ELSEVIER

Agricultural Economics 27 (2002) 217–232

AGRICULTURAL ECONOMICS

www.elsevier.com/locate/agecon

Spatially explicit micro-level modelling of land use change at the rural–urban interface

Kathleen P. Bell [a,*], Elena G. Irwin [b]

[a] *Department of Resource Economics and Policy, 5782 Winslow Hall, University of Maine, Orono, ME 04469-5782, USA*
[b] *Department of Agricultural, Environmental, and Development Economics, Ohio State University, Columbus, OH, USA*

Abstract

This paper describes micro-economic models of land use change applicable to the rural–urban interface in the US. Use of a spatially explicit micro-level modelling approach permits the analysis of regional patterns of land use as the aggregate outcomes of many, disparate individual land use decisions distributed across space. In contrast to the models featured by Nelson and Geoghegan, we focus on models that require spatially articulated data on parcel-level land use changes through time. In characterising the spatially disaggregated models, we highlight issues uniquely related to the management and generation of spatial data and the estimation of micro-level spatial models.

Keywords: Spatial models; Land use change; Rural–urban interface; Land economics

1. Introduction

The ability to understand and predict changes in land use patterns is necessary for policymakers concerned with a variety of public finance, quality of life, and environmental protection issues. Changes in land use patterns affect both human and natural systems. Potential social and economic impacts of changes in land use patterns include increased costs of providing public services, loss of open space, and increased congestion. Potential ecological impacts include loss of habitat, fragmentation of habitat, and alteration of the hydrological regime. In this paper, we focus on the causes of land use change and describe micro-economic models of land use change applicable to the rural–urban interface in the US.

Employment of a spatially explicit micro-level modelling approach permits the analysis of regional patterns of land use as the aggregate outcomes of many, disparate individual land use decisions distributed across space. Under this modelling framework, an understanding of large-scale changes in land use, such as urbanisation, start from a model of individual land use decisions with a micro-level scale of analysis. Estimation of such a model requires a variety of spatially articulated, parcel-level variables, ranging from the natural features of land parcels (e.g. soil type, slope, elevation) to locational characteristics (e.g. proximity to amenities and disamenities) to regulatory features that vary over space (e.g. zoning policies).

In what follows, we discuss the spatially disaggregated, micro-economic models of land use change applicable to the rural–urban interface. Because we rely on a data rich environment to estimate these models, this approach is most applicable to the US and other countries (e.g. Canada) in which parcel-level land use

* Corresponding author.
E-mail address: kathleen.p.bell@umit.maine.edu (K.P. Bell).

0169-5150/02/$ – see front matter © 2002 Elsevier Science B.V. All rights reserved.
PII: S0169-5150(02)00079-8

data are electronically recorded and tracked using a Geographic Information System (GIS). In our discussion of these models, we highlight issues uniquely related to the management and generation of large spatial datasets and the estimation of parcel-level, land use change models. The remainder of this paper is divided into four sections. Section 2 offers an overview of the public policy issues related to land use change and the rural–urban interface in the US. Section 3 provides an abbreviated description of economic models of land use change. Section 4 focuses on various research issues related to spatial data, with particular emphasis on data rich environments. Finally, conclusions and suggestions for future research are presented in Section 5.

2. Rural–urban interface and land use change

2.1. Rural–urban interface in the US

The rural–urban interface refers to the "exurban" portion of the landscape, defined here as those areas that fall beyond the outer-belt of a major metropolitan area but within its commutershed.[1] The rural–urban interface begins where suburbs end and extends into rural areas. In the US, significant changes in land use and population have recently occurred in the rural–urban interface. Exurban counties accounted for over one-fourth of total population growth from 1960 to 1990. By 1990, approximately 60 million people (24% of the total population) were living in "exurbia" in the US (Nelson, 1992) and evidence shows that this proportion increased substantially in the 1990s in certain regions of the US (e.g. Sharp and Reece, 2001).

The US Department of Commerce defines a rural population as any population not living within an urbanised area of 2500 population or more (US Census Bureau, 1990) and therefore, most exurbanites are classified as rural. In the US, changes in the composition of rural population reflect the simultaneous increase in exurban populations and decrease in traditional rural populations. Fig. 1, adapted from Hart (1995), displays the components of US rural population from 1910 to 1990. In 1910, the percent of US persons living in rural areas and considered farm population was approximately 65%. By 1950, it had dropped to 37%. In 1960, it was approximately 25%, and in 1990, the percentage was approximately 6%. However, due to a substantial increase in the non-farm population living outside incorporated places (from 18.5% in 1910 to 76% in 1990), the total rural population has remained relatively constant over this period.

2.2. Public policy significance of land use change

Changes in exurban land use are interesting to economists because of the connections between individual economic choices regarding land use and the aggregate impacts of land use changes, including the various implications for public policy. As exurban areas develop, communities are faced with a variety of changes and trade-offs. For example, research shows that the costs of providing local public services is a function of the pattern of development and the rate at which conversion of land to development occurs (Altschuler and Gomez-Ibanez, 1993; Burchell et al., 1998; Frank, 1989; Ladd, 1992). The environmental effects of changes in the spatial distribution of land use on the ecosystem are many and include the loss and fragmentation of wildlife habitat and reduced water quality due to increased urban runoff. Lastly, changes in land use patterns can alter the aesthetics, dynamics, and sense of place of an area. Changes in community attributes, such as loss of open space and changes in the mix of residents, are often viewed as costs by long-time residents of a community (Porter, 1997). Many of these impacts are expressed in the form of externalities and therefore lead to inefficiencies in land use pattern. For all these reasons, the ability to understand and predict changes in land use patterns is necessary for policymakers interested in achieving a vibrant local economy, while also managing growth and maintaining the social and environmental resources of their community.

The causes or drivers of land use change are nearly as diverse as the consequences. From an economics perspective, factors that affect the desirability of a given location for residential, commercial, or some other use are important determinants of the demand for development and hence land use change. Location

[1] Various operational definitions of exurban have been offered in the literature (e.g. Nelson, 1992). The Oxford dictionary defines exurbia as a quasi proper name for regions outside the suburbs of a city; exurbs collectively.

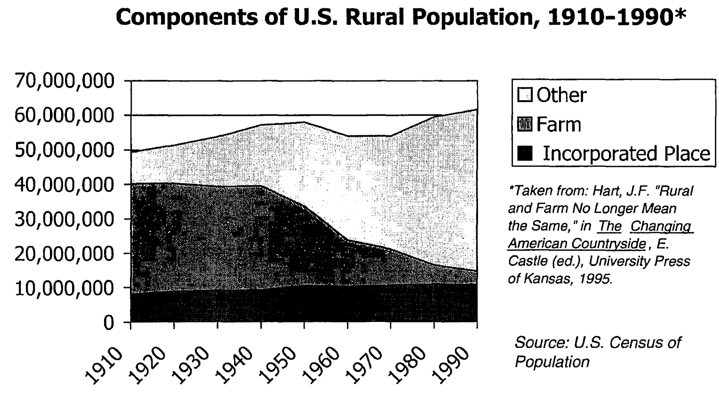


Fig. 1. Components of US rural population, 1910–1990.

decision models suggest that individuals and firms consider a variety of locational and land attributes and recognise the trade-offs among these attributes. When examining the demand for residential development in exurban areas, the trade-off between lower land prices and increased travel costs to an urban or suburban centre with employment and shopping opportunities often assumes a central role. For this reason, increased accessibility to exurban areas (e.g. due to a new road building or changes to transportation networks) and the relocation of employers from central city locations to suburban or exurban locations are major factors that determine land use changes in the rural–urban interface. Rising housing prices and/or tax rates in urban and suburban areas, as well as decreases in the quality of life in these areas (e.g. lower school quality, higher crime rates) are additional factors that contribute to exurban growth. Finally, as changes in the population structure (e.g. more retirees) and changes in technology (e.g. telecommuting) reduce the requirement to locate near a major employment centre, there is likely to be an increase in the spatial distribution of population away from these centres.

While these factors explain the amount and rate of growth in exurban areas, they do not determine the spatial pattern of land use changes. Changes in land use vary across locations because of spatially heterogeneous variables that change across different locations and therefore make some locations more desirable relative to others. These spatial factors include proximity to employment; proximity to other activities (e.g. shopping, recreation, entertainment); the spatial distribution of the provision of public services (e.g. sewer and water); natural features (e.g. rivers, mountains, slope); surrounding land uses of an area; and zoning policies and other growth management policies that regulate the allowable density of development and control surrounding land uses. Just as total demand for new growth responds to locational attributes, so does the spatial distribution of this growth. The spatial pattern of new development is important because different patterns over space will result in different social, economic, and ecological impacts. This latter point is usually not accounted for in studies of land use change that employ highly aggregated areas as their observational units (e.g. counties). The ability to study land use change at the rural–urban interface in a spatially explicit manner facilitates an improved understanding of these impacts and enables an assessment of the role of various factors, including public policies, on individual landowner decisions.

3. Economic models of land use change

3.1. Overview of conceptual models

Conceptual models related to land use change include those that directly model the landowner's land use conversion decision as well as those that predict land use change outcomes based on household and firm location behaviour. In each case, these models may be estimated either at the individual (e.g. parcel) or aggregate (e.g. county) level, depending on the data available. In this section, we briefly summarise these approaches and then focus the rest of the paper on micro-scale land use conversion models estimated at the parcel-level.

3.1.1. Models of an individual's land use conversion decision

The first type of model focuses on the landowner's decision regarding a land use change, in which the individual selects an optimal land use or mix of land uses to maximise profits or expected utility. Returns to conversion are a function of a variety of land attributes that are hypothesised to influence land use conversion. These attributes may include the distance to urban centres and other destination points; neighbourhood amenities, including surrounding land uses; public services and policies, including zoning; and natural features of the land parcel, such as its slope and soil type. A basic discrete-choice formulation of the individual landowner's decision is that the landowner of parcel k, which is currently in state u will choose the land use of parcel k in period t that maximises net expected returns. The one-period, static conversion rule that corresponds to this decision states that parcel k, which is currently in state u, will be converted to state r in time t if

$$R_{krt|u} \geq R_{kjt|u};\ \forall\ j = 1, \dots, J$$

where $R_{krt|u}$ represents the net expected returns from converting parcel k (which is currently in undeveloped land use u) to use r in time period t and j includes the set of potential, alternative land uses 1 through J. If this condition is not met for at least one j other than u, then $j = u$ in period t. The net expected returns can be thought of as having two components: the present value of the future stream of returns to parcel k in state r at time t and the cost of converting parcel k from state u to state r at time t. Both the components are assumed to be influenced by a host of spatially heterogeneous variables. For example, if state r is residential or commercial, expected returns will be a function of distance to residential, employment, and shopping sites, as well as other neighbourhood and locational amenities.

This approach focuses on the individual's decision and does not necessarily offer a theory that explains how individual land use decisions aggregate over space. Instead, land use change is described as the result of many individual landowners who make conversion decisions simultaneously or over time. These models can be estimated using either aggregate or disaggregate data. If aggregate data are used (e.g. at the county-level), land use transitions may be modelled using a land use shares formulation (e.g. Plantinga and Miller, 1997; Parks and Kramer, 1995; Parks and Hardie, 1995; Wu and Segerson, 1995) or some other functional form that estimates the proportion of land that is converted to alternative uses (e.g. Hsieh et al., 2002). If spatially disaggregate data are used, e.g. at the plot- or parcel-level, a discrete choice model is usually estimated in which the probability of land conversion from one discrete use to another is a function of parcel-level attributes (e.g. Bockstael, 1996; Bockstael and Bell, 1998).

Incorporating temporal considerations into this basic formulation adds another dimension to the individual landowner's decision. Changes arise here because the landowner is now assumed to maximise the net expected returns from a parcel over an infinite time horizon. Choices involve not only the type of conversion (e.g. land use), but the timing of conversion as well. For example, an expression of a dynamic conversion rule corresponding to this decision for a binary choice between developed versus undeveloped land use posits that parcel k will be developed in the first period in which the following conditions hold (Irwin and Bockstael, 2002)

$$R_{krT|u} - \sum_{t=0}^{\infty} R_{kuT+t}\delta^{T=t} > 0$$

$$R_{krT|u} - R_{kuT} > \delta R_{krT+1|u}$$

where $R_{krt|u}$ represents the net expected return from converting parcel k (which is currently in undeveloped land use u) to use r at time t and δ is the discount rate. The first condition states that the parcel k will be converted from use u to use r in the time period T, which is the first time period in which the net returns from this conversion are greater than the present value of the foregone returns associated with land use u over the infinite time horizon. The second condition states that parcel k will be converted in period T only if the expected returns from converting net the one-period opportunity cost of conversion is greater than the discounted net returns from converting in period $T + 1$.

3.1.2. Equilibrium-based models of urban structure

Household and firm location models are also based on individual behaviour, but differ from the first type in that, by solving for equilibrium outcomes, a description of the regional pattern of land use change emerges. In order to do so, however, the treatment of space is simplified to a one-dimensional measure of distance from a single point and most of the spatial heterogeneity that exists in reality is ignored. The traditional urban bid–rent model of land use (namely, the monocentric model), which posits that location decisions are driven by relative distance to a single urban centre, is a primary example of this type of model (Alonso, 1964). This model predicts the formation of homogeneous rings of commercial, industrial, and residential land use around the city centre surrounded by a contiguous region of agricultural land. Extensions of this model include polycentric models, in which the urban area is assumed to contain more than one urban centre. Empirical work has included estimation of population and land rent gradients to test the degree to which actual urban areas conform to the monocentric spatial structure. Results have shown that many cities exhibit a polycentric structure and some even a more dispersed structure in reality (e.g. Waddell and Shukla, 1993).

More sophisticated models, in which the urban spatial structure of a city is endogenously determined (e.g. *whether* a city is monocentric or polycentric), have also been developed. These models posit a fundamental interdependence among spatially distributed agents that influences their location decisions and the resulting spatial structure of the urban area. Interdependencies may arise through market forces, such as transportation costs and pecuniary externalities (Krugman, 1991, 1995); they may occur directly through agents' preferences over the spatial distribution of other agents (Page, 1999); or they may arise through spatial externalities from congestion externalities (Anas and Kim, 1996) or knowledge spill-overs (Zhang, 1993). These models are much more complex in their treatment of space since they consider the relative distance between agents, but abstract from any other spatial heterogeneity of the landscape. To date, these models have been theoretical and empirical evidence of the existence of these interactions is largely absent.[2]

Lastly, an alternative approach to modelling the determinants of land use change are models of regional economic flows that describe the equilibrium flows from an origin to destination point, e.g. the flow of households moving from one point to another. These models have their origins as "gravity models" and focus on understanding how the spatial separation between origin and destination nodes influences the magnitude of the flows of people or economic goods across the nodes. Individual interaction flows are modelled as functions of average values, e.g. the average costs incurred by individuals moving between zones and the average frequency of moves between zones. As such, these models are best suited for understanding the impacts of shifts in regional population on overall changes in the spatial interaction pattern (Sen and Smith, 1995) and are not appropriate for studying the determinants of land use change at a spatially disaggregate scale.

3.2. Empirical models

As noted previously, the estimation of a micro-scale spatial model necessitates a host of spatially articulated variables. The selection and specification of this suite of variables is ideally determined by the factors hypothesised to be driving spatial variation in the expected net returns. For example, heterogeneity in returns from conversion is related to landscape features such as soil type, slope, land use and zoning requirements, accessibility, and property tax rates. In reality, the selection of explanatory variables is constrained by data availability, an issue that is discussed in the final section of this paper. A variety of estimation approaches of spatially explicit, micro-scale models of land use change are observed in the economics literature. Spatially-explicit models at the parcel- or plot-level include discrete choice models (e.g. Bockstael, 1996; Bockstael and Bell, 1998; McMillen, 1989; Kline and Alig, 1999; Landis and

[2] An exception is Irwin and Bockstael (2002), who use this approach to motivate an empirical model of exurban land use conversion in which they find evidence of negative spillover effects among developed parcels and argue that this interaction has led to a sprawl pattern of development.

Zhang, 1998) and duration models (e.g. Irwin and Bockstael, 2002; Nickerson, 1999; Hite et al., 2000). In addition, a related approach explicitly models the factors influencing land values, which are often the prime determinants of land use change (e.g. Palmquist, 1991; Taylor, 2002). In this section, we briefly review each of these approaches.

3.2.1. Discrete choice

Returning to the previous discussion of static, one-period land conversion decision models, parcel k currently in state u is converted to state r at time t if

$$R_{krt|u} \geq R_{kjt|u};\ \forall\ j = 1, \dots, J$$

where $R_{krt|u}$ represents the net expected return from converting parcel k (which is currently in undeveloped land use u) to use r in time period t and j includes the set of potential, alternative land uses 1 through J. Let $R_{krt|u}$ be comprised of two components as follows

$$R_{krt|u} = V_{krt|u} - C_{krt|u}$$

where we define $V_{krt|u}$ as the present value of the future stream of returns to parcel k in state r at time t, given that the parcel was in state u in time $t-1$ and $C_{krt|u}$ as the cost of converting the parcel from state u to state r (which will be 0 when $u = r$).

Given that only some factors affecting V and C are observable to researchers, the model is rewritten such that the net returns include a random portion, η, which is unobserved to the researcher and $R_{krt|u}$ is redefined as the observable portion. The probability that parcel k, which is in land use u at time $t-1$, will be found in land use r at time t is given by

$$\Pr(R_{krt|u} + \eta_{krt|u} \geq R_{kjt|u} + \eta_{kjt|u};\ \forall\ j = 1, \dots, J)$$

By making assumptions about the distribution of η and the relevant set of land uses, the form of the land use decision model is determined. For example, one common practice is to limit the choice set to undeveloped land uses and residential use. In doing so, the individual landowner's decision can be characterised by estimating a binary discrete choice model.

The relevant set of land uses, J, will vary across regions as landscapes exhibit considerable heterogeneity. In addition, the designation of land use categories is likely to vary with the research questions being asked. In some cases, detailed land use categories will be appropriate. In other instances, broad categories, such as developed and undeveloped, will suffice. The range of categories incorporated into the empirical model shape the data requirements of the model. Observing the expression above, the model rests on specifying V and C for a variety of land use states for each parcel including the current use, u, and the remaining uses contained in set J. Interesting challenges arise in predicting the expected returns, V, of a parcel in these J land uses, especially when predicting the returns of undeveloped parcels in developed uses. While information is available to facilitate the designation of values to agricultural and forested lands that may comprise the undeveloped states, challenges arise in assigning residential or commercial land values for yet undeveloped parcels. One approach that has been employed estimates the model in two stages because of the need to specify the expected returns of converting to residential use (e.g. Bockstael and Bell, 1998). In the first stage, a hedonic model of residential land values is estimated as a function of parcel characteristics. Given the estimates from this model, the residential value of yet undeveloped parcels is predicted and then used in a second stage estimation of the discrete choice land use conversion model. A second approach is to simply estimate a reduced form model in which the probability of conversion is modelled as a function of the factors that influence the expected returns of a parcel in a residential or commercial use and the factors that influence the costs of conversion (e.g. Irwin and Bockstael, 2002).

3.2.2. Survival analysis

Survival analysis[3] is explicitly concerned with the timing of a change from one qualitative state to another. Here, the observed timing of conversions is treated as realisations of a random process. This approach allows for the incorporation of time-varying variables to capture the cumulative effect of these changes on the conversion probability. For this reason, it is an appealing estimation method to land use change modellers. It is often cumulative effects over time that lead to the conversion of a parcel rather than the particular conditions associated with any particular time period.

[3] This is also known as "duration," "hazard," "event history," "failure time," or "lifetime" analysis.

The distribution of duration associated with events (e.g. the duration of a land parcel in an undeveloped state) is described either in terms of a survival function or hazard function. The survival function is the probability that the event does not occur in period t and is equal to $S(t) = 1 - G(t)$, where $G(t) = \Pr(T \geq t)$, which is the cumulative distribution function of the random variable T, the duration length. The hazard function is the conditional probability that the event occurs between t and Δt, given that $T \geq t$ (i.e. given that the event has not yet occurred). This function is interpreted as the rate at which the event occurs and is defined as

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr\{t \leq T < t + \Delta t | T \geq t\}}{\Delta t}$$

This can be rewritten as

$$h(t) = \lim_{\Delta t \to 0} \frac{G(t + \Delta t) - G(t)}{\Delta S(t)} = \frac{g(t)}{S(t)},$$

where $g(t)$ is the continuous probability density function.[4] In addition to being a function of time, the hazard rate may also be modelled as a function of exogenous variables (called "co-variates"). In this case, the hazard rate can generally be expressed as $h(i, t) = f(t, x_i, \beta)$, where x_i are the covariates associated with observation i and β is a parameter vector to be estimated.

In the land use conversion case, the hazard rate (i.e. the conversion rate of parcels) is the function of interest. It is typically modelled as a function of time and explanatory variables that may be spatially heterogeneous and some of which may be time-varying (e.g. population growth rates). Different assumptions are possible regarding the distribution of duration lengths. Fully parametric models, including the exponential, Weibull, log–normal, log–logistic, and complementary log–log models, can be specified. For an application of the complementary log–log model to a model of deforestation, see Vance and Geoghegan in this special issue. Alternatively, a semi-parametric approach, commonly referred to as the proportional hazards model or Cox regression model, is also possible. For example, Irwin and Bockstael (2002) use a proportional hazards model to incorporate time-varying measures of surrounding neighbourhood development to identify the effect of neighbourhood development spill-overs on the conversion rate of parcels from an undeveloped to a residential use. This specification allows them to capture the cumulative effects of changes in neighbourhood development levels on the rate of conversion, which is found to be negative and significant.

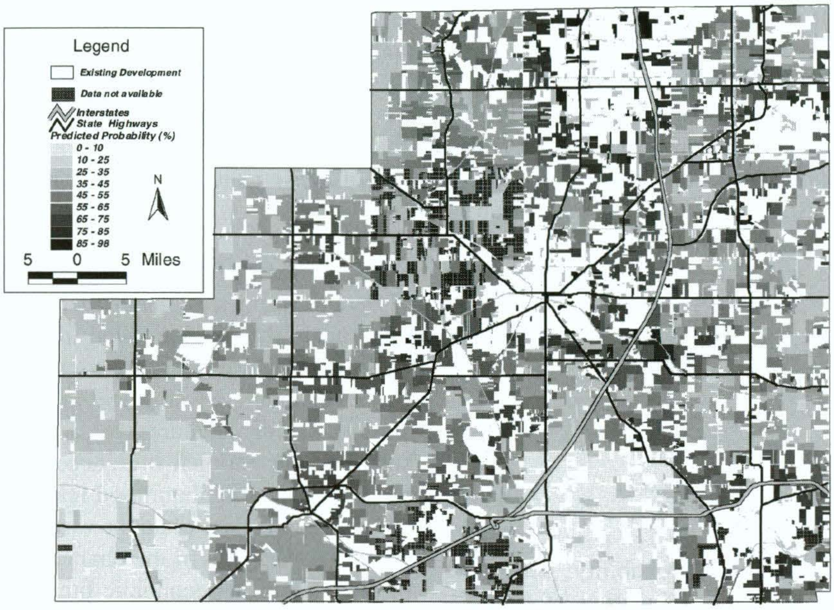
[4] Note that in the discrete case, this expression can be written as $h(t) = [G(t+1) - G(t)]/S(t)$, which corresponds to the expression for the hazard rate in the Vance and Geoghegan paper of this special issue.

3.2.3. Hedonic property value models

Hedonic property value models offer a useful means to estimate the relative value of parcel-level characteristics in determining the overall value of the land parcel, including physical features (e.g. size, soil type, slope), locational features (e.g. access to urban centres, shopping, recreational sites, access to markets, infrastructure), and neighbourhood features. Hedonic property value models explain the variation in property values using variation in the characteristics or attributes of the parcel. The economic literature is replete with applications of hedonic methods to property values. Rosen (1974) provides the theoretical foundation of economic applications of hedonic price models.

Hedonic property value models rest on the assumption of a competitive land market that fosters buyer and seller interactions of properties with a range of characteristics and results in the emergence of an equilibrium hedonic price schedule. When specifying models that designate property values to be a function of property characteristics, researchers estimate a model that corresponds to the equilibrium price schedule. The price of a land parcel currently in use h, y^h, is posited to be a function of m attributes $X : y^h = X\beta + \varepsilon$, where y^h is an $N \times 1$ vector of property transaction prices (of parcels in land use h), X is an $N \times m$ matrix of explanatory variables (property attributes), β is an $m \times 1$ vector of parameters to be estimated, and ε is an $N \times 1$ vector of error terms. Each component of the parameter vector, β, represents the marginal willingness to pay for that property characteristic. By identifying the relative value of a parcel's characteristics, this approach is useful for illuminating the parcel features that contribute to the expected returns, V, of parcel k in use h. In addition, knowledge of the parameter vector, β, facilitates the prediction of the expected return in use h of parcels currently not in use h.

Predicted Probability of Conversion of Undeveloped Land in Medina County, Ohio*



* From: Carrion, C. and Irwin, E.G. (2002). "Using a Spatial Economic Model of Land Use Conversion to Explain Residential Sprawl at the Rural-Urban Fringe." Ohio State University Working Paper.

Fig. 2. Example of model output.

Just as models of land use change have benefited from increases in spatial data availability and gains in spatial computing, so to have models of property values. The most common application of hedonic price methods is explaining residential property values. Palmquist (1991) and Taylor (2002) offer excellent summaries of environmental economic studies of residential property values. Spatially explicit data have broadened the range of explanatory variables employed in these models of residential property values to include parcel-level landscape characteristics (e.g. Acharya and Bennett, 2001; Irwin, 2002; Geoghegan et al., 1997). Hedonic price models have also been used to examine the returns of lands in agricultural use (e.g. Hardie et al., 2001; Maddison, 2000; Roka and Palmquist, 1997; Xu et al., 1993).

3.2.4. Model output

Results from land use change and land value models can be used to test the hypotheses regarding the determinants of land use change and residential land values and to predict the future conversion probability or future land value of yet undeveloped parcels. Fig. 2 illustrates how the empirical results generated from a typical discrete choice or duration analysis model can be used to construct a predicted probability map. The probability map reveals the likelihood that a given undeveloped parcel will be converted to residential use and is calculated using the estimated parameters from the model to predict the conversion probabilities of these parcels. An advantage of this spatially explicit approach is that it provides a means by which predictions regarding individual-level land use decisions can be "aggregated up" to regional-level changes in urban form. Such an understanding of how individual-level decisions influence regional phenomena such as suburbanisation and sprawl is not possible in an aspatial framework.

A weakness of the probabilistic modelling approach is that it does not predict the *amount* of land that will be converted. Rather, the output from this model (a probability map) must be combined with other data sources and models to predict future land use patterns. For example, the probability map might be combined with information from a regional planning authority about future housing demand. Rules of thumb might be applied to distribute this demand across the landscape using information on the likelihood of conversion to residential use. An additional empirical challenge arises when considering forecasts that account for spatial dependence, an issue that we discuss in the following section.

4. Spatially explicit micro-level data environments

Estimation of micro-level models of the type discussed in the previous section is best performed within a data rich environment. The minimal data requirements are land use data at the parcel-level from at least two points in time and corresponding data on a host of explanatory variables that may or may not be time-invariant. When such data are not available, the feasibility of certain modelling tasks will be compromised. In this section, empirical issues related to data and econometric modelling are outlined. A discussion of data collection and management issues is followed by a discussion of analysis and modelling issues.

Spatial data are data that vary over space. A simple rule of thumb in assessing whether to use spatial data is to ask the question: does location matter? When values are measured at specific locations and relative location matters, data are inherently spatial. There are several issues that are unique to spatial data. In this section, we briefly discuss data availability, data quality, data management, data measurement, and spatial econometrics.

4.1. Data availability

The creation of a spatially explicit micro-level dataset is often time consuming and sometimes data must be purchased (although usually only for a nominal fee). The availability of GIS (Geographic Information Systems) data has improved tremendously in the last 5–10 years in the US and is likely to continue improving, making it increasingly easier to assemble such datasets. Many communities are moving towards GIS-based management systems for tax assessment, emergency services, and environmental resource management. In cases where assessment and taxation records are geocoded and computerised, there is much potential for using this information in land use change modelling. These offices track land use, assessed value, and the details of land and housing transactions, e.g. when the transaction occurred and the transacted price. These data are often electronically stored using a GIS, which makes creating a parcel-level land use change dataset possible. For example, the State of Maryland's Office of Planning created an outstanding product called MD Property View that combines data resources from various state and county agencies in a GIS format (http://www.mdp.state.md.us/data/mdview.htm). Land record information will typically include information on the boundary of parcels, parcel acreage, land use, assessed value, timing and size of structures, and transaction information. A useful contact for initiating regional GIS contacts is the National States Geographic Information Council (http://www.nsgic.org).

In the US, small area data are increasingly being made available by federal, state, and local governments. For example, small area files of US Census Data (e.g. by block group and census tract) are widely available in GIS format. In addition, numerous communities are developing land use/land cover data in a GIS format. Road maps and zip code and other political boundaries are other examples of social GIS data and these files are available from the US Department of Commerce Census Bureau (http://tiger.census.gov). The US Department of Agriculture also makes socio-economic GIS data available. Extensive biophysical information is available from government agencies such as the US Geological Survey (http://mapping.usgs.gov/), the US Environmental Protection Agency (http://www.epa.gov/nsdi/), and the National Oceanic and Atmospheric Administration. A primary source of land use change data in the US is the National Resources Inventory (NRI), maintained by the US Department of Agriculture (http://www.nhq.nrcs.usda.gov/NRI/). These are plot-level data collected via a random sampling of land parcels from across the US. Data include a variety of detailed information about land use and cover, soil type, and surrounding land features. These data can be aggregated up to create land use estimates at the state and, in some cases, county-level. These data are available for multiple years (1982, 1987, 1992, and 1997) and therefore it is possible to construct a land use transition matrix to describe aggregate land use changes over time. Private and non-profit groups also provide considerable GIS data. ESRI, the maker of ArcGIS, maintains the Geography Network website (http://www.geographynetwork.com), which is an online clearinghouse of data and interactive mapping resources. For details on some of these and other national sources of data, see Appendix A. Despite these advances, other types of data may simply not be available or may require extensive efforts to store the data in a geo-coded, electronic format. For example, local zoning maps are often only available in paper format and require digitising before zoning variables can be generated using a GIS.

4.2. Data quality/accuracy

Measurement errors in both data attributes and specification of locations are commonly found when scrutinising spatial data. For example, measurement errors are introduced when points are used to represent polygon or line features. Using points to represent city locations where the point is the centroid of the city, introduces measurement error when distance to the city is measured. In addition, GIS data coverages are often incomplete. Data are simply not available for all areas. For these and other reasons, researchers are urged to inspect the quality of the spatial data.

When including spatial variables in a model, the researcher is likely to combine data from different sources that are defined at different temporal and spatial scales. In addition, data from different sources may be in different formats (e.g. vector or raster) and are likely to be defined in different projections[5] (e.g. conic, cylindrical, planar). These differences can make combining GIS datasets challenging. Although rectifying them is quite doable using GIS, the researcher has to be aware of the limitations of the data. For example, the accuracy of a dataset created by combining data defined at a coarse scale with data at a finer scale is limited by the data defined with the lesser precision. Secondly, different projections are designed to maintain the accuracy of specific features (e.g. distance or area) at distinct scales.

[5] Snyder (1987) provides an excellent discussion of map projections.

Lastly, if a research project involves data that have been drawn over space, it is important to consider what the sampling criteria were for the collection of the data. In some cases, the criteria will not include spatial considerations. As a result, imposition of a spatial framework may result in misleading conclusions.

4.3. Data management

A variety of GIS software packages, ranging in sophistication and cost, are available. Most of these programs allow the user to store and manipulate data in ways that are useful for land use change modelling. In addition to making maps, one of the primary uses of GIS in developing a land use change model is to generate spatial variables that can be used in estimation. Most GIS programs are able to perform distance calculations (either "as the crow flies" or along a roads network) between land parcels and destination sites and to create buffers to determine the features (e.g. towns, roads, land uses) within a specified distance of a parcel. More sophisticated packages, such as ESRI's ArcGIS can also be used to run simulation models that use the results of the estimation model to predict future changes in land use pattern. A practical challenge in using GIS and statistical software packages is interfacing between programs, which requires repeatedly outputting variables from one program and inputting them into another. Several software programs are capable of being linked, e.g. SpaceStat, a spatial econometrics software package, has an ESRI ArcView extension that allows some amount of interface between the two programs. MATLAB and S+ are statistical packages with extensive spatial components.

After making the decision regarding what software package to use, another important decision involves what data formats to use. There are two standard GIS data formats: vector and raster data. Vector formats store data in the form of points, lines, and polygons whereas raster models store data as a collection of cells. For a more complete discussion of GIS data types, see the Nelson and Geoghegan paper in this special issue.

4.4. Measurement and definition of spatial variables

Selecting the unit of observation and/or scale of the analysis is important. Ideally, the spatial scale of the data should match that of the relevant economic model. For example, when considering land use decisions at the micro-scale, the relevant spatial scale is the parcel because parcel boundaries correspond to individual land ownership. However, it is often the case that parcel-level data are not available and therefore the analysis must proceed at a scale that does not correspond to the individual decision maker. For example, satellite imagery data are often used in studies of land use change. These data are usually based on an arbitrary division of the landscape, e.g. 30 × 30 cells, in which each cell is identified as a homogeneous land use/land cover type. These arbitrary cell boundaries may result in measurement error and biased estimates of spatial influences. For example, treating each cell as an independent land use conversion decision could generate misleading results regarding the significance of spatial spill-over effects since it can easily be the case that two neighbouring cells are part of the same land parcel. Alternatively, data on land use change may be limited to a much more aggregate scale, e.g. counties. In this case, the researcher will not be able to model fine-scale processes, e.g. interactions among neighbouring parcels, but rather must limit the analysis to modelling larger-scale processes, e.g. the regional pattern of specific land substitutions across counties (Hsieh et al., 2002; Plantinga and Miller, 1997; Parks and Kramer, 1995; Parks and Hardie, 1995; Wu and Segerson, 1995). One notable issue that arises in estimating models of land use change with aggregate data is unobservable heterogeneity within the unit of observation, e.g. unobservable variation in land quality within a county. Stavins and Jaffe (1990) offer one approach to dealing with this problem. They assume a distribution for the unobserved land quality and estimate the parameters of the distribution econometrically. A final measurement scale consideration is combining data that have been collected at different spatial scales for the land use change model, e.g. combining tract or county-level data on the sociodemographic features of a parcel's neighbourhood. When combining data stored at different spatial scales, it may be worthwhile to perform a sensitivity analysis that examines the sensitivity of results to different assumptions. Choices may include county, tract, block group, block, parcel, or plot. Effects may vary across scales, so that certain variables may be very significant at a fine scale, but lose significance at a more aggregated scale (Acharya and Bennett, 2001).

The definition and measurement of neighbourhoods and regions is fundamental to spatial analysis. Dependencies in space manifest themselves through interactions among neighbours or regions. Patterns are observed by analysing values defined over regions and/or comparing the relative size of values across these areas. As discussed at length in Anselin's paper on spatial econometrics in this special issue, the concept of neighbours is crucial to spatial econometric applications. There are no firm rules for creating regional or neighbourhood definitions. Defining regions according to area (buffering a circle or square around a feature such as a point or a line) or distance are common. A spatial weight matrix is a more formal method used to describe neighbours. This $N \times N$ matrix specifies the spatial relationship between each observation and other observations. Observations may be at an individual parcel-level, in which case the neighbourhood would be a local neighbourhood comprised of neighbouring parcels, or at a more aggregate scale, e.g. county-level, in which case the neighbourhood would be a regional area that encompasses multiple counties. The matrix represents the researcher's assumption about the structure of spatial dependence within the sample and is guided by the underlying theoretical assumptions regarding the nature of the spatial process that is of concern. Fig. 3 displays the ba-

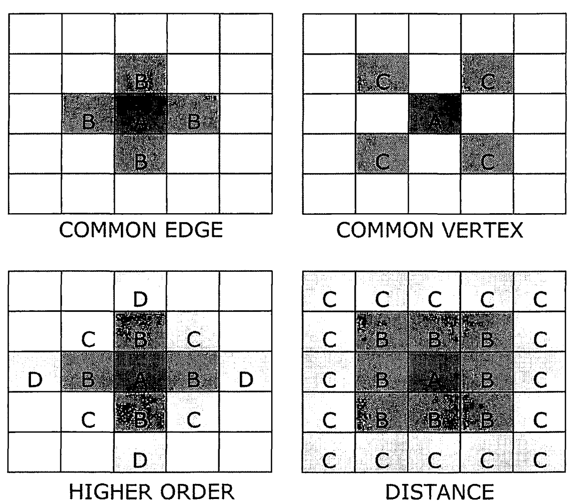


Fig. 3. Defining spatial weight matrices.

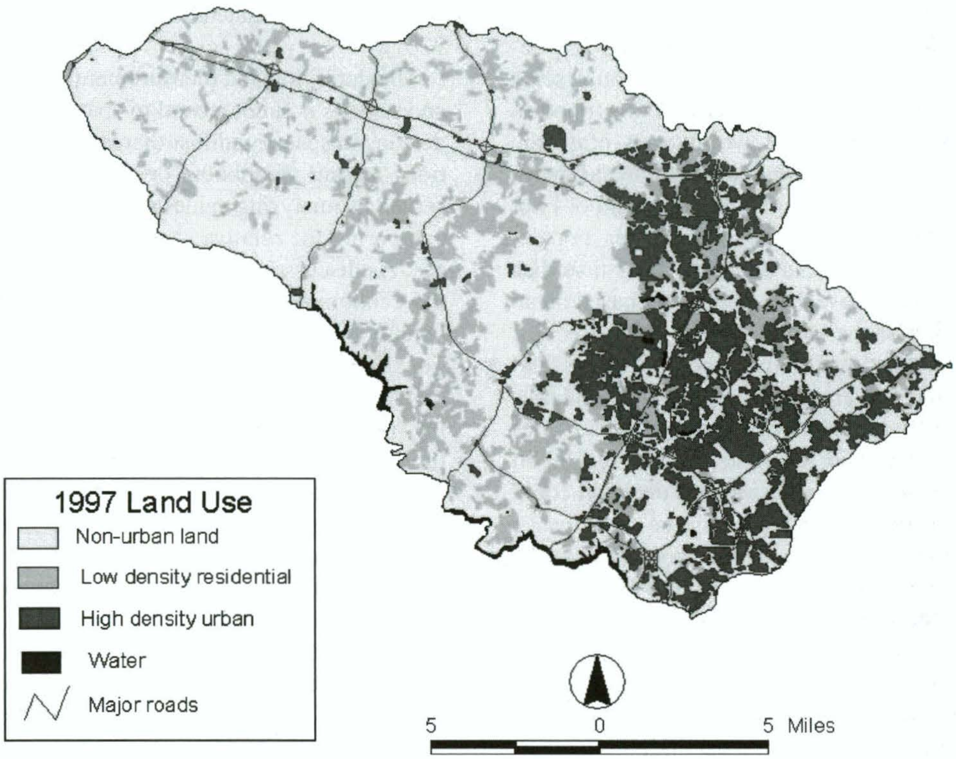


Fig. 4. Pattern of urban land use in Howard Country, MD.

sic format for several types of spatial weight matrices (Anselin, 1988). The definition of neighbours may vary with the scale of the data. For example, contiguity weight matrices are commonly employed with aggregate data. Alternatively, distance–decay weight matrices are commonly used with micro-scale data, especially in cases where observations are scattered across space and discrete rather than continuous.

4.5. Spatial dependence

When working with spatial data, issues of spatial dependence and spatial heterogeneity are common. As discussed at length by Anselin in this special issue, spatial dependence arises when observations in space are functionally related and is either due to structural dependencies or spatially autocorrelated error terms. The conversion of land parcels may illustrate spatial dependence due to a variety of spatial effects, including clustering of local services (e.g. public sewer) that induce a clustered development or due to interdependencies among neighbouring parcels that arise due to land use externalities. For example, Fig. 4 illustrates the urban land use pattern of Howard County, located just to the north of Washington, DC and west of Baltimore, MD. The pattern of higher density urban development supports this notion that is concentrated in the southern portion of the county. On the other hand, spatial dependence among the errors is often due to omitted variables, which are themselves spatially correlated. For example, housing values may depend on neighbourhood attributes, some of which are unobserved to the researcher and are therefore omitted from empirical models of housing values. Another cause of spatial dependence among the errors is measurement error that arises from a mismatch between the spatial boundaries of observations and the boundaries of the spatial process. For example, the measurement of certain, micro-socio-economic data at the county-level may result in spatial dependence of the error terms since county boundaries may be an arbitrary delineation of the spatial process that generates the socio-economic values. When estimating spatially explicit micro-level models, spatial econometric issues cannot be safely overlooked.

There are a number of "exploratory spatial data analysis" techniques that can be employed to explore the pattern of spatial dependencies exhibited by particular variables. These methods can be used to examine the particular pattern of spatial clustering that is exhibited and to identify local "hotspots" or outliers that indicate local areas of potential spatial instability (Anselin, 1998; Haining, 1990). In addition, a number of more formal tests of spatial association have been developed in the literature (see Cliff and Ord, 1973 for an extensive treatment and Haining, 1990 for an overview). These tests allow one to test the hypothesis that values are correlated in space against a null hypothesis that there is no spatial correlation among values. Examples of these tests include Moran's I and Geary's c for tests of global association of continuous variables and the join count statistic for a test of global spatial association of categorical variables.

The usual method for correcting spatial dependence requires assuming a structure for the spatial dependence and estimating one or more parameters of that structure in conjunction with the parameters of the economic model (Anselin, 1988; Anselin and Florax, 1995, 2002).[6] Spatial econometric techniques have been used in micro-level analyses of economic land use and land value models. Maximum likelihood and generalised method of moment approaches have been employed successfully to estimate continuous models correcting for spatial dependence. While it is straightforward to apply these methods for estimating hedonic models of land values, application of these methods to discrete choice land use change models is much more challenging. This arises because of the likely heteroscedasticity that is induced by the spatially correlated covariance structure that arises from the spatial dependence.[7] While heteroscedastic errors in a continuous model do not result in inconsistent estimates, they do lead to problems of inconsistency in discrete choice and duration models. As detailed by Fleming (2002), several approaches have been proposed for dealing with this problem in a discrete choice framework.[8] Pinkse and Slade (1998) have proposed a GMM estimator for the binary probit model that corrects for heteroscedasticity arising from a first order autoregressive specification of spatial error autocorrelation. However, this method ignores the nonzero off diagonal elements of the variance–covariance matrix and, because it does not incorporate the full spatial information contained in the covariance structure, the resulting estimates are inefficient. As a result, hypothesis testing is invalid. To obtain both consistency and efficiency, the full spatial information must be incorporated into the estimation procedure. In this case, the incorporation of the non-zero covariance structure implies that the likelihood function cannot be simplified to an expression containing the product of N independent univariate distributions, but rather must be expressed in terms of an N-dimensional integral. Evaluation of this N-dimensional integral is computational difficult. Solutions that have been developed include the EM algorithm, Gibbs sampling, and simulation methods. Implementation of these solutions is challenging and often limited to datasets with a small number of observations (e.g. 500 or less) due to the computation difficulties that arise from estimation with a large N. For a full discussion of these issues and a discussion of an alternative approach using a weighted non-linear least squares estimator, see Fleming (2002).

5. Conclusions

There are advantages and disadvantages of working with spatial data at a micro-level scale. The primary advantage extends from using data at a scale that corresponds to the economic decision of interest. Land use change is the result of many separate decisions made by individual landowners and therefore an understanding of the determinants of land use change requires an understanding of individual decision making at the parcel-level. However, the con-

[6] We omit a general discussion of this modelling technique here and instead refer the reader to Anselin's paper in this special issue, which deals extensively with issues involving the specification of spatial dependence and the implications of overlooking such dependence.

[7] While under certain specifications of the spatial lag or error process, heteroskedasticity may not result, it has been shown to result under the most common specification of spatial error or lag dependence, the first order autoregressive process (Fleming, 2002).

[8] To date, no one has considered potential solutions to the spatial dependency problem within a duration modelling framework.

sequences of land use change are often realised at more aggregate scales, e.g. the inefficiencies of sprawl generate additional costs that are realised at regional scales in the form of added congestion and a mismatch between the demand and supply of infrastructure within a metropolitan area. Therefore, micro-level models that can spatially aggregate up individual-level decisions regarding land use to regional-level changes in urban form are necessary for explaining such phenomena as sprawl at the rural–urban fringe as a spatial economic process. Spatially articulated models of individual land use conversion provide a means by which this transition from individual-level behaviours to aggregate-level outcomes is possible.[9] By modelling land use change in a two-dimensional, spatially explicit framework, the influence of a variety of spatially differentiated features on individual-level land use conversion decisions can be estimated and used to predict future changes in urban form at a regional-scale. Because this approach links predicted outcomes with underlying behaviour of individual actors, it improves predictions for policy analysis. The effects of policies that either directly (e.g. zoning) or indirectly (e.g. tax incentives) influence land use conversion decisions can be considered because the influence of these policies on underlying behaviour can be predicted. Lastly, because the unit of observation, i.e. the land parcel, corresponds directly with the scale at which the underlying spatial process takes place, data measurement problems are minimised, which reduces a source of spatial error autocorrelation.

Despite these advantages, there are clear challenges to using micro-level models in a data-rich environment. Datasets that are generated when analysing land use changes at a parcel-level are often massive, e.g. one county may contain over 100,000 land parcels. As a result, data management planning and computer resources are required to control otherwise unwieldy datasets. In addition, as datasets grow in size, the challenges of modelling correspondingly increase. For example, certain spatial econometric techniques become onerous as sample size increases because of (among other things) the size of the spatial weight matrix (Bell and Bockstael, 2000). In summary, while spatially explicit micro-level data offer more possibilities in terms of hypothesis testing and policy analysis, they also necessitate significant management efforts and computer resources to organise data and estimate models.

[9] Agent-based simulation models of land use change provide a complementary approach to understanding the linkages between individual-level decisions and regional patterns of land use. For an overview of these models, see Parker et al. (2002).

Acknowledgements

This research was financed in part by the Maine Agricultural and Forest Experiment Station. All errors and omissions are the sole responsibility of the authors. Maine Agricultural and Forest Experiment Station Publication No. 2588.

Appendix A. Data resources for micro-level models of land use change

US Federal Government
- Federal Geographic Data Committee, http://www.fgdc.gov/data/data.html
- US Department of Commerce, Census, http://tiger.census.gov
- USDA, National Resource Inventory, http://www.nhq.nrcs.usda.gov/NRI/
- USDA, Forest Inventory Analysis Program, http://fia.fs.fed.us/
- USGS, National Mapping Information, http://mapping.usgs.gov/
- US EPA, Geospatial Data Clearinghouse, http://www.epa.gov/nsdi/
- US Fish and Wildlife, National Wetlands Inventory, http://www.nwi.fws.gov/

Private
- The Geography Network, Produced by ESRI, http://www.geographynetwork.com
- The GIS Data Depot, http://www.gisdatadepot.com/

References

Acharya, G., Bennett, L., 2001. Valuing open space and land-use patterns in an urban watershed. J. Real Estate Finance Econ. 22 (2–3), 221–237.

Alonso, W., 1964. Location and Land Use: Towards a General Theory of Land Rent. Harvard University Press, Cambridge, MA.

Altschuler, A., Gomez-Ibanez, J.A., 1993. Regulation for Revenue: the Political Economy of Land Use Exactions. The Brookings Institution, Washington, DC.

Anas, A., Kim, I., 1996. General equilibrium models of polycentric urban land use with endogenous congestion and job agglomeration. J. Urban Econ. 402, 232–256.

Anselin, L., 1988. Spatial Econometrics: Methods and Models. Kluwer Academic Publishers, Dordrecht.

Anselin, L., 1998. Exploratory spatial data analysis in a geocomputational environment. In: Longley, P., Brooks, S., Macmillan, B., McDonnell, R. (Eds.), GeoComputation, a Primer, Wiley, New York, pp. 77–94.

Anselin, L., Florax, R.J. (Eds.), 1995. New Directions in Spatial Econometrics. Springer, New York.

Anselin, L., Florax, R.J. (Eds.), 2002. Advances in Spatial Econometrics. Springer, Berlin (in press).

Bell, K., Bockstael, N.E., 2000. Applying the generalized methods of moments approach to spatial problems involving micro-level data. Rev. Econ. Stats. 821, 72–82.

Bockstael, N.E., 1996. Modelling economics and ecology: the importance of a spatial perspective. Am. J. Agric. Econ. 785, 1168–1180.

Bockstael, N.E., Bell, K., 1998. Land use patterns and water quality: the effect of differential land management controls. In: Just, R., Netanyahu, S. (Eds.), International Water and Resource Economics Consortium, Conflict and Cooperation on Trans-Boundary Water Resources. Kluwer Academic Publishers, Dordrecht.

Burchell, R.W., Shad, N.A., Listokin, D., Phillips, H., Downs, A., Seksin, S., Davis, J., Moore, T., Helton, D., Gall, M., 1998. The Costs of Sprawl—Revisited. Transportation Research Board, National Research Council. National Academy Press, Washington, DC.

Cliff, A., Ord, J.K., 1973. Spatial Autocorrelation. Pion Publishing, London.

Fleming, M., 2002. A review of techniques for estimating spatially dependent discrete choice models. In: Anselin, L., Florax, R. (Eds.), Advances in Spatial Econometrics (in press).

Frank, J.E., 1989. The Costs of Alternative Development Patterns: a Review of the Literature. Urban Land Institute, Washington, DC.

Geoghegan, J., Wainger, L., Bockstael, N.E., 1997. Spatial landscape indices in a hedonic framework: an ecological economics analysis using GIS. Ecol. Econ. 233, 251–264.

Haining, R., 1990, Spatial Data Analysis in the Social and Environmental Sciences. Cambridge University Press, Cambridge.

Hardie, I.W., Narayan, T.A., Gardner, B.L., 2001. The joint influence of agricultural and nonfarm factors on real estate values: an application to the mid-Atlantic region. Am. J. Agric. Econ. 83 (1), 120–132.

Hart, J.F., 1995. Rural and farm no longer mean the same. In: Castle, E. (Ed.), The Changing American Countryside Rural People and Places. Kansas University Press, Kansas.

Hite, D., Sohngen, B., Simpson, J., Templeton, J., 2000. Competing risks in the suburbanization of agricultural land. In: Proceedings of the 2000 Annual Meeting of the American Association of Agricultural Economists, Tampa, FL.

Hsieh, W., Irwin, E.G., Forster, L., 2002. Do Spillovers Induce Sprawl? The Influence of County-Level Urbanization Spillovers on the Rate and Pattern of Urban Land Conversion. Ohio State University Working Paper.

Irwin, E.G., 2002. The effects of open space on residential property values. Land Econ. 78 (4), 465–481.

Irwin, E.G., Bockstael, N.E., 2002. Interacting agents, spatial externalities, and the evolution of residential land use patterns. J. Econ. Geog. 2 (1), 31–54.

Kline, J.D., Alig, R.J., 1999. Does land use planning slow the conversion of forest and farm lands? Growth Change 30, 3–22.

Krugman, P., 1991. Increasing returns and economic geography. J. Polit. Econ. 99, 438–499.

Krugman, P., 1995. Development, Geography, and Economic Theory. MIT Press, Cambridge, MA.

Ladd, H.F., 1992. Population growth, density, and the costs of providing public services. Urban Studies 292, 273–295.

Landis, J., Zhang, M., 1998. The second generation of the California urban futures model. Part 1. Model logic and theory. Environ. Plan. A 30, 657–666.

Maddison, D., 2000. A hedonic analysis of agricultural land prices in England and Wales. Eur. Rev. Agric. Econ. 27 (4), 519–532.

McMillen, D.P., 1989. An empirical model of urban fringe land use. Land Econ. 652, 138–145.

Nelson, A., 1992. Characterising exurbia. J. Plan. Lit. 6 (4), 350–368.

Nickerson, C., 1999. Characterising participation in farmland preservation programs. Working Paper 99-17. Department of Agricultural and Resource Economics, University of Maryland.

Page, S., 1999. On the emergence of cities. J. Urban Econ. 451, 184–208.

Palmquist, R.B., 1991. Hedonic methods. In: Braden, J.B., Kolstad, C.D. (Eds.), Measuring the Demand for Environmental Quality. North-Holland, Amsterdam, pp. 77–120.

Parker, D., Manson, S., Janssen, M., Hoffmann, M., Deadman, P., 2002. Multi-agent systems for the simulation of land use and land cover change. Ann. Assoc. Am. Geogr. (in press).

Parks, P.J., Hardie, I.W., 1995. Least-cost forest carbon reserves: cost-effective subsidies to convert marginal agricultural land to forests. Land Econ. 711, 122–136.

Parks, P.J., Kramer, R.A., 1995. A policy simulation of the wetlands reserve program. J. Environ. Econ. Manage. 28, 223–240.

Pinkse, J., Slade, M.E., 1998. Contracting in space: an application of spatial statistics to discrete-choice models. J. Econ. 85 (1), 125–154.

Plantinga, A.J., Miller, D.J., 1997. Maximum entropy estimation of land use shares and transitions. Maine Agricultural and Forest Experiment Station Technical Bulletin 166.

Porter, D., 1997. Managing Growth in America's Communities. Island Press, Washington, DC.

Roka, F., Palmquist, R., 1997. Examining the use of national databases in a hedonic analysis of regional farmland values. Am. J. Agric. Econ. 79 (5), 1651–1656.

Rosen, S., 1974. Hedonic prices and implicit markets: product differentiation in pure competition. J. Polit. Econ. 82, 34–55.

Sen, A., Smith, T., 1995. Gravity Models of Spatial Interaction Behaviour. Springer, Berlin.

Sharp, J., Reece, J., 2001. Population characteristics of Ohio's townships 1960 to 2000. Ohio State University Report EX-1. Available on-line at: http://aede.osu.edu/programs/exurbs/report1.htm.

Snyder, J.P., 1987. Map projections—a working manual. US Geological Survey Professional Paper 1395. Supt. of Docs. No. I19.16:1395, Government Printing Office, Washington, DC.

Stavins, R.N., Jaffe, A.B., 1990. Unintended impacts of public investments on private decisions: the depletion of forested wetlands. Am. Econ. Rev. 803, 337–352.

Taylor, L., 2002. The hedonic method. In: Champ, P., Brown, T., Boyle, K. (Eds.), A Primer on the Economic Valuation of the Environment. Kluwer Academic Publishers, Dordrecht (in press).

US Census Bureau, 1990. Appendix A: Area classifications, STF3 Technical Documentation.

Waddell, P., Shukla, V., 1993. Employment dynamics, spatial restructuring, and the business cycle. Geog. Anal. 21 (1), 35–52.

Wu, J., Segerson, K., 1995. The impact of policies and land characteristics on potential groundwater pollution in Wisconsin. Am. J. Agric. Econ. 774, 1033–1047.

Xu, F., Mittelhammer, R.C., Barkley, P., 1993. Measuring the contribution of site characteristics to the value of agricultural land. Land Econ. 69 (4), 356–369.

Zhang, W., 1993. Location choice and land use in an isolated state: endogenous capital and knowledge accumulation. Ann. Reg. Sci. 271, 23–39.