Targeting Incentives to Reduce Habitat Fragmentation

David J. Lewis
University of Wisconsin-Madison

Andrew J. Plantinga
Oregon State University

JunJie Wu
Oregon State University

April 14, 2007

Abstract: The fragmentation of wildlife habitat has long been recognized as a principal threat to terrestrial biodiversity. In this paper, we develop a theoretical model to analyze the spatial targeting of incentives for the restoration of forested landscapes when land quality is spatially heterogeneous and wildlife habitat can be enhanced by reducing fragmentation. We consider a regulator who uses subsidies to encourage the conversion of private agricultural land to forest on a pre-defined set of landscapes. The regulator can observe land-use choices, but not the opportunity costs on individual land parcels. The important insight to emerge from the theoretical analysis is that solutions at or near corners are a strong possibility—on each landscape, either none or all of the agricultural land should be converted to forest. Corner solutions are directly linked to the spatial process determining habitat benefits. To verify the theoretical insight, we present a simulation of the effects of incentive-based policies on the spatial distribution of forests in South Carolina. The empirical methodology integrates an econometric model of land-use change with GIS-based landscape simulations. The empirical findings strongly support our conjecture regarding corner solutions, and the optimal targeting policy is shown to produce substantial welfare gains over a spatially-uniform incentive.

Keywords: land use, habitat fragmentation, spatial modeling, biodiversity conservation, forests.

Acknowledgments: The authors acknowledge helpful comments from seminar participants at Iowa State University, the University of California-Santa Barbara, the University of Maryland, the University of Minnesota, the University of Wisconsin, Camp Resources XIV, the ASSA Annual Meeting 2006, and the AAEA Annual Meeting 2005. Lewis acknowledges financial support from U.S.D.A. Hatch and the Wisconsin Alumni Research Foundation. Lewis and Plantinga acknowledge financial support from the U.S.D.A. Forest Service Pacific Northwest Research Station.

Targeting Incentives to Reduce Habitat Fragmentation

1. Introduction

The fragmentation of wildlife habitat has been widely recognized as a primary threat to biodiversity (Armsworth et al. 2004). In a terrestrial ecosystem, habitat fragmentation can occur when land conversion transforms a contiguous habitat patch into disjunct patches. Many species are negatively impacted by habitat fragmentation, including amphibians (Kolozsvary and Swihart 1999, Lehtinen et al. 2003) and large mammals (Noss 1994, Costa et al. 2005), though the majority of ecological evidence has been assembled on neotropical migratory songbirds (Askins 2002, Faaborg 2002). Songbirds are of considerable conservation interest because they serve as indicators of ecosystem quality and provide significant values to recreationists.

An important impact of fragmentation on songbird populations arises from edge effects (Askins 2002, Faaborg 2002). Edge refers to discontinuity between habitat types (e.g., the border of a forest and agricultural field). The breeding success of many bird species falls as edge increases due to heightened impacts of predators and nest parasites.[1] For forest-nesting birds, which includes many neotropical migratory species, edge effects have been found to extend from 50 m (Paton 1994) to 300 m (Van Horn et al. 1995) into forest patches. Core forest is defined as the interior area of a forest patch beyond the reach of edge effects. In core forest patches, breeding success is higher (Askins 2002, Robinson et al. 1995).

The broad purpose of this paper is to evaluate incentive-based conservation policies to reduce habitat fragmentation. We focus the analysis on the spatial targeting of incentives to private landowners to increase the area of core forest habitat. The problem of how to optimally allocate habitat for species conservation has been addressed previously in the reserve-site selection literature (e.g., Kirkpatrick 1983, Vane-Wright et al. 1991, Fischer and Church 2003, Onal and Briers 2003). The objective in these studies is to select reserves to maximize the number of protected species subject to a constraint on the total area of reserved land. In some studies, the spatial pattern of the reserves affects the quality of protected habitat. Economists have contributed to this literature by accounting for land costs and modeling baseline losses of habitat (Ando et al. 1998, Costello and Polasky 2004, Newburn et al. 2006, Polasky et al. 2001). A feature of reserve-site selection studies is that, once reserves are established, the habitat within them is fixed at initial levels. Nalle et al. (2004) relax this assumption by allowing timber management practices to be optimally determined conditional on satisfying wildlife population goals. The authors also model wildlife population dynamics in a spatially-explicit framework.

Our methodological approach shares some similarities with reserve-site selection studies, but also departs from them in important ways. First, as in many earlier studies, a regulator makes conservation decisions for a set of pre-determined geographical units, or sections of the landscape. However, following Nalle et al. (2004), habitat is not fixed. The regulator can increase the area of core forest within each section by encouraging afforestation (the conversion of non-forest land to forest). This emphasis on land use is appropriate for many species, including neotropical migratory songbirds.[2] Second, earlier studies assume an omnipotent and omniscient regulator. As such, the regulator is free to select habitat for conservation or, as in Nalle et al. (2004), modify management practices. This approach may be relevant for a public agency that manages a large portion of the landscape, but is unrealistic when land-use decisions are made by a large number of private individuals. In our analysis, the regulator uses voluntary incentives to increase forest area, and we adopt the realistic assumption that the regulator has incomplete information on the opportunity costs of private landowners. Finally, we focus on changes in the amount of core forest habitat and do not model populations of particular species as in the reserve-site selection literature.[3]

We begin, in section 2, with an analytical treatment of the optimal targeting of conservation incentives. As such, we depart from much of the related literature that focuses on the solution of numerical optimization problems. The regulator determines the afforestation subsidy for each section of the landscape (i.e., targets the subsidy) to maximize the expected net social benefits from converting agricultural land to forest. Land parcels are heterogeneous due to spatial variation in parcel characteristics. These characteristics influence forest and agricultural rents (and, thus, the opportunity costs of afforestation), but depend on private information not observed by the regulator. Because the regulator knows only the probability distribution for opportunity costs, the exact placement of forest parcels cannot be controlled. A further challenge is that land-use decisions are made at the parcel scale whereas the spatial process determining core forest benefits operates at a multi-parcel scale. The solution reveals how the optimal subsidy rate depends on the initial spatial distribution of forests within each section. Thus, targeting of the policy is determined by differences across sections in these initial conditions. We also find that corner solutions, in which all or none of the agricultural land in a section is converted to forest, are a strong possibility. This result is due to the convexity of expected marginal benefits, which is directly linked to the fine-scale spatial process generating core forest benefits and the regulator's inability to control the exact location of forested parcels.

In the theoretical analysis, we cannot rule out the possibility of interior solutions and so we conduct an empirical analysis to clarify the optimal solution. Section 3 presents a simulation of the effects of an incentive-based policy on the spatial distribution of forests in South Carolina. The empirical methodology, based on earlier work by Lewis and Plantinga (2007), integrates an an econometric model of land-use change with GIS-based landscape simulations. For this study, we simulate policy-induced changes in core forest area for 244 sections of the landscape and compute corresponding marginal costs and marginal habitat benefits. The empirical findings strongly support our conjecture regarding corner solutions. For the large majority of sections, we find that either less than 10% or more than 90% of the available agricultural land should be converted to forest. We compare the performance of this policy to that of an incentive applied uniformly across all sections and find large efficiency gains from targeting.

An important contribution of this study is the identification of a practical targeting rule for reducing forest fragmentation. In section 4, we discuss this and other policy implications, and summarize our findings.

2. Targeting Incentives

This section presents a theoretical model of a regulator who pays a per-acre subsidy to landowners to convert land in an alternative use (hereafter, agriculture) to forest. The costs of the policy are the foregone rents from the land in agriculture net of forest rents. These costs are weighed against the expected benefit of increasing the number of core forest parcels. The regulator could apply a uniform subsidy across the landscape, offering the same per-acre payment to all owners of agricultural land. While this is an efficient policy if the objective is to increase the total area of forest (Plantinga and Ahn 2002), it does not account for spatial variation in expected benefits. For example, in a lightly forested area, afforestation may create few new core forest parcels, while the same amount of afforestation may significantly increase the number of core forest parcels if the area is heavily forested to begin with. This suggests that a more efficient policy would target the subsidy according to initial landscape conditions.

2.1. *Model Set-up*

The landscape is partitioned into M (m=1,…,M) sections. Each section is further divided into an $N \times N$ grid, where each cell in the grid represents a homogeneous parcel of land managed by a private landowner.[4] The regulator applies afforestation subsidies that are constant within sections, but can vary across sections to account for heterogeneity in initial landscape conditions. Our analysis focuses on how targeting the incentives in this way can increase the efficiency of the policy relative to a spatially-uniform incentive. The sections of the landscape are assumed to be pre-determined. Thus, we do not address the problem of how to define the sections, though this is another avenue for increasing the efficiency of the policy.

Each landowner allocates their parcel to forest or agriculture to maximize rents. We assume that landowners differ from one another in terms of knowledge and managerial skills. As well, there may be differences among parcels in the physical characteristics (e.g., soil composition) of the land. The attributes of a parcel are summarized by a parcel quality index, q, which measures both owner and physical characteristics. Parcel quality affects the rents earned from forestry (f) and agriculture (a). We specify the rents from parcel (i,j) in section m as $R_{ijm}^{f} = \overline{R}_{m}^{f} + q_{ijm}^{f}$ and $R_{ijm}^{a} = \overline{R}_{m}^{a} + q_{ijm}^{a}$, where $\overline{R}_{m}^{f}$ and $\overline{R}_{m}^{a}$ are the average rents[5] earned by all landowners and q_{ijm}^{f} and q_{ijm}^{a} measure deviations from the mean rent due to parcel quality. It follows that a rent-maximizing landowner will allocate a parcel to forest if $q_{ijm} \equiv q_{ijm}^{a} - q_{ijm}^{f} \leq \overline{R}_{m}^{f} - \overline{R}_{m}^{a}$ and to agriculture if $q_{ijm} > \overline{R}_{m}^{f} - \overline{R}_{m}^{a}$.[6] We define $q_{m}^{*} = \overline{R}_{m}^{f} - \overline{R}_{m}^{a}$ as the threshold value of land quality at which landowners switch from forest to agriculture.

In addition to economic rents, a forested parcel provides wildlife habitat benefits if it is a core forest parcel. A forest parcel is defined as core forest if its eight immediate neighbors are forested. Formally, let $\delta_{ijm} = 1$ if parcel (*i*,*j*) in section *m* is forested and $\delta_{ijm} = 0$ if the parcel is in agricultural use. Then, the core forest benefits from the parcel, B_{ijm}, are:

$$
B_{ijm} = \begin{cases} B \;\; if \;\; \prod_{s=-1}^{1}\prod_{t=-1}^{1} \delta_{i+s,\, j+t,m} = 1, i = 2,..., N-1, \, j = 2,..., N-1 \\ 0 \quad \text{Otherwise} \end{cases} \tag{1}
$$

where *B* is the benefit from one core forest parcel.[7] Core forest benefits are pure public goods when people have existence values for wildlife species. In addition, the benefits may be use values derived from recreational activities such as wildlife viewing. There are various ways to treat the benefits from parcels on the boundary of a section. We assume that boundary parcels do not generate core forest benefits, implying $B_{ijm} = 0$ for *i*=1,*N* or *j*=1,*N*. Boundary parcels become relatively less important as the size of the total grid increases. Specifically, the share of boundary parcels in an $N \times N$ grid is $(4N\text{-}4)/N^2$, which is decreasing in *N*.

2.2. *The Regulator's Information*

Landowners are assumed to ignore the benefits from wildlife habitat when making land-use decisions. Thus, the privately-optimal landscape will, in general, differ from the socially-optimal landscape that accounts for both economic rents and wildlife benefits. The regulator's objective is to maximize the social value of the landscape through the use of afforestation incentives. We assume the regulator knows the mean rents in each section, $\overline{R}_m^f$ and $\overline{R}_m^a$, and, thus, the threshold value q_m^*. As well, the regulator can observe land-use decisions *ex post*. That is, the regulator can determine, for each parcel, whether forest or agriculture was chosen. However, the quality of any particular parcel depends on a landowner's knowledge and skills, which we assume is private information. Therefore, the regulator cannot know the quality of an individual parcel, only whether the quality is above or below q_m^*.

If mean rents vary over time and repeated observations of land-use decisions are available for the entire landscape, the regulator might attempt to infer the quality of each parcel. This effort would be complicated by ownership changes over time that affect the unobservable components of parcel quality. Alternatively, the regulator can assume a distribution for parcel quality, with probability density function denoted $f_m(q)$. We assume $f_m(q) > 0$, $q \in [\underline{q}, \overline{q}]$, implying positive probabilities for all parcel qualities. The probability that any parcel in section *m* is forested is given by the cumulative distribution function $F_m(q_m^*)$.

The parcel quality distributions are the same for all parcels within a section, but may differ across sections. One reason for this difference is spatial dependence in parcel quality. Suppose that most of section *m* is in agricultural use. For a given parcel within this section, one might expect $f_m(q)$ to be greater for large values of *q* compared to parcels in a section dominated by forests. Thus, our formulation is consistent with spatial dependence in parcel quality, with the proviso that the underlying spatial process affects the parcel quality distribution within a section in the same way.

2.3. *Expected Benefits and Costs of the Policy*

The regulator chooses an afforestation incentive for each section, s_m, to increase the average rent from forestry to $\overline{R}_m^f + s_m$. The subsidy raises the threshold value of parcel quality to $q_m^* + s_m$ and increases the probability that land is allocated to forest to $F_m(q_m^* + s_m)$. We assume no land-use changes in the absence of the policy (i.e., q_m^* does not change).[8] For $s_m > 0$, the probability that an agricultural parcel converts to forest increases by:

(2) $$\Delta F_m(s_m) = \frac{F_m(q_m^* + s_m) - F_m(q_m^*)}{1 - F_m(q_m^*)}.$$

The normalization in (2) ensures that $\Delta F_m(s_m)$ equals one at $\overline{q}$, and incorporates the prior information that the quality of the agricultural parcel is above q_m^*.

Consider a block of nine parcels in section *m*, where parcel (*i*,*j*) is the center parcel (hereafter, focal parcel) in the block. Define α_{ijm} as the number of forested parcels in the block, or $\alpha_{ijm} = \sum_{s=-1}^{1}\sum_{t=-1}^{1}\delta_{i+s,j+t,m}$. Then, the expected core forest benefit from (non-boundary) parcel (*i*,*j*) with incentive s_m is:

(3) $$E[B_{ijm}] = B\left[\Delta F_m(s_m)\right]^{9-\alpha_{ijm}}.$$

The bracketed term in (3) is the probability that the $9-\alpha_{ijm}$ agricultural parcels in the block convert to forest, thus making the focal parcel at location (*i*,*j*) a core forest parcel.

The cost of the incentive is the foregone rents from agriculture net of forest rents. For a change in parcel quality from q_m^* to $q_m^* + s_m$, the expected cost for parcel (*i*,*j*) is written:

(4) $$E[C_{ijm}] = \int_{q_m^*}^{q_m^*+s_m} (R_{ijm}^a - R_{ijm}^f)\, f_m(q)dq$$

Noting that $R_{ijm}^a - R_{ijm}^f = q - q_m^*$, we can change the limits of integration to obtain:

(5) $$E[C_{ijm}] = \int_0^{s_m} s f_m(q_m^* + s)ds$$

The subsidy equals the payment needed to induce conversion to forest and, thus, equals the marginal opportunity cost of the policy. Equation (5) gives the expected value of the cost for a subsidy of s_m.

2.4. *Solution to the Regulator's Targeting Problem*

The regulator's objective is to choose s_m, m=1,…,M, to maximize the expected increase in net social benefits:

$$\max_{\{s_m\}} E[NSB] = \sum_{m=1}^{M}\sum_{i=1}^{N}\sum_{j=1}^{N}\left[B[\Delta F_m(s_m)]^{9-\alpha_{ijm}} - \int_0^{s_m} sf_m(q_m^* + s)ds \right], \tag{6}$$

subject to $0 \le s_m \le \bar{s}$, where $F_m(\bar{s}) = 1$. The upper bound on the afforestation incentive corresponds to conversion of the entire section to forest. It is important to recognize that (6) does not yield the first-best solution to the problem of maximizing private rents and core forest benefits on a landscape. The reason is that the expectation of core forest benefits is conditioned on the initial spatial configuration of forest parcels (through the term α_{ijm}), but does not account for how this configuration will be affected by the policy itself. To illustrate this point, suppose we were to select 100 agricultural parcels within a section and convert them to forest. In addition to possibly creating core forest parcels, the new parcels also change the configuration of land uses, thus influencing the benefits of converting additional parcels to forest. There is a feedback from the policy into the benefits of the policy. The first-best solution requires that afforestation decisions be simultaneously considered for every parcel on the landscape. This presents a challenge analogous to the "curse of dimensionality" problem encountered with dynamic optimization. As the number of parcels increases, the number of possible land-use configurations increases exponentially.[9] Thus, except for small problems, it is infeasible to examine all of the possible landscape configurations to determine the one that generates the largest benefits.[10] In any event, it is difficult to imagine how the first-best solution would be implemented and so its usefulness from a policy standpoint may be limited.

The Kuhn-Tucker first-order condition for the regulator's problem in (6) is:

$$
(7) \qquad f_m(q_m^* + s_m)[MB_m(s_m) - N^2 s_m] \begin{array}{ll} \leq 0 & s_m = 0 \\ = 0 & 0 \leq s_m \leq \bar{s} \\ \geq 0 & s_m = \bar{s} \end{array},
$$

for m=1,…,M, where:

$$
(8) \qquad MB_m(s_m) = \frac{B}{1 - F_m(q_m^*)} \sum_{i=2}^{N-1} \sum_{j=2}^{N-1} (9 - \alpha_{ijm}) \left[\Delta F_m(s_m) \right]^{8-\alpha_{ijm}}
$$

The first term in (7) is strictly positive, and so the solution depends on the sign of the term in brackets. $MB_m(s_m)$ is proportional to expected marginal benefits. It is computed by summing over the $(N\text{-}1)^2$ interior parcels in the section, where each term in the summation is proportional to the marginal probability that the focal parcel becomes a core forest parcel. Denote this probability:

$$
(9) \qquad MP_{ijm}(s_m) = (9 - \alpha_{ijm}) \left[\Delta F_m(s_m) \right]^{8-\alpha_{ijm}} .
$$

It is clear that a uniform afforestation subsidy (s_m is the same for all sections) is inefficient relative to a targeted incentive in which s_m varies by section. If the uniform subsidy satisfies condition (7) in one section, there is no guarantee it will do so in other sections unless all sections are identical. This implies a divergence between expected marginal benefits and costs, and a missed opportunity to increase net benefits.

Returning to the targeted incentive, the condition for a corner solution at $s_m = 0$ is always satisfied,[11] but, since it does not increase net social benefits, we must check whether interior solutions and the solution at $s_m = \bar{s}$ produce positive increases. In this regard, note that $MP_{ijm}(s_m)$ is a convex function of $\Delta F_m(s_m)$. When α_{ijm} is small, $MP_{ijm}(s_m)$ remains near zero as $\Delta F_m(s_m)$ increases but then rises rapidly as $\Delta F_m(s_m)$ approaches 1. Intuitively, if most of the nine parcels are in agricultural use initially and the probability of conversion to forest is low, the likelihood that all parcels convert to forest is very low. Once the probability of conversion is sufficiently high, however, the probability of all parcels converting increases rapidly. The top panel in Figure 1 shows the actual relationship between $MP_{ijm}(s_m)$ and $\Delta F_m(s_m)$ for different values of α_{ijm}. As shown, $MP_{ijm}(s_m)$ becomes "less convex" as α_{ijm} increases. When $\alpha_{ijm} = 8$, $MP_{ijm}(s_m)$ is constant at 1. A unit increase in the probability of conversion has the same effect on the marginal probability of creating core forest because only one parcel in a block of nine needs to be converted.

$MP_{ijm}(s_m)$ is a convex function of $\Delta F_m(s_m)$ because of the spatial process determining core forest benefits. Particularly when there are few forested parcels initially, there is an extreme degree of convexity due to the exponential term $8 - \alpha_{ijm}$ in (9). For example, when $\alpha_{ijm} = 1$, a 0.1 increase in $\Delta F_m(s_m)$ raises $MP_{ijm}(s_m)$ by only 0.0000008 when $\Delta F_m(s_m) = 0$, compared to a 4.17 increase in $MP_{ijm}(s_m)$ when $\Delta F_m(s_m) = 0.9$. For commonly-used density functions, $MP_{ijm}(s_m)$ is also a convex function of s_m.[12] In this case, there is a convex relationship between $\Delta F_m(s_m)$, which sums $MP_{ijm}(s_m)$ for each focal parcel, and s_m.

Convexity of $MB_m(s_m)$ suggests solutions at or near the corners $s_m = 0$ and $s_m = \bar{s}$. In sections with little forest initially, marginal costs will tend to be well above marginal benefits for most values of s_m, indicating a corner solution at $s_m = 0$. This possibility is illustrated in the bottom panel of Figure 1 with the curve MB_1. The opposite is true for sections with many forest parcels initially. In this case, illustrated with the curve MB_3, $MB_m(s_m)$ can be strictly positive at $s_m = 0$ (if there are parcels for which $\alpha_{ijm} = 8$) and, if sufficiently convex, a corner solution at $s_m = \bar{s}$ will be optimal. Corner solutions are interesting cases from a policy perspective because they imply a simple targeting strategy—convert either all or none of a section to forest. Of course, where the solution occurs will depend on the relative magnitudes of $MB_m(s_m)$ and s_m. Interior solutions are possible, as would be the case for the curve MB_2 in Figure 1. Because our theoretical results are suggestive, but not conclusive, we turn to empirical analysis to yield additional insights into the targeting solution.

3. Empirical Analysis of Targeted Incentives

We simulate the effects of an incentive-based policy on the area of core forest in South Carolina. An econometric land-use model is estimated with data on private land-use decisions, net revenues from alternative uses, and parcel characteristics. Because the model measures the relationship between land-use change and economic returns, we can use it to simulate the response by landowners to incentives that increase the relative return to forest land. The econometric model is used to simulate a range of incentive levels for each section of the landscape, in each case determining the associated increases in forest area. Next, we estimate the expected change in the area of core forest corresponding to each level of the incentive. For this step, we perform a GIS-based landscape simulation to determine the effects of the policy on the spatial configuration of forest. Lewis and Plantinga (2007) developed the econometric land-use model used here. The present study applies the model in a landscape-scale simulation that empirically investigates the optimal targeting of incentives at the section level. (Note: a reviewer's appendix contains relevant sections from Lewis and Plantinga (2007), which documents the development of the econometric land-use model.).

3.1 Study Area

The study area is the 4,000 sq. km coastal plain of South Carolina (Figure 2). This region provides an excellent setting for studying optimal incentives for reducing habitat fragmentation.

Approximately 83% of the land is privately owned. In 1997, 69% of this 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. The study area is also important from a conservation standpoint. Many species of migratory songbirds nest in the region and have been negatively impacted by fragmentation of forested habitat (Askins 2002, Faaborg 2002).

In Figure 2, we overlay U.S. Geological Service (USGS) quadrangles (quads) on the map of the study region. We analyze 244 USGS quads in coastal plain region, each of which is approximately 40,000 acres in area.[13] These quads are used to define sections of the study area. This definition is convenient (the GIS data used below are delineated by USGS quads), but it also provides us with a large range of initial landscape conditions (e.g., land-use shares, forest patch sizes and shapes). This enables us to effectively test the performance of the targeting strategy.

3.2 Econometric Land-Use Model

The econometric model is described in detail in Lewis and Plantinga (2007) and here we discuss only its key elements. Private landowners are assumed to allocate a homogeneous land parcel to one of three uses (agriculture, forest, or urban) to maximize annualized net revenues minus conversion costs. Following the theoretical analysis in section 2, the annualized net revenue from each use is a function of observable and unobservable factors. The unobservable components are modeled as random disturbances with an IID Type I extreme value distribution, yielding a conditional multinomial logit model of individual land-use choices (Train 2003). The probability that a parcel transitions from its initial use j (j=agriculture, forest, urban) to the ending use k (k=agriculture, forest, urban) is a function of the observable components of net revenues from all uses and parameters to be estimated. Unobservable parcel characteristics result in a probabilistic response to an incentive-based policy.

The primary data set used for the econometric analysis is the U.S. Department of Agriculture's National Resources Inventory (NRI). The NRI is a survey of land use, land cover, and soil characteristics of non-federal lands in the contiguous U.S. It provides repeated plot-level observations for three time periods, 1982-1987, 1987-1992, and 1992-1997. We analyze a sample of 29,714 privately-owned plots in North and South Carolina. The data set is expanded to include plots outside the coastal plain of South Carolina to increase variation in land-use changes and the explanatory variables. For each plot and time period, we observe the beginning and ending land use (agriculture, forest, or urban). Agriculture is a composite category that includes cropland and pasture. Our sample includes only plots starting in agriculture and forest because we do not observe transitions out of urban use.

Annual per-acre net revenues (in 1997 dollars) for the three uses are taken from Lubowski (2002), and described in detail there. The returns to forest are the annualized revenues from timber production less management costs. Agricultural returns equal the annual revenue from crop and pasture production less costs and plus government payments. Because we do not observe the exact locations of the NRI plots, the forest and agricultural returns are measured as county averages where the weights reflect the existing mix of timber types and crops. The return to urban land is the annualized county median value of a recently-developed parcel used for a single-family home, less the value of structures. Returns at the plot level may differ from county average returns. To account for such deviations, the county returns to agriculture and forest are interacted with dummy variables for the land capability class rating[14] of the plot, and entered in the econometric model as separate variables. For urban returns, we include an urban influence dummy variable that takes the value one if the plot is close to population centers, and zero otherwise.[15] Data on conversion costs are unavailable, and so their effects are measured implicitly in constant terms specific to each land-use transition.

Maximum likelihood procedures are used to estimate separate models for plots beginning in agriculture and forest (Table 1).[16] The estimation results indicate good model fit[17] 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 influence variable is positive and significantly different from zero, indicating that agricultural and forest parcels near population centers are more likely to convert to urban use.

3.3 Simulating Incentives

The econometric analysis yields land-use transition probabilities expressed as functions of net revenues from agriculture, forest, and urban uses. As in the theoretical model, a per-acre afforestation subsidy (s_m) is added to forest net revenues for land starting in agriculture. The effects of the policy are measured relative to a baseline scenario with a zero subsidy.[18] Because baseline transition probabilities lie within the unit interval, baseline land-use changes are nonzero.[19] To discourage land from leaving forest, we apply a deforestation tax, also equal to s_m. The deforestation tax is subtracted from agricultural and urban returns for land starting in forest. Similar to $\Delta F_m(s_m)$ in the theoretical model (equation 2), the two-part incentive increases the probability that agricultural land moves to forest and reduces the probability that forest moves to urban or agricultural use.

For incentive s_m, the change in forest area is denoted $\Delta A_m^f(s_m) = A_m^f(s_m) - A_m^f(0)$, where $A_m^f(s_m)$ is the forest area in section *m* with the incentive and $A_m^f(0)$ is the baseline forest area. To compute $A_m^f(s_m)$, we apply the transition probabilities—modified by s_m in the manner described above—to the corresponding initial land areas (initial land areas are measured with GIS data discussed in more detail below). For example, the amount of land afforested with incentive s_m is the product of the initial area of agricultural land and the modified agriculture-to-forest transition probability, net of baseline afforestation. We increase s_m in \$1 increments up to the point at which all land besides urban and other land is forested.[20] We refer to this maximum amount of forest as the *potential forest area*.

Two issues deserve further discussion. First, reaching the potential forest area requires that we simulate incentive levels outside the range of our data.[21] This is an unavoidable limitation of our analysis. Second, the logit specification used for our econometric model implies that changes in forest area are a convex function of the incentive as the potential forest area is approached. Further, because the logit probability is strictly less than one, the potential forest area is reached only in the limit with an infinitely-high incentive. We increase the incentive up to the level at which changes in forest area become negligible. It is assumed that any remaining landowners will not convert to forest, no matter the incentive offered.

3.4 Estimating Changes in Core Forest Area

For each level of the incentive, we need to determine the expected number of core forest parcels, which requires simulating changes in the spatial pattern of the landscape. Our approach integrates the econometric results discussed above with GIS data on actual landscapes. The land-use transition probabilities from the econometric model are differentiated by starting and ending use, county, land quality class, and urban influence status. We, first, match the transition probabilities to 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. As noted above, these data are delineated by USGS quads.

Land-use maps were developed by SCDNR from 1:40,000 scale infrared photography and are available in vector format at 10-acre minimum resolution for the year 1989. The SCDNR uses finer land-use categories, which we combine to match the three uses (agriculture, forest, and urban) in the econometric model. The soil quality layer is derived from county surveys available from the Natural Resources Conservation Service. These data were digitized by SCDNR, and we linked them to STATSGO and SSURGO soils tables to obtain LCC ratings for each parcel. GIS layers on political boundaries and ownership status from the SCDNR database were also used to identify county boundaries and public lands. Finally, a GIS layer for urban influence status, obtained from ERS, was used to identify the urban influence status of each parcel. We overlay the GIS data to obtain an average of approximately 7,500 uniquely-identified parcels per section (quad), with an average size of approximately 5 acres. Each parcel in the GIS is indexed by land use, county, LCC group, ownership, and urban influence status. We focus on the privately-owned parcels in agriculture, forest, and urban use, each of which is matched to a set of transition probabilities from the econometric analysis.

The transition probabilities provide a set of rules that determine land-use changes in the simulation. 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. To conduct the simulations, a random number generator is used to repeat the choice situation five hundred times[22] for each parcel in the landscape.[23] The ending use for each parcel will, on average, satisfy the underlying transition probabilities (e.g., conversion to forest 20% of the time). While the simulated landscapes all conform to the transition rules, there may be great differences between them in spatial pattern and, thus, the number of core forest parcels. The software Fragstats (v. 3) is used to calculate the number of core forest acres in each section at the end of each simulation round. A forested parcel is considered core if it is at least 200 m from the nearest forest edge, consistent with studies of edge effects by avian ecologists.

The transition probabilities are modified with different levels of the incentive in the manner described above. Because the landscape simulations are computationally expensive, we simulate the baseline and five incentive levels: $1, $10, $25, $40, and $70 per acre. For each incentive level and section, we calculate the mean core forest acres, $Core_m(s_m)$, by averaging the results of the five hundred simulations. We also calculate this statistic for the baseline landscape and for a landscape that achieves the potential forest area. The net effect of s_m on mean core forest acres is denoted $\Delta Core_m(s_m) = Core_m(s_m) - Core_m(0)$. $B\Delta Core_m(s_m)$ is the total expected benefit. For each section, polynomial functions are fit to the simulated data to quantify the continuous relationship between mean core forest acres and forest area. We find that a third-order polynomial fits the data extremely well (R^2 statistics exceed 0.99), and in the large majority of cases the estimated function is convex.

3.5 The Targeting Solution

We present the solution to the targeting problem as the optimal share of potential forest area in each section to convert to forest. To identify this solution, we compute expected net benefits, as in (6), for each section. Total expected benefits are given by $\tilde{B}\Delta Core_m(s_m)$, where $\tilde{B}$ is the benefit from a core forest acre. We do not have direct estimates of $\tilde{B}$ and so we consider a range of values, from \$25 to \$75 in increments of \$10. These values are comparable to annual per-acre payments offered under the CRP, which in some cases are provided for the establishment of wildlife habitat.

To compute the total expected costs of increasing forest area, we must first compute marginal costs at each level of the incentive. For incentive *s*, marginal costs in section *m* equal:

$$MC_m(s) = \frac{sA_m^f(s) - (s-1)A_m^f(s-1)}{A_m^f(s) - A_m^f(s-1)}. \tag{10}$$

Because *s* is equal to the opportunity cost of the last parcel converted to or retained in forest, the numerator in (10) represents the change in total cost from increasing the incentive from *s*-1 to *s*. The cost per unit of land is obtained by dividing this quantity by the associated change in forest area. $MC_m(s)$ is computed for each section and incentive level. To ease the calculation of total costs—the integral of marginal costs—we fit eighth-order polynomial functions (one for each section) to the simulated data. The functions fit the data extremely well, with R^2 statistics exceeding 0.99 in all cases.

The targeting solution is identified for each section by increasing forest area in one hundred equal increments up to the potential forest area, and determining the point at which expected net benefits are greatest. The first set of results, in the top part of Table 2, indicate the prevalence of corner solutions. For varying values of $\tilde{B}$, we report the percentage of the potential forest area that is forested under the optimal policy. The first entry indicates that for approximately 85% of the sections, less than 10% of the potential forest area should be forested when $\tilde{B}$ equals \$25. Overall, the results reveal that it is optimal to convert to forest either small areas (<10% of potential forest) or a large share of the section (>90% of potential forest). Across the different values of $\tilde{B}$, never more than 23% of the sections have optimal forest areas between 10% and 90% of potential forest. At $\tilde{B}$=\$75, the optimal forest area for 91% of the sections is either less than 10% or greater than 90%. As discussed above, it may be impossible to reach the potential forest area, preventing corner solutions at 100% of potential forest area. However, as $\tilde{B}$ rises above \$50, corner solutions at 100% do become optimal for an increasing share of the sections (11.52% when $\tilde{B}$=\$75). Note, finally, that as $\tilde{B}$ increases, the optimal solution for many sections jumps from a small to a large share of potential forest area, a result due to the convexity of marginal benefits.

For each level of $\tilde{B}$, we report the total increase in forest and core acreage for all sections relative to the baseline, as well as the associated total costs and net benefits (Table 2). The ratio of the increase in core forest acreage to the increase in total forest acreage is always greater than one. Conversion of a single forest parcel can cause more than one neighboring parcel to be surrounded by forest. This ratio is increasing in $\tilde{B}$ up to \$65. As the landscape becomes more heavily forested, conversion of an additional parcel has a greater chance of joining together separate forest parcels. However, the increasing benefits of additional forest parcels must be balanced against rising marginal costs, and we find that the ratio is lower for $\tilde{B}$=\$75. Net benefits are found to be positive for all levels of $\tilde{B}$.

For comparison purposes, we also simulate the effects of an incentive that is equal for all sections. To determine the level of the uniform incentive, the total cost associated with the optimal policy for each level of $\tilde{B}$ was taken as a fixed budget. Then, we solved for the uniform incentive that increases forestland at a budget equal to the fixed budget. This approach ensures that the total budgets of the optimal and uniform policies are identical for each level of $\tilde{B}$. Results are presented at the bottom of table 2, where one can see that the total costs are equal to those under the optimal policy for each level of $\tilde{B}$. The uniform policy maximizes the area of land converted to forest for a given budget, yielding for each $\tilde{B}$ approximately 1.5 times the amount converted under the optimal policy. However, because the uniform policy disregards the the benefits of core forest, it produces far fewer core forest acres than the optimal policy. Only about 0.6 acres of core forest are created for each acre of land converted to forest, compared to as many as 1.8 acres under the optimal policy. Also of note are the negative net benefits of the uniform policy for all levels of $\tilde{B}$ except \$25. The differences in net benefits are striking. At $\tilde{B}$=\$75, net benefits are \$29.4 million under the optimal policy and -\$15.2 million under the uniform policy. Even when net benefits are positive under the uniform policy, they are over three times higher with the optimal policy.

To better understand how the incentive is targeted under the optimal policy, we examine characteristics of the sections for which a large share of potential forest is converted (Table 3). Each entry in Table 3 is calculated by averaging the characteristics of sections for which either less than 70% of potential forest is forested under the optimal policy or more than 70% is forested. The results reveal that the sections targeted for a large amount of forest under the optimal policy tend to have more forest in the baseline, more land that can be forested (i.e., greater potential forest), lower agricultural returns, and higher forest returns. In percentage terms, the largest difference between the two groups of sections is in the initial amount of forest. For sections with more baseline forest, marginal benefits will tend to be positive initially—see the curve labelled MB_3 the lower panel of Figure 1—making it optimal to convert all of the section to forest. In sections with more potential forest area, there is a greater likelihood that separate groups of forest parcels will be joined together, thus creating more core forest. In quads with significant amounts of urban and other land, it is less likely that the steep portion of the marginal benefit curve will ever be reached.

4. Conclusions

Habitat fragmentation poses a critical threat to terrestrial biodiversity. In this paper, we examine the problem of how to spatially target incentives to reduce forest fragmentation, an important factor in the decline of many important bird species. Our study advances the methodology for analyzing landscape-scale conservation policy in several directions. First, in contrast to most earlier reserve site selection studies, the regulator is able to modify the existing habitat. Second, to make our analysis relevant to landscapes with large numbers of private landowners, we relax the assumption of an omnipotent and omniscent regulator. In our study, the regulator uses voluntary incentives to increase forest area, and is assumed to have incomplete information on the opportunity costs of landowners. Finally, rather than focusing on numerical optimization, we present an analytical treatment of the regulator's targeting problem.

In the theoretical model, the regulator chooses an afforestation subsidy for each section of the landscape to maximize expected net benefits. Habitat benefits depend on the spatial configuration of forested parcels, and the expected benefits of the policy are conditioned on the initial spatial pattern. Our results reveal how these initial landscape conditions affect expected marginal benefits and, thereby, influence the spatial targeting of the policy. The key insight from the analysis is that corner solutions are a strong possibility because of the the convexity of expected marginal benefits. This convexity results from the spatial process generating core forest benefits and the regulator's inability to control the exact location of forested parcels. The results of the empirical application confirm the prevalence of corner solutions. For a large majority of 244 sections analyzed, either less than 10% or more than 90% of the available land should be converted to forest.

Incentive-based policies are increasingly being used to achieve wildlife conservation goals through programs such as the U.S. Wildlife Habitat Incentives Program (WHIP) and the Conservation Reserve Program (CRP). In the case of WHIP, while multiple factors are used to determine payment levels,[24] one common targeting scheme is to offer payments only to individuals whose parcels lie in pre-defined portions of the landscape,[25] an approach similar to the one considered in this paper. To the extent that species of conservation interest are sensitive to habitat fragmentation, our theoretical and empirical results provide practical insights for conservation policy. To reduce forest fragmentation, a simple targeting rule should be employed in which all or none of a landscape section is converted to forest. Other factors the same, sections targeted for afforestation should be those with larger amounts of existing forest and more land available to be forested and also with lower returns to agricultural use. In these sections, there is a greater likelihood of joining together existing forest patches and creating core forest. In the empirical analysis, this simple targeting approach is shown to greatly increase expected net benefits relative to an incentive applied uniformly across the landscape.

We analyzed the targeting of conservation payments to pre-determined geographic sections. Additional welfare gains may be generated by defining the sections in an optimal manner. Theoretically, as long as the marginal net benefits of afforestation subsidies are not uniform within a section, dividing it into smaller geogrpahic areas will improve the efficiency of the incentive-based policy. However, the increased spatial differentiation of the subsidy rates will it more difficult to implement. Thus, the optimal design of a spatially-diferentiated, incentive-based policy must consider both the increased economic efficiency and the additional implementation costs.

References

Ando, A., Camm, J., Polasky, S. and A. Solow. 1998. "Species Distributions, Land Values, and Efficient Conservation." *Science*, 279 (27 Mar.): 2126-2128.

Armsworth, P.R., B.E. Kendall, and F.W. Davis. 2004. "An Introduction to Biodiversity Concepts for Environmental Economists." *Resource and Energy Economics,* 26: 115-136.

Askins, R.A. 2002. *Restoring North America's Birds.* Yale University Press, New Haven, CT.

Costa, L.P., Leite, Y.L.R., Mendes, S.L., and A.D. Ditchfield. 2005. "Mammal Conservation in Brazil." *Conservation Biology* 19(3): 672-679.

Costello, C., and S. Polasky. 2004. "Dynamic reserve site selection." *Resource and Energy Economics* 26:157–174.

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

Fischer, D.T., and R.L. Church. 2003. "Clustering and Compactness in Reserve Site Selection: An Extension of the Biodiversity Management Area Selection Model." *Forest Science,* 49(4): 555-565.

Kirkpatrick, J.B. 1983. "An Iterative Method for Establishing Priorities for the Selection of Nature Reserves: An Example from Tasmania." *Biological Conservation*, 25(2): 127-134.

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): 1288-1299.

Lehtinen, R.M., Ramanamanjato, J.B., and J.G. Raveloarison. 2003. "Edge Effects and Extinction Proneness in a Herpetofauna from Madagascar." *Biodiversity and Conservation* 12(7): 1357-1370.

Lewis, D.J. 2005. Managing the Spatial Configuration of Land: The Economics of Land Use and Habitat Fragmentation. Unpublished PhD Dissertation, Department of Agricultural and Resource Economics, Oregon State University.

Lewis, D.J., and A.J. Plantinga. 2007. "Policies for Habitat Fragmentation: Combining Econometrics with GIS-Based Landscape Simulations." *Land Economics* 83(2):109-127.

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. Dissertation, Harvard University, Cambridge, MA.

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

Newburn, D.A., Berck, P., and A.M. Merenlender. 2006. "Habitat and Open Space at Risk of Land-Use Conversion: Targeting Strategies for Land Conservation." *American Journal of Agricultural Economics* v88, n1 (February): 28-42.

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

Onal, H., and R.A. Briers. 2003. "Selection of a Minimum Boundary Reserve Network using Integer Programming." *Proceedings of the Royal Society of London B*, 270: 1487-1491.

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

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): 128-145.

Polasky, S., Camm, J.D., and B. Garber-Yonts. 2001. “Selecting Biological Reserves Cost-Effectively: An Application to Terrestrial Vertebrate Conservation in Oregon.” *Land Economics,* 77(1): 68-78.

Robinson, S.K., F.R. Thompson, T.M. Donovan, D.R. Whitehead, and J. Faaborg. 1995. “Regional Forest Fragmentation and the Nesting Success of Migratory Birds.” *Science,* 267(5206): 1987-1990.

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): 337-352.

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

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

Van Horn, M.A., R.M. Gentry, and J. Faaborg. 1995. “Patterns of pairing success of the Ovenbird within Missouri Forest Fragments.” *Auk*, 112: 98-106.

Vane-Wright, R.I., Humphries, C.J., and P.H. Williams. 1991. “What to Protect? Systematics and the Agony of Choice.” *Biological Conservation*, 55(3): 235-254.

Table 1. Econometric Results for Land-Use Transition Model

Parameter	Starting Use Agriculture	Forest
Agriculture Constant		-4.78*
		-(40.71)
Agriculture Returns	0.003*	0.006*
	(3.61)	(3.68)
Agriculture Returns × LCC III,IV	-0.002	-0.001
	-(1.69)	-(0.78)
Agriculture Returns × LCC V-VIII	-0.006*	0.002
	-(3.93)	(1.12)
Forest Constant	-4.05*	
	-(34.73)	
Forest Returns	0.05*	0.02*
	(6.02)	(2.53)
Forest Returns × LCC III,IV	0.002	0.006
	(0.36)	(0.95)
Forest Returns × LCC V,VI		0.03*
		(3.72)
Forest Returns × LCC VII,VIII		0.06*
		(5.97)
Forest Returns × LCC V-VIII	0.06*	
	(5.18)	
Urban Constant	-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

Table 2: Landscape Conversion under the Optimal vs. Uniform Policies

Percentage of Potential Forest Converted	**Percent of Landscapes (Quads) in Each Category under the Optimal Policy**					
	$\tilde{B}$ **=$25**	$\tilde{B}$ **=$35**	$\tilde{B}$ **=$45**	$\tilde{B}$ **=$55**	$\tilde{B}$ **=$65**	$\tilde{B}$ **=$75**
0%-10%	85.19%	80.25%	72.02%	63.37%	55.97%	48.56%
10%-20%	2.47%	3.29%	5.35%	4.53%	2.88%	1.65%
20%-30%	4.53%	1.23%	0.82%	0.41%	1.23%	0.41%
30%-40%	1.65%	0.41%	1.23%	0.00%	0.41%	0.41%
40%-50%	3.70%	0.82%	0.00%	0.41%	0.41%	0.00%
50%-60%	2.06%	2.47%	0.41%	0.41%	0.41%	0.00%
60%-70%	0.00%	2.88%	0.41%	1.23%	0.82%	0.41%
70%-80%	0.41%	6.58%	3.70%	1.65%	0.82%	2.06%
80%-90%	0.00%	2.06%	11.52%	8.64%	2.88%	4.12%
90%-99%	0.00%	0.00%	4.53%	18.93%	28.81%	30.86%
100%	0.00%	0.00%	0.00%	0.41%	5.35%	11.52%
Optimal Policy						
Afforested acres	79,382	138,870	224,098	370,131	523,647	722,805
Core acres gained	101,138	207,308	377,034	665,605	951,235	1,281,199
Ratio of core to forest acres	1.27	1.49	1.68	1.80	1.82	1.77
Total Cost	$1,640,447	$4,858,931	$11,753,565	$26,380,794	$43,570,996	$66,632,631
Net Benefits	$888,009	$2,396,852	$5,212,959	$10,227,465	$18,259,263	$29,457,291
Uniform Policy						
Forest Acreage	114,482	210,551	352,220	598,956	837,352	1,092,374
Core Acreage	76,157	133,419	210,744	340,769	484,049	686,391
Ratio of core to forest acres	0.67	0.63	0.60	0.57	0.58	0.63
Total Cost	$1,640,447	$4,858,931	$11,753,565	$26,380,794	$43,570,996	$66,632,631
Net Benefits	$263,476	-$189,252	-$2,270,064	-$7,638,485	-$12,107,798	-$15,153,343

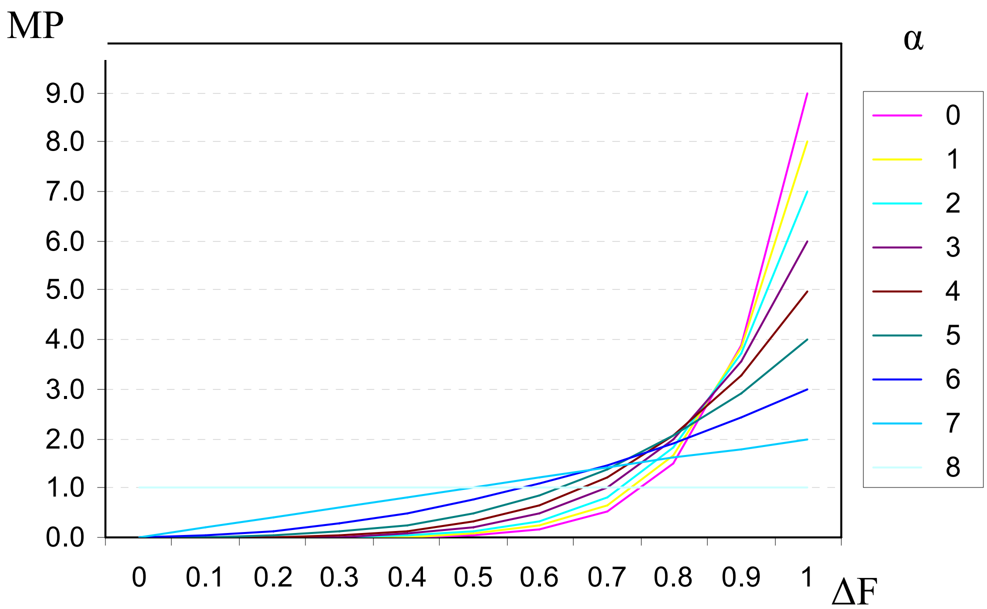
Table 3: Average Landscape Characteristics for Optimal Conversion

Share of Potential Forest that is Forested	Value of $\tilde{B}$	Baseline Forest (% of Quad Area)	Potential Forest (% of Quad Area)	Ag. Net Revenues	Forest Net Revenues	Urban Net Revenues
≤ 70%	\$25	63.05%	89.40%	\$40.09	\$12.68	\$1,432.45
	\$35	60.81%	88.94%	\$41.22	\$12.52	\$1,398.70
	\$45	58.02%	88.56%	\$41.65	\$12.29	\$1,359.06
	\$55	55.37%	87.76%	\$43.00	\$12.23	\$1,360.58
	\$65	53.16%	87.12%	\$44.34	\$12.10	\$1,367.25
	\$75	50.90%	86.98%	\$46.38	\$11.94	\$1,311.04
> 70%	\$25	92.13%	97.07%	\$23.90	\$17.16	\$773.12
	\$35	88.13%	94.60%	\$27.44	\$14.56	\$1,757.88
	\$45	84.11%	92.97%	\$33.45	\$14.35	\$1,716.89
	\$55	81.70%	93.40%	\$32.97	\$13.81	\$1,594.00
	\$65	79.61%	93.22%	\$32.95	\$13.68	\$1,532.30
	\$75	76.17%	92.03%	\$33.29	\$13.50	\$1,555.48

Note: All entries are averages across quads for which either less than 70% of potential forest is forested under the optimal policy or more than 70% is forested.

Figure 1. The Solution to the Regulator's Targeting Problem

a) The relationship between MP and ΔF for different values of α



b) Hypothetical relationships between MB and sN^2

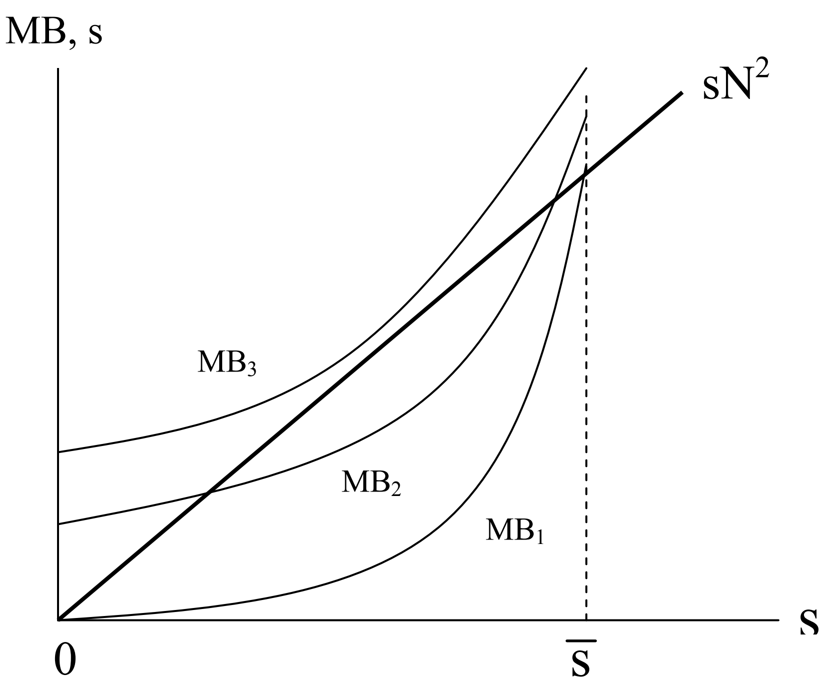
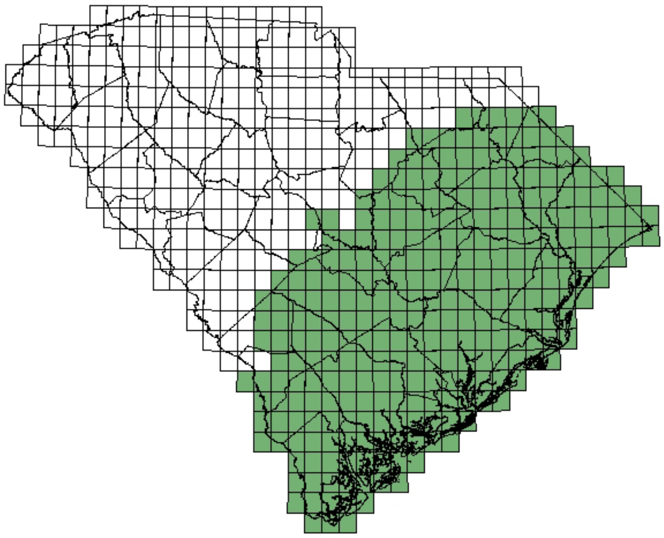


Figure 2. The Coastal Plain of South Carolina (in Green) with Overlay of USGS Quads



[1] Common predators include house cats from neighboring urban lands and nest parasites include the brown-headed cowbird from neighboring agricultural lands.

[2] Avian ecologists have found much clearer effects of fragmentation from non-forest uses on songbirds compared to fragmentation from timber harvesting (Faaborg 2002). Nevertheless, it is well established that some bird species, such as the northern spotted owl, are sensitive to the age structure, as well as the spatial configuration, of forests.

[3] This emphasis on landscape pattern is consistent with conservation strategies proposed for the study area considered in section 3. 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 habitat for core-forest birds.

[4] With more complicated notation, we can accommodate grids of irregular sizes and grid sizes that differ across sections.

[5] Rents are assumed to be constant across sections and determined exogenously. Even so, mean rents can vary across sections due to differences in the distributions of parcel quality (see below).

[6] We assume constant returns to scale in forestry and agricultural production on each land parcel, implying a rent-maximizing landowner will always allocate their entire parcel to a single use.

[7] For simplicity, B is assumed to be constant. The analysis presented below can be modified in a straightforward way to allow for diminishing marginal benefits.

[8] This analysis can be modified in a straightforward way to allow for baseline increases or decreases in forest. The empirical simulation presented below allows for such changes.

[9] If x out of a total of y agricultural parcels are to be converted, then the number of potential configurations is approximately y^x. For the example given above, suppose there are a total of

500 agricultural parcels. Then, there are approximately 7.9×10^{269} possible ways to afforest 100 parcels.

[10] For numerical problems, an alternative to enumeration is the use of heuristic algorithms (see, for example, Nalle et al. 2004). These algorithms can be used to improve on sub-optimal solutions, but do not guarantee an optimal solution.

[11] $MP_m(s_m)$ is undefined when $\alpha_{ijm}=9$ and $s_m=0$. Since this involves the uninteresting case in which the focal parcel is already a core forest parcel, we set this value to zero. $MP_m(s_m)=0$ for $\alpha_{ijm}=9$ and all positive values of s_m.

[12] The second derivative of $MP_m(s_m)$ with respect to s_m depends on second-order changes in $F_m(q_m^*+s_m)$, specifically the term $f_m'(q_m^*+s_m)$. If this term is non-negative or negative but small in absolute value, then $MP_m(s_m)$ is a convex function of s_m. The condition for convexity is always satisfied for the uniform and logistic densities. We use the latter to model the unobserved component of parcel quality in the empirical application below.

[13] We omitted coastal plain quads from the analysis (a total of 51 out of 295) when forest area was found to be unresponsive to the incentive, or for other anomalies. The omitted quads typically have very little agricultural land, land that is mostly in public ownership (e.g., national forest), or large amounts of urban and other land.

[14] The land capability class (LCC) rating for each plot is taken from the NRI database. The LCC rating indicates the productivity of the land for agriculture, and takes values from I (the most productive) to VIII (the least productive). To ensure a sufficient number of observations, the LCC categories are combined into three or four groups depending on the starting use. See Lewis and Plantinga (2007) for details.

[15] The urban influence measure was developed by the U.S. Department of Agriculture, Economic Research Service, using 1990 Census-tract population data.

[16] Lewis and Plantinga (2007) address estimation issues related to the panel structure of the data and potential spatial correlation of the model error terms.

[17] 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.

[18] The time-step in the NRI data is five years and, thus, land-use changes in the simulation occur over a five-year period.

[19] This is an implication of the logit specification, and is also observed in the historical data.

[20] As explained above, land in urban uses cannot be converted to forest. Land in other uses includes public lands and any land not classified as agriculture, forest, or urban.

[21] Net revenues from forest land vary from $9/acre/year to $38/acre/year in our data, while simulated subsidy levels are as high as $137/acre/year.

[22] Lewis (2005) discusses formal tests used to determine the appropriate number of simulations. The results reveal that five hundred simulations is sufficient for the convergence of empirical densities defined over fragmentation metrics (including the number of core forest parcels).

[23] 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.

[24] For example, many states offer WHIP bonus payments to riparian landowners, parcels that contain habitat for rare or endangered species, or to parcels in close proximity to publicly-conserved land.

[25] For example, Wisconsin allocates 50% of its WHIP funds to a small set of geographic regions, Iowa allocates its funds for forestland by differentiating payments across hundreds of pre-defined geographic regions, and Georgia offers differential payments for Quail conservation across counties, and in some counties provides no payments.