ECONOMICS AND CONTEMPORARY LAND USE POLICY

Development and Conservation at the Rural-Urban Fringe

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Describing Land Use Change in Multidisciplinary Analyses

Jeffrey D. Kline

Economists increasingly face opportunities to collaborate with ecologists and other scientists in multidisciplinary research involving landscape-level analyses of socioeconomic and ecological processes. A common goal of such analyses is to describe potential changes in ecosystem processes and conditions resulting from forest policies and management actions addressing timber, wildlife, and wildfire objectives (e.g., Spies et al. 2002; Hayes et al. 2004). In particular, land use economists often are called upon to describe potential future land use changes that are likely to influence the effectiveness and outcomes of policies and management actions of interest. This typically involves developing statistical spatial empirical models describing land use changes and projecting 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 data, the need to adapt existing modeling methods to particular research issues of interest and data at hand, and unresolved econometric issues associated with spatial autocorrelation. Recent papers in economics literature have addressed spatial land use modeling issues and presented illustrative models (e.g., Bockstael 1996; Irwin and Geoghegan 2001). These papers are invaluable for their focus on the development of conceptually rigorous structural models and examination of econometric issues associated with spatial autocorrelation.

This chapter 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. It begins by describing

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 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 more than 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 (Alig 1986; Alig and Healy 1987; Alig et al. 1988, 2004; Cropper et al. 1999; Hardie and Parks 1997; Hardie et al. 2000; Lichtenberg 1989; Parks and Murray 1994; Plantinga 1996; Plantinga et al. 1990, 1999; Stavins and Jaffe 1990; White and Fleming 1980). 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 2002). 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 the 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 discrete choice (e.g., logit or probit) models describing the likelihood of a particular land use change occurring at a given location and point in time (Bockstael 1996; Bradshaw and Muller 1998; Chomitz and Gray 1996; Kline and Alig 1999; Kline et al. 2001; Nelson and Hellerstein 1997; Wear and Bolstad 1998; Wear et al. 1996). By focusing on general land use categories, these models differ from related research focused on describing changes in land cover, such as deforestation or cropping patterns, that may occur within the general categories (e.g., Lambin et al. 2003), although the empirical methods used in both types of models often are similar. In terms of information provided, 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 the most appropriate combination of conceptual frameworks, data, and econometric methods for spatial land use modeling (Bockstael 1996; Irwin and Geoghegan 2001). Less attention has been given to whether land use models meet the informational needs of ecologists or others involved in the provision of policy guidance.

A weakness of many spatial land use models is their reliance on discrete data describing land use as a simple hierarchy of forestry, agricultural, and urban uses. Often defined by data sources, such as the National Resources Inventory (Nusser and Goebel 1997) and the 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. They 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, discrete choice models estimated with land use data typically result in predicted probabilities—the probability of conversion, for example—which can be difficult to interpret in ecological or natural science models. Conversion probabilities may be good relative indicators of change, but more information may be needed to predict new development (Bockstael 1996, *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 terms 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 is often 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. More generally, confidentiality problems related to spatial socioeconomic data often occur when data-gathering agencies restrict the uses of certain information to protect the privacy of surveyed individuals. Considering such factors, it is clear that the development of appropriate econometric specifications for any land use model necessarily requires trade-offs among conceptual rigor, data quality and availability, and the particular research needs at hand.

A final issue involves potential spatial dependence present in spatial land use data, which area-base models typically have not addressed. Spatial dependence 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 first leads to inefficient but asymptotically unbiased estimated coefficients; the second 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. The development of standard protocols for addressing spatial dependence in statistical models is relatively recent (e.g., Sohngen and Alig 2001; Fleming 2004). Among the more popular methods in applied work at the time of the study described in this chapter were purposeful sampling (Fortin et al. 1989; Haining 1990; Helmer 2000) and the 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 provided by 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 stand-alone 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 5-1). 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 northern spotted owls (*Strix occidentalis caurina*) and coho salmon (*Oncorhynchus kisutch*). The 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 (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

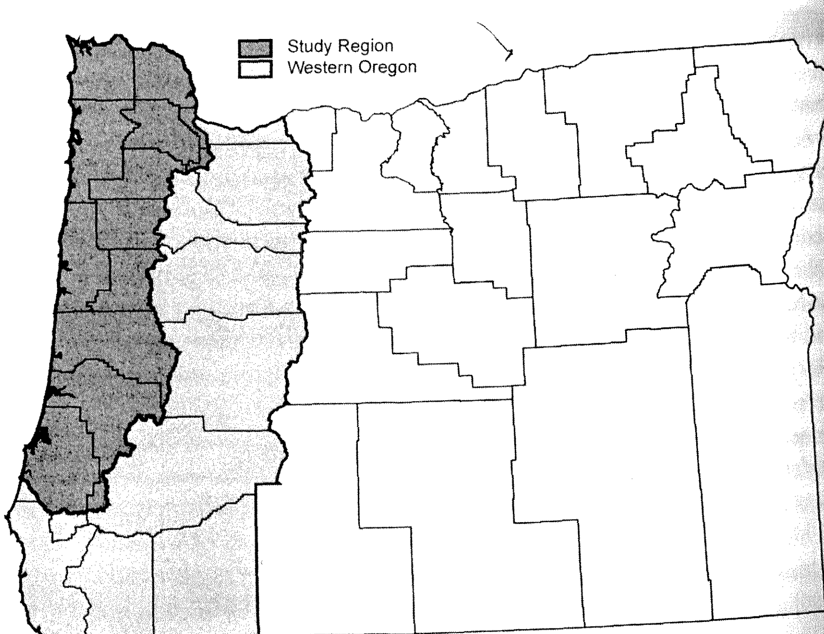

Figure 5-1. Coastal Landscape Analysis and Modeling Study Region in Western Oregon

residential, commercial, and industrial uses. Currently, 70 percent of Oregon's 3.4 million people live in the Willamette Valley, and the population there is expected to grow by 1.3 million new residents in the next 40 years (Franzen and Hunsberger 1998). Research in western Oregon and elsewhere suggests that as forest landscapes become more populated, the intensity with which remaining forest landowners manage their lands for timber production declines, resulting in variety of potential economic and ecological implications (Kline et al. 2004). In this study, land use modeling must account for such effects 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 et al. 2001). Integrating projected conversion probabilities into timber production and ecology models proved difficult, however. Forestland area in western Oregon historically has been substantially greater than urban land area, 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. 2002). Such development has become a concern of forest managers and policymakers 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. 2002). 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 geographical 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 that landowners choose the land use that maximizes the present value of future net returns derived from their land (Bockstael 1996; Irwin and Geoghegan 2001). For example, they 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. Such assumptions are implied in the survival-time analyses found in Chapters 3 and 4 of this book, as well as in the assessment of use value taxation in Chapter 8.

Characterizing individual behavior in this way applies neatly to estimating discrete choice (logit or probit) models describing observed changes among discrete land use classes on individual parcels, or models of development timing seeking to forecast the future time at which individual farm or forest parcels will convert to alternative uses. The 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. Hence, 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 regarding 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 is assumed to 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 (Capozza and Helsley 1989; Fujita 1982; Mills 1980; Miyao 1981; Wheaton 1982). 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, *37*). Modern society, however, 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, business, 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. We describe the influence of city size and location using a gravity index (Haynes and Fotheringham 1984; Reilly 1929) to account for the combined influence of population and proximity as economic forces effecting land use change (Shi et al. 1997). The gravity index is combined with variables describing other factors, such as topography, existing development, and land use zoning mandated by Oregon's Land Use Planning Program, which also can influence development patterns. Land use zoning in Oregon, for example, requires cities and counties to focus new development inside urban-growth boundaries and restrict development outside of these boundaries by zoning those lands for exclusive farm or forest use.

Variable Selection

We describe the development potential of land using a gravity index computed as

$$GRAVITY\ INDEX_i = \sum_{1}^{K} POPULATION_k \left(\frac{60 - TIME_{ik}}{60} \right), \qquad (5\text{-}1)$$

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. 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 our 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. Incorporated into the gravity index computation are 45 western Oregon cities having 5,000 or more persons in 1990 (U.S. 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 GIS map of roads existing in 2001 to create a friction surface based on average driving times assumed for different types of roads. We assume that drivers 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 road data from a single point in time, because data describing road improvements are unavailable. As a consequence, we ignore 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, we fail to account for improved physical access to land provided by new roads in the future. Second, because 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 model coefficient underestimated, in magnitude. Both problems could result in underestimating projected changes in building counts.

We combine the gravity index with other explanatory variables describing existing building counts, topographic features of slope and elevation, and dummy variables describing land use zoning adopted under Oregon's Land Use Planning Program (Abbott 1994). We assume that together the variables characterize the value of land in developed uses over its value in undeveloped forest and agriculture. We expect greater numbers of new buildings in areas with higher gravity index values, and fewer in areas with low values. We further expect that higher existing building counts 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. We anticipate slope to be negatively correlated with new buildings, because steeper slopes can be more difficult to build on. High elevations also can be negatively correlated with new buildings if they impede construction with poor physical access. The correlation can be positive, however, if they provide desirable views (Wear and Bolstad 1998). Hence, the net effect of elevation is an empirical question. We expect that land located within urban-growth boundaries adopted under Oregon's Land Use Planning Program will gain greater numbers of new buildings than land in forest or farm zones.

Model Estimation

The dependent variable $\Delta BUILDINGS$ 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. To adjust the building-count observations to consistent 10-year intervals, building counts for 1984 were approximated by interpolating between 1982 and 1994 values, and rounding to the nearest whole number. The dependent variable $\Delta BUILDINGS$ is measured as a count and is not continuous. Assuming $\Delta BUILDINGS$ is distributed as a Poisson leads to the negative binomial model

$$pr(\Delta BUILDINGS = y_i|\gamma) = \frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!} \tag{5-2}$$

$$y_i = 0, 1, 2, \ldots; i = 1, 2, \ldots, n$$
$$\text{where } \ln(\lambda_i) = \ln(\hat{\lambda}_i) + \gamma = \beta' x_i + \gamma$$

where γ is a random variable and $\exp(\gamma)$ has a gamma distribution with mean 1 and variance α, x_i is a vector of independent variables, and β' 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. We can account for these potential correlations

using a random effects negative binomial model (Greene 1995, *570–71*). Because group effects are conditioned out (not computed), projected values cannot be computed using the random effects model (Greene 1995, *567*), but the estimated coefficients can be compared with 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 that the 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 the development of reliable spatial lags of $\Delta BUILDINGS$, because sample points neighboring each observation cannot be identified with certainty. Given these difficulties, we assume 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 we estimate the final model leaving potential spatial autocorrelation untreated.

Recognizing the potential for spatial autocorrelation, however, we did test four alternative spatial autocorrelation remedies using the fuzzed UTM coordinates: two based on purposeful sampling and two on the inclusion of spatial lag variables. The four models yielded estimated coefficients that were similar in sign, magnitude, and statistical significance to those of the presented model. Estimated spatial lag coefficients in the two models that included them 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 percent for undeveloped land, and 0.3 to 0.5 percent for undeveloped and low-density developed land combined (the two categories of particular interest here). Based as they are on imperfect UTM coordinates and somewhat ad hoc remedies, the alternative model results are not shown, but they 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 unfuzzed coordinates. Because the fuzziness is limited to one kilometer and the data span a geographic area 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, where the specific explanatory variables are described in Table 5-1.

Table 5-1. Descriptions of Explanatory Variables Tested in the Empirical Model

Variable	*Description*
GRAVITY INDEX	Equal to the average of the gravity index computed (using Equation 5-2) at the beginning of each time period and the gravity index computed at the end of each time period (times 1/100,000). City populations for noncensus years estimated by interpolating between populations reported for census years (U.S. Bureau of Census 1992).
BUILDING COUNT	Number of buildings within an 80-acre circle surrounding photo-point (Azuma et al. 2002) at the beginning of each time period (times 1/100).
SLOPE	Percent slope at the sample point (times 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.

This equation is given as

$$\Delta BUILDINGS = f(GRAVITY\ INDEX,\ BUILDING\ COUNT,\ SLOPE,\ ELEVATION,\ URBAN\text{-}GROWTH,\ BOUNDARY,\ FARM\ ZONE,\ FOREST\ ZONE,\ 1994). \qquad (5\text{-}3)$$

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 model coefficients are reasonably consistent with negative binomial coefficients, although the statistical significance of the beta coefficient in the random effects regression suggests that statistically significant random effects may be present.

Estimated coefficients for the linear and quadratic GRAVITY INDEX variables are statistically significant (P<0.01) and together suggest that, over time, building counts rise at an increasing rate with greater proximity to cities within commuting distance and higher population sizes of those cities (Table 5-2). Estimated coefficients for the linear and quadratic BUILDING-COUNT variables are statistically significant (P<0.01) and together suggest that 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), suggesting 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), suggesting 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.

Table 5-2. Estimated Coefficients of Negative Binomial Models Describing Changes in Building Counts in Western Oregon

	Negative binomial regression		*Negative binomial regression with random effects*
Variable	*Coefficient*	*Marginal effect*	
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-L = −37,214 $\chi^2 = 39{,}597, = 9,\ P < 0.0001$ Negative binomial log-L = 24,647 $\chi^2 = 25{,}134,\ df = 1,\ P < 0.0001$[a]		Log-L = 24,357

Notes: $N = 44,928$. The t-statistics for each estimated coefficient are in parentheses.
[a]Tested against the null of the Poisson model.

Model Validation

In multidisciplinary research, an important part of empirical modeling is validating models by examining the potential accuracy of projected values. We evaluated the forecasting performance of previous versions of the negative binomial land use model by looking at the percentage of correct projections within the sample, estimating auxiliary models after reserving validation data sets; and examining several information indices suggested by Hauser (1978) and Wear and Bolstad (1998). We briefly describe only the first of these here; details regarding the other validation procedures can be found in Kline et al. (2003). Their general results, however, were that estimated coefficients of five auxiliary models, each estimated by excluding 20 percent of the sample, were consistent in sign, magnitude, and statistical significance with those of the main model estimated using the full sample, and also fell within the 95 percent confidence bounds of the main model coefficients; and that information indices suggested that the empirical models were both statistically significant and accurate, but that the models were better at predicting coarser (less precise) rather than finer (more precise) ending building-density classes.

Regarding the percentage of correct projections within-sample, we used the estimated negative binomial model coefficients (Table 5-2) 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 ($N = 44,928$). Projected changes in building counts were estimated by using the empirical model to compute the expected value of y_i as

$$E[y_i] = \lambda_i \tag{5-4}$$

(Greene 1995, *551*). We compared projected to actual ending building counts to compute the percentage of correct projections. This percentage decreases as ending building counts increase, from a high of 100.0 percent for observations having an ending building count of zero to a low of 19.3 percent for observations having an ending building count of eight (Table 5-3). The percentage of correct projections within one building is higher, ranging from 100.0 percent for observations having an ending building count of zero or one to a low of 48.8 percent for those with an ending building count of eight. Greater accuracy at the lower range of ending building counts likely is due in part to the relatively large proportion of observations with relatively low building counts.

The purpose of the model in the Coastal Landscape Analysis and Modeling Study is to locate forestland with 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. 2002), 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. (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 8 buildings per 80 acres. The percentage of correct projections falling above and below the threshold is relatively high—99.6 percent for the ≤8 class and 82.8 percent for the >8 class—suggesting that the model is probably adequate for the immediate purposes for which it is used.

Table 5-3. Percentage of Within-Sample Correct Base Model Projections of Ending Building Counts and Ending Broad Building-Count Class

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

Note: N = 44,928

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

Integrating Land Use Projections with Timber Production and Ecology Models

The estimated negative binomial coefficients (Table 5-2) 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 (Office of Economic Analysis 1997) and on extrapolation for 2040 to 2054. Building-density projections are used to create GIS maps of future low-density and urban development of forestlands that are inputs to timber production and habitat viability models (Kline et al. 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 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. These 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 to be 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, which most likely could be achieved only on lands zoned within urban-growth boundaries. Additionally, once low-density and urban lands are delineated, quarter-acre open vegetation patches (building footprints) are created for each projected new building. The building footprints are intended to represent the indirect impact of buildings on timber production and wildlife habitat in terms of their direct impacts on vegetative cover. The quarter-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 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

As shown in Table 5-4, land use data for 1994 indicate that western Oregon comprised about 9.9 million acres of nonfederal forest (7.2 million, 73 percent), agricultural (1.9 million, 19 percent), and mixed forest–agricultural land (0.8 million, 8 percent). Building-density data indicate that 61,920 acres (0.9 percent) of forestland, 136,787 acres (7.0 percent) of agricultural land, and 35,573 acres (4.6 percent) of mixed forest–agricultural land fell in the low-density class (64 to 640 buildings per square mile). Land exceeding the urban threshold (>640 buildings per square mile) is assumed to have converted from forest and agricultural uses to predominantly urban uses. Building-density projections suggest that by 2024, 37,440 acres (0.5 percent) of forestland, 113,666 acres (5.8 percent) of agricultural land, and 23,405 acres (3.0 percent) of mixed forest–agricultural land that existed in 1994 will have been converted to urban uses. Also by 2024, 103,680 acres (1.4 percent) of remaining forestland, 268,328 acres (14.7 percent) of agricultural land, and 70,215 acres (9.3 percent) of mixed forest–agricultural land will fall in the low-density class. By 2054, 105,840 acres (1.5 percent) of forestland, 350,129 acres (18.0 percent) of agricultural land, and 69,285 acres (8.9 percent) of mixed forest–agricultural land that existed in 1994 will have been converted to urban uses. Also by 2054, 141,840 acres (2.0 percent) of remaining forestland, 457,965 acres (28.8 percent) of agricultural land, and 105,400 acres (14.9 percent) of mixed forest–agricultural land will fall in the low-density class.

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 that are outside the range of data used to estimate the empirical model. To evaluate how reasonable the building density projections are, we compared per capita increases in low-density and urban development indicated by our spatial projections with per capita development rates indicated by 1997 National Resources Inventory data for Oregon (NRCS 1999). Our projections suggest that low-density and urban development will increase an average of 0.44 acre per new resident from 1994 to 2054. This rate

Table 5-4. Projected Low-Density and Urban Development on Nonfederal Forested and Agricultural Land in Western Oregon, 1994–2054

	Building-density class[a]			
Land cover	*Undeveloped (≤64)*[b]	*Low-density (65 to 640)*[b]	*Urban (>640)*	*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	739,427	35,573	—	775,000
Total	9,683,720	234,280	—	9,918,000
Projected in 2024				
Forest	7,058,880	103,680	37,440	7,162,560
Agriculture	1,561,006	268,328	113,666	1,829,334
Mixed	681,380	70,215	23,405	751,595
Total	9,301,266	442,223	174,511	9,743,489
Projected in 2054				
Forest	6,952,320	141,840	105,840	7,094,160
Agriculture	1,134,906	457,965	350,129	1,592,871
Mixed	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. (2002).

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 acre per new resident, based on National Resources Inventory data.

Conclusions

The building-count model and resulting building-density projections are one example of how useful, 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, we used information about city populations and locations to proxy potential rents earned from land in developed uses. Combined 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 suggest 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 ones. The validation illustrates the trade-offs inherent in choosing between precision and accuracy when building-density classes, or any land use classes, are projected using spatial models.

This particular modeling approach was made possible by obtaining building-count data, which are unavailable from national land inventories and other common data sources and are relatively expensive to collect independently. Where such data are available, however, they can enable analyses that more closely match the needs of ecologists and others seeking to forecast natural resource productivity. Here, the data enabled empirical modeling of new buildings, which provides more information relevant to timber production and ecological 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 that potentially can be applied to a broader range of research issues.

Spatial land use models often suffer from a weak link between their conceptual framework and empirical application because of poor availability of data with which to construct conceptually appropriate explanatory variables. In this case, better information regarding potential forestry rents would enable more accurate accounting of the opportunity costs of forestland development. Related to this is the need to consider heterogeneity across forest stands when describing landowners' decisions to convert forestland to developed uses. An ideal data set would include information describing both land and landowners. In this particular application, such factors as species, age class, and standing volume likely are important in landowners' timber harvest decisions, which

often coincide with forestland conversion. Other potentially influential factors might include a landowner's age, education, and income level; how much forestland he or she owns; and the overall management objectives (Kline et al. 2000). Obtaining linked data describing both land and landowners often is not possible, however, because of concerns about protecting the privacy of survey respondents. 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 trade-offs associated with different types of data and modeling methods as they determine how best to meet their research objectives in a cost-effective manner.

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