# University of Wisconsin-Madison
# Department of Agricultural & Applied Economics



Staff Paper No. 531 November 2008


## Targeting Incentives to Reduce Habitat Fragmentation


By

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**AGRICULTURAL &**

**APPLIED ECONOMICS**

**STAFF PAPER SERIES**

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11/19/08

*Abstract:* This paper develops a theoretical model to analyze the spatial targeting of incentives for the restoration of forested landscapes when wildlife habitat can be enhanced by reducing fragmentation. The key theoretical result is that the marginal net benefits of increasing forest are convex, indicating that corner solutions – converting either none or all of the agricultural land in a section to forest – may be optimal. Corner solutions are directly linked to the spatial process determining habitat benefits and the regulator's incomplete information regarding landowner opportunity costs. We present findings from a large-scale empirical landscape simulation that supports our key theoretical results.

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

*Suggested Running Head*: Targeting Incentives to Reduce Habitat Fragmentation

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## Targeting Incentives to Reduce Habitat Fragmentation

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 affected by habitat fragmentation, including amphibians (Kolozsvary and Swihart 1999, Lehtinen, Ramanamanjato, and Raveloarison 2003), large mammals (Noss 1994, Costa et al. 2005), and 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 effect 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 effects 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, Gentry and Faaborg 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, Humphries and Williams 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, Wu, Zilberman and Babcock 2001, Polasky, Camm and Garber-Yonts 2001, Costello and Polasky 2004, Newburn, Berck and Merenlender 2006). 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.[2] 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.[3] 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.[4]

In an empirical analysis of voluntary incentives for reducing forest fragmentation, Lewis and Plantinga (2007) (hereafter, LP) found that the marginal costs of reducing fragmentation are significantly lower on landscapes with larger initial amounts of forest. This paper differs in three fundamental ways from LP. First, we evaluate a policy derived theoretically as the solution to a net social benefit maximization problem, in contrast to the policies in LP which were selected on an *ad hoc* basis. Second, the spatial targeting strategy in our paper differs from the one examined in LP. In LP, parcels *within* a geographical area (section) are targeted according to the number of neighboring forested parcels. Under the targeted policy derived in this paper, all parcels in a section are eligible for the subsidy but the subsidy levels differ across sections according to initial landscape conditions. Finally, the scales of the analyses differ. We evaluate an entire landscape consisting of 244 sections, whereas LP presents separate analyses of three sections.[5]

We begin, in the next section, 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. A large landscape is assumed to be subdivided into smaller geographical sections that contain well-defined ecosystems. Within a section, the marginal benefits of core forested parcels are assumed to be constant. 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. Our key theoretical result is that the optimal targeting policy involves corner solutions under a weaker set of conditions than those required for interior solutions. This suggests a simple targeting strategy in which all or none of the agricultural land in a section is converted to forest. Corner solutions result from 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.

An empirical analysis is conducted to determine whether this simple targeting rule would apply in practice. Specifically, we present a simulation of the effects of an incentive-based policy on the spatial distribution of forests in South Carolina. The empirical methodology, based on the earlier work of LP, integrates 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 expected costs and benefits. The empirical findings strongly support our theoretical findings 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. As well, we demonstrate that, in some cases, the targeting rule is more efficient than a policy that only converts parcels that create core forest.

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

**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.

*Model Set-up*

The landscape is partitioned into $M$ ($m$=1,…,$M$) sections that each contain a well-defined ecosystem. 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.[6] 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 or a "core only" policy. Targeting at the sub-landscape level, such as a watershed, has several advantages, including benefits from taking into account potential threshold effects (Wu and Boggess, 1999; Wu and Skelton, 2002). In our analysis, 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 annual rent 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[7] 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 higher rents will be earned from forest if land quality satisfies $q_{ijm} \equiv q_{ijm}^{a} - q_{ijm}^{f} \leq \overline{R}_{m}^{f} - \overline{R}_{m}^{a}$ and from agriculture if $q_{ijm} > \overline{R}_{m}^{f} - \overline{R}_{m}^{a}$.[8] We define $q_{m}^{*} = \overline{R}_{m}^{f} - \overline{R}_{m}^{a}$ as the threshold value of parcel quality at which rents from forest and agriculture are equal.

In addition to economic rents, a forested parcel provides wildlife habitat benefits, which are largest if the parcel is a core forest parcel. A forest parcel is defined as core forest if its eight immediate neighbors are forested. If some of the neighboring parcels are in agricultural use, wildlife habitat benefits will be reduced because of increased risks of edge effects. Consider a block of nine parcels in section *m*, where parcel (*i*,*j*) is the center parcel (hereafter, focal parcel) in the block and $\alpha_{ijm}$ is the number of forested parcels in the block. The wildlife habitat benefit from parcel (*i, j*), $B_{ijm}$, is assumed to be:

(1) $$B_{ijm} = \begin{cases} B & if \quad \alpha_{ijm} = 9 \\ \gamma^{9-\alpha_{ijm}} B & if \quad \alpha_{ijm} < 9 \end{cases}$$

where *B* is the benefit from one core forest parcel[9] (the $\alpha_{ijm} = 9$ case), and $\gamma \in [0,1)$ is a parameter measuring the risk of edge effects from neighboring agricultural parcels. When $\gamma = 0$, a parcel will offer no core benefit unless it is completely surrounded by forest parcels. As $\gamma$ approaches 1, the difference in benefits between core and non-core parcels becomes small.

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. In (1) the benefit of a single core forest parcel is assumed constant, though one might expect *B* to decline as the number of such parcels increases. We do not consider this possibility, but note that in equation (11), below, it would have the effect of diminishing expected marginal benefits as the subsidy level increases. 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 $(4N-4)/N^2$, which is decreasing in *N*. Nevertheless, a weakness of our approach is that we ignore the possibility that boundary parcels could themselves be core forest because they may border forest parcels in adjacent sections.

*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, $\bar{R}_m^f$ and $\bar{R}_m^a$, 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 $f_m(q)$. We assume $f_m(q)$ is a uniform distribution on the interval $[\underline{q}_m, \bar{q}_m]$. This assumption simplifies the analysis, and makes our results more transparent. With a uniform distribution, the probability that any parcel in section *m* is forested is given by the cumulative distribution function for $f_m(q)$ evaluated at $q_m^*$: $F_m(q_m^*) = (q_m^* - \underline{q}_m)/(\bar{q}_m - \underline{q}_m)$. The probability that any parcel is in agriculture is given by $1 - F_m(q_m^*) = (\bar{q}_m - q_m^*)/(\bar{q}_m - \underline{q}_m)$.

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 correlation in parcel quality. Suppose that most of section *m* is in agricultural use. For a given parcel within this section, one might expect a greater probability of large values of $q$ compared to parcels in a section dominated by forests. In this case, the interval $[\underline{q}_m, \overline{q}_m]$ would be defined over relatively high parcel qualities. Thus, our formulation is consistent with spatial dependence in parcel quality, with the proviso that the underlying spatial process affects parcel quality probabilities within a section in the same way.

*Expected Benefits and Costs of the Policy*

The regulator chooses an afforestation incentive for each section, $s_m$, to increase the average rent from converted forest to $\overline{R}_m^f + s_m - s_0$, where $s_0$ is the conversion cost. When $s_m < s_0$, no agricultural land will be converted. When $s_m \geq s_0$, the subsidy raises the threshold value of parcel quality to $q_m^* + s_m - s_0$, increasing the probability that the land is allocated to forest to $F_m(q_m^* + s_m - s_0) = (q_m^* + s_m - s_0 - \underline{q}_m)/(\overline{q}_m - \underline{q}_m)$.[10] Then the probability that an agricultural parcel converts to forest equals:

$$(2) \qquad \begin{aligned} P_m(s_m) &= \frac{F_m(q_m^* + s_m - s_0) - F_m(q_m^*)}{1 - F_m(q_m^*)} = \frac{s_m - s_0}{\overline{q}_m - q_m^*} && \text{if } s_m \geq s_0 \\ &= 0 && \text{if } s_m < s_0 \end{aligned}.$$

The normalization in (2) ensures that $P_m(s_m)$ equals one when $q_m^* + s_m - s_0 = \overline{q}_m$, and incorporates the prior information that the quality of the agricultural parcel is above $q_m^*$.

Consider a focal parcel $(i, j)$ in section $m$ that is forested initially and has $9 - \alpha_{ijm}$ non-forested neighbors. If $s_m < s_0$, the core forest benefit from the parcel remains at $B_{ijm} = \gamma^{9-\alpha_{ijm}} B$ because none of its neighbors convert to forest. When $s_m \geq s_0$, the probability that a neighboring agricultural parcel converts to forest is $P_m(s_m)$, and the expected core forest benefit from the parcel is:

$$(3) \qquad E(B_{ijm}) = \sum_{k=0}^{9-\alpha_{ijm}} \left[ \binom{9-\alpha_{ijm}}{k} P_m(s_m)^k \left(1 - P_m(s_m)\right)^{9-\alpha_{ijm}-k} B\gamma^{9-\alpha_{ijm}-k} \right]$$

where $\binom{9-\alpha_{ijm}}{k} P_m(s_m)^k \left(1 - P_m(s_m)\right)^{9-\alpha_{ijm}-k}$ is the probability that $k$ of the non-forested neighbors convert to forest. Equation (3) gives the gross expected benefit under subsidy $s_m$. The *net* expected benefit is written:

$$(4) \qquad \begin{aligned} E(B_{ijm}) &= B\left[\gamma\left(1 - P_m(s_m)\right) + P_m(s_m)\right]^{9-\alpha_{ijm}} - B\gamma^{9-\alpha_{ijm}} \\ &= B\left[\gamma + (1-\gamma)\left(\frac{s_m - s_0}{\bar{q}_m - q_m^*}\right)\right]^{9-\alpha_{ijm}} - B\gamma^{9-\alpha_{ijm}} \end{aligned},$$

where the first term in (4) is derived using the binomial theorem and $B\gamma^{9-\alpha_{ijm}}$ is the benefit from the parcel when no incentive is offered.

When focal parcel ($i$, $j$) is in agricultural use initially, it will not produce a core forest benefit unless it is converted to forest, which occurs with probability $P_m(s_m)$. The net expected benefit from the parcel under subsidy $s_m \geq s_0$ is written:

$$(5) \qquad \begin{aligned} E(B_{ijm}) &= BP_m(s_m)\left[\gamma\left(1 - P_m(s_m)\right) + P_m(s_m)\right]^{8-\alpha_{ijm}} \\ &= B\left(\frac{s_m - s_0}{\bar{q}_m - q_m^*}\right)\left[\gamma + (1-\gamma)\left(\frac{s_m - s_0}{\bar{q}_m - q_m^*}\right)\right]^{8-\alpha_{ijm}} \end{aligned},$$

where the benefit in the absence of the subsidy is zero. Define $\delta_{ijm} = 1$ if parcel ($i$, $j$) is initially in agricultural use and $\delta_{ijm} = 0$ if it is forested. Then, we obtain a single expression for the expected net benefit from the parcel under subsidy $s_m \geq s_0$:

$$(6) \qquad E(B_{ijm}) = \begin{cases} B\left(\frac{s_m - s_0}{\bar{q}_m - q_m^*}\right)^{\delta_{ijm}} \left[\gamma + (1-\gamma)\left(\frac{s_m - s_0}{\bar{q}_m - q_m^*}\right)\right]^{9-\alpha_{ijm}-\delta_{ijm}} - (1-\delta_{ijm})B\gamma^{9-\alpha_{ijm}} & s_m > s_0 \\ 0 & s_m \leq s_0 \end{cases}$$

Note that expected net benefits are a convex function of $s_m$.[11]

The social cost of the policy is the foregone rents from agriculture net of forest rents plus conversion costs.[12] For a change in parcel quality from $q_m^*$ to $q_m^* + s_m - s_0$, the expected social cost for parcel (*i*,*j*) is written:

(7) $$E(C_{ijm}) = \delta_{ijm} \int_{q_m^*}^{q_m^* + s_m - s_0} (R_{ijm}^a - R_{ijm}^f + s_0) f_m(q) dq ,$$

where the term $\delta_{ijm}$ sets expected costs to zero for parcels that are already forested. Substituting $f_m(q) = 1/(\overline{q}_m - \underline{q}_m)$ and $R_{ijm}^a - R_{ijm}^f = q - q_m^*$, (7) can be solved to obtain:

(8) $$E(C_{ijm}) = \delta_{ijm} \frac{(s_m^2 - s_0^2)}{2(\overline{q}_m - \underline{q}_m)} .$$

Equation (8) shows that expected costs are a function of the subsidy $s_m$ and conversion costs $s_0$. The term $s_m - s_0$ equals the payment needed to induce conversion to forest and, thus, equals the marginal opportunity cost of the policy.

*Solution to the Regulator's Targeting Problem*

The regulator's objective is to choose $s_m$, $m$ =1,…,*M*, to maximize expected net social benefits[13]:

(9) $$\max_{\{s_m\}} E[NSB] = \sum_{m=1}^{M} \sum_{i=1}^{N} \sum_{j=1}^{N} \left[ E[B_{ijm}(s_m)] - E[C_{ijm}(s_m)] \right],$$

subject to $0 \le s_m \le \overline{s}_m$. Note that differences among sections in the initial spatial pattern of forest will, in general, require the subsidy $s_m$ to vary by section. The upper bound on the afforestation incentive, $\overline{s}_m = \overline{q}_m - q_m^* + s_0$, corresponds to conversion of all of section *m* to forest. It is important to recognize that (9) 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 $\alpha_{ijm}$), 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.[14] 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.[15] 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 targeting problem in (9) is:

$$(10) \qquad \underbrace{\sum_{i=2}^{N-1}\sum_{j=2}^{N-1} E(MB_{ijm})}_{\textit{Expected marginal benefits}} - \underbrace{\frac{W_m}{\overline{q}_m - \underline{q}_m} s_m}_{\textit{Expected marginal costs}} \quad \begin{matrix} \leq 0 & s_m = s_0 \\ = 0 & s_0 \leq s_m \leq \overline{s}_m \\ \geq 0 & s_m = \overline{s}_m \end{matrix},$$

for $m$ =1,…,$M$. Subsidies smaller than $s_0$ are ignored since all such subsidies have no effect on land use. Expected marginal benefits ($EMB_m$) are computed by summing over the $(N\text{-}1)^2$ interior parcels in the section, where each term in the summation is the expected net marginal forest benefit from $(i,j)$ when the subsidy level is $s_m$:

$$(11) \quad E(MB_{ijm}) = \begin{cases} B\dfrac{1}{\overline{q}_m - q_m^*}\left(\delta_{ijm}\gamma + \phi_{ijm}\left(\dfrac{s_m - s_0}{\overline{q}_m - q_m^*}\right)^{\delta_{ijm}}\right)\left(\gamma + (1-\gamma)\dfrac{s_m - s_0}{\overline{q}_m - q_m^*}\right)^{8-\alpha_{ijm}-\delta_{ijm}} & s_m > s_0 \\ B\dfrac{1}{\overline{q}_m - q_m^*}\delta_{ijm}\gamma^{9-\alpha_{ijm}-\delta_{ijm}} & s_m = s_0 \end{cases},$$

where $\phi_{ijm} = (1-\gamma)(9-\alpha_{ijm})$. Under a mild assumption about the degree of fragmentation, $EMB_m$ is an increasing, convex function of $s_m$ for $s_m > s_0$:

ASSUMPTION 1. *For at least one parcel in section m,* $\alpha_{ijm} < 8$.

Assumption 1 says there is at least one block of nine parcels in the section that contains two or more agricultural parcels. Because expected costs for each agricultural parcel are the same (equation 8), expected marginal costs ($EMC_m$) are a simple function of the total number of agricultural parcels in the section, denoted $W_m$. Note that $EMC_m$ is a linear function of the subsidy $s_m$.

The convexity of expected marginal benefits and the linearity of expected marginal costs indicate that corner solutions are a possibility. The following conditions are used to define when corner solutions will occur:

CONDITION 1. $\dfrac{B}{\overline{q}_m - q_m^*}\sum_{i=2}^{N-1}\sum_{j=2}^{N-1}\gamma^{8-\alpha_{ijm}} < \dfrac{W_m}{\overline{q}_m - \underline{q}_m}s_0$

CONDITION 2. $\dfrac{2B(1-\gamma)}{\gamma(\overline{q}_m - q_m^*)^2}\sum_{i=2}^{N-1}\sum_{j=2}^{N-1}\gamma^{8-\alpha_{ijm}}(8-\alpha_{ijm}) > \dfrac{W_m}{\overline{q}_m - \underline{q}_m}$

The first condition implies that $EMB_m$ is less than $EMC_m$ at $s_m = s_0$. Condition 2 implies that the slope of $EMB_m$ exceeds the slope of $EMC_m$ at $s_m = s_0$. We can now state the following proposition:

PROPOSITION 1. (i) *If either Condition 1 or Condition 2 is satisfied, the optimal subsidy is* $s_m = s_0$ *or* $s_m = \bar{s}_m$. (ii) *The optimal subsidy in section m is* $s_m \in (s_0, \bar{s}_m)$ *only if both Condition 1 and Condition 2 are violated.*

The proof of Proposition 1 is found in an appendix. The proposition reveals that the conditions for a corner solution *within* a small landscape section are weaker than those for an interior solution. In a landscape comprised of many smaller sections, Condition 1 and Condition 2 would be evaluated for each section to determine the optimal subsidy payment specific to that section. While either Condition 1 or 2 is sufficient for a corner solution, both conditions must be violated for an interior solution. Moreover, violation of the conditions is not sufficient for an interior solution. The result is illustrated in Figure 1. The expected marginal benefits represented by $EMB_{m,1}$ and $EMB_{m,2}$ satisfy Condition 1. In case 1, a corner solution at $s_0$ is optimal because the marginal benefits of afforestation are always less than the marginal costs. Case 2 illustrates an example where an interior solution is a minimum rather than a maximum, as the second-order condition is violated at the intersection of $EMC_m$ and $EMB_{m,2}$. When the expected marginal benefits are represented by $EMB_{m,4}$, a corner solution at $\bar{s}_m$ occurs because $EMB_{m,4}$ satisfies Condition 2. Last, $EMB_{m,3}$ violates Conditions 1 and 2. The first intersection with $EMC_m$ is a potential interior optimum, though a corner solution at $\bar{s}_m$ is also possible in this case (e.g., if $EMB_{m,3}$ were to rise sharply following the second intersection with $EMC_m$). Note that the second-order condition is violated at the second intersection of $EMB_{m,3}$ and $EMC_m$, and so this cannot be a maximum.

The tendency for corner solutions is due to the convexity of expected marginal benefits and the linearity of expected marginal costs. Convexity results from the spatial process determining core forest benefits and the regulator's incomplete information. In combination, these two factors produce the exponential relationship in (11) between expected marginal benefits and the incentive payment. In contrast, expected marginal costs depend simply on the opportunity costs of each parcel and, thus, are a linear function of the incentive.

Inspection of Conditions 1 and 2 reveals whether corners solutions are more likely to occur at $s_m = s_0$ or $s_m = \overline{s}_m$. Consider a section with many agricultural parcels and few forested parcels. In this case, $W_m$ and $\overline{q}_m - q_m^*$ will be relatively large and $\sum_{i=2}^{N-1}\sum_{j=2}^{N-1}\gamma^{8-\alpha_{ijm}}$ will tend to be small since $8-\alpha_{ijm}$ will be large and $0 \le \gamma < 1$.[16] This suggests that Condition 1 will be satisfied and Condition 2 will be violated, indicating that expected marginal benefits will initially be below expected marginal costs and will likely remain there. This corresponds to a corner solution at $s_m = s_0$, as illustrated with the curve labelled $EMB_{m,1}$ in Figure 1. When there are a large number of forested parcels initially, the opposite result—Condition 1 is violated and Condition 2 is satisfied—is expected, corresponding to a corner solution at $s_m = \overline{s}_m$. This case is illustrated with the curve labelled $EMB_{m,4}$ in Figure 1. In the extreme case in which a section is so heavily forested that Assumption 1 does not hold, expected marginal benefits are constant for all values of $s_m$. Corner or interior solutions are possible depending on the relative magnitudes of $EMB_m$ and $EMC_m$.

A straightforward targeting rule is suggested by Proposition 1. Depending on the initial amount and configuration of forest land in a section, convert either all or none of the agricultural parcels to forest. The simplicity of this rule has obvious appeal from a practical policy standpoint. From theory, however, it is uncertain whether the conditions required for corner solutions will hold on actual landscapes. In other words, is one likely to find cases in which interior solutions are optimal, indicating a more complicated targeting rule? This question can only be answered with information on the magnitudes of expected benefits and costs. We turn, therefore, to an empirical application to clarify the targeting strategy.

**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, we compute expected total costs and benefits of the specific policies and use them to determine the optimal incentive level. A GIS-based landscape simulation is used to determine the effects of the policy on benefits derived from the spatial configuration of forest. In devising an empirical test of the theoretical framework, the simulation approach assumes that the regulator cannot observe parcel-scale land quality and cannot directly control the spatial configuration of land-use change.

*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 affected 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.[17] 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.

*Econometric Land-Use Model*

A conditional multinomial logit model of individual land-use choices, described in detail in LP, is estimated. The assumptions underlying the logit model are similar to those employed in the theoretical analysis of section 2. Private landowners allocate a homogeneous land parcel to one of three uses (agriculture, forest, or urban) to maximize net revenues minus conversion costs, where annualized net revenues from each use are a function of observable and unobservable factors. Differences in the unobservable components, corresponding to $q_{ijm}$ from above, are assumed to have a logistic distribution. The model is estimated with plot-level data from the U.S. Department of Agriculture's National Resources Inventory (NRI). The NRI provides 29,714 observations of land-use transitions over three periods (1982-87, 1987-92, 1992-97) for plots in North and South Carolina. These transitions are explained by average per-acre net revenues from each use ($\overline{\mathbf{NR}}_n$, where $n$ indexes counties), plot-level dummy variables indicating land capability class (**LCC**), and a plot-level dummy variable indicating urban influence status (*UI*). The estimation results yield expressions for the probability that a parcel changes from starting use $k$ ($k$=agriculture, forest) to ending use $l$ ($l$=agriculture, forest, urban) as a function of the conditioning variables and estimated parameters ($\hat{\boldsymbol{\beta}}_{kl}$),

$$P_{kln} = F(\overline{\mathbf{NR}}_n, \mathbf{LCC}, UI; \hat{\boldsymbol{\beta}}_{kl}) \tag{12}$$

where $F(\cdot)$ is a logistic function. We assume that parcels do not change out of urban use because no such transitions are observed in the data.

*Simulation of Forestation Incentives*

We simulate forestation[18] incentives in each section using the land-use transition probabilities in (12). The first step in this procedure is to link the probabilities to corresponding GIS data for the coastal plain of South Carolina. We obtain data layers on land use, county boundaries, land capability class, and urban influence status (details on the data are provided in LP). By overlaying these data, we identify spatially-distinct land parcels.[19] Each of our 244 sections has an average of 7,500 parcels averaging 5 acres in size. Using the same attributes—starting use, county, land capability class, and urban influence status—, each parcel in the GIS is matched to a set of transition probabilities from (12). These probabilities give the likelihood that the parcel will be allocated to ending use $l$ (agriculture, forest, or urban). In our simulations, the probabilities serve as sets of rules governing parcel-level changes in land use.

The probabilities in (12) are functions of the net revenue from forestry. As in the theoretical analysis, a per-acre afforestation subsidy ($s_m$) is added to forest net revenues for land starting in agriculture. In the simulation, we measure the effects of the subsidy relative to a baseline scenario with $s_m = 0$. The logistic specification in (12) results in baseline transition probabilities that lie within the unit interval, implying non-zero baseline land-use changes. 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 net revenues for land starting in forest. Similar to the theoretical model (equation 2), the two-part forestation incentive increases the probability that a parcel initially in agricultural use switches to forest and reduces the probability that a forest parcel moves to urban or agricultural use.

*Computing Expected Total Costs and Benefits*

We compute expected total costs at each level of the incentive. For this calculation, we need information on the expected forest area at each level of the incentive. For given $s_m$, the expected forest area in section $m$ is denoted $A_m^f(s_m)$, where $A_m^f(0)$ gives the expected baseline forest area. $A_m^f(s_m)$ and $A_m^f(0)$ are computed in two steps. First, the area of land in each parcel is multiplied by the corresponding probability, from (12), that the parcel will be allocated to forest.[20] When the incentive $s_m$ is given, the probability is modified in the manner described above. Second, these products are summed to obtain the expected forest areas for each section and incentive level. For incentive $s \geq 1$, expected marginal costs in section $m$ are given by:

$$EMC_m(s) = \frac{sA_m^f(s) - (s-1)A_m^f(s-1)}{A_m^f(s) - A_m^f(s-1)}. \tag{13}$$

Because $s$ is equal to the opportunity cost of the last parcel converted to or retained in forest, the numerator in (13) 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.

We increase $s_m$ in \$1 increments up to the point at which all land besides urban and other land is forested.[21] We refer to this maximum amount of forest as the *potential forest area*. Three issues deserve further comment. First, because we have limited information on conversion costs ($s_0$), we assume they equal zero. This implies that $EMC_m = 0$ at $s_m = 0$, a point we return to below. Second, reaching the potential forest area requires that we simulate incentive levels outside the range of our data.[22] This is an unavoidable limitation of our analysis. Third, the logit specification used for our econometric model implies that changes in forest area are a concave function of the incentive, and therefore, the marginal cost function becomes convex 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.[23] It is assumed that any remaining landowners will not convert to forest, no matter the incentive offered. 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 on marginal costs. The functions fit the data extremely well, with $R^2$ statistics exceeding 0.99 in all cases.

To derive expected total benefits, we compute the expected number of core forest parcels, which requires knowledge of the spatial pattern of forest in each section. There are many ways in which the spatial pattern can change that will be consistent with the underlying transition rules. Thus, to capture this variation we simulate a large number of landscapes. To illustrate the approach, suppose that the value of the agriculture-to-forest transition probability is 0.20 for a particular parcel. Then, the owner of the parcel will convert to forest 20% of the time if the choice occasion is repeated enough times. To conduct the simulations, a random number generator is used to repeat the choice occasion five hundred times[24] for each parcel in the landscape.[25] The ending use for each parcel will, on average, satisfy the underlying transition probabilities (e.g., conversion to forest 20% of the time). 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 $\Delta Core_m(s_m) = Core_m(s_m) - Core_m(0)$. 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.

To derive total expected benefits, we focus on a limiting case of the benefit function in (1) in which $\gamma = 0$ for $\alpha_{ijm} = 0,1,...,8$. This implies that a forested parcel provides the core forest benefit *B* only when it is completely surrounded by other forested parcels. This assumption is consistent with the definition of core forest used in the ecology literature, and also greatly reduces computational costs because it allows us to quickly compute landscape metrics within Fragstats.[26] Our assumption about benefits, together with the assumption from above that $s_0 = 0$, implies that $EMB_m$ is greater than or equal to $EMC_m$ at $s_m = 0$. In addition, the slope of $EMB_m$ may be greater than, equal to, or less than the slope of $EMC_m$ at this point. As such, we avoid making any assumptions in the empirical analysis that predetermine a finding of corner or interior solutions.

*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 social benefits, as in (9), 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 \$15 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.

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 social benefits are greatest. This approach ensures that we find a maximum and not a minimum. The first set of results, in the top part of Table 1, indicate the prevalence of near-corner solutions – the targeting solution is close to, but not exactly at, the corner. For varying values of $\tilde{B}$, we report the percentage of the potential forest area that is forested under the targeted policy. The first entry indicates that for approximately 92% of the sections, less than 10% of the potential forest area should be forested when $\tilde{B}$ equals \$15. 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 converted forest areas between 10% and 90% of potential forest. At $\tilde{B}$=\$75, the targeted policy generates a forest area for 91% of the sections that is either less than 10% or greater than 90% of the potential forest area. 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 targeted 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 social benefits (Table 1). 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, a result related to the percolation threshold in landscape ecology (Burel and Baudry 2003). 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 social 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 targeted policy for each level of $\tilde{B}$ was taken as a fixed budget. Then, we solved for the uniform incentive that increases forest area at a social cost equal to the fixed budget. This approach ensures that the social cost of the targeted and uniform policies are identical for each level of $\tilde{B}$. Results are presented at the bottom of table 1. 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 targeted policy. However, because the uniform policy disregards the benefits of core forest, it produces far fewer core forest acres than the targeted 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 targeted policy. Also of note are the negative net social benefits of the uniform policy for all levels of $\tilde{B}$ except \$25. The differences in net social benefits are striking. At $\tilde{B}$=\$75, net social benefits are \$29.4 million under the targeted policy and -\$15.2 million under the uniform policy. Even when net social benefits are positive under the uniform policy, they are over three times higher with the targeted policy.

To better understand how the incentive is allocated under the targeted policy, we examine characteristics of the sections for which a large share of potential forest is converted (Table 2). Each entry in Table 2 is calculated by averaging the characteristics of sections for which either less than 70% of potential forest is forested under the targeted policy or more than 70% is forested. The results reveal that the sections targeted for a large (small) amount of forest under the targeted policy tend to have more forest (agricultural land) in the baseline, a finding predicted by our theoretical model. In percentage terms, the largest difference between the two groups of sections is in the initial amount of forest. More forestation also occurs in sections with more land that can be forested (i.e., greater potential forest), lower agricultural returns, and higher forest returns. 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. Potential forest area is reduced in sections with significant amounts of urban and other land, and this makes it less likely that the steep portion of the marginal benefit curve will ever be reached. The main implication of our results is that efficiency gains are greatest from targeting effort to landscapes with significant amounts of existing forest, as opposed to undertaking massive afforestation efforts on landscapes with little forest.

*Comparison to a 'Core Only' Policy*

An alternative policy mechanism is to only pay for parcels that create at least one new core forest parcel upon conversion. Since the regulator can observe which parcels are forested initially, the payment can be refused if conversion of the parcel will not create new core forest. There are multiple ways to structure such a policy mechanism[27] and a thorough treatment of alternative policy designs is beyond the scope of this paper. The most straightforward approach is to restrict the subsidy offer in period $t$ to those parcels that create new core forest upon conversion, update the set of eligible parcels in $t$+1 to reflect the changes that occurred in period $t$, and repeat. While this 'core only' policy has an obvious strength of only paying for core forest, its efficiency relative to the targeted policy examined above is unclear. The targeted policy may convert some parcels that do not create new core forest. However, by allowing a larger set of eligible parcels than the 'core only' policy, it has the potential to create large areas of new core forest at low cost by converting entire sections of low-cost parcels to forest.

We use the empirical model to compare the performance of the two policies. Empirical implementation of the 'core only' policy proceeds over a 30-year time period in 5-year increments with the following steps. First, the set of eligible parcels is identified. Parcel $i$ is eligible to receive $s$ if upon conversion to forest, either parcel $i$ or one of its neighbors becomes a core forest parcel. Second, the forest transition probability for eligible parcels is augmented with the per-acre afforestation subsidy $s_m$ while all other transition probabilities remain at the baseline values ($s_m$=0). Third, we simulate land-use decisions for all parcels, as above. Fourth, we re-calculate the set of eligible parcels accounting for the transitions that occur during the 5-year interval. We repeat this process for six intervals, keeping the subsidy rate the same, and calculate the amount of core forest at the end of 30 years.[28] The entire process is repeated 500 times and for multiple values of $s_m$, yielding a distribution of core forest area for each level of the incentive. As above, we use this information to identify marginal cost and benefit functions.

Simulating this 'core only' policy is extremely expensive computationally because of the need to repeatedly calculate the land uses of *each* parcel's neighbors. Thus, we illustrate the performance of this policy by examining three sections that vary in their initial landscape conditions. Since the share of initial forest cover strongly affects the performance of the targeted policy, we select landscapes with 35%, 50%, and 75% initial forest cover. Expected benefit and cost curves are estimated for the 'core only' policy as described above and, for comparison, we also derive the targeted solution on the same three landscapes. We compare the relative efficiency of the two policies by fixing $\widetilde{B}$ and converting land to forest under each policy approach until expected net social benefits are greatest.

The results are presented in Table 3 for different levels of $\widetilde{B}$. The 'core only' policy generates higher net social benefits than the targeted policy for low values of $\widetilde{B}$ (\$15 through \$35), but the targeted policy generates higher net social benefits at higher levels of $\widetilde{B}$. The targeted policy converts most of the agricultural land to forest on the section with more initial forest, while converting little land to forest in the sections with less initial forest. While the 'core only' policy consistently has a high ratio of core forest to forest acres converted, the limited set of eligible parcels constrains the overall amount of new core forest created at high levels of $\widetilde{B}$. Results in table 3 also demonstrate the importance of the initial amount of forest cover in determining whether the targeted or 'core only' policy is more efficient. For landscape sections with low amounts of initial forest, the 'core only' policy is more efficient because it ensures that newly forested parcels will create core forest. In contrast, the targeted policy is more efficient on landscape sections that have high amounts of initial forest, as the set of eligible parcels is larger under the targeted policy and newly afforested parcels are likely to be adjacent to forested neighbors. Further, when examining landscape sections with significant amounts of initial forest, the difference in net social benefits between the targeted and 'core only' policy is increasing in the value of core forest. This analysis demonstrates that the targeted policy – offering a uniform subsidy payment to all agricultural parcels *within* sections but varying the payment *across* sections – can be more efficient than the "core only" policy, especially for landscape sections with significant amounts of initial forest.

**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 wildlife 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 omniscient 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 social 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 this analysis is that corner solutions are likely to be optimal because of the convexity of expected marginal benefits. While Boscolo and Vincent (2003) show how fixed logging costs and administrative constraints can lead to spatial specialization in the management of lands for forestry and biodiversity, the convexity of marginal benefits in this paper 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 near-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.

When combined with results from the earlier work of Lewis and Plantinga (2007), this paper provides insights into the importance of scale in the design of spatially-targeted conservation policies. While targeting policies at the parcel scale has the potential advantage of limiting payments for spatially-clustered habitat, such approaches can be expensive because they restrict the regulator's set of eligible parcels. Offering spatially uniform payments *within* sections of the landscape, but allowing them to vary *across* sections, increases the set of eligible parcels and has the potential to create large sections of new core habitat. Results derived in this paper highlight the efficiency gains of such a targeting approach. Future research could consider mechanisms that might improve the efficiency of fine-scale targeting by encouraging coordination across landowners (e.g. Parkhurst et al. 2002; Warziniack, Shogren and Parkhurst 2007)

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,[29] one common targeting scheme is to offer payments only to individuals whose parcels lie in pre-defined portions of the landscape,[30] 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, our results suggest efficiency gains from employing a simple targeting rule 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 significant amounts of existing forest, more land available to be forested, and relatively higher returns to forest. 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 social benefits relative to an incentive applied uniformly across the landscape and, in some cases, to outperform a policy focused only on converting parcels that will create core forest.

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. From a theoretical perspective, as long as the marginal net benefits of afforestation subsidies differ within a section, dividing it into smaller geographic 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.

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## Appendix

PROOF OF PROPOSITION 1: The proof of part (i) relies on the properties of expected marginal benefits and costs: (a) $EMB_m$ is an increasing, convex function of $s_m$ and (b) $EMC_m$ is an increasing, linear function of $s_m$. If Condition 1 holds, (a) and (b) imply there is at most one value of $s_m \in (s_0, \bar{s}_m)$ at which $EMB_m = EMC_m$. At the point of equality, (a) and (b) imply $dEMB_m / ds_m > dEMC_m / ds_m$, which violates the second-order condition for a maximum. Therefore, Condition 1 is a sufficient condition for a corner solution. If Condition 2 holds, then the properties of (a) and (b) imply that $EMB_m = EMC_m$ for $s_m \in (s_0, \bar{s}_m)$ is possible only if Condition 1 is satisfied. Therefore, Condition 2 is a sufficient condition for a corner solution. Part (ii) follows immediately from part (i). Either Condition 1 or Condition 2 is sufficient for a corner solution. Therefore, violation of both conditions is necessary for an interior solution.

Table 1: Landscape Conversion under the Targeted vs. Uniform Policies

| **Percentage of Potential Forest Converted** | **Percent of Landscapes (Quads) in Each Category under the Targeted Policy** | | | | | | |
|---|---|---|---|---|---|---|---|
| | $\tilde{B}$ **=\$15** | $\tilde{B}$ **=\$25** | $\tilde{B}$ **=\$35** | $\tilde{B}$ **=\$45** | $\tilde{B}$ **=\$55** | $\tilde{B}$ **=\$65** | $\tilde{B}$ **=\$75** |
| 0%-10% | 91.80% | 85.19% | 80.25% | 72.02% | 63.37% | 55.97% | 48.56% |
| 10%-20% | 6.56% | 2.47% | 3.29% | 5.35% | 4.53% | 2.88% | 1.65% |
| 20%-30% | 0.82% | 4.53% | 1.23% | 0.82% | 0.41% | 1.23% | 0.41% |
| 30%-40% | 0.00% | 1.65% | 0.41% | 1.23% | 0.00% | 0.41% | 0.41% |
| 40%-50% | 0.41% | 3.70% | 0.82% | 0.00% | 0.41% | 0.41% | 0.00% |
| 50%-60% | 0.00% | 2.06% | 2.47% | 0.41% | 0.41% | 0.41% | 0.00% |
| 60%-70% | 0.00% | 0.00% | 2.88% | 0.41% | 1.23% | 0.82% | 0.41% |
| 70%-80% | 0.00% | 0.41% | 6.58% | 3.70% | 1.65% | 0.82% | 2.06% |
| 80%-90% | 0.00% | 0.00% | 2.06% | 11.52% | 8.64% | 2.88% | 4.12% |
| 90%-99% | 0.00% | 0.00% | 0.00% | 4.53% | 18.93% | 28.81% | 30.86% |
| 100% | 0.00% | 0.00% | 0.00% | 0.00% | 0.41% | 5.35% | 11.52% |
| **Targeted Policy** | | | | | | | |
| Increase in forest acres | 32,043 | 79,382 | 138,870 | 224,098 | 370,131 | 523,647 | 722,805 |
| Increase in core acres | 39,879 | 101,138 | 207,308 | 377,034 | 665,605 | 951,235 | 1,281,199 |
| Ratio of core to forest acres | 1.24 | 1.27 | 1.49 | 1.68 | 1.80 | 1.82 | 1.77 |
| Total Cost (1000s) | \$395 | \$1,640 | \$4,858 | \$11,753 | \$26,380 | \$43,570 | \$66,632 |
| Net Social Benefits (1000s) | \$202 | \$888 | \$2,396 | \$5,212 | \$10,227 | \$18,259 | \$29,457 |
| **Uniform Policy** | | | | | | | |
| Increase in forest acres | 46,020 | 114,482 | 210,551 | 352,220 | 598,956 | 837,352 | 1,092,374 |
| Increase in core acres | 31,801 | 76,157 | 133,419 | 210,744 | 340,769 | 484,049 | 686,391 |
| Ratio of core to forest acres | 0.69 | 0.67 | 0.63 | 0.60 | 0.57 | 0.58 | 0.63 |
| Total Cost (1000s) | \$395 | \$1,640 | \$4,858 | \$11,753 | \$26,380 | \$43,570 | \$66,632 |
| Net Social Benefits (1000s) | \$81 | \$263 | -\$189 | -\$2,270 | -\$7,638 | -\$12,107 | -\$15,153 |

Table 2: Average Landscape Characteristics for Targeted 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% | \$15 | 63.17% | 89.43% | \$40.03 | \$12.70 | \$1,429.75 |
| | \$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% | \$15 | NA | NA | NA | NA | NA |
| | \$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 targeted policy or more than 70% is forested.

Table 3. Landscape Conversion under the Targeted vs. ‘Core Only’ Policies on Selected Landscapes

| | $\tilde{B}$=\$15 | $\tilde{B}$=\$25 | $\tilde{B}$=\$35 | $\tilde{B}$=\$45 | $\tilde{B}$=\$55 | $\tilde{B}$=\$65 | $\tilde{B}$=\$75 |
|---|---|---|---|---|---|---|---|
| **Targeted Policy** | | | | | | | |
| | -----------------------------% Potential Forest Converted--------------------------- | | | | | | |
| 75% Initial Forest | 16.96% | 30.78% | 50.24% | 82.21% | 88.73% | 93.08% | 96.76% |
| 50% Initial Forest | 2.25% | 3.49% | 4.82% | 6.24% | 7.80% | 9.52% | 11.50% |
| 35% Initial Forest | 1.90% | 2.68% | 3.50% | 4.34% | 5.22% | 6.15% | 7.12% |
| | -------------------------------Increase in Core Forest (Acres)----------------------- | | | | | | |
| 75% Initial Forest | 1,038 | 2,070 | 3,940 | 9,636 | 11,237 | 12,203 | 12,931 |
| 50% Initial Forest | 59 | 113 | 172 | 237 | 308 | 390 | 485 |
| 35% Initial Forest | 25 | 46 | 67 | 89 | 113 | 138 | 165 |
| | --------------------------------------Net Social Benefits----------------------------- | | | | | | |
| 75% Initial Forest | \$7,015 | \$22,228 | \$50,898 | \$121,437 | \$226,748 | \$344,221 | \$470,030 |
| 50% Initial Forest | \$339 | \$1,197 | \$2,622 | \$4,663 | \$7,383 | \$10,864 | \$15,222 |
| 35% Initial Forest | \$159 | \$512 | \$1,074 | \$1,855 | \$2,866 | \$4,120 | \$5,632 |
| Total | \$7,513 | \$23,937 | \$54,594 | \$127,955 | \$236,997 | \$359,205 | \$490,883 |
| **‘Core Only' Policy** | | | | | | | |
| | -----------------------------% Potential Forest Converted--------------------------- | | | | | | |
| 75% Initial Forest | 12.86% | 14.95% | 16.19% | 17.13% | 17.90% | 18.57% | 19.16% |
| 50% Initial Forest | 1.98% | 3.37% | 4.68% | 5.84% | 6.84% | 7.71% | 8.48% |
| 35% Initial Forest | 1.81% | 3.10% | 4.30% | 5.34% | 6.22% | 6.97% | 7.63% |
| | -------------------------------Increase in Core Forest (Acres)----------------------- | | | | | | |
| 75% Initial Forest | 1,411 | 1,634 | 1,766 | 1,865 | 1,947 | 2,018 | 2,081 |
| 50% Initial Forest | 322 | 544 | 751 | 931 | 1,085 | 1,217 | 1,332 |
| 35% Initial Forest | 295 | 503 | 696 | 862 | 1,001 | 1,119 | 1,222 |
| | --------------------------------------Net Social Benefits----------------------------- | | | | | | |
| 75% Initial Forest | \$5,456 | \$20,828 | \$37,866 | \$56,041 | \$75,116 | \$94,951 | \$115,451 |
| 50% Initial Forest | \$2,440 | \$6,774 | \$13,272 | \$21,708 | \$31,808 | \$43,331 | \$56,084 |
| 35% Initial Forest | \$2,192 | \$6,184 | \$12,204 | \$20,018 | \$29,349 | \$39,962 | \$51,677 |
| Total | \$10,088 | \$33,786 | \$63,342 | \$97,768 | \$136,274 | \$178,244 | \$223,213 |

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

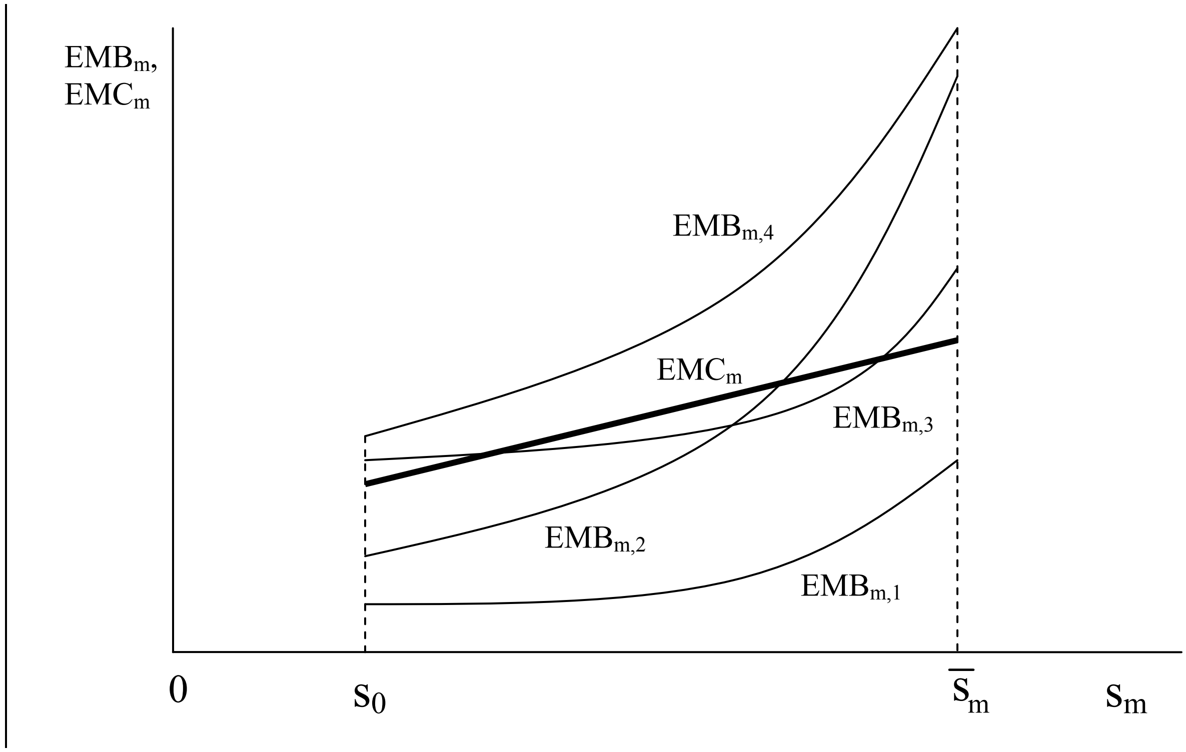
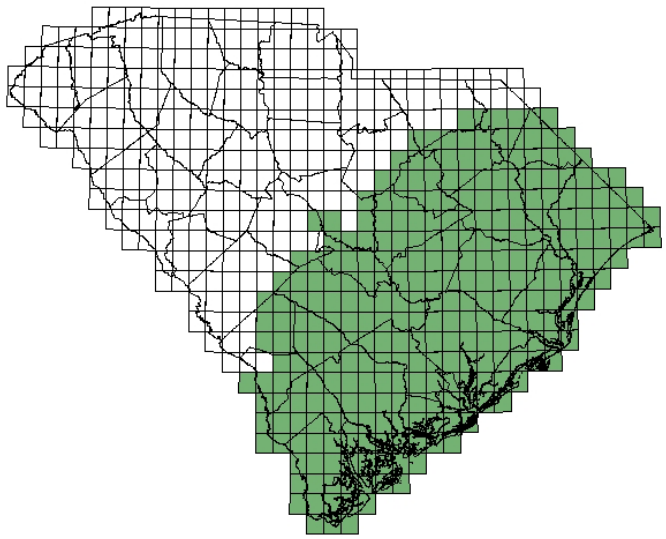


Figure 2. The Coastal Plain of South Carolina (in Green) with Overlay of USGS Quads



Footnotes

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

[2] Other work looking at species persistence probabilities has focused on optimally changing wildlife habitat (e.g. see Polasky et al. 2008).

[3] 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.

[4] 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.

[5] While LP demonstrated their empirical methodology by simulating landscape-scale fragmentation outcomes for a baseline landscape and a landscape subject to a $25 uniform afforestation subsidy, computational restrictions limited their marginal cost analysis to a smaller set of three sections.

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

[7] Rents are determined exogenously. Mean rents can vary across sections due to differences in the distributions of parcel quality (see below).

[8] 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.

[9] 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.

[10] We assume no land-use changes in the absence of the policy (i.e., there are no changes in $q_m^*$). The 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.

[11] We are ignoring the degenerate case in which all parcels are forested initially ($9-\alpha_{ijm}=0$). This case is rule out by construction when $\delta_{ijm}=1$.

[12] This specification of costs ignores the option value of future development. See Schatzki (2003) for an analysis of the effects of option values on land-use change decisions.

[13] Under a spatially-uniform policy, we would require $s_m$ to be the same in each section. A straightforward implication of Samuelson's Le Chatelier Principle is that this constraint, if binding at the optimum, will reduce expected net social benefits.

[14] 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 $7.9\times10^{269}$ possible ways to afforest 100 parcels.

[15] For numerical problems, an alternative to enumeration is the use of heuristic algorithms (see, for example, Nalle et al. 2004 and Polasky et al. 2008). These algorithms can be used to improve on sub-optimal solutions, but do not guarantee an optimal solution.

[16] The effect of a larger $8-\alpha_{ijm}$ on the $\sum_{i=2}^{N-1}\sum_{j=2}^{N-1}\gamma^{8-\alpha_{ijm}}(8-\alpha_{ijm})$ term in Condition 2 is ambiguous.

[17] 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.

[18] The term “forestation” is used to refer to both afforestation (the conversion of non-forest land to forest) and avoided deforestation (the retention of land in forest).

[19] An additional data layer on ownership is used to remove publicly-owned parcels.

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

[21] Land in other uses includes public lands and any land not classified as agriculture, forest, or urban.

[22] For example, 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.

[23] Our criteria for “negligible” is defined as the point at which the change in the slope of the marginal cost curve exceeds one. Further increases in the subsidy beyond this point have essentially no effect on forest area.

[24] 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).

[25] 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.

[26] Fragstat computes the number of core forest parcels, but its output does not include the number of forested neighbors for each parcel, information that would be needed to compute benefits when $0 < \gamma < 1$. Obtaining this information by other methods (see the 'core only' policy below) is prohibitively costly given the large number of sections analyzed.

[27] See Parkhurst et al. (2002) and Warziniack, Shogren and Parkhurst (2007) for analyses of agglomeration bonuses for conservation of private land and the role played by communication across landowners.

[28] Note that it is possible for a parcel that is core in early periods to leave core forest status by year 30 due to conversions out of forest by neighboring parcels.

[29] 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.

[30] 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.