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ORIGINAL ARTICLES

Integrating Urbanization into Landscape-level Ecological Assessments

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ABSTRACT

Economists and ecologists are often asked to collaborate on landscape-level analyses designed to jointly assess economic and ecological conditions resulting from environmental policy scenarios. This trend toward multidisciplinary projects, coupled with the growing use of geographic information systems, has led to the development of spatially explicit models that can be used to examine and project land-use change. Although spatial land-use models are still evolving, most published efforts have modeled the conversion of nonurban land to urban uses as a function of explanatory variables based on population density and the spatial proximity of land to roads, markets, and population centers. In this paper, we use a gravity model to describe the urbanization potential of forest and agricultural land as a combination of population and proximity. We develop an empirical model that describes the probability that forests and agricultural land in western Oregon and western Washington were transformed to residential, commercial, or industrial uses over a 30-year period as a function of urbanization potential, other socioeconomic factors, and geographic and physical land characteristics. Land-use data were provided by the USDA Forest Service's Forest Inventory and Analysis program. We use this empirical model to generate geographic information system maps depicting the probability of future land-use change that can be integrated with landscape-level ecological models developed for western Oregon's Coast Range.

Key words: land-use change; urbanization; spatial models; ecological economics.

INTRODUCTION

Economists and ecologists are often asked to collaborate on landscape-level analyses designed to jointly assess economic and ecological conditions resulting from environmental policy scenarios. This trend toward multidisciplinary efforts, coupled with the growing use of geographic information systems, has led to the development of spatially explicit models that can be used to examine and project the rate and location of land-use change. One class of models generally relies on discrete (point) land-use data derived from satellite imagery, aerial photographs, or systematic land inventories combined with other spatially referenced data that describe socioeconomic factors and geographic and physical land characteristics believed to affect land use. These data are used to estimate the probability of a particular land use or land-use change occurring at a given location and particular point in time using logit or probit regression models. These kinds of probabilistic land-use models have been used to examine owner influences on land-use change (Turner and others 1996; Wear and others 1996), land-use impacts on water quality (Bockstael

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1996), causes of deforestation (Chomitz and Gray 1996; Nelson and Hellerstein 1997), urbanization of farmland (Bradshaw and Muller 1998), forest succession (Helmer 2000), and land-use impacts on timber and ecological resources (Munn and Evans 1998; Wear and Bolstad 1998). These models differ from more deterministic ones that simulate land-use change based on a series of decision rules (see, for example, Wilkie and Finn 1988; Southworth and others 1991; Dale and others 1993, 1994; Gilruth and others 1995).

Although spatial data describing geographic and physical land characteristics hypothesized to affect land use generally are available, obtaining spatial socioeconomic data can be a challenge. Geographic and physical land characteristics, such as slope or soil quality, tend to be temporally static and can usually be described using a single geographic information system map. Socioeconomic factors, such as the spatial distribution of population across a landscape, are often temporally dynamic. An adequate description of socioeconomic factors may require data across a number of time periods, and these data may not be readily available in digitized form. Inadequate temporal breadth in socioeconomic data can be a problem because socioeconomic variables, such as population, tend to be among the most important drivers of land-use change and are necessary to make reliable projections of future land use. Changing socioeconomic conditions tend to induce land-use change, whereas geographic and physical land characteristics tend to constrain the choice set of land-use alternatives.

These traits are particularly true of socioeconomic factors that motivate urbanization. Population density is often a key explanatory variable included in land-use change models describing urbanization (see, for example, Bradshaw and Muller 1998; Munn and Evans 1998; Wear and Bolstad 1998). Its inclusion in estimated empirical models enables analysts to project future land-use change by substituting projected density values for actual population or housing density values. However, although population density data can be obtained at fairly fine spatial scales, such as the census tract level, it is often impossible to obtain these data in digitized form for all but the most recent years. This problem effectively restricts land-use change analysis to narrow or very recent time spans.

Furthermore, although population density can describe population pressure at a given location, it may not adequately account for the spatial influence of cities as commuting destinations for work and other economic activities. Some studies have included variables describing the distance of land to

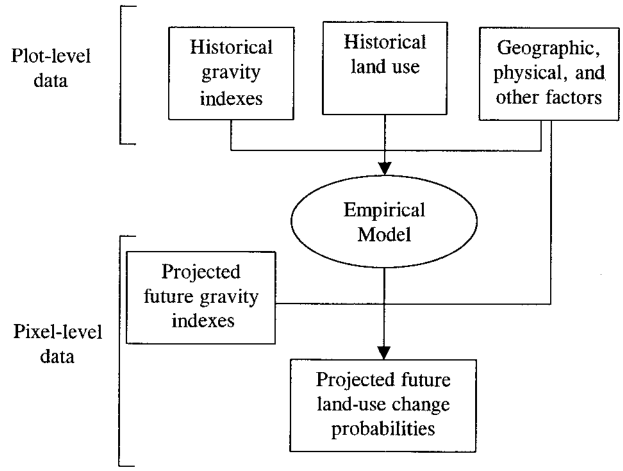

Figure 1. General research procedure.

major cities (Bockstael 1996; Bradshaw and Muller 1998; Munn and Evans 1998), but selecting which cities to include in the analysis can be a somewhat arbitrary process and may not account for the combined influence of multiple cities within urbanizing corridors. An alternative to the use of individual population density and city–distance variables is the use of gravity models or indexes describing urbanization potential as a function of the combined influence of population and proximity.

The objective of this paper was to develop and test a gravity index describing urbanization potential as a predictor of forest and agricultural land conversion. We use geographically referenced plot-level data depicting historical land use to develop an empirical model of land-use change in western Oregon and western Washington (Figure 1). Land-use data are from the USDA Forest Service's Forest Inventory and Analysis program. The model describes the probability that forest and agriculture plots have been converted to urban uses since 1961 as a function of historical gravity indexes computed for each plot, as well as plot-level geographic and physical land characteristics and other factors. The empirical model is used to generate geographic information system coverages depicting projected probabilities of future land-use change at the pixel level. The land-use change probabilities can be integrated with landscape-level ecological models developed for western Oregon's Coast Range to evaluate potential risks associated with future urbanization throughout the study region.

The Study Region

The Coastal Landscape Analysis and Modeling Study (Bettinger and others 2000) is a multidisci-

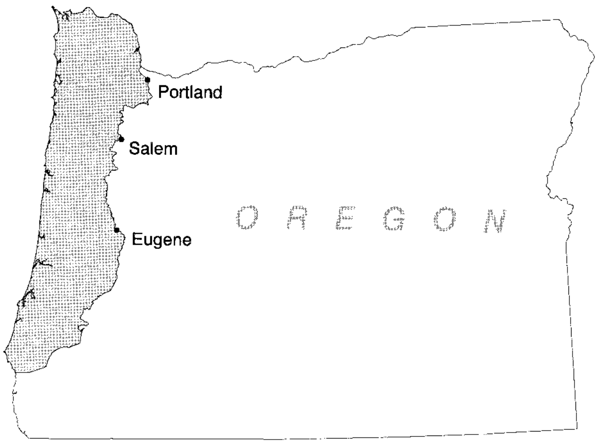

Figure 2. Coastal landscape analysis and modeling study region.

plinary research effort designed to analyze the aggregate ecological, economic, and social consequences of forest policies in western Oregon's Coast Range mountains. The study region borders the Pacific Ocean on the west and the Willamette Valley on the east (Figure 2). Current forest policies in the region attempt to achieve a particular mix of forest goods and services by spatially distributing different forest practices over watersheds or landscapes and across multiple ownerships. A particular policy concern in recent years has been ensuring sufficient habitat for spotted owls (*Strix occidentalis caurina*) and coho salmon (*Oncorhynchus kisutch*). The project is intended to provide quantitative analyses testing the assumptions of current forest policies to determine if projected future outcomes are consistent with policy goals. Specific objectives include (a) characterizing current spatial patterns and historical dynamics of ecological, economic, and social components of the Coast Range ecosystem; (b) developing ecological, economic, and social models to describe these components and the linkages among each; and (c) projecting the aggregate impacts of current forest policies in the Coast Range on ecosystem conditions and economic outputs over time.

One economic component that is expected to have a significant effect on projected forest policy outcomes in the Coast Range is land-use change resulting from the conversion of forest land to urban uses. Currently, 70% of Oregon's 3.4 million people live in the Willamette Valley, and the valley's population is expected to grow by 1.3 million new residents in the next 40 years (McGinnis and others 1996; Franzen and Hunsberger 1998). Projected population growth has led to increasing interest in examining where land-use changes are most likely to affect forests and the goods and services they provide throughout the region. Urbanization may cause the forestland base to become more fragmented, adversely affecting ecosystem conditions and economic outputs. The ecological consequences could include the direct loss of habitat or diminished habitat quality. The economic consequences could include less intensive forest management for commercial timber production (see, for example, Wear and others 1999), resulting in reduced economic output. The goal of land-use modeling in the Coastal Landscape Analysis and Modeling Study is to place current and future forest policies in an appropriate socioeconomic context by accounting for the pace and location of future land-use change.

Conceptual and Empirical Framework

The conceptual foundations of existing spatial land-use change models are based on several earlier nonspatial studies. Nonspatial studies have applied variations of the area-base approach to describe the proportion of land in forest, agriculture, and urban use categories within well-defined geographic areas (usually counties), as a function of socioeconomic variables and land characteristics aggregated at a geographic level (White and Fleming 1980; Alig 1986; Alig and Healy 1987; Alig and others 1988; Lichtenberg 1989; Plantinga and others 1990, 1997; Stavins and Jaffe 1990; Parks and Murray 1994; Plantinga 1996; Cropper and others 1999; Hardie and Parks 1997). Both spatial and nonspatial empirical models describing the conversion of nonurban land to urban uses have been based on the assumption that landowners choose to convert forest or agricultural land to urban uses when the present value of future net returns generated by land in urban uses rises above the present value of future net returns generated by the land remaining in nonurban uses (Bockstael 1996).

We assume that a landowner will convert a nonurban land parcel i to an urban use when the present value of the future net returns generated by the parcel in an urban use less conversion costs V_{iU} equals or exceeds the present value of the future net returns generated by the parcel remaining in a nonurban use V_{iF} as

$$V_{iU} \geq V_{iF} \tag{1}$$

The subscript U denotes a developed use; the subscript F denotes an existing nonurban forest or agricultural use. Letting v represent the observed portion of V and μ represent the unobservable random portion, we express the probability that parcel i that is observed in a nonurban land use at t–1 will be observed in an urban land use at time t as

$$P(develop) = P(v_{iUt} + \mu_{iUt} \geq v_{iFt} + \mu_{iFt}) = P(v_{iUt} - v_{iFt} \geq \mu_{iFt} - \mu_{iUt}) \quad (2)$$

Empirically estimating the model in Eq. (2) requires us to specify appropriate explanatory variables describing v_{iUt}–v_{iFt} and to choose a distribution for the error term μ_F–μ_U (Bockstael 1996).

The empirical modeling techniques available for examining land-use change depend to some degree on the types of historical land-use data that are available for analysis and the manner in which the model will be used to project land-use change. Nonspatial area-base land-use models generally are estimated using variations of multiple regression, such as seemingly unrelated regression, to estimate the proportion of land in different uses within counties. The models are used to project future land-use shares within counties, as well as aggregate land-use areas for a study region. Their reliance on county-level data precludes projecting land use on a spatial scale finer than a county. County-level aggregation often is unacceptable to landscape ecologists, who generally want land-use projections provided on a spatial scale more relevant to the ecological systems under study.

Spatial land-use models are developed to project the rate and location of land-use change, on a pixel-by-pixel basis, by exploiting the additional information contained in spatially referenced land-use data increasingly available from geographic information systems. These models generally rely on discrete (point) land-use data sampled from satellite imagery or aerial photographs and combined with other spatially referenced data describing socioeconomic factors and geographic and physical land characteristics. Spatial land-use data often consist of discrete observations of land use on sample plots at several points in time. These data are used to estimate logit or probit models describing the probability of a land-use change occurring at a given point in time.

A structural model describing the probability of a land-use change y_i* occurring can be written as

$$y_i^* = \beta' x_i + \varepsilon_i \quad (3)$$

where x is a vector of explanatory variables describing the conceptual parameters v_{iUt}–v_{iFt} included in (2), ε is an error term accounting for μ_F–μ_U, β is a vector of estimated coefficients, and $i = 1, \ldots, n$. In practice, y_i* is unobservable. What is observed is a vector of dummy variables y_i defined by

$$y_i = 1 \text{ if } y_i^* > 0, \text{ 0 otherwise} \quad (4)$$

In this case, y_i equals 1 for plots i observed in a forest or agricultural use at one point in time and in an urban use at a later point in time; it equals 0 for plots observed in a forest or agricultural use at both the initial and later point in time.

If we assume that the error term ε in Eq. (3) is normally distributed, the dummy variable y_i can be used to estimate a probit model describing the likelihood that sample plots were converted from a forest or agricultural use to an urban use from one occasion to the next. This is represented as

$$P(y_i = 1) = \Phi(\beta' x_i) \quad (5)$$

where Φ is the standard normal distribution (Greene 1997). If we assume that the error term ε is logistically distributed, we can estimate a logit model as

$$P(y_i = 1) = \frac{e^{\beta' x_i}}{1 + e^{\beta' x_i}} \quad (6)$$

where e is the base of the natural logarithm. Initially, we have no definitive reason to prefer one estimation procedure over the other.

Often, spatial land-use data contain multiple observations of sample plots at several different points in time. In such cases, the dependent variable y_i can be constructed from multiple observations of beginning and ending land use on individual plots at several occasions. For example, if land-use observations exist for a plot at four subsequent occasions, we have three observations of beginning and ending land use for that plot. If land-use observations exist for a plot at two subsequent occasions, we have only one observation of beginning and ending land use for that plot. Because spatial land-use data vary cross-sectionally through time, there is the potential for correlation among the time-series observations for individual sample plots to deflate standard errors and bias estimated coefficients. Two ways to account for the time-series nature of discrete land-use data in empirical estimation are fixed-effects logit and random-effects probit (Greene 1997).

Fixed-effects logit accounts for potential correlation among observations across time by estimating an individual intercept term for each cross-sectional set of time-series observations. The method requires at least two or more observations of land-use change for each sample plot included in the data set and so may not be feasible with data sets comprising sample plots for which there are only single observations of land-use change. Alternatively, the random-effects probit model assumes that correlation between successive disturbances for individual plots can be reduced to a single constant ρ (Butler and Moffitt 1982). The structural model in Eq. (3) is modified to account for multiple time periods t as

$$y_{it}^* = \beta_*' x_{it} + \varepsilon_{it} \tag{7}$$

where $t = 1, \ldots T$, $\varepsilon_{it} = u_{it} + v_i$, and $\beta = \beta_*/\sigma_\varepsilon$, and

$$Var[u_{it} + v_i] = Var[\varepsilon_{it}] = \sigma_u^2 + \sigma_v^2 \tag{8}$$

The correlation across time is estimated as

$$Corr[\varepsilon_{it}, \varepsilon_{is}] = \rho = \sigma_v^2/(\sigma_v^2 + \sigma_u^2) \tag{9}$$

and can be evaluated using a simple t-test (Greene 1995, p. 427). Random-effects probit models can be used to analyze data sets that include some sample plots for which there are only single observations of land-use change.

Land-Use Data

Few sources provide a comprehensive and consistent depiction of historical land-use change except where land-use changes have occurred in recent decades. Tradeoffs often must be made among data quality and consistency, temporal coverage, and spatial detail. A growing trend in land-use modeling is to rely on remotely sensed data, such as satellite imagery or aerial photos, collected on one or two occasions. These data can provide a fairly comprehensive depiction of different land uses and can be merged with other spatially referenced data using geographic information systems. Remotely sensed data also can be effective for examining land-use changes that have occurred during more recent years for which such data is available. However, remotely sensed data can present difficulties associated with its cost and complexity, and its accuracy may not be well established. Remotely sensed data can also be limited in their temporal scope, which can hinder model estimation if too little change in land use is observed. They can also misrepresent land-use trends if major changes occurred before the observed time frame that are different from those that occurred within the observed time frame. In the Pacific Northwest, although some areas have experienced relatively rapid growth rates in recent years, forest and agricultural land conversions to urban uses have occurred on a relatively small proportion of the total land base (Zheng and Alig 1999). Also, it can be difficult to differentiate between certain land uses, such as recently harvested forests and agricultural land.

A viable alternative to remotely sensed data is data collected by the USDA Forest Service's Forest Inventory and Analysis (FIA) program. FIA conducts periodic nationwide assessments of all nonfederal land in the United States, as authorized by the Forest and Rangeland Renewable Resources Research Act of 1974. FIA inventory data are gathered using photo interpretation and ground truthing on a systematic sampling of plots defined as pinpoints on the ground. The data include land use and ownership characteristics of sample plots, among other information. In this case, the advantage of FIA data over remotely sensed data is that the FIA data are available for western Oregon and western Washington for time spans of over 30 years. Detailed discussion regarding FIA sampling and sampling error can be found in USDA Forest Service reports (Gedney and others 1986a, 1986b, 1987; MacLean and others 1991a, 1991b, 1991c).

FIA inventories sample a fixed set of field plots and provide data that can be used to examine actual land-use changes on plots between successive inventories. In western Oregon, data are available from four inventories (1961–62, 1974–76, 1985–86, and 1994–96) and provide three opportunities to observe beginning and ending land use. In western Washington, data are available from three inventories (1963–67, 1978–79, and 1988–89) and provide two opportunities to observe beginning and ending land use. There are 1466 field plots in western Oregon and 1405 field plots in western Washington. We restrict the data set to privately owned forest and agriculture plots and omit those observations where beginning ownership was public or where beginning land use was either urban, roads, or miscellaneous uses. In western Oregon, this yields 1241 observations of beginning and ending land use for the 1961–62 and 1974–76 inventories, 1170 observations for the 1974–76 and 1985–86 inventories, and 1164 observations for the 1985–86 and 1994–96 inventories. In western Washington, there are 1009 observations for the 1963–67 and 1978–79 inventories and 966 observations for 1978–79 and 1988–89. The complete data set includes 5550 observations of beginning and ending land use over an average time step of 11 years (Table 1).

We restrict our analysis to conversions of forest and agricultural land to urban uses and ignore conversions between forest and agricultural uses. Although historically in western Oregon and western Washington land has moved between forest and agricultural uses, these shifts are difficult to measure. For example, recently harvested forestland is sometimes mistaken for rangeland and misclassified

Table 1. Number of FIA Plot Observations of Beginning and Ending Land Use from One Inventory to the Next on Privately-owned Forest and Agricultural Land in Western Oregon and Western Washington[a]

	Ending Land Use				
Initial Land Use	Forest	Agriculture	Urban[b]	Roads[c]	Miscellaneous[d]
Western Oregon					
Forest	2488	33	14	30	3
Agriculture	42	928	29	6	2
Western Washington					
Forest	1581	14	25	25	2
Agriculture	5	314	8	1	0

[a] *Reports cumulative number of FIA plot observations of beginning and ending land use between the inventories of 1961–62, 1974–76, 1985–86, and 1994–96 in western Oregon and 1963–67, 1978–79, and 1988–89 in western Washington. Total number of observations is 5550. Data set does not include observations of public land that converted to private ownership and private land that converted to public ownership between inventories.*
[b] *Includes town sites, clustered suburbs, residential and industrial buildings*
[c] *Includes constructed roads, power lines, pipelines, and railroads*
[d] *Includes barren rock, sand, glaciers, marsh, lakes, streams, and reservoirs*

as agricultural. Rangeland possessing sparse tree cover is sometimes misclassified as forest. Also, conversions between forest and agricultural land historically have not had a significant effect on the total area of land in either use relative to the conversion of forest and agricultural land to urban uses. FIA plot data for western Oregon show that net conversions between forest and agricultural land since 1961 sum to nine plots (42 − 33) converting from agricultural to forest use, whereas 43 plots (14 + 29) in forest and agricultural uses converted to urban uses (Table 1). Net conversions between forest and agricultural uses in western Washington sum to nine plots (14–5) converting from forest to agricultural use, whereas 33 plots (25 + 8) in forest and agricultural uses converted to urban uses. When data for western Oregon and western Washington are combined, net conversions between forest and agricultural uses sum to zero.

There are two ways to define urban conversions using FIA data. One approach treats as converted only those lands changing to an urban use and excludes lands converting to roads. FIA classifies town sites, clustered suburbs, and residential and industrial buildings as urban, whereas constructed roads, power lines, pipelines, and railroads are classified as roads. Much of the land classified by FIA as roads consist of roads built by the forest industry to access timberland. A second approach treats lands changing to both roads and urban uses as converted. Changes over time in FIA's definition of roads confound our choice. The 1961–62 western Oregon inventory classifies forest roads less than 120 feet wide as forest, although later inventories classify all forest roads—regardless of width—as roads (MacLean 1990). Some conversions of forest to roads from the 1961–62 to the 1974–76 inventory may be due to this change in definition. In light of these difficulties, we test two models—one assuming that land is developed when it is converted either to urban uses or roads and another assuming that land is developed when it is converted only to urban uses.

A final estimation issue arises from our use of spatial observations of land use. 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 neighboring sample plots. The first leads to inefficient but asymptotically unbiased estimated coefficients, whereas the second can lead to inefficient and biased estimated coefficients (Nelson and Hellerstein 1997). Although no standard statistical protocols exist with which to treat spatial autocorrelation in land-use analyses, some methods have been devised and tested.

One remedy is to include spatial lag (or neighborhood) variables based on the land use of neighboring pixels. Another method is to purposefully sample (Fortin and others 1989; Haining 1990) to reduce autocorrelation arising from spatial behavioral relationships. For example, if autocorrelation is thought to arise from multiple plots falling under common ownership, the entire set of plots can be sampled at a spacing purposefully selected to reduce the likelihood that any sample plots have a common owner. In our case, FIA data are based on a systematic sampling of plots roughly spaced on a 5.5-km grid. We are unable to construct a spatial lag variable because pixel-level information regarding land use between sample plots is unavailable. However, because a 5.5-km average spacing between plots implies that each plot represents, on average, 7400 acres and that figure exceeds the land holdings of most private landowners in the study region, we assume that the likelihood that plots fall under the same ownership is minimal.

Gravity Model of Urbanization Potential

Conceptually, the value of land in urban 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). Although spatial proximity does influence the costs associated with transporting forest and agricultural commodities to market, modern society associates spatial proximity more with maximizing the difference between commuting costs and quality-of-life factors such as housing and neighborhood amenities. Empirical specifications generally have described urban values using population density (Alig 1986; Alig and Healy 1987; Alig and others 1988; Plantinga and others 1990; Parks and Murray 1994; Hardie and Parks 1997; Cropper and others 1999; Kline and Alig 1999) or the proximity of land to cities likely to influence the conversion of nonurban land to urban uses (Bockstael 1996; Plantinga and others 1990; Munn and Evans 1998). However, data with which to compute population density variables rarely are disaggregated enough geographically to describe different rates of population growth in different locales. Variables that simply measure the proximity of land to select cities do not necessarily account for the changing influence of cities as their populations grow or decline. An alternative way to describe population growth and its spatial distribution is with a gravity model that integrates population and proximity into a single index of urbanization potential.

Gravity models were initially developed by Reilly (1929) to describe the degree to which cities attract retail trade from surrounding locations (see, for example, Haynes and Fotheringham 1984). A common gravity index specification for a single city is

$$Gravity\ index = \frac{Population}{(Distance)^2}, \qquad (10)$$

which is directly proportional to the population of the city and inversely proportional to the square of the distance between the city and the location of interest. Gravity indexes also have been used to account for the combined influence of population and proximity as economic forces affecting land-use change. For example, Shi and others (1997) include a gravity index as an explanatory variable in a county-level hedonic model of farmland prices. Their "urban influence potential variable" is constructed as the sum of the gravity indexes computed for each of the three major cities nearest to each county and is a statistically significant variable in their empirical model of farmland value. Mathematical specifications other than Eq. (10) are possible by varying the number of cities and the exponents on *population* and *distance*, to adapt the gravity index to the specific conditions or "social context" of the geographic region under study (Haynes and Fotheringham 1984, pp. 12–16).

We tested several gravity index specifications by varying the exponents on population and distance, and the number of cities included in the index computation. The specification that consistently performed best in terms of its t-value and log likelihood ratio tests is

$$Gravity\ index_i = \sum_{k=1}^{3} \frac{(Population_k)^{0.5}}{Distance_{ik}} \qquad (11)$$

where k represents the three cities having the greatest urban influence potential on each plot as measured by the individual gravity index computed for each city. Although our inclusion of only the three most influential cities is somewhat arbitrary, the specification seems to adequately describe urbanization patterns in the Pacific Northwest. To reduce the total potential number of cities included in the analysis, we include only those 95 cities in the Pacific Northwest–westside region that have a population of more than 5000 persons (US Bureau of Census 1992). Although this cutoff does not capture the influence of every single city, it captures the effect of those most likely to influence land-use conversions. We compute *Distance* as the Euclidian distance between sample plots and each city center included in the analysis, based on the universal transverse mercator coordinates of sample plots and cities. Our use of a gravity index as an explanatory variable in an empirical land-use model assumes that land-use change in western Oregon and western Washington is at least partially dependent on the proximity of land to existing cities and the sizes of those cities.

Model Estimation

Probit and random-effects probit models are specified describing the likelihood that FIA plots were converted from forest or agricultural uses to an urban use from one inventory occasion to the next,

Table 2. Descriptions of Explanatory Variables Tested in the Probit Models

Variable	Description
GRAVITY INDEX	Index computed following Eq. (4) and equal to the average of the three largest values of individual city indexes each computed as the ratio of the square root of a city's population (US Bureau of Census 1992) divided by a city's proximity to the plot measured as the shortest straight line (Euclidian) distance. The 95 largest cities located in western Oregon and western Washington, all having a population greater than 5000 in 1990, are included. Population for FIA inventory years is derived by interpolating between census years.
FOREST RATIO	For forest plots, 5-year moving average of sold stumpage price per 1000 board feet (1992 dollars), Pacific Northwest west-side region (Sohngen and Haynes 1994), weighted by the ratio of plot site index to average site index for all plots, divided by 5-year moving average of logging and hauling costs for saw and veneer logs per 1000 board feet (1992 dollars), Pacific Northwest, west-side region (Adams and others 1988), weighted by the ratio of county average slope to regional average slope. Variable equals zero for agriculture plots.
FARM RATIO	For agriculture plots, 5-year moving average of annual value of agricultural products sold per acre (1992 dollars), by county (US Bureau of Census 1994), divided by 5-year moving average of annual production expenses per acre (1992 dollars) by county. Value and cost figures for noncensus years found by interpolation between census years. Variable equals zero for forest plots.
INCOME	Five-year moving average of median annual household income ($1000s) by county (US Bureau of Census 1992), adjusted to 1992 dollars. Income for noncensus years derived by interpolating between census years.
FOREST INDUSTRY	Variable equals 1 if plot is forest industry or corporate-owned; 0 otherwise.
NIPF OWNER	Variable equals 1 if plot is nonindustrial privately owned; 0 otherwise.
COASTAL LOCATION	Variable equals 1 if plot is located within 4 km of the Pacific Ocean; 0 otherwise.
INTERSTATE 5	Variable equals the shortest, straight-line distance (100s of kilometers) between plot and Interstate 5.
ELEVATION	Variable equals plot elevation (1000s of meters).
OREGON	Variable equals 1 if plot is located in Oregon; 0 otherwise.

as a function of explanatory variables. The explanatory variables x include plot- and county-level proxy variables describing the value of land in urban (GRAVITY INDEX), forest (FOREST RATIO), and agricultural (FARM RATIO) uses (Table 2). We expect GRAVITY INDEX to have a positive influence on the conversion of nonurban land to urban uses, because we suspect that urbanization is motivated primarily by the combined influence of population and proximity. We expect FOREST RATIO and FARM RATIO to have a negative influence on land conversion, because we expect that lands possessing greater nonurban value are less likely to be converted to urban uses. County-level household income (INCOME) is also included in the model and is expected to have a positive influence on the conversion of land to urban uses. Higher household incomes tend to be correlated with greater urban land use.

Additional plot-level variables describing landownership by industrial (FOREST INDUSTRY) and nonindustrial private (NIPF OWNER) interests are included to test for differences across owner groups. Geographic and topographic characteristics (COASTAL LOCATION, INTERSTATE 5, and ELEVATION) may influence the value of land in different uses. For example, location near the Pacific Ocean or closer to Interstate 5 may increase the potential value of land in residential or other urban uses because of superior views or ready access to highways. Land located at higher elevations may show reduced urban potential due to poor access or steep slopes. Although a variable specifically describing the slope of sample plots is desirable, it is not included because FIA inventories do not record the slope of nonforested plots. The variable OREGON provides a test of differences between urbanization rates in western Oregon and western Washington.

The total number of observations of 5550 contained in the full data set is reduced to 4619 by omitting 931 observations for sample plots having a slope of greater than 40%. Current land-use regulations prohibit building on land comprising a slope

Table 3. Estimated Coefficients of Probit and Random-Effects Probit Models of Probability that Private Land Is Converted to Urban Uses and Roads in Western Oregon and Western Washington

	Probit		Random-Effects Probit	
Variable	Estimated Coefficient	Marginal Effect	Estimated Coefficient	Marginal Effect
Intercept	-1.939^{c} (−5.58)	−0.0783	-2.464^{c} (−3.75)	−0.0234
GRAVITY INDEX	0.021^{c} (5.53)	0.0009	0.033^{c} (3.31)	0.0003
FOREST RATIO	-0.587^{c} (−8.40)	−0.0237	-0.780^{c} (−4.65)	−0.0074
FARM RATIO	-0.654^{c} (−7.00)	−0.0264	-0.886^{c} (−3.94)	−0.0084
INCOME	0.025^{b} (2.36)	0.0010	0.031^{b} (2.30)	0.0003
NIPF-OWNED	0.105 (0.95)	0.0042	0.138 (0.88)	0.0013
COASTAL LOCATION	0.313^{b} (2.28)	0.0126	0.412^{a} (1.84)	0.0039
INTERSTATE 5	−0.108 (−0.58)	−0.0044	−0.132 (−0.55)	−0.0012
ELEVATION	−0.181 (−0.92)	−0.0073	−0.217 (−0.78)	−0.0020
OREGON	-0.254^{c} (−2.84)	−0.0103	-0.314^{b} (−2.57)	−0.0030
Rho (ρ)	—	—	0.404 (1.02)	—
Summary Statistics:	n = 4619 Log likelihood = −538.97 $\chi^2 = 155.88$, df = 9, $P < 0.001$ Pseudo $R^2 = 0.38$		n = 4619 Log likelihood = −537.31 $\chi^2 = 3.31$, df = 1, $P < 0.07$ Pseudo $R^2 = 0.52$	

[a,b] and [c] indicate that the probability of the t*-statistic (in parentheses) for each coefficient exceeding the critical* t*-value is greater than 90%, 95%, and 99%.*
Total number of observations of 5550 (Table 1) is reduced to 4619 by omitting 931 observations for plots having a slope of greater than 40%.
Pseudo R^2 *values computed following Zavoina and McElvey (1975)*

of greater than 40% (Oregon Revised Statutes 1997). In fact, the complete set of 5550 observations includes no occurrence of a sample plot having a slope greater than 40% and converting to an urban use.

The estimated probit models are highly significant ($P < 0.01$) with chi-square values of 155.88 and 167.21, each with nine degrees of freedom (Tables 3 and 4). The signs of all explanatory variables are consistent with expectations in both models. Estimation using random effects probit yields a similar set of estimated coefficient values (Tables 3 and 4) and ρ values of 0.404 and 0.386, with t-statistics of 1.02 ($\alpha > 0.30$) and 0.68 ($\alpha > 0.49$). Log likelihood ratio tests of the ρ coefficient yielded χ^2 values of 3.31 ($P < 0.10$) and 1.92 ($P < 0.20$), suggesting that random effects probit estimation is marginally superior. As in the probit models, the signs of all of the explanatory variables are consistent with our expectations.

The statistical significance of the estimated coefficients for individual variables is generally superior in the probit and random-effects probit models that exclude roads as an urban use (Table 4). Because most observations of road building involve the construction of forest roads rather than new highways and other roads associated with new urban uses, the empirical models that exclude roads as a developed use are probably more consistent with our conceptual model of urbanization. It would seem reasonable as well to assume that the rate at which forest roads are constructed in the future will be substantially less than the rate at which they were constructed during the past 30 years—the time period described by the present data. For these reasons, we focus our discussion on the empirical re-

Table 4. Estimated Coefficients of Probit and Random-Effects Probit Models of Probability that Private Land Is Converted to Urban Uses in Western Oregon and Western Washington

	Probit		Random-Effects Probit	
Variable	Estimated Coefficient	Marginal Effect	Estimated Coefficient	Marginal Effect
Intercept	−2.735[c] (−5.70)	−0.0287	−3.346[c] (−3.29)	−0.0037
GRAVITY INDEX	0.023[c] (5.52)	0.0002	0.035[b] (2.39)	0.0000
FOREST RATIO	−0.620[c] (−6.37)	−0.0065	−0.802[c] (−3.30)	−0.0009
FARM RATIO	−0.614[c] (−5.35)	−0.0064	−0.818[c] (−2.78)	−0.0009
INCOME	0.039[c] (2.88)	0.0004	0.045[b] (2.48)	0.0000
NIPF-OWNED	0.396[b] (2.08)	0.0042	0.526 (1.62)	0.0006
COASTAL LOCATION	0.318[a] (1.74)	0.0033	0.394 (1.48)	0.0004
INTERSTATE 5	−0.406 (−1.44)	−0.0043	−0.503 (−1.35)	−0.0006
ELEVATION	−1.419[c] (−3.12)	−0.0149	−1.872[b] (−2.04)	−0.0021
OREGON	(−0.124 (−1.02)	−0.0013	−0.157 (−0.89)	−0.0002
Rho (ρ)	—	—	0.386 (0.68)	—
Summary Statistics:	n = 4619 Log likelihood = −3.03.91 χ^2 = 167.21, df = 9, P < 0.01 Pseudo R^2 = 0.48		n = 4619 Log likelihood = −3.02.95 χ^2 = 1.92, df = 1, P < 0.17 Pseudo R^2 = 0.62	

The [a,b] and [c] indicate that the probability of the t-statistic (in parentheses) for each coefficient exceeding the critical t-value is greater than 90%, 95%, and 99%.
Total number of observations of 5550 (Table 1) is reduced to 4619 by omitting 931 observations for plots having a slope of greater than 40%.
Pseudo R^2 values computed following Zavoina and McElvey (1975)

sults produced by the models that exclude roads as an urban use (Table 4).

Estimated coefficients for the variable GRAVITY INDEX describing urban influence potential are positive, statistically significant ($P < 0.05$), and consistent with a higher likelihood of urban conversion on land located closer to population centers and increasing with the size of those population centers. Estimated coefficients for the variables FOREST RATIO and FARM RATIO are all negative, statistically significant ($P < 0.01$), and consistent with a lower likelihood of development on land that has substantial forest or agricultural value. Estimated coefficients for INCOME are positive ($P < 0.05$) and suggest a greater likelihood of urban conversion on land located in counties with a higher household income.

The variable FOREST INDUSTRY is omitted from both models to avoid perfect colinearity among the ownership variables. Estimated coefficients for NIPF OWNER are positive and suggest that land owned by nonindustrial private owners is more likely to be converted to urban uses than forest industry land. Estimated coefficients for COASTAL LOCATION are positive and consistent with a greater likelihood of urban conversion on lands located within the Pacific coastal strip. Estimated coefficients for INTERSTATE 5 are negative and consistent with an expected increase in the likelihood of urban conversion as distance to Interstate 5 decreases. Estimated coefficients for ELEVATION are negative and suggest a diminishing likelihood of urban conversion as elevation increases. Because elevation and slope often are correlated, negative ELEVATION coefficients could indicate a lower likelihood of urban conversion occurring on sample plots with steeper slopes.

Estimated coefficients for OREGON are negative but not statistically significant ($P > 0.30$), suggesting no discernable statistical difference between urbanization rates in western Oregon and western Washington as defined in the empirical model (Table 4). The empirical model does not explicitly account for land-use laws and policies that likely effect the rate and pattern of land-use change. Oregon's land-use planning program, in particular, has served as a national model in land-use planning and growth control (Abbott and others 1994). It could therefore be expected to account for measurable differences in the rate and pattern of urbanization occurring in western Oregon and western Washington. However, previous research suggests that Oregon's land-use planning program has had little measurable effect on the land-use change described by FIA data (Kline and Alig 1999). Explanatory variables accounting for land-use zoning adopted under Oregon's land-use planning program were initially included in the current analysis, but estimated coefficients for these variables were consistently found to be statistically insignificant.

Validating the forecasting performance of an estimated empirical model is useful in determining if projected outcomes are reasonable. A feasible method of model validation is to reserve a portion of the data sample from empirical analysis for validation purposes. Projected outcomes resulting from the estimated empirical model then can be compared to actual outcomes described by the reserved data sample (see, for example, Wear and Bolstad 1998). For this validation method, sufficient data must exist to both estimate and validate the model. Although the complete data sample includes 4619 observations, only a small proportion of these comprise conversions of forest or agricultural land to urban uses. As a result, we do not have a sufficient number of observations of land-use change with which to both estimate and validate the empirical model. The statistical significance of the empirical models and many of the explanatory variable coefficients do suggest a good fit with the available data.

Projecting Future Land Use

The estimated model coefficients, when combined with projected values of population and other explanatory variables, are used to project the likelihood of future land-use change at 11-year intervals throughout the Coastal Landscape Analysis and Modeling Study region. The 11-year interval is determined by the average 11-year interval between FIA inventories. We use the gravity model to compute a set of pixel-level gravity indexes for future time intervals using projected population growth for cities in the region. Population projections for all 95 cities used in the analysis are based on county-level projected population growth through 2010 (McGinnis and others 1996, 1997) and on state-level projected population growth for 2010 to 2050 (US Bureau of Census 1992).

The complete set of gravity indexes describes the projected spatial distribution of urbanization potential throughout the study region at five future points in time from our base year of 1996 to 2051. Figure 3 compares 1996 land use to the gravity index computed for 2007. The 1996 land-use base map was developed for the Coastal Landscape Analysis and Modeling Study (Bettinger and others 2000) by combining analysis of remotely sensed forest and vegetation data with existing city limit boundaries to describe forest, agriculture, and urban land-use categories. Significant effort has been taken to ensure that the resulting base map land-use categories are as consistent as possible with FIA land-uses categories. Still, some differences may exist between the land-use data with which the model was estimated and data to which the model projections are applied. The gravity index projected for 2007 suggests that the urbanization potential of forest and agricultural land will be greatest near the more populated cities of the Willamette Valley, such as Portland, Salem, and Eugene, and within the corridors between these cities. The forested regions of the Coastal Landscape Analysis and Modeling study region tend to show less urbanization potential due to generally poor physical access and greater distance to the more populated cities.

Each set of gravity indexes can be combined with projected values of other socioeconomic variables included in the empirical model to compute pixel-level probabilities representing the likelihood that forest and agricultural land will be converted to urban uses during each of the five 11-year intervals occurring between our 1996 base year and 2051. In this example, we assume that the socioeconomic variables describing forestry (FOREST RATIO) and agricultural values (FARM RATIO) and household income (INCOME) remain constant. We assume that urbanization potential (GRAVITY INDEX) grows according to projected population growth, as shown in Figure 3. We compute pixel-level conversion probabilities for each 11-year interval using Eq. (5) and the estimated random-effects probit coefficients for the model that excludes roads as a developed use (Table 4). Conversion probabilities for in-years can be approximated by interpolation, whereas conversion probabilities for years after

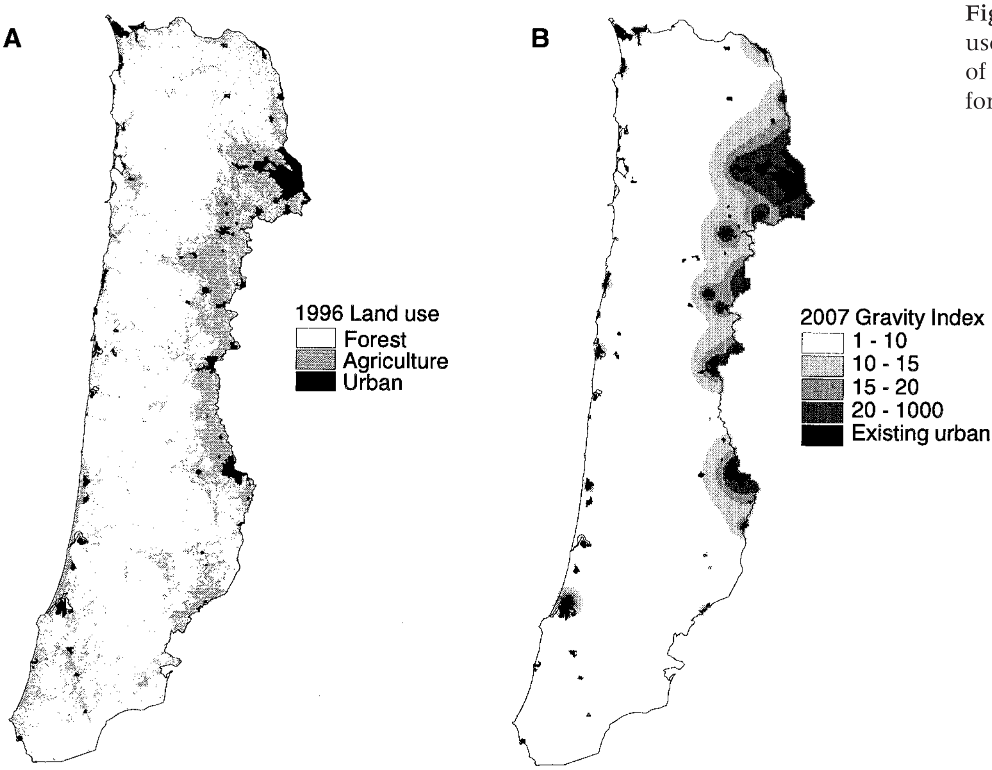

Figure 3. **(A)** 1996 land use and **(B)** gravity index of urbanization potential for 2007.

2051 can be computed using additional population projections.

We summarize the five sets of 11-year interval conversion probabilities over time by combining them into a single set of probabilities representing the likelihood that land in forest and agricultural uses during the 1996 base year will be converted to urban uses by 2051. The 1996 to 2051 conversion probabilities are computed as

$$P_i^{1996\text{–}2051} = 1 - \prod_{i-1}^{5} (1 - P_i) \qquad (12)$$

where P_i are the conversion probabilities computed at each of the five 11-year intervals using Eq. (4). In this example, the 1996 to 2051 conversion probabilities are combined with a 1996 base year land-use map to depict existing urban land and the probable distribution of future urban land for the portion of the Coastal Landscape Analysis and Modeling Study region surrounding Portland and Salem, Oregon (Figure 4). Projected conversion probabilities are greatest in areas immediately surrounding city boundaries and diminish with greater distance from each city. Conversion probabilities diminish rapidly on forest lands located west of the cities due to generally higher elevations and poorer physical access.

Projected land-use conversion probabilities can be used in landscape-level analyses to incorporate information regarding the effects of urbanization on the economic and ecological conditions of forestland. Computed conversion probabilities can be used to identify economic or ecosystems most at risk by anticipating where urbanization is most likely to occur. Conversion probabilities can also be converted into discrete units of urban conversion to simulate future urbanization patterns. For example, pixel-level probabilities can be combined with a probabilistic algorithm to switch a proportion of pixels from their existing nonurban uses to urban uses over time. Alternatively, the pixel-level probabilities can be combined with qualitative information about zoning and other land-use regulations to assign urban land-use conversions to specific locations (see, for example, Bradshaw and Muller 1998). Whichever method is used, analysts must remember that simulations characterize the likelihood of future land-use change rather than predict actual change.

In this model, a key determinant of land-use change is assumed to be the proximity of land to existing cities of varying sizes. Although the inclusion of other explanatory variables in the model does allow for more remote land to be converted to urban uses, model projections reflect the assump-

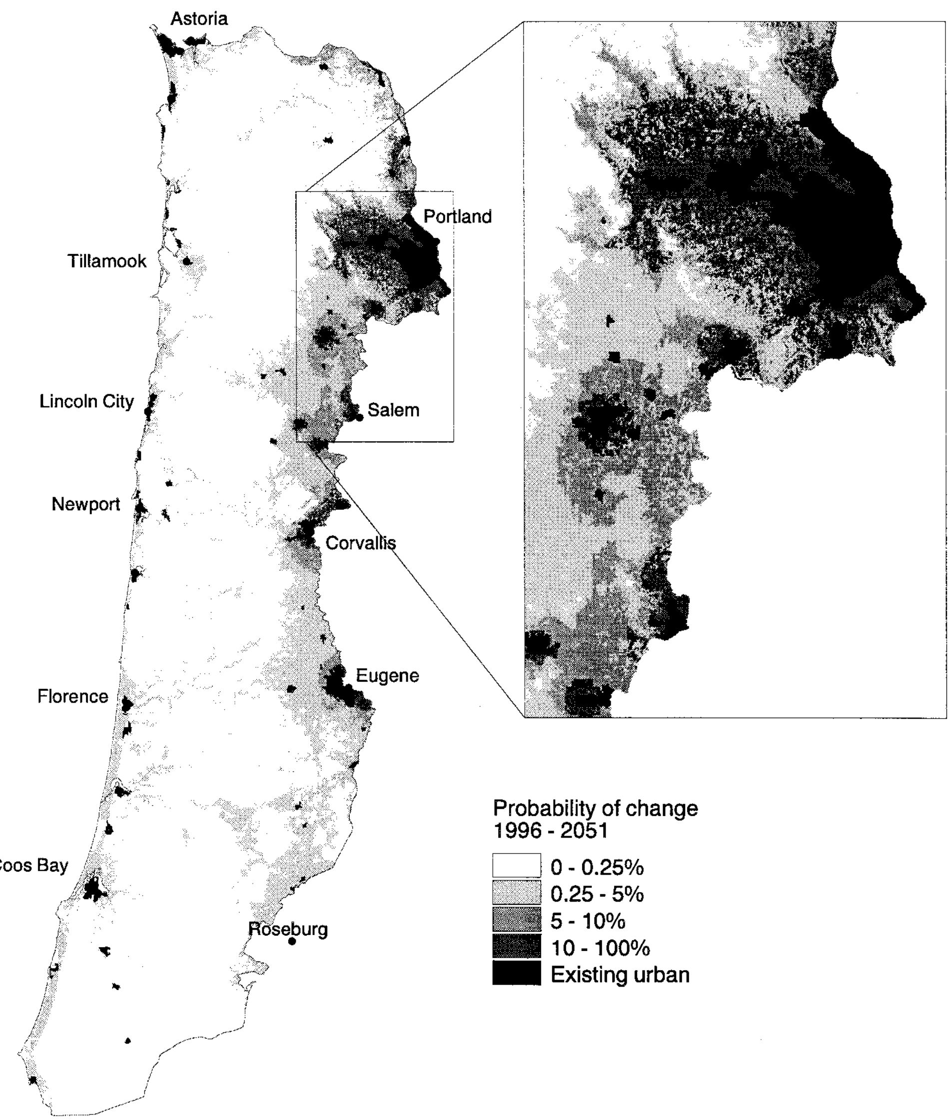

Figure 4. Predicted likelihood of urbanization.

tion that land located closer to existing cities faces a greater likelihood of conversion. This assumption seems consistent with historical land-use change observed in the study region of western Oregon and western Washington during the time period under analysis. In reality, land-use change may be caused by a variety of factors with varying influences over time and space. The process of modeling land-use change must begin with a careful consideration of all factors potentially influencing land-use change in the region and time period under study.

Summary and Conclusions

The inclusion of explanatory variables based on gravity models of urbanization provides one alternative to the use of population density data as a way to represent the spatial influence of population growth in spatial land-use models. The method assumes that historical and future conversions of nonurban land to urban uses are at least partly a function of population growth within existing urban centers. Digitized data describing population density often do not exist for all but the most recent years, and population density may not adequately account for the spatial influence of cities as drivers of regional land-use change. Alternatively, gravity models can be constructed by combining historical population data for individual cities with the geographic coordinates of cities and may better account for population pressure within spatial corridors between cities. Gravity models do, however, require more empirical computation than population density variables.

The relatively recent availability of spatial data describing land use and other socioeconomic information presents new opportunities for analyzing and projecting the rate and location of land-use change. These models have potential applications to a wide range of economic and ecological policy issues and could serve as important components of landscape-level assessments (see, for example, Quigley and others 1996). Population growth inevitably leads to continued land-use change. Spatial land-use models enable researchers to account for the effect of land-use change on future economic and ecological forest outputs. For policy makers, spatial land-use models help portray the socioeconomic context in which future forest policies will function.

In the near term, the development and use of spatial land-use models may be limited by available land-use and socioeconomic data and the expense of processing spatial information. Satellite imagery is often limited in its temporal scope and can be limited as well in its spectral or spatial resolution. Aerial photos may be expensive to digitize. Existing national land-use inventories—such as the Forest Inventory and Analysis Program discussed here or the Natural Resource Inventory conducted by the Natural Resource Conservation Service—are designed to document specific forest and agricultural resources and may not provide a comprehensive depiction of all potential land uses in a given region. Other socioeconomic data may be unavailable at spatial scales relevant to many ecological assessments. Tradeoffs must be considered when assessing the costs and benefits associated with spatial detail in multidisciplinary landscape-level analyses.

The incorporation of spatial socioeconomic information into landscape-level ecological assessments is a necessary first step toward a comprehensive understanding of the social and political implications of protecting and enhancing ecological conditions. If economists and ecologists are to collaborate successfully on landscape-level analyses, they require at least a rudimentary mutual understanding of the conceptual and empirical issues that guide the separate economic and ecological components of integrated analyses. Many of these issues are rooted in the basic elements of the research process, such as the quality and spatial scale of the available data, the existence of theoretical models on which to base empirical analyses, and expectations regarding the rigor and timeliness of the individual components of multidisciplinary projects. This paper has presented one method that can be used to incorporate urbanization into landscape-level ecological assessments. The intent has been to highlight some of the conceptual and empirical issues involved in the development of empirical land-use change models based on socioeconomic information.

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