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Landscape simulations with econometric-based land-use models

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I. Introduction

The spatial configuration of land use and land cover has important influences on populations of birds (Askins 2002, Faaborg 2002) and amphibians (Kolozsvary and and Swihart 1999, deMaynadier and Hunter 2000), the health of riverine systems (Gergel et al. 2002) and estuaries (Hale et al. 2004), human perceptions of scenic quality (Palmer 2004), and the extent of urban sprawl (Carrion-Flores and Irwin 2004). Land-use change results in changes in the spatial pattern of land use, often in ways that diminishes environmental quality. For example, habitat fragmentation can occur when changes in land use transform a contiguous habitat patch into disjunct patches. Many species of conservation interest are sensitive to habitat fragmentation, including birds (Askins 2002, Faaborg 2002), amphibians (Kolozsvary and and Swihart 1999, Lehtinen et al. 2003), and large mammals (Noss 1994, Costa et al. 2005). 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). In landscapes dominated by private ownership, landowners lack the incentive to coordinate decisions in order to influence the spatial land-use pattern and the environmental outcomes that depend on it. Econometric-based landscape simulation models have been developed to understand the nature and extent of this market failure problem and to identify and quantify the effects of corrective land-use policies. A landscape simulation begins with a spatial representation of the landscape, such as a land-use map where the unit of analysis is a land parcel, and simulates changes in the landscape through the use of rules applied at the unit scale. An econometric-based simulation model uses rules derived from econometric estimation. For example, Lewis and Plantinga (2007) estimate an econometric model that relates observed land-use changes to economic returns to alternatives uses. The econometric results are then incorporated into a landscape simulation model used to study how forest fragmentation is affected by incentive-based policies that modify the relative returns to different uses. Lewis, Plantinga, and Wu (2009) analyze the spatial targeting of incentives to increase contiguous forest habitat and Lewis et al. (2011) consider the relative efficiency of voluntary incentive-based policies in achieving biodiversity conservation objectives. The latter analysis combines an econometric land-use model, landscape simulations, and a biological model of biodiversity that depends on the spatial pattern of land use.

The development of econometric-based simulations for landscapes dominated by private ownership presents four basic challenges. The first is to represent variation in the private economic returns to land at the same scale at which land use varies. Hedonic price studies reveal that returns to urban land uses vary considerably at fine spatial scales. Housing prices, for example, are affected by proximity to the central business district, roads, and amenities (Wu, Adams, and Plantinga 2004), as well as spatial interactions with neighboring parcels (Irwin and Bockstael 2002). Returns to rural land uses, such as cropland and forests, typically exhibit little variation at this scale because output and input prices for land-based commodities are relatively constant over space. Factors that can cause varation in rural land returns include soil quality, which affects crop and timber yields, and access to markets. Land-use regulations, such as zoning restrictions, can also have important effects on economic returns (Grout, Jaeger, and Plantinga 2011).

The second challenge is to model the private information that landowners possess about the returns to their land. Researchers have incomplete information about private returns because of unobservable parcel attributes, landowner characteristics such as managerial expertise, and private non-market benefits (e.g., recreation) associated with particular uses of the land. The random utility framework is a common way to accommodate the incomplete information. The returns to land are represented by a deterministic component and a random error observed only by the landowner. This gives rise to a probabilistic model of land-use change, as in Lubowski, Plantinga, and Stavins (2006). Lewis et al. (2011) estimate a mixed logit model that includes random parameters to account for spatial and temporal correlation in land-use decisions. Their results indicate a significant degree of unobserved heterogeneity in returns to land.

The third challenge is how to best account for land-use intensity. In addition to choosing the use of their land, landowners must decide on the intensity of use. For example, once the landowner has chosen to develop her land, she must also decide on how many housing lots to build per acre or how many floors to add to a commercial building. Likewise, a farmer who allocates his land to crops must decide which crops to produce and how intensively to cultivate them. Finally, the forest owner must chose species and rotation length, among other management decisions. Land-use intensity is, thus, the set of secondary choices faced by a landowner once the land-use decision has been made. Land-use intensity has important implications for econometric land-use models because it affects the economic return to the chosen use. In many previous studies, land-use intensity is implicitly assumed in the measurement of net returns to each use (e.g., Stavins and Jaffe 1990; Plantinga 1996; Lubowski, Plantinga, and Stavins 2006).[1] Lewis, Provencher, and Butsic (2009) and Lewis (2010), however, model land intensity as a joint decision with land use. Explicit representation of land-use intensity may be warranted if differences in intensity are important for the landscape-level processes of interest. For example, in the application presented below, the intensity of development—measured as the number of shoreline housing lots—has important effects on the green frog population we study.

The fourth challenge arises from the probabilistic nature of the land-use transition rules derived from econometric analysis (Bockstael 1996). The researcher can determine whether a particular parcel is more likely to convert than another parcel, but not that any particular parcel will convert with certainty. Some analysts present maps showing the spatial distribution of the estimated probabilities (Bockstael 1996; Cropper et al. 2001), while others form deterministic rules from probabilistic ones (e.g., Chomitz and Gray 1996; Irwin and Bockstael 2002). A problem with the latter approach is that a given deterministic rule is only one of many possible rules. Thus, the simulation produces a single landscape that represents only one of what is typically a very large number of potential landscapes. An alternative is to generate a large number of different landscapes conforming to the underlying probabilistic rules. However, one must then summarize this information in a way that effectively conveys the range of potential outcomes.

This chapter will discuss landscape simulations based on econometric land-use models, emphasizing ways to overcome the four challenges mentioned above. The next section will review the related literature. Section 3 will present the basic methodology for econometric modeling of private land-use decisions and section 4 will describe the use of these models in landscape simulations. An application of the methods is provided in section 5 and a final section considers directions for future research.

2. Previous Literature

Numerous studies in the economics literature seek to explain observed land-use decisions in terms of profit-maximizing behavior. Early studies employed aggregate (typically county-level) data on land use (Stavins and Jaffe 1990, Plantinga 1996, Hardie and Parks 1997), while more recent analyses have used plot-level data (Lubowski, Plantinga, and Stavins 2006, Lewis et al. 2011) and spatially-explicit land-use or land-cover data (Bockstael 1996, Nelson et al. 2001, Cropper et al. 2001, Irwin and Bockstael 2002, 2004, Carrion-Flores and Irwin 2004). An advantage of spatial data is that they allow spatial processes to be modeled explicitly. For example, Bockstael (1996) uses a hedonic function of residential development value to predict the potential developed value of agricultural parcels. The hedonic function includes measures of distances to cities, water access, and neighborhood characteristics. The potential development values are used, along with other controls, in a probit model of land conversion estimated with spatially-explicit data.

The results of econometric estimation provide a set of rules governing parcel-level changes in land use. By combining econometric results with a GIS-based landscape representation, Lewis and Plantinga (2007), Lewis, Plantinga, and Wu (2009), Nelson et al. (2010), and Lewis et al. (2011) simulate future land-use patterns under alternative biodiversity conservation policy scenarios. Their simulations account for land conversion into urban use as well as exchanges between rural uses (e.g., cropland to forest), which have important implications for species habitat. Many earlier landscape simulation studies focused on urbanization (e.g., Bockstael 1996, Carrion-Flores and Irwin 2004) or deforestation (e.g., Nelson et al. 2001). Researchers in other disciplines, notably geography, have also made important contributions to the development of spatial models of landscape change (Clarke and Gaydos 1998, Guzy et al. 2008, Li and Gar-On Yeah 2000, Wu 1998, 2002, Allen and Lu 2003). A criticism of the models in the geography literature is that the transition rules represent human decisions, yet typically are not based on well-specified and empirically-validated models of human behavior (Wu and Webster 2000).

The literature on systematic conservation planning (SCP) is also concerned with characterizing future landscapes (Margules and Pressey 2000). In contrast to the simulation approach discussed above, SCP uses optimization methods to identify sites for conservation. In the basic formulation of the problem, sites are chosen to 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). More recent studies in the SCP literature have analyzed complex 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).

3. Econometric models

The results of econometric estimation provide a set of rules governing land-use change in landscape simulations. In this section, we present a general framework for specifying and estimating econometric land-use models with parcel-scale data. We also discuss strategies to address the first three challenges described above—how to represent variation in the private economic returns to land at the same scale at which land use varies, how to model the private information that landowners possess about the returns to their land, and how to account for land-use intensity.

3.1 Model specification

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. It is convenient to assume landowners form static expectations. That is, landowners consider currently available information and form an expectation about the future annual return to their land that is constant (though can be updated as new information becomes available). 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 problem with relaxing this assumption is that the land-use decision then depends on the future sequence of net returns, and one must apply Bellman's equation to find the optimal solution. This complicates the estimation problem considerably, though previous authors have estimated structural models of dynamic decision making (e.g., Rust 1989, Provencher 1995). An interesting application of these methods would be to the land-use decision problem.

Assuming static expectations, the landowner compares the annualized net return to alternative uses and allocates her parcel to the use providing the greatest return. The net return (NR_{ikt}) equals the annual net revenues generated from parcel (R_{ikt}) less annualized conversion costs (C_{ijkt}), where i indexes the parcel, k the chosen use, j the initial use, and t the time. In general, the researcher cannot observe all of the factors that determine net returns to the landowner, motivating a specification of net returns that includes deterministic and random components, such as:

(1) $$NR_{ikt} = \beta_{0jk} + \beta_{1jk} R_{ikt} + \beta_{2jk} C_{ijkt} + \mu_{ijkt}$$

where $(\beta_{0jk}, \beta_{1jk}, \beta_{2jk})$ are parameters specific to the *j*-to-*k* transition and μ_{ijkt} is a random error term.

Lewis et al. (2011) adopt the following specification of net returns, which is a special case of (1):

(2) $$NR_{ikt} = \beta_{0jk} + \beta_{1jk} R_{c(i)kt} + \beta_{2jk} LCC_i R_{c(i)kt} + \mu_{ijkt}$$

where $R_{c(i)kt}$ 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*. The LCC system assigns a rating of I through VIII to a land parcel, where lower numbers indicate higher productivity for agricultural crops. 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 due to observable land quality. The effects of annualized conversion costs are assumed to be constant across parcels and time and are measured implicitly by β_{0jk}. Similar specifications are used in Lubowski et al. (2006) and Lewis and Plantinga (2007).

The three studies mentioned above meet the first modeling challenge—representing variation in the private economic returns to land at the same scale at which land use varies—using the interaction of the county average net return and parcel-level land quality. An alternative approach is to use parcel-level data to estimate separate hedonic price models for the net returns to each use. These models can incorporate spatial variables, such as distances to urban centers and features of the surrounding landscape, and be used to predict net returns for the unselected land uses in the choice set. In this fashion, Bockstael (1996) estimates a hedonic price model of the value of land in residential housing. Parcel-level predictions of the value of land in residential use are then incorporated into a probit model to explain development of agricultural land. Carrion-Flores and Irwin (2004) and Newburn, Berck, and Merenlender (2006) enter the determinants of net returns (e.g., slope, elevation, soil characteristics, distances to cities, zoning, and neighboring land uses) directly into the land-use change model. The disadvantage of this reduced-form approach is that one loses economic information—specifically, the relationship between land-use decisions and net returns—that can be used in simulations of incentive-based policies, such as subsidies for land conversion.

The random utility framework, adopted for all of the econometric land-use models discussed in this section, addresses the second challenge—modeling the private information that landowners possess about the returns to their land. In (1), the deterministic component of net returns, $\beta_{0jk} + \beta_{1jk} R_{ikt} + \beta_{2jk} C_{ijkt}$, is assumed to be common knowledge, whereas the random error μ_{ijkt} is observed by the landowner, but not by the researcher. The average net revenues from crop production in a county, R_{ikt}, are typically observable, but the researcher is unlikely to observe deviations from the mean return due to landowner-specific skills, knowledge, and other individual attributes. These deviations are captured in μ_{ijkt} and represent a landowner's private information about her returns. In all but one of the studies mentioned above, researchers impose assumptions on the distribution of μ_{ijkt} that yield probit or multinomial logit models. Lewis et al. (2011) have panel data on land-use change and, thus, can use a more flexible random parameters specification:

(3) $$\mu_{ijkt} = \sigma_{1jk} \varpi_{1c(i)jk} + \sigma_{2jk} \varpi_{2ijk} + \varepsilon_{ijkt}$$

where $(\varepsilon_{ijkt}, \varpi_{1c(i)jk}, \varpi_{2ijk})$ are random variables and $(\sigma_{1jk}, \sigma_{2jk})$ are parameters. The random parameters allow for spatial correlation ($\sigma_{1jk}\varpi_{1c(i)jk}$ takes the same value for all parcels within a county) and temporal correlation ($\sigma_{2jk}\varpi_{2ijk}$ takes the same value for a given parcel in all time periods).[2]

A useful property of random utility models is that they define a distribution over—in the land-use context—the maximum net return from each land parcel. Given the starting use *j*, and *K* possible land-use choices, the maximum net return derived from parcel *i* in time *t* is:

$$(4) \qquad R^*_{ijt} = \max\left\{\beta_{0jk} + \beta_{1jk}R_{ikt} + \beta_{2jk}C_{ijkt} + \mu_{ijkt}\right\}_{k=1}^{K}$$

The assumption that μ_{ijkt} is distributed type I extreme value allows (4) to be re-written:

$$(5) \qquad R^*_{ijt} = \frac{1}{\xi_j}\left(\ln\left[\sum\nolimits_k \exp(\beta_{0jk} + \beta_{1jk}R_{ikt} + \beta_{2jk}C_{ijkt})\right] - \gamma\right) + \nu_{ijt}$$

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 (5) can be used in landscape simulations to introduce land uses other than those in the original choice set, as long as one can assume that landowners will accept the maximum net return from their parcel as compensation for adopting the new use. Lewis et al. (2011) use this approach to model habitat conservation on private land. In this context, equation (5) defines a distribution over landowners' willingness-to-accept conservation payments.

The above discussion assumes that the net returns in (1) are fixed. In most cases, however, the net return is chosen by the landowner when she selects the land-use intensity. The appropriate way to model this is the third challenge discussed above. Formally, for parcel *i*, use *k*, and time *t*, the landowner chooses the intensity *m* to solve:

(6) $$NR_{ikt} = \max_{m} \left\{ NR_{ikt,m} \right\}_{m=1}^{M_k}$$

where M_k is the number of intensity choices associated with use k. The simplest approach is for the researcher to assume she knows the solution to (6) (or at least the deterministic component of the solution). Provided that one can observe the choice of intensity, a more flexible approach is to model the intensity decision explicitly. A natural extension of the random utility models discussed above is to model intensity as a nested choice conditional on land use. In this formulation, the landowner is assumed to simultaneously choose land use and intensity, conditional on the net returns to each use-intensity combination. Lewis, Provencher, and Butsic (2009) estimate a probit model of the binary development decision jointly with a count model of the number of housing lots. They address the sample selection problem inherent to their data, namely, that the number of housing lots are observed only for developed parcels. Landscape simulations are normally concerned with the population of land parcels, which argues for the use of econometric methods that can mitigate sample selection bias.

4. Landscape simulations

The results from the estimation of econometric land-use models translate into a set of rules governing land-use change. In the case of random utility models, specifically, the researcher obtains a $K \times K$ matrix of land-use transition probabilities for each parcel:

(6) $$P_{ijkt} = F\left(\mathbf{X}_{it}' \hat{\boldsymbol{\beta}}_{jk} \right)$$

where $\mathbf{X}_{it}$ is a vector of explanatory variables for parcel i in time t (e.g., the net returns to each of the alternative uses) and $\hat{\boldsymbol{\beta}}_{jk}$ is the vector of estimated parameters associated with the use j-to-k transition. The transition matrices are then matched to parcels in a GIS using the variables in $\mathbf{X}_{it}$. Figure 26.1 illustrates how this is done for the model specification in (2). One obtains GIS layers on land ownership, political boundaries, soil quality, and initial land cover and overlays them to define distinct parcels on the landscape. Each parcel corresponds to a set of transition probabilities defined in (6). The land ownership layer is needed to eliminate public land parcels since the econometric model applies only to private lands. The county and soil quality layers indicate the values of $R_{c(i)kt}$ and LCC_i to use in applying (6) and the land cover layer indicates the initial set of estimated parameters to use. If *j* is the initial land use of the parcel, then the relevant parameter set is $\hat{\boldsymbol{\beta}}_{jk}$, *k*=1,…,*K*. In a similar fashion, one can associate a maximum net return distribution with each parcel in the GIS.

[INSERT FIGURE 26.1 HERE]

Once this matching exercise is complete, Monte Carlo methods are used to simulate future changes in the landscape. To begin, suppose that parcel *i* is initially in crop use and, according to the matched set of transition probabilities for the parcel, will remain in crops with a 70% probability and change to pasture, forest, and urban use, each with a 10% probability. A random draw from a specified distribution, such as a U(0,1), determines whether the parcel remain in crops (e.g., if the random draw is between 0 and 0.70), changes to pasture (between 0.70 and 0.80), and so on. This procedure is repeated for every parcel and results in a period *t*+1 landscape. The transition probabilities are then updated for each parcel on the *t*+1 landscape. For example, if parcel *i* changed to pasture use, then transition probabilities for this parcel must be computed with a different parameter set. Or, net returns may be different in period *t*+1 due, for example, to endogenous price feedbacks. This process is repeated until a landscape representation is obtained for the future period of interest.

Of course, the simulated landscape is only one of many possible landscapes consistent with the underlying transition rules. Some earlier authors have used the transition probabilities to form a deterministic rule for land-use change (Chomitz and Gray 1996; Irwin and Bockstael 2002). For example, Nelson and Hellerstein (1997) and Nelson et al. (2001) assume that each parcel will be put to the use with the highest estimated transition probability. This practice, however, is at odds with the random utility framework underlying the econometric model. Because of the unobserved component of net returns, the researcher does not have the information needed to predict changes in land use with certainty. Only probabilistic statements about land-use changes can be made. To characterize the range of potential outcomes, one can repeat the process described above many times to generate a large number of future landscapes, each of which is consistent with the probabilistic transition rules. This, however, raises our fourth modeling challenge—how does one summarize this information in a way that effectively conveys the range of potential outcomes?

Lewis and Plantinga (2007) solve this informational challenge with landscape metrics that summarize the spatial pattern of land use. The focus of their study is forest fragmentation and so for each landscape they compute the average forest patch size and the area of core forest (forest parcels that are completely surrounded by other forest parcels). This defines a distribution over the landscape metrics. In a similar fashion, Lewis et al. (2011) convert each landscape into a biodiversity score using a biological model that combines simulated landscapes with information on species and habitats. They summarize the results by computing the mean biodiversity score.

An important question that arises in Monte Carlo analysis is how many repetitions are enough? In the context of our problem, how many landscapes need to be simulated? In most cases, the number of possible landscapes will be astronomically large. For instance, there are 5×10^{47} possible ways to arrange three land uses on a 100-parcel landscape. Fortunately, the researcher is interested not in describing all possible landscapes, but rather with characterizing the distribution over the outcome of interest, such as a fragmentation metric or a biodiversity score. Stability in the outcome distribution is likely to be achieved after a relatively small number of simulations. The ideal approach would be to implement a convergence rule that would end the simulations when additional landscapes change the outcome distribution in a sufficiently small way, though this may not be feasible if multiple computer programs are in use. In his study of forest fragmentation, Lewis (2005) found that the first three moments of the distributions defined over five fragmentation indices changed very little once 500 landscapes had been simulated. As a further test, Lewis generated two samples of 500 landscapes and tested for differences in the sample moments across the two samples. Of course, these tests need to be done for each application to ensure the stability of the outcome distributions.

The power of econometric-based landscape simulations lies with their use for investigating effects of land-use policies on landscape-scale environmental outcomes. If $\mathbf{X}_{it}$ includes measures of net returns, then one can simulate the effects of incentive-based policies such as subsidies for afforestation or habitat conservation. Lewis et al. (2011) evaluate a suite of conservation policies, ranging from a simple per-acre subsidy applied uniformly across the landscape to targeted policies that account for biological characteristics of land parcels. The authors generate landscapes for each policy scenario, comparing the mean biodiversity score in each case to the mean score obtained under a reference scenario with no policy.

5. Application

In this section, we present an application of an econometric-based landscape simulation model based on Lewis et al. (2009) and Lewis (2010). A model of shoreline development along 140 lakes in northern Wisconsin, USA, is described. The model represents both the decision to develop and the development intensity, where the unit of observation is a parcel of land. The model is used in a landscape simulation and coupled with a previously published regression model of green frog populations expressed as a function of a lake's development density (Woodford and Meyer 2003).

5.1 Econometric Specification

A landowner is assumed to make a binary decision to develop shoreline parcel *i* or leave it undeveloped. Denoting development by *k*=1 and the current undeveloped use by *k*=0, conversion is optimal if the net value of conversion (*NVC*) is positive:

$$(7) \qquad NR_{i1t} - NR_{i0t} = NVC_{it} = U(\mathbf{X}_{it}) + \mu_l > 0$$

where *NVC* is measured as a reduced-form function of observable parcel attributes $\mathbf{X}_{it}$ (e.g., soil quality, distance to town centers, etc.) and an unobservable μ_l specific to lake *l* (e.g., the scenic beauty of the lake). *NVC* is an indirect function of the land-use intensity decision upon conversion to the developed use. Formally, the value of choosing density *m* (i.e., *m* housing lots) is given by:

$$(8) \qquad V_{1m}(\mathbf{X}_{it}) + \varphi_{i1m} + \varepsilon_{i1t}$$

where V_{1m} is a density-specific function of observable variables $\mathbf{X}_{it}$, φ_{i1m} is a time-invariant density-specific unobservable for development, and ε_{i1t} is an unobservable for developed use in time *t* that is independent of density. The optimally chosen density is, then:

$$(9) \qquad m_{it}^{*}(\mathbf{X}_{it}, \omega_i) = \underset{m}{\operatorname{argmax}} \left\{ V_{1m}(\mathbf{X}_{it}) + \varphi_{i1m} \right\}_{m=1}^{M_1}$$

and the net return to developed use is given by:

$$(10) \qquad NR_{i1t} = V_{1m^*}(\mathbf{X}_{it}) + \varphi_{i1m^*} + \varepsilon_{i1t}$$

The net return to developed use is a random variable because it is derived by maximizing over a set of random variables.

A logical modeling approach would be to estimate an econometric model of expected land-use intensity Em_{it}^{*} as a function of a set of observable variables $\mathbf{X}_{it}$. However, since both Em_{it}^{*} and the net value of conversion NVC_{it} are derived from operations on the same set of random variables φ_{i1m}, there necessarily exists a sample selection problem in estimation of Em_{it}^{*}: the analyst only observes the intensity decision for those parcels converted to the developed use. We assume that we can represent (9) as a Poisson process, where Em_{it}^{*} depends on $\mathbf{X}_{it}$ and the random variable ω_i, where ω_i reinforces that the optimal density choice in (9) is a random variable generated by an operation on the set of random variables φ_{i1m}. The probability that $m_{it}^{*} = m$, m=1,2,…,M_1 is follows a zero-truncated Poisson distribution:

$$\text{(11)} \qquad \Pr[m_{it}^{*} = m \,|\, \mathbf{X}_{it}, \gamma_i] = \frac{\exp[-\exp(\theta \mathbf{X}_{it} + \sigma_2 \gamma_i)][\exp(\theta \mathbf{X}_{it} + \sigma_2 \gamma_i)]^m}{m!(1 - \exp[-\exp(\theta \mathbf{X}_{it} + \sigma_2 \gamma_i)])}$$

where $\omega_i = \sigma_2 \gamma_i$ is a normally distributed random variable with standard deviation σ_2, implying that γ_i is a standard normal random variable, and θ is a parameter vector.

To account for the sample selection problem discussed above, we assume that the net value of conversion depends on the unobservable ε_{i1t} that is correlated with γ_i, specifically:

$$\text{(12)} \qquad NVC_{it} = U(\mathbf{X}_{it}) + \mu_l = \delta \mathbf{X}_{it} + \mu_l + \varepsilon_{i1t}$$

In sum, the binary decision to develop is determined by (12), which features i) spatial correlation in the unobservables induced by the presence of a common unobservable (μ_l) for all parcels on lake l, and ii) an unobservable (ε_{i1t}) that is correlated with the unobservables in the land-use intensity decision (γ_i). If we make the assumption that ε_{i1t} is a standard normal, then the conditional probability of development ($d_{it}=1$) is given by,

$$(13)\qquad \Pr(d_{it}=1\,|\,\mathbf{X}_{it},\mu_l)=\Phi(\delta\mathbf{X}_{it}+\mu_l)$$

And, if we assume that ε_{i1t} and γ_i are joint standard normal with correlation coefficient ρ, then using the properties of the joint normal distribution (Greene 2012), we obtain:

$$(14)\qquad \Pr(d_{it}=1\,|\,\mathbf{X}_{it},\mu_l,\gamma_i)=\Phi([\delta\mathbf{X}_{it}+\mu_l+\rho\gamma_i]/\sqrt{1-\rho^2})$$

Conditioning the probability in (14) only on observables $\mathbf{X}_{it}$ requires integrating out μ_l and γ_i:

$$(15)\qquad \Pr(d_{it}=1\,|\,\mathbf{X}_{it})=\int\int \Pr[m_{it}^*=m\,|\,\mathbf{X}_{it},\gamma_i][\Pr(d_{it}=1\,|\,\mathbf{X}_{it},\mu_l,\gamma_i)]\phi(\gamma_i)\phi(\mu_l)d\gamma_i d\mu_l$$

where ϕ is the standard normal density function. Thus, the probability of the observed behavior (d_{it},m_{it}) on parcel *i* at time *t* is,

$$(16)\qquad \begin{aligned}\Pr(d_{it},m_{it}\,|\,\mathbf{X}_{it})=\int\int&[(1-d_{it})+d_{it}\Pr[m_{it}^*=m_{it}\,|\,\mathbf{X}_{it},\gamma_i]][\Phi((2d_{it}-1)(\delta\mathbf{X}_{it}+\mu_l+\rho\gamma_i]/\\&\sqrt{1-\rho^2})]\phi(\gamma_i)\phi(\mu_l)d\gamma_i d\mu_l\end{aligned}$$

Of particular importance in this model is the lack of statistical independence across parcel decisions, as γ_i captures parcel specific and time-invariant unobservables while μ_l captures lake specific and time-invariant unobservables. Thus, this specification includes both temporal and spatial correlation in the unobservables.

Lewis et al. (2009) estimate (16) by maximum simulated likelihood, where D_l denotes the full set of development and intensity decisions on lake *l*. Conditional on a draw of γ_i and μ_l, the probability of D_l is,

$$(17)\qquad \Pr(D_l)=\prod_i\prod_t[(1-d_{it})+d_{it}\Pr[m_{it}^*=m_{it}\,|\,\mathbf{X}_{it},\gamma_i]][\Phi((2d_{it}-1)(\delta\mathbf{X}_{it}+\mu_l+\rho\gamma_i]/\sqrt{1-\rho^2})]$$

Taking *R* sets of draws of γ_i and μ_l, the simulated approximation to the likelihood function is,

$$\text{(18)} \qquad \Pr^{Sim}(D_l) = R^{-1}\sum_{r=1}^{R}\Pr(D_l^r)$$

The econometric model is applied to legally subdividable lakeshore parcels across 140 lakes in Vilas County, a popular vacation destination in northern Wisconsin. The panel data were derived from a number of sources, including a GIS parcel database, the Wisconsin Department of Natural Resources (WI DNR), USDA soil surveys, and town governments in Vilas County. The GIS parcel database was constructed from county tax parcel data and historic plat maps, and consists of complete spatial coverage of all parcel boundaries in 4 year intervals from 1974 through 1998. The set of independent variables used to estimate (18) consists of parcel characteristics (size, soil restrictions, distance to town, zoning), lake characteristics (water clarity, lake size and depth, shoreline open-space), and time-period dummy variables. There were 335 individual subdivisions that occurred between 1974 and 1998 on a landscape that began with 1,310 legally subdividable shoreline parcels. The lakeshore development process was dominated by fairly small developments, as 82% of recorded subdivisions generated less than six new parcels each. More details on the model, in addition to estimation results and treatment of potentially endogenous variables are found in Lewis et al. (2009).

5.2 Simulation Model and Results

In this sub-section, we illustrate two important simulation issues. First, we show how to include both categorical land-use change and land-use intensity measures within a landscape simulation. Second, we demonstrate how an econometric land-use model can be coupled with an ecological model as a solution to the problem of summarizing information from a large number of simulated landscapes. We draw on Lewis's (2010) simulation study of shoreline land development in northern Wisconsin. The econometric model in this chapter treats the net returns to land as a reduced form expression of a set of soil characteristics, lake characteristics (water clarity, lake size, etc.), and a zoning policy variable indicating the minimum shoreline frontage for new residential lots. Output from the econometric model includes parcel-specific estimates of the probability of subdivision (a Probit model) and the expected number of new lots upon subdivision (a Poisson model). Importantly, the Poisson model of the expected number of lots can also be used to estimate the probability of each possible choice of density (one new lot, two new lots, etc.).

The development and intensity probabilities are functions of the set of independent variables, enabling Lewis (2010) to use the model to simulate the landscape effects of changes to shoreline zoning policies. The use of a joint model of categorical land-use change and land-use intensity raises the challenge of using two probability models (with correlation across the models) for the simulation. The following steps were used in the simulation:

1. Following the Krinsky and Robb method (1986), draw a parameter vector from the econometrically-estimated distribution to calculate the estimated Probit and Poisson probabilities for each parcel.[3]
2. Standard normal random draws are multiplied by the corresponding standard deviations from step (1) to generate a draw from the estimated random parameter distributions.
3. A complete time path (t=1….T) of development is estimated for each lake.
   - Draw a U ~ [0,1] random number r_1 for each parcel, where development occurs if r_1 is less than or equal to the estimated subdivision probability; otherwise, the parcel is assumed to remain in its current state.
   - If developed, use the estimated Poisson probability, $\Pr[m^*=m]$, of the number of new lots m as follows: Draw a U ~ [0,1] random number r_2; one new lot is created if $r_2 \leq \Pr[m^*=1]$,

two new lots are created if $\Pr[m^*=1] < r_2 \leq \Pr[m^*=2]$, and so forth until m^* is equal to the maximum number of lots allowable under zoning.

- Repeat these two steps until t=T.

4. Steps (1)-(3) are repeated to produce a large number of simulated landscapes.

This simulation procedure accounts for variation in the estimated model parameters and the random error terms. Further, since step one uses the covariance matrix of parameters from the joint estimation of the Probit and Poisson models, the simulation accounts for the estimated unobserved correlation between land development and land intensity and implicitly addresses the sample selection problem discussed above.

Each simulated landscape is evaluated in terms of habitat for green frog populations. The coupled economic-ecological model exploits the predictions from the econometric model of landscape pattern, which are then used as input to the ecological model. Lewis (2010) predicts shoreline development across each of 140 lakes, and shoreline development density is used to predict the population of green frogs. The green frog population model is a regression model developed by Woodford and Meyer (2003) that includes shoreline development density as an independent variable.[4] Notably, the Woodford and Meyer (2003) model was estimated with green frog data from lakes in our study region in northern Wisconsin. The spatial scale of the model is a lake (i.e., each lake is a habitat patch), which nicely fits the scale of Lewis' (2010) simulations, which provide lake-level estimates of development density. Since development density is the driver of green frog populations, this model also illustrates the value of modeling a land-use intensity choice rather than just land-use categories.

Figure 26.2 illustrates a twenty-year forecast from the econometric model as an empirical distribution of the number of lots on a select lake in northern Wisconsin. As expected, elimination of the zoning policy increases the likelihood of a larger number of lots being built. The coupling of the econometric model with the ecological model is performed by using the predicted shoreline development density for each simulation as an input into the ecological model to generate a predicted probability of extinction for green frogs.[5] Figure 26.2 illustrates how relaxing the zoning constraint along the lakes translates in a greater probability of extinction for green frog populations. The results in Figure 26.2 draw on a large number of probabilistic landscape simulations, each of which is consistent with the underlying econometric models. Thus, the results are represented in terms of empirical distributions of development densities and extinction probabilities. By modifying an independent variable in the econometric model, we see how these empirical distributions change as a function of a policy change.

[INSERT FIGURE 26.2 HERE]

6. Future Research

In landscapes dominated by private ownership, landowners lack the incentive to coordinate decisions in order to influence the spatial land-use pattern and the environmental outcomes that depend on it. Econometric-based landscape simulation models have been developed to understand the nature and extent of this market failure problem and to identify and quantify the effects of corrective land-use policies. In this chapter, we have discussed—and suggested solutions to—four challenges that arise with econometric-based landscape simulations: 1) representing variation in the private economic returns to land at the same scale at which land use varies, 2) modeling the private information that landowners possess about the returns to their land, 3) accounting for land-use intensity as part of the land-use decision process, and 4) recognizing the probabilistic nature of the land-use transition rules derived from econometric analysis.

Further challenges remain, including what we term the "salt-and-pepper" effect. To illustrate this, we present a simulated future landscape for the area surrounding Madison, Wisconsin (Figure 26.3). The simulation was done using land-use transition probabilities of the form in (6) applied to 30-meter pixels.[6] The existing urban areas are the large black shapes and most of the small black dots are projected future urban land. Clearly, the degree to which future urban land is scattered across the landscape is unrealistic. One would expect most future urban land to be added near existing urban areas and along transportation corridors. One of the reasons for this result is the decision-making scale. We assumed in this simulation that a land-use decision is made at the scale of each pixel on the landscape, which produces implausibly small areas (dots) of urban land. But, what is the right decision-making scale? This is a question critical to land-use modeling[7], but not one that can be easily answered in practice. One approach would be to assume that ownership determines the scale at which land-use decisions are made. That is, each landowner could be assumed to allocate her parcel to a single use. But, clearly there are many exceptions to this, as in the case of a diversified farm with land in crops, pasture, and forests. In the case of rented land, the use—and, particularly, the intensity—decision may be made by somebody other than the owner. And, finally, ownership can involve complicated legal arrangements that make it difficult to establish the actual owner of a particular parcel of land. In their simulation analysis, Lewis and Plantinga (2007) defined decision-making units in terms of contiguous blocks of land allocated to single uses. This mitigated the salt-and-pepper effect, but likely had other shortcomings.

[INSERT FIGURE 26.3 HERE]

The salt-and-pepper effect can occur, as well, if the econometric land-use model fails to account for important spatial processes. For example, urban development is often more likely to occur near roads. Ignoring this dependency in the econometric model will carry through to landscape simulations and likely produce a scattered pattern of future urbanization. The remedy is to estimate spatially-explicit econometric models of land use, which we regard to be the most important next step in the development of econometric-based landscape simulations. The earlier work in this chapter focused on the linkage between the spatial pattern of land use at the landscape scale and ecological outcomes, but has not emphasized the spatial relationships that affect land-use decisions. To represent these spatial processes, one needs high-quality spatial data to use in the estimation of econometric land-use models. These data are increasingly available, but their use gives rise to a number of additional econometric challenges. We conclude this chapter by emphasizing the importance of economic theory in guiding the development of spatial econometric models to be used for landscape simulations. Readers are referred to Brady and Irwin (2011) for a more complete discussion.

There are surely important spatial processes that affect land-use decisions, but what are they exactly? Why is urban development more likely to occur near to existing urban land, if it is (one can imagine negative externalities pushing development farther away)? If a person's land borders a farm, are they more likely to choose an agricultural use and, if so, why? These are examples of theoretical questions that should motivate the specification of spatial econometric models. One finds theoretically grounded spatial land-use models in Irwin and Bockstael (2002) and Lewis et al. (2011). Irwin and Bockstael (2002) conjecture that residential development creates a negative spatial externality that affects land-use decisions on neighboring land parcels. Their empirical analysis is motivated by and finds support for the underlying theory. Lewis et al. (2011) model the growth in organic dairy farms in Wisconsin, accounting for a positive spatial externality that reduces the fixed costs of learning. In these studies, the underlying theory makes clear that neighboring land uses are determined endogenously, requiring the use of instrumental variables as in Irwin (2002) or panel data methods as in Lewis et al. (2011). The combination of economic theory and appropriate econometric procedures is critical if intent is to use the econometric results in a landscape simulation. In this case, the underlying spatial process is identified explicitly and, thus, can be reproduced in the simulation.

References

Allen, J. and K. Lu. 2003. "Modeling and Prediction of Future Urban Growth in the Charleston Region of South Carolina: A GIS-Based Integrated Approach." *Conservation Ecology* **8**(2):2.

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

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

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*. Cambridge, MA: MIT Press.

Bockstael, N.E. 1996. "Modeling Economics and Ecology: The Importance of a Spatial Perspective." *American Journal of Agricultural Economics* 78(5): 1168-1180.

Brady, M., and E. Irwin. 2011. Accounting for Spatial Effect in Economic Models of Land Use: Recent Developments and Challenges Ahead. *Environmental and Resource Economics* 48(3): 487-509.

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.

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

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

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

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

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

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

Cropper, M., J. Puri, and C. Griffiths. 2001. “Predicting the Location of Deforestation: The Role of Roads and Protected Areas in North Thailand.” *Land Economics* 77(2): 172-186.

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.

deMaynadier, P.G., and M.L. Hunter. 2000. “Road Effects on Amphibian Movements in a Forested Landscape.” *Natural Areas Journal* 20: 56-65.

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

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

Gergel, S.E., Stanley, E.H., Turner, M.G., Miller, J.R., and J.M. Melack. 2002. “Landscape Indicators of Human Impacts to Riverine Systems.” *Aquatic Sciences* 64(2): 118-128.

Greene, W.H. 2012. *Econometric Analysis*. 7th edition. Prentice Hall.

Grout, C.A., Jaeger, W.K., and A.J. Plantinga. 2011. Land-Use Regulations and Property Values in Portland, Oregon: A Regression Discontinuity Design Approach. *Regional Science and Urban Economics* 41:98-107.

Guzy, M. R., C. L. Smith, J. P. Bolte, D. W. Hulse and S. V. Gregory. 2008. Policy research using agent-based modeling to assess future impacts of urban expansion into farmlands and forests. *Ecology and Society* **13**(1): 37.

Hale, S.S., Paul, J.F., and J.F. Heltshe. 2004. “Watershed Landscape Indicators of Estuarine Benthic Condition.” *Estuaries* 27(2): 283-295.

Hardie, I.W., and P.J. Parks. 1997. “Land Use with Heterogeneous Land Quality: An Application of an Area Base Model.” *American Journal of Agricultural Economics* 79: 299-310.

Irwin, E. and N.E. Bockstael. 2002. “Interacting Agents, Spatial Externalities and the Evolution of Residential Land Use Patterns.” *Journal of Economic Geography* 2: 331-54.

Irwin, E.G., and N.E. Bockstael. 2004. "Land Use Externalities, Open Space Preservation, and Urban Sprawl." *Regional Science and Urban Economics* 34: 705-725.

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.

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

Kolozsvary, M.B., and R.K. Swihart. 1999. "Habitat Fragmentation and the Distribution of Amphibians: Patch and Landscape Correlates in Farmland." *Canadian Journal of Zoology* 77(8): 1288-1299.

Krinsky, I. and A. Robb. 1986. "On Approximating the Statistical Properties of Elasticities." *The Review of Economics and Statistics* 86: 715-719.

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

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

Lewis, D.J. 2010. "An Economic Framework for Forecasting Land Use and Ecosystem Change." *Resource and Energy Economics,* 32(2): 98-116.

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., Plantinga, A.J., Nelson, E., and S. Polasky. 2011. The Efficiency of Voluntary Incentive Policies for Preventing Biodiversity Loss. *Resource and Energy Economics* 33(1):192-211.

Lewis, D.J., Plantinga, A.J., and J. Wu. 2009. Targeting Incentives to Reduce Habitat Fragmentation. *American Journal of Agricultural Economics* 91(4):1080-1096.

Lewis, D.J., Provencher, B., and V. Butsic. 2009. "The Dynamic Effects of Open-Space Conservation Policies on Residential Development Density." *Journal of Environmental Economics and Management,* 57(3): 239-252.

Li, X., and A. Gar-On Yeh. 2000. "Modeling Sustainable Urban Development by the Integration of Constrained Cellular Automata and GIS." *International Journal of Geographic Information Science* 14(2): 131-152.

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

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. *Living Beyond Our Means: Natural Assets and Human Well-Being.* 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.

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. *Perspectives on Species Imperilment: A Report from the Natural Heritage Data Center Network.* The Nature Conservancy, Arlington, VA.

Nelson, E., Polasky, S., Lewis, D.J., Plantinga, A.J., Lonsdorf, E., White, D., Bael, D., and J.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):9471-6.

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

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

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.

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

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

Palmer, J.F. 2004. "Using Spatial Metrics to Predict Scenic Perception in a Changing Landscape: Dennis, Massachusetts." *Landscape and Urban Planning* 69(2-3): 201-218.

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

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., 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.

Provencher, B. 1995. Structural Estimation of the Stochastic Dynamic Decision Problems of Resource Users: An Application to the Timber Harvest Decision. *Journal of Environmental Economics and Management* 29:321-38.

Rust, J. 1989. Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher. *Econometrica* 55(5): 999-1033.

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.

Stavins, R.N., and A.B. Jaffe. 1990. "Unintended Impacts of Public Investments on Private Decisions: The Depletion of Forested Wetlands." *American Economic Review* 80(3): 337-352.

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

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.

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.

Woodford, J.E., and M.W. Meyer. 2003. Impact of Lakeshore Development on Green Frog Abundance. *Biological Conservation,* 110: 277-284.

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

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

Wu, F. and C.J. Webster. 2000. "Simulating Artificial Cities in a GIS Environment: Urban Growth under Alternative Regulation Regimes." *International Journal of Geographic Information Science* 14(7): 625-648.

Wu, J., Adams, R.M., and A.J. Plantinga. 2004. Amenities in an Urban Equilibrium Model: Residential Development in Portland, Oregon. *Land Economics* 80(1):19-32.

Figure 26.1. Matching land-use transition matrices to parcels in a GIS

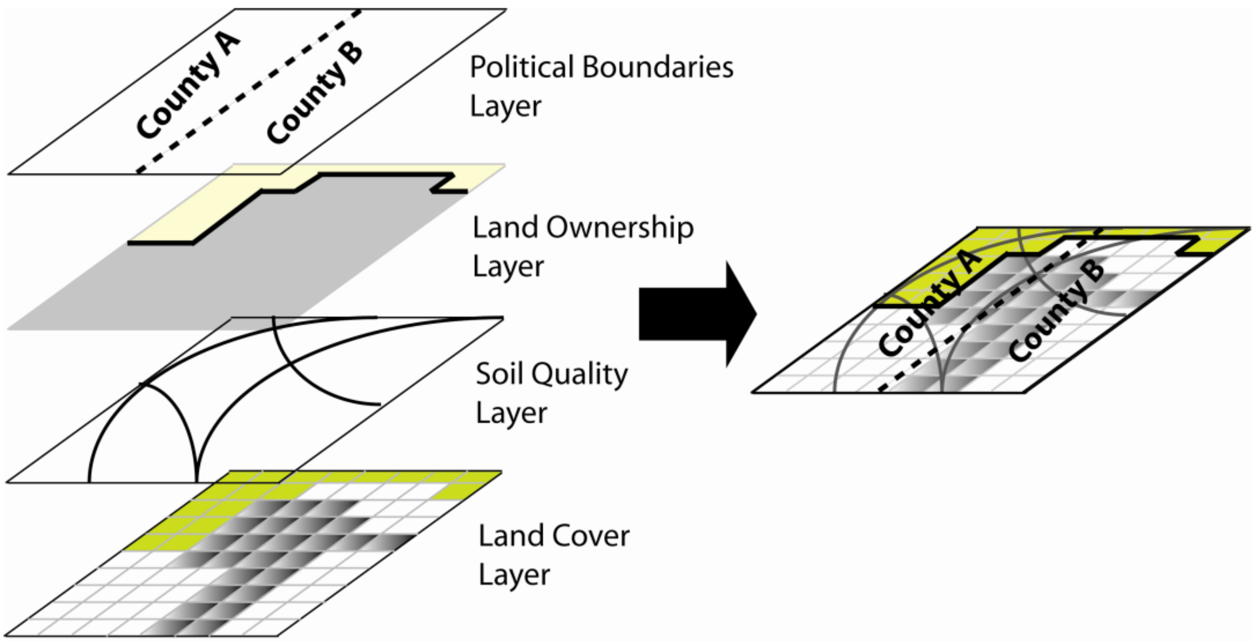


Figure 26.2. Coupling a Landscape Simulation with an Ecological Model for a Select Lake – Two Frequency Plots

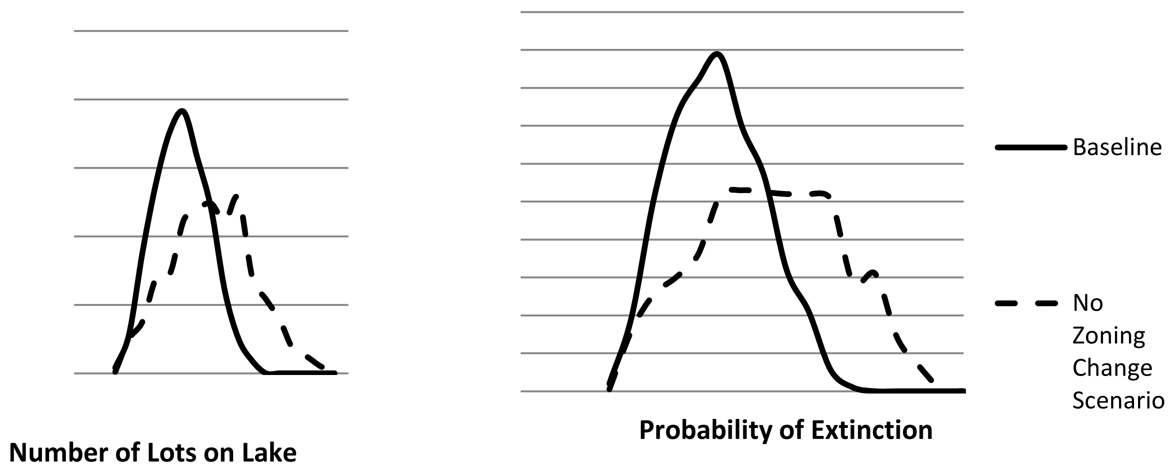
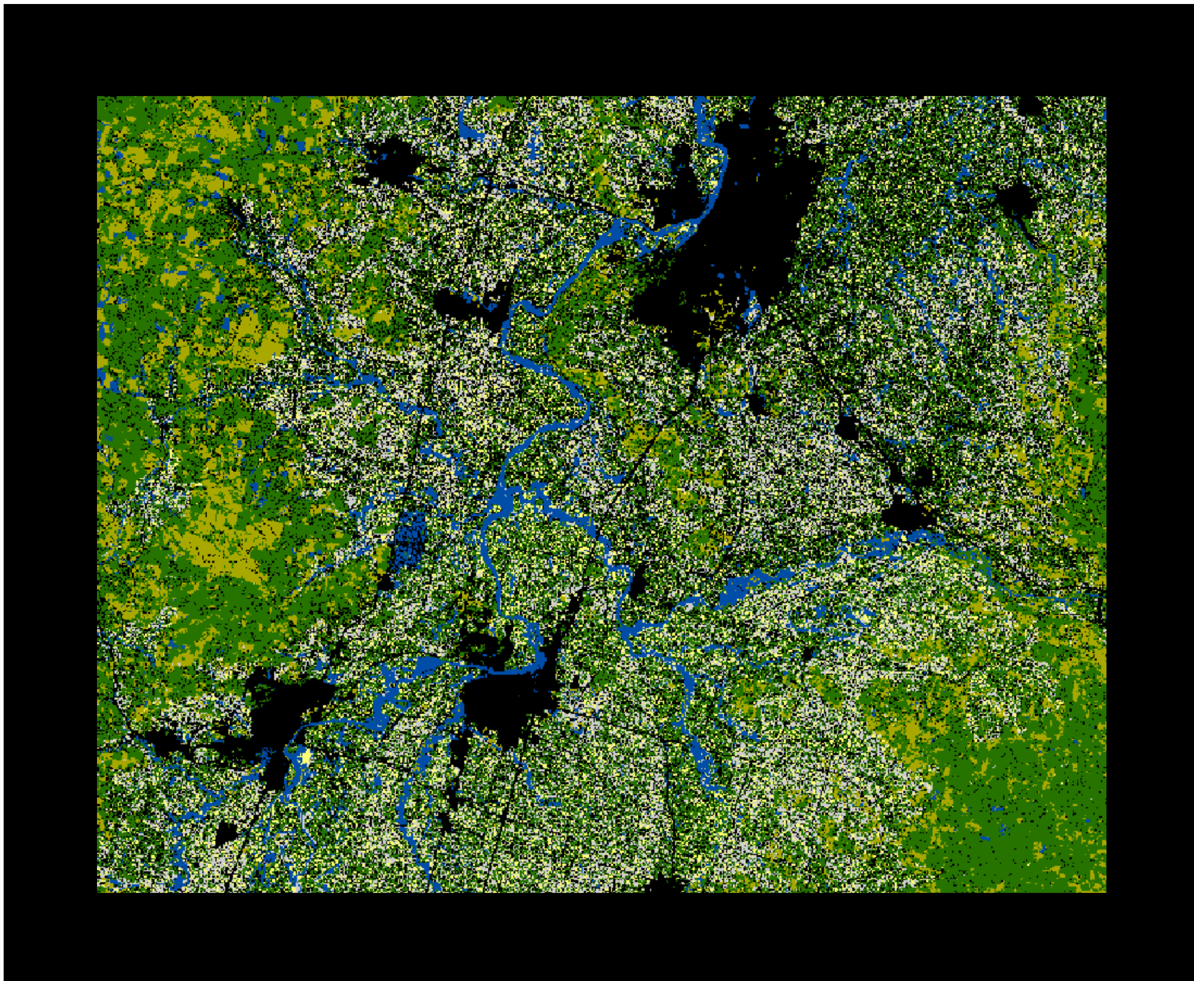


Figure 26.3. The Salt-and-Pepper Effect (urban land is shown in black)



[1] Lubowski, Plantinga, and Stavins (2006), for example, construct net returns to forest by assuming that landowners choose the existing mix of forest species in their county and follow the Faustmann rule in determining the rotation length.

[2] Many econometric challenges arise with the estimation of econometric land-use models, particularly when spatial processes are an important feature of land-use decisions. See Brady and Irwin (2011) for discussion of these issues.

[3] A simulated parameter vector is equal to $\boldsymbol{\psi}_s = \hat{\boldsymbol{\psi}} + \mathbf{C}'\boldsymbol{\lambda}_K$, where $\hat{\boldsymbol{\psi}}$ is the estimated parameter vector, **C** is the *K*x*K* Cholesky decomposition of the estimated variance-covariance matrix, and $\boldsymbol{\lambda}_K$ is a *K*-dimensional vector of draws from a standard normal distribution.

[4] The regression model from Woodford and Meyer (2003) is very simple and is estimated as $E(Frogs \mid Lots) = 2.537 - 1.189 \times Lots$, where *Frogs* is the number of Frogs per 100 m shoreline and *Lots* is the number of developed lots per 100 m shoreline. This function is slightly revised from the original published version that was sent directly to us by James Woodford. See the original paper Woodford and Meyer (2003) for additional information. The *Lots* variable is generated during each iteration of the simulation and plugged into this function to get a *Frogs* measure. More complex ecological models can be coupled to the economic model provided that the ecological outcomes of interest can be related to the predicted landscapes. See Lewis et al. (2011) for an example involving a larger set of species.

[5] Rather than use the expected number of green frogs, we use the properties of the simple regression function to generate extinction probabilities. The regression function from Woodford and Meyer has an estimated mean number of green frogs per 100m of $E(Frogs \mid Lots) = 2.537 - 1.189 \times Lots$. Also, using the sum of squared residuals, the model has an estimate of $\sigma=1.48$. The

probability of extinction is calculated at each simulation iteration by plugging the predicted *Lots* into the regression function, and using the cumulative normal distribution function with mean E(*Frogs* | *Lots*) and σ=1.48 to find the probability that less than zero frogs occur on each lake.

[6] In particular, each $K \times K$ set of transition probabilities varies only by soil quality and county.

[7] In addition to affecting simulated landscape patterns, as demonstrated in Figure 3, the decision-making scale can have important influences on land-use decisions if scale economies are present.