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The Efficiency of Voluntary Incentive Policies for Preventing Biodiversity Loss

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The Efficiency of Voluntary Incentive Policies for Preventing Biodiversity Loss

Abstract: In this paper we analyze the efficiency of voluntary incentive-based land-use policies for biodiversity conservation. Two factors combine to make it difficult to achieve an efficient result. First, the spatial pattern of habitat across multiple landowners is important for determining biodiversity conservation results. Second, the willingness of private landowners to accept a payment in exchange for enrolling in a conservation program is private information. Therefore, a conservation agency cannot easily control the spatial pattern of voluntary enrollment in conservation programs. We begin by showing how the distribution of a landowner's willingness-to-accept a conservation payment can be derived from a parcel-scale land-use change model. Next we combine the econometric land-use model with spatial data and ecological models to simulate the effects of various conservation program designs on biodiversity conservation outcomes. We compare these results to an estimate of the efficiency frontier that maximizes biodiversity conservation at each level of cost. The frontier mimics the regulator's solution to the biodiversity conservation problem when she has perfect information on landowner willingness-to-accept. Results indicate that there are substantial differences in biodiversity conservation scores generated by the incentive-based policies and efficient solutions. The performance of incentive-based policies is particularly poor at low levels of the conservation budget where spatial fragmentation of conserved parcels is a large concern. Performance can be improved by encouraging agglomeration of conserved habitat and by incorporating basic biological information, such as that on rare habitats, into the selection criteria.

Keywords: biodiversity, land use, conservation, spatial modeling, wildlife.

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1. Introduction

Preventing the loss of biodiversity in the face of an expanding human population and growing economy is a formidable challenge, but failure to do so could have dramatic consequences (Levin 1999, Wilson 1988). In terrestrial ecosystems, land-use change is the leading driver of biodiversity loss, and is expected to remain so in the future (Millenium Ecosystem Assessment 2005, Sala et al. 2000, Wilcove et al. 2000). Much of the habitat important for biodiversity conservation occurs on privately-owned land. One study found that 70% of species listed under the U.S. Endangered Species Act (ESA) depend on non-federal land, most of which is privately-owned, for the majority of their habitat (Natural Heritage Data Center Network 1993). On privately-owned lands, voluntary incentives are the most common mechanism used to encourage the provision of species habitat. For example, the Conservation Reserve Program (CRP) and the Wildlife Habitat Incentives Program (WHIP) provide payments to private landowners in exchange for dedicating their land to habitat conservation. Conservation easements are the dominant mechanism used by land trusts and conservation organizations for habitat preservation (Kiesecker et al. 2007, Plantinga 2007, Rissman et al. 2007). Further, while the ESA still operates much like a traditional regulatory policy, conservation banking was adopted to give private landowners greater flexibility in managing wildlife habitat (U.S. Fish and Wildlife Service 2003).

In this paper, we examine the efficiency of policies for species conservation using voluntary agreements with private landowners. We combine econometric models of landowner decisions with biological models that predict species persistence as a function of the spatial pattern of land use. We use observed land-use decisions to specify an econometric model of land-use choice and develop a method to recover the distribution of a landowner's willingness-to-accept

(WTA) a conservation payment for each parcel on the landscape. The method is generally applicable when parcel-level land-use decisions are observed, but information on the net returns to alternative land uses is only available at a higher spatial scale.

We then use estimated landowner WTA to simulate landowner responses to a range of incentive-based habitat conservation policies. In each case, we assume asymmetric information between landowners and the regulator. Landowners know their own WTA, but regulators know only the distribution of WTA. Simulated land-use patterns are used as inputs into a spatially-explicit biological model to generate persistence probabilities for a set of terrestrial species of conservation concern. We compare outcomes under incentive-based policies with an estimate of the efficiency frontier that maximizes the biodiversity score at each level of cost. The efficiency frontier mimics the solution of a fully-informed regulator whose goal is to maximize social welfare given a range of values for biodiversity conservation. The difference in biodiversity scores between the incentive-based policies and the optimal policy indicates the potential gains from gathering information on landowner-specific WTA.

Our analysis connects two strands of literature on habitat conservation policy. Systematic conservation planning (SCP; Margules and Pressey 2000) considers the optimal choice of habitats to preserve for species conservation subject to a constraint on the total area conserved or total budget allotted (e.g., Camm et al. 1996, Church et al. 1996, Csuti et al. 1997, Kirkpatrick 1983, Vane-Wright et al. 1991).[1] Extensions of the basic optimization problem incorporate land costs (e.g., Ando et al. 1998, Balmford et al. 2000, Polasky et al. 2001), considerations of compactness or contiguity (e.g., Fischer and Church 2003, Onal and Briers 2003), and dynamics (e.g., Costello and Polasky 2004, Meir et al. 2004, Newburn et al. 2006, Strange et al. 2006). As it has matured, the SCP literature has incorporated more complex analysis of spatial patterns that affect species persistence, including habitat fragmentation and dispersal ability (e.g., Cabeza and Moilanen 2003, Moilanen et al. 2005, Jiang et al. 2007, Nalle et al. 2004, Nicholson et al. 2006, Polasky et al. 2005, 2008). Significantly, the SCP literature has not addressed issues of conservation plan implementation with asymmetric information. In theory, an optimal solution could be successfully implemented by a conservation agency that had complete information and the power to dictate land-use decisions. This description may be a reasonable characterization of the problem faced by public land managers, but it is unrealistic when applied to a landscape with a significant number of private landowners.

The second strand of literature examines the use of incentive-based policies for voluntary habitat conservation on privately-owned land. Unlike the SCP literature, asymmetric information is a central element in these studies. The literature includes analyses of payments under fixed price contracts, conservation auctions, and regulatory approaches (Connor et al. 2008, Feng 2007, Ferraro 2008, Innes et al. 1998, Latacz-Lohmann and Van der Hamsvoort 1997, Polasky 2001, Polasky and Doremus 1998, Smith and Shogren 2002, Stoneman et al. 2003, Kirwan et al. 2005, Wu and Babcock 1995, 1996). Regulatory approaches to habitat conservation tend to work poorly when landowners have the ability to act on private information (Polasky and Doremus 1998). Among voluntary approaches in which landowners are paid for enrolling in conservation programs, evidence from experiments reveals that conservation auctions tend to be more efficient than fixed price contracts when regulators lack full information about landowner payoffs (Cason and Gangadharan 2004, Schillizzi and Latacz-Lohmann 2007).

One component of the SCP literature that the voluntary habitat conservation literature has only just begun to consider explicitly is the role of habitat pattern in biodiversity conservation. Because effective biodiversity conservation often requires large amounts of habitat, it is important to coordinate conservation decisions across multiple landowners. Several papers have investigated policies that make payments to landowners a function of the decisions of neighboring landowners (e.g., Parkhurst et al. 2002, Parkhurst and Shogren 2007). In work closer to the present paper, Lewis and Plantinga (2007) combine an econometric model of landowner decisions with GIS-based landscape simulations to examine the ability of simple incentive policies to reduce habitat fragmentation in South Carolina. Using a biological model that considers habitat pattern and species' ability to disperse across patches of habitat, Nelson et al. (2008) compare species conservation outcomes under five simple policy alternatives with efficient solutions.

In this paper, we bring together the strength of the SCP literature—spatially-explicit models of biological benefits—with the strength of the literature on incentive-based policies—realistic informational and political constraints—to analyze the relative efficiency of various incentive-based policies for conservation. We apply our methods using data from the Willamette Basin of Oregon. We analyze how close voluntary incentive-based policies come to achieving efficient species conservation solutions when the spatial pattern of conservation matters and landowners have private information about WTA. The answer to this question can help identify the most promising policies from among the set of alternative voluntary incentive approaches and shed light on what type of information, biological or economic, is most important in improving the design of policies. We find that incentive-based policies tend to achieve only a small portion of the potential conservation gains when landowners have private information about WTA. However, the performance of incentive-based policies relative to the efficient result with full information tends to improve as the conservation budget increases. In addition, we find that encouraging agglomeration of habitat and adding biological criteria to the policy design, particularly the targeting of rare habitat types, can yield large improvements in performance.

2. Simulating Responses to Conservation Incentives

In this section, we describe the development of an econometric land-use model and its use in a simulation of responses by private landowners to incentive-based conservation policies. A random parameters logit (RPL) model is estimated with panel data from Oregon and Washington on private land-use decisions, net revenues from alternative uses, and parcel characteristics. In the non-market valuation literature, random utility models are commonly used to measure compensating surplus for changes in environmental quality (Freeman 2003). We adapt this approach to recover the distribution of maximum net revenue for each parcel on the landscape. A parcel's maximum net revenue is assumed to represent the landowner's WTA a conservation payment in exchange for restoring their land to its native pre-Euro-American settlement land cover. A landscape simulation is used to determine the response to conservation incentives on each parcel. The simulation algorithm integrates the WTA distributions from the econometric analysis with spatially-explicit data on land parcels in the Willamette Basin of Oregon.

2.1 Econometric Model

Landowners are assumed to allocate a land parcel of uniform quality to the use that maximizes the present discounted value of expected net revenues minus conversion costs. Landowners consider current and historic values of net revenues to form static expectations of future returns. The assumption of static expectations yields a simple decision rule under which the use generating the greatest annualized net revenues net of conversion costs is chosen (Plantinga 1996). The annualized net revenue from each use is specified as a function of deterministic and random factors.[2] For parcel i that begins period t in use j and ends period t in use k, real annualized net revenues (R_{ikt}) less annualized conversion costs (rC_{ijkt}) are:

$$R_{ikt} - rC_{ijkt} = \alpha_{jk} + \sigma_{1jk}\varpi_{1c(i)jk} + \sigma_{2jk}\varpi_{2ijk} + \beta_{0jk}R_{c(i)kt} + \beta_{1jk}LCC_i R_{c(i)kt} + \varepsilon_{ijkt}, \qquad (1)$$

for all uses k=1,…,K and time periods t=1,…,T, where $(\alpha_{jk}, \sigma_{1jk}, \sigma_{2jk}, \beta_{0jk}, \beta_{1jk})$ are parameters, $(R_{c(i)kt}, LCC_i)$ are observable explanatory variables, and $(\varepsilon_{ijkt}, \varpi_{1c(i)jk}, \varpi_{2ijk})$ are random variables. $R_{c(i)kt}$ is the average net revenue from use k at time t in the county $c(i)$ where parcel i is located and LCC_i indicates the productivity, as measured by the Land Capability Class (LCC) rating, of parcel *i*.[3] The interaction of $R_{c(i)kt}$ and LCC_i allows the net revenue for parcel *i* to deviate from the county average net revenue. Real annualized conversion costs (rC_{ijkt}) are assumed to be constant across parcels and time and are measured implicitly in the estimates of the constant terms α_{jk}.

As in a standard logit model, the random terms ε_{ijkt} are assumed to have a type I extreme value distribution with a common scale parameter ξ_j for all *k* uses. The terms $\varpi_{1c(i)jk}$ and ϖ_{2ijk} are standard normal random variables specific to county $c(i)$ and parcel *i*, respectively. Thus, $\sigma_{1jk}\varpi_{1c(i)jk}$ and $\sigma_{2jk}\varpi_{2ijk}$ are error components that allow correlation of net revenues in the spatial dimension (all parcels within a county share a common $\varpi_{1c(i)jk}$ term) and the temporal dimension (each parcel has a common ϖ_{2ijk} term across periods).

The RPL model is estimated with maximum simulated likelihood using data for Oregon and Washington west of the crest of the Cascade Mountains. We include data from areas outside of the Willamette Basin to increase variation and the number of observations. The main data source is the National Resources Inventory (NRI), which provides 15,356 repeated plot-level observations of land use for 1982, 1987, 1992, and 1997, as well as the LCC rating of each plot. We focus on the major private land uses within the region: cropland, pasture, forest, and urban. These private land uses account for approximately two-thirds of the total land area in the Willamette Basin (most of the remaining land is owned by the federal government). County-level estimates of annual net revenues from these uses are taken from Lubowski (2002) and discussed in greater detail in Lubowski *et al*. (2006). The net revenues from forest are measured as annualized revenues from timber production less management costs. Agricultural net revenues equal the annual revenue from crop and pasture production less costs and plus government payments. The forest and agricultural net revenues are county averages reflecting the existing mix of timber types and crops and their associated yields. Net revenues from urban land are measured as the annualized median value of a recently-developed parcel used for a single-family home, less the value of structures. Landowners are assumed to form expectations of future net revenues by computing the average of annual net revenues over the preceding five-year period.

The NRI data reveal that no plots leave urban use and a very small percentage leave forest use between 1982 and 1997. Thus, we focus on modeling the parcels that begin the periods 1982-1987, 1987-1992, or 1992-1997 in crop and pasture uses. Separate models are estimated for each starting use with a total of 3,504 pooled observations for crops and 4,637 pooled observations for pasture. We have too few observations within the LCC categories to estimate the full set of interaction terms in (1) and, therefore, must place restrictions on β_{1jk} parameters. For the models that describe cropland and pasture conversion to use *k* we collapse the eight LCC categories into three categories: LCC 1,2, LCC 3,4, and LCC 5,6,7,8. We estimate interaction terms for net revenues and the combined LCC 3,4 and LCC 5,6,7,8 (LCC 1,2 is the omitted category).

A well-known property of logit models is that the scale of random utilities (in our case, random net revenues) does not affect the decision maker's choice (Train 2003). While the scale of utilities is arbitrary in most applications, we want net revenues to reflect a landowner's foregone returns so that the model produces meaningful WTA measures. We accomplish this by setting the parameter on average net revenues for the starting use to one in each model (i.e., $\beta_{0jj} = 1$). For starting use *j*, (1) can then be written:

$$R_{ijt} = R_{c(i)jt} + (\alpha_{jj} + \beta_{1jj} LCC_i R_{c(i)jt}) + (\sigma_{1jj} \varpi_{1c(i)jj} + \sigma_{2jj} \varpi_{2ijj} + \varepsilon_{ijjt}), \qquad (2)$$

where $rC_{ijjt} = 0$. In (2), the net revenue for parcel *i* is equal to the county average net revenue from use *j* plus two types of adjustment factors. The first term in parentheses measures the deviation from the county average net revenue due to parcel-level land quality (α_{jj} measures the effect of the omitted LCC category).[4] The second term includes spatial and temporal random adjustments to the county average net revenue. The normalization in (2) scales the random net revenues for all uses to the average net revenue from the starting use, ensures that all net revenues are expressed in money-metric terms, and identifies the scale parameter ξ_j. When the model is estimated, all of the coefficients are normalized on the scale parameter and so the estimated coefficient on $R_{c(i)jt}$ equals $1/\hat{\xi}_j$.

A final estimation issue is that one of the alternative-specific constants (α_{jk}) must be set to zero. We impose the restriction $\alpha_{jj} = 0$ in both models, which implies that the estimated constant terms for all other ending uses *k* are $\hat{\alpha}_{jk} - \hat{\alpha}_{jj}$. As above, this restriction affects the level of net revenues, but not their ordinal ranking. Below, we discuss a procedure for recovering $\hat{\alpha}_{jj}$. We then use $\hat{\xi}_j$ and $\hat{\alpha}_{jj}$ to restore equation (2) for the starting use and equation (1) for the non-starting uses, thereby preserving the desired scale for net revenues.

All parameters in (1) are estimated using maximum simulated likelihood and results are presented in Table 1. The reported coefficient estimates correspond to the unnormalized parameters (i.e., the estimated coefficients have been multiplied by $\hat{\xi}_j$, and the standard errors have been adjusted with the Delta Method). The model estimated for parcels beginning in cropland conforms closely to expectations. All coefficients on net revenues are expected to be positive, as this indicates that landowners are more likely to choose a use if its net revenues increase (all else equal). The coefficients on pasture, forest, and urban net revenues are positive and, with the exception of forests, are significantly different from zero. For cropland, the results indicate that the marginal effect of net revenues decreases as land quality falls. Because LCC 1,2 is the omitted category, the coefficient for LCC 3,4 is 0.49 (=1-0.51). The coefficient for LCC 5,6,7,8 lands is lower by about 0.09, but this difference is not statistically significant. The coefficients σ_{1jk} and σ_{2jk} measure the standard deviation of the error component terms. All four coefficients for the county effects are significantly different from zero and three of the four for the parcel effects are significantly different from zero, indicating unobserved heterogeneity at the county and parcel level.

The results for the model that describes pasture conversion to use *k* are mixed. Pasture net revenues have the expected positive effect on the pasture choice on higher quality lands (LCC 1,2 and 3,4) but a negative coefficient is estimated for low quality lands (LCC 5,6,7,8). The coefficient for cropland net revenues is positive on the high quality lands (LCC 1,2) but turns negative for LCC 3,4 and LCC 5,6,7,8. The coefficient on urban net revenues is positive and significantly different from zero with a one-tailed test and a 10% level of significance. Finally, the coefficient on forest net revenues is negative but not significantly different from zero. The coefficients for the county- and parcel-level error components are significantly different from zero in all cases, with the exception of the parcel effect for urban use, again indicating unobserved heterogeneity at the county and parcel level.

2.2 Willingness to Accept Conservation Payments

Given the starting use *j*, and *K* possible land-use choices, the maximum net revenue derived from parcel *i* in time *t* is:

$$R_{ijt}^{*} = \max\left\{\alpha_{jk} + \sigma_{1jk}\varpi_{1c(i)jk} + \sigma_{2jk}\varpi_{2ijk} + \beta_{0jk}R_{c(i)kt} + \beta_{1jk}LCC_{i}R_{c(i)kt} + \varepsilon_{ijkt}\right\}_{k=1}^{K}. \quad (3)$$

Under the stated distributional assumptions for ε_{ijkt}, (3) can be re-written:

$$R_{ijt}^{*} = \frac{1}{\xi_j}\left(\ln\left[\sum_k \exp(\alpha_{jk} + \sigma_{1jk}\varpi_{1c(i)jk} + \sigma_{2jk}\varpi_{2ijk} + \beta_{0jk}R_{c(i)kt} + \beta_{1jk}LCC_i R_{c(i)kt})\right] - \gamma\right) + \nu_{ijt}, \quad (4)$$

where γ is Euler's constant and ν_{ijt} is distributed type I extreme value with location parameter equal to zero and scale parameter ξ_j (Ben-Akiva and Lerman 1985). Equation (4) is used to estimate a WTA distribution for each parcel *i* under the assumption that landowners are indifferent between receiving the maximum net revenue from the *K* uses and an equivalent payment for returning their land to its original cover.

Before we can apply (4), we must recover the parameter α_{jj}, which we restricted to zero in the estimation. Because the NRI provides a large random sample of parcels, we can exploit the relationship between parcel-level net revenues and the county average net revenue for the starting use:

$$R_{cjt} = \frac{1}{N_{cjt}}\sum_{i=1}^{N_{cjt}} R_{ijt}^{c}, \quad (5)$$

where N_{cjt} is the number of parcels in county *c* in use *j* at time *t* and the R_{ijt}^{c} are net revenues for parcels in county *c*. Substitute R_{ijt} in (2) into the right-hand side of (5). Equation (5) holds provided that:

$$\alpha_{jj} + \sigma_{1jj}\varpi_{1cjj} + \frac{1}{N_{cjt}}\sum_{i=1}^{N_{cjt}}\sigma_{2jj}\varpi_{2ijj} + \frac{1}{N_{cjt}}\sum_{i=1}^{N_{cjt}}\beta_{1jj}LCC_i^{c}R_{cjt} + \frac{1}{N_{cjt}}\sum_{i=1}^{N_{cjt}}\varepsilon_{ijjt}^{c} = 0, \quad (6)$$

where LCC_i^{c} and ε_{ijjt}^{c} are corresponding values for parcels in county *c*. We assume that our sample of parcels is sufficiently large so that the mean of $\sigma_{2jj}\varpi_{2ijj}$ is zero. Further, the mean of the random terms ε_{ijjt}^{c} is zero because we include alternative-specific constants (Train 2003, p. 24). Thus, (6) is satisfied when:

$$\alpha_{jj} + \sigma_{1jj}\varpi_{1cjj} = -\frac{1}{N_{cjt}}\sum_{i=1}^{N_{cjt}} \beta_{1jj} LCC_i^c R_{cjt} \tag{7}$$

We compute the right-hand side of (7) for each county at four points in time, and regress these values on a complete set of county fixed effects with no intercept. Because $\sigma_{1jj}\varpi_{1cjj}$ is zero on average, the mean of the estimated coefficients is $\hat{\alpha}_{jj}$.

The estimate $\hat{\alpha}_{jj}$ is added to each of the alternative specific constants in (4) in order to restore the original scale of net revenues. To simplify the notation, we denote the WTA for parcel *i* as $WTA_i(\mathbf{\Omega}_{ij})$ where $\mathbf{\Omega}_{ij} = (\boldsymbol{\varpi}_{1c(i)j}, \boldsymbol{\varpi}_{2ij}, \boldsymbol{\alpha}_j, \boldsymbol{\beta}_j, \boldsymbol{\sigma}_j, \nu_{ijt})$ is a vector of all of the random variables on the right-hand side of (4) associated with parcel *i* in starting use *j*. Annual per-acre WTA distributions can be obtained by repeated sampling of the elements of $\mathbf{\Omega}$.[5] We show average distributions for crop and pasture parcels in the Willamette Basin in Fig. 1.[6]

2.3 Matching Land Parcels to WTA Distributions and Land-Use Transition Probabilities

We conduct a spatially-explicit simulation of conservation incentives in the Willamette Basin (Fig. 2). The Willamette Basin is a large watershed consisting of 2.93 million hectares in western Oregon. The Basin includes the urban areas of Portland, Salem, Albany, Corvallis, and Eugene-Springfield, as well as significant areas of agricultural land on the valley floor and forests in the surrounding mountains. To develop the simulation algorithm, we must match WTA distributions and land-use transition probabilities from the econometric analysis to land parcels in a GIS.

We use a parcel map constructed from a 30-meter grid cell land cover map for 1990 (ORNHIC 2000). To create a parcel map we combined adjacent cells of similar land cover to form 10,372 parcels, ranging in size from 0.09 to 750 hectares. Parcels in industrial, commercial, and dense urban uses were excluded. The parcel map is described in detail in Polasky et al. (2008).

Given our emphasis on the conservation of private land, we eliminate parcels that are publicly owned, permanently covered in water, and within urban growth boundaries.[7] This leaves 4,940 privately-owned parcels, of which 2,319 are in crop and pasture use. The remaining private parcels are in forest uses, rural-residential use, and private conservation. While the 2,319 cropland and pasture parcels are the focus of the conservation policy, existing private and public conservation lands contribute to the biodiversity benefits generated by the landscape.

The original parcel map has fourteen land use or land cover categories. These categories are combined to match the four land uses in the econometric model. For example, the categories row crops, grass seed, and orchards/vineyards are combined to form a cropland category. Spatial data layers for LCC and county boundaries (Oregon Department of Land Conservation and Development [n.d.]) are overlaid on the parcel map, thus associating each parcel *n* with an initial land use, a county, and an LCC category. Each parcel can now be matched to a WTA expression, $WTA_n(\boldsymbol{\Omega})$, based on equation (4).[8]

In order to determine baseline land-use changes, each crop and pasture parcel is also matched to a set of land-use transition probabilities derived from the econometric results. According to our model, the probability that parcel *i* changes from use *j* (cropland or pasture) to *k* (cropland, pasture, forest, or urban) during the time period beginning in *t* is given by (modify based on notation above):

$$P_{ijkt} = F(\mathbf{R}_{c(i)t}, LCC_i, \boldsymbol{\varpi}_{1c(i)j}, \boldsymbol{\varpi}_{2ij}; \boldsymbol{\alpha}_j, \boldsymbol{\beta}_j, \boldsymbol{\sigma}_j)\,, \qquad (8)$$

where *F* is a logistic function, and $\mathbf{R}_{c(i)t}$ is a vector of all of the net revenue variables and $\boldsymbol{\varpi}_{1c(i)j}, \boldsymbol{\varpi}_{2ij}, \boldsymbol{\alpha}_j, \boldsymbol{\beta}_j$ and $\boldsymbol{\sigma}_j$ denote vectors of random terms associated with starting use *j*. For given values of these random terms, (8) is used to compute transition probabilities for each of the eight possible land-use changes from starting uses (cropland, pasture) to ending uses (cropland, pasture, forest, urban). Other initial land uses change according to sample transition probabilities computed with the NRI data (private forests) or are assumed to remain in their initial use with probability one. As with the WTA values, each set of transition probabilities differs by initial use, county, and LCC category and is matched accordingly to the parcels on the initial land-use map. The set of 5-year transition probabilities for parcel n is a 1×8 vector denoted $\boldsymbol{P_{n5}}$.

2.4 Simulating the Spatial Pattern of Conservation Lands

We consider policies that convert cropland and pasture parcels to natural land cover. The type of natural land cover a conserved parcel adopts is given by the parcel's pre-Euro-American settlement vegetation cover and includes the covers of prairie, emergent marsh, scrub/shrub, oak and other hardwoods, old-growth conifer, or riparian forest (Christy et al. 1998). Due to a lack of data, we do not explicitly account for costs of converting crops and pasture to native cover. Our econometric model does implicitly measure the costs of conversion to non-agricultural uses (e.g., forest) and these costs are reflected in the WTA values.

We simulate a range of different policies, described in detail below, that differ in terms of the subset of cropland and pasture owners that are eligible for a per-acre conservation payment. For each policy, eligible landowners are offered a payment, and landowners who have a WTA less than the payment offered are assumed to enroll their parcels. Enrollment continues until a budget constraint is met. Because of our interest in the relative efficiency of policies, our budget is expressed in terms of landowners' opportunity costs, equal to the sum of WTA for conserved parcels. We do not consider the cost of the policy to the government, which also includes transfer payments to landowners.[9] If there were no subsidies or other distortions to market prices, and no externalities from land-use choices, total WTA would be an accurate measure of the social cost of conservation. In our application, however, there are subsidies to agricultural producer and other market distortions in addition to externalities (e.g., actions that affect water quality, air quality, aesthetics, and other environmental benefits). Here total WTA is used to represent cost, recognizing that is an imperfect measure of true social cost because of market and policy imperfections. We evaluate cost budgets of \$5, \$10, \$20, and \$30 million dollars per year.

The simulations use Monte Carlo methods to characterize the range of potential landscape patterns. For a given policy that offers conservation payment Z, we randomly generate the value $WTA_n(\mathbf{\Omega})$ to determine if the parcel n is enrolled in the conservation program. If not, then parcel n either remains in its current use or switches to one of the alternative uses according to the transition probabilities $\boldsymbol{P_{n5}}$. As in Lewis and Plantinga (2007), the transition probabilities and WTA distributions can be interpreted as a set of rules that govern changes in a parcel's use. The landscape simulations work as follows:

1) Values of the random variables in $\mathbf{\Omega}$ are drawn from their estimated distributions (Krinsky and Robb 1986) for each parcel n on the landscape and used to compute $WTA_n(\mathbf{\Omega})$.
2) The period 0 conservation decision for each parcel eligible for a conservation payment is determined by comparing $WTA_n(\mathbf{\Omega})$ to Z. If $WTA_n(\mathbf{\Omega}) \leq Z$, then parcel n is returned to its native cover and remains in this state for all future periods.
3) If a parcel is not conserved in period 0, equation (8) is used to derive a vector of 50-year transition probabilities $\boldsymbol{P_{n50}}$.[10]. The 50-year land-use choice for each parcel is determined by drawing a random variable r from a $U(0,1)$ distribution. The resulting land-use choice is determined by comparing r to the set $\boldsymbol{P_{n50}}$.[11]

Using these steps we simulate a landscape of private land-use and conservation decisions that would exist fifty years after the policy is enacted. Each time we repeat these steps, we produce a simulated future landscape that is consistent with the underlying decision rules from the econometric model and incentives created by the conservation policy. We conduct 500 rounds of the simulation for each policy and budget level, including a baseline with no conservation policy (i.e., $Z = 0$), in order to characterize the spatial distribution of conservation and working lands.[12]

3. Biological Model and Optimal Landscape

We evaluate the outcomes of landscape conservation by computing a biodiversity score for each simulated landscape pattern. In addition, we use a large-scale integer programming algorithm to search over the set of feasible landscape patterns to maximize the biodiversity score for a given opportunity cost of conservation. The combination of the biological model and the optimal landscape algorithm allows us to evaluate the efficiency of incentive-based policies.

3.1 Biological Model

The biological model uses land-use patterns from the simulation along with information on species and habitats to evaluate the likelihood that species will be sustained in the future (Polasky et al. 2005, 2008). The biological model uses three species-specific traits to predict species persistence as a function of the land-cover pattern: a) species-habitat compatibility (i.e., what land covers are considered habitat for the species), b) the amount of habitat required for a breeding pair, and c) the ability of the species to move between patches of habitat. The biological model uses information on each species' geographic range, habitat compatibility and land cover to generate a map of habitat for the species. Total habitat area is divided by the amount of habitat required for a breeding pair to estimate the maximum number of breeding pairs the landscape could support. An estimate for the minimum number of breeding pairs on the landscape uses only the number of breeding pairs in habitat patches large enough to support viable populations within the patch assuming no migration from other patches. Information on the pattern of habitat patches and species' dispersal ability is then used to generate a connectivity score between 0 and 1 to weight the landscape score between the maximum and minimum estimates. Habitat that is fully connected in a single large habitat patch gets a connectivity score of one and the landscape score equals the maximum number of breeding pairs. With fragmented habitat patches and species with less than perfect dispersal ability, the connectivity score is less than one and the landscape score is a weighted average of the maximum and minimum number of breeding pairs. We convert the landscape score for the number of breeding pairs into a probability that the species will be sustained on the landscape using a saturating function with parameters set so that 500 breeding pairs generates a probability of 0.50 and 1000 breeding pairs generates a probability of 0.95.[13] Finally, we aggregate species survival probabilities across all species and divide by the number of species to generate a biodiversity score for the simulated landscape. A complete description of the biological model can be found in Polasky et al. (2008).

3.2 Optimal Landscape

To gain a sense of the relative efficiency of various incentive-based policies, we compare outcomes under these policies to the optimal land-use patterns that maximize the biodiversity score for a given cost. As above, costs are measured as the sum of annual WTA over all conserved parcels. However, in contrast to the voluntary incentive mechanisms discussed above, in solving for the optimal solution we assume the regulator knows the WTA for each parcel (not just the distribution of WTA) and can freely choose parcels to conserve. Solving for the optimal land-use patterns in the Willamette Basin application is a large-scale integer programming problem that involves choosing among five land-use alternatives (crops, pasture, forest, urban or conservation) on over 2,000 parcels. This optimization problem is particularly challenging because of the non-linear spatial considerations in the biological model. Instead of optimizing, which is extremely difficult in this application, we use heuristic methods to find good – though not necessarily optimal – solutions. The approach used was developed in Nelson et al. (2008) and Polasky et al. (2008) and details can be found there. Here, we discuss its key features.

The heuristic methods involve finding land-use patterns that maximize the biodiversity score for three simpler versions of the biology model. These simpler biological models are linear in land-use pattern, which allows us to find optimal solution for these models. The first linear biological model considers the amount of habitat area on the landscape but not the spatial pattern of habitat. The second biological model maximizes the total number of breeding pairs as a function of total habitat area, but not spatial pattern, up to an upper limit on breeding pairs for each species. This model has the advantage of assigning no further credit for additional habitat to species with sufficient adequate existing habitat to support a viable population. The third biological model modifies the second model by penalizing breeding pair counts as habitat becomes less connected on the landscape. We solve for optimal solutions for all three biological models at various budget levels. We then evaluate each of these solutions with the full biological model described in section 3.1. The particular land-use pattern that produces the highest biological score for a given budget level is used to approximate the optimal land-use pattern for that budget level.[14]

4. The Application

4.1 Terrestrial Species Included

The data needed to evaluate the full biological model (and the simpler linear versions) are available for a set of 267 terrestrial vertebrate species native to the Willamette Basin (Polasky et al. 2008). Many conservation agencies specifically target funding to species of conservation concern. In this application we included only those species whose conservation status can potentially be improved by land-use change in the Willamette Basin. We included a species if its population is predicted to substantially decline over the 50-year period under a baseline of no conservation policy, or if the initial population of the species is low but could be substantially improved with habitat restoration. We included species with low initial populations if we could find at least one land-use pattern generating a survival probability of 0.5 or higher using the approach in Polasky et al. (2008).[15] Of the 267 original terrestrial species evaluated, we find 24 species that satisfy the above criteria for being of "conservation concern".[16]

4.2 Incentive-Based Policies Analyzed

We examine a wide range of alternative incentive-based policies, some of which are modeled on existing federal programs (e.g., the CRP and the WHIP). We have two main objectives in analyzing alternative policies. First, we wish to assess the relative performance of realistic policies to find what types of policy approaches are likely to be most efficient. Second, we wish to assess the value of including more information about the economic and biological environment into policy design. In analyzing incentive-based policies, we assume the regulator knows the probability density function for WTA (i.e., $WTA_n(\mathbf{\Omega})$ for each parcel *n*) but does not know the realization of WTA for any individual parcel. Comparing the solutions for incentive-based policy alternatives with the approximated optimal solutions illustrates the potential gains from obtaining information on parcel-specific WTA combined with perfect control of conservation decisions.

We designed several of the incentive-based policies based on insights we gathered by examining the approximately optimal solutions (Table 2). Four insights relevant for designing incentive-based policies emerge. First, the biodiversity score is sensitive to increasing the conservation of relatively rare habitat types, particularly oak savanna, prairie, and emergent marsh. These habitats comprise approximately 95% of conserved parcels under the approximately optimal solutions. Second, it is important to target locations that contain large numbers of species. Approximately 60% of the parcels chosen under the approximately optimal solutions are within the range of fourteen or more of the species under consideration. Third, targeting conservation to create large contiguous conserved habitat has a large impact on species persistence. Under the approximately optimal solutions, conserved parcels tend to have large size and between 70% and

80% of these parcels are adjacent to conserved parcels (either parcels selected for conservation or existing conserved parcels). Finally, efficient solutions tend to target parcels with a relatively low WTA when the conservation budget is low. Selection shifts towards parcels with high biological benefits as the budget increases. Enrolling low cost land is particularly important at low budget levels.

We evaluate twelve policies described in Table 3. The policies fall into two basic groups. First, we consider least-cost policies under which a uniform per-acre payment is offered to all landowners who meet specified eligibility requirements.[17] For some of these policies, the eligibility constraints incorporate basic biological principles and draw on insights from Table 2, including the importance of specific habitat types and large contiguous blocks of habitat. Second, we consider policies that target payments according to their estimated benefit-cost ratios. Benefit indices are derived using the same basic biological principles used to define eligibility constraints. Cost is the parcel-specific expected per-acre cost as derived from the estimated distributions of WTA. The benefit-cost policies target those parcels with the highest benefit-cost ratio, where the regulator is assumed to offer sufficiently high payments to induce enrollment. Costs for all policies are calculated using the actual WTA for parcels that enroll in the conservation program.

5. Results

The relative performances of the approximately efficient solutions and incentive-based policies are presented in Table 4. For each policy and budget combination, we report the change in the biodiversity score relative to the baseline land use map, averaged over the 500 simulated landscapes. Also shown is the mean change in the biodiversity score for each incentive-based policy relative to the mean change in the biodiversity score under the approximately optimal solution.[18]

The approximately efficient solution displays increasing returns at low levels of budget (up to $10 million), as shown by the more than doubling of the change in the biodiversity score in going from $5 to $10 million annual budget, and decreasing returns at high levels of budget (above $10 million) .[19] In this application, many of the species of conservation concern begin with little conserved habitat. These species need significant amounts of habitat conserved before they exhibit much increase in estimated survival probability. For low budget levels, not much land can be conserved and this land adds little to survival probabilities. At a budget of $10 million, a sufficient amount of land, which is suitably compact, is conserved to achieve critical levels of habitat protection. Beyond this point further habitat conservation has a progressively lower marginal benefit. The incentive-based policies also exhibit increasing returns. With few exceptions, the incentive-based policies exhibit increasing returns through the $20 million budget level and some policies show increasing returns throughout. Increasing returns occurs especially for incentive-based policies that do not take special account of spatial patterns. For such policies, initially conserved lands tend to be highly fragmented. As more land is conserved, fragmentation decreases leading to improved conservation outcomes (Lewis *et al*. 2009).[20]

None of the incentive-based policies do particularly well at low budget levels. At a budget of $5 million, the best incentive-based policy (*Agglomeration – Rare Habitat*) achieves only 24% of the maximum attainable increase in the biodiversity score. Somewhat surprisingly, the benefit-cost policies do particularly poorly at the budget of $5 million. All of the benefit-cost policies achieve less than 10% of the increase in biodiversity score as compared to the estimated efficient solution. It was our expectation that benefit-cost policies would generally outperform least-cost policies because they incorporate information about both biological benefits and cost in choosing priority sites. The least-cost policies enroll the cheapest land, a desirable property at low budget levels especially when combined with eligibility constraints that reflect basic biological principles.

Incorporating biological benefits via simple rules like only choosing sites with rare habitat types and that adjoin to other conserved sites, as in the *Agglomeration – Rare Habitat* policy, proves to be the best of the policies we analyzed at a budget of $5 million.

The *Agglomeration – Rare Habitat* policy consistently performs best amongst the least-cost policies. It is also worthwhile to note that the difference between each of the least-cost policies is generally small compared to the difference between the least-cost policies and the approximately optimal solution. Adding the *Large* or *Rare Habitat* eligibility constraints is generally more efficient than the *Simple Uniform* policy, although not by a large magnitude. Further, the simple *Agglomeration* design – which gives incentive for adjacent conserved parcels – improves efficiency relative to all other least-cost policies, especially when combined with the *Rare Habitat* eligibility constraint.

As the budget increases, the performance of benefit-cost policies improves vis-à-vis the least-cost policies and the estimated efficient result. At a budget of $10 million the performance of one of the benefit-cost policies, *Lot Size Agglomeration*, improves dramatically with a 10-fold increase in the change in biodiversity score at the $10 million budget relative to the $5 million budget. The other benefit-cost policies continue to do poorly at the $10 million budget level. Beyond the $10 million budget level, however, all of the benefit-cost policies, with the exception of the *WHIP* policy, generally outperform their least-cost counterparts. The benefit-cost policy *Rare Habitat – Large – Range* has the best performance of all policies we analyzed at both the $20 and $30 million budgets. At the $30 million budget, *Rare Habitat – Large – Range* achieves 87.2% of the change in biodiversity score of the approximated efficient result. The *WHIP* policy most closely mimics current conservation policy in the region. That it does so poorly gives considerable room for policy reform to improve conservation performance.

In Table 4 we report the average change for the 500 simulations, but there is considerable variation in results across simulations. In Figure 4 we show the entire distribution of the biodiversity scores for each incentive-based policy. There are two general findings. First, the variance of the biodiversity score always increases as the budget gets larger. Increasing budgets result in more conserved land, implying an increasing number of patterns in which the landscape could be arranged, and a wider array of biodiversity outcomes. Second, the variance in the biodiversity score resulting from the least-cost policies is always larger than the variance resulting from the benefit-cost policies. Successful biodiversity conservation with least-cost policies is heavily dependent on the somewhat random location of low cost land, while a well-defined benefit-cost policy is more tightly focused on achieving particular landscape patterns. This difference in variance between the two basic policy approaches could be important to policy makers concerned with minimizing the potential for undesirable outcomes.

The results illustrate the degree to which adding biological and economic information improves the efficiency of policy. The policies with the most information, in particular policies that incorporate features to include rare habitat types and minimize fragmentation, tend to yield the largest gains in biodiversity for a given cost. In addition, results in Table 4 provide striking evidence that there is room for large efficiency gains as most of the incentive-based policies yield well under 50% of the potential biodiversity improvement, as represented by the approximately optimal solution.

6. Conclusion

This paper addresses an unresolved question for policies aimed at conserving biological diversity, namely how well can voluntary incentive-based policies achieve efficient solutions? To answer this question, we develop a methodology that integrates an econometric model of private land-use decisions, landscape simulations, spatially-explicit data, a biological model that estimates species persistence, and an algorithm that approximates the set of efficient solutions. Of particular interest for future analyses of land conservation, we also develop a novel method for deriving distributions of a landowner's willingness-to-accept a conservation payment from an econometric land-use change model. The method is applicable to the common situation where land-use data sets consist of parcel-specific data on land-use change, and aggregate data on the net returns to alternative land uses. Given the importance of the spatial pattern of habitat for many species, a central feature of the overall methodology is the ability to simulate the effects of voluntary incentives on both the aggregate amount and the spatial distribution of habitat for a diverse set of species whose conservation status is significantly affected by private land-use decisions.

We find that simple voluntary incentive-based policies are often inefficient in achieving conservation objectives. There can be substantial differences between the biodiversity changes achieved with voluntary incentive-based policies compared to those that are theoretically possible through the direct control of landscape pattern. The inefficiency of incentives in improving biodiversity arises primarily from the inability of regulators to control the spatial pattern of landscapes with a voluntary payment mechanism. The decision of any particular landowner to convert their land to conservation depends on their willingness to accept a payment for such action. Since the willingness to accept a conservation payment is private information, a regulator is uncertain *ex-ante* of the spatial landscape pattern that will result from a given set of payments offered to a group of landowners. Future development of auction mechanisms to elicit landowners' willingness-to-accept a conservation payment—combined with an explicit attention to habitat fragmentation—appears to be a necessary step to achieving efficient conservation.

The results presented in this paper are influenced by the landscape context and the species we include in our analysis. Therefore, while our results represent the first explicit empirical estimates of the inefficiency of incentive-based policies in conserving biodiversity, it is difficult to extrapolate our findings to other landscapes to make general conclusions. Nevertheless, our results suggest the following testable hypotheses: a) incentive-based policies tend to achieve only a small portion of the potential conservation gains when landowners have private information about willingness-to-accept, b) the performance of incentive-based policies relative to the efficient result with full information tends to improve as the conservation budget increases, c) adding biological criteria to policy design (e.g., including rare habitat types or minimizing fragmentation) can yield large improvements in performance, d) least-cost policies are more cost-effective than benefit-cost policies when budgets are low but the reverse is true when budgets are high, and e) policies that explicitly target conservation based on benefit-cost ratios are likely to achieve biodiversity outcomes with lower variance than least-cost policies. The accumulation of other case-studies, or the scaling up of our methodology to larger landscapes, would be a fruitful approach to testing the generality of our findings.

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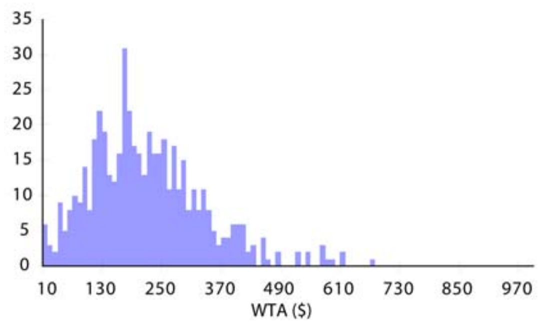
Fig. 1 – Frequency of estimated annual per-acre WTA for a typical parcel in the Willamette Basin

a. Land starting in cropland



b. Land starting in pasture

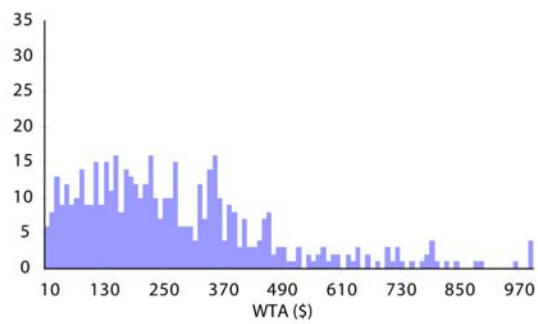


Fig. 2 –The Willamette Basin

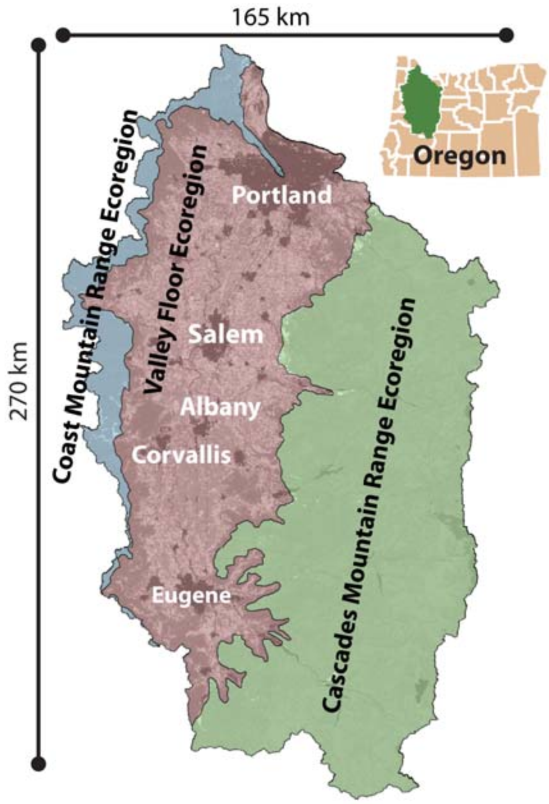
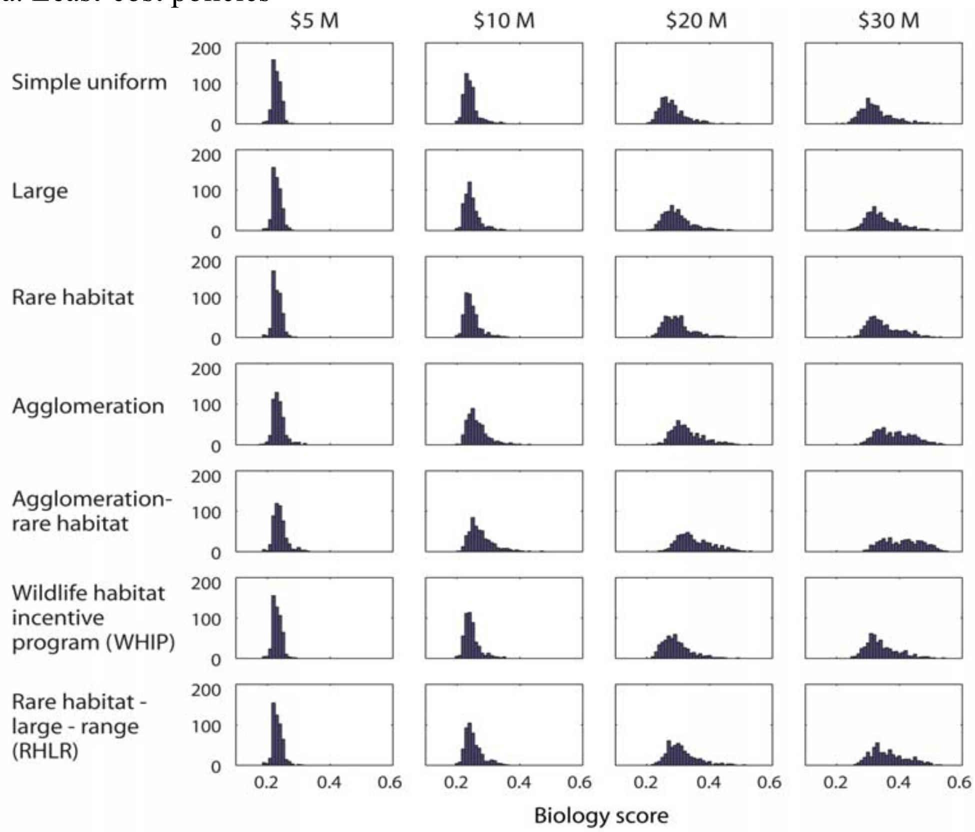


Fig. 3 - Frequency distributions of performance of alternative voluntary policies

a. Least-cost policies



b Benefit-cost policies

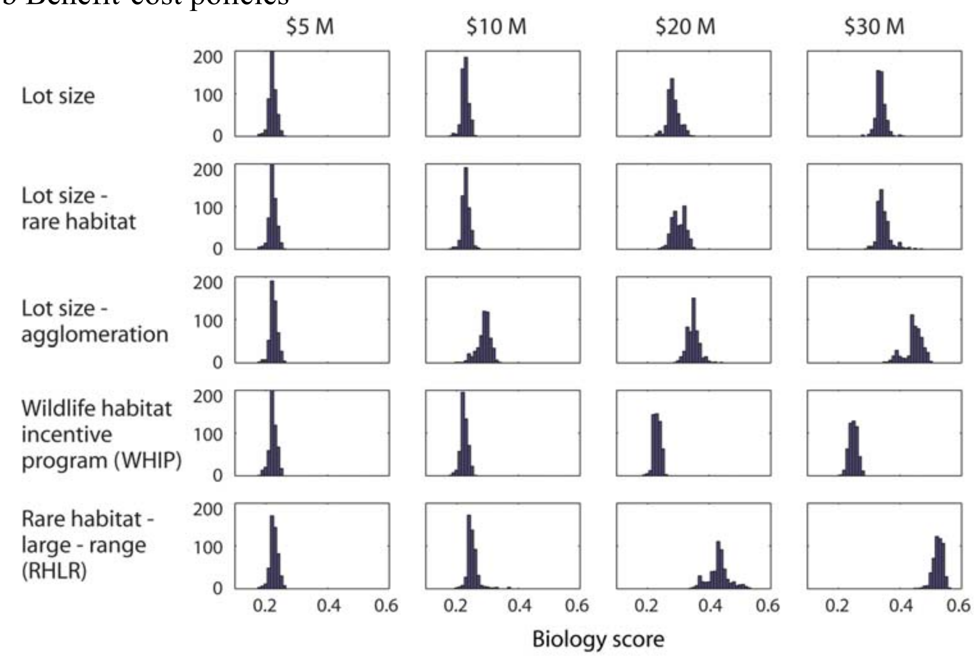


Table 1 -- Estimation Results for Random Parameters Models			
Parameter	Estimate	St. Error	*t*-statistic
Starting use is crops (n=3,504)			
1/scale	1.204	0.267	4.510
Crop Returns	1.000	NA	NA
Crop Returns * LCC34	-0.511	0.210	-2.429
Crop Returns * LCC5678	-0.094	0.563	-0.166
Pasture Intercept	-2.095	0.528	-3.969
Pasture Returns	0.326	0.142	2.292
Forest Intercept	-7.799	2.116	-3.686
Forest Returns	0.242	0.964	0.251
Urban Intercept	-4.788	1.137	-4.210
Urban Returns	0.013	0.005	2.560
Random Parameters - county effects			
Crop St. Dev.	0.372	0.144	2.591
Pasture St. Dev.	0.381	0.119	3.189
Forest St. Dev.	1.112	0.433	2.567
Urban St. Dev.	0.761	0.274	2.778
Random Parameters - parcel effects			
Crop St. Dev.	0.524	0.141	3.705
Pasture St. Dev.	0.140	0.139	1.005
Forest St. Dev.	2.017	0.605	3.334
Urban St. Dev.	0.494	0.193	2.563
Starting use is pasture (n=4,637)			
1/scale	0.693	0.201	3.457
Pasture Returns	1.000	NA	NA
Pasture Returns * LCC34	-0.662	0.263	-2.515
Pasture Returns * LCC5678	-1.782	0.551	-3.233
Const Crop	-4.886	1.382	-3.534
Crop Returns	0.339	0.358	0.946
Crop Returns * LCC34	-2.427	0.919	-2.641
Crop Returns * LCC5678	-1.478	0.843	-1.753
Const Forest	-6.310	1.852	-3.407
Forest Returns	-0.117	0.573	-0.205
Const Urban	-8.135	2.506	-3.246
Urban Returns	0.001	0.001	1.225
Random Parameters - county effects			
Pasture St. Dev.	1.944	0.690	2.817
Crop St. Dev.	0.940	0.332	2.835
Forest St. Dev.	0.720	0.352	2.044
Urban St. Dev.	1.305	0.711	1.834
Random Parameters - parcel effects			
Pasture St. Dev.	0.603	0.222	2.723
Crop St. Dev.	0.762	0.262	2.905
Forest St. Dev.	1.656	0.506	3.271
Urban St. Dev.	0.133	0.307	0.435
Crop starting use: Log likelihood function = -837.93			
Pasture starting use: Log likelihood function=-1191.45			

Table 2 – Characteristics of Conserved Parcels in the Solution for the Estimated Efficiency Frontier at Different Levels of Cost

Cost (Million $)	Average Size (Acres)	Percentage of Conserved Parcels Containing Rare Habitat*	Percentage of Conserved Parcels within the Range of Fourteen or more Species	Percentage of Conserved Parcels Adjacent to a Conserved Parcel	Average WTA Per Acre	Maximum WTA Per Acre
5	899	93.16%	59.72%	79.21%	$53.26	$164.16
10	933	94.96%	63.88%	79.32%	$72.52	$232.81
20	895	94.70%	60.98%	78.48%	$90.30	$358.43
30	913	96.34%	61.49%	79.83%	$99.96	$414.44

*Rare habitat types include oak savanna, prairie, old growth forest, and emergent marsh.

Table 3 – Incentive-based policies evaluated

	Eligible parcels	Benefit index
Least-cost policies		
Simple uniform	All	NA
Large	Parcels with greater than 800 acres	NA
Rare Habitat	Parcels whose native habitat is oak savanna, prairie, old growth forest, or emergent marsh	NA
Agglomeration	Parcels whose immediate neighbor also accepts a conservation payment	NA
Agglomeration - Rare Habitat	Parcels satisfying both the Agglomeration and Rare Habitat criteria	NA
Oregon's Wildlife Habitat Incentives Program (WHIP)	Parcels with at least 100 points based on implementation of Oregon's WHIP program	NA
Rare Habitat – Large – Range (RHLR)	Parcels with at least three of the following: i) ≥ 400 acres ii) ≥ 800 acres iii) Rare Habitat iv) w/in range of at least 14 species	NA
Benefit-cost policies		
Lot Size	All	The size of the parcel
Lot Size - Rare Habitat	Parcels satisfying the Rare Habitat criteria	The size of the parcel
Lot Size - Agglomeration	Parcels satisfying the Agglomeration criteria	The combined size of two adjacent conserved parcels
Oregon's Wildlife Habitat Incentives Program (WHIP)	All	Assigned points based on Oregon's WHIP program
Rare Habitat – Large – Range (RHLR)	All	One point for each: v) ≥ 400 acres vi) ≥ 800 acres vii) Rare Habitat viii) w/in range of at least 14 species

Note: Least-cost policies offer uniform payments and enroll the least-cost parcels subject to eligibility constraints. Benefit-cost policies rank parcels according to the ratio of benefits to expected costs, where expected costs are derived from estimated WTA distributions.

Table 4 – Estimated Mean Change in Biodiversity Score Relative to Baseline

	$5m	$10m	$20m	$30m
Approximate Optimal Policy	0.0840	0.2377	0.3289	0.3493
Uniform Policies				
Simple Uniform	0.0100	0.0224	0.0603	0.1061
	(11.92%)	(9.43%)	(18.35%)	(30.37%)
Large	0.0112	0.0267	0.0759	0.1242
	(13.29%)	(11.23%)	(23.08%)	(35.57%)
Rare Habitat	0.0112	0.0271	0.0781	0.1300
	(13.33%)	(11.40%)	(23.75%)	(37.22%)
Agglomeration	0.0165	0.0435	0.1091	0.1650
	(19.65%)	(18.32%)	(33.17%)	(47.23%)
Agglomeration - Rare Habitat	**0.0203**	0.0545	0.1314	0.1899
	(24.22%)	(22.94%)	(39.95%)	(54.36%)
WHIP	0.0113	0.0264	0.0732	0.1228
	(13.52%)	(11.12%)	(22.26%)	(35.15%)
Rare Habitat – Large – Range	0.0124	0.0323	0.0900	0.1450
	(14.81%)	(13.59%)	(27.38%)	(41.51%)
Benefit-Cost Policies				
Lot Size	0.0019	0.0082	0.0644	0.1181
	(2.29%)	(3.43%)	(19.59%)	(33.82%)
Lot Size - Rare Habitat	0.0027	0.0105	0.0822	0.1274
	(3.22%)	(4.42%)	(24.99%)	(36.48%)
Lot Size Agglomeration	0.0060	**0.0686**	0.1278	0.2254
	(7.14%)	**(28.86%)**	(38.85%)	(64.52%)
WHIP	0.0032	0.0050	0.0116	0.0291
	(3.76%)	(2.12%)	(3.54%)	(8.34%)
Rare Habitat – Large – Range	0.0067	0.0309	**0.2112**	**0.3046**
	(7.94%)	(13.00%)	**(64.23%)**	**(87.20%)**

Note: Numbers in parentheses represent the average change in the biodiversity score relative to the baseline as a percentage of the average change in the biodiversity score on the estimated efficiency frontier relative to the baseline. **Bold** indicates the incentive-based policy with the highest estimated change in the biodiversity score.

Endnotes

[1] This literature is also known as the reserve-site selection literature.

[2] A similar specification is used in Lubowski et al. (2006) and Lewis and Plantinga (2007). One important difference is the inclusion of random parameters in the present model. Oregon has a well-known land-use planning system that largely prohibits urban development outside of designated growth areas. Because we do not know the exact location of the plots used in estimation, we cannot control explicitly for influences of land-use regulations. The RPL model allows us to measure implicitly these and other unobservable parcel-level effects.

[3] LCC_i is defined as a vector of dummy variables for the eight LCC categories 1-8, where lower numbers indicate higher quality (U.S. Department of Agriculture 1973). β_{1jk} is similarly defined as a conformable vector of parameters corresponding to each of the LCC categories.

[4] The term α_{jj} plays an important role here. If the coefficient on β_{1jj} is negative (positive) then α_{jj} allows for upward (downward) adjustments in the average net revenue due to observable parcel-specific land quality. Without α_{jj}, equation (2) could not be interpreted as a deviation from the county average net revenue.

[5] Fixed and random parameters are drawn using the Krinsky-Robb (1986) method, which accounts for correlations across parameters through the use of the estimated variance-covariance matrix.

[6] Since v_{ijt} in equation (4) is unbounded, it is possible to have a negative WTA. For parcels starting in crop (pasture), the probability of a negative WTA is, on average, 5% (12%). Given the low probabilities of a negative WTA, truncating the WTA distribution at zero is of small consequence (Haab and McConnell 2003 p. 97).

[7] In Oregon each city and town is required to designate an urban growth boundary, within which high-density development is permitted.

[8] If a parcel has more than one LCC rating or is within more than one county, we construct an area-weighted average of WTA values (the same procedure is used for the transition probabilities discussed below).

[9] In practice, the cost to the government is likely to be the relevant constraint on the conservation of land parcels. Our policies could, alternatively, be constrained by budgets defined in these terms, as in Nelson et al. (2008). However, in this case, the opportunity costs would vary across policies and budget levels, making efficiency comparisons difficult.

[10] The transition probabilities in (8) correspond to land-use changes over a five-year period. If $\mathbf{M}$ is a matrix of five-year transition probabilities, $\mathbf{M}^{10}$ is the matrix of 50-year probabilities. Elements of the 50-year matrix give the probability that a parcel in use j in year 0 is in use k by year 50, accounting for all possible paths from use j to k that can be taken.

[11] For example, suppose that a crop parcel has a 75% probability of remaining in crops, and converts to pasture, forest, and urban use with probabilities of 15%, 5%, and 5%, respectively. For this example, if $0 \leq r \leq 0.75$, the parcel remains in crops. If $0.75 < r \leq 0.90$, the parcel switches to pasture, and so on.

[12] Generating two independent sets of 500 simulated landscapes reveals that all statistics presented in this paper do not differ across the two sets of simulations.

[13] The saturating function generates low probabilities of survival and small change with increased habitat for low numbers of breeding pairs, rapidly increasing probability of survival with increased habitat around a survival probability of 0.5, and high probability of survival and small change with increased habitat for high numbers of breeding pairs.

[14] Because the optimization process is computationally costly, we apply it using the WTA values from the baseline simulations that produce the 1st, 25th, 50th, 75th, and the 99th percentile

biodiversity scores from among all 500 baselines. The maximum biodiversity scores obtained with each set of WTA values are then averaged.

[15] Polasky et al. (2008) includes land-use patterns where conservation decisions on public as well as private land can be changed and the opportunity cost of conservation can reach as high as $25 billion in net present value. across the whole Basin.

[16] The 24 species are: American Bittern, Canada Goose, Green-Winged Teal, Cinnamon Teal, Ruddy Duck, White-Tailed Kite, Bald Eagle, Osprey, Northern Goshawk, Red-Shouldered Hawk, Marbled Murrelet, Spotted Owl, Belted Kingfisher, Short-Eared Owl, Grasshopper Sparrow, Common Muskrat, Wolverine, White-Tailed Deer, Painted Turtle, Western Pond Turtle, Northern Harrier, Acorn Woodpecker, Western Meadowlark, and Fisher.

[17] We refer to these as least-cost policies because a uniform per-acre payment will create a desired amount of habitat at least cost.

[18] We use all 500 simulations for the incentive-based policies when comparing the result with the estimated efficiency frontier, though we only have five simulated landscapes for the latter. Using only the five simulated landscapes for which we have efficiency frontier results yields virtually identical results to those presented in table 4.

[19] Although not presented in table 4, we also estimated the biodiversity score for all policies with a total cost of $1 million. Very little change in the biodiversity score was achieved with this low budget level under either the incentive-based policies or the approximately optimal solution.

[20] In the limiting case where all private land is conserved, the incentive-based policies and the efficient solutions will be identical.