Policies for Habitat Fragmentation: Combining Econometrics with GIS-Based Landscape Simulations

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ABSTRACT. *Habitat fragmentation is widely considered a primary threat to biodiversity. In this paper, we analyze incentive-based policies designed to reduce 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. We analyze how subsidies for afforestation affect distributions defined over fragmentation metrics and derive the marginal costs of altering landscape patterns. We find the costs of reducing fragmentation vary greatly with initial landscape conditions and that a simple uniform subsidy performs well relative to a more complicated spatially targeted policy.* (JEL R14, R52)

I. INTRODUCTION

The spatial configuration of land use and land cover influences many important aspects of environmental quality, including populations of birds (Askins 2002; Faaborg 2002) and amphibians (Kolozsvary and and Swihart 1999; deMaynadier and Hunter 2000), health of riverine systems (Gergel et al. 2002) and estuaries (Hale, Paul, and Heltshe 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, 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. Market-based approaches, such as those used with the Conservation Reserve Program (CRP) (Feng et al. 2003), can encourage landowners to 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 incentive-based policies on habitat fragmentation. In a terrestrial ecosystem, habitat fragmentation can occur when changes in land use or land cover transform a contiguous habitat patch into disjunct patches. Many species of conservation interest are sensitive to habitat fragmentation, including birds (Askins 2002; Faaborg 2002), amphibians (Kolozsvary and and Swihart 1999; Lehtinen, Ramanamanjato, and Raveloarison 2003), and large mammals (Noss 1994; Costa et al. 2005). For many species, the two most important biological effects of fragmentation are edge effects and patch-size effects (Faaborg 2002). Edge refers to the boundary between habitat types (e.g., the border of a forest and agricultural field). Increases in edge often impact fragmentation-sensitive species by increasing predation and

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parisitism.[1] Patch size refers to the area of contiguous habitat. Large blocks of habitat are required for species with relatively large home ranges.[2]

To study edge and patch-size effects in a meaningful way, we must know the spatial configuration of land uses. Moreover, land use must be represented at an appropriate scale to characterize fragmentation effects on species of interest. If our focus is on landscapes with private landowners, we must also understand the role of markets in influencing land-use change and the behavioral response to incentives arising from land-use policies. Previous studies of habitat conservation have emphasized the optimal placement of reserves for the conservation of biodiversity (e.g., Kirkpatrick 1983; Vane-Wright, Humphries, and Williams 1991; Ando et al. 1998; Polasky, Camm, and Garber-Yonts 2001). In these analyses, and in related optimization studies (e.g., Nalle et al. 2004), a social planner selects parcels to be included in the reserve, constrained only by the opportunity cost of the land. These costs are assumed to be observable and are measured as foregone income from the land in its original use. In practice, however, many conservation policies are voluntary and incentive-based[3] and conservation agencies operate with incomplete information about the opportunity costs of prospective parcels to be conserved. This incomplete information may arise from unobservable parcel attributes, landowner characteristics such as managerial expertise, and private non-market benefits (e.g., recreation) associated with particular uses of the land. In this case, agencies can only know the location of conserved parcels after a policy has been implemented. Ex ante, policies must be evaluated in a framework that recognizes uncertainty over landowner responses and, thus, the amount and location of habitat conserved.

This paper presents a methodology for analyzing the spatial configuration of private forests under incentive-based land-use policies and incomplete information. While we focus on forest habitat, the methodology is general and can be used to analyze other habitat types (e.g., grasslands). Our approach presents a novel integration of 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 that allows the net returns from different land-use choices to depend on unobserved factors. The econometric model is estimated with plot-level data and yields land-use transition probabilities expressed as functions of observed 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. We summarize landscape pattern with fragmentation indices that characterize edge and patch-size effects.

We demonstrate the methodology with an application to the coastal plain of South Carolina, an area that is dominated by private landownership and where forest fragmentation poses risks to species of significant conservation value. We evaluate the most common types of incentive-based policies, those involving subsidies to private landowners for conservation activities. Specifically, we model afforestation subsidies by increasing the per-acre net return to

[1] For example, increases in edge often affect forest birds by increasing the penetration of brood parasites (e.g., the brown-headed cowbird) from neighboring agricultural lands and predators (e.g., house cats) from neighboring urban lands. Ritters et al. (2002) found that approximately 62% of forest patches in the lower 48 states are located within 150 m of the nearest edge, suggesting that fragmentation is a pervasive feature of U.S. forests.

[2] There is a large and largely consistent literature on patch-size effects. The most evidence has been found for birds (Ambuel and Temple 1983; Howe 1984; Robbins, Dawson, and Dowell 1989; Wilcove and Robinson 1990), but greater patch sizes have also been associated with increases in populations of large carnivores (Noss 1994) and amphibians (Marsh and Pearman 1997).

[3] Examples of such policies in the United States include a variety of programs operated by the Natural Resources Conservation Service (e.g., CRP, Environmental Quality Incentives Program, Wildlife Habitat Incentives Program, Wetlands Reserve Program) as well as the purchase of land and development rights by private conservation groups.

forestry, which increases the probability that land is converted to forest. We, first, consider a simple uniform policy that pays all landowners the same amount per acre of land converted to forest. A similar policy was used with the early sign-ups of the CRP. Next, we analyze a spatial policy that subsidizes landowners only if their parcel shares a border with at least one forested parcel. This policy is in the spirit of later CRP sign-ups that ranked bids according to, among other factors, the proximity of the parcel to water and protected wildlife habitat. Based on theoretical results, Smith and Shogren (2002) and Parkhurst et al. (2002) proposed a similar agglomeration bonus for endangered species conservation in fragmentated landscapes.

The next section reviews existing models of landscape change and discusses the contribution of this study to that literature. Section 3 discusses the study area and presents 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 6 presents our conclusions.

II. RELATIONSHIP TO PREVIOUS LITERATURE

Numerous studies in the economics literature seek to explain observed land-use decisions in terms of profit-maximizing behavior (Stavins and Jaffe 1990; Plantinga 1996; Hardie and Parks 1997; Miller and Plantinga 1999). Until recently, empirical land-use studies have employed aggregate land-use data and, thus, have not explicitly considered the spatial configuration of land use. A number of recent analyses combine empirical land-use models with spatially-explicit simulations. These studies include several on deforestation (Nelson, Harris, and Stone 2001; Cropper, Puri, and Griffiths 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). Geographers have also made important contributions to the development of spatial models of landscape change (Clarke and Gaydos 1998; Li and Gar-On Yeah 2000; Wu 1998, 2002; Allen and Lu 2003).[4]

A challenge with spatial land-use models 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 analysts present maps showing the spatial distribution of the estimated probabilities (Bockstael 1996; Cropper, Puri, and Griffiths 2001), while others form deterministic rules from probabilistic ones (Chomitz and Gray 1996; Irwin and Bockstael 2002).[5] 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.

With the exception of studies on deforestation, earlier analyses have focused on urban growth patterns. Given our interest in forest fragmentation, we must account for transitions between forest and agricultural uses in addition to urban development. According to the National Resources Inventory (NRI), in South Carolina approximately 460 thousand acres of forest

[4] Most of these papers use simulation models based on cellular automata (CA). CA models landscape change on a set of discrete grids with transition rules 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).

[5] For example, Nelson and Hellerstein (1997) and Nelson, Harris, and Stone (2001) assume that each parcel will convert to the use with the highest estimated transition probability.

converted to urban use between 1982 and 1997, while 580 thousand acres of agricultural land converted to forest and 140 thousand acres of forest converted to agriculture. The challenge for econometric estimation is that net returns to agriculture and forestry exhibit little variation at small spatial scales (e.g., within counties). Thus, we need a long time-series on land use and net returns, a study area large enough to provide sufficient variation in these variables, or both. The NRI database, which provides observations on a large cross-section of randomly selected plots at four points in time, is the best alternative given our objectives.[6] A limitation of the NRI is that plots are dispersed geographically and their exact location is undisclosed. This means that we cannot econometrically model spatial interactions between neighboring parcels. Earlier studies have shown these interactions to be important for urban development (e.g., Irwin and Bockstael 2002). However, the primary focus in this study is on policies that convert agricultural land to forest.

Our study makes several contributions to the literature on modeling landscape change. 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 index values. These distributions describe the range of landscape patterns consistent with the underlying behavioral model. 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, Mauldin, and Miller 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).

[6] The Census of Agriculture provides a long time-series on land use at the county level, but excludes land owned by non-farmers. Remotely-sensed data sets tend to provide little or no time-series information or use coarse land cover categories that do not adequately distinguish between non-urban uses (e.g., recently harvested forests and pasture).

III. METHODS

Study Area for Landscape Simulations

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 United States with similar initial conditions, including the heavily forested northern and Appalachian regions and urbanized areas of the Northeast and Midwest.

The study area is also important from a conservation standpoint. In the United States, approximately 20% of resident bird species have experienced significant population declines in recent years (National Audubon Society 2002). While there are many possible causes, 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). Particularly at risk are migratory songbirds, many of which nest in

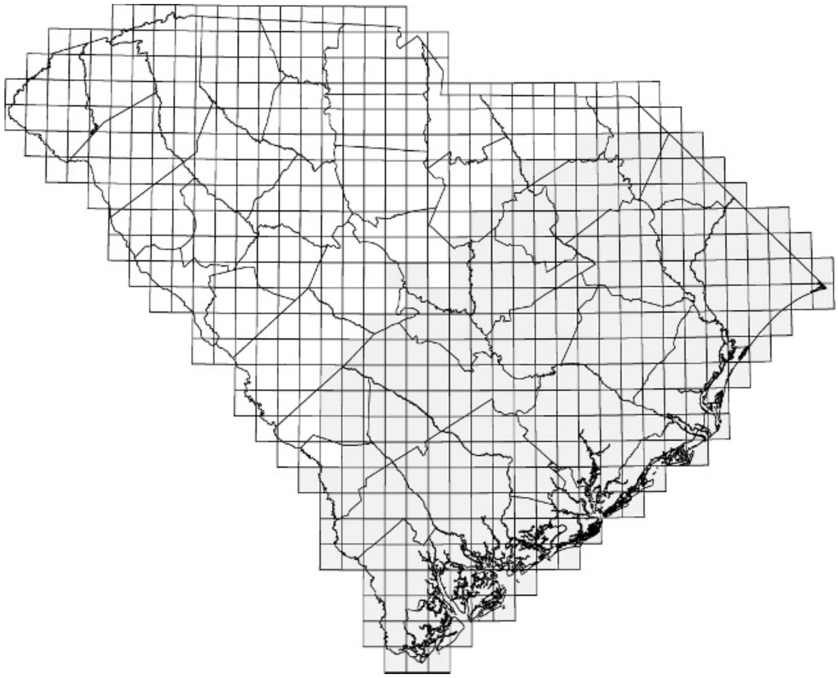


FIGURE 1
THE COASTAL PLAIN OF SOUTH CAROLINA (IN GRAY) WITH OVERLAY OF USGS QUADS

forests of the eastern United States.[7] These species are of significant conservation interest because they serve as indicators of ecosystem quality and are of considerable value to recreationists.[8] Partners in Flight, a consortium of government agencies and private conservation groups, has expressed the need for large forest blocks in the southeastern United States to provide nesting habitiat for interior-forest birds.

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. Some bird species, such as the northern spotted owl, are known to be sensitive to the spatial configuration, as well as the age structure, of forests. However, considering the broader taxon of birds, avian ecologists have found much clearer effects of fragmentation from non-forest uses compared to fragmentation from timber harvesting (Faaborg 2002). Thus, our analysis considers fragmentation by non-forest uses, emphasizing edge and patch-size effects.

Econometric Model of Land-Use Change

We estimate an econometric model of land-use transitions for parcels beginning in agriclutural and forest use. Land in agriculture can change to forest or urban or remain in agriculture. Land in forest can change to agriculture or urban or remain in forest. Land in agricultural use includes both cropland and pasture. 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. Previous theoretical results (Stavins and Jaffe 1990; Plantinga 1996) show that this is the optimal

[7] Studies also show that woodland amphibians are more prone to extinction in heavily fragmented landscapes (Gibbs 1998; Guerry and Hunter 2002).

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

allocation rule when landowners have static expectations of conversion costs and future net returns. In this case, the owner of parcel i in use j at the start of period t will convert to use k if

$$R_{ikt} - rC_{ijkt} \geq R_{ijt}, \quad [1]$$

for all alternative uses k ($k = 1,\ldots,K$) and where R_{ikt} is the annual (or annualized) 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:

$$\pi_{ijkt} = R_{ikt} - rC_{ijkt} + \varepsilon_{ijkt}. \quad [2]$$

We denote the deterministic component of net revenue, $R_{ikt} - rC_{ijkt}$, as $\boldsymbol{\beta}_{jk}{}'\mathbf{x_{ijkt}}$, where $\boldsymbol{\beta}_{\mathbf{jk}}$ 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

$$pr(\boldsymbol{\beta}'_{jk}\boldsymbol{x}_{\mathbf{ijkt}} - \boldsymbol{\beta}'_{jl}\boldsymbol{x}_{\boldsymbol{ijlt}} \geq \varepsilon_{ijlt} - \varepsilon_{ijkt}), \quad [3]$$

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:[9]

$$P_{ijkt} = \frac{\exp(\boldsymbol{\beta}'_{jk}\mathbf{ijkt})}{\sum_{l=1}^{K}\exp(\boldsymbol{\beta}'_{jl}\mathbf{ijlt})}. \quad [4]$$

The specification in [4] embodies the well-known independence of irrelevant alternatives (IIA) property. In a similar application to land use, Lubowski, Plantinga, and Stavins (2006) uses a nested logit specification that imposes the IIA property within, but not across, groups of alternatives (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 United States. We focus on privately owned agricultural (crop and pasture), forest, and urban land in North Carolina and South Carolina.[10] 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 (2002), and described in detail there and in Lubowski, Plantinga, and Stavins (2006). The returns to forest are measured as annualized revenues from timber production less management costs. Agricultural returns equal the weighted average of the annual revenues 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.[11] 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.

[9] Due to the logit structure of the model, this specification based on the levels of net returns is identical to one where the net return variables are all rescaled as differences from the net returns to one base land-use category. Any additive component of utility that is constant across alternatives will drop out of the probabilities in [4].

[10] 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.

[11] 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.

The deterministic components of net revenue are written such that the coefficients differ for each combination of starting and ending use:

$$\beta_{0,jk}+\beta_{1,jk}R_{ikt}+\beta_{2,jk}LCC_i\cdot R_{ikt} \quad k=agriculture,\ forest,$$
$$\beta_{0,jk}+\beta_{1,jk}R_{ikt}+\beta_{3,jk}UI_i \qquad k=urban \qquad [5]$$

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.[12] 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 12 factors (e.g., soil type, slope) that influence the productivity of the land for agriculture. Dummy variables are constructed for soil quality categories[13] and these variables are interacted with county average returns to scale the returns up or down according to the productivity of the parcel. 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 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.[14] We do not have data on conversion costs. Their effects are measured in constant terms, $\beta_{0,jk}$, specific to each transition.[15]

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).[16] However, there are likely to be unobserved factors (e.g., distance to major roads) that exhibit such correlation. Thus, to maximize the number of 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.[17] We do not make adjustments for potential spatial correlation of the model error terms. 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,

[12] If the net return variables perfectly captured the net returns for each land use at the level of the individual parcel, then the coefficients on net returns would simply reflect the marginal utility of income and be constant across the alternatives. However, in our specification the net return variables are county averages and the LCC interaction terms scale these averages based on parcel-level land quality differences. The magnitude of this adjustment is expected to vary across uses based on the sensitivity of the net returns to land quality and the quality distribution of the land initially in each use. Thus, we allow the coefficients on the net returns variables to vary by alternative.

[13] 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 $\beta_{2,1,jk} = 0$.

[14] 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.

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

[16] Random parameters (or mixed) logit can be used to estimate panel data models with unobservables that are correlated over time. However, the maximum simulated likelihood methods required to estimate these models often result in biased estimates for models with small true probabilities (Hajivassilou 2000), such as we have in the land conversion model.

[17] 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.

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	9,692	20,721

Note: t-statistics in parentheses.
* Significantly different from zero at the 1% level.

Harris, and Stone 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 assume that once land is urbanized it remains in that state with probability one. The estimation results indicate good model fit[18] 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, and indicate that forestry tends to be more profitable than agriculture on low quality lands. 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

[18] 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.

that agricultural and forest parcels in rural areas are less likely to convert to urban uses.

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. 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 and 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 ten-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.[19] 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 five acres.[20] 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.

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[21] 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).

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

[20] 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.

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

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.[22] Fragstats accepts raster images and generates metrics characterizing area, density, edge, shape, core area, isolation and proximity, contagion and interspersion, connectivity, and diversity. Given our interest in the biological effects of habitat fragmentation, we focus here on indices that measure patch size and edge effects: the mean forest patch size and the percentage of the landscape in core forest.[23] Mean patch area is defined as the average area of contiguous forest blocks (or patches). The percentage of the landscape in core forest equals the area of forest parcels at least 200 m from the nearest forest edge divided by the total landscape area. Avian ecologists have found that edge effects extend from 50 to 300 m into forest patches (Paton 1994).

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. Our simulation requires the use of different software packages and, therefore, we are unable to apply 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 for these quads to converge.[24] Following Ross (1997), we examine how the confidence interval lengths for the estimates of the first three moments of the distributions change with the number of simulations.[25] 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.

IV. 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. Net returns (R_{ikt}) are computed for each land use and county for the year 1989 and, along with the plot-level land quality and urban influence variables, remain constant throughout the simulation.[26] The affores-

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

[23] We computed additional indices that represent other features of landscape pattern. These results are available from the authors upon request.

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

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

[26] We might reasonably expect these variables, especially the urban influence measure, to change during the simulation period. However, these changes would affect both the policy and the baseline scenarios. Thus, since we measure the effects of the policies relative to the baseline, changes in these variables would have second-order effects on our results.

tation subsidies are annual payments added to the 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 for all 295 quads in the study area.[27] 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.[28]

Under our spatial policy, owners of agricultural parcels receive the afforestation subsidy if they share a border with one or more forested parcels. The GIS land-use layer is put in raster format with 50 m pixels and, thus, land use is designated for each 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 spatial subsidy will increase the size of all forest patches on the landscape provided existing forested parcels do not transition to another use. Thus, the spatial subsidy is likely to increase the mean forest patch size. 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.[29]

The computational cost of analyzing the spatially targeted policy is high. The run time is approximately ten hours per quad for each level of the subsidy. To limit the total run time, 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 compute the marginal costs of increasing mean forest patch size and the percentage of the landscape in core forest. For subsidy level s, marginal costs equal:

$$MC_s = \frac{s\bar{F}_s - (s-5)\bar{F}_{s-5}}{\bar{I}_s - \bar{I}_{s-5}}, \qquad [6]$$

where $\bar{F}_s$ and $\bar{I}_s$ 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.[30]

V. SIMULATION RESULTS

Uniform Subsidy

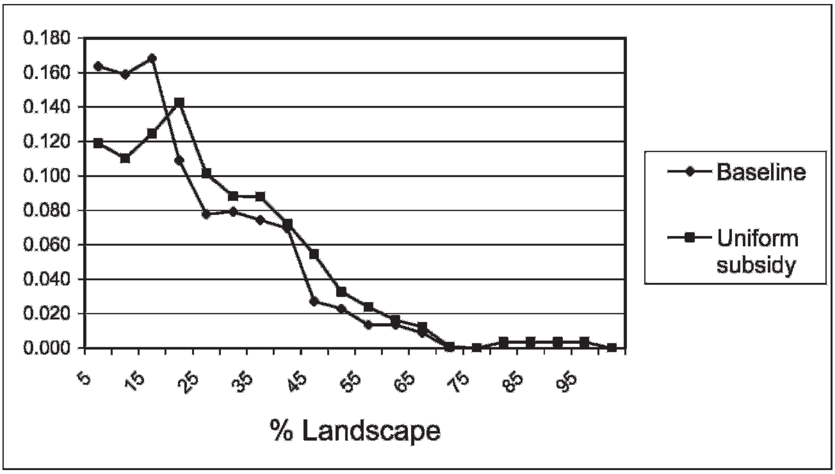
For the uniform subsidy, we derive empirical distributions for each fragmenta-

[27] 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.

[28] In general, the decision to convert a given parcel to forest cannot be considered independently of the decisions made for all other parcels since the fragmentation metric is a function of all of the actions taken. This implies that the marginal cost of changing a fragmentation metric is endogenous.

[29] We also evaluated a spatial policy requiring three or more forested neighbors, with the idea that this would increase the likelihood of creating core forest. However, this policy was dominated by the other policies.

[30] If $\bar{I}_s - \bar{I}_{s-5}$ is an unbiased estimator of the true difference in means, then the standard deviation of $\bar{I}_s - \bar{I}_{s-5}$ is equal to $sd_s = \sqrt{\mathrm{var}(\bar{I}_s)/n + \mathrm{var}(\bar{I}_{s-5})/n}$ 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 $\bar{I}_s - \bar{I}_{s-5}$ 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 $\mathrm{var}(F^s) = 0$.



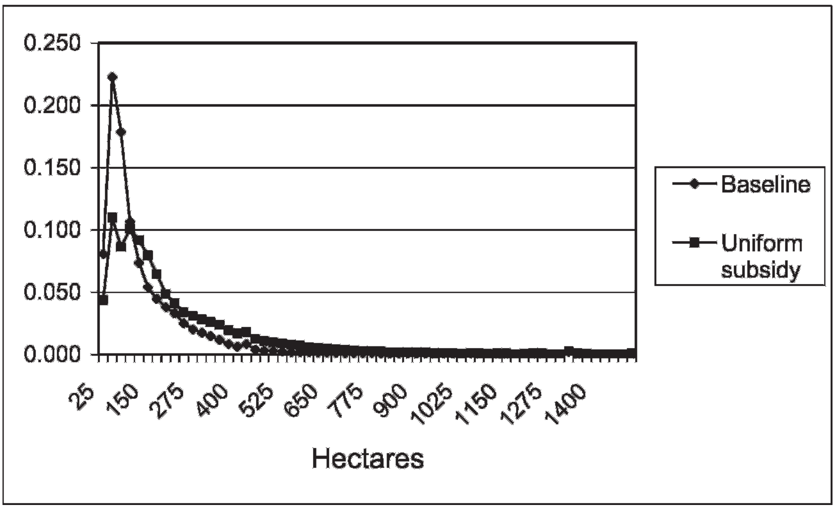


FIGURE 2
The Effects of a $25 Uniform Subsidy on the Core Forest and Mean Forest Patch Size Distributions

tion 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 mean patch size increases by more than the increase in total forest area (65% compared to about 7%, on average). Mean patch size can increase greatly when new forest parcels connect previously disjoint patches.

Core forest and mean 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

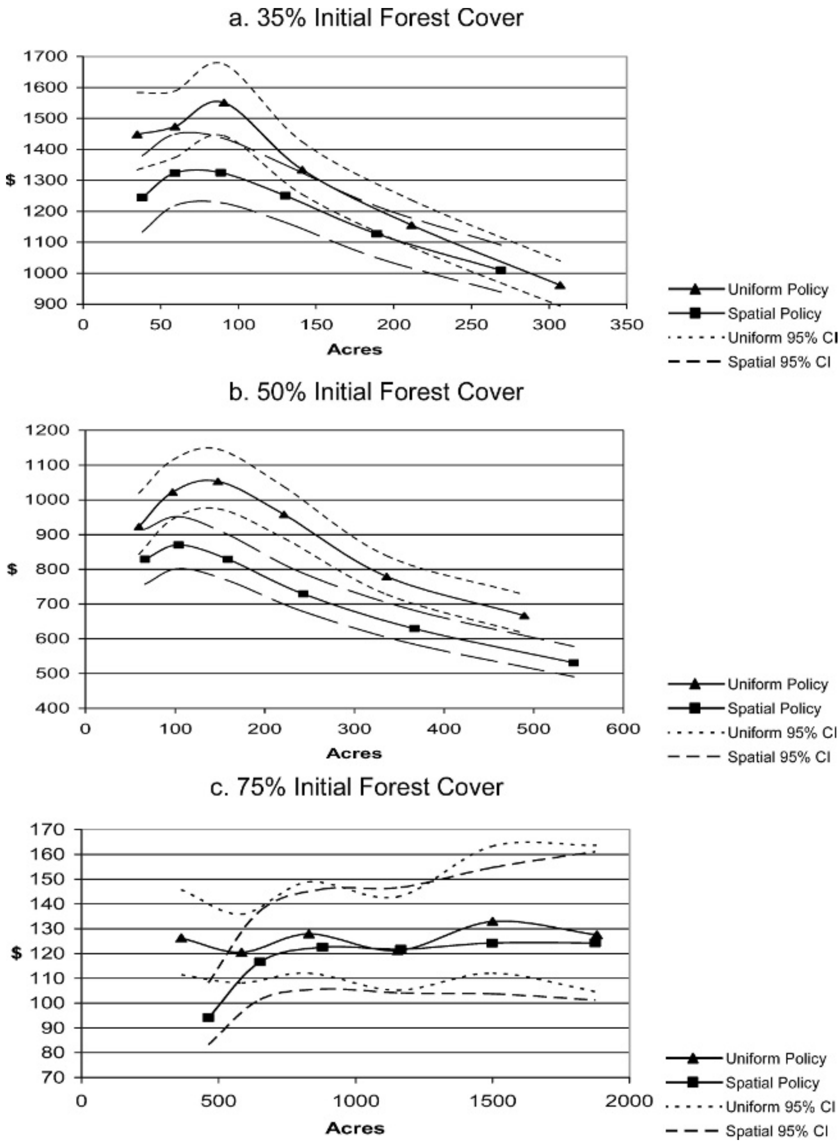


FIGURE 3
MARGINAL COSTS OF INCREASING MEAN FOREST PATCH SIZE ON SELECTED QUADS
NOTE: DASHED LINES INDICATE 95% CONFIDENCE INTERVALS

distribution. The uniform policy increases the probability that higher values of the indices are obtained and this increases the variance of the distributions. Changes in core forest and mean patch size differ throughout the state. 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 that initially have a large share of land in forest.

The role of incomplete information in influencing predicted responses to the policy is evident in the empirical distributions derived for each of the 295 quads. For each quad, a 95% confidence interval was calculated from the 500 simulations. Across the 295 quads, the average length of the confidence intervals for the patch size and core forest indices is 213 hectares and 5.6% of the landscape, respectively. The minimum length is zero for both indices and the maximum length is 3,530 hectares for the patch size index and 17% of the landscape for the core forest index. The distributions on the fragmentation indices reflect the inability of the conservation agency to predict the exact location of conservation lands and reveal that a wide range of landscape patterns are consistent with the agency's ex ante information about policy responses.

Spatial Policy

We derive marginal costs for the uniform and spatial policy and for each of the selected quads. Marginal cost for the mean patch size metric is interpreted as the cost of increasing the mean forest patch by one acre. As shown in Figure 3, 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. For the 35% and 50% quads, the declining marginal costs 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 mean 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 mean patch size with the spatial 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. As long as existing forest does not convert to other uses, every parcel converted to forest with the spatial policy increases mean 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 mean patch size if a new parcel is unconnected to existing forest 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 4). As with mean 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 spatial policy increases the likelihood that core forest will be created, although this advantage is outweighed by the added cost of selecting from smaller sets of agricultural parcels.

It is also instructive to compare marginal costs across the three quads and across the fragmentation indices. The costs of increasing mean patch size and core forest fall as the initial share of the landscape in forest rises. The effect is especially pronounced for mean 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, the uniform and spatial policies have lower marginal costs when applied to the most heavily forested quad. Moving from the least 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 with the exception of the 50% initial forest quad, the uniform policy has comparable or lower costs than the spatial policy.

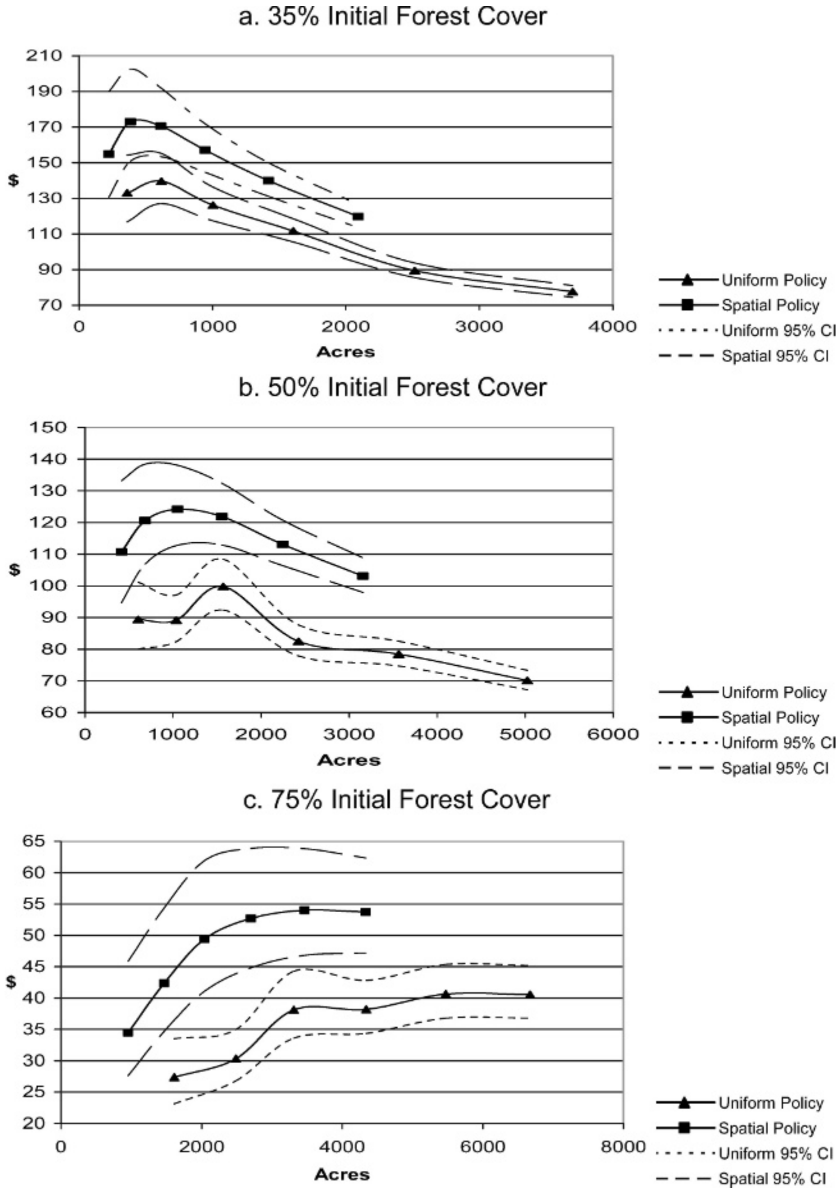


FIGURE 4
MARGINAL COSTS OF INCREASING CORE FOREST ON SELECTED QUADS
NOTE: DASHED LINES INDICATE 95% CONFIDENCE INTERVALS

VI. 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 evaluate two types of subsidies similar to those used in practice. We consider how these policies affect indices of forest fragmentation; specifically mean patch size and the area of core forest. These metrics have been shown in the ecology literature to be indicators of habitat quality for amphibians, large mammals, and many bird species with significant conservation values.

Our analysis has a number of distinguishing features. First, we model incentive-based policies where conservation agencies have incomplete information on the opportunity costs of landowners and, hence, imperfect control over the spatial location of conservation lands. This is in contrast to the reserve-site selection literature which assumes the agencies can choose the exact location of reserves. Second, 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 logical focus of policies designed to reduce forest fragmentation. Third, we quantify the costs of achieving given changes in landscape pattern. 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, and add approximately 400,000 new core forest parcels. The policy would also significantly increase the mean forest patch size (by 65%). Our results indicate that the policy would shift the region-wide distribution over the core forest and mean 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 a spatially-targeted policy. 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 mean 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 both policies examined the marginal costs of increasing mean 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. More generally, if the goal is to provide large carnivores, amphibians, or humans with large contiguous tracts of land in a particular use, our findings suggest it will be cheaper to focus conservation efforts on regions with large amounts of land already in the desired use.

The selection of a uniform or spatial 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. The uniform subsidy converts a given area of land to forest at the lowest possible cost, 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. In the case of core forest, it is unclear, a priori, whether it is less expensive to increase core forest area by a given amount with a uniform or a targeted policy. Increasing mean patch size should be cheaper with the targeted policy since each converted parcel increases the size of an existing patch. We find in our application that the uniform policy has the lowest costs for increasing core forest. As well, the costs of increasing mean patch size are lower with the spatial policy, but not by a large degree. Our findings suggest that a simple uniform policy that converts land at least cost may be more efficient than spatial 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.

References

Allen, J., and K. Lu. 2003. "Modeling and Prediction of Future Urban Growth in the Charleston Region of South Carolina: A GIS-Based Integrated Approach." *Conservation Ecology* 8 (2): 2. URL: http://www.consecol.org/vol8/iss2/art2/.

Ambuel, B., and S. Temple. 1983. "Area-Dependent Changes in the Bird Communities and Vegetation of Southern Wisconsin Forests." *Ecology* 64 (5): 1057–68.

Ando, A., J. Camm, S. Polasky, and A. Solow. 1998. "Species Distributions, Land Values, and Efficient Conservation." *Science* 279 (27 Mar.): 2126–28.

Askins, R. A. 2002. *Restoring North America's Birds: Lessions from Landscape Ecology.* 2nd ed. New Haven, Conn.: Yale University Press.

Bockstael, N. E. 1996. "Modeling Economics and Ecology: The Importance of a Spatial Perspective." *American Journal of Agricultural Economics* 78 (5): 1168–80.

Carrion-Flores, C., and E. G. Irwin. 2004. "Determinants of Residential Land-Use Conversion and Sprawl at the Rural-Urban Fringe." *American Journal of Agricultural Economics* 86 (4): 889–904.

Chomitz, K. M., and D. A. Gray. 1996. "Roads, Land Use, and Deforestation: A Spatial Model Applied to Belize." *The World Bank Economic Review* 10 (3): 487–512.

Clarke, K. C., and L. J. Gaydos. 1998. "Loose-Coupling a Cellular Automaton Model and GIS: Long-Term Urban Growth Prediction for San Francisco and Washington/Baltimore." *International Journal of Geographic Information Science* 12 (7): 699–714.

Costa, L. P., Y. L. R. Leite, S. L. Mendes, and A. D. Ditchfield. 2005. "Mammal Conservation in Brazil." *Conservation Biology* 19 (3): 672–79.

Cropper, M., J. Puri, and C. Griffiths. 2001. "Predicting the Location of Deforestation: The Role of Roads and Protected Areas in North Thailand." *Land Economics* 77 (May): 172–86.

deMaynadier, P. G., and M. L. Hunter. 2000. "Road Effects on Amphibian Movements in a Forested Landscape." *Natural Areas Journal* 20 (1): 56–65.

Devore, J. L. 1995. *Probability and Statistics for Engineering and the Sciences*. Belmont, Calif.: Duxbury Press, Wadsworth Publishing Company.

Faaborg, J. 2002. *Saving Migrant Birds: Developing Strategies for the Future*. Austin, Tex.: University of Texas Press.

Feng, H., C. L. Kling, L. A. Kurkalova, and S. Secchi. 2003. "Subsidies! The Other Incentive-Based Instrument: The Case of the Conservation Reserve Program." Working Paper 03-WP 345., Center for Agricultural and Rural Development, Iowa State University.

Gergel, S. E., E. H. Stanley, M. G. Turner, J. R. Miller, and J. M. Melack. 2002. "Landscape Indicators of Human Impacts to Riverine Systems." *Aquatic Sciences* 64 (2): 118–28.

Gibbs, J. P. 1998. "Distribution of Woodland Amphibians along a Forest Fragmentation Gradient." *Landscape Ecology* 13 (4): 263–68.

Guerry, A. D., and M. L. Hunter. 2002. "Amphibian Distribution in a Landscape of Forest and Agriculture: An Examination of Landscape Composition and Configuration." *Conservation Biology* 16 (3): 745–54.

Hajivassiliou, V. A. 2000. "Some Practical Issues in Maximum Simulated Likelihood." In *Simulation-Based Inference in Econometrics: Methods and Applications*, ed. R. Mariano, M. Weeks, and T. Schuermann. New York: Cambridge University Press.

Hale, S. S., J. F. Paul, and J. F. Heltshe. 2004. "Watershed Landscape Indicators of Estuarine Benthic Condition." *Estuaries* 27 (2): 283–95.

Hardie, I. W., and P. J. Parks. 1997. "Land Use with Heterogeneous Land Quality: An Application of an Area Base Model." *American Journal of Agricultural Economics* 79 (2): 299–310.

Howe, R. 1984. "Local Dynamics of Bird Assemblages in Small Forest Habitat Islands in Australia and North America." *Ecology* 65 (5): 1585–1601.

Irwin, E., and N. E. Bockstael. 2002. "Interacting Agents, Spatial Externalities and the Evolution of Residential Land Use Patterns." *Journal of Economic Geography* 2 (3): 331–54.

———. 2004. "Land Use Externalities, Open Space Preservation, and Urban Sprawl." *Regional Science and Urban Economics* 34: 705–25.

Kirkpatrick, J. B. 1983. "An Iterative Method for Establishing Priorities for the Selection of Nature Reserves: An Example from Tasmania." *Biological Conservation* 25 (2): 127–34.

Kolozsvary, M. B., and R. K. Swihart. 1999. "Habitat Fragmentation and the Distribution of Amphibians: Patch and Landscape Correlates in Farmland." *Canadian Journal of Zoology* 77 (8): 1288–99.

Lehtinen, R. M., J. B. Ramanamanjato, and J. G. Raveloarison. 2003. "Edge Effects and Extinction Proneness in a Herpetofauna from Madagascar." *Biodiversity and Conservation* 12 (7): 1357–70.

Li, X., and A. Gar-On Yeh. 2000. "Modeling Sustainable Urban Development by the Integration of Constrained Cellular Automata and GIS." *International Journal of Geographic Information Science* 14 (2): 131–52.

Lubowski, R. N. 2002. "Determinants of Land-Use Transitions in the United States: Econometric Analysis of Changes among the Major Land-Use Categories." Ph.D. diss. Political Economy and Government, John F. Kennedy School of Government, Harvard University, Cambridge, Mass.

Lubowski, R. N., A. J. Plantinga, and R. N. Stavins. 2006. "Land-Use Change and Carbon Sinks: Econometric Estimation of the Carbon Sequestration Supply Function." *Journal of Environmental Economics and Management* 51 (2): 135–52.

Marsh, D. M., and P. B. Pearman. 1997. "Effects of Habitat Fragmentation on the Abundance of Two Species of Leptodactylid Frogs in an Andean Montane Forest." *Conservation Biology* 11 (6): 1323–28.

Miller, D. J., and A. J. Plantinga. 1999. "Modeling Land Use Decisions with Aggregate Data." *American Journal of Agricultural Economics* 81 (1): 180–94.

Nalle, D. J., C. A. Montgomery, J. L. Arthur, S. Polasky, and N. H. Schumaker. 2004. "Modeling Joint Production of Wildlife and Timber." *Journal of Environmental Economics and Management* 48 (3): 997–1017.

National Audubon Society. 2002. *Audubon Watchlist 2002*. http://www.audubon.org/bird/watchlist/index.html.

Nelson, G. C., and D. Hellerstein. 1997. "Do Roads Cause Deforestation? Using Satellite Images in Econometric Analysis of Land Use." *American Journal of Agricultural Economics* 79 (1): 80–88.

Nelson, G. C., V. Harris, and S. W. Stone. 2001. "Deforestation, Land Use, and Property Rights: Empirical Evidence from Darien, Panama." *Land Economics* 77 (2): 187–205.

Noss, R. 1994. "Habitat Fragmentation." In *Principles of Conservation Biology*, ed. G. K. Meffe and C. R. Carrol. Sunderland, Mass.: Sinquer Associates.

Palmer, J. F. 2004. "Using Spatial Metrics to Predict Scenic Perception in a Changing Landscape: Dennis, Massachusetts." *Landscape and Urban Planning* 69 (2–3): 201–18.

Parkhurst, G. M., J. F. Shogren, C. Bastian, P. Kivi, J. Donner, and R. B. W. Smith. 2002. "Agglomeration Bonus: An Incentive Mechanism to Reunite Fragmented Habitat for Biodiversity Conservation." *Ecological Economics* 41 (2): 305–28.

Paton, P. W. C. 1994. "The Effect of Edge on Avian Nest Success: How Strong is the Evidence?" *Conservation Biology* 8 (1): 17–26.

Plantinga, A. J. 1996. "The Effect of Agricultural Policies on Land Use and Environmental Quality." *American Journal of Agricultural Economics* 78 (4): 1082–91.

Plantinga, A. J., and S. Ahn. 2002. "Efficient Policies for Environmental Protection: An Econometric Analysis of Incentives for Land Conversion and Retention." *Journal of Agricultural and Resource Economics* 27 (1): 128–45.

Plantinga, A. J., T. Mauldin, and D. J. Miller. 1999. "An Econometric Analysis of the Costs of Sequestering Carbon in Forests." *American Journal of Agricultural Economics* 81 (4): 812–24.

Polasky, S., J. D. Camm, and B. Garber-Yonts. 2001. "Selecting Biological Reserves Cost-Effectively: An Application to Terrestrial Vertebrate Conservation in Oregon." *Land Economics* 77 (Feb.): 68–78.

Ritters, K. H., J. D. Wickham, R. V. O'Neill, K. B. Jones, E. R. Smith, J. W. Coulston, T. G. Wade, and J. H. Smith. 2002. "Fragmentation of Continental United States Forests." *Ecosystems* 5 (8): 815–22.

Robbins, C. S., D. K. Dawson, and B. A. Dowell. 1989. "Habitat Area Requirements of Breeding Forest Birds of the Middle Atlantic States." *Wildlife Monographs* 103 (1): 1–34.

Ross, S. M. 1997. *Simulation*. Burlington, Mass.: Harcourt/Academic Press.

Smith, R. B. W., and J. F. Shogren. 2002. "Voluntary Incentive Design for Endangered Species Protection." *Journal of Environmental Economics and Management* 43 (2): 169–87.

Stavins, R. N. 1999. "The Costs of Carbon Sequestration: A Revealed-Preference Approach." *American Economic Review* 89 (4): 994–1009.

Stavins, R. N., and A. B. Jaffe. 1990. "Unintended Impacts of Public Investments on Private Decisions: The Depletion of Forested Wetlands." *American Economic Review* 80 (3): 337–52.

Train, K. 2003. *Discrete Choice Methods with Simulation*. New York: Cambridge University Press.

United States Fish and Wildlife Service. 2001. *2001 National Survey of Fishing, Hunting, and Wildlife-Associated Recreation*. Washington, D.C.: U.S. Department of the Interior, Fish and Wildlife Service and U.S. Department of Commerce, U.S. Census Bureau.

Vane-Wright, R. I., C. J. Humphries, and P. H. Williams. 1991. "What to Protect? Systematics and the Agony of Choice." *Biological Conservation,* 55 (3): 235–54.

Wilcove, D. S., and S. K. Robinson. 1990. "The Impact of Forest Fragmentation on Bird Communities in Eastern North America." In *Biogeography and Ecology of Forest Bird Communities*, ed. A. Keast, 319–31. The Hague, Netherlands: Academic Publishing.

Wu, F. 1998. "SimLand: A Prototype to Simulate Land Conversion through the Integrated GIS and CA with AHP-Derived Transition Rules." *International Journal of Geographic Information Science* 12 (1): 63–82.

———. 2002. "Calibration of Stochastic Cellular Automata: the Application to Rural-Urban Land Conversions." *International Journal of Geographic Information Science* 16 (8): 795–818.

Wu, F., and C. J. Webster. 2000. "Simulating Artificial Cities in a GIS Environment: Urban Growth under Alternative Regulation Regimes." *International Journal of Geographic Information Science* 14 (7): 625–48.