sessions, and K. Boston. 1997. Using tabu search to schedule timber harvests subject to spatial wildlife goals for big game. *Ecol. Modeling* 94:111-123.
- Bettinger, P., J. Sessions, and K.N. Johnson. 1998. Ensuring the compatibility of aquatic habitat and commodity production goals in Eastern Oregon with a tabu search procedure. *For. Sci.* 44(1):96-112.
- Bigger, D. and D. Vesely. 2000. Life history database for vertebrates of the Willamette River Basin. Report on file at U.S. Environmental Protection Agency. Corvallis, OR. 76 p.
- Boston, K., and P. Bettinger. 1999. An analysis of Monte Carlo integer programming, simulated annealing, and

- tabu search heuristics for solving spatial harvest scheduling problems. *For. Sci.* 45(2):292-301.
- Caswell, H. 1989. *Matrix population models*. Sinauer Associates, Sunderland, MA.
- Cohen, W. B. 2000. Pacific Northwest Research Consortium: Willamette River Basin Mapping Project. <http://www.fsl.orst.edu/larse/wrb/wrb.html>.
- Csuti, B., S. Polasky, P.H. Williams, R.L. Pressey, J.D. Camm, M. Kershaw, A.R. Kiester, B. Downs, R. Hamilton, M. Huso, and K. Sahr. 1997. A comparison of reserve selection algorithms using data on terrestrial vertebrates in Oregon. *Biol. Cons.* 80:83-97.
- Curtis, R.O., G.W. Clendenen, and D.J. DeMars. 1981. A new stand simulator for coastal Douglas-fir: DFSIM users guide. USDA For. Serv. Gen. Tech. Rep. PNW-GTR-128.
- Gendreau, M., A. Hertz, and G. Laporte. 1994. A tabu search heuristic for the vehicle routing problem. *Manage. Sci.* 40(10):1276-1290.
- Greene, W.H. 1997. *Econometric analysis*. Prentice Hall, New York.
- Haight, R.G. 1995. Comparing extinction risk and economic cost in wildlife conservation planning. *Ecol. Applic.* 5(3):767-775.
- Haight, R.G., and L.E. Travis. 1997. Wildlife conservation planning using stochastic optimization and importance sampling. *For. Sci.* 43(1):129-139.
- Holland, D.N., R.J. Lillieholm, and D.W. Roberts. 1993. Economic trade-offs of managing forests for timber production and vegetative diversity. *Can. J. For. Res.* 24:1260-1265.
- Hyde, W.F. 1989. Marginal costs of managing endangered species: The case of the red-cockaded woodpecker. *J. Agr. Econ. Res.* 41(2):12-19.
- Johnson, K.N. (Team Leader), J. Agee, R. Beschta, V. Dale, L. Hardesty, J. Long, L. Nielsen, B. Noon, R. Sedjo, M. Shannon, R. Trosper, C. Wilkinson, and J. Wondolleck. 1999. *Sustaining the people's lands: Recommendations for stewardship of the National Forests and Grasslands into the next century*. USDA Committee of Scientists Report. U.S. Govt. Printing Office, Washington, D.C.
- Kirkpatrick, S., C.D. Gelatt, and M. Vecchi. 1983. Optimization by simulated annealing. *Science* 220:671-680.
- Laroze, A.J., and B.J. Greber. 1997. Using tabu search to generate stand-level, rule-based bucking patterns. *For. Sci.* 43(2):157-169.
- Lockwood, C., and Moore. 1992. Harvest scheduling with spatial constraints: A simulated annealing approach. *Can. J. For. Res.* 23: 468-478.
- Maddala, G.S. 1983. *Limited-dependent and qualitative variables in econometrics*. Econometric Society Monograph 3. Cambridge University Press, Cambridge.
- Montgomery, C.A., G.M. Brown Jr., D.M. Adams. 1994. The marginal cost of species preservation: the northern spotted owl. *J. Environ. Econ. Manage.* 26: 111-128.
- Montgomery, C.A., R.A. Pollak, K. Freemark, and D. White. 1999. Pricing biodiversity. *J. Environ. Econ. Manage.* 38: 1-19.
- Murray, A.T., and R.L. Church. 1995. Heuristic solution approaches to operational forest planning problems. *Oper. Res. Spektrum [Op. Res.]* 17: 193-203.
- Polasky, S., J.D. Camm, and B. Garber-Yonts. [Forthcoming]. Selecting biological reserves cost-effectively: an application to terrestrial vertebrate conservation in Oregon. *Land Econ.*
- Reeves, C.R. 1993. *Modern heuristic techniques for combinatorial problems*. John Wiley & Sons, New York.
- Schumaker, N. H. 1996. Using landscape indices to predict habitat connectivity. *Ecology* 77(4): 1210-1225.
- Schumaker, N. H. 1998. A users guide to the PATCH model. EPA/600/R-98/135. U.S. Environmental Protection Agency, Environmental Research Laboratory, Corvallis, OR.
- Sessions, J., and J.B. Sessions. 1993. SNAP II + version 2.07 users guide. USDA Forest Service, Washington Office, Ft. Collins, CO.
- Sharer, B. 1999. Heuristic solution techniques for a spatial harvest scheduling problem involving wildlife habitat and timber income. M.Sc. thesis, Oregon State Univ., Corvallis, OR. 94 p.
- Turner, M., R. Costanza, and F. Sklar. 1989. Methods to evaluate the performance of spatial simulation models. *Ecol. Modeling* 48: 1-18.