Market-Based Policies to Reduce Forest Fragmentation and Risks to Interior-Forest Birds

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Paper Prepared for the 2005 AERE Workshop
on Natural Resources at Risk
Grand Teton National Park
June 12-14, 2005

The authors acknowledge financial support from the U.S.D.A. Forest Service and the Department of Agricultural and Resource Economics, Oregon State University.

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Abstract: Forest fragmentation occurs when a contiguous patch of forest is transformed into disjunct patches. This reduces the quality of habitat for bird species of ecological and recreational importance, and is considered to be a primary cause of declines in the populations of many migratory songbirds. In this paper, we analyze the effects of market-based policies on forest fragmentation in the coastal plain region of South Carolina. Our approach integrates an econometric model of land use with simulations that predict the spatial pattern of land-use change. The spatial configuration of each simulated landscapes is summarized with fragmentation indices (average forest patch size, area of core forest, etc.) shown in the ecology literature to be indicators of habitat quality. We analyze how subsidies for afforestation affect distributions defined over the fragmentation metrics and derive the marginal costs of increasing the indices. We examine spatially uniform and spatially-targeted policies. We find that the costs of reducing forest fragmentation vary greatly with initial landscape conditions and that a simple uniform subsidy appears to perform well relative to more complicated spatially-targeted policies.

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I. Introduction

The spatial configuration of land use and land cover influences many important indicators of environmental quality, including bird populations (Askins 2002; Faaborg 2002), amphibian populations (deMaynadier and Hunter 2000), health of riverine systems (Gergel et al. 2002) and estuaries (Hale et al. 2004), human perceptions of scenic quality (Palmer 2004), and the extent of urban sprawl (Carrion-Flores and Irwin 2004). In landscapes dominated by private ownership, land-use decisions are typically made at a finer scale than those at which environmental processes operate. Moreover, landowners lack the incentive to coordinate decisions in order to influence the spatial land-use pattern and the environmental outcomes that depend on it. Land-use policies provide a mechanism for modifying private incentives to achieve socially desired changes in the spatial configuration of land uses. In practice, these policies take one of two forms: 1) regulatory restrictions on allowable land uses such as zoning ordinances and 2) market-based incentives that encourage landowners to either convert land to or retain it in the desired use (Plantinga and Ahn 2002).

The purpose of this paper is to analyze the effects of market-based policies on forest fragmentation and attendant effects on interior-forest birds. Forest fragmentation occurs when land conversion transforms a contiguous patch of forest into disjunct patches. In the United States, approximately twenty percent of resident bird species have experienced significant population declines in recent years (National Audubon Society 2002). While there are many possible causes of these declines, one central factor is thought to be the fragmentation of forested habitat, particularly along the eastern seaboard and in the Midwest region (Askins 2002; Faaborg 2002). Densities for many bird species are lower in small patches of forest than in larger ones, principally because predators and brood parasites from the surrounding matrix can penetrate a greater proportion of small than of large patches (Ambuel and Temple 1983; Hoover *et al*. 1995; Lynch and Whigham 1984). Particularly at risk are migratory songbirds, many of which nest in forests of the eastern U.S. These species are of significant conservation interest because they serve as indicators of ecosystem quality and are of considerable value to recreationists.[1]

This paper presents a methodology for analyzing the spatial structure of forests under alternative market conditions and policy scenarios. Our approach integrates a behavioral model of landowner decision-making with simulations that predict the spatial pattern of land-use change. The first component is an econometric model of land-use conversion estimated with plot-level data. The econometric analysis yields land-use transition probabilities expressed as functions of market returns and physical characteristics of the land. The second component is a GIS-based landscape simulation model. The simulations relate the transition probabilities to actual landscapes so that future spatial patterns of land use can be predicted under baseline and policy scenarios. The resulting landscape patterns are summarized using fragmentation indices. The indices include the average forest patch size and the percentage of the landscape in core forest (forest parcels that are a specified minimum distance from a non-forest edge).[2]

We apply the methodology to the coastal plain of South Carolina. Partners in Flight, a consortium of government agencies and private conservation groups, has expressed the need for large forest blocks in the southeastern U.S. to provide nesting habitiat for interior-forest birds.

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[1] The U.S. Fish and Wildlife Service (2001) estimates that 46 million U.S. residents are involved in bird-watching each year, similar to the total number who participate in recreational angling and hunting.

[2] Heavily fragmented landscapes have fewer core (or interior) parcels. Such interior parcels provide the best habitat for many sensitive bird species (Robbins et al. 1989, Robinson et al. 1995, Askins 2002). For example, some species of interior-forest songbirds require habitat that is more than 200 m from the nearest non-forest edge (Temple and Cary 1988). Ritters et al. (2002) found that approximately 62% of forest in the lower 48 states is located within 150 m of the nearest edge, suggesting that fragmentation is a pervasive feature of U.S. forests.

One policy approach is to subsidize private landowners for afforestation (conversion of non-forest land to forest). Similar subsidies are offered to farmers under the federal Conservation Reserve Program and have been proposed as an approach to sequestering carbon in forests (Plantinga et al. 1999). We model afforestation subsidies by increasing the per-acre net return to forestry, which increases the probability that land is converted to forest. We first consider a uniform policy that pays all landowners the same amount per acre of land converted to forest. Then, we analyze spatially-targeted policies that subsidize landowners only if their parcel shares a border with forested parcels. This policy is similar to the agglomeration bonus proposed by Smith and Shogren (2002) and Parkhurst et al. (2002) for endangered species conservation.

There are interesting tradeoffs between the uniform and spatial policies. The uniform subsidy converts a given area of land to forest at the lowest possible cost (Plantinga and Ahn 2002), but may have limited effects on fragmentation metrics because it ignores the existing spatial pattern of forests. In contrast, the targeted policy would have greater impacts on landscape pattern, but the cost of converting land to forest is higher because the policy selects from the smaller set of parcels that are eligible for the subsidy. Thus, it is unclear, *a priori*, whether it is less costly to achieve a given change in a landscape metric with a uniform or a targeted policy. Which approach is less costly, *ex post*, will depend on the initial landscape pattern and the landscape metric of interest. For example, on a landscape with few and fragmented forest parcels, a uniform subsidy may be a more expensive approach to increasing the amount of interior forest. While the policy is cheap from the standpoint of converting land to forest, it is less likely to create new interior forest parcels. However, if the initial area of forest is high, a uniform policy may be less costly because the chance of creating interior forest parcels is greater.

The next section reviews existing models of landscape change and discusses the contribution of this study to that literature. The section concludes with a brief review of the impacts of forest fragmentation on birds. Section 3 discusses the study area and, in section 4, we present the key components of the analysis—the econometric land-use model, the landscape simulation model, and fragmentation indices. The next two sections discuss the policy application and present the simulation results. Section 7 presents our conclusions and discusses directions for future work.

2. Relationship to the Previous Literature

2.1 Models of landscape change

Geographers have made important contributions to the literature on spatially-explicit models of landscape change (Clarke and Gaydos 1998; Li and Gar-On Yeah 2000; Wu 1998, 2002; Wu and Webster 2000; Allen and Lu 2003). Most of these papers use simulation models based on cellular automata (CA). CA models a landscape as a set of discrete grids which transition from one state (e.g., land use) to another based on deterministic or probabilistic rules. In most cases, transition rules are specified by the researcher or by calibration to historical digital maps. A criticism of CA models in the geography literature is that the transition rules represent human decisions, yet typically are not based on well-specified models of human behavior (Wu and Webster 2000). This shortcoming has been addressed, to some degree, through the use of empirically-derived transition rules. For example, Wu (2002) uses transition probabilities derived from a logit analysis relating observed land-use changes to physical site characteristics. Other landscape simulation models with empirical foundations are Berry et al. (1996), Veldkamp and Fresco (1996), Allen and Lu (2003), and Landis and Zhang (1998a, 1998b).

In the economics literature, a great deal of attention has been given to estimating land-use models based on profit-maximizing behavior. The emphasis in this literature is on explaining observed land-use decisions in terms of market-based returns to alternative uses (Stavins and Jaffe 1990, Plantinga 1996, Hardie and Parks 1997, Miller and Plantinga 1999). In contrast to geographers, economists have been less involved in using these models to predict changes in spatial landscape patterns. The relevant list of papers includes several on deforestation (Nelson *et al*. 2001; Cropper *et al*. 2001) and urban sprawl (Carrion-Flores and Irwin 2004) and a number from the Patuxent River Watershed project at the University of Maryland (Bockstael 1996; Irwin and Bockstael 2002, 2004).

One of the challenges in combining empirical land-use models with spatially explicit simulations arises from the probabilistic nature of transition rules derived from econometric analysis (Bockstael 1996). In this case, the researcher can determine whether a particular parcel is more likely to convert than another parcel, but not that any particular parcel will convert with certainty. Some researchers present GIS maps showing the spatial distribution of the estimated probabilities (Bockstael 1996; Cropper *et al*. 2001), while others form deterministic rules from probabilistic ones (Chomitz and Gray 1996; Irwin and Bockstael 2002).[3] A problem with the latter approach is that a given deterministic rule is only one of many possible rules. Thus, the simulation produces a single landscape that represents only one of what is typically a very large number of potential landscapes. An alternative is to generate a large number of different landscapes conforming to the underlying probabilistic rules. However, one must then summarize this information in a way that effectively conveys the range of potential outcomes.

[3] For example, Nelson and Hellerstein (1997) and Nelson *et al*. (2001) assume that each parcel will convert to the use with the highest estimated transition probability.

Our study makes several contributions. First, we use probabilistic transition rules derived from econometric analysis to conduct repeated landscape simulations. To overcome the informational challenges posed by this approach, we compute fragmentation indices to summarize the spatial pattern of each simulated landscape and then derive empirical distributions defined over the indice values. Second, we develop a framework for analyzing the effects of market-based policies on the spatial pattern of land use. While econometric land-use models have been used earlier in policy simulations (e.g., Plantinga et al. 1999; Stavins 1999), our study is the first (to our knowledge) to explicitly link market-based incentives and the spatial configuration of land uses. Finally, our model accounts for transitions between three major land uses (agriculture, forest, and urban). With the exception of studies on deforestation, earlier analyses have focused on urban growth patterns. In our study area, conversions between forest and agricultural uses are an important driver of habitat fragmentation.

2.2 Forest Fragmentation and Interior-Forest Birds

Forest fragmentation has long been considered a primary threat to terrestrial biodiversity (Armsworth *et al*. 2004). In the U.S., neo-tropical migratory songbirds are one group of species with well-documented population/fragmentation relationships. Among the most important fragmentation effects on songbird populations are edge effects and patch-size effects (Askins 2002; Faaborg 2002). Edge refers to discontinuity between habitat types (e.g., the border of a forest and agricultural field) and regions with more fragmentation typically have more edge habitat (Faaborg 2002). The effects of edge on bird populations are often due to nest parasites such as brown-headed cowbirds from neighboring agricultural lands, and predators such as house cats from neighboring urban lands. Edge effects have been found to extend from 50 m (Paton

1994) to 300 m (Van Horn *et al*. 1995) into forest patches. Birds typically have greater breeding success in core habitat than edge habitat because of reduced effects of nest parasites and predators.

There is a large and largely consistent literature on the effects of patch size on birds (Ambuel and Temple 1983; Howe 1984; Robbins *et al*. 1989; Wilcove and Robinson 1990). Many bird species prefer large blocks of habitat because they have a large home range (Askins 2002). Robbins *et al*. (1989) is one of the most comprehensive and well-known studies on the effect of patch size on birds. They found that most neo-tropical migrant songbirds have a much higher probability of occurrence in large patches of forest than small patches. Robbins *et al*. also showed that larger habitat sizes coincided with increased species diversity. Faaborg (2002) notes that the results of Robbins *et al*. are consistent with a great deal of biological research on bird populations. There is also evidence that increased patch size is associated with an increase in non-bird species diversity (Noss 1994).

Our focus in this study is on forest fragmentation caused by non-forest uses, specifically agriculture and urban uses. We do not consider modifications of forest habitat caused by timber harvesting. Avian ecologists have found much clearer effects of fragmentation from non-forest uses compared to fragmentation from timber harvesting (Faaborg 2002).

3. Study Area

Our study area is the 4,000 sq. km coastal plain of South Carolina (Figure 1). This region provides an excellent setting for studying incentive policies designed to influence the spatial configuration of private forest land. Approximately 83% of the land is privately owned. Land use in the region is diverse and dynamic. In 1997, 69% of privately-owned land was in forest, 25% was in agricultural use (cropland and pasture), and 6% was in urban use. In recent decades, there have been significant exchanges between forest and agricultural uses as well as conversion of forest and agricultural land to urban uses. Finally, there is considerable variation within the region in initial land-use shares, patch sizes, and patch shapes. As such, the findings for sub-regions of the South Carolina coastal plain could be applied to other regions in the eastern U.S. with similar initial conditions, including the heavily forested northern and Appalachian regions and urbanized areas of the Northeast and Midwest.

4. Methods

4.1 Econometric Model of Land-Use Change

We estimate an econometric model that represents transitions between agriculture, forest, and urban uses. Each landowner is assumed to allocate a homogeneous land parcel to the use generating the greatest present discounted value of net returns minus conversion costs. This is the optimal allocation rule when landowners have static expectations of conversion costs and future net returns (Stavins and Jaffe 1990; Plantinga 1996). In this case, the owner of parcel *i* in use *j* at the start of period *t* will convert to use *k* if:

(1) $$R_{ikt} - rC_{ijkt} \geq R_{ijt}$$

for all alternative uses *k* (*k*=1,…,*K*) and where R_{ikt} is the annual net return to use *k* in time *t*, *r* is the interest rate, and C_{ijkt} is the one-time cost of converting land from use *j* to use *k* ($C_{ijjt} = 0$). Following the discrete-choice literature, the net revenue from use *k*, assuming the parcel begins in use *j*, depends on a random component, ε_{ijkt}, that is unobserved by the researcher:

(2) $$\pi_{ijkt} = R_{ikt} - rC_{ijkt} + \varepsilon_{ijkt}$$

We denote the deterministic component of net revenue, $R_{ikt} - rC_{ijkt}$, as $\beta_{jk}'\mathbf{x}_{ijkt}$, where β_{jk} is a vector of parameters to be estimated, and $\mathbf{x}_{ijkt}$ is a vector of observable variables.

The probability that parcel *i* will convert from use *j* to use *k* in time *t* is defined as:

(3) $$pr(\beta_{jk}'\mathbf{x}_{ijkt} - \beta_{jl}'\mathbf{x}_{ijlt} \geq \varepsilon_{ijlt} - \varepsilon_{ijkt})$$

for all uses *l*. We assume that the error terms are IID Type I extreme value, and obtain a conditional logit model with the following transition probability:

(4) $$P_{ijkt} = \frac{\exp(\beta_{jk}'\mathbf{x}_{ijkt})}{\sum_{l=1}^{K} \exp(\beta_{jl}'\mathbf{x}_{ijlt})}$$

The specification in (4) embodies the well-known independence of irrelevant alternatives (IIA) property. In a similar application to land use, Lubowski (2002) uses a nested logit specification that imposes the IIA property within, but not across, nests. We conduct Hausman specification tests and fail to reject IIA as the null hypothesis at the 5% level. Thus, we proceed with the unnested model.

The U.S. Department of Agriculture's National Resources Inventory (NRI) is the main data source for our application. The NRI is a panel survey of land use, land cover, and soil characteristics of non-federal lands in the contiguous U.S. We focus on privately-owned agricultural (crop and pasture), forest, and urban land in North and South Carolina.[4] These uses accounted for 81% of the non-federal land in the two states in 1997. Annual per-acre net returns to the three uses are taken from Lubowski (2002), and described in detail there. The returns to forest are measured as annualized revenues from timber production less management costs.

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[4] Our sample consists of 29,714 plots that began at least one of the time periods in forest or agricultural use. We focus on plots beginning in forest and agriculture because once land is converted to urban use, it does not transition out of that use. The data set is expanded to include plots outside the study region in order to increase the variation in land-use changes and determinants of these changes.

Agricultural returns equal the annual revenue from crop and pasture production less costs and plus government payments. The forest and agricultural returns are county averages reflecting the existing mix of timber types and crops and their associated yields.[5] Returns to urban land measure the annualized median value of a recently-developed parcel used for a single-family home, less the value of structures. Landowners are assumed to form expectations of future returns by computing the average of annual net returns over the preceding five-year period.

The deterministic components of net revenue are written:

$$\begin{array}{ll} \beta_{0,jk} + \beta_{1,jk} R_{ikt} + \beta_{2,jk} LCC_i \cdot R_{ikt} & k = \text{agriculture, forest} \\ \beta_{0,jk} + \beta_{1,jk} R_{ikt} + \beta_{3,jk} UI_i & k = \text{urban} \end{array} \tag{5}$$

where *k* denotes the ending use and *j* the starting use (*j*=agriculture, forest). R_{ikt} is the average (or median) return to use *k* in the county where plot *i* is located. To account for plot-level deviations from average agricultural and forest returns, we include the product of the county return and LCC_i, which measures the land capability class (LCC) rating of the plot. The LCC rating is a composite index representing twelve factors (e.g., soil type, slope) that influence the suitability of the land for agriculture.[6] The LCC data are from the NRI database. We also expect the plot-level return to urban use to deviate from the county median return. We include a dummy variable, UI_i, equal to zero if a plot is urban-influenced, and one otherwise. This

[5] We are unable to measure returns at the plot level because the NRI database does not disclose plot locations below the level of counties. In any event, we do not have data to measure many components of net returns (e.g., commodity prices) at a sub-county level. However, we do account for within-county variation in net returns in the econometric specification discussed below.

[6] The LCC index ranges from I to VIII, where I indicates the most productive land. To ensure sufficient observations in each group, we combine the LCC categories. For plots either starting or ending in agriculture, we use three categories: 1=I,II; 2=III,IV; 3=V,VI,VII,VIII. For plots starting and ending in forest, we use four categories: 1=I,II; 2=III,IV; 3=V,VI; 4=VII,VIII. We form dummy variables, $D_{m,i}$, where *m* denotes the appropriate category. If *j*=agriculture or *k*=agriculture, $\beta_{2,jk} LCC_i = D_{1,i}\beta_{2,1,jk} + \beta_{2,2,jk} D_{2,i} + \beta_{2,3,jk} D_{3,i}$ and if *j*=forest and *k*=forest, $\beta_{2,jk} LCC_i = D_{1,i}\beta_{2,1,jk} + \beta_{2,2,jk} D_{2,i} + \beta_{2,3,jk} D_{3,i} + \beta_{2,4,jk} D_{4,i}$. To avoid perfect collinearity with the net returns variable, we set $\beta_{2,1,jk} = 0$.

variable was constructed by the U.S.D.A. Economic Research Service (ERS) and based on an index of urban proximity derived from 1990 Census-tract population data.[7] We do not have data on conversion costs. Their effects are measured in constant terms, $\beta_{0,jk}$, specific to each transition.[8]

The NRI provides observations of plot-level land-use changes over three time intervals (1982–1987, 1987–1992, 1992–1997). Panel data estimation of a logit model is appropriate only if the unobserved components of net revenue are uncorrelated over time (Train 2003). However, there are likely to be unobserved factors (e.g., distance to major roads) that exhibit such correlation. Thus, to maximize the observations of land-use changes and to ensure consistent and efficient estimation, we employ a pooling strategy that provides some of the benefits of panel data estimation without requiring the above restriction on the unobserved components.[9] We do not make adjustments for potential spatial correlation of the model error terms. Spatial dependencies between land-use choices have been identified in earlier studies (Irwin and Bockstael 2002). The NRI data are generated by a stratified sampling routine that ensures that plots are geographically dispersed. Prior researchers have used a similar sampling approach to purge data of spatial correlation (Nelson et al. 2001, Carrion-Flores and Irwin 2004).

Maximum likelihood procedures are used to estimate separate models for lands beginning in agriculture and forest (Table 1). We do not observe transitions out of urban use and so we

[7] The urban influence measure is similar to a gravity index, and provides a measure of accessibility to population concentrations. We thank Vince Breneman at ERS for linking urban influence to the NRI plots and Shawn Buckholtz at ERS for providing the corresponding GIS layer on urban influence.

[8] To identify the model parameters, we normalize the constant terms to zero for each starting use.

[9] For land parcels that remain in a given land use for three (two, one) periods, we randomly select one-third (one-half, all) of the parcels from each time period. Observations sampled at 1/3, 1/2, and 1/1 intensity are then weighted by 3, 2, and 1. In addition, each observation is weighted according to NRI expansion factors to reflect the geographic sampling intensity.

assume that once land is urbanized it remains in that state with probability one. The estimation results indicate good model fit[10] and are consistent with profit-maximizing behavior. In both equations, the transition-specific constant terms are negative and significantly different from zero (1% level), suggesting that conversion costs deter conversions out of the starting use. Likewise, coefficients on the net returns variables are all positive and significantly different from zero, indicating that higher returns to a given use (holding returns to other uses constant) encourage conversion to that use. Four of the coefficients on the land quality interaction terms are significantly different from zero. On the lowest quality lands, agricultural returns have a diminished effect on the probability that land remains in agriculture. In contrast, on these lands forest returns have a greater effect on the probability that agricultural land transitions to forest and the probability that forest land remains forested. Finally, the coefficient on the urban status of the plot is negative and significantly different from zero, indicating that agricultural and forest parcels in rural areas are less likely to convert to urban uses.

4.2 Landscape Simulations

We develop a landscape simulation model that integrates the econometric results with data on actual landscapes. Using (4) and the estimated parameter values in Table 1, we obtain land-use transition probabilities that are differentiated by starting and ending use, county, land quality class, and urban influence status. To develop the simulation model, we obtain corresponding spatial data layers for the coastal plain of South Carolina. The main source for the GIS data is the South Carolina Department of Natural Resources' (SCDNR) GIS data clearinghouse. The data are delineated by quadrangles (quads), as defined by the U.S.

[10] The likelihood ratio index (Train 2003) is 0.79 (0.89) for land starting in agriculture (forest), indicating that the models increase the log-likelihood function above its value with zero parameters.

Geological Service (USGS). Each USGS quad covers approximately 40,000 acres of land, resulting in 566 maps for the state and 295 maps for the coastal plain region (Figure 1).

The land-use maps were developed by SCDNR in conjunction with the U.S. Fish & Wildlife Service National Wetlands Inventory (NWI). The land-use data are delineated from 1:40,000 scale infrared photography (from 1989) and available in vector format at 10-acre minimum resolution. The SCDNR uses finer land-use categories and so we combine them as needed to match the three uses—agriculture, forest, and urban—represented in the econometric model. The soil quality layer is derived from existing county surveys available from the Natural Resources Conservation Service. The data were digitized by SCDNR and linked to STATSGO tables of soil attributes. To match the soils layer to our transition probabilities we further linked these tables to SSURGO soils tables to obtain LCC information on each parcel.[11] We also used GIS layers on political boundaries and ownership status from the SCDNR database to identify county boundaries and public lands (e.g., national forests). Finally, we used a GIS layer of urban influence status, available from ERS, to identify the urban influence status of each parcel.

We overlay these data and obtain an average of approximately 7,500 uniquely-identified parcels per quad, with an average size (for land parcels) of approximately 5 acres.[12] Each parcel in the GIS is indexed by land use in 1989 (agriculture, forest, urban, or water/missing), county, LCC rating, ownership, and urban influence status. We focus on privately-owned parcels in agriculture, forest, and urban use. Thus, we can match each parcel in the GIS to a set of transition probabilities from the econometric analysis.

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[11] We thank Ben Stuckey for providing the relevant SSURGO data.

[12] The number of parcels is typically much lower for quads covering the coastline. In these cases, the water portion of the quad is counted as one parcel.

From the standpoint of the simulations, we interpret the fitted transition probabilities as a set of rules that govern land-use change in the study area. For example, if the value of the agriculture-to-forest transition probability is 0.20 for a particular parcel, the owner of the parcel will convert to forest 20% of the time if the choice situation is repeated enough times. In the simulations we use a random number generator to repeat the choice situation many times[13] for each parcel in the landscape. To illustrate, suppose that a parcel is in agricultural use initially and has a 0.70 probability of remaining in agriculture, a 0.20 probability of converting to forest, and a 0.10 probability of converting to urban use. A random draw is generated from a uniform distribution defined on the unit interval. If the value is between 0 and 0.70, the parcel remains in agriculture, between 0.70 and 0.90, it converts to forest, and between 0.90 and 1, it converts to urban use. For a large number of simulations, the ending uses of a parcel will satisfy the proportions implied by the transition rules (e.g., forest 20% of the time).

4.3 Fragmentation Indices

Our simulations generate numerous landscape outcomes, each consistent with the underlying transition rules. To organize such a large amount of information, we use the software Fragstats (v. 3) to calculate fragmentation indices for the landscape produced at the end of each simulation round.[14] Fragstats accepts raster images and generates metrics characterizing area, density, edge, shape, core area, isolation and proximity, contagion and interspersion, connectivity, and diversity. As a first step, we calculated 32 metrics in each of the 295 quads for the forested portion of the initial landscape. Because many of these metrics are closely related,

[13] Below, we discuss the criteria used to determine the number of simulations.

[14] Details on Fragstat are available at: http://www.umass.edu/landeco/research/fragstats/fragstats.html.

we followed Ritters et al. (1995) and performed a principal components analysis to identify a smaller group of four metrics that capture a high percentage of the variation across the quads in the larger set of indices.[15] The four indices, with Fragstat acronyms in parentheses, are the percentage of the landscape in core habitat (CPLAND), the mean of the shape index (SHAPE_MN), the splitting index (SPLIT), and the clumpiness index (CLUMPY). We also include two additional indices, mean patch area (AREA_MN) and largest patch index (LPI), that are commonly used in the ecology literature to describe the spatial configuration of forest habitat.[16]

The results from many simulation rounds define empirical distributions over each of the fragmentation metrics. Because these distributions are the key result of this analysis, we want them to be insensitive to the number of simulation rounds. Computational challenges preclude us from applying a convergence rule that ends a simulation once a specified criterion is met. Instead, we select five representative quads and analyze the number of simulations required for the fragmentation distributions to converge.[17] Following Ross (1997), we examine how the confidence interval lengths for the estimates of the first three moments of the distributions

[15] First, we examined simple correlation coefficients between metrics and formed groups of metrics such that all within-group correlations were larger than 0.85. We selected one metric to represent each group, leaving us with 16 metrics. Second, we applied the principal components method to the correlation matrix of the remaining indices and examined the eigenvalues associated with each metric. As is standard practice, we retained those factors with an associated eigenvalue greater than one. The four metrics satisfying this criteria explain approximately 79% of the variation in the 16 indices.

[16] Three of the indices have straightforward interpretations. The percentage of the landscape in core habitat equals the area of forest parcels at least 200 m from the nearest forest edge divided by the total landscape area. Mean patch area is the average size of contiguous forest blocks (or patches). The largest patch index is the percentage of the landscape comprised of the largest forest patch. The other metrics are less intuitive. Definitions can be found at the Fragstat website.

[17] Representative quads were selected according to the degree of initial fragmentation and the expected change in forest habitat as indicated by the econometric model.

change with the number of simulations.[18] The interval lengths decrease at a declining rate as we increase the number of simulations but change very little beyond 500 simulations. To further investigate whether 500 simulations adequately characterize the distributions, we generate two samples of 500 simulations and test for differences in the first three sample moments. In all cases, we fail to the reject the null hypothesis of no difference at the 1% level. Based on this evidence, we conclude that 500 is an adequate number of simulations.

5. Policy Application

The land-use transition probabilities in (4) are functions of net returns to agricultural, forest, and urban uses. As such, we can simulate the effects of afforestation subsidies by increasing the forest net returns variables in the transition probabilities for land starting in agriculture. This increases the probability that agricultural land transitions to forest and reduces the probability that it remains in agriculture and transitions to urban use. Because the probabilities determine the transition rules in the landscape simulation, we can measure how afforestation subsidies affect the spatial configuration of forest land. The simulations begin in 1989 and proceed in five-year time steps (the increment for the transition probabilities) for a period of 30 years. Base net returns (R) are computed for 1989 and remain constant throughout the simulation. The afforestation subsidies are added to the appropriate base net return for forest.

We consider, first, a spatially-uniform subsidy of $25 per acre that is paid to all owners who convert agricultural land to forest. The effects of the subsidy on each fragmentation metric are measured relative to a baseline scenario in which the subsidy is zero. This simulation is run

[18] We use bootstrapping to derive the standard errors of the estimates of the second and third moments.

for all 295 quads in the study area.[19] The uniform subsidy maximizes the area of agricultural land converted for a given budget (Plantinga and Ahn 2002), but may have limited success in influencing the fragmentation metrics. Thus, similar to the agglomeration bonus analyzed by Smith and Shogren (2002) and Parkhurst et al. (2002), we consider a second approach that targets owners of agricultural parcels adjacent to forested parcels. An alternative would be to identify efficient policies—for example, an incentive that would achieve a given increase in core forest habitat at least cost. Such policies are extremely complicated even in settings much simpler than ours, and so we focus on a set of practical, albeit less efficient, policies.

We analyze two types of the spatially-targeted policies. Under the first version, owners of agricultural parcels receive the afforestation subsidy if they share a border with one or more forested parcels. We label this the ST-1 subsidy. The GIS land-use layer is in 50 m pixels and, thus, land use is designated for each 50 × 50 sq m parcel. We use an eight neighbor rule for determining adjacency. As the simulation proceeds, we recompute adjacency—and, thus, eligibility for the subsidy—at the start of each five-year period. In contrast to a uniform subsidy, the ST-1 subsidy will increase the size of all forest patches on the landscape provided existing forested parcels do not transition to another use. Thus, the ST-1 subsidy is likely to increase the mean patch area and the largest patch index. However, it will not necessarily increase the area of core forest habitat since this requires forest parcels to be at least 200 m from the nearest non-forest edge. The second type of spatially-targeted policies, labeled ST-3, makes the subsidy available only to parcels that are adjacent to three or more forest parcels. While this policy

[19] On a desktop computer, it takes approximately one hour per quad to simulate 500 landscapes and do the respective fragmentation calculations. This translates to roughly 12 days of computing to simulate the $25 uniform subsidy for the entire study region.

cannot guarantee the creation of core forest, it is more likely to have this effect than the other policies examined.[20]

The computational costs of analyzing the spatially-targeted policies are high. The run time is approximately ten hours per quad for each type of policy and level of the subsidy. For both types of spatially-targeted policies, we analyze three quads and levels of the subsidy ranging from \$15 to \$45 in increments of \$5. The selected quads had significant response to the uniform subsidy and differ considerably from each other in initial forest cover (35%, 50%, and 75%). We use the results to compute the marginal costs of increasing two of the fragmentation metrics with straightforward interpretations—mean forest patch size and the percentage of the landscape in core forest. For subsidy level *s*, marginal costs equal:

$$MC_s = \frac{s\overline{F}_s - (s-5)\overline{F}_{s-5}}{\overline{I}_s - \overline{I}_{s-5}} \quad (6)$$

where $\overline{F}_s$ and $\overline{I}_s$ are mean changes in forest area and a given fragmentation index, respectively, relative to the baseline and corresponding to subsidy *s*. Because we generate distributions for changes in forest area and the fragmentation indices, we can compute confidence intervals for marginal costs.[21]

[20] We are unable to evaluate a policy that directly subsidizes the creation of core forest because this would require embedding the Fragstat software in the Visual Basic code that runs within ArcGIS.

[21] If $\overline{I}_s - \overline{I}_{s-5}$ is an unbiased estimator of the true difference in means, then the standard deviation of $\overline{I}_s - \overline{I}_{s-5}$ is equal to $sd_s = \sqrt{\mathrm{var}(\overline{I}_s)/n + \mathrm{var}(\overline{I}_{s-5})/n}$ where n = 500 is the number of simulations (Devore 1995). Since n is large, we can appeal to the Central Limit Theorem and assume that $\overline{I}_s - \overline{I}_{s-5}$ has an approximately normal distribution. The variance of forest area is very small relative to the variance of the fragmentation indices and so we assume $\mathrm{var}(F_s) = 0$.

6. Simulation Results

6.1 Uniform Subsidy

For the uniform subsidy, we derive empirical distributions for each fragmentation index and each quad. Computed as an average across quads, we find that the uniform subsidy increases total forest area by 6.9%. The proportion of the landscape in core forest increases by significantly less because not all of the new forest parcels become or help to create core forest. The core forest metric increases by 3.5%, on average, implying a cost of $49 per acre of core forest. In percentage terms, the average patch size and the largest patch index increase by more than the increase in total forest area (respectively, by 65% and 10% on average). These metrics can increase greatly when new forest parcels connect previously disjoint patches.

Core forest and average patch size distributions for the entire study area are constructed using the mean values for the 295 quads (Figure 2). As shown, the uniform policy shifts the distributions to the right. For both indices, the mean of the distribution increases with the uniform policy, and the distribution for the uniform policy first-order stochastically dominates the baseline distribution. The uniform policy increases the probability that higher values of the indices are obtained and this increases the variance of the distributions. The spatial distribution of the changes in core forest and average patch size are shown in Figure 3. The largest changes occur in the western portion of the state, which initially has a large share of land in agricultural use. The effects of the policy are smaller along the coast. This region includes the urban-rural fringe around Charleston and areas farther north which initially have a large share of land in forest.

6.2 Spatially-targeted Policies

We derive marginal costs for the uniform and spatially-targeted policies (ST-1 and ST-3) and for each of the selected quads. Marginal cost for the average patch size metric is interpreted as the cost of increasing the average forest patch by one acre. As shown in Figure 4, marginal costs increase initially and then decline for quads with 35% and 50% initial forest. In contrast, the marginal cost curves are relatively flat for the quad with 75% initial forest. These results appear to reflect a concept from landscape ecology referred to as the percolation threshold. The idea is that additional forest results in large changes in average patch size once forests occupy approximately 60% of the landscape. Around this threshold, an additional forest parcel has a high probability of joining existing patches. On the quads with 35% and 50% initial forest, the afforestation subsidies increase the forest share to close to or above the 60% threshold. The quad with 75% initial forest begins above the threshold and so marginal costs do not decline.

Increasing average patch size with the ST-1 policy is less costly than the uniform policy, though there is significant overlap in the respective 95% confidence intervals on all but the 50% initial forest quad. Every parcel converted with the ST-1 policy increases average patch size because the total number of forest patches must remain the same or decline under the policy. In contrast, the uniform policy will decrease average patch size if a new parcel is unconnected to existing forest parcels. The ST-3 policy must also increases average patch size, but because it targets a limited subset of agricultural parcels—those with three or more forested neighbors—it entails considerably higher costs. Comparing ST-3 to the uniform policy, we see that the costs of selecting from a small set of parcels greatly outweigh the costs of creating disjoint parcels.

Marginal cost for the core forest metric is interpreted as the cost of increasing core forest by one acre. For the quads with 35% and 50% initial forest, marginal costs of increasing core forest increase initially and then decline with all three policies (Figure 5). As with average patch size, once the forested area of a quad is sufficiently great, additional forest parcels have a high probability of creating core forest. In the most heavily forested quad, any converted parcel has a high probability of creating core forest. In this case, marginal costs rise for all policies, simply reflecting the increasing marginal cost of converting agricultural land.

The marginal costs of increasing core forest are lowest with the uniform policy in all three quads. The spatially-targeted policies increase the likelihood that core forest will be created. However, this advantage is outweighed by the added cost of selecting from smaller sets of agricultural parcels. The costs of the ST-1 and ST-3 policies are similar for the quads with 35% and 50% initial forest. This suggests that the ST-3 policy can be more effective than ST-1 at creating core forest. However, in these cases, the added cost of converting land to forest under ST-3 offsets this advantage. In the heavily forested landscape, the costs of the ST-3 policy rise above those for ST-1. In this case, further targeting of the policy increases afforestation costs by more than it increases the creation of core forest.

It is also instructive to compare marginal costs across the three quads and across the fragmentation indices. The costs of increasing average patch size and core forest fall as the initial share of the landscape in forest rises. The effect is especially pronounced for average patch size. In this case, marginal costs are an order of magnitude lower for the 75% initial forest quad compared to the 35% initial forest quad. Indeed, all of the three policies have lower marginal costs when applied to the most heavily forested quad. The decline in the marginal costs of increasing core forest is less dramatic. For a given change in core acreage, there is an approximately linear relationship between marginal cost and the share of the initial landscape in forest. Finally, when we compare costs across the fragmentation indices, we see that the uniform policy dominates ST-3 and, with the exception of the 50% initial forest quad, has comparable or lower costs than ST-1.

7. Conclusions

In this paper, we examine how market-based policies can be used to influence the spatial pattern of forests on landscapes dominated by private ownership. We consider how policies can affect indices of forest fragmentation, including average patch size and the area of core forest. These metrics have been shown in the ecology literature to be indicators of habitat quality for interior-forest birds. Our analysis has several distinguishing features. First, we model three major land uses. Many earlier analyses have emphasized the effects of urban development on landscape pattern. We also examine agricultural land use, which plays a critical role in determining the spatial pattern of forests and which would be a focus of policies designed to reduce forest fragmentation. Second, we analyze the effects of market-based incentives on the spatial configuration of forests. This is possible within our framework because land-use decisions are econometrically modeled as functions of market returns. Finally, we use probabilistic transition rules and characterize the distribution of potential effects that afforestation policies can have on landscape outcomes.

Our results show that even spatially uniform incentives can have significant effects on the spatial pattern of forest land. A uniform subsidy of $25 per acre would result in an increase of over 800 thousand acres of forest in the Coastal Plain region, of which approximately one-half would be core forest. The policy would also significantly increase the average forest patch size (by 65%) and the share of the landscape occupied by the largest forest patch (by 10%). Our results indicate that the policy would shift the regionwide distribution over the core forest and average patch size indices. Even so, the distribution is still skewed toward higher values of the indices, indicating that many parts of the regions would continue to have fragmented forests. In particular, we find that the policy has larger effects on the indices in agricultural regions of the state compared to urbanizing and heavily forested areas.

We compare the performance of the uniform policy to spatially-targeted policies. A key finding is that initial landscape conditions play a critical role in determining the performance of fragmentation policies. On landscapes with relatively little initial forest cover (less than 50%), the marginal costs of increasing average patch size and core forest area decline as the values of these indices increase. Once the area of forest land is sufficiently high (near what landscape ecologists refer to as the percolation threshold), additional forest parcels can have large effects on these indices as forest patches become connected and increase in size. We find that, in most cases examined, the choice of the area to implement the policy has much greater implications for costs than the choice of a uniform or targeted policy. For example, for all three policies examined the marginal costs of increasing average forest patch size are dramatically lower on a heavily forested landscape. Our results suggest that initial landscape conditions, rather than the policy approach, should be the foremost consideration for wildlife managers deciding how to allocate a limited budget to conservation efforts.

The selection of a uniform or spatially-targeted policy involves a tradeoff between the cost of converting land to forest and the effects that new forest parcels have on fragmentation metrics of interest. We find that the uniform policy has the lowest costs for increasing core forest and costs for increasing average patch size that, in most cases, are similar to the least-cost spatially-targeted policy. This finding suggests that a simple uniform policy that converts land at least cost may be more efficient than spatially-target policies, particularly if the goal is to influence more than one fragmentation metric. This conclusion must be qualified for the core forest index. In this case, we could not model a policy that directly affected the area of core forest due to programming complexities. We note that it also would be very complicated to implement this approach in practice.

In sum, the key policy insights from our study are that the costs of reducing forest fragmentation vary greatly with initial landscape conditions and that a simple spatially uniform subsidy appears to perform well relative to more complicated spatially-targeted policies. The next step in this research is to estimate how changes in landscape metrics affect the populations of interior-forest birds, since this would ultimately be the goal of a conservation policy. We are presently working with a wildlife ecologist to translate fragmentation metrics into abundance measures for selected bird species.[22] The bird ecology model is estimated with data on species incidence from the national Breeding Bird Survey and co-variates such as climate, land cover, and landscape pattern. This model will be used to predict species abundance for each simulated landscape and, as above, to develop frequency distributions defined over abundance.

[22] These results will be available to present at the AERE Workshop.

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Table 1. Econometric Results for Land-Use Transition Model

Parameter	Starting Use Agriculture	Forest
Ag Intercept		-4.78*
		-(40.71)
Ag Returns	0.003*	0.006*
	(3.61)	(3.68)
Ag Returns * LCC 3,4	-0.002	-0.001
	-(1.69)	-(0.78)
Ag Returns * LCC 5,6,7,8	-0.006*	0.002
	-(3.93)	(1.12)
Forest Intercept	-4.05*	
	-(34.73)	
Forest Returns	0.05*	0.02*
	(6.02)	(2.53)
Forest Returns * LCC 3,4	0.002	0.006
	(0.36)	(0.95)
Forest Returns * LCC 5,6		0.03*
		(3.72)
Forest Returns * LCC 7,8		0.06*
		(5.97)
Forest Returns * LCC 5,6,7,8	0.06*	
	(5.18)	
Urban Intercept	-3.68*	-3.27*
	-(33.11)	-(28.03)
Urban Influence	-1.38*	-1.41*
	-(12.53)	-(17.93)
Urban Returns	0.0003*	0.0002*
	(7.24)	(6.79)
Likelihood ratio index	0.79	0.89
N	9692	20721

* Significantly different from zero at the 1% level; *t*-statistics in parentheses

Figure 1. The Coastal Plain of South Carolina (in Green) with Overlay of USGS Quads

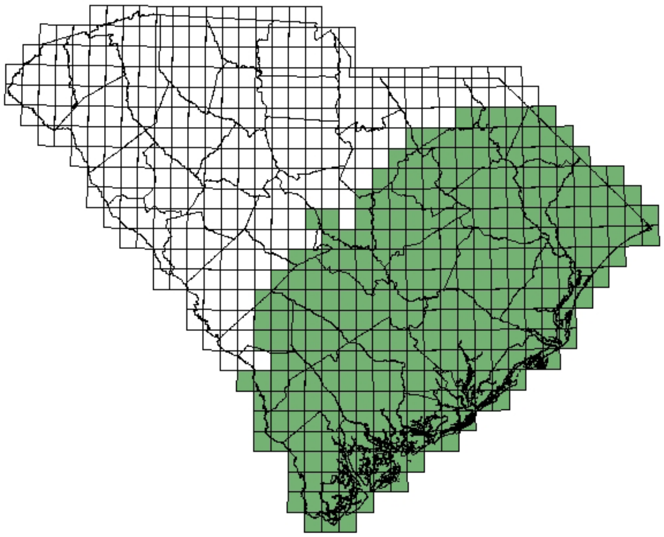
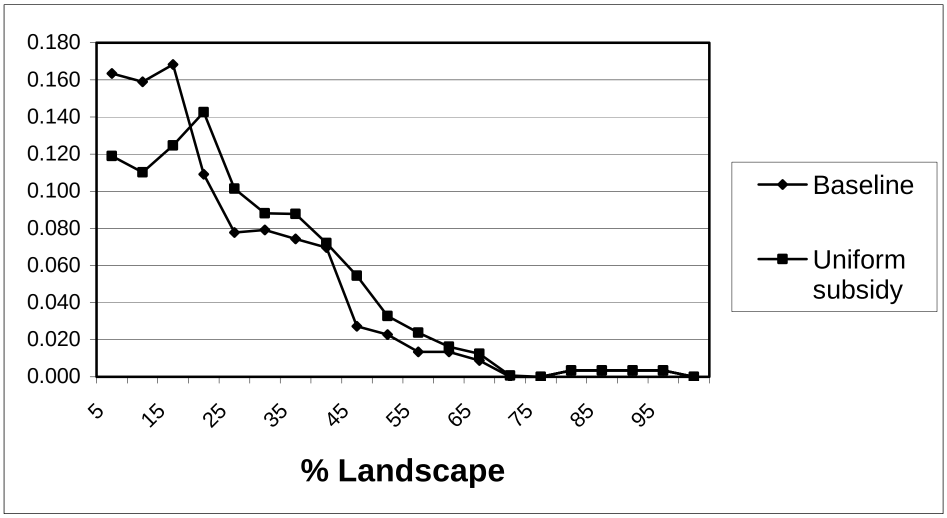


Figure 2. The Effects of a $25 Uniform Subsidy on the Core Forest and Average Forest Patch Size Distributions



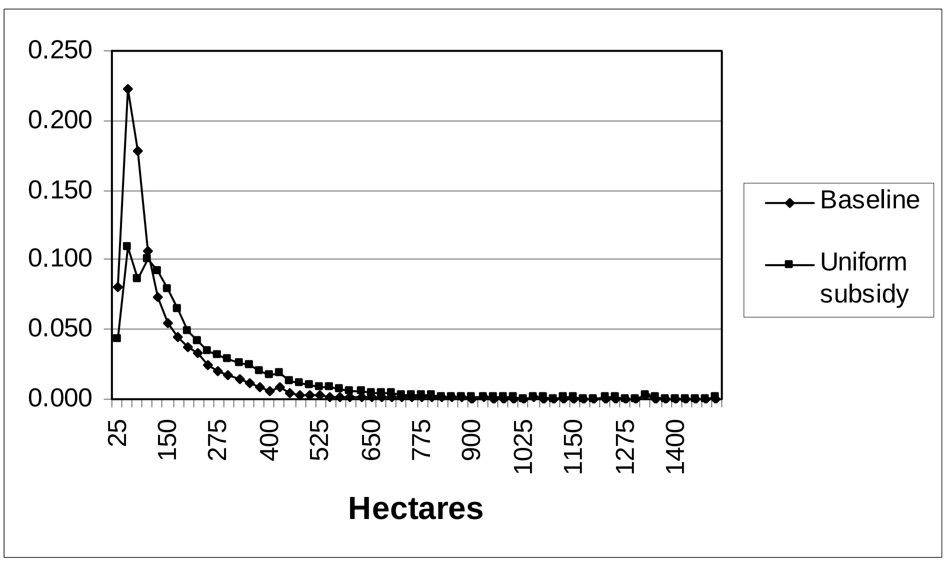
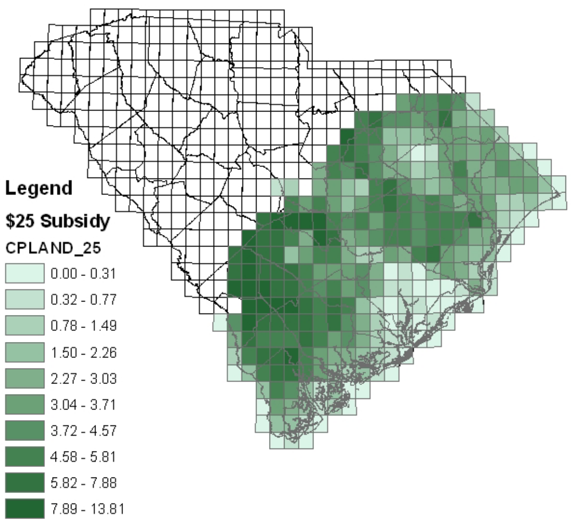
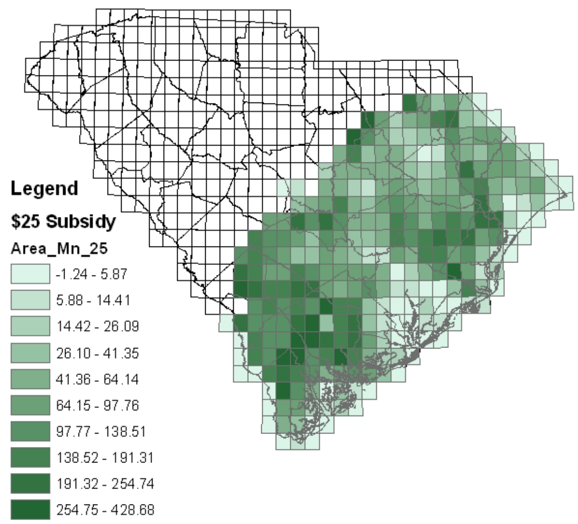


Figure 3 The Spatial Effects of a $25 Uniform Subsidy on the Percentage of the Landscape in Core Forest and the Average Forest Patch Size

Percentage of Landscape in Core Forest



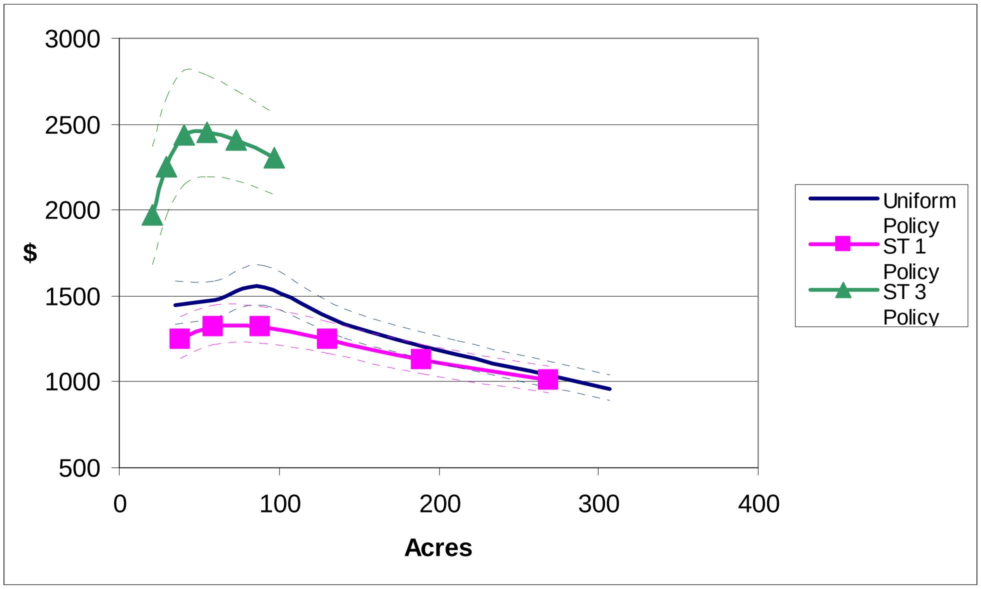
Average Forest Patch Size



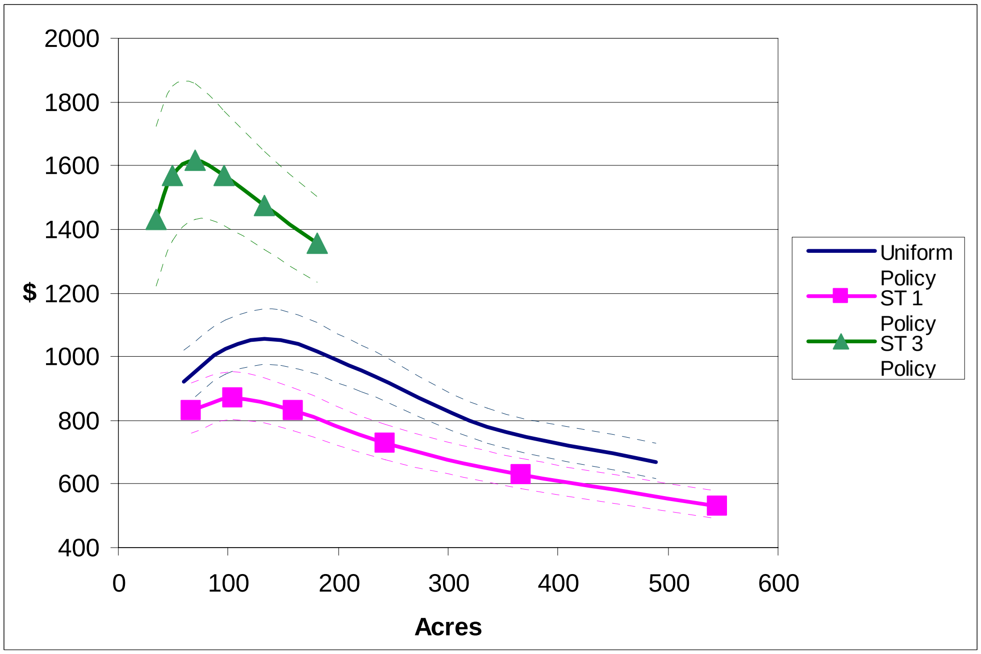
Note: The figures show the change in the percentage of the landscape in core forest (left) and the change (in hectares) in the average forest patch size (right) relative to the baseline.

Figure 4. Marginal Costs of Increasing Average Patch Size on Selected Quads

a) 35% Initial Forest Cover



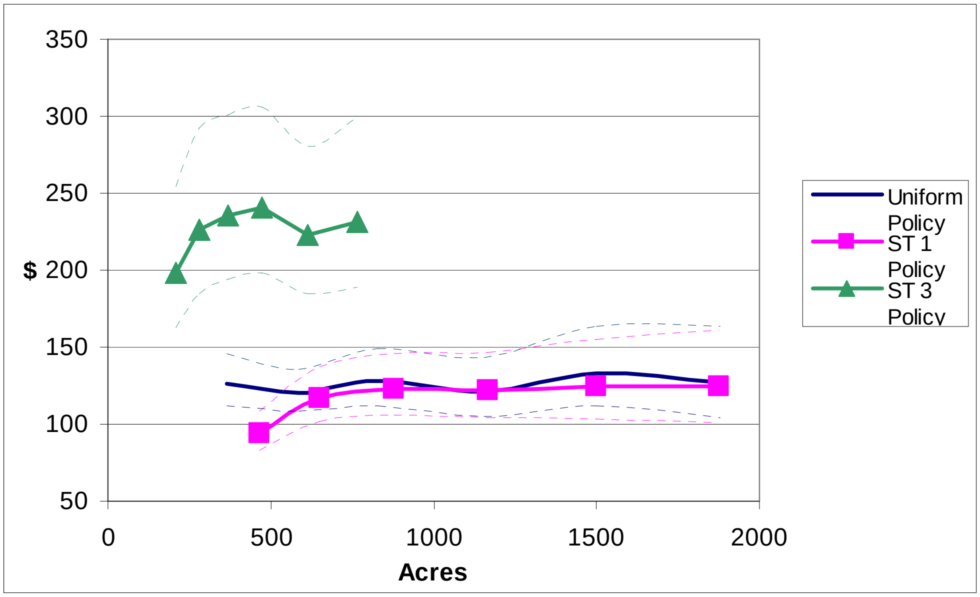
b) 50% Initial Forest Cover



Note: Dashed lines indicate 95% confidence intervals

Figure 4. Marginal Costs of Increasing Average Patch Size on Selected Quads, Continued

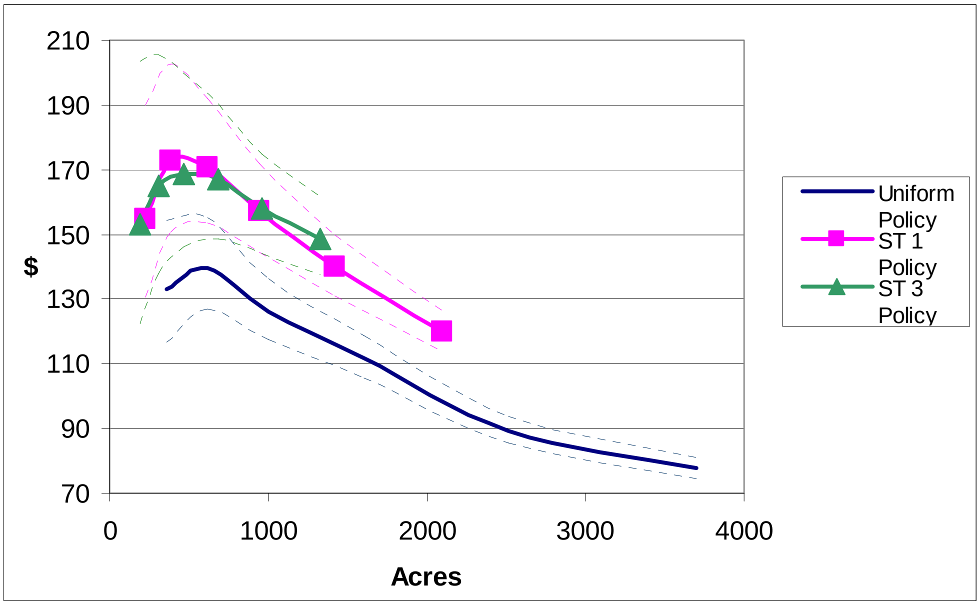
c) 75% Initial Forest Cover



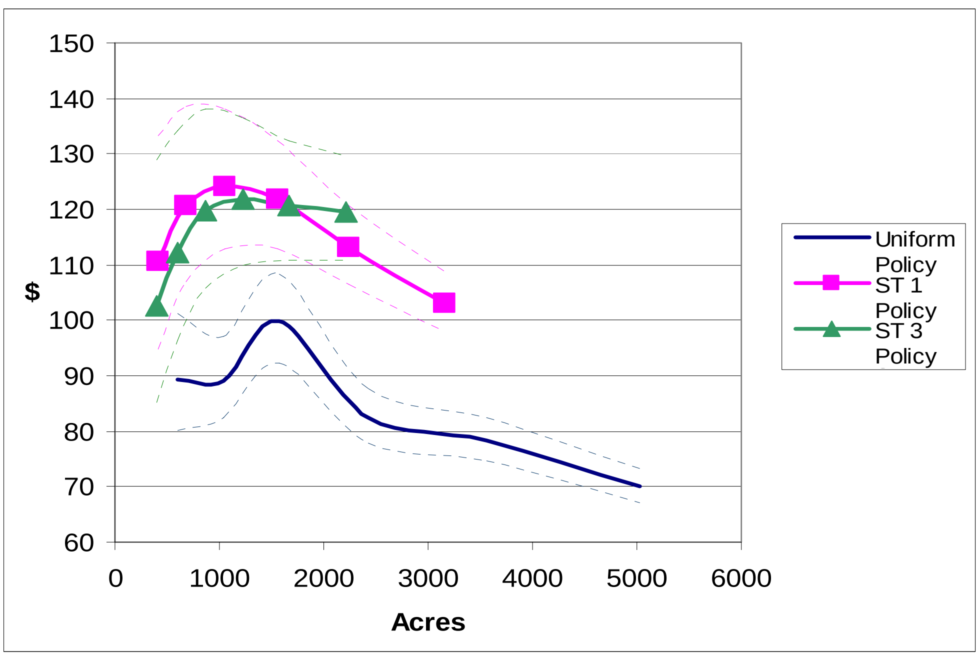
Note: Dashed lines indicate 95% confidence intervals

Figure 5. Marginal Costs of Increasing Core Forest on Selected Quads

a) 35% Initial Forest Cover



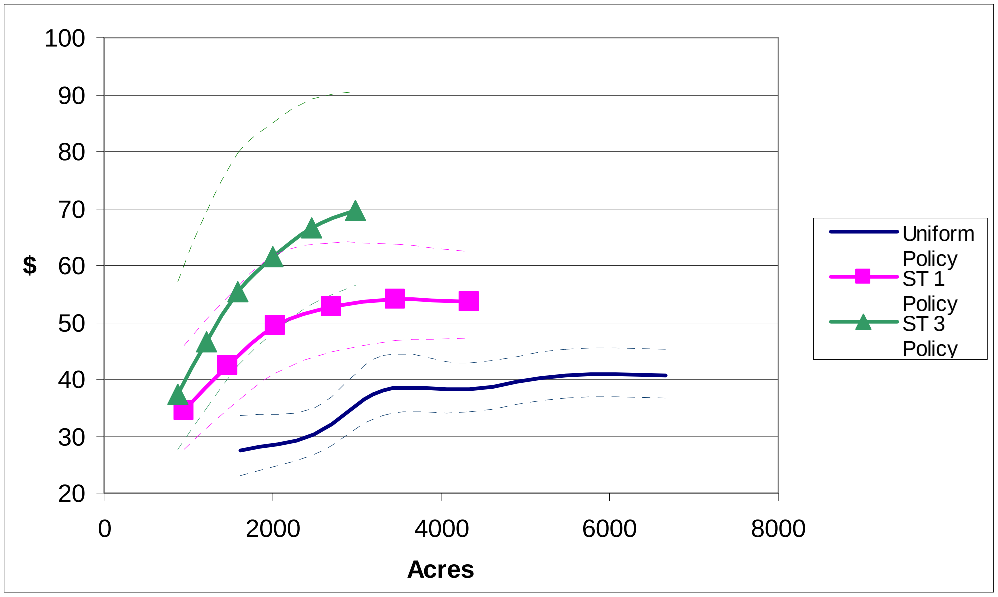
b) 50% Initial Forest Cover



Note: Dashed lines indicate 95% confidence intervals

Figure 5. Marginal Costs of Increasing Core Forest on Selected Quads, Continued

c) 75% Initial Forest Cover



Note: Dashed lines indicate 95% confidence intervals