

# **An Economic Framework for Forecasting Land-Use and Ecosystem Change**

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**Abstract:** This paper develops a joint econometric-simulation framework to forecast detailed empirical distributions of the spatial pattern of land-use and ecosystem change. In-sample and out-of-sample forecasting tests are used to examine the performance of the parcel-scale econometric and simulation models, and the importance of multiple forecasting challenges is assessed. The econometric-simulation method is integrated with an ecological model to generate forecasts of the probability of localized extinctions of an amphibian species. The paper demonstrates the potential of integrating economic and ecological models to generate ecological forecasts in the presence of alternative market conditions and land-use policy constraints.

**Keywords:** spatial modeling, biodiversity conservation, land-use, landscape forecasting, shoreline development.

**JEL Codes:** Q24, Q57.

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## **1. Introduction**

Many of the most significant environmental management challenges can be informed by forecasts of ecological change (Clark et al. 2001). Since land development is widely viewed as a major driver of changes in aquatic and terrestrial ecosystems (Naiman and Turner 2000; Armsworth et al. 2004), an accurate forecast of ecological change will typically require a forecast of human-induced land development (Stein et al. 2005). In addition to providing basic information on the magnitude of expected changes in ecosystems, forecasting ecological change can also inform a classic economic problem: the allocation of scarce conservation effort across a spatially heterogeneous landscape. An efficient allocation of conservation effort will consider the heterogeneous benefits associated with protecting alternative locations, along with the fact that some locations are forecast to be more threatened with conversion to development than others (Costello and Polasky 2004; Newburn et al. 2006).

Predicting ecosystem change generally requires a method to forecast land-use change at the parcel scale (Nilsson et al. 2003), as many ecosystem goods and services are sensitive to the spatial configuration of developed and undeveloped land. However, parcel-scale land-use predictions suffer from uncertainties associated with projecting future rental values and land-use policies, and are fraught by the idiosyncratic nature of individual land-use decisions. For example, while residential development may be noticeably increasing at a regional scale, predicting its precise location is extremely challenging as the prior literature has estimated parcel-scale development probabilities of 5-10% over time periods of 5 to 10 years (e.g. Irwin and Bockstael 2004; Lewis and Plantinga 2007). Scaling up highly uncertain parcel-scale predictions to a broader landscape pattern adds an additional challenge since econometric estimation yields stochastic transition probabilities, and the same expected aggregate land-use shares in a

particularly region could be generated by very different parcel configurations. While errors in predicting different configurations may have little influence on outcomes that only depend on aggregate land-use predictions (e.g. carbon sequestration), the wildlife and predicted biodiversity benefits associated with a particular landscape can be extremely sensitive to particular configurations. Therefore, any empirical methodology used to estimate spatial land-use patterns must account for the potentially high confidence intervals associated with such predictions.

The purpose of this paper is to develop an economic framework to forecast detailed empirical distributions of the spatial pattern of land-use and ecosystem change. A spatial-temporal dataset of parcel-scale land development is the foundation of the analysis, which is conceptually outlined in figure 1. The framework begins with a parcel-scale econometric model estimated from *observed* development decisions of private landowners derived from the spatial data. The econometric model uses a Probit-Poisson framework to jointly estimate the probability and expected density of each parcel-scale development. The econometric estimates generate a set of transition rules to be used in a series of spatially-explicit landscape simulations that produce distributions of the spatial pattern of changes in development density. The landscape simulations are used as inputs into an ecological model that translates the landscape forecasts into metrics that describe a particular ecosystem change.<sup>1</sup> A key feature of the framework is the ability of the underlying econometric model of landowner behavior to generate alternative landscape forecasts – and hence, ecosystem forecasts – resulting from alternative market conditions and land-use policy scenarios.

The method is applied to forecasting the spatial pattern of residential development and the probability of localized extinctions of an amphibian species – green frogs – across a diverse set of 140 lake shorelines in northern Wisconsin, USA. Some of the modeling choices in this paper are necessarily specific to the application of lakeshore development in northern Wisconsin. However,

the overall modeling strategy of combining econometric models of land-use change with spatially-explicit simulations and ecological models is generally applicable to forecasting ecosystem change in a variety of other settings.

The landscape simulations generate forecasts of the spatial pattern of development density for each lake in the sample. Given the importance of each lake as a habitat patch for multiple species, assessing the spatial pattern of development density *across* lake shorelines is the relevant scale for understanding the biological effects of development in this application.<sup>2</sup> Of particular interest for biodiversity conservation is the recent finding that green frogs are likely to suffer localized extinctions once lakes reach certain development thresholds (Woodford and Meyer 2003). The estimated empirical distributions of development density are integrated with the Woodford and Meyer green frog model to forecast future extinction probabilities at the lake-scale. Incorporating the entire empirical distributions associated with land-use predictions – rather than just a single estimate of land development – provides valuable information for conservation because while a species may not be predicted to go extinct with an average development path, there may still be some positive probability of localized extinctions.

This paper's methodology builds off the econometric model developed in Lewis et al. (2009) and the landscape simulation method originally developed in Lewis and Plantinga (2007). Contributions to the land-use and biodiversity conservation literatures consist of the following. First and foremost, the paper develops an economic method for forecasting ecosystem change – in particular, localized species extinctions – in the presence of alternative land development policies and uncertain future macroeconomic conditions. As noted elsewhere, economically-driven and spatially-explicit landscape forecasts linked with ecological effects are rare in the literature (Nilsson et al. 2003). This paper highlights the importance of using a long time-series in estimation to account for a wide range of macro-conditions that can alter the development

incentives of all parcels. Second, this paper develops a method for calculating confidence intervals for predicting the spatial pattern of land use and ecosystem change that accounts for all sources of variation in the various stages of modeling. Prior analyses in conservation science use simple extrapolations at aggregate scales to predict species loss and ecosystem change (e.g. Pimm and Raven 2000, Tillman et al. 2001), and are unable to account for either different policy effects on land-use, or the uncertainty associated with predicting spatial landscape pattern. Third, given the importance of forecasting for predictions of ecosystem change, this paper assesses the importance of multiple econometric and simulation challenges on the in-sample and out-of-sample forecasting performance of the empirical framework. Forecasting tests are relatively rare in the literature on parcel-scale econometric models. The importance of using models estimated from observed landowner decisions – particularly in the estimation of development *density* – is emphasized.

## **2. Econometric and forecasting challenges**

If landowner behavior is well captured by an econometric model, then models estimated from one time period should closely predict landowner behavior in other time periods. However, despite the importance of empirical land-use models for many resource economics analyses, there has been relatively little systematic evaluation of the in-sample and out-of-sample forecasting ability of parcel-scale land-use conversion models with an econometric foundation.<sup>3</sup> Accurate in-sample forecasting is desirable because quantifying the landscape effects of *historical* policies is typically implemented via counter-factual simulations where all but the policy variables are held at their historical values (e.g. Stavins and Jaffe 1990, Plantinga 1996). Accurate out-of-sample forecasting is desirable because many analyses are interested in quantifying the effects of future landscape changes on ecosystem services (e.g. Jackson et al. 2004) or quantifying the effects of a *proposed* or existing policy (e.g. Lubowski et al. 2006; Lewis and Plantinga 2007).

Econometric challenges associated with estimating a landowner's decision to develop can be seen by considering, for example, the problem of capturing the effects of scenery on the development of land. Land prices are likely to be bid up on particularly scenic landscapes, thereby increasing the probability that each parcel develops. In addition, to the extent that scenery is separable from lot size in the land value function, landowners have an incentive to develop more densely on a scenic landscape to capture the "scenery premium" associated with each new parcel. Since scenery is typically unobserved to the researcher, two particular econometric challenges arise. First, since scenery affects both the likelihood of development and the number of new lots created with each development, sample selection bias arises in a model aimed at quantifying the determinants of development *density*.<sup>4</sup> Second, unobserved spatial heterogeneity arises since scenery affects the development decisions on multiple neighboring parcels. A discrete-choice model that fails to account for such spatial correlation will produce inconsistent and inefficient parameter estimates (Anselin 2002) and presents researchers with endogeneity challenges when attempting to estimate the landscape effects of policies that influence neighboring development (e.g. minimum lot zoning). Other spatially correlated unobservables that influence land development<sup>5</sup> will cause similar challenges.

In addition to econometric challenges, forecasting the spatial pattern of land-use change requires a translation of probabilistic outputs derived from econometric analysis to landscape-scale changes (Bockstael 1996). Econometric results can be used to determine the probability that a parcel develops, but a landscape forecast requires an actual land-use be assigned to each parcel, as opposed to probabilities. Prior literature that uses discrete-choice models for landscape forecasting typically form deterministic rules from probabilistic econometric estimates (Chomitz and Gray 1996; Irwin and Bockstael 2002), such as assuming that each parcel will convert to the use with the highest estimated probability (Nelson and Hellerstein 1997; Nelson et al. 2001; Irwin

et al. 2006). While such approaches are attractive for their simplicity and ability to produce a single forecasted landscape, Train (2003) argues that using choice probabilities to specify a deterministic rule is “opposed to the meaning of probabilities and the purpose of specifying choice probabilities” (p.73). An approach that uses land-use transition probabilities in a manner consistent with the underlying econometric model is to simulate a large number of different landscapes that conform to the underlying probabilistic rules (Lewis and Plantinga 2007). Since the simulation approach does not generate one forecasted landscape, empirical distributions of landscape pattern must be estimated by calculating spatial indices for each simulated landscape.

Projecting future rental values can present forecasting challenges. The aggregate amount of land to be developed in the future – and hence, the rental value of developed land – is theoretically found at the intersection of the supply and demand curves for new developed land, and can be influenced by many macro-scale economic factors such as changes in interest rates and gas prices, among other factors. One approach to account for macro-scale economic factors is to estimate the model from a long time-series of development decisions with dummy variables to account for conditions that have historically affected the development probabilities for all parcels.

Finally, land-use decisions typically operate in the presence of local zoning policies that specify minimum lot sizes. Much of the economics and planning literatures have focused on understanding the probability of parcel-scale development and assume that any development occurs at the maximum extent allowable by current zoning laws (e.g. Bockstael 1996; Carrion-Flores and Irwin 2004; Levine 2005). Further, a common land-use planning tool is a “build-out” analysis (e.g. Conway and Lathrop 2004; Lathrop et al. 2007), which refers to a steady-state where all land has been developed to the maximum extent allowable by current zoning laws. However, the extent to which density decisions are bound by zoning rules is an empirical question that can

only be answered by basing forecasts on models of *observed* density decisions in response to alternative zoning rules.

### 3. Econometric framework and application

In contrast to the commonly modeled case of an agricultural landowner converting their land to residential use, the development process on lake shorelines is dominated by the further subdivision of existing residential parcels. An extended exposition of the model used here can be found in Lewis et al. (2009), who originally developed the model to examine and test for the separability between an individual landowner's lot size and neighboring open space. While the land-use literature has consistently found evidence that open-space conservation can stimulate the development of neighboring agricultural lands (e.g. Bockstael 1996; Irwin and Bockstael 2004), results in Lewis et al. (2009) show that local open-space conservation can reduce the probability of further subdividing *existing* residential land when open-space and lot size are complements in the land value function.<sup>6</sup>

#### 3.1 Econometric model

A lake shoreline owner's decision problem is modeled in terms of the reduced-form net value of creating  $m_t$  new parcels at time  $t$ ,  $m_t = 1, 2, \dots$ . Let  $m^*$  define the number of new lots that maximize the value of land, conditional on subdivision. Given the integer nature of data regarding the number of new parcels, the variable  $m^*$  is assumed to be Poisson-distributed, and its expected value depends on a set of parcel and lake characteristics  $w_{nt}$ , and a random variable  $\eta_n$ , observable to landowner  $n$  but not the researcher. Conditional on subdivision and  $w_{nt}$  and  $\eta_n$ , the probability that  $m^* = m$ , is a zero-truncated Poisson:

$$\Pr[m^* = m | w_{nt}, \eta_n] = \frac{e^{-\exp(\theta w_{nt} + \sigma_2 \eta_n)} (\exp(\theta w_{nt} + \sigma_2 \eta_n))^m}{m!(1 - e^{-\exp(\theta w_{nt} + \sigma_2 \eta_n)})} \quad (1)$$

where  $\eta_n \sim N(0,1)$ , and  $\theta$  and  $\sigma_2$  are parameters to be estimated. The inclusion of  $\eta_n$  in (1) accounts for unobserved heterogeneity and allows for over-dispersion (Cameron and Trivedi 2005).

The binary decision to subdivide,  $y_{nt}$ , depends on the net land value of subdivision,  $U(w_{nt}, \mu_l, \nu_{nt})$ . The random variable  $\mu_l \sim N(0, \sigma_1^2)$  denotes a characteristic specific to lake  $l$  that is observed by the parcel owner but not by the analyst, and  $\nu_{nt} \sim N(0,1)$  denotes a parcel and time specific characteristic observed by the parcel owner but not by the analyst. The landowner subdivides their land ( $y_{nt} = 1$ ) if  $U(w_{nt}, \mu_l, \nu_{nt})$  is positive. Since the net land value of subdivision is a function derived from the decision of how many new lots to create,  $U$  and  $m^*$  are derived from operations on the same set of random variables, and  $m^*$  is necessarily correlated with the net land value of subdivision  $U(w_{nt}, \mu_l, \nu_{nt})$  (Lewis et al. 2009). Therefore, sample selection is present when econometrically estimating the parameters to (1). Following the basic estimation framework developed by Greene (2006), sample selection can be accounted for (parametrically) by assuming that  $\nu_{nt}$  and  $\eta_n$  are joint normal with correlation parameter  $\rho$ . Assuming a simple form for the net land value of subdivision,  $U(w_{nt}, \mu_l, \nu_{nt}) = \delta w_{nt} + \mu_l + \nu_{nt}$ , the probability of the observed subdivision behavior – conditional on  $w_{nt}$ ,  $\mu_l$ , and  $\eta_n$  – is derived by appealing to the properties of a joint normal distribution, and given by

$$\Pr[y_{nt} | w_{nt}, \mu_l, \eta_n] = \Phi\left(\frac{(2y_{nt} - 1) \cdot [\delta w_{nt} + \mu_l + \rho \eta_n]}{\sqrt{1 - \rho^2}}\right). \quad (2)$$

where  $\Phi(\cdot)$  denotes the standard normal cumulative distribution function, and the term  $2y_{nt} - 1$  is an expositional convenience that exploits the symmetry of the normal distribution.

The inclusion of  $\mu_l$  allows for the error structure in the basic Probit model to be spatially-correlated across all parcels within a lake. While the relevant spatial neighborhood for many

applications is unclear, in this particular application the lakes themselves serve as natural neighborhoods for modeling spatial correlation. Such correlation could arise because of the absence of lake-specific data on variables like the fishing quality of each lake or the scenery of the landscape surrounding the lake. One advantage of specifying spatial correlation with lake-effects is the ability to jointly estimate the decision to subdivide with the decision about the number of new lots to generate. Incorporating a more general spatial dependence structure among parcels (e.g. Fleming 2004) is beyond the scope of this joint estimation exercise and has not been attempted elsewhere when jointly estimating discrete-choice and count models.

Conditional on the independent random variables  $\eta_n$  and  $\mu_l$ , the decision to subdivide is statistically independent from the decision regarding the number of parcels created upon subdivision. However, the unconditional probability of the observed behavior on parcel  $n$  at time  $t$  requires integrating out  $\eta_n$  and  $\mu_l$ , and is generally stated,

$$\Pr(y_{nt}, m_{nt} | w_{nt}) = \iint \left\{ (1 - y_{nt}) + y_{nt} \cdot \Pr[m^* = m | w_{nt}, \eta_n] \right\} \cdot \Pr[y_{nt} | w_{nt}, \mu_l, \eta_n] \phi(\eta_n) \phi(\mu_l) d\eta_n d\mu_l, \quad (3)$$

where  $\phi(\eta)$  and  $\phi(\mu)$  are the density functions for  $\eta$  and  $\mu$ . Equation (3) can be estimated through simulation, and the full simulated log-likelihood function to be maximized is:

$$\sum_{l=1}^L \log \left[ \frac{1}{R} \sum_{r=1}^R \Pr \left( \prod_{n \in N_l} \prod_t \left\{ (1 - y_{nt}) + y_{nt} \cdot \Pr[m^* = m | w_{nt}, \eta_n^r] \right\} \cdot \Pr[y_{nt} | w_{nt}, \mu_l^r, \eta_n^r] \right) \right], \quad (4)$$

where there are  $N_l$  members of lake  $l$  making a full set of subdivision decisions  $(m, y)$  over all time periods in the dataset. Random draws from the independent normal distributions of  $\eta$  and  $\mu$  can be used to simulate the likelihood function by taking  $R$  sets of draws, with each set  $r$  comprised of a single draw from the distribution of  $\mu$ , and  $N_l$  draws from the distribution of  $\eta$ .

The set of estimated parameters consists of  $\{\delta, \theta, \sigma_1, \sigma_2, \rho\}$ . The simulation approach to

estimation is required because the presence of correlated random variables across observations implies that the observed development decisions are not statistically independent.

### 3.2 Data used for estimation

The application in this paper is to lakeshore property in Vilas County, Wisconsin, a popular vacation destination with one of the highest concentrations of freshwater lakes in the world. The sample used for econometric analysis consists of legally subdividable lakeshore parcels in Vilas County. The unit of observation is the parcel, and data are derived from a GIS database on parcel boundaries, the Wisconsin Department of Natural Resources (WI DNR), USDA soil surveys, and town governments in Vilas County. The GIS database of parcel boundaries enables the consistent tracking of development for all subdividable parcels on 140 individual lakes<sup>7</sup> between 1974 and 1998 in four year intervals, resulting in a highly detailed spatial-temporal database of land development – see Lewis et al. (2009) for a description of the data construction process. In the first year of the sample (1974) there were 1,310 parcels that could be legally subdivided across all the lakes, and 335 individual subdivisions occurred by 1998.

Summary statistics for the variables used in estimation are presented in table 1. Given the conceptual setup above, and with one variable as an exception, the same variables are used to specify both the probability of subdivision and the number of new parcels created upon subdivision. The components of  $w_{nt}$  consist of the parcel's lake frontage (*Frontage*) in linear and squared form, soil limitations for development (*PSL* and *PSNR*), and a variety of lake characteristics representing water clarity, lake size, lake depth, the proportion of lakeshore in public conservation land<sup>8</sup>, and distance to the nearest town with major services. Prior research has found that the development density of neighboring lands affects subdivision probabilities (Irwin and Bockstael 2002), and so the average frontage of privately-owned parcels on each lake (*AvFront*) is included to proxy for the level of development on each lake. The endogeneity of

*AvFront* is discussed below. The dummy variable *SPLIT* is included in the Probit model because the location of an existing residential structure may have a particularly strong effect on the potential to subdivide small parcels that can be legally split into only two parcels.<sup>9</sup> Economy-wide fluctuations that affect the development decision of all parcels (e.g. gas prices, changes in the broader housing market, etc.) are accounted for by specifying dummy variables for each four-year time interval.

The primary tool used to manage lakeshore development in northern Wisconsin is minimum frontage zoning (*Zoning*) – a restriction that all subdivided parcels must have a specified minimum amount of shoreline frontage. In this analysis, *Zoning* is reasonably modeled as exogenous, based on the observation that shoreline zoning is uniformly set at the town level, and there are scores of lakes in each town.<sup>10</sup> During the study period used for estimation, the default minimum frontage for subdivision was Wisconsin’s state minimum of 100 feet, though 7 of the 14 towns in Vilas County were allowed to exceed the state minimum and set a town-specific minimum shoreline frontage requirement at 200 feet by the end of the study period. Zoning can have both a direct effect on the development decision by placing a physical constraint on the number of parcels that can be created upon subdivision, and an indirect effect by restricting the number of new parcels that can be created by other properties on the lake, thereby ensuring a higher amount of future open space (Spalatro and Provencher 2001). To ensure functional flexibility in capturing both effects of zoning, an interaction between *Zoning* and a parcel’s frontage (*Frontage*) is included, as is an interaction between *Zoning* and the average frontage of all parcels on the lakeshore (*AvFront*).

To the extent that there is time-invariant unobserved spatial heterogeneity ( $\sigma_1 > 0$ ), the average frontage of all parcels on the lakeshore (*AvFront*) is likely endogenous because it is a function of past subdivision decisions which were influenced by the lake-specific unobservables.

However, the panel structure of the data implies that such endogeneity can be accounted for by specifying the lake-specific effect as a function of each lake's average frontage in the initial year of data (1974):  $\mu_i = \lambda AvFront_{i,74} + \xi_i$ , where  $\xi_i \sim N(0, \sigma_1^2)$ . The initial state of development on each lake in 1974 is used as a proxy for the unobserved attractiveness of each lake for development, with identification of the parameter on  $AvFront$  arising because each lake becomes increasingly developed over time. This specification follows prior work on correlated random effects models (e.g. Zabel 1992), and the parameter  $\lambda$  is included in estimation.<sup>11</sup>

### 3.3 Alternative model assumptions

A key goal of the analysis is to compare the forecasting performance of models with varying assumptions regarding the econometric challenges of sample selection and unobserved spatial heterogeneity. The first estimated model – hereafter labeled *Basic Model* – is a simple binary Probit model estimated separately from a Poisson model with unobserved heterogeneity. There is assumed to be no sample selection ( $\rho = 0$ ) and no unobserved spatial heterogeneity ( $\sigma_1 = 0$ ) in the *Basic Model*, which is estimated by maximum simulated likelihood.<sup>12</sup> The second model is a full-information likelihood model – hereafter labeled *FIML* – that estimates the Probit and Poisson models jointly, accounts for sample selection (the parameters  $\sigma_2$  and  $\rho$  are estimated), and ignores unobserved spatial heterogeneity ( $\sigma_1 = 0$ ). The third model is a full information model – hereafter labeled *FIML-Spatial* – that estimates the Probit and Poisson models jointly, and accounts for both sample selection and unobserved spatial heterogeneity by estimating the full parameter set  $\{ \sigma_1, \sigma_2, \rho \}$ .

### 3.4 Econometric estimation results

All three models are estimated with maximum simulated likelihood techniques using original Matlab code with Halton draws and a BFGS non-linear gradient algorithm. Halton draws

are a systematic method of drawing from distributions that is useful for reducing the number of simulations while increasing the accuracy of the estimation (Train 2003).<sup>13</sup> The results in table 2 are generally as expected and yield the following basic insights.<sup>14</sup> First, the probability of subdivision, and the expected number of new parcels created upon subdivision, is increasing at a decreasing rate with frontage size. Second, the probability of subdivision is lower for parcels with greater soil restrictions. Third, the lake-specific characteristics have mixed effects on the development probabilities. Fourth, there is evidence of unobserved spatial and parcel heterogeneity, as indicated by the statistically significant values of  $\sigma_1$  and  $\sigma_2$ . And finally, likelihood ratio tests reject the null hypotheses of no sample selection ( $\rho = 0$ ), and no unobserved spatial heterogeneity ( $\sigma_1 = 0$ ) at the 10% and 5% level respectively.

Since minimum frontage zoning is the focus of policy simulations later in the paper, the estimated marginal effects of zoning on development are estimated for each of the three models. Because zoning is set at either 100 or 200 minimum feet of frontage, the marginal effect of stricter zoning is a discrete-change effect, with standard errors calculated by the Delta Method. All three models give very similar discrete-change effects for the probability of subdivision<sup>15</sup>, and the expected number of new lots<sup>16</sup>. In general, stricter zoning has no statistically significant effect on the probability of subdivision, but does have a significant negative effect on the expected density of subdivisions.

#### 4. Forecasting with the econometric – simulation model

While the decisions of any one landowner typically have minimal impacts on local ecosystems and the welfare of other landowners, the aggregation of numerous individual decisions gives rise to broad landscape patterns that can significantly alter ecosystem processes and individual welfare. This section builds off Lewis and Plantinga's (2007) landscape simulation approach and develops a method to use the econometric estimates in a series of simulations to forecast distributions of landscape pattern. The method differs from Lewis and Plantinga in that i) both a probability of land-use change *and* the number of new lots created are used in simulations, and ii) the simulation is more general in that random draws arise from all sources of variation in the model, including the estimated parameters.

##### 4.1 Landscape simulation methodology

Using the estimated parameter values in table 2, every parcel in the GIS dataset is matched with estimated subdivision and density probabilities. The fitted probabilities are interpreted as a set of rules that govern land-use change along the shoreline of each lake. For example, if the subdivision probability is 0.1 for a particular parcel, the owner of the parcel will subdivide 10% of the time if the choice situation is repeated enough times. The simulations work as follows.

1. A parameter vector is drawn from the estimated distribution to calculate the estimated Probit and Poisson probabilities for each parcel<sup>17</sup> (Krinsky and Robb 1986).
2. Standard normal random numbers are drawn for the set of random parameters, and multiplied by the corresponding standard errors drawn in step 1 to generate a draw from the estimated random parameter distributions.
3. A complete time path ( $t=1 \dots T$ ) of development is estimated for each lake.

- a) A  $U \sim [0,1]$  random number  $r_1$  is drawn for each parcel and subdivision occurs if  $r_1$  is less than or equal to the estimated subdivision probability for that parcel; otherwise the parcel is assumed to remain in its current state.
- b) If a parcel subdivides, the number of new lots is determined by the estimated Poisson probability (1). A  $U \sim [0,1]$  random number  $r_2$  is drawn and one new lot is created if  $r_2 \leq \Pr[m^* = 1 | w_m, \eta_n]$ , otherwise two new lots are created if  $\Pr[m^* = 1 | w_m, \eta_n] < r_2 \leq \Pr[m^* = 2 | w_m, \eta_n]$ , and so forth until  $m^*$  is equal to the maximum number of lots allowable under zoning.
- c) The subdivision probability and development density estimates are updated for  $t=t+4$  and step (a) is repeated until  $t=T$ .

4. Step (1) is repeated until all simulations ( $S=1000$ ) have been completed.

The simulation procedure outlined here accounts for all sources of variation in the model: the estimated parameters, the random parameters, and the random error terms. Two sets of  $S=1000$  simulations were generated for each policy scenario, and all results presented in this paper are the same across both sets, therefore 1000 simulations was deemed adequate.

As argued earlier, there are multiple macroeconomic shocks – such as changes in gas prices and mortgage rates – that can influence the aggregate supply and demand of development across a landscape. Macroeconomic shocks are incorporated in the econometric model through the use of time-specific dummy variables for each of the 4-year time periods between 1974 and 1998. For example, examining the estimated parameters from table 2, the positive and highly significant dummy coefficient for the period 1986-1990 indicates a significantly higher probability of subdivision for all parcels during this period than during any of the other periods.<sup>18</sup> The range of observed historical macroeconomic shocks are incorporated into future (out-of-sample) landscape forecasting by randomly drawing from the set of six estimated time-specific dummy coefficients

for the Probit and Poisson models. Specifically, the subdivision and density probabilities are calculated with one of the six estimated time-specific dummy coefficients for each simulation run. The method of randomly drawing from the time dummies increases forecast variance but better accounts for the range of historical shocks experienced between 1974 and 1998.

#### *4.2 In-sample forecast test (1974-1998)*

Empirical distributions of the aggregate amount of development across all lakes are generated with 1000 simulations and are presented in figure 2a.<sup>19</sup> There are three conclusions to be drawn from figure 2a and table 3. First, assumptions regarding unobserved spatial heterogeneity or sample selection appear to make little difference in forecasting either aggregate development or the spatial pattern of development at the lake-level. Second, an assumption that land is always developed to the maximum extent allowed by zoning greatly overstates the amount of development and provides high lake-level forecasting errors, a result evidenced by forecasting with a simple Probit model only.

#### *4.2 Out-of-sample forecast test (1998-2006)*

Out-of-sample forecasting is complicated somewhat by a county-wide change in minimum frontage zoning policy. In 1999, Vilas County adopted a county-wide zoning classification – the Vilas County Lake Classification (VCLC) – in which every lake in the county is classified according to its 1999 level of development and its ecological sensitivity.<sup>20</sup> The most relevant features for this analysis are minimum lake frontage standards of either 300 feet for low development – high sensitivity lakes, or 150 feet for high development – low sensitivity lakes. Town ordinances that are stricter than the VCLC supersede it; so, for instance, the minimum frontage requirement for a new lot on a high development – low sensitivity lake in the town of Presque Isle is not the VCLC-mandated 150 feet, but rather the town-mandated 200 feet.

There are three conclusions to be drawn by examining the empirical distributions of the aggregate amount of out-of-sample development (fig. 2b and 2c). First, assumptions regarding the macroeconomic conditions have a strong influence on forecasting. The forecast accuracy of the estimated mean number of new lots derived from most of the models depends on the assumption of which macroeconomic conditions apply. For example, if the conditions of 1982-1986 are assumed to apply to the forecast period (by setting the 1982 time dummy variables to one in the econometric model), the forecasted mean number of new lots is 283, about 40% lower than if the conditions of 1986-1990 are assumed to apply. The second conclusion is that there is a relatively small difference in aggregate forecasts between the *Basic Model*, the *FIML Model*, and the *FIML-Spatial Model*. Third, the assumption that all subdivisions create the maximum number of new lots allowed by zoning generates forecasts that are too high and have tremendous variance.

Examining the forecasts of the spatial pattern of development out-of-sample at the lake level (table 3) provides three conclusions. First, accounting for sample selection and unobserved spatial heterogeneity makes little difference in the spatial forecast accuracy of the model. Second, while assuming the 1986-1990 macroeconomic conditions hold for the 1998-2006 period yields the most accurate aggregate forecasts, this assumption provides forecasts with the highest lake-level errors. Third, looking at median forecast errors, there is evidence that while simple extrapolations may generate reasonable short-term aggregate landscape forecasts, the econometric-simulation framework provides more accurate forecasts at finer spatial scales (i.e. the lake level) and has the advantage of being able to adjust forecasts to changes in policy.

## **5. Ecological forecasts (green frog extinction probabilities)**

The status of amphibian populations is a significant concern for biodiversity conservation as global amphibian populations are generally believed to be declining at a faster pace than either birds or mammals (Stuart et al. 2004). Populations of amphibians are extremely sensitive to the

loss and fragmentation of habitat, and can be especially prone to localized extinctions (Gibbs 1998) which can affect the long-term viability of wildlife populations by making them more susceptible to environmental shocks (With and King 1999). An extinction threshold has been estimated for green frogs on northern Wisconsin lakes at a shoreline development density of approximately 7.9 houses per 1000 feet shoreline (Woodford and Meyer 2003). The Wisconsin state minimum frontage for development is 100 feet, which implies a “build out” density of approximately 10 houses per 1000 feet shoreline, surpassing the green frog extinction threshold. In our study region, the new zoning regime that passed in 1999 has minimum frontage requirements of 150ft., 200ft., or 300ft., implying a less dense “build out” scenario than before the zoning change.<sup>21</sup> Of course, if zoning regulations are not binding and residents consume larger lots than allowable under zoning, then even the state minimum standard may not necessarily imply extinction. In general, the degree to which a zoning constraint is binding will vary across jurisdictions and should always be treated as an empirical question. The results from section 4 strongly suggest that, at least in this region, zoning regulations are not always binding.

Extinction thresholds are estimated for each lake 20 years into the future.<sup>22</sup> Rather than using the deterministic threshold of 7.9 houses per 1000 ft shoreline, the estimated regression coefficients and standard errors from Woodford and Meyer (2003) are used to calculate the probability of green frog extinctions for each simulated development density on each lake. The average extinction probability can be calculated by averaging the estimated extinction probabilities across each of the 1000 simulated landscapes. Figure 3 demonstrates the model’s final output by presenting estimated frequency distributions of the 20-year extinction probabilities for two select lakes that vary in their initial conditions and final estimated outputs. As shown in figure 3, the estimated distributions of extinction probabilities can be used to examine the effects of alternative land policy scenarios on extinction.

The spatial configuration of green frog extinction probability forecasts across the entire lake system are presented in figure 4. The forecasts are very similar across the *Basic*, *FIML*, and *FIML-Spatial* models, and therefore, only the results from the *FIML-Spatial* model are presented. The forecasted extinction probabilities differ substantially across lakes, ranging from 0% to 90% (Fig. 4.a). The estimated standard deviation of the extinction probabilities also varies across lakes, and lakes with higher estimated extinction probabilities do not necessarily have higher standard deviations (Fig. 4.b). In addition, the standard deviation is quite high on some lakes, indicating the high degree of uncertainty in generating these forecasts. The effects of the 1999 zoning change on extinction probabilities are shown in figure 4.d, and results indicate that the zoning change reduces extinction probabilities in ranges from 0 to 35 percentage points, relative to what would have occurred if the pre-1999 zoning regime remained in effect on each lake.

In addition to the 20-year extinction probability forecasts, the model is used to generate expected long-run steady-state forecasts of lake-level development density.<sup>23</sup> The estimated steady-state development levels are then compared to a “build-out” analysis. Common in landscape planning (e.g. Lathrop et al. 2007), “build-out” refers to a steady-state where *all* subdividable parcels are assumed to be developed to the maximum extent allowable by current zoning laws.<sup>24</sup> In this application, the “build-out” assumption generates approximately 60% more new developed lots than the estimated steady-state development levels. Such over-predictions arise from assuming that landowners develop at a greater density than observed in the data, and result in substantial over-estimates of extinction probabilities ranging from 0 percentage points to as high as 48 percentage points (Fig. 4.c).<sup>25</sup> The over-predictions arising from the “build-out” assumption are far from uniform across lakes<sup>26</sup>, making it difficult to derive “rules-of-thumb” regarding a more appropriate “build-out” assumption.

The value of the full forecasting framework for environmental management is apparent in figure 4, as the extinction probability estimates are quite heterogeneous across space and the probability of extinction – and thus the need for conservation attention – is low on many lakes. Only 20% of the lakes have an expected 20-year extinction probability greater than 10%. Since the forecasting framework is capable of modeling the behavioral response to the primary land-use planning tool used in the region – minimum frontage zoning – the conservation effects of zoning policies on extinction probabilities can also be examined. In particular, although 20% of the lakes have a 20-year extinction probability greater than 10%, the effects of the zoning change varies substantially across these lakes, with very little effect on most of the lakes with high extinction probabilities. Since optimal conservation targeting strategies can be significantly influenced by spatially heterogeneous development probabilities (Costello and Polasky 2004; Newburn et al. 2006), the forecasting framework in this paper would be particularly useful in designing efficient spatial targeting strategies for conservation.

## **6. Conclusions**

The purpose of this paper is to develop an empirical economic framework for forecasting the spatial pattern of land-use and ecosystem change. The framework is applied to the case of forecasting amphibian extinction probabilities driven by residential development on lake shorelines across 140 lakes in northern Wisconsin. The application demonstrates the potential for developing and integrating parcel-scale econometric land-use models with GIS and ecological models as a means of forecasting ecosystem change. Given the role of human-induced land development as a driver of ecosystem change, the discipline of environmental and resource economics has much to offer when it comes to forecasting ecosystem change. Using data on historical landowner behavior allows the estimation of models that examine the behavioral response of landowners to a variety of market conditions and policy variables. However, since

parcel-scale forecasts of land-use change are highly uncertain, and since forecasts of ecosystem change depend on the spatial configuration of individual parcel forecasts, the results in this paper demonstrate that confidence intervals are generally wide when generating forecasts of the spatial pattern of land-use change. The extent to which there are wide confidence intervals for ecosystem forecasts depends on the sensitivity of the ecosystem good to the spatial distribution of land-use change. In addition to being unable to examine policy changes, a weakness of using simple extrapolations of land-use change is the absence of any confidence interval estimates, and therefore, an absence of information on the uncertainty associated with forecasts.

Empirical challenges for landscape forecasting include i) estimating both the probability of development *and* the expected density of developments, ii) accounting for sample selection and unobserved spatial heterogeneity, and iii) projecting uncertain future rental values and land-use policy constraints. In assessing the importance of these challenges for landscape forecasting, results presented here have three implications. First, while it is common in both the economics and landscape planning literature to assume that all developments occur at the maximum density allowable by zoning (e.g. Bockstael 1996; Irwin and Bockstael 2002; Levine 2005; Lathrop et al. 2007), most developments in this dataset occur at a density far less than that allowable by zoning. Results demonstrate that development and extinction probability forecasts are too high when densities are assumed to be the maximum allowed under zoning – i.e. when zoning is assumed to be binding. There are significant gains in forecast accuracy to be achieved by modeling the density decision from *observed* developments. Second, differing assumptions regarding the presence of sample selection and unobserved spatial heterogeneity in econometric estimation have a relatively minor impact on landscape forecasts. While this result is specific to the dataset examined here, the result is similar to the findings of Provencher and Bishop (2004), who showed that accounting for unobserved heterogeneity with random parameters discrete-choice models does

not improve the forecasting performance of a recreation demand model.<sup>27</sup> Third, accounting for the range of historical time-specific shocks with dummy variables that change temporally and affect development decisions of all parcels is a simple way of accounting for the range of historical supply and demand conditions within the landscape. Sampling from estimated time-specific dummy variables has a larger effect on landscape forecasts than alternative assumptions regarding sample selection and unobserved heterogeneity. In addition, modeling observed land-use change in response to varying land-use policy constraints allows for an explicit analysis of alternative future land-use policy constraints on land development and ecosystem change.

The analysis in this paper is admittedly focused on a relatively small-scale case study: forecasting shoreline development and amphibian extinction probabilities in northern Wisconsin. However, the modeling challenges present in this study are common to many other situations. Further, the general methodological framework of integrating detailed parcel-scale econometric land-use models with GIS and ecological models is widely applicable to other regions and other management cases in which environmental quality is sensitive to the spatial configuration of land development. Future research could be improved by extending the modeling framework in Figure 1 to account for the feedback effect of development-induced ecological change on the development decision. While the ecosystem effect examined in this paper – localized extinction of an amphibian species – probably doesn't have an effect on landowners' development decisions, there are many types of development-induced ecological change that could feed back to the development decision. For example, lakeshore development has been shown to have adverse effects on sport fisheries (e.g. Schindler et al. 2000), which could then lower future development rates. Accounting for such feedbacks would require detailed historical data on ecosystem changes that could be used in econometric estimation.

The method developed in this paper is certainly data-intensive, although recent advances in the availability of large-scale spatial databases are rapidly lowering the research costs associated with conducting such analyses. For example, all counties in the state of Wisconsin, U.S., are expected to have complete digitized spatial parcel data within the near future. The widespread availability of spatial datasets and the increasing sophistication of econometric approaches suitable for analyzing such micro data present a significant opportunity for environmental and resource economists to more broadly engage in generating forecasts of ecosystem change that would be widely applicable to the broader field of conservation science. Since land conversion is a decision made within the context of local land markets and global commodity markets, the field of economics has much to contribute to such forecasting endeavors. To be biologically meaningful, landscape forecasts at the parcel-scale are generally required for forecasts of ecosystem change, and the accumulation of multiple case studies of ecosystem forecasting such as that presented here could help to further our understanding of conservation science.

**Table 1. Variables Used in Estimation**

<b>Variable</b>	<b>Description</b>	<b>Data Source</b>	<b>Average</b>	<b>Min</b>	<b>Max</b>
<b><i>Parcel-Specific Characteristics</i></b>					
<i>Frontage</i>	Shoreline frontage of the property (1000's of feet)	GIS Maps	0.75	0.2	13
<i>PSL</i>	<i>Percent Soil Limitation:</i> Proportion of the parcel with soil limitations for development	USDA – Soil Surveys	0.56	0	1
<i>PSNR</i>	<i>Percent Soil Not Rated:</i> Proportion of the parcel with no soil rating (e.g. bog)	USDA – Soil Surveys	0.24	0	0.67
<i>Split</i>	Dummy variable taking a value of one if the only subdivision possible is a split of the parcel;	GIS Maps	0.4	0	1
<b><i>Lake-Specific Characteristics</i></b>					
<i>AvFront</i>	Average frontage for all private properties on the lake (1000's of feet)	GIS Maps	0.41	0.11	2.4
<i>Public</i>	Proportion of the lake's shoreline owned by County, State, or Federal government	GIS Maps	0.07	0	0.87
<i>Water Clarity</i>	Secchi depth visibility (feet)	WI DNR	6.23	1.23	20.6
<i>Lake Size</i>	Surface area of the lake (acres)	GIS Maps	484	3	3555
<i>Lake Depth</i>	Maximum depth of the lake (feet)	WI DNR	37	3	86
<i>Distance</i>	Distance to the nearest town with major services - Minoquoa or Eagle River (km)	GIS Maps	6.47	0.26	17
<i>Zoning</i>	100 ft. (Zone=0) or 200 ft. (Zone=1) minimum frontage zoning	GIS Maps / Town governments	0.22	0	1

**Table 2.** Econometric Parameter Estimates (standard errors in parentheses)

	Probit (1= Subdivide, 0=not)			Poisson (# Lots)		
	Basic	FIML	FIML-Spatial	Basic	FIML	FIML-Spatial
<i>Constant</i>	-1.42*	-1.42*	-1.52*	0.03	-0.06	-0.10
	(.15)	(.15)	(.18)	(.28)	(.28)	(.26)
<i>Frontage</i>	0.41*	0.42*	0.42*	0.85*	0.82*	0.82*
	(.06)	(.06)	(.07)	(.08)	(.08)	(.07)
<i>Frontage ^ 2</i>	-0.49*	-0.50*	-0.48*	-0.59*	-0.45*	-0.46*
	(.1)	(.1)	(.1)	(.11)	(.1)	(.1)
<i>PSL</i>	-0.29*	-0.28*	-0.30*	-0.40**	-0.27	-0.25
	(.12)	(.12)	(.13)	(.24)	(.23)	(.23)
<i>PSNR</i>	-1.24*	-1.22*	-1.22*	0.12	0.14	0.15
	(.19)	(.19)	(.21)	(.37)	(.37)	(.36)
<i>Two</i>	-0.68*	-0.68*	-0.71*			
	(.09)	(.09)	(.09)			
<i>AvFront</i>	-0.47*	-0.48*	-0.45	0.20	0.03	0.01
	(.18)	(.18)	(.27)	(.28)	(.27)	(0.28)
<i>Public</i>	0.38	0.39	0.40	-0.61	-0.43	-0.44
	(.28)	(.28)	(.31)	(.7)	(.66)	(.66)
<i>Water Clarity</i>	0.01	0.01	0.01	0.03*	0.03*	0.03*
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
<i>Lake Size</i>	1.56E-04*	1.56E-04*	1.23E-04	-4.48E-05	-8.11E-05	-9.15E-05
	(5.94E-05)	(5.94E-05)	(8.44E-05)	(1.15E-04)	(1.29E-04)	(1.22E-04)
<i>Lake Depth</i>	-3.38E-03	-3.34E-03	-2.36E-03	-4.61E-03	-5.61E-03	-5.81E-03
	(2.03E-03)	(2.04E-03)	(2.74E-03)	(4.10E-03)	(3.93E-03)	(3.94E-03)
<i>Distance</i>	0.10	0.10	0.13	0.07	0.10	0.09
	(.07)	(.07)	(.09)	(.14)	(.12)	(.12)
<i>AvFront * Zoning</i>	0.28	0.28	0.30	-0.24	-0.39	-0.39
	(.17)	(.17)	(.19)	(.28)	(.27)	(.27)
<i>Frontage * AvFront</i>	0.16*	0.16*	0.15*	-0.09	-0.12	-0.12
	(.07)	(.07)	(.08)	(.09)	(.09)	(.09)
<i>Frontage * Zoning</i>	0.02	0.02	0.03	-0.24*	-0.15**	-0.15**
	(.08)	(.08)	(.87)	(.08)	(.08)	(.08)
<i>Frontage * Zoning * AvFront</i>	-0.14	-0.15	-0.12	0.12	0.15	0.15
	(.09)	(.09)	(.1)	(.09)	(.1)	(.09)
<i>Frontage * Public</i>	-0.51*	-0.52*	-0.52*	0.30	0.15	0.16
	(.2)	(.21)	(.22)	(.4)	(.39)	(.39)
<i>1974 dummy</i>	0.04	0.04	0.03	0.36*	0.46*	0.49*
	(.1)	(.1)	(.1)	(.18)	(.17)	(.16)
<i>1978 dummy</i>	0.09	0.09	0.09	0.23	0.37*	0.38*
	(.1)	(.1)	(.1)	(.17)	(.16)	(.16)
<i>1982 dummy</i>	-0.14	-0.14	-0.14	0.23	0.42*	0.43*
	(.1)	(.1)	(.11)	(.19)	(.17)	(.17)
<i>1986 dummy</i>	0.23*	0.22*	0.23*	0.12	0.24	0.25
	(.09)	(.09)	(.1)	(.16)	(.15)	(.15)
<i>1990 dummy</i>	0.05	0.05	0.05	-0.11	-0.01	-0.01
	(.1)	(.1)	(.1)	(.19)	(.18)	(.18)
<i>AvFront - 1974</i>			0.01			
			(.17)			
<i>Std Err. – Lake Effect</i>			0.23*			
			(.05)			
<i>Std Err. – Parcel Effect</i>				0.53*	0.53*	0.53*
				(.04)	(.04)	(.04)
$\rho$		0.06	0.08**			
		(.07)	(.06)			
<i>Log-Likelihood</i>	-1879.93	-1877.69	-1869.31			

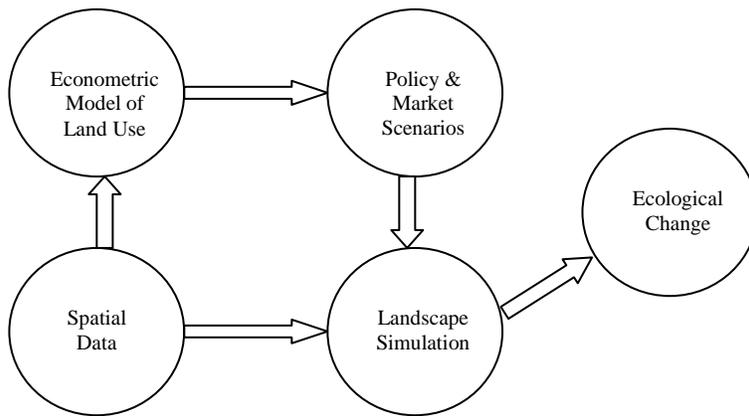
\*significantly different from zero at 5% level; \*\*significantly different from zero at 10% level.

**Table 3.** Lake-Level Forecasting Errors

	In-Sample		Out-of-Sample	
	Average	Median	Average	Median
<i>Econometric Model</i>				
Basic Model	6.18	3.45	3.15	1.13
FIML	6.11	3.11	3.24	1.15
FIML – Spatial	6.04	2.69	3.30	1.25
Probit Only - Max Dens	14.41	7.28	4.56	2.11
Lake-level Extrapolation			3.21	2.00
Landscape-level Extrapolation			2.81	2.41
<i>Macro conditions assumed to apply (FIML - Spatial Model)</i>				
'74-'78			3.31	1.33
'78-'82			3.43	1.38
'82-'86			3.03	0.86
'86-'90			3.66	1.44
'90-'94			3.22	1.14
'94-'98			3.20	1.08

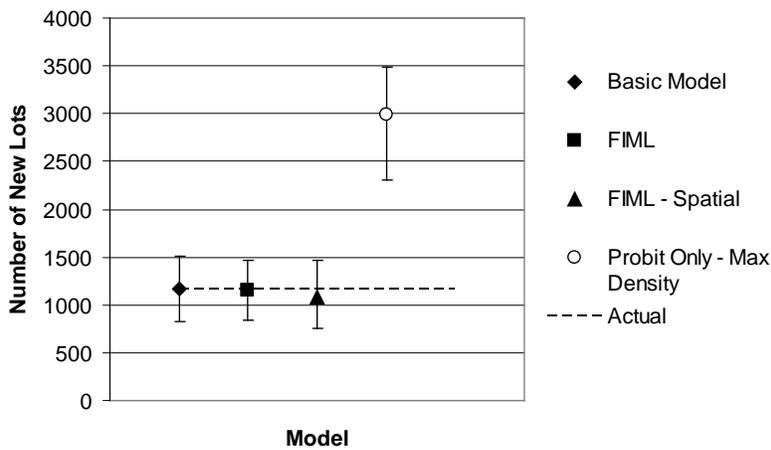
**Note:** Results reflect the average and median absolute deviations between the actual number of new lots developed on each lake and the number of new lots predicted by each model.

**Figure 1 – Schematic Representation of Modeling Framework**

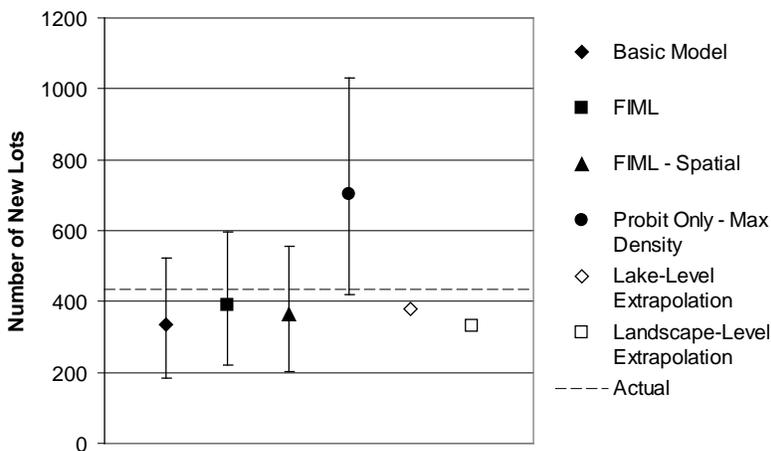


**Figure 2.** Aggregate Landscape Forecasts with 95% Confidence Intervals

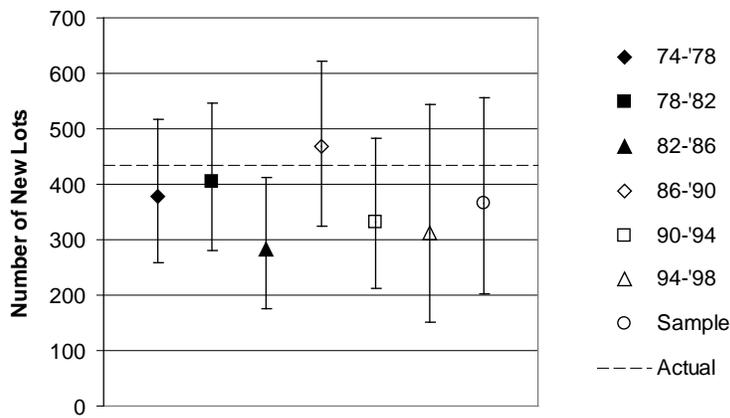
*2.a In-sample forecasts (1974-1998)*



*2.b Out-of-sample forecasts (1998-2006) for alternative econometric specifications*

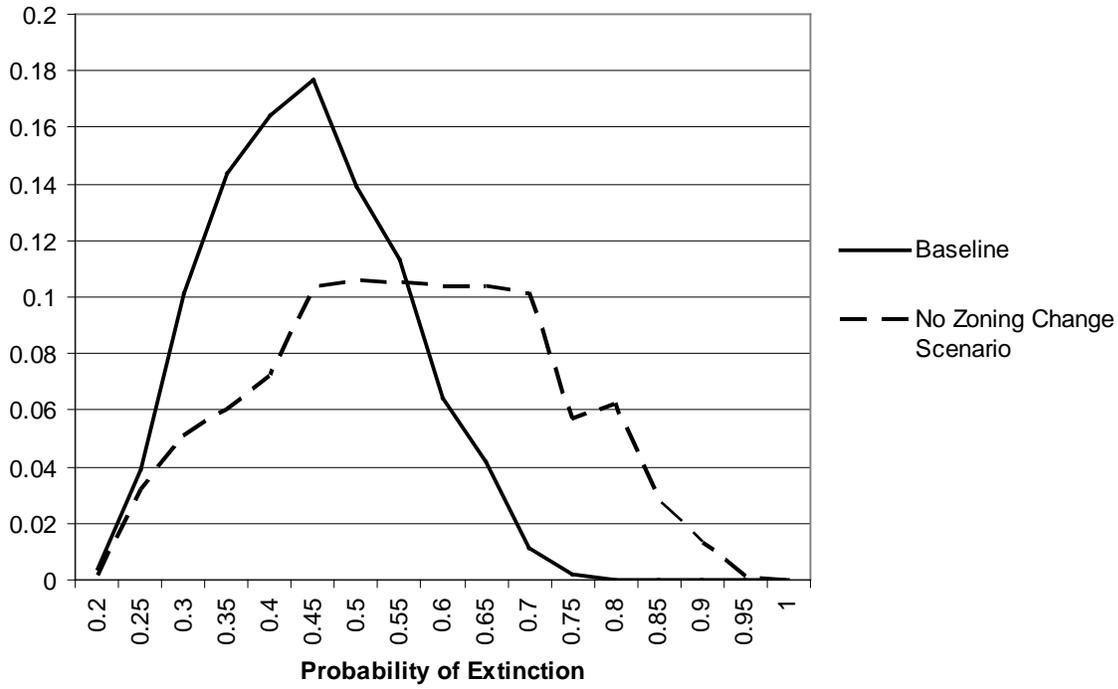


*2.c Out-of-sample forecasts (1998-2006) with alternative assumptions for which macro conditions apply (FIML-Spatial Model)*

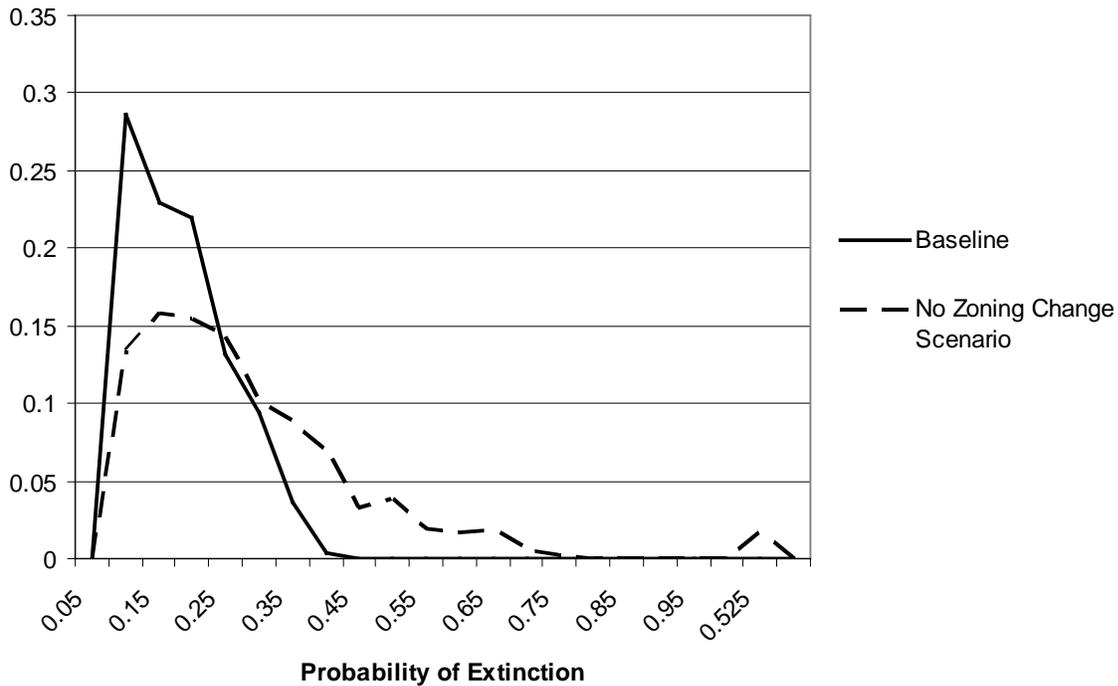


**Figure 3.** Estimated Frequency Distributions for 20-year Green Frog Extinction Probability for Select Lakes

3.a. Lake 1 - Extinction probability in 2006 = 18%; 20-year expected density growth = 14.8%



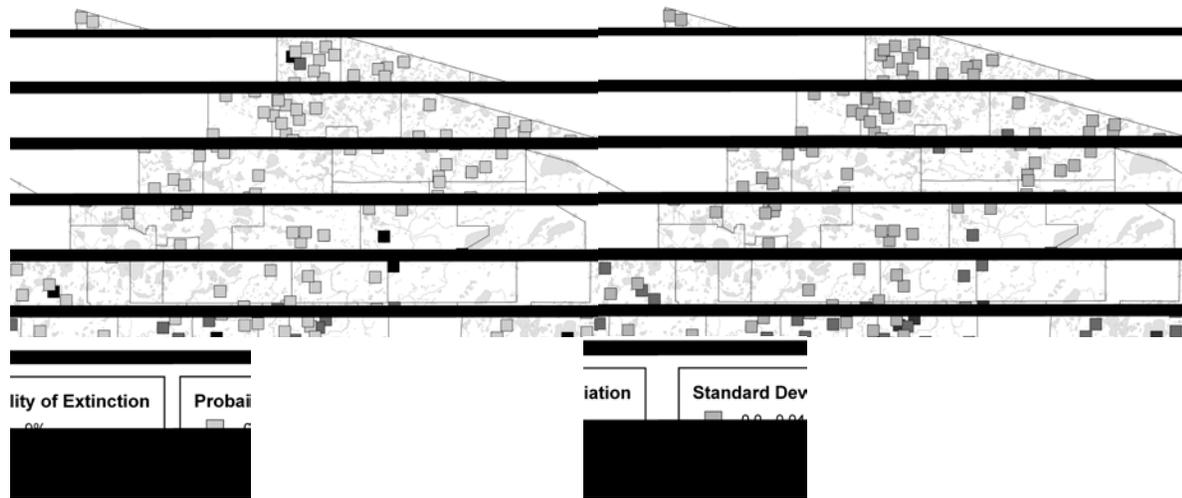
3.b. Lake 2 - Extinction probability in 2006 = 6%; 20-year expected density growth = 12.1%



**Figure 4. Spatial Forecast of Green Frog Extinction Probabilities on Individual Lakes**

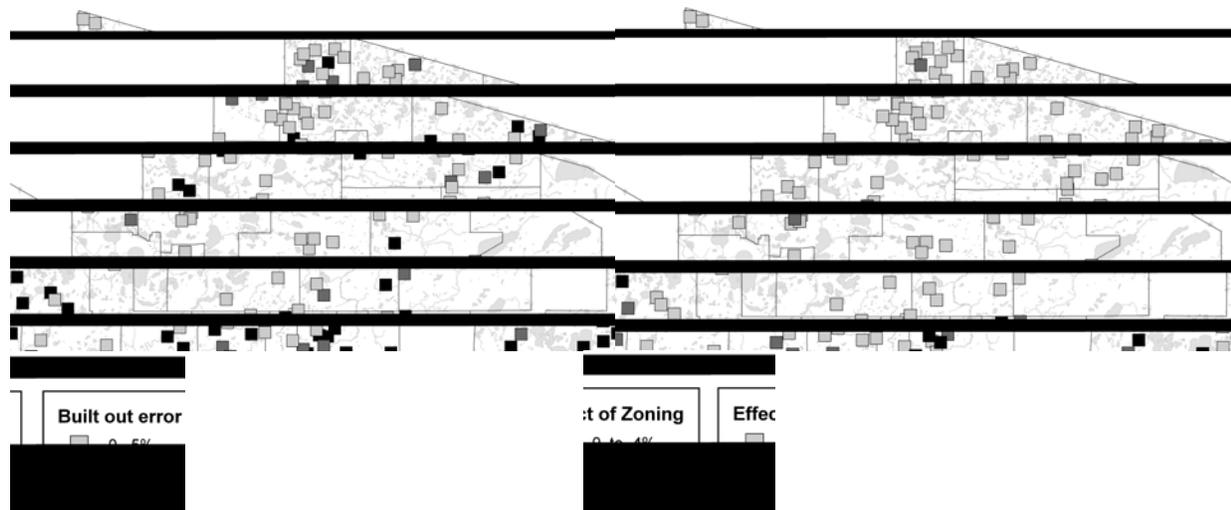
*4.a Probability of Extinction (20 years)*

*4.b Standard Deviation (20 years)*



*4.c Difference between Estimated Steady-State Extinction Probability and “Build Out” Extinction Probability*

*4.d Effects of Stricter Zoning Change on Extinction Probability (20 years)*



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## Endnotes

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<sup>1</sup> The framework can be extended to account for the circular effects of development-induced ecological change on development. This would require detailed historical ecological data to be used in the original econometric estimation. The data is not available for this analysis.

<sup>2</sup> While the spatial pattern of development within lakes may have welfare effects, most ecological models of shoreline development focus on the effects of lake-level development density on eutrophication (Schindler 2006), and species such as sport fish (Schindler et al. 2000) and songbirds (Lindsay et al. 2002).

<sup>3</sup> One likely reason for the lack of formal forecasting tests is the difficulty of obtaining spatial land use datasets for multiple points in time.

<sup>4</sup> Sample selection is assumed away in analyses that assume all development occurs to the maximum extent allowed by zoning (Bockstael 1996; Irwin and Bockstael 2002). However, for the dataset used in this paper, less than 15% of subdivisions develop to the maximum extent allowed by zoning. Further, this dataset may not be unique, as McConnell et al.'s (2006) analysis of development density in a Maryland urban-rural fringe region finds that only 8% of all subdivisions were directly constrained by zoning.

<sup>5</sup> As Irwin and Bockstael (2002) note, almost all factors that affect land development are likely to be spatially correlated to some degree, such as distance to amenities and disamenities, school quality, tax rates, etc.

<sup>6</sup> Intuitively, when the decision is whether to subdivide an existing residential lot, open-space conservation can increase the rents to both subdividing and keeping the land in its current state. In contrast, when the decision is whether to develop agricultural land, open-space conservation unambiguously increases the rents to development relative to the rents from agriculture.

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<sup>7</sup> Lakes that were not included either lacked digitized parcel maps in 2003, or a single individual owned the lake.

<sup>8</sup> Public conservation land is reasonably modeled as exogenous in this application since most of the public lands in Vilas County were acquired in response to widespread land abandonment that arose from failed attempts at farming cutover forestland in the 1930's-1950's (Flader 1983), as opposed to the specific targeting of lakefront amenities.

<sup>9</sup> While 40% of the observations have  $SPLIT=1$ , only 8.6% of the observed subdivisions have  $SPLIT=1$ . A Poisson model is an appropriate model for the number of new lots even if  $SPLIT=1$  because approximately 28% of the subdivided lots that had  $SPLIT=1$  actually violated their zoning restrictions and created more than 1 new lot.

<sup>10</sup> In addition, zoning is enforced in this region: only 5% of the recorded shoreline subdivisions clearly violated the minimum frontage standards at the time of subdivision.

<sup>11</sup> This same identification issue arises in Irwin and Bockstael's (2002) model of spatial interactions between parcels. The panel data approach used here for identification differentiates the present model from Irwin and Bockstael.

<sup>12</sup> If  $\sigma_2$  were assumed to be gamma distributed as opposed to normal, then the *Basic Model* could be estimated without simulation as the count model would be negative binomial. The assumption of a normally distributed  $\sigma_2$  is maintained to keep the basic assumptions consistent across the three models presented here.

<sup>13</sup> Two hundred Halton draws are used in estimation. Estimating the model with two different sets of two hundred draws yields no significant changes to the estimates, thus two hundred is deemed a sufficient number of draws.

<sup>14</sup> Standard errors for the structural Probit coefficients in the *FIML* and *FIML-Spatial Model* are calculated with the Delta Method.

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<sup>15</sup> The average discrete-change effects of the stricter zoning standard on the probability of subdivision are estimated as: 0.004 (1.16) for the *Basic Model*; 0.004 (1.14) for the *FIML Model*; and 0.005 (1.03) for the *FIML-Spatial Model*, where z-statistics are presented in parentheses.

<sup>16</sup> The average discrete-change effect of the stricter zoning standard on the expected number of new lots is estimated as: -0.61 (-1.92) for the *Basic Model*; -0.50 (-1.90) for the *FIML Model*; and -0.48 (-1.89) for the *FIML-Spatial Model*, where z-statistics are presented in parentheses.

<sup>17</sup> A simulated parameter vector is equal to  $\beta_s = \hat{\beta} + C'x_K$ , where  $\hat{\beta}$  is the estimated parameter vector,  $C$  is the  $K \times K$  Cholesky decomposition of the estimated variance-covariance matrix, and  $x_K$  is a  $K$ -dimensional vector of draws from a standard normal distribution.

<sup>18</sup> Historically low gas prices during this time period could be one reason for the increased development in this region of second-homes.

<sup>19</sup> Residential density is calculated in each simulation by assuming that each parcel has one residence. Digitizing the presence of buildings from 2001 aerial photos indicates that there are, on average, 1.1 buildings per parcel on our sample lakes. Since some buildings are likely not residences (e.g. tool sheds), the assumption of one residence per parcel is reasonable.

<sup>20</sup> The zoning rules are based on three classes of lakeshore development, and three classes of ecological sensitivity, yielding a nine-cell matrix of lake classes.

<sup>21</sup> Parcels that had previously subdivided below the new zoning standards were grandfathered in, so the “build out” density will be more dense than suggested by the new standards.

<sup>22</sup> Since the zoning change passed in 1999 set standards lake-by-lake based on the lake’s development density, zoning is endogenous if the econometric model is estimated with data after 1999. As such, estimation results from the 1974-1998 period are used in generating the 20-year extinction probabilities.

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<sup>23</sup> Steady-state development densities are generated by running the simulations until all subdividable lots have developed. Expected steady-state density is the average density across all simulations.

<sup>24</sup> Parcels that are not subdividable are assumed to remain in their current state.

<sup>25</sup> Lakes where “build-out” does not over-estimate extinction probabilities tend to be lakes with i) substantial shoreline in public ownership, ii) historically high minimum frontage zoning standards, or iii) few subdividable parcels in 2006.

<sup>26</sup> On lakes predicted to have more than 10 new residences, the “build-out” assumption generates between 18% and 95% more new lots than found with the estimated steady-state development levels.

<sup>27</sup> As argued by Provencher and Bishop (2004), too much parameterization can harm forecasting performance when econometric models suffer from at least some form of misspecification.