Characterizing Land Use Change in Multidisciplinary Landscape-Level Analyses

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Economists increasingly face opportunities to collaborate with ecologists on landscape-level analyses of socioeconomic and ecological processes. This often calls for developing empirical models to project land use change as input into ecological models. Providing ecologists with the land use information they desire can present many challenges regarding data, modeling, and econometrics. This paper provides an overview of the relatively recent adaptation of economics-based land use modeling methods toward greater spatial specificity desired in integrated research with ecologists. Practical issues presented by data, modeling, and econometrics are highlighted, followed by an example based on a multidisciplinary landscape-level analysis in Oregon's Coast Range mountains.

Key Words: ecological economics, forest/urban interface, spatial land use and landscape models

Economists increasingly face opportunities to collaborate with ecologists and other scientists in multidisciplinary research involving landscape-level analyses of socioeconomic and ecological processes. For economists specializing in land use issues, such collaboration often calls for developing spatial empirical models describing land use change and projecting potential future land use change scenarios for integration with other models describing socioeconomic and ecological processes. Providing ecologists with the specific types of land use information they desire can present challenges regarding the availability of appropriate land use and other data, the need to adapt existing land use modeling methods to particular research issues of interest and data at hand, and unresolved econometric issues associated with spatial autocorrelation.

Recent papers in the economics literature have addressed spatial land use modeling issues and presented example models (see, e.g., Bockstael, 1996; Irwin and Geoghegan, 2001). These papers are invaluable for their focus on developing conceptually rigorous structural models and examining econometric issues associated with spatial autocorrelation. This paper focuses on practical issues involved in providing land use information that is both conceptually rigorous and usable to researchers outside of economics, using spatial data that are often imperfect.

The study begins with a description of the relatively recent adaptation of land use modeling methods of economists toward greater spatial specificity desired in integrated research with ecologists, focusing on data, conceptual modeling, and econometrics issues. This discussion is followed by an example of a spatially explicit land use model developed as part of a multidisciplinary landscape-level analysis of socioeconomic and ecological processes in Oregon's Coast Range. The model characterizes the spatial dynamic distribution of humans on the forest landscape of western Oregon in terms of building densities, which serves as input into other models describing timber production and wildlife habitat.

The Challenges of Integration

Spatial land use models can be viewed as extensions of area-base models first developed by economists

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over 20 years ago. Area-base models describe proportions (or shares) of land in forest, agriculture, urban, or other discrete use categories, within well-defined geographic areas, usually counties, as functions of socioeconomic and geophysical variables aggregated at the particular geographic unit of analysis. Published examples are numerous (White and Fleming, 1980; Alig, 1986; Alig and Healy, 1987; Alig, White, and Murray, 1988; Lichtenberg, 1989; Plantinga, Buongiorno, and Alig, 1990; Stavins and Jaffe, 1990; Parks and Murray, 1994; Plantinga, 1996; Cropper, Griffiths, and Muthukumara, 1999; Hardie and Parks, 1997; Plantinga, Mauldin, and Alig, 1999; Hardie et al., 2000).

Future land use shares are computed using projected explanatory variable values and provide aggregate regional or national land use projections commonly reported in national resource assessments, such as the Resources Planning Act Assessment (Haynes, 2003). Although the spatial detail of such projections is limited to the geographic unit of analysis—usually counties—this has sufficed for national resource assessments. Ecologists, however, often desire land use projections at finer spatial scales more relevant to ecological processes they study. The desire to account for land use change in ecological analyses has led to the development of more spatially explicit models to project the rate and location of land use change at finer spatial scales.

What economists have come to call "spatial" land use models generally rely on discrete land use data sampled from satellite imagery, aerial photographs, or systematic land inventories, combined with other spatial data describing socioeconomic and geophysical variables. These data are used to estimate logit or probit models describing the likelihood of a particular land use change occurring at a given location and point in time (Bockstael, 1996; Chomitz and Gray, 1996; Wear, Turner, and Flamm, 1996; Nelson and Hellerstein, 1997; Bradshaw and Muller, 1998; Wear and Bolstad, 1998; Kline and Alig, 1999; Kline, Moses, and Alig, 2001).

In terms of the information they provide, the primary difference between spatial land use models and their area-base ancestors is the unit of analysis—typically a county with area-base models versus a pixel or point observation with spatial models. This refinement in spatial scale has led economists to focus on reconsidering what combination of conceptual framework, data, and econometric method is most appropriate in spatial land use modeling (Bockstael, 1996; Irwin and Geoghegan, 2001). Less attention has been given to whether land use models meet the information needs of ecologists.

A weakness of many spatial land use models is their reliance on discrete data describing land use as a simple hierarchy of forest, agriculture, and urban. Often defined by data sources, such as the National Resources Inventory (Nusser and Goebel, 1997) and the U.S. Department of Agriculture (USDA)/Forest Service's Forest Inventory and Analysis Program (Frayer and Furnival, 1999), discrete land use classes imply a level of abstraction that may be inappropriate in multidisciplinary analyses. Discrete land use classes tend to describe where humans are and are not present on landscapes, and may be inadequate to characterize the spatial and temporal interactions of humans as agents affecting landscape-level ecological processes. Also, logit and probit models estimated with discrete land use data result in predicted probabilities, which can be difficult to interpret in ecological models. Conversion probabilities may be good relative indicators of change, but more information may be needed to predict new development (Bockstael, 1996, p. 1174).

Another difficulty in spatial land use modeling is a frequent lack of appropriate data with which to construct conceptually rigorous explanatory variables. Empirical models typically are specified using proxy variables describing potential rents earned from different land uses in the context of socioeconomic and geophysical factors. Although spatial data describing geophysical factors, such as slope, elevation, and soil quality, increasingly are available from geographic data sources, socioeconomic data are less so. For example, models describing forest and farmland conversion to urban uses typically call for timber and agricultural commodity prices as proxies for forestry and farming land rents, which generally are unavailable at spatial scales finer than states or regions. Potential urban land rents can be described using proxies such as population densities (Bradshaw and Muller, 1998; Wear and Bolstad, 1998), but obtaining these in digitized form at census tract and block levels often is not possible for all but recent years. Land prices increasingly are available from digitized tax lot data, but these too can lack temporal coverage and can poorly represent actual land values if not kept current by local tax assessors. Developing appropriate econometric specifications for any land use model necessarily requires tradeoffs among conceptual rigor, data quality and availability, and the particular research needs at hand.

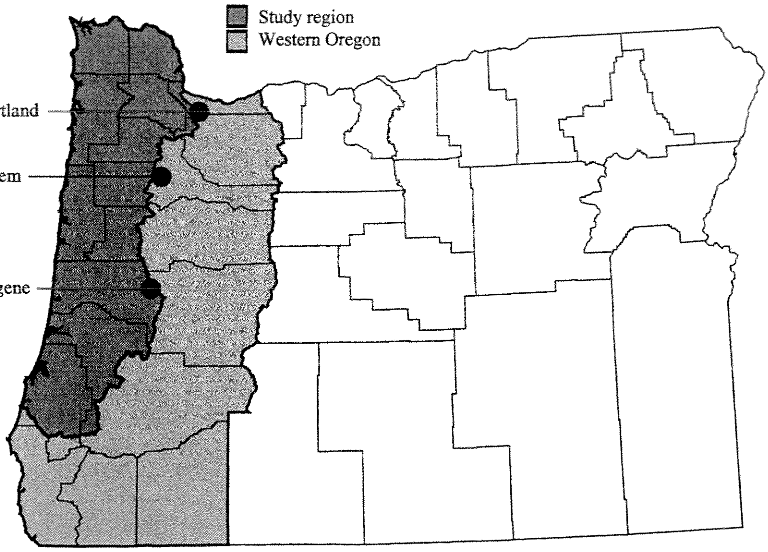

Figure 1. Coastal Landscape Analysis and Modeling Study Region in Western Oregon

A final issue involves potential spatial autocorrelation present in spatial land use data, which typically has not been addressed in area-base models. Spatial autocorrelation can result from omitted spatial variables that influence the land use decisions of landowners, such as weather-related variables, and spatial behavioral relationships, such as common ownership of sampled plots of land. The former leads to inefficient but asymptotically unbiased estimated coefficients, while the latter can lead to inefficient and biased estimated coefficients (Nelson and Hellerstein, 1997). Bockstael (1996), and Irwin and Geoghegan (2001), among others, review empirical issues involved in estimating spatial land use models. Although no standard statistical protocols yet exist, methods to account for spatial autocorrelation in land use analyses have been devised (Sohngen and Alig, 2001). Among the more popular methods in applied work are purposeful sampling (Fortin, Drapeau, and Legendre, 1989; Haining, 1990; Helmer, 2000) and inclusion of spatial lag variables (e.g., Wear and Bolstad, 1998).

A Spatial Land Use Model from Oregon

An example of how land use change can be characterized in multidisciplinary analyses is a spatial land use model developed for the Coastal Landscape Analysis and Modeling Study (Spies et al., 2002). The study analyzes the aggregate socioeconomic and ecological effects of forest policies in western Oregon's Coast Range mountains by linking standalone models describing land use change, timber production, and wildlife habitat, among other factors. The study region is bordered by the Pacific Ocean on the west and the Willamette Valley, extending from Portland south to Eugene, on the east (figure 1).

Forest policies in the region attempt to achieve a mix of forest goods and services by spatially distributing different forest practices over watersheds, landscapes, and ownerships. Recent policy concerns have focused on maintaining habitat for spotted owls (*Strix occidentalis caurina*) and coho salmon (*Oncorhynchus kisutch*). The Oregon study integrates quantitative analyses of ecological and socioeconomic processes to test whether forest policy goals (restricting cutting near spotted owl nest sites, for example) are consistent with projected future outcomes (projected availability of spotted owl habitat).

Identifying Relevant Land Use Information

One socioeconomic factor expected to have a significant impact on forestry in western Oregon is land use change resulting from forestland conversion to residential, commercial, and industrial uses. Currently, 70% of Oregon's 3.4 million people live in the Willamette Valley, and the valley population is expected to grow by 1.3 million new residents in the next 40 years (Franzen and Hunsberger, 1998). Resulting urban encroachment likely will fragment some existing forestland, with a variety of ecological and socioeconomic impacts. In this study, land use modeling must account for these impacts by describing the future distribution of humans throughout the study region.

Probit models initially developed for the study described land use change among discrete forest, agriculture, and urban categories (Kline and Alig, 1999; Kline, Moses, and Alig, 2001). However, integrating projected conversion probabilities into timber production and ecology models proved difficult. Forestland area in western Oregon historically has been quite high relative to urban land, causing projected forestland conversion probabilities to be very low over much of the study area and of little value in identifying likely locations of future conversion.

Also, although forestland conversion to urban use categories has been a relatively slow process, significant land use change has occurred as dispersed, low-density development (Azuma et al., 1999). Low-density development has become a concern of forest managers and policy makers in recent years because of its potential adverse impacts on forestry productivity (Barlow et al., 1998; Wear et al., 1999), incompatibility with timber production (Egan and Luloff, 2000), and increased wildfire risk near homes. Characterizing this form of development was of particular interest to the study.

An alternative to discrete land use data exists in spatial data depicting historical building counts in western Oregon developed by the Pacific Northwest Research Station's Forest Inventory and Analysis Program. The data consist of aerial photo-point observations of building counts (number of buildings of any size or type within 80-acre circles surrounding points on aerial photos) on nonfederal land. Aerial photos were taken in 1974, 1982, and 1994 (Azuma et al., 1999).

With nearly 24,000 photo-points, the data provide almost 72,000 observations of building counts varying in space and time. Tracking building counts on individual photo-points at each of three points in time provides two observations of change in building counts (number of new buildings constructed) for each photo-point. When combined with other spatial data using a geographic information system (GIS), the entire data set comprises 44,928 observations.

Conceptual Framework

Spatial land use models based on discrete land use data generally assume landowners choose that use which maximizes the present value of future net returns derived from their land (Bockstael, 1996; Irwin and Geoghegan, 2001). For example, landowners might convert a forest or farmland parcel to an urban use once the present value of future returns generated by the parcel in urban use less conversion costs equals or exceeds returns generated by the parcel remaining as forest or farmland. Characterizing individual behavior in this way applies neatly to estimating logit or probit models describing observed changes among discrete land use classes on individual parcels. Building count data in this study, however, describe locally aggregated decisions of unknown numbers of individual landowners regarding construction of new buildings on land of all types. A conceptual framework characterizing development as numbers of new buildings within relatively local geographic areas is needed.

Within any local area, landowners face a range of development opportunities regarding new housing, businesses, and industry. Decisions relating to such opportunities are influenced by potential future rents to be earned from any one opportunity relative to rents earned from existing land uses. Within the 80-acre vicinity of sample points comprising building count observations in this study, local landowners likely face similar types of development opportunities, subject to zoning and topographic differences that affect potential building sites. The extent to which we observe new buildings in any given local area will be a function of the potential returns to be earned from new development, as well as local zoning and topographic characteristics. The building counts identify newly constructed buildings, and can be used to estimate Poisson and negative binomial models describing new development as a function of these factors.

Regionally disaggregated economic data describing potential land rents earned from new development relative to forestry and agriculture are not available, so proxy variables must be identified. Conceptually, the value of land in developed uses has been viewed as a function of the spatial proximity to city centers (Mills, 1980; Miyao, 1981; Fujita, 1982; Wheaton, 1982; Capozza and Helsley, 1989). Von Thunen viewed spatial proximity in terms of costs associated with transporting forest and agricultural commodities to markets, influencing whether forestry and agriculture were profitable in any given location (Barlow, 1978, p. 37). However, modern society views spatial proximity in terms of the difference between quality-of-life factors, such as housing, neighborhood characteristics, and environmental amenities, and the costs associated with commuting to employment destinations. More consistent with central place theory, this view explains location choices based on the relative economic advantages of locating people, businesses, and industries in particular clusters and patterns (King, 1984).

One of the most important factors affecting land's development potential in western Oregon is its commuting proximity to employment opportunities offered by major cities of the Willamette Valley. Land within short commuting distances likely will have greater development potential than land within relatively longer commuting distances. Also, land within commuting distance to a large city likely will have greater development potential than land within a comparable commuting distance to a smaller city. Cities beyond reasonable commuting distances likely will have very little, if any, influence on development potential. The influence of city size and location can be described using a gravity index (Reilly, 1929; Haynes and Fotheringham, 1984) to account for the combined influence of population and proximity as economic forces affecting land use change (Shi, Phipps, and Colyer, 1997).

Selection of Variables

Using a gravity index, the development potential of land is computed as:

$$(1)\qquad \textit{Gravity Index}_i = \sum_{1}^{K} \textit{Population}_k \left(\frac{60 - \textit{Time}_{ik}}{60} \right),$$

where K represents the number of cities within a 60-minute drive (or commute) of each photo-point i, *Population* is the population [U.S. Department of Commerce (USDC), Bureau of the Census, 1992] of each city k, and *Time* is the driving time in minutes between photo-point i and city k. The gravity index is the sum of populations of cities within a 60-minute commute of each photo-point, weighted by the estimated driving time to each city's edge.

The index sets a 60-minute threshold on the "reasonable" commuting time, based on the assumption that most Oregonians probably commute no more than one hour to work. Varying this threshold to reflect somewhat shorter or longer maximum commuting times did not substantially affect the sign, magnitude, or statistical significance of the gravity index estimated coefficient. The cities incorporated into the gravity index computation include 45 western Oregon cities comprising 5,000 or more persons in 1990 (USDC, Bureau of the Census, 1992). Adjacent cities are combined and treated as larger metropolitan areas, reducing the total number of cities and metropolitan areas included in the analysis to 30.

Driving times used to calculate the gravity index were estimated using a geographic information system map of existing roads to create a friction surface based on average driving times assumed for different types of roads. Drivers are assumed to average speeds of 60 miles per hour on primary roads, 25 miles per hour on secondary roads, and 10 miles per hour where there are no roads. Driving times are based on roads data from a single point in time, because data describing road improvements are unavailable. As a consequence, the analysis ignores potential endogeneity between land use change and road building noted by Irwin and Geoghegan (2001), among others.

Ignoring such endogeneity can lead to two potential problems. First, there is a failure to account for improved physical access to land provided by new roads in the future. Second, since driving times are based on the modern road network rather than a potentially less extensive network existing when new buildings were constructed in the past, gravity indices could be overestimated, and their estimated model coefficient underestimated, in magnitude. Both problems could result in underestimating projected future changes in building counts.

In this study, the gravity index is combined with other explanatory variables describing existing building counts, topographic features of slope and elevation, and land use zoning adopted under Oregon's Land Use Planning Program (Abbott, 1994). Together, the variables are assumed to characterize the value of land in developed uses over its value in undeveloped forest and agriculture. It is expected that greater numbers of new buildings are found in areas having higher gravity index values, and fewer are found in areas having low gravity index values. Higher existing building counts are hypothesized to have a positive but diminishing impact on new buildings, because factors attracting existing development likely attract new development before building density limits mandated by zoning are achieved. Slope is expected to be negatively correlated with new buildings, because steeper slopes can be more difficult to build upon. Elevation also can be negatively correlated with new buildings if high elevations impede construction with poor physical access. However, elevations can be positively correlated with new buildings if they provide desirable views (Wear and Bolstad, 1998). Finally, land located within urban growth boundaries adopted under Oregon's Land Use Planning Program is predicted to gain greater numbers of new buildings than land located within forest or farm zones.

Model Estimation

The dependent variable *ΔBuildings* was constructed by computing changes in building counts observed within 80-acre circles surrounding sample points at 10-year intervals between 1974 and 1984, and between 1984 and 1994. Building counts for 1984 were approximated by interpolation between 1982 and 1994 values, and rounding to the nearest whole number. The dependent variable *ΔBuildings* is measured as a count and is not continuous. Assuming *ΔBuildings* is distributed as a Poisson leads to the negative binomial model:

$$(2)\qquad \Pr\left(\Delta Buildings = y_i \mid \gamma\right) = \frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!},$$

$$y_i = 0, 1, 2, \ldots \text{ and } i = 1, 2, \ldots, n,$$

where

$$\ln(\lambda_i) = \ln(\hat{\lambda}_i) + \gamma = \boldsymbol{\beta}'\mathbf{x}_i + \gamma,$$

and where γ is a random variable and $\exp(\gamma)$ has a gamma distribution with mean 1 and variance α, $\mathbf{x}_i$ is a vector of independent variables, and $\boldsymbol{\beta}'$ is a vector of coefficients to be estimated (Greene, 1997). The negative binomial model is a general form of the Poisson model relaxing the Poisson assumption that the dependent variable's mean equals its variance (Wear and Bolstad, 1998).

The panel nature of the data—generally two observations of building count change per photo-point—creates the potential for correlation among pairs of time-series observations for individual photo-points to deflate standard errors and bias estimated coefficients. These potential correlations can be accounted for using a random-effects negative binomial model (Greene, 1995, pp. 570–571). Because group effects are conditioned out (not computed), projected values cannot be computed using the random-effects model (Greene, 1995, p. 567), but the estimated coefficients can be compared to those of the model estimated without random effects.

A final estimation issue is potential spatial autocorrelation among the building count observations, which to our knowledge has not previously been addressed in count-data models. In this case, peculiarities in data reporting complicate remedies routinely used in discrete models. Although the building count data are based on a systematic photo-point sampling spaced on roughly a 1,370-meter average grid, Forest Inventory and Analysis Program policy requires the Universal Transverse Mercator (UTM) x- and y-coordinates of sample points each be "fuzzed" by up to 1,000 meters to protect the precise point locations. This inhibits both purposeful sampling and developing reliable spatial lags of *ΔBuildings*, because sample points neighboring each observation cannot be identified with certainty. Given these difficulties, it is assumed that the 1,370-meter average spacing of sample points likely minimizes any spatial behavioral relationships unaccounted for by the gravity index, zoning, and other spatial explanatory variables, and the model is estimated leaving potential spatial autocorrelation untreated.

However, four alternative spatial autocorrelation remedies were tested using the fuzzed UTM coordinates—two based on purposeful sampling, and two based on inclusion of spatial lag variables. The four alternative models yielded estimated coefficients that were similar in sign, magnitude, and statistical significance to those of the presented model. In the two models where they were included, estimated spatial lag coefficients were positive and statistically significant ($P < 0.01$), suggesting that building count changes observed on individual sample points do seem to be accompanied by changes on neighboring sample points. Building density projections made using the alternative models differed from those of the presented model by 0.3% to 0.7% for undeveloped land, and 0.3% to 0.5% for undeveloped and low-density developed land combined (the two categories of particular interest, and defined later in table 4). Because they are based on imperfect UTM coordinates and somewhat ad hoc remedies, the alternative model results are not presented, but are available from the author upon request.

Fuzzy UTM coordinates do not affect the slope, elevation, and land use zoning variables included in the analysis, because they were developed using un-fuzzed coordinates. Since the fuzziness is limited to one kilometer and the data span a geographic area

Table 1. Descriptions of Explanatory Variables Tested in the Empirical Model

Variable	Description
Gravity Index	Equal to the average of the gravity index computed [using equation (2)] at the beginning of each time period and the gravity index computed at the end of each time period (× 1/100,000). City populations for non-Census study years estimated by interpolating between populations reported for Census years (USDC/Bureau of the Census, 1992).
Building Count	Number of buildings within an 80-acre circle surrounding photo-point (Azuma et al., 1999) at the beginning of each time period (× 1/100).
Slope	Percent (%) slope at the sample point (× 1/100).
Elevation	Elevation in meters.
Urban Growth Boundary	Variable equals 1 if plot is located in an urban growth boundary or rural residential land use zone; 0 otherwise.
Farm Zone	Variable equals 1 if plot is located in a farm zone; 0 otherwise.
Forest Zone	Variable equals 1 if plot is located in a forest zone; 0 otherwise.
1994	Variable equals 1 if observation describes building density change from 1984 to 1994; 0 otherwise.

of roughly 78,000 square kilometers, impacts to the gravity index variable are negligible. The general regression equation describes changes in building counts on photo-points from one time point to the next as:

(3) $\Delta Buildings =$
$$f\,(Gravity\ Index,\ Building\ Count,\ Slope,\ Elevation,\ Urban\ Growth\ Boundary,\ Farm\ Zone,\ Forest\ Zone,\ 1994),$$

where the specific explanatory variables are described in table 1. The model is highly significant, based on log-likelihood ratio tests of the Poisson model ($\chi^2 = 39{,}597$, df = 9, $P < 0.0001$) and negative binomial model tested against the null of the Poisson ($\chi^2 = 25{,}134$, df = 1, $P < 0.0001$). Random effects coefficients are reasonably consistent with negative binomial coefficients, although the statistical significance of the beta coefficient in the random effects regression indicates the possible presence of statistically significant random effects.

Estimated coefficients for the linear and quadratic *Gravity Index* variables are statistically significant ($P < 0.01$), and together suggest that, over time, building counts increase at an increasing rate with greater proximity to cities within commuting distance and greater population sizes of those cities (table 2). Estimated coefficients for the linear and quadratic *Building Count* variables are statistically significant ($P < 0.01$), and in combination indicate existing building numbers have a positive but diminishing impact on future building count increases.

Estimated coefficients for *Slope* and *Elevation* are negative and statistically significant ($P < 0.01$), showing that slope and elevation have a negative impact on building count changes. Relative to *Farm Zone* and *Forest Zone*, estimated coefficients for *Urban Growth Boundary* are positive and statistically significant ($P < 0.01$). This result suggests that Oregon's Land Use Planning Program has tended to concentrate new building construction within urban growth boundaries since it mandated the adoption of statewide zoning.

Model Validation

In multidisciplinary research, an important component of empirical modeling is the validation of models by examining the potential accuracy of projected values. The forecasting performance of previous versions of the negative binomial land use model was evaluated by: (*a*) examining the percentage of correct within-sample projections, (*b*) estimating auxiliary models after reserving validation data sets, and (*c*) examining several information indices and statistics suggested by Hauser (1978) and by Wear and Bolstad (1998). The first of these validation techniques is briefly described here. Details regarding the other validation procedures can be found in Kline, Azuma, and Moses (2003).

The estimated negative binomial model coefficients (table 2) were used to compute projected changes in building counts, which were added to initial building counts to compute within-sample projections of ending building counts for each observation ($N = 44{,}928$). To compute the percentage of correct projections, projected ending building counts were compared to actual ending building counts. The percentage of correct projections

Table 2. Estimated Coefficients of Negative Binomial Models Describing Changes in Building Counts in Western Oregon (N = 44,928 observations)

Variable	Negative Binomial Regression: Coefficient	Negative Binomial Regression: Marginal Effect	Negative Binomial Regression with Random Effects
Gravity Index	-0.308 (-13.66)	-0.410	-0.045 (-2.36)
Gravity Index^2	0.048 (12.48)	0.064	0.009 (3.52)
Building Count	24.999 (46.63)	33.312	16.971 (63.22)
Building Count^2	-26.572 (-45.88)	-35.408	-26.720 (-59.28)
Slope	-7.530 (-30.59)	-10.034	-5.851 (-20.28)
Elevation	-2.127 (-28.43)	-2.835	-1.714 (-20.44)
Urban Growth Boundary	1.076 (7.13)	1.433	0.716 (5.22)
Farm Zone	0.162 (1.09)	0.215	0.547 (3.97)
Forest Zone	-0.363 (-2.39)	-0.484	0.062 (0.43)
1994	-1.088 (-8.09)	-1.450	-1.168 (-9.70)
Alpha	4.385 (50.73)	—	2.148 (30.88)
Beta	—	—	0.884 (23.67)
Summary Statistics:	Poisson Log Likelihood = -37,214 χ^2 = 39,597, df = 9, $P < 0.0001$ Negative Binomial Log Likelihood = -24,647 χ^2 = 25,134, df = 1, $P < 0.0001$ [a]		Log Likelihood = -24,357

Note: Values in parentheses are t-statistics for each of the estimated coefficients.
[a] Tested against the null of the Poisson model.

decreases as ending building counts increase, from a high of 100% for observations having an ending building count of 0 buildings to a low of 19.3% for observations having an ending building count of 8 (table 3). The percentage of correct projections within one building is higher, ranging from 100% for observations having an ending building count of 0 or 1 building to a low of 48.8% for observations having an ending building count of 8. Greater accuracy at the lower range of ending building counts likely is due in part to the relatively large proportion of observations comprising relatively low building counts.

The purpose of the model in the Coastal Landscape Analysis and Modeling Study is to locate forestland comprising building densities of greater than 64 buildings per square mile—the point at which timber management and production are assumed to end in the study's timber production models. This threshold is consistent with an average forest parcel size of 10 acres per building (house), which is the minimum forest parcel size eligible for preferential assessment as forestland for property tax purposes in Oregon (Oregon Department of Revenue, 1998).

Based on an average household size of 2.45 persons (Azuma et al., 1999), the 64 buildings per square mile threshold also is equivalent to 157 people per square mile, which is relatively consistent with the population density found by Wear et al.

Table 3. Percentage of Within-Sample Correct Base Model Projections of Ending Building Counts and Ending Broad Building Count Class (N = 44,928 observations)

Class	Percent in Class	Percent of Class Correctly Projected	Percent Correctly Projected Within One Building
Ending Building Count: [a]			
0	68.7	100.0	100.0
1	8.9	80.0	100.0
2	5.5	63.0	88.9
3	3.9	48.2	82.2
4	2.6	40.2	74.4
5	1.8	33.2	65.8
6	1.5	27.8	56.3
7	1.0	20.2	52.4
8	0.9	19.3	48.8
>8	5.2	81.8	86.4
Ending Broad Building Count Class:			
≤ 8	94.8	99.6	99.8
>8	5.2	82.8	86.4

[a] Building count within an 80-acre circle surrounding sample photo-point.

(1999) to be the point at which commercial timber production ends on private forestlands. Using the 80-acre basis of our building count data, the 64 buildings per square mile density threshold is equivalent to eight buildings per 80 acres. The percentage of correct projections falling above and below the threshold is relatively high—99.6% for the ≤8 class and 82.8% for the >8 class—suggesting the model is probably adequate for the immediate purposes for which it is used (table 3).

Integrating Land Use Projections with Timber Production and Ecology Models

The estimated negative binomial coefficients (table 2) are combined with projected gravity index values to compute increases in building counts on forest and agricultural land in western Oregon given existing land use zoning. Existing and projected 80-acre building counts are converted to building densities per square mile. Projected city populations are based on county population projections for western Oregon through 2040 (Oregon Department of Administrative Services, Office of Economic Analysis, 1997) and on extrapolation for 2040 to 2054. Building density projections are used to create geographic information system maps of future low-density and urban development of forestlands that are inputs to timber production and habitat viability models (Kline, Azuma, and Moses, 2003).

Forestlands were delineated from agricultural lands using a vegetation map of 1995 forest and nonforest cover, and these delineations remain constant throughout the modeling time horizon. A base year 1994 map of building densities was developed from the 1994 building count data by interpolating between photo-point building count values, and converting these to densities per square mile. Projected changes in building densities at each 10-year modeling interval were added to the beginning building density map for that interval to obtain the ending building density map. For example, projected changes between 1994 and 2004 were added to 1994 building densities to obtain a 2004 building density map. Building density maps delineate the forestland area available for timber production and wildlife habitat at each 10-year modeling interval according to low-density and urban building density thresholds (Spies et al., 2002).

Timber production is assumed to end on forestlands attaining a low-density threshold of 64 buildings per square mile, the point at which standing trees are assumed no longer available for harvest for the remainder of the modeling time horizon. Wildlife habitat is assumed to end on forestlands attaining an urban threshold of 640 buildings per square mile. Additionally, once low-density and urban lands are delineated, ¼-acre open vegetation patches (building footprints) are created for each projected new building. The building footprints are

Table 4. Projected Low-Density and Urban Development on Nonfederal Forest and Agricultural Land in Western Oregon, 1994–2054 (acres)

	Building Density Class[a]			
Land Cover	Undeveloped[b] (≤ 64 bldgs.)	Low-Density[b] (65 to 640 bldgs.)	Urban (> 640 bldgs.)	Total Undeveloped and Low-Density[b]
Existing in 1994:[c]				
Forest	7,138,080	61,920	—	7,200,000
Agriculture	1,806,213	136,787	—	1,943,000
Mixed Forest/Agriculture	739,427	35,573	—	775,000
Total	9,683,720	234,280	—	9,918,000
Projected 2024:				
Forest	7,058,880	103,680	37,440	7,162,560
Agriculture	1,561,006	268,328	113,666	1,829,334
Mixed Forest/Agriculture	681,380	70,215	23,405	751,595
Total	9,301,266	442,223	174,511	9,743,489
Projected 2054:				
Forest	6,952,320	141,840	105,840	7,094,160
Agriculture	1,134,906	457,965	350,129	1,592,871
Mixed Forest/Agriculture	600,315	105,400	69,285	705,715
Total	8,687,541	705,205	525,254	9,392,746

[a] Buildings per square mile computed from projected building counts.

[b] Coastal Landscape Analysis and Modeling Study assumptions allow only forestland in the undeveloped class to contribute to timber production, while forestland in both the undeveloped and low-density classes contributes to wildlife habitat. Agricultural land was included in land use modeling, but is not included in the other study analyses.

[c] Reported in Azuma et al. (1999).

intended to represent the indirect impact of buildings on timber production and wildlife habitat in terms of their direct impacts on vegetative cover. The ¼-acre footprints are consistent with the average vegetation patch sizes found among a sampling of buildings in the study area. The footprints also are roughly equivalent in size to the basic spatial simulation unit used in the Coastal Landscape Analysis and Modeling Study timber production models. The specific locations of building footprints are selected randomly according to estimated building densities for each unit.

Projected Low-Density and Urban Development

Land use data for 1994 indicate that western Oregon was comprised of approximately 9.9 million undeveloped and low-density acres, with nonfederal forestland totaling 7.2 million acres, agricultural land totaling 1.9 million acres, and mixed forest/agricultural land totaling 0.8 million acres. Building density data show 61,920 acres (0.9%) of forestland fell in the low-density class (64 to 640 buildings per square mile), with corresponding figures of 136,787 acres (7%) for agricultural land, and 35,573 acres (4.6%) for mixed forest/agricultural land (table 4).

Land exceeding the urban threshold (>640 buildings per square mile) is assumed to have converted from forest and agricultural uses to predominantly urban uses. Based on building density projections, by 2024, 37,440 acres (0.5%) of forestland existing in 1994 will have been converted to urban uses, with corresponding figures of 113,666 acres (5.8%) for agricultural land, and 23,405 acres (3%) for mixed forest/agricultural land. Also, by 2024, 103,680 acres (1.4%) of remaining forestland will fall in the low-density class, along with 268,328 acres (14.7%) of agricultural land and 70,215 acres (9.3%) of mixed forest/agricultural land.

By 2054, 105,840 acres (1.5%) of forestland existing in 1994 will have been converted to urban uses, as well as 350,129 agricultural acres (18%) and 69,285 mixed forest/agricultural acres (8.9%). Further, by 2054, 141,840 acres (2%) of remaining forestland will fall in the low-density class, in addition to 457,965 acres (28.8%) of agricultural land and 105,400 acres (14.9%) of mixed forest/agricultural land (table 4).

Along with forest and agricultural land lost to urban uses, building density projections suggest that greater numbers of people will be living in closer proximity to remaining forestlands in the future. The projected building densities are based on population values outside the range of data used to estimate the empirical model. To evaluate how reasonable the building density projections are, per capita increases in low-density and urban development indicated by our spatial projections were compared with per capita development rates indicated by 1997 National Resources Inventory data for Oregon (USDA/Natural Resources Conservation Service, 1999). The projections of this analysis suggest low-density and urban development will increase an average of 0.44 acres per new resident from 1994 to 2054. This rate is quite close to the average 0.46-acre increase in "developed land" per new resident in Oregon from 1982 to 1997, and below the national average of 0.69 acres per new resident, based on National Resources Inventory data.

Summary and Conclusions

The building count model and resulting building density projections are one example of how beneficial, conceptually rigorous land use information can be provided in multidisciplinary settings when data are imperfect. In the absence of spatial economic data describing land rents, information about city populations and city locations was combined to proxy potential rents earned from land in developed uses.

In combination with data describing topographic features and land use zoning, the empirical model describes potential future land development in terms of numbers and locations of new buildings. Model validation procedures reveal that the likelihood of correctly projecting future building densities improves with the increasing coarseness of building density classes desired. The model is better at projecting close to actual future building density classes than it is at projecting exact building density classes. The validation illustrates the tradeoffs inherent in choosing between precision and the accuracy when building density classes, or any land use classes, are projected using spatial models.

The particular modeling approach presented here was made possible by the availability of building count data, which are unavailable from national land inventories and other common data sources, and are relatively expensive to collect independently. The data enabled empirical modeling of new buildings, which provide more information to timber production and ecology analyses than do discrete land use classes. The model enables analysts to account for ranges of human occupation of forestland that are relevant to timber production and wildlife habitat. Unconstrained by discrete forest and urban delineations, the model provides land use information which potentially can be applied to a broader range of research issues.

Spatial land use models often suffer a weak link between their conceptual framework and their empirical application, due to poor availability of data with which to construct conceptually appropriate explanatory variables. In this case, better information regarding potential forestry rents would enable a better accounting of the opportunity costs of forestland development.

Related to this caveat is the need to consider heterogeneity across forest stands when describing landowners' decisions to convert forestland to developed uses. Such factors as species, age class, and standing volume can be important in landowners' timber harvest decisions, which often coincide with forestland conversion. In this application, land use information is treated as an exogenous input into timber production models. Greater integration of land use and timber production analyses would allow for land use change and forest production decisions to be modeled as the endogenous decisions they often are.

Developing spatial land use models calls for new types of data and relatively new empirical techniques to address econometric issues presented by spatial data. Integrating spatial land use information into multidisciplinary research necessarily involves identifying relevant research issues and specific information needs of cooperating analysts, obtaining conceptually relevant spatial data with which to estimate empirical models, and adapting existing spatial econometric methods to suit the particular modeling objectives and data at hand.

Given the wide variety of potential multidisciplinary research topics, a lack of regular and consistent spatial data sources, and an absence of universally accepted protocols regarding spatial land use analysis, no universal approach is likely to emerge for some time. Analysts will need to consider conceptual and empirical tradeoffs associated with different types of data and modeling methods as they determine how best to meet their research objectives in a cost-effective manner.

References

Abbott, C. (1994). *Planning the Oregon Way.* Corvallis, OR: Oregon State University Press.

Alig, R. J. (1986). "Econometric Analysis of the Factors Influencing Forest Acreage Trends in the Southeast." *Forest Science* 32(1), 119–134.

Alig, R. J., and R. G. Healy. (1987). "Urban and Built-up Land Area Changes in the United States: An Empirical Investigation of Determinants." *Land Economics* 63(3), 215–226.

Alig, R. J., F. C. White, and B. C. Murray. (1988). "Economic Factors Influencing Land Use Changes in the South-Central United States." Research Paper No. SE-272, USDA/Forest Service, Southeastern Forest Experiment Station, Asheville, NC.

Azuma, D. L., K. R. Birch, P. DelZotto, A. A. Herstrom, and G. J. Lettman. (1999). "Land Use Change on Non-Federal Land in Western Oregon, 1973–1994." Oregon Department of Forestry, Salem, OR.

Barlow, R. (1978). *Land Resource Economics: The Economics of Real Estate.* Englewood Cliffs, NJ: Prentice-Hall, Inc.

Barlow, S. A., I. A. Munn, D. A. Cleaves, and D. L. Evans. (1998). "The Effect of Urban Sprawl on Timber Harvesting." *Journal of Forestry* 96, 10–14.

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

Bradshaw, T. K., and B. Muller. (1998). "Impacts of Rapid Urban Growth on Farmland Conversion: Application of New Regional Land Use Policy Models and Geographical Information Systems." *Rural Sociology* 63, 1–25.

Capozza, D. R., and R. W. Helsley. (1989). "The Fundamentals of Land Prices and Urban Growth." *Journal of Urban Economics* 26, 295–306.

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, 487–512.

Cropper, M., C. Griffiths, and M. Muthukumara. (1999). "Roads, Population Pressures, and Deforestation in Thailand, 1976–1989." *Land Economics* 75(1), 58–73.

Egan, A. F., and A. E. Luloff. (2000). "The Exurbanization of America's Forests: Research in Rural Social Science." *Journal of Forestry* 98(3), 26–30.

Fortin, M., P. Drapeau, and P. Legendre. (1989). "Spatial Autocorrelation and Sampling Design in Plant Ecology." *Vegetation* 83, 209–222.

Franzen, R., and B. Hunsberger. (1998, December 13). "Have We Outgrown Our Approach to Growth?" *The Sunday Oregonian* [Portland, OR], p. 1.

Frayer, W. E., and G. M. Furnival. (1999). "Forest Survey Sampling Designs: A History." *Journal of Forestry* 97(12), 4–10.

Fujita, M. (1982). "Spatial Patterns of Residential Development." *Journal of Urban Economics* 12, 22–52.

Greene, W. H. (1995). *LIMDEP Version 7.0: User's Manual.* Bellport, NY: Econometric Software, Inc.

———. (1997). *Econometric Analysis.* Upper Saddle River, NJ: Prentice-Hall.

Haining, R. (1990). *Spatial Data Analysis in the Social and Environmental Sciences.* New York: Cambridge University Press.

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(2), 299–310.

Hardie, I., P. Parks, P. Gottleib, and D. Wear. (2000). "Responsiveness of Rural and Urban Land Uses to Land Rent Determinants in the U.S. South." *Land Economics* 76(4), 659–673.

Hauser, J. R. (1978). "Testing the Accuracy, Usefulness, and Significance of Probabilistic Choice Models: An Information-Theoretic Approach." *Operations Research* 26, 406–421.

Haynes, K. E., and A. S. Fotheringham. (1984). *Gravity and Spatial Interaction Models.* Beverly Hills, CA: Sage Publications.

Haynes, R. W. (2003). "An Analysis of the Timber Situation in the United States, 1952 to 2050: A Technical Document Supporting the 2000 USDA Forest Service RPA Assessment." General Technical Report No. PNW-GTR-560, U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station, Portland, OR.

Helmer, E. H. (2000). "The Landscape Ecology of Tropical Secondary Forest in Montane Costa Rica." *Ecosystems* 3, 98–114.

Irwin, E. G., and J. Geoghegan. (2001). "Theory, Data, Methods: Developing Spatially Explicit Economic Models of Land Use Change." *Agriculture, Ecosystems, and Environment* 85(1–3), 7–23.

King, L. J. (1984). *Central Place Theory.* Beverly Hills, CA: Sage Publications.

Kline, J. D., and R. J. Alig. (1999). "Does Land Use Planning Slow the Conversion of Forest and Farmlands?" *Growth and Change* 30, 3–22.

Kline, J. D., D. L. Azuma, and A. Moses. (2003, in press). "Modeling the Spatial Dynamic Distribution of Humans on a Landscape." *Landscape Ecology.*

Kline, J. D., A. Moses, and R. J. Alig. (2001). "Integrating Urbanization into Landscape-Level Ecological Assessments." *Ecosystems* 4(1), 3–18.

Lichtenberg, E. (1989, February). "Land Quality, Irrigation Development, and Cropping Patterns in the Northern High Plains." *American Journal of Agricultural Economics* 71, 187–194.

Mills, E. S. (1980). *Urban Economics.* Glenview, IL: Scott, Foresman and Co.

Miyao, T. (1981). *Dynamic Analysis of the Urban Economy.* New York: Academic Press.

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.

Nusser, S. M., and J. J. Goebel. (1997). "The National Resources Inventory: A Long-Term Multi-Resource Monitoring Program." *Environmental and Ecological Statistics* 4, 181–204.

Oregon Department of Administrative Services, Office of Economic Analysis. (1997). "Long-Term Population and Employment Forecasts for Oregon: State and Total Populations." Salem, OR.

Oregon Department of Revenue. (1998). "Specially Assessed Forestland." Property Tax Division, Valuation Section, Salem, OR.

Parks, P. J., and B. C. Murray. (1994). "Land Attributes and Land Allocation: Nonindustrial Forest Use in the Pacific Northwest." *Forest Science* 40(3), 558–575.

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

Plantinga, A. J., J. Buongiorno, and R. J. Alig. (1990). "Determinants of Changes in Non-Industrial Private Timberland Ownership in the United States." *Journal of World Forest Resource Management* 5, 29–46.

Plantinga, A. J., T. Mauldin, and R. Alig. (1999). "Land Use in Maine: Determinants of Past Trends and Projections of Future Changes." Research Paper No. PNW-RP-511, U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station, Portland, OR.

Reilly, W. J. (1929). "Methods for the Study of Retail Relationships." Bulletin No. 2944, University of Texas, Austin.

Shi, Y. J., T. T. Phipps, and D. Colyer. (1997). "Agricultural Land Values Under Urbanizing Influences." *Land Economics* 73, 90–100.

Sohngen, B., and R. Alig. (2001). "Spatial Econometrics: Potential Application to Land Use Change and Forestry." Working paper, Department of Agricultural Economics, Ohio State University, Columbus.

Spies, T. A., G. H. Reeves, K. M. Burnett, W. C. McComb, K. N. Johnson, G. Grant, J. L. Ohmann, S. L. Garman, and P. Bettinger. (2002). "Assessing the Ecological Consequences of Forest Policies in a Multi-Ownership Province in Oregon." In J. Liu and W. W. Taylor (eds.), *Integrating Landscape Ecology into Natural Resource Management* (pp. 179–207). New York: Cambridge University Press.

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

U.S. Department of Agriculture, Natural Resources Conservation Service. (1999). "Summary Report: 1997 National Resources Inventory (NRI)" [revised December 2000]. Washington, DC.

U.S. Department of Commerce, Bureau of the Census. (1992). *1990 Census of Population and Housing*. USDC/Economic and Statistics Administration, Washington, DC.

Wear, D. N., and P. Bolstad. (1998). "Land Use Changes in Southern Appalachian Landscapes: Spatial Analysis and Forecast Evaluation." *Ecosystems* 1, 575–594.

Wear, D. N., R. Lui, J. M. Foreman, and R. Sheffield. (1999). "The Effects of Population Growth on Timber Management and Inventories in Virginia." *Forest Ecology and Management* 118(1–3), 107–115.

Wear, D. N., M. G. Turner, and R. O. Flamm. (1996). "Ecosystem Management with Multiple Owners: Landscape Dynamics in a Southern Appalachian Watershed." *Ecological Applications* 6, 1173–1188.

Wheaton, W. C. (1982). "Urban Residential Growth Under Perfect Foresight." *Journal of Urban Economics* 12, 1–12.

White, F. C., and F. N. Fleming. (1980). "An Analysis of Competing Agricultural Land Uses." *Southern Journal of Agricultural Economics* 12(4), 99–103.