The Efficiency of Voluntary Incentive Policies for Preventing Biodiversity Loss

*David J. Lewis
Department of Economics, University of Puget Sound, 1500 N. Warner St., Tacoma, WA 98416,
Ph: 253-879-3553; Email: djlewis@pugetsound.edu

Andrew J. Plantinga
Department of Agricultural and Resource Economics, Oregon State University, 232 Ballard Ext.
Hall, Corvallis, OR 97331; Ph: 541-737-1423; Email: plantinga@oregonstate.edu

Erik Nelson
The Natural Capital Project, Woods Institute for the Environment, Stanford University, 371 Serra
Mall, Stanford, CA 94305; Ph: 612-624-6260; Email: nels1069@umn.edu

Stephen Polasky
Department of Applied Economics, University of Minnesota, 1994 Buford Ave., St. Paul, MN
55108; Ph: 612-625-9213; Email: polasky@umn.edu

February 24, 2010

*Corresponding author.

The Efficiency of Voluntary Incentive Policies for Preventing Biodiversity Loss

Abstract: Habitat loss is a primary cause of loss of biodiversity but conserving habitat for species presents challenges. Land parcels differ in their ability to produce returns for landowners and landowners may have private information about the value of the land to them. Land parcels also differ in the type and quality of habitat and the spatial pattern of land use across multiple landowners is important for determining the conservation value of parcels. This paper analyzes the relative efficiency of simple voluntary incentive-based policies in achieving biodiversity conservation objectives. This topic is important not just for biodiversity conservation but for any effort to provide a public good requiring coordination across multiple decision-makers who have some degree of private information. We develop a method that integrates spatially explicit data, an econometric model of private land-use decisions, landscape simulations, a biological model of biodiversity as a function of landscape pattern, and an algorithm that estimates the set of efficient solutions. These methods allow us to simulate landowner responses to policies, measure the consequences of these decisions for biodiversity conservation, and compare these outcomes to efficient outcomes to show the relative efficiency of various policy approaches. We find substantial differences in biodiversity conservation scores generated by simple voluntary 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: incentive policies, biodiversity, conservation, land use, spatial modeling.

The Efficiency of Voluntary Incentive Policies for Preventing Biodiversity Loss

1. Introduction

Land-use change is the leading driver of biodiversity loss in terrestrial ecosystems 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). Voluntary incentives are the most common mechanism used to encourage conservation on privately-owned lands. For example, the Conservation Reserve Program (CRP) and the Wildlife Habitat Incentives Program (WHIP) provide payments to private landowners in exchange for land uses consistent with conservation objectives. 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).

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. In particular, we use observed land-use decisions to specify an econometric model of land-use choice and develop a method to recover the distributions of landowners' willingness-to-accept (WTA) conservation payments in exchange for using their land for habitat conservation. The method we develop 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 coarser spatial scale such as a county rather than an individual parcel.

We then use estimated WTA to simulate landowner responses to a range of incentive-based habitat conservation policies. We assume landowners know their own WTA, but regulators interested in conservation know only the probability distribution of landowners' WTAs. Simulated land-use patterns are used as inputs into a spatially-explicit biological model to generate a biological score, which is based on the probabilities that a set of terrestrial species of conservation concern will persist on the landscape. We then compare outcomes under incentive-based policies with outcomes of an efficient solution that maximizes the biodiversity score at each level of economic opportunity cost. The difference in biodiversity scores between the landscapes generated by the incentive-based policies and the efficient solution indicates the potential gains in species conservation from gathering information on landowner-specific WTA and spatially optimizing conservation efforts.

Our analysis connects two strands of literature on habitat conservation methods and policies. Systematic conservation planning (SCP; Margules and Pressey 2000) involves choosing the collection of sites that maximize species conservation subject to a constraint on the total area conserved or total conservation budget allotted (e.g., Camm et al. 1996, Church et al. 1996, Csuti et al. 1997, Kirkpatrick 1983, Vane-Wright et al. 1991). 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 on landscapes with privately-owned land

4

and asymmetric information between the landowners and the regulating agency. 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.

A second strand of the habitat conservation 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, Stoneham et al. 2003, Kirwan et al. 2005, Wu and Babcock 1995, 1996). Regulatory approaches to habitat conservation on privately held lands 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 contiguous 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) and Lewis et al. (2009) 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. While we draw on methods, models, and data sets used in previous studies (Lewis and Plantinga 2007, Nelson et al. 2008, Polasky et al. 2008, Lewis et al. 2009), we make a number of improvements in this paper on these prior works. First, we develop and apply a new theoretically-grounded method for estimating WTA that avoids the need to equate WTA for commodity-producing land uses (e.g., forest) to WTA for conservation uses, as was done previously in Nelson et al. (2008). Second, we estimate a random parameters logit model that allows us to account for unobserved temporal and spatial components of WTA. This model is more flexible than those used in all the studies referenced above. As well, we estimate it using data for our study region rather than using results from a national-level econometric model as was done previously in Nelson et al. (2008). Third, we measure the social costs of policies instead of the budgetary costs to the government, as in Nelson et al. (2008), thus permitting an evaluation of the efficiency of policies. Fourth we explore the attributes of policy alternatives, including both least-cost and benefit-cost policies, related to good performance. Finally, we combine the most appropriate econometric and biological modeling approaches from prior work into an integrated model. Only Nelson et al. (2008) has previously done so. Polasky et al. (2008) measure land value directly from parcel characteristics but do not incorporate information about landowner

decision-making, which is included in the econometric approach. Lewis and Plantinga (2007) and

Lewis et al. (2009) evaluate policies for reducing habitat fragmentation but do not model the

persistence of species of conservation concern.

2. Simulating Responses to Conservation Incentives

Estimating the effects of voluntary land-use policies on the spatial pattern of landscape

change requires two primary tools: 1) a method to simulate baseline landscape change in the

absence of policy, and 2) a method to estimate the distribution of WTA for conservation payments

for a *population* of landowners. While econometric land-use models provide an obvious tool for

simulating baseline landscape changes (e.g., Lubowski et al. 2006; Lewis and Plantinga 2007),

estimating the WTA distribution is more challenging for at least two reasons. First, using data on

actual conservation programs (e.g., prices paid for conservation easements) will likely cause

sample selection bias because unobservable characteristics may influence both landowner WTA

and the decision to enroll in the program. To control for sample selection bias requires data on

both participating and non-participating landowners. An alternative approach that avoids sample

selection bias is to use micro-scale data on land rental rates or land prices. Rental rate data

provide information on a landowner's opportunity cost of remaining in the current use, but do not

account for the foregone value of converting to a more profitable use in the future, such as urban

development. In theory, land prices capitalize the stream of rents from the highest-valued uses.

For our application, we lacked comprehensive data on land sales, especially observations of non-

developed parcels that are candidates for conservation.

Here we describe an econometric land-use model and its use in simulating responses of

private landowners to incentive-based conservation policies. The method combines county-level

estimates of the net returns to multiple land-uses with observed land-use decisions to estimate

WTA distributions for a *population* of landowners. Importantly, the method does not suffer from

the sample selection bias problem that arises when working with data on actual conservation decisions. In addition, the method uses a large, comprehensive sample of observed land-use conversions to measure the opportunity cost of remaining in current use or converting to any alternative use. A notable feature of the approach is our ability to simulate both baseline and policy-induced landscape change from the same underlying model. We use data on observed land-use decisions in Oregon and Washington to estimate WTA distributions 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.[1] 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:

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

for all uses $k=1,\ldots,K$ and time periods $t=1,\ldots,T$, 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 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.[2] The inclusion of $R_{c(i)kt}$ and LCC_i allows the net revenue for parcel i to deviate from the county

average net revenue due to observable land quality. 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}.

The specification of equation (1) has a flexible error structure and allows the net revenue for parcel i to deviate from the county average net revenue due to unobservable parcel and county factors. 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 net revenues to be correlated spatially (all parcels within a county share a common $\varpi_{1c(i)jk}$ term) and temporally (each parcel has a common ϖ_{2ijk} term across periods). We can identify the random parcel effect because of the panel structure of our data (the land-use decision on each plot is observed at multiple points in time). As such, we account for plot-level unobservables (e.g., road proximity) that are likely to be correlated across time. In addition, since the error components vary by starting and ending land-use, the variance of the error structure in (1) is heteroskedastic (the variance varies by land use).

The model in (1) is a random parameters logit (RPL) model that is estimated with maximum simulated likelihood using data for Oregon and Washington west of the crest of the Cascade Mountains. 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 land uses that account for most of the region's private landbase: cropland, pasture, forest, and urban. 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 forests 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. There were 1,197 NRI plots in cropland use in 1982, and by 1997 there were 176 plots that converted to pasture, 9 plots that converted to forest, and 95 plots that converted to urban. There were 1,574 NRI plots in pasture in 1982, and by 1997 there were 177 plots that converted to crops, 79 plots that converted to forest, and 87 plots that converted to urban. 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 - 8. We estimate interaction terms for net crop revenues and the combined LCC 3 & 4 and LCC 5 - 8 (LCC 1 & 2 is the omitted category). Due to a lack of variation in LCC categories for cropland conversions to pasture, we only estimate interaction terms for net pasture revenues and the LCC categories when pasture is the starting use. There is not sufficient LCC variation in conversions to forest or urban use to estimate interaction terms.

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 term in the first set of 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).[3] The second term includes the spatial and temporal random adjustments to the county average net revenue described above. 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 $\alpha_{jj} = 0$, 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.[4] 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 plots beginning in cropland conforms closely to expectations – all coefficients on net revenues are positive, and the marginal effect of net revenues on cropland falls as land quality falls. The results for the model that describes pasture conversion to use k are mixed. The coefficient for pasture and cropland net revenues has the expected positive effect on higher quality lands, but turns negative for low quality lands (LCC>4 for pasture; LCC>2 for crops). This likely reflects the fact that there are few parcels in such uses for low land quality. The coefficient on urban net revenues in the pasture equation is positive and significantly different from zero with a one-tailed test and a 10% level of significance, while the coefficient on forest net revenues is negative but not significantly different from zero. Finally, there is evidence of substantial unobserved heterogeneity at the county and parcel-levels, as 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 in the pasture equation.

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 found by considering the net revenue for each of K possible land-uses:

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

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

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

where γ is Euler's constant and v_{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

putting their land into conservation.

It should be noted that we do not model uncertainty over future net revenues or the

potential irreversibility of land-use decisions (Schatzki 2003). As such, option values associated

with delaying conversion decisions are not explicitly represented in our WTA measures, though

they may be implicitly captured in the estimated model parameters. If there is an option value

associated with converting land to conservation uses, we may underestimate WTA. This problem

is partially mitigated given our interest in the relative performance of different conservation

policies.

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[5], 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:

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

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:

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

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 $WTA_i(\Omega_{ij})$, where $\Omega_{ij} = (\varpi_{1c(i)j}, \varpi_{2ij}, \alpha_j, \beta_j, \sigma_j, \nu_{ijt})$ 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 Ω.[6] We show average

distributions for crop and pasture parcels in the Willamette Basin in Fig. 1.[7]

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

We conduct a spatially-explicit simulation of conservation incentives in the 2.93 million

hectare Willamette Basin (Fig. 2). 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 match

WTA distributions and land-use transition probabilities from the econometric analysis to privately-

owned land parcels in the Basin. We use a parcel map constructed from a 30-meter grid cell land cover map for 1990 (ORNHIC 2000). To create the 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, dense urban uses, and inside urban growth boundaries 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.[8] 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.

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, $WTA_n(\mathbf{\Omega})$, based on equation (4).[9]

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:

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

where F is a logistic function, and $\mathbf{R}_{c(i)t}$ is a vector of all of the net revenue variables and $\mathbf{\varpi}_{1c(i)j}, \mathbf{\varpi}_{2ij}, \mathbf{\alpha}_j, \mathbf{\beta}_j$ and $\mathbf{\sigma}_j$ 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 (urban). 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 4×4 matrix denoted $\boldsymbol{P_{n5}}$.

2.4 Simulating the Spatial Pattern of Conservation Lands

We consider policies that pay landowners to 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. It is assumed that landowners know their own WTA but the regulator knows only the distribution of WTA. 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.[10] 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 producers and other market distortions in addition to externalities (e.g., actions that affect water quality, air quality, aesthetics, and other environmental benefits). We evaluate budgets of $5, $10, $20, and $30 million dollars per year.

We use Monte Carlo methods in the simulations to characterize the range of potential landscape patterns. 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 Ω are drawn from their estimated distributions (Krinsky and Robb 1986) for each parcel n on the landscape and used to compute $WTA_n(\Omega)$.

2) The period 0 conservation decision for each parcel eligible for a conservation payment is determined by comparing $WTA_n(\Omega)$ to the payment Z. If $WTA_n(\Omega) \leq Z$, 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 P_{n50}.[11] 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 P_{n50}.[12]

Using these steps we simulate a landscape of private land-use and conservation decisions that would exist fifty years after the policy is enacted. In each round that 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.[13]

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 relative 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.[14] 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 that can range from 0 to 1. 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 solutions 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 (i.e., this simplified model assumes that all patches are perfectly connected). 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.[15]

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).[16] Of the 267 original terrestrial species evaluated, we found 24 species that satisfy the above criteria for being of "conservation concern".[17]

4.2 Incentive-Based Policies Analyzed

We evaluate alternative incentive-based policies. Several are motivated by the types of habitat conserved in the estimated efficient solutions (Table 2). Four insights relevant for designing incentive-based policies emerge. First, efficient solutions tend to target the conservation of relatively rare habitat types, particularly oak savanna, prairie, and emergent marsh. These habitats comprise approximately 95% of conserved parcels in the approximate efficient solutions. Second, it is important to target locations that contain large numbers of species. Approximately 60% of the parcels chosen under the approximate efficient 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 approximate efficient solutions, conserved parcels tend to be large – the average size of conserved parcels is on the upper end of the parcel size distribution – 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.

We evaluate six 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.[18] Second, we incorporate a spatial agglomeration bonus (e.g. Parkhurst et al. 2002) that restricts eligibility to parcels whose immediate neighbor also accepts a payment. Further, we incorporate insights from Table 2 by

restricting the agglomeration payments only to those parcels with rare habitat. Finally, in an effort to combine multiple insights from Table 2, we evaluate a policy that incorporates multiple eligibility constraints, limiting eligibility to parcels that contain rare habitat, are large, and within the range of at least 14 species.

The second group of policies we examine target payments according to estimated benefit-cost ratios, an approach often used to find efficient solutions (e.g., Murdoch et al. 2007, Weitzman 1998). Benefit indices are derived using the same basic biological principles used to define eligibility constraints for the least-cost policies. Expected cost is the parcel-specific mean per-acre cost as derived from the estimated distributions of WTA. For example, under the *Lot Size - Agglomeration* policy, the benefits for a parcel are the combined size of conserving that parcel and a neighboring parcel (in acres). We rank parcels by the benefit-to-expected-cost ratio in descending order, and the parcel with the highest benefit-cost ratio is targeted first and paid its simulated WTA. Each subsequent parcel in the ranking is conserved up until the point that the budget (computed as the sum of actual WTA for conserved parcels) is exhausted. In addition to the *Lot Size - Agglomeration policy*, we also design a policy that partially mimics Oregon's Wildlife Habitat Incentives Program (*WHIP*) [19] and a policy that incorporates a benefit index for multiple criteria.

5. Results

The relative performance of the incentive-based policies at the four annual budget levels is presented in Table 4. The first row reports the changes in the biodiversity score relative to the baseline for the estimated efficient solution. We then present the mean change in the score (averaged over 500 simulated landscapes and measured relative to the baseline) for each policy and budget combination. In parentheses is the mean change in the biodiversity score for each

policy expressed as a percentage of the change in the biodiversity score in the estimated efficient solution.[20]

The estimated efficient solution displays increasing returns at low levels of the 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, and decreasing returns at levels of the budget above $10 million. In this application, many of the species of conservation concern need significant increases in conserved habitat before they exhibit much increase in estimated survival probabilities. At low budget levels, little land can be conserved and conservation efforts have small effects. At a budget of $10 million, a sufficient amount of land is conserved to achieve critical levels of habitat protection. Beyond the budget of $10 million, further habitat conservation generates progressively lower marginal benefits.

The incentive-based policies also exhibit increasing returns over a range of budget levels. With few exceptions, the policies display increasing returns up to the $20 million budget level and some policies show increasing returns at all levels. Increasing returns occur for a wider range of budgets because the incentive-based policies cannot control as precisely the spatial pattern of conserved land so that habitat additions tend to be more fragmented than in the efficient solution. Those policies that do not take special account of spatial patterns tend to exhibit increasing returns over a wider range of budget levels. For such policies land conserved tends to be fragmented, especially at low levels of conservation. As more land is conserved, there is a greater chance that conserved parcels will be joined, and this produces improved conservation outcomes (Lewis *et al*. 2009).[21]

None of the incentive-based policies do particularly well relative to the estimated efficient solution at low budget levels. At a budget of $5 million, the best incentive-based policy (*Agglomeration – Rare Habitat*) achieves only 24% of the estimated maximum increase in the

biodiversity score. The benefit-cost policies do particularly poorly at the budget of $5 million, achieving less than 10% of the increase in the biodiversity score under the estimated efficient solution. We had expected the benefit-cost policies to 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 choosing sites with rare habitat types or that border 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 outperforms the other least-cost policies, achieving greater increases in the biodiversity score at all budget levels. This policy restricts eligibility to parcels that contain rare habitat types important for conservation and to parcels that border other conserved parcels, which reduces habitat fragmentation. The *Rare Habitat – Large – Range* policy consistently scores below the *Agglomeration – Rare Habitat* policy, but higher than the *Simple Uniform* policy. The difference between each of the least-cost policies is generally small compared to the difference between the least-cost policies and the estimated efficient solution. The least-cost policies achieve only about 30-50% of the estimated maximum potential increase in the biodiversity score at a budget of $30 million, 20-40% at a budget of $20 million, and 10-20% at budgets of $5 or $10 million.

As the budget increases, the performance of benefit-cost policies improves compared to the least-cost policies and the estimated efficient result. At a budget of $10 million the performance of *Lot Size Agglomeration* improves dramatically with a 10-fold increase in the change in biodiversity score compared 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, 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% of the estimated maximum attainable change in biodiversity score.

Figure 3 summarizes the relative performance of the policies by presenting the estimated efficiency frontier along with the best and worst policy frontiers. The policy frontiers depict the change in the biodiversity score achieved by the best or worst performing policy at each of the budget levels. The worst frontier is defined at most budget levels by the *WHIP* benefit-cost policy, which most closely mimics current conservation policy in the region. However, Oregon's WHIP program is targeted towards a different set of goals than maximizing a biodiversity score for the terrestrial species modeled here. In particular, Oregon's WHIP program has a focus on aquatic species (e.g., Salmon), species listed under the Federal Endangered Species Act and Oregon state programs, and particular Conservation Opportunity Areas that may not spatially align with the best habitat areas for the 24 terrestrial species modeled here. The best policy frontier provides guidance with respect to the type of information that should be incorporated into the policy design. The policies on the best frontier are those that target rare habitat types and that minimize fragmentation. Even though the best policies do much better than the worst, at most budget levels they still achieve a relatively small percentage of the estimated maximum increase in the biodiversity score at low budget levels.

Across the 500 simulations, there is considerable variation in the results for many of the policies we analyzed. In Figure 4 we demonstrate this variation by showing the entire distribution of the biodiversity scores (not just the means) for the *Rare Habitat – Large – Range* policy, as applied in its least-cost and benefit-cost versions. There are two general findings. First, the

variance of the biodiversity score increases as the budget gets larger. Increasing budgets result in more conserved land, which increases the number of ways the landscape could be arranged, and yields a wider array of biodiversity outcomes. Second, the variance in the biodiversity score resulting from the least-cost policies is 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 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.

We also examined the sensitivity of the relative rankings of policies to assumptions in the biological model. In particular, we compared results when we varied parameter values on the saturating function so that a 50% probability of species persistence was made to equal 250, 500, and 750 breeding pairs. As the number of breeding pairs needed for a 50% probability of persistence shrinks, the amount of habitat needed to achieve conservation targets declines making the reduction in breeding pairs work to some extent like an increase in the conservation budget. The relative rankings of the incentive policies did not change with alternative assumptions about the saturation function for large budgets (no changes at the $30 million budget and only one change at the $20 million budget). At the $5 million budget, two benefit-cost policies, *Rare Habitat – Large – Range* and *Lot Size-Agglomeration*, do markedly better at 250 breeding pairs than at 500 or 750 breeding pairs. Both of these strategies do well as the conservation budget increases. Full results of this analysis are available from the authors upon request.

6. Conclusion

This paper addresses the efficiency of simple voluntary incentive-based policies in achieving biodiversity conservation objectives. This issue is important not just for biodiversity

conservation but for any effort to provide a public good requiring coordination over multiple decision-makers who have some degree of private information. We developed a method 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. These methods allow us to simulate landowner responses to policies and the consequences of these decisions for biodiversity conservation and to compare these outcomes to efficient outcomes to show the relative efficiency of various policy approaches. Our approach draws on the strengths of earlier conservation planning and incentive-based policy literatures, while improving the methods applied in our previous papers (Lewis and Plantinga 2007, Nelson et al. 2008, Polasky et al. 2008, Lewis et al. 2009).

We find that simple voluntary incentive-based policies are often highly 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 with full information and control over 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. Our results demonstrate that information revealing mechanisms such as auctions to elicit landowners' willingness-to-accept combined with an explicit attention to habitat fragmentation may be a necessary step to achieving efficient conservation with incentive-based policies. The results of our analysis comparing simple incentives to the efficient

solution indicate the degree to which the efficiency of voluntary incentives in conserving biodiversity can be improved through gathering further information on WTA.

The results presented in this paper are influenced by the landscape context and the species we included in our analysis. Other applications that analyze incentive-based policies in different landscapes and with different species will be needed before we can be confident about general conclusions. Nevertheless, our results suggest a set of testable general 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 relative efficiency of incentive-based policies 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 tend to be more efficient than benefit-cost policies when budgets are low but the reverse tends to be true when budgets are high, and e) policies 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.

References

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

Balmford, A., K.J. Gaston, A.S.L. Rodrigues and A. James. 2000. "Integrating Conservation Costs into International Priority Setting." *Conservation Biology* 11: 597-605.

Ben-Akiva, M. and S. Lerman. 1985. Discrete Choice Analysis. MIT Press, Cambridge, MA.

Cabeza, M. and A. Moilanen. 2003. "Site-Selection Algorithms and Habitat Loss." *Conservation Biology* 17: 1402-1413.

Camm, J.D., S. Polasky, A. Solow and B. Csuti. 1996. "A Note on Optimal Algorithms for Reserve Site Selection." *Biological Conservation* 78: 353-355.

Cason, T. and L. Gangadharan. 2004. "Auction Design for Voluntary Conservation Programs." *American Journal of Agricultural Economics* 86(5): 1211-1217.

Christy, J., E. Alberson, M. Dougherty, S. Kolar, L. Ashkenas and P. Minear. 1998. "Presettlement Vegetation for the Willamette Valley, Oregon." Compiled from records of the General Land Office Surveyors (c. 1850). Oregon Natural Heritage Program, Portland, OR.

Church, R.L., D.M. Stoms and F.W. Davis. 1996. "Reserve Selection as a Maximal Coverage Problem." *Biological Conservation* 76: 105-112.

Connor, J., J. Ward and B. Bryan. 2008. "Exploring the Cost Effectiveness of Land Conservation Auctions and Payment Policies." *The Australian Journal of Agricultural and Resource Economics* 51(3): 303-319.

Costello, C. and S. Polasky. 2004. "Dynamic Reserve Site Selection." *Resource and Energy Economics* 26: 157–174.

Csuti, B, S. Polasky, P.H. Williams, R.L. Pressey, J.D. Camm, M. Kershaw, A.R. Kiester, B. Downs, R. Hamilton, M. Huso and K. Sahr. 1997. "A Comparison of Reserve Selection

Algorithms Using Data on Terrestrial Vertebrates in Oregon." *Biological Conservation* 80: 83-97.

Feng, H. 2007. "Green Payments and Dual Policy Goals." *Journal of Environmental Economics and Management* 54: 323–335.

Ferraro, P.J. 2008. "Asymmetric Information and Contract Design for Payments of Environmental Services." *Ecological Economics* 65(4):810-821.

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

Haab, T.C. and K.E. McConnell. 2003. Valuing Environmental and Natural Resources. Edward Elgar Publishing, Northampton, MA.

Innes, R., S. Polasky and J. Tschirhart. 1998. "Takings, Compensation and Endangered Species Protection on Private Land." *Journal of Economic Perspectives* 12(3):35-52.

Jiang, Y., S.K. Swallow and P.W.C. Paton. 2007. "Designing a Spatially-Explicit Nature Reserve Network Based on Ecological Functions: An Integer Programming Approach." *Biological Conservation* 140: 236-249.

Kirwan, B., Lubowski, R.N., and M.J. Roberts. 2005. "How Cost-Effective Are Land Retirement Auctions? Estimating the Difference between Payments and Willingness to Accept in the Conservation Reserve Program." *American Journal of Agricultural Economics* 87: 1239-1247.

Kiesecker, J. M., T. Comendant, T. Grandmason, E. Gray, C. Hall, R. Hilsenbeck, P. Kareiva, L. Lozier, P. Naehu, A. Rissman, M. R. Shaw and M. Zankel. 2007. "Conservation Easements in Context: a Quantitative Analysis of Their Use by The Nature Conservancy." *Frontiers in Ecology and the Environment* 5(3): 125-130.

Kirkpatrick, J.B. 1983. "An Iterative Method for Establishing Priorities for the Selection of Nature

    Reserves: An Example from Tasmania." *Biological Conservation* 25(2): 127-134.

Krinsky, I. and A. Robb. 1986. "On Approximating the Statistical Properties of Elasticities." *The*

    Review of Economics and Statistics 86: 715-719.

Latacz-Lohmann, U. and C. Van der Hamsvoort. 1997. "Auctioning Conservation Contracts: A

    Theoretical Analysis and Application." *American Journal of Agricultural Economics* 79(2):

    407-418.

Lewis, D.J. and A.J. Plantinga. 2007. "Policies for Habitat Fragmentation: Combining

    Econometrics with GIS-Based Landscape Simulations." *Land Economics* 83(2): 109-127.

Lewis, D.J., A.J. Plantinga and J. Wu. 2009. "Targeting Incentives for Habitat Fragmentation."

    American Journal of Agricultural Economics 91(4): 1080-1096.

Lubowski, R.N. 2002. *Determinants of Land-Use Transitions in the United States: Econometric*

    Analysis of Changes among the Major Land-Use Categories. Ph.D. Dissertation, Harvard

    University, Cambridge, MA.

Lubowski, R.N., A.J. Plantinga and R.N. Stavins. 2006. "Land-Use Change and Carbon Sinks:

    Econometric Estimation of the Carbon Sequestration Supply Function." *Journal of*

    Environmental Economics and Management 51: 135-52.

Margules, C.R. and R.L. Pressey. 2000. "Systematic Conservation Planning." *Nature* 405: 242-

    253.

Meir, E., S. Andelman and H.P. Possingham. 2004. "Does Conservation Planning Matter in a

    Dynamic and Uncertain World?" *Ecology Letters* 7: 615-622.

Millennium Ecosystem Assessment. 2005. <u>Living Beyond Our Means: Natural Assets and Human</u>

    <u>Well-Being</u>. Island Press, Washington, DC.

Moilanen, A., A.M.A. Franco, R.I. Early, R. Fox, B. White and C.D. Thomas. 2005. "Prioritizing Multiple-Use Landscapes for Conservation: Methods for Large Multi-Species Planning Problems." *Proceedings of the Royal Society*, *Series B* 272: 1885-1891.

Murdoch, W., S. Polasky, K. Wilson, H. Possingham, P. Kareiva, and R. Shaw. 2007. "Maximizing Return on Investment in Conservation." *Biological Conservation* 139: 375-388.

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

Natural Heritage Data Center Network. 1993. <u>Perspectives on Species Imperilment: A Report from the Natural Heritage Data Center Network</u>. The Nature Conservancy, Arlington, VA.

Nelson, E., S. Polasky, D. Lewis, A. Plantinga, E. Lonsdorf, D. White, D. Bael and J. Lawler. 2008. "Efficiency of Incentives to Jointly Increase Carbon Sequestration and Species Conservation on a Landscape." *Proceedings of the National Academy of Sciences* 105(28): 9471-9476.

Newburn, D.A., P. Berck and A.M. Merenlender. 2006. "Habitat and Open Space at Risk of Land-Use Conversion: Targeting Strategies for Land Conservation." *American Journal of Agricultural Economics* 88(1): 28-42.

Nicholson, E., M.I. Westphal, K. Frank, W.A. Rochester, R.L. Pressey, D.B. Lindenmayer and H.P. Possingham. 2006. "A New Method for Conservation Planning for the Persistence of Multiple Species." *Ecology Letters* 9: 1049-1060.

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

Oregon Department of Land Conservation and Development. [n.d.] Oregon Rural Lands Database. http://geography.uoregon.edu/infographics/rldatabase/. (January 29, 2008).

Oregon Natural Heritage Information Center (ORNHIC). 2000. <u>Integrated Willamette Basin Landcover ARCINFO Coverage and Related Metadata</u>. Portland, Oregon.

Plantinga, A.J. 1996. "The Effect of Agricultural Policies on Land Use and Environmental Quality." *American Journal of Agricultural Economics* 78: 1082-1091.

Plantinga, A.J. 2007. "The Economics of Conservation Easements." In Ingram, G.K., and Y.-H. Hong (Eds.), <u>Land Policies and their Outcomes</u>. Proceedings of the 2006 Land Policy Conference, Lincoln Institute of Land Policy.

Parkhurst, G.M. and J.F. Shogren. 2007. "Spatial Incentives to Coordinate Contiguous Habitat." *Ecological Economics* 64: 344–55.

Parkhurst, G.M., J.F. Shogren, C. Bastian, P. Kivi, J. Donner, and R.B.W. Smith. 2002. "Agglomeration Bonus: An Incentive Mechanism to Reunite Fragmented Habitat for Biodiversity Conservation." *Ecological Economics* 41: 305-328.

Polasky, S. 2001. "Investment, Information Collection and Endangered Species Conservation on Private Land." In J. Shogren and J. Tschirhart (Eds.). <u>Endangered Species Protection in the United States: Biological Needs, Political Realities, Economic Consequences</u>. Cambridge University Press, Cambridge, U.K.

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

Polasky, S. and H. Doremus. 1998. "When the Truth Hurts: Endangered Species Policy on Private Land with Imperfect Information." *Journal of Environmental Economics and Management* 35(1): 22-47.

Polasky, S., E. Nelson, E. Lonsdorf, P. Fackler and A. Starfield. 2005. "Conserving Species in a Working Landscape: Land Use with Biological and Economic Objectives." *Ecological Applications* 15: 1387-1401.

Polasky, S., E. Nelson, J. Camm, B. Csuti, P. Fackler, E. Lonsdorf, D. White, J. Arthur, B. Garber-Yonts, R. Haight, J. Kagan, C. Montgomery, A. Starfield, and C. Tobalske. 2008. "Where to Put Things? Spatial Land Management to Sustain Biodiversity and Economic Production." *Biological Conservation* 141(6): 1505-1524.

Rissman, A., L. Lozier, T. Comendant, P. Kareiva, J.M. Kiesecker, M.R. Shaw, A.M. Merenlender. 2007. "Conservation Easements: Biodiversity Protection and Private Use." *Conservation Biology* 21 (3): 709–718.

Sala, O.E., F. S. Chapin, III, J.J. Armesto, E. Berlow, J. Bloomfield, R. Dirzo, E. Huber-Sanwald, L.F. Huenneke, R.B. Jackson, A. Kinzig, R. Leemans, D.M. Lodge, H.A. Mooney, M. Oesterheld, N.L. Poff, M.T. Sykes, B.H. Walker, M. Walker, and D.H. Wall. 2000. "Global Biodiversity Scenarios in the Year 2100." *Science* 287: 1770–1774.

Schatzki, T. 2003. "Options, Uncertainty and Sunk Costs: An Empirical Analysis of Land Use Change." *Journal of Environmental Economics and Management* 46(1): 86-105.

Schillizzi, S. and U. Latacz-Lohmann. 2007. "Assessing the Performance of Conservation Auctions: An Experimental Study." *Land Economics* 83(4): 497-515.

Smith, R.B.W. and J.F. Shogren. 2002. "Voluntary Incentive Design for Endangered Species Protection." *Journal of Environmental Economics and Management* 43(2): 169-187.

Stoneham, G., V. Chaudri, A. Ha and L. Strappazzon. 2003. "Auctions for Conservation Contracts: An Empirical Examination of Victoria's Bush Tender Trial." *The Australian Journal of Agricultural and Resource Economics* 47(4): 477-500.

Strange, N., B.J. Thorsen and J. Bladt. 2006. "Optimal Reserve Selection in a Dynamic World."
Biological Conservation 131: 33-41.

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

U.S. Department of Agriculture. 1973. Land Capability Classification. Soil Conservation Service
Agricultural Handbook No. 210, Washington, DC.

U.S. Department of Agriculture – National Resources Conservation Service (USDA-NRCS).
2010. Wildlife Habitat Incentive Program (WHIP). Accessed at
http://www.nrcs.usda.gov/programs/whip/

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

Weitzman, M.L. 1998. "The Noah's Ark Problem." *Econometrica* 66: 1279-1298.

Wilcove, D.S., D. Rothstein, J. Dubow, A. Phillips and E. Losos. 2000. "Leading Threats to
Biodiversity: What's Imperiling U.S. Species." In: B.A. Stein, L.S. Kutner and J.S. Adams
(Eds.), Precious Heritage: The Status of Biodiversity in the United States. Oxford University
Press, Oxford, U.K., pp. 239-254.

Wu, J. and B.A. Babcock. 1995. "Optimal Design of a Voluntary Green Payment Program under
Asymmetric Information." *Journal of Agricultural and Resource Economics* 20(2): 316–327.

Wu, J. and B.A. Babcock. 1996. "Contract Design for the Purchase of Environmental Goods from
Agriculture." *American Journal of Agricultural Economics* 78: 935–945.

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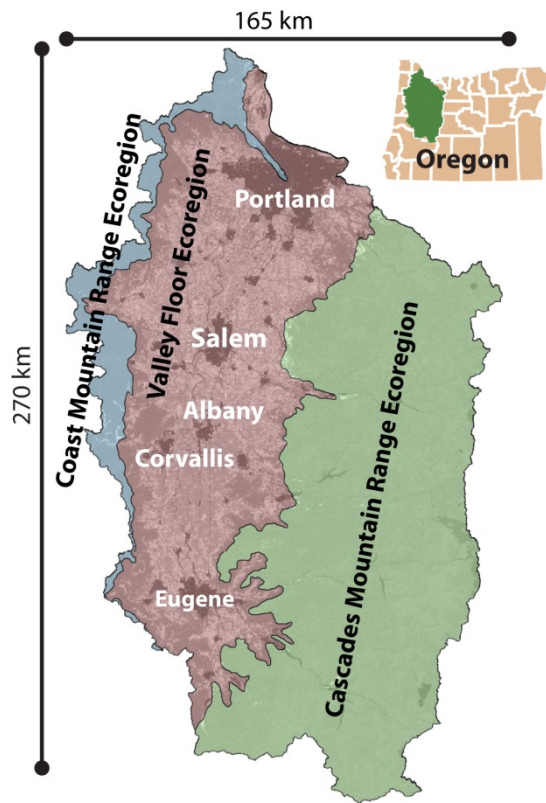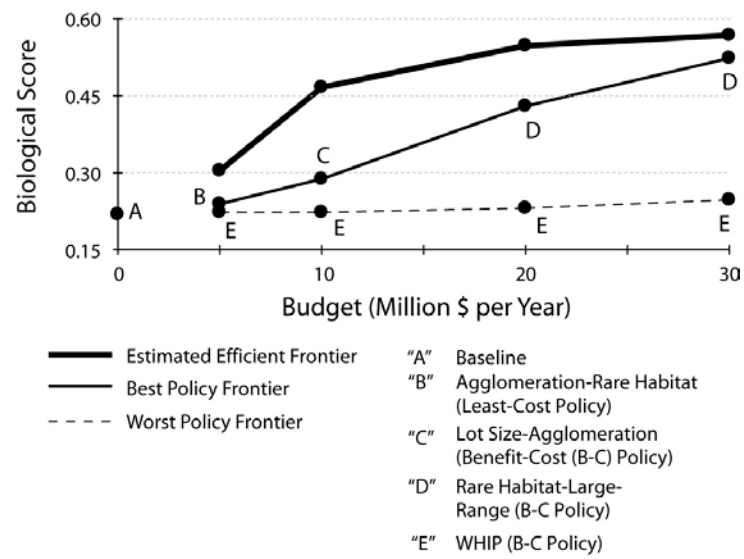
a. Land starting in cropland
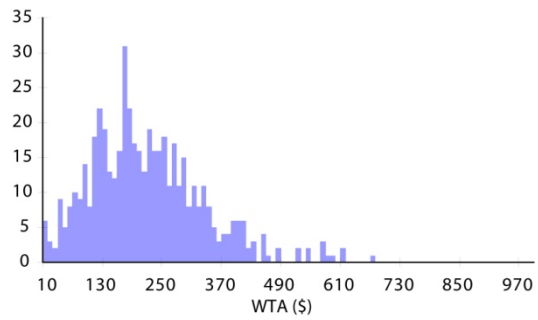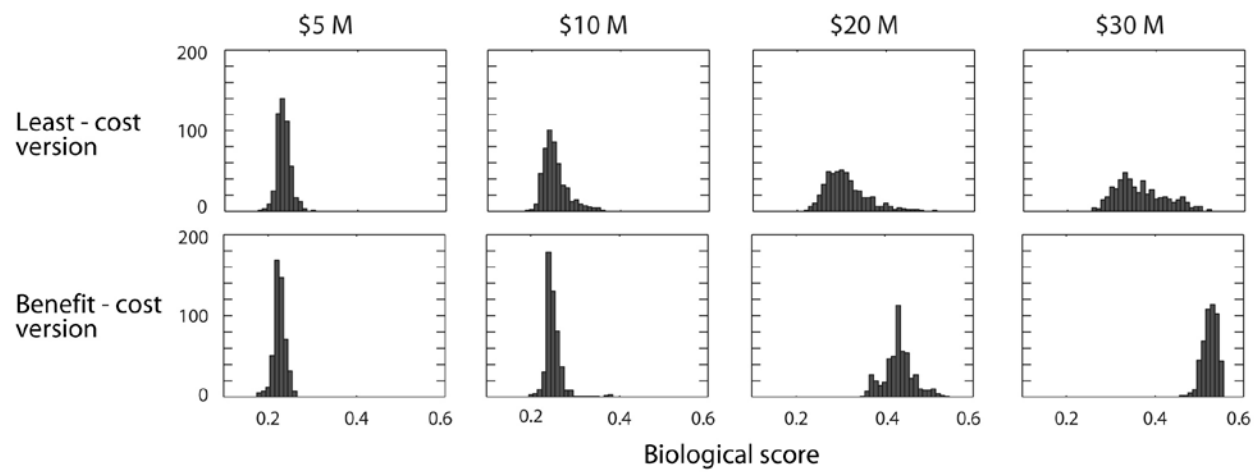

b. Land starting in pasture
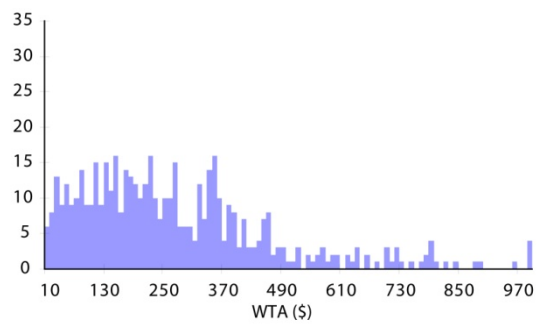
Fig. 2 –The Willamette Basin

Fig. 3 – The estimated efficiency, best policy, and worst policy frontiers

Fig. 4 - Frequency of biological scores under the Rare Habitat – Large – Range policy

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
Crop Intercept	-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
Forest Intercept	-6.310	1.852	-3.407
Forest Returns	-0.117	0.573	-0.205
Urban Intercept	-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 Estimated Efficiency Solution 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
Agglomeration - Rare Habitat	Parcels satisfying both the Agglomeration and Rare Habitat criteria	NA
Rare Habitat – Large – Range	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 - 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	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
Estimated Efficient Solution	0.0844	0.2456	0.3293	0.3498
Uniform Policies				
Simple Uniform	0.0105	0.0227	0.0615	0.1058
	(12.45%)	(9.23%)	(18.66%)	(30.24%)
Agglomeration - Rare Habitat	**0.0199**	0.0555	0.1321	0.1919
	(**23.62%**)	(22.61%)	(40.13%)	(54.86%)
Rare Habitat – Large – Range	0.0131	0.0330	0.0907	0.1454
	(15.54%)	(13.42%)	(27.53%)	(41.56%)
Benefit-Cost Policies				
Lot Size Agglomeration	0.0060	**0.0685**	0.1278	0.2253
	(7.06%)	(**27.88%**)	(38.82%)	(64.43%)
WHIP	0.0032	0.0051	0.0116	0.0292
	(3.80%)	(2.06%)	(3.52%)	(8.34%)
Rare Habitat – Large – Range	0.0065	0.0310	**0.2120**	**0.3050**
	(7.67%)	(12.61%)	(**64.39%**)	(**87.21%**)

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] 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 random parameters model allows us to measure implicitly these and other unobservable parcel-level effects.

[2] 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.

[3] 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) adjustment 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.

[4] Each observation is weighted according to NRI expansion factors to reflect the geographic sampling intensity that is present in the NRI. To avoid shrinking standard errors due to this weighting, the weights are scaled so that they sum to the total number of observations.

[5] The NRI is a stratified random sample of plots, whereby information on the geographic sampling intensity is provided by the NRI's expansion factor. The expansion factor is used to weight the likelihood function in estimation.

[6] 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.

[7] 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).

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

[9] 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).

[10] 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.

[11] 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.

[12] 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.

[13] 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.

[14] 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.

[15] 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.

[16] 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.

[17] 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.

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

[19] WHIP is a federal program that offers financial assistance for wildlife habitat on private land (USDA-NRCS 2010). Scarce cost-share assistance is allocated according to a system that ranks applications for cost share according to the land's habitat potential. Each state helps determine its own ranking system.

[20] 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.

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