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Accounting for Spatial Effects in Economic Models of Land Use: Recent Developments and Challenges Ahead

Michael Brady · **Elena Irwin**

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Abstract The marked increase in the availability of spatial data has forced researchers engaged in land use modeling to directly confront the question of space and the theoretical and methodological challenges involved in developing spatial models. Advances have come from multiple disciplines, most notably through the development and application of spatial theory and methods from regional science, geography, urban economics and more recently, theoretical and applied econometrics. The main goal of this paper is to summarize the econometric challenges of spatial data and to highlight spatial models and methods with a particular focus on models of land markets and land use change. We also discuss the data and modeling challenges associated with modeling the underlying spatial economic mechanisms that give rise to land use patterns and the complexities involved in modeling land use as a coupled economic-ecological system.

Keywords Spatial econometrics · Hedonic · Land use change

1 Introduction

Land use change and its impacts on the environment occur across multiple spatial and temporal scales. At a global scale, world economic conditions drive regional and country-level changes in land use, which can generate large environmental impacts, including tropical deforestation, carbon emissions and biodiversity loss. At more spatially disaggregate scales, household land use and location decisions both influence and are influenced by local ecosystem services, including natural resource availability and the quality of spatially heterogeneous natural amenities. In recent years, researchers have taken advantage of the growing body

M. Brady
School of Economic Sciences and IMPACT Center, Washington State University, Pullman, WA, USA

E. Irwin (✉)
Agricultural, Environmental, and Development Economics, The Ohio State University, Columbus, OH, USA
e-mail: irwin.78@osu.edu

of increasingly rich spatially explicit data to develop spatial models of land use and land values. These models have been used in a variety of contexts within environmental and resource economics, e.g., to estimate the influence of spatially varying policies on land use change; the welfare effects associated with specific urban or rural land uses, environmental amenities or other ecosystem services; and the efficiency of spatially targeted policies that seek to reduce environmental damages.

The marked increase in the availability of spatial data has forced researchers in this field to directly confront the question of space and the theoretical and methodological challenges involved in developing spatial models. Advances have come from multiple disciplines, most notably through the development and application of spatial theory and methods from regional science, geography, urban economics and more recently, theoretical and applied econometrics. Well-established theories of location and land use developed by regional scientists and urban economists provided an important theoretical framework that has guided specification of econometric land use models since their infancy in the 1980s. With the advent of GIS and increasing availability of spatial micro data in the 1990s, spatial econometrics has provided an important methodological approach for accounting for spatial effects in models of land values and land use.

The main goal of this paper is to summarize the econometric challenges of spatial data and to highlight, within the context of modeling land markets and land use change, spatial models and methods that have been developed to deal with the challenges. The rest of the paper is structured as follows. In the following section, we provide a brief historic account of econometric land use modeling. Section 3 then reviews the primary econometric challenges of spatial data and provides an abbreviated discussion of spatial models and methods designed to address these issues. Section 4 highlights a sampling of recent spatial models of land markets and land use change drawn from the fields of regional science, geography, urban economics and environmental economics. Section 5 discusses what we see as primary challenges to the further development of spatial economic models of land use, namely the data and modeling challenges associated with modeling the underlying spatial economic and biophysical mechanisms that give rise to land use patterns. Section 6 concludes the paper.

It is worthwhile pausing here to provide a bit more context to our discussion of spatial econometric models and methods. We discuss spatial regression models, in which some form of spatial structure has been imposed via functional form restrictions, as well as other econometric models and methods that have been usefully applied to address the econometric challenges posed by spatial data. The main distinction lies in the approach to model specification and parameter identification, which, in practice, usually boils down to whether the spatial structure is fully parameterized using an exogenously defined spatial weights matrix and a multiplicative coefficient (that is then estimated) or whether an alternative approach is used that imposes less structure on the data. The latter include nonparametric and semiparametric models that provide greater flexibility in modeling the spatial data structure and quasi-experimental methods that have potential to isolate causal effects from unobserved spatially correlated variables. Many of the published review articles on spatial econometrics (e.g., Anselin 2002, 2007, 2010; Arbia and Fingleton 2008; Florax and van der List 2003; Holloway et al. 2007; Páez 2009) do not include any or much discussion of these other approaches. In contrast, two recently published papers in the 50th anniversary edition of the *Journal of Regional Science* (McMillen 2010; Pinkse and Slade 2010) take a broader view. We follow their lead, given that many of the challenges posed by spatial data can be usefully addressed by these models and methods and that, due to the complexity of spatial data, multiple approaches to model specification and parameter identification are often warranted.

2 Econometric Modeling of Land Use

A large literature on econometric modeling of land use change has emerged since its beginnings in the early to mid-1980s. An econometric approach to modeling land use change was spurred in part by the planning needs of federal agencies that sought large-scale regional projections of future land and water needs. Problems in estimating future US cropland availability based on regional and national production economic models led economists to seek out alternative approaches to forecasting future land use change (Burnham 1973, Alig personal communication). In addition, regional data on gross land use transitions from the USDA revealed a much more dynamic process, e.g., of land coming into agricultural production and being converted to forest or retired to a natural state, than what was revealed by net statistics.

White and Fleming (1980) were among the first to estimate the determinants of Markov transition probabilities of land use change using historical data on land in agriculture and forest uses for the state of Georgia from 1945 to 1975. They estimated a three-stage least squares regression of crop, pasture and forest acres with lagged prices, lagged net income and government payment programs as explanatory variables. Alig (1986) estimated the first land use shares model, in which the proportion of land dedicated to farm, forest, industrial forest, crops, pasture and urban within each survey unit area (comprised of multiple counties) was regressed on a number of explanatory variables hypothesized to influence land rents. Building on an aggregate empirical model of urban sprawl by Brueckner and Fansler (1983); Alig and Healy (1987) investigate the relationship between several different urban area measures, including the newly available 1982 NRI estimates of urban land, and the economic and demographic factors hypothesized to influence urban area size. This model was estimated for 363 urbanized areas within the contiguous US using both census definitions of urban area as well as at a state level using NRI data to measure urban extent.

From these highly aggregated, sparse data beginnings, economists greatly improved upon econometric land use modeling through the use of better data and methods. With better data available through the USDA's National Resource Inventory (NRI), subsequent land use shares models were estimated at the county level (e.g., Lichtenburg 1989; Hardie and Parks 1997; Parks and Kramer 1995; Wu and Segerson 1995). Heterogeneity within counties is accounted for by positing a parameteric distribution for land quality and jointly estimating the parameters of this distribution with the land conversion model (Stavins and Jaffe 1990). Dynamic considerations are explicitly modeled by accounting for future expected net returns from forestry (Plantinga 1990; Stavins and Jaffe 1990). NRI plot-level data permits the estimation of discrete choice land use conversion models that accounted for land conversion among multiple types of agricultural use as well as forest and urban uses (e.g., Lubowski et al. 2006). However, because the NRI are sample points without explicit geographic location, spatial modeling using these data is not possible.

Beginning in the 1990s, spatially disaggregate data on land use and land cover became increasingly available from two major sources: (1) remotely sensed data from aerial photography and satellite imagery and (2) parcel-level tax data from county assessors' offices. The latter were traditionally available in paper format, but the revolution in Geographical Information Systems (GIS) in the early 1990s led many counties to eventually develop electronic geo-coded databases of land parcel data that typically included land use, parcel and structural characteristics and, in some cases, sales data. Both sources of data, particularly the availability of remotely sensed data, have led to an explosion of research on land use.

McMillen (1989) was the first to use parcel-level data in a dichotomous empirical model that estimated the probability that a parcel was in an urban, agricultural or vacant use. Chomitz and Gray (1996) and Nelson and Hellerstein (1997) were among the first spatially disaggregate land use models to be estimated using remotely sensed data from Belize and Mexico respectively. In both cases, a theoretical model of deforestation derived from the urban economic monocentric model was used to motivate a reduced from empirical model in which access to roads is a key variable. Bockstael (1996) laid out a basic framework for a discrete choice model of land use in which land is fully allocated to the use that maximizes the net present discounted value of returns and applied the model using a two-step modeling procedure to urban land development in a central Maryland region. The first step consisted of estimating a hedonic model of residential property values using transactions data to estimate the expected residential value of yet undeveloped land. The second stage then used observations on developable land that was either subsequently developed or not to estimate the probability of development as a function of expected net returns to development.

These seminal papers spawned an active and still growing area of research on spatially disaggregate, econometric modeling of land conversion and these researchers were among the first environmental and resource economists to grapple with the methodological challenges posed by spatial data. Early applications of spatial econometrics, e.g., by Can (1992), Case (1991), Case (1992), Dubin (1988), Dubin (1992), McMillen (1992), and the pioneering work by Anselin (1988) provided critical guidance for environmental and resource economists on how to account for spatial effects in continuous variable models and, to a lesser extent, in limited dependent variable models. Spatial data analysis and spatial econometrics has advanced since this time, but nonetheless many challenges remain in accounting for spatial effects in econometric models. In the next section, we provide a brief overview of the econometric challenges that arise in using spatial data and the models and methods that have been developed to deal with these.

3 Econometric Spatial Models

Incorporating "space" into econometric models presents a number of challenges to econometric estimation, hypothesis testing and prediction. The importance of proximity in many economic processes implies that spatially distributed economic agents and outcomes are not independent of each other. That spatial dependence is common in geographic data is well-established and was expressed succinctly in Tobler's (1979) first law of geography that "everything is related to everything else, but closer things more so." Land and housing markets are prime examples. The values of two neighboring houses are similar because of their shared proximity to relevant geographic features, including proximity to employment, shopping and local public goods. The data generated from such distance-related processes are spatially dependent. An econometric model that does not include all the relevant spatial variables will suffer from omitted spatially correlated variables that can bias results since the omitted spatial variables are likely to be correlated with one or more of the observed spatial variables.

Other forms of spatial dependence can arise from interactions among spatially distributed agents. Examples abound in land use settings. In agriculture, for example, processing is often constrained in the short run by the capacity of facilities in the region. Thus a grower will have to consider the acreage decisions of other growers when deciding whether or not to expand production. In imperfectly competitive urban land markets, a developer's decision to develop land at a particular location may be dependent on the decision of other developers around him. Households may make location choices dependent on the choices of other households that are similar in terms of income, race or education. In the latter case, space is not geographic, but instead is measured in one or more dimensions of socioeconomic status. Such interactions among agents create feedback effects across space, commonly referred to as a spatial lag, that are endogenous in a cross-sectional model of agent decision making. Omission of a relevant spatial lag leads to the standard endogeneity bias. However, this form of spatial dependence can introduce other complications as well. Capturing such effects in an econometric model requires data on the full population rather than just a representative sample of agents and thus missing observations can also lead to endogeneity problems. Too much interdependence among observations on the outcome of interest can lead to unstable models, e.g., in which there is no equilibrium, multiple equilibria or a situation in which the addition of new observations could cause the equilibrium to shift nonmarginally (Pinkse and Slade 2010).

Spatial heterogeneity makes measurement of spatial data a key concern. Measurement error generated by the aggregation of spatially heterogeneous variables is extremely common and can produce spatial dependence. For example, population data collected at the Census tract level may mask clusters of low or high income households within tracks. Data at an individual household scale would reflect this finer scale pattern, whereas data at more aggregate scales may not and thus the results of any empirical analysis are dependent on the scale and method by which the data are collected. This problem, called the modifiable areal unit problem (MAUP), can arise anytime when the spatial units of the data do not correspond to the spatial scale of the economic process. Because measurement errors spillover across neighboring boundaries, spatial error autocorrelation is common in models that use such data. In the absence of other sources of spatial error autocorrelation, e.g., from omitted spatial variables, this type of spatial error dependence results in inefficient parameter estimates and biased standard errors.

In addition to creating measurement problems, the presence of spatial heterogeneity can imply a lack of stability across space in the model parameters (Anselin 1988). For example, the influence of environmental amenities, such as public parks or preserved open space, on housing values may vary markedly with the socioeconomic characteristics of households across neighborhoods. In such cases, functional forms that do not allow for flexibility in parameters can generate severely biased results (McMillen 2010).

On a more fundamental level, the location of economic agents and the outcomes associated with their choices are often endogenous. The timing and location of new housing, for example, is the result of developer expectations over the supply of land and demand for housing across varying locations, which are influenced by policies and other factors that are themselves endogenous to land and housing markets. This implies a number of complications to developing a suitable econometric model, including that distance among observations may be endogenous, the number of observations may be endogenous and that the location decisions of interest are often jointly determined with other spatial variables of the model (Pinkse and Slade 2010).

3.1 Spatial Regression Models

Spatial econometrics is defined as a subfield of econometrics that deals with spatial interaction (spatial dependence or autocorrelation) and spatial structure (spatial heterogeneity) in regression models for cross-sectional and panel data (Anselin 2001). Work on spatial econometric techniques originated in regional science and geography and was pioneered by Dutch regional scientists and British economists and geographers, as summarized by Florax and van der List (2003). The field was further established and advanced by Anselin's (1988) book on methods and models in spatial econometrics, which emphasized the distinction between a data-driven geostatistical representation of space and a model-driven spatial econometrics approach. Since these early contributions, the field has grown rapidly (see Anselin 2010 for a historical review). While limited initially to regional science and geography journals, general econometricians gained an interest in the challenges of spatial models and by the 1990s, articles on spatial econometric methods and applications of spatial econometric models began appearing in econometric journals.

The objective of spatial econometrics at its most general level is to learn about the nature of a spatial function $\boldsymbol{m}_n$, in which

$$\boldsymbol{m}_n(\boldsymbol{A}) = \boldsymbol{u}, \tag{1}$$

where $\boldsymbol{A}$ is an n x k matrix whose i^{th} row corresponds to the i^{th} observation and $\boldsymbol{u}$ is an n-dimensional independent and identically distributed (i.i.d.) error vector.[1] In a cross-sectional analysis of spatial data, i refers to location whereas in a panel data setting, i refers to a particular location and time pair. It is clearly not possible to estimate $\boldsymbol{m}$ without restricting the function, given that $\boldsymbol{m}$ is an n-dimensional function, we have only one draw of $\boldsymbol{A}$ and, without further simplification, the number of parameters varies with the number of observations (the so-called incidental parameters problem). There are many ways to restrict $\boldsymbol{m}$ and it is the specific set of simplifying assumptions imposed by the researcher that distinguishes different spatial econometric models.

By far the most common approach is to specify the spatial relationship among the n observations as a pairwise dependence between two locations, i and j using a spatial weights matrix, $\boldsymbol{W}$. This is an n x n matrix comprised of nonstochastic weighting elements w_{ij}, which are exogenous and represent the researcher's maintained assumption about the nature of the spatial relationship between any two locations. Further simplification is imposed by assuming that the spatial process can be represented by a multiplicative spatial coefficient that captures a spatial effect that is common to the spatial relationship of all pairwise locations in the data set. The standard linear form of the general spatial autoregressive specification of the model is written as:

$$\begin{gathered}\boldsymbol{y} = \rho \boldsymbol{W}_y \boldsymbol{y} + \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \\ \boldsymbol{\varepsilon} = \lambda \boldsymbol{W}_\varepsilon \boldsymbol{\varepsilon} + \boldsymbol{u} \\ \boldsymbol{u} \sim N\left(0, \sigma^2 \boldsymbol{I}_n\right),\end{gathered} \tag{2}$$

where $\boldsymbol{A} = [\boldsymbol{y}|\boldsymbol{X}]$, β is a k x 1 vector of coefficients, $\boldsymbol{W}_y$ and $\boldsymbol{W}_\varepsilon$ are n x n spatial weight matrices for the spatial lag and spatial error respectively and ρ and λ are respectively the spatial lag and spatial error parameters that are estimated using a cross-section of observations on $\boldsymbol{y}$ and $\boldsymbol{X}$. Given $\boldsymbol{W}_y$ and $\boldsymbol{W}_\varepsilon$, estimation of $\boldsymbol{m}$ is reduced to estimating ρ and λ. This simplification of $\boldsymbol{m}$ rests on a number of restrictions on the degree of spatial dependence and heterogeneity exhibited by the data generating process. For example, the pairwise spatial dependencies as represented by $\boldsymbol{W}$ should decay sufficiently rapidly with distance so that the process is non-explosive. These and other assumptions about the spatial process

[1] We borrow this notation from Pinkse and Slade (2010).

are discussed in more detail elsewhere (e.g., Anselin 1988; Anselin 2002; Anselin and Bera 1998).

Following specification testing, the general spatial weights model expressed in (2) is often further simplified to the spatial autoregressive model (SAR or spatial lag model as it is also known) and the spatial error model (SEM), which can be arrived at by setting $\lambda = 0$ or $\rho = 0$ respectively (Anselin 1988). The traditional approach is to estimate a non-spatial model, test for spatial dependence resulting from either an omitted spatial lag or spatially autoregressive errors, and then, if necessary, specify and estimate the relevant spatial model. Lagrange multiplier tests, including robust tests (Anselin 1996) for spatial error (lag) that are robust to the model misspecification of a spatial lag (error), are a standard approach to specification testing. Although the spatial lag (SAR) and spatial autoregressive error (SEM) regression models are the most commonly used, a variety of other model specifications that use the exogenously defined spatial weights matrix $\boldsymbol{W}$ have also been implemented, e.g., the spatial error components model, spatial moving average specifications and the spatial common factors (or spatial Durbin) model and SAR models with higher ordered lags (see Anselin and Bera 1998 for further discussion). A variety of additional specification tests have also been developed to guide specification of these models, e.g., extensions to the LM tests to test for misspecification of functional form and spatial error autocorrelation (Baltagi and Li 2001) and tests for different types of spatial error autocorrelation (Anselin and Moreno 2003). Florax et al. (2004) discuss and evaluate the performance of various approaches to model specification.

Maximum likelihood is the conventional estimation method and remains popular, but advances in other estimation techniques have proven quite valuable. Generalized method of moments (GMM) estimators have made it possible to dispense with normality and independence assumptions and also ease estimation of complicated data sets compared to maximum likelihood. The computational difficulty of calculating the log-determinant of the matrix $(\mathbf{I}_n - \rho\mathbf{W})$ increases quickly as the number of observations grows and the weight matrix increases in complexity. Bell and Bockstael (2000) show that parameter estimates from the spatial GMM estimator introduced by Kelejian and Prucha (1999) are less sensitive to specification of the weight matrix with large micro-level data sets. Conley (1999) introduces a nonparametric GMM estimation approach for spatial dependence that is robust to measurement errors.

The flexibility provided by GMM is particularly valuable for overcoming some of the challenges that arise in spatial versions of discrete choice models, which are common in spatially disaggregate land use models. Until the implementation of GMM and other estimation techniques, estimation of spatial discrete choice models was severely hampered by the computational challenge presented by the multidimensional integration necessary to evaluate the discrete choice likelihood function (although see Case (1992) and McMillen (1992) for alternative specifications of the spatial dependence that enable consistent estimation of binary probit models). In contrast to continuous dependent variable models, spatial error autocorrelation in a discrete choice model results in inconsistent estimates due to the heteroskedasticity implied by the spatial error structure. Pinkse and Slade (1998) and Fleming (2004) apply GMM to develop consistent estimators of spatial error correlation for binary probit models.

Bayesian models with Markov chain Monte Carlo estimation are also useful for estimating models that would be very difficult computationally with maximum likelihood. Bayesian techniques have been used to estimate a spatial latent variable model that accounts for the nonzero off-diagonal elements of the covariance matrix while avoiding the problem of multidimensional integration. This provides a computationally feasible approach to obtaining consistent and efficient estimates of the spatial probit model (e.g., LeSage 2000; Smith and LeSage 2004). Hepple (2004) provides a useful discussion of model selection when using a Bayesian approach. In addition, hierarchical models have been used to overcome a number of computational difficulties that arise when estimating discrete choice models in a Bayesian framework (Holloway et al. 2007; Banerjee et al. 2004).

Structural modeling of latent variables is another area of active research in which the goal is to relax one or more of the restrictions imposed by the traditional SAR and related models. Folmer and Oud (2008) propose a class of structural equation models that use latent variables. This approach removes some of the inflexibility inherent in a spatial weight matrix applied to either lagged dependent variables or the disturbances. Rather than regressing the dependent variable on a function of the spatially weighted lag of itself, an observed latent variable for neighboring spatial units is used. Folmer and Oud (2008) use this approach to allow for a richer consideration of the possible forms that spillovers can take.

As in other areas of econometrics, panel data models hold great promise for identification in spatial models since observations across time allow for changes in spatial effects in one period to affect decisions in another period. Such space-time dependencies are not uncommon, e.g., there are natural rigidities in housing markets that cause temporal lags in responses. Elhorst (2003) emphasizes two complications with extending a non-spatial model to include spatial effects. First, a change in location i in period t can affect behavior in location j in period $t+n$, which can lead to a complicated error structure. Second, the prospect of parameters varying over time *and* space is daunting, but only capturing average effects may be unsatisfactory (Fotheringham et al. 1997). For a recent comprehensive review of spatial panel models, see Elhorst (2010).

The success of the SAR, SEM and related models is striking. Since the mid-1990's, hundreds of papers applying these models to a variety of spatial problems have been published in a wide-ranging set of academic journals (e.g., for partial reviews, see Florax and van der List 2003; Anselin 2002, 2007, 2010; Arbia and Fingleton 2008). This marked uptake in spatial regression modeling has been greatly facilitated by the availability of easy-to-use software for spatial data exploratory analysis and ML estimation of these basic models, e.g., the GeoDa software package, as well as the open source code for the statistical package *R* (see Bivand 2010 for a review) and ® Matlab spatial econometrics toolboxes, such as those developed by LeSage (1999) and Pace and colleagues (Pace and Barry 1998).

The specification of spatial econometric models using an exogenously imposed $\boldsymbol{W}$ to reduce the estimable spatial structure to one or several unknown multiplicative spatial coefficients is admittedly highly restrictive. A recent review by Pinkse and Slade (2010) emphasizes the exceedingly complex nature of spatial problems relative to the simplified spatial structure as represented by SAR and other specification of the $\rho\boldsymbol{W}$ spatial lag model. While they do not outright reject the these models, they argue vigorously that, rather than applying standard reduced form spatial autocorrelation models to a wide variety of economic problems, one should start first with the particular economic question and characteristics of the data and then derive an econometric model using restrictions based on current theoretical methods that are appropriate for the given application. From this vantage point, SAR and other such pre-specified models are justified only if the underlying structural model leads to a functional form in which the true spatial interaction is represented by $\rho\boldsymbol{Wy}$.

While some type of structure is unavoidable when the goal is to identify spatial interactions, the same cannot be said of spatial econometric models that attempt to identify one or more spatial error autocorrelation parameters by applying structure to the error term using $\boldsymbol{W}$ (as is done in spatial error models and as is sometimes done to motive a spatial lag specification, e.g., see Anselin and Bera 1998). In this case, there is no way of knowing that the structure imposed by any exogenously defined $\boldsymbol{W}$ is in fact the true model and thus it is impossible to conclude whether the model is correctly specified. The best one can do is to investigate the robustness of the results to different $\boldsymbol{W}$ assumptions, implying that these models of spatial error autocorrelation are useful only for descriptive purposes and specification testing (McMillen 2010).

3.2 Other Econometric Spatial Models

Other approaches to spatial modeling in econometrics have evolved alongside the development of spatial regression models. In many cases, researchers using spatial data are fully aware of the challenges posed by spatial data, but, given the pitfalls of model misspecification, are unwilling to impose excessive structure on the data to achieve identification. In other cases, computational limitations have led to alternative approaches to spatial model specification. Given the increasing availability of spatial micro data, relying exclusively on functional form assumptions for identification may often be overly restrictive. Data that are commensurate with the scale of the underlying economic process (e.g., data on individual households and firms) open the door to more flexible estimation approaches. For example, Florax and van der List (2003) advocate direct representation models that are common in geostatistics (Cressie 1993), in which distance decay functions are estimated rather than exogenously parameterized. Alternatively, it may be possible to collect auxiliary data to guide specification of the spatial structure of interactions. For example, Conley and Udry (2010) go to great lengths to collect intricate details of interactions, including discussions of production practices, among neighboring pineapple farmers in Ghana and use these data to create a more refined set of neighborhoods. They then estimate a microeconomic model of technology spillovers based on social learning.

When the goal is to identify a spatial lag, or more generally the effect of any endogenous spatial variable, instrumental variable estimation is often possible. Indeed, Pinkse and Slade (2010) argue that a distinct advantage of spatial data over $i.i.d.$ data is the availability of instruments. It is common, for example, to use spatially lagged explanatory variables as an instrument for a spatially lagged dependent variable. Nonetheless, missing spatially correlated variables are a ubiquitous problem and thus it may be difficult to find spatial instrumental variables that are truly orthogonal to the error term. In such cases, partial identification may be possible, e.g., by identifying the upper or lower bound of a spatial lag parameter. Given the natural positive correlation of spatial data, estimates of spatial lags that control for endogeneity, but not for omitted spatially correlated variables, will be biased upward and therefore provide an upper bound estimate of the spatial lag parameter. Thus the effect is only identified if the estimated spatial lag parameter is negative. This is analogous to the case of negative duration bias that results in duration models in the presence of unobserved individual heterogeneity, which the duration dependence is identified only if the estimated duration dependence parameter is positive (Heckman and Singer 1982).

The goal of spatial modeling is not always the identification of spatial interactions, but instead consistent and efficient parameter estimates that are robust to model misspecification and unobserved spatially correlated variables. McMillen (2010) expresses the importance of more flexible approaches that can complement the SAR, SEM and other conventional spatial econometric models in assessing model robustness. Given that the true spatial structure is unknown and thus obtaining consistent, efficient estimates of a known model structure is virtually impossible, he argues that spatial econometric models should be largely viewed as just another tool to guide the model specification. Nonparametric and semiparametric approaches, including spline functions, Fourier analysis, locally weighted regression (LWR), and kernel estimation, are additional methods that should also be used to investigate the robustness of alternative model specifications. Such methods can also be used to provide reliable estimates of predicted values of the dependent variable and the marginal effects of explanatory variables. He provides examples of several flexible estimation approaches.

In cases in which the focus is on a specific spatial effect rather than a full structural model, quasi-experimental techniques can sometimes be usefully applied. By removing or at least reducing the unobserved spatial correlation that can otherwise bias results, these methods provide the potential for isolating a specific causal effect without imposing undue structure on the data. For example, Black (1999) uses a regression discontinuity design to isolate the effect of school quality on housing prices by comparing housing prices on either side of school district boundaries. By limiting the sample to observations that are very close to the boundary, she effectively controls for the effect of unobserved correlated variables. McMillen (2010) views such boundary estimators designed to identify average treatment effects as a useful approach to measuring average treatment effects in the presence of omitted spatial variables that could otherwise severely bias the estimation. He draws the comparison between this and nonparametric estimation in the sense that each seek to minimize the effects of unobserved spatial correlation by comparing predicted values from a narrow window of observations.

4 Advances in Spatial Modeling of Land Markets and Land Use

A variety of modeling approaches have been used in recent years to study the spatial relationships embedded in land markets and land use processes. In some cases, SAR, SEM or other models that exogenously impose some form of a $\boldsymbol{W}$ spatial structure have been usefully applied to examine these spatial dependencies. In other cases, alternative estimation approaches have been used in an attempt to identify the spatial data structure or spatial effects without imposing the full structure of traditional spatial econometric models or in cases in which estimation of the spatial model is computationally difficult. Here we highlight examples of various modeling approaches in recent applications to modeling housing markets and rural and urban land use change that have been developed by regional scientists and applied economists alike.

4.1 Spatial Hedonic Models of Housing and Land Markets

The spatial variant of the hedonic model, which estimates the price of a good as a function of its attributes, was first considered by Dubin (1992) and Can (1990). In the last ten years spatial hedonic models have been applied widely and have developed substantially in terms of methods. Here we highlight important methodological advances and reference relevant studies that have used such approaches in an environmental application.[2]

A standard hedonic model incorporating locational amenities begins by assuming utility is a function of a composite good x, environmental amenities q, a vector of structural characteristics $\boldsymbol{S}$, a vector of neighborhood characteristics $\boldsymbol{N}$, and a vector of locational characteristics $\boldsymbol{L}$, where the individual or household seeks to maximize their utility subject to an income (M) constraint and given housing price P:

[2] For a recent extensive review of spatial hedonic models, see Anselin and Lozano-Gracia (2009).

$$Max\ U\ (x, q, \boldsymbol{S}, \boldsymbol{N}, \boldsymbol{L})\ s.t.M = P + x \tag{3}$$

Because preferences are assumed to be weakly separable, first order conditions derive the marginal willingness-to-pay,

$$\frac{\partial U/\partial q}{\partial U/\partial x} = \frac{\partial P}{\partial q} \tag{4}$$

Parameters from the estimated regression that assumes housing price is some function of characteristics, $P = P\ (q, \boldsymbol{S}, \boldsymbol{N}, \boldsymbol{L})$, are the marginal prices for the relevant characteristic. Options for functional forms include linear, log-linear, log-log, and Box-Cox.

Methodological approaches to spatial hedonic models have progressed steadily in their treatment of spatial heterogeneity and dependence. Early studies took advantage of advances in GIS to generate variables that capture characteristics of the landscape neighboring a location that otherwise would have been omitted. Geoghegan et al. (1997) create spatial indices that measure neighboring land use that are used to test hypotheses about the presence of land use externalities in housing markets.

Subsequently, a rapidly growing list of studies employed a spatial weights matrix approach to estimate SAR and SEM variants of hedonic models. $\boldsymbol{W}$ has taken on a variety of forms based on both continuous and discrete measures of distance. Identical to a non-spatial hedonic model, the marginal implicit price for the characteristic k in an SEM model is β_k. Leggett and Bockstael (2000) were among the first in environmental economics to use a spatial weight matrix to estimate a spatial error hedonic model to account for autocorrelated errors and proximity to polluted water.

The coefficient is *not* the marginal implicit price when there are spatial interactions. Writing the SAR hedonic model as $\boldsymbol{P} = [\boldsymbol{I} - \rho \boldsymbol{W}]^{-1} \boldsymbol{X\beta} + \boldsymbol{u}$ where $\boldsymbol{X}$ is the vector of variables in (3) and $\boldsymbol{\beta}$ is a vector coefficients (all other variables are as described earlier), the marginal value is equal to $\boldsymbol{\beta}\ [\boldsymbol{I} - \rho \boldsymbol{W}]^{-1}$ (Kim et al. 2003). The intuition is that the price of a house is affected by a change in the amenity level in its location *and* the total of the effect of changes in the amenity in other areas. Written for a house in location $i = 1$, this can be written as $\sum_{i=2}^{n} \partial P_1/\partial q_i$, which comes from summing across a row of the Jacobian matrix of the hedonic price function. The implication is that a non-spatial hedonic model will underestimate the welfare effects of an increase in the supply of an environmental amenity. Small and Steimetz (2006) provide an argument for only having to consider these indirect effects in specific cases. One of the more popular applications of SAR hedonic models for valuing environmental amenities has been air quality (e.g., Ready and Abdalla 2005; Herriges et al. 2005; Kim and Goldsmith 2009). Kim et al. (2003) use both SEM and SAR hedonic models to estimate the marginal value of air quality improvements in Seoul, South Korea. They find evidence of spillovers from changes in air quality between neighborhoods.

While spatial hedonic models are most commonly used to consider marginal valuations for the increase of an environmental good, they can also look at removing an environmental bad. For example, Brasington and Hite (2005) look at the effect of removing a negative environmental amenity on house prices. What makes environmental hazards interesting is that policy makers often want to know the non-marginal value of completely removing them. Estimating the second stage hedonic regression to derive the inverse demand function makes this theoretically possible. However, there are often significant obstacles to doing this correctly, which is why it is rarely done in practice. Environmental and urban economists have used household locational equilibrium models to estimate the structural parameters of a sorting equilibrium for a given distribution of environmental amenities. These estimates can then be used to predict the new equilibrium given a non-marginal change in an environmental amenity and thus provide an economic structural approach to non-marginal valuation of locational amenities (Bayer et al. 2009; Bayer and Timmins 2007; Sieg et al. 2004; Klaiber and Phaneuf 2010; Walsh 2007).

Anselin and Le Gallo (2006) propose an alternative where a simulation approach is used that involves computing predicted values for each individual household that can then be aggregated however the researcher decides. They describe this as being a discrete approximation of marginal willingness-to-pay. Environmental applications often must interpolate to create a surface of values capturing amenity levels for every location. Anselin and Le Gallo (2006) warn against ignoring the sensitivity of results to choices of interpolation methods. Comparing a number of different approaches they find kriging to be preferable. Hoshino and Kuriyama (2010) use a kriging approach to measure the effect of urban parks on house prices in Japan.

There are opportunities to be more creative in thinking about how environmental amenities are consumed by households. For example, Cavailhes et al. (2009) combine elevation data with amenity and house location to determine whether the amenity is actually visible from a given location. They find that the direction and magnitude of the effect of a (dis)amenity depends on whether it can be seen.

With spatially explicit data the degree of disaggregation often gets the lion's share of attention. However, as Schmidt and Courant (2006) show, deeper thinking about the spatial extent of the relevant system can be just as important. Using estimates of compensating differentials in housing prices and wages to value locational amenities, they examine the spatial extent over which environmental amenities influence housing values. They show that high value amenities, like national parks, that are hundreds of miles from a metropolitan area are positively associated with housing values. Given that households choose metropolitan areas that are proximate to these large scale open spaces, they argue that methods of valuing environmental amenities like the travel cost method are likely to underestimate the value of open space since households have shortened their travel distance through location choice.

Other approaches to modeling spatial effects in hedonic models include locally weighted regression models (LWR), where spatial heterogeneity is addressed by using the data, and proximity measures as weights, to estimate the variability of parameters spatially. Cho et al. (2006) and Farber and Yeates (2006) provide applications of GWR, These approaches are compared with geographically weighted regression (GWR), a variant of LWR, to spatial hedonic models. McMillen (2003) applies a Fourier expansion method to a model of repeat house sales. Páez et al. (2008) provide a comparison of the performance of GWR against two alternatives, moving windows regression and moving windows kriging.

Quasi-experimental techniques have proven to be effective at addressing the endogeneity biases that arises from problems of sample selection and unobserved spatial variables that hinder identification of policy and other spatial effects. For example, the issue of endogenous zoning and selection bias in this setting was further investigated by McMillen and McDonald (1989, 1991). These researchers used a sample selection approach to correct for the endogeneity bias that arises due to the simultaneity between land values and land use zoning. Recent work has made use of matching methods (e.g. Heckman et al. 1998), which address the sample selection problem by providing a means of linking treated observations (in this case, zoned parcels of land) with untreated counterfactuals (unzoned parcels of land) and estimating an average treatment effect. McMillen and McDonald (2002) provide one of the first applications of matching in the land use policy literature with their investigation of how endogenous residential zoning influenced land values in the early 20th century in Chicago.

Carrion-Flores and Irwin (2010) use a different type of natural experiment to identify the influence of spatial land use spillovers on housing values. They take advantage of exogenous physical soil boundaries that impose a direct constraint on residential development on some, but not all, of the land that falls within their study region and use this natural discontinuity in the data to identify the presence of land use spillover effects using a partial population identification strategy. They find that this approach solves the endogeneity problem and reduces spatial error autocorrelation and that estimation using a more restricted sample in combination with the partial population identification strategy is successful in eliminating residual spatial error autocorrelation. In comparison, results from a fully specified spatial error model (SEM) parameterized with an exogenously defined $\boldsymbol{W}$ mask the spatial interactions and lead to very different conclusions about the spatial structure of the data.

4.2 Spatial Models of Land Use and Land Use Change

Spatial econometric models have been usefully applied by regional scientists and geographers, as well as by agricultural, environmental and urban economists, to gain a better understanding of the spatial relationships that are embedded in patterns and determinants of land use and land use change. A host of spatially explicit econometric models have demonstrated the utility of using spatial microdata to better identify the direct and indirect effects of spatially explicit variables, including spatial interactions and spatially differentiated policies (see Irwin et al. 2009 and Irwin 2010 for partial reviews). Here we omit a much broader discussion of land use models that have used spatially explicit data and instead focus on selected examples of econometric models designed explicitly to address specification and parameter identification of spatial effects in models of land use change.

Because land use is most often characterized as a categorical variable, estimation of land use and land use change models using microdata typically necessitates a discrete choice framework. This was traditionally quite difficult because of the multi-dimensionality of the likelihood function and the computational challenges that this imposes on evaluation the likelihood function. Nelson and Hellerstein (1997) provide one of the earliest attempts at controlling for spatial error dependence in a discrete choice model of deforestation. They use spatially lagged explanatory variables and a spatial sampling strategy, in which observations are randomly selected and their nearest neighbors then dropped in an attempt to minimize problems of spatial error autocorrelation. This approach implicitly results in a conditional versus simultaneous specification of the problem, in which the results are conditional on given neighboring values (Anselin and Bera 1998). Other discrete choice models of categorical land conversion have used this technique to reduce problems of spatial error autocorrelation (e.g., Carrion-Flores and Irwin 2004; Munroe et al. 2002) and have found this “workaround” to be effective at minimizing spatial dependence, but that results are not always robust to the sampling routines. Robertson et al. (2009) investigate the ability of this and other specification strategies to improve model prediction in discrete choice models with different types of spatial effects. In terms of prediction of categorical land use outcomes, they find that inclusion of spatially lagged explanatory variables performs somewhat better than other strategies.

Parker and Munroe (2007) investigate the effect of negative spatial externalities from traditional farms, in the form of herbicides and cross-pollination from hybrid seeds, on the probability that a farm is certified as organic in the Central Valley of California. To account for spatial autocorrelation, they apply the non-linear generalized least squares GMM estimator developed by Fleming (2004) that returns a consistent, but inefficient, estimate of the spatial lag parameter. This technique is computationally simpler since allows for the estimation of the spatially autoregressive parameter without having to compute the Jacobian of the spatial covariance matrix. This avoids the problem of multidimensional integration, but at the cost of generating an inefficient estimate of the spatial lag parameter.

Holloway et al. (2002) provide one of the first applications of Bayesian MCMC techniques to spatial modeling of land use in a spatial lag model of farmer adoption of a particular crop choice. Two recent contributions published in a special issue of *Papers in Regiaonl Science,* dedicated to spatial analysis of economic systems and land use change, adopt Bayesian simulation techniques to estimate spatial probit models of land use change. Chakir and Parent (2009) use MCMC techniques to estimate a spatial multinomial probit model that accounts for both spatial dependence and interdependence among land use choice alternatives. Unobserved factors that influence the profits of landowners are separated into an individual component, which is taken to be conditionally independent, and spatial effects generated by the spillovers among neighboring land parcels. They apply this model to data on land use transitions in the Rhône region of France from 1992 to 2003 and find strong evidence of spatial dependence. Wang and Kockelman (2009) also use MCMC techniques to estimate a dynamic spatial ordered probit model using satellite land cover data that is defined at a resolution of 300 m x 300 m. This modeling approach allows them to test for, and in the end find, temporal and spatial autocorrelation.

Spatial modeling approaches that avoid the imposition of the $\boldsymbol{W}$ structure have also been usefully applied to identifying spatial effects in categorical models of land use conversion. Irwin and Bockstael (2002) provide an example of a bounding strategy applied to the estimation of spatial land use interactions among neighboring landowners. Because unobserved spatial variables are positively spatially correlated, the spatial interaction effect will be biased in a positive direction and thus the direction of the spatial interaction effect is identified only if the estimated effect is negative. Using a semiparametric duration model to estimate the hazard rate of residential subdivision development, they find evidence of negative spatial interaction effects among undeveloped parcels that were eligible for residential subdivision and show that this effect contributed substantially to the sprawl pattern of development in their exurban Maryland study region.

Other flexible estimation methods that allow for unobserved sources of spatial heterogeneity include the random parameters logit (RPL or mixed logit) model, which generalizes the standard logit by allowing parameters to take on different values for different parcels. Newburn and Berck (2006) apply a RPL model to a categorical model of land development to account for heterogeneity across land parcels in compliance with maximum-density development restrictions. Similarly, Lewis et al. (2010) use this model to account for unobserved spatial and temporal components of the landowner's willingness-to-pay function that is estimated using both plot-level data on land characteristics and county-level estimates on the net revenues of alternative land uses. Using National Resource Inventory (NRI) panel data on repeated plot-level observations, they are able to control for unobserved correlations at the county level as well as serially correlated unobservables at the plot level.

Matching and other quasi-experimental methods have been shown to be useful in controlling for missing spatial variables and isolating the effects of spatially explicit land use regulations on the timing and location of land development. Bento et al. (2007) used propensity score matching methods to estimate the effect of an adequate public facilities ordinance on new housing construction in Howard County, Maryland. This policy is designed to temporarily slow growth until additional public facilities (e.g., schools, roads, etc.) can be provided. The findings showed that this policy was effective in reducing new housing in the first two years following the moratoria. Using residential subdivision data for the same county, Towe

(2010) also uses propensity score matching to investigate the spatial spillovers of agricultural land preservation on the timing of residential development. He finds large, non-marginal effects associated with neighboring farmland preservation that attracted residential development and accelerated land development around these preserved parcels. Lynch and Liu (2007) use this same technique to evaluate the consequences of a rural land preservation program (the Rural Legacy program) in Maryland. Their findings showed that this program did indeed lead to more preserved land in the targeted areas, but failed to reduce new development in those areas.

5 Improving Spatial Economic Models of Land Use Dynamics

While researchers working in different areas are likely to have their own set of priorities, we believe that a critical and yet unmet need is the development of economic models that facilitate the study of spatial land use dynamics. There are at least two specific modeling needs in this regard: (i) better spatial micro data and spatial models that can reveal the microeconomic foundations of land use change and (ii) methods that can better represent spatial dynamics and coupled interactions of economic and ecological systems across multiple spatial and temporal scales.

5.1 Microeconomic Foundations of Land Use Change

Econometric models of land use change posit an underlying structural model of economic decision making, but typically are unable to fully recover these structural parameters. As a result, these models provide evidence regarding the spatial relationships exhibited in the pattern outcomes, but not of the spatial economic mechanisms that underlie these patterns. Dynamic modeling of land use change requires a structural approach that goes beyond reduced-form models to a a more fully structural approach that can recover the parameters of the underlying economic mechanisms (decisions, constraints, feedbacks) that give rise to land use changes. Such an approach is necessary for the evaluation of welfare given non-marginal changes in environmental amenities or other locational attributes (Timmins and Schlenker 2009).

If one of the ultimate goals of economic modeling is to inform policy, then improved understanding of these microeconomic processes is critical. One policy question that brings these issues to light is the impending retirement of the large cohort of baby boomers. There is evidence that preferences for particular amenities change throughout the lifecycle (Chen and Rosenthal 2008). Is there are particular amenity that will be in high demand as workers retire and gain greater geographic flexibility now that they are no longer have to consider wage tradeoffs? In developing countries large portions of the population are now just reaching adulthood. What will be the locational and amenity preferences of the new middle class of young adults in India and how will this shape the growth of cities in that part of the world? What are the implications for resource use?

Our ability to develop spatial land use models with more explicit microeconomic foundations depends heavily on the increased availability of spatial data on firms and households (Irwin et al. 2009; Bell and Dalton 2007). However, there are a number of challenges in making this happen. Much of the spatially explicit data that resulted in the explosion of spatial land use modeling was, essentially, manna from heaven. The data was created for other purposes but happened to be useful for economic analysis. Creating spatial data sets that can test more refined micro level models is likely to require a considerable increase in thought, effort, and resources. The effort to gather the data on information sharing in the paper by Conley and Udry (2010) is a good example. The dearth of spatial micro data on firms explains why the theoretical literature on agglomeration has a long history (Marshall 1890), but actual empirical estimation remains limited (Puga 2010). While observed outcomes seem to correspond strongly with model predictions, measurement of the underlying causes of agglomeration is rare. An exception is Ellison et al. (2010), who take advantage of detailed firm level production data that is combined with various spatial data. Firm locations are used to create co-agglomeration measures. They are only located to county or metropolitan area, but this is adequate for capturing effects like labor pooling, given typical commuting distances. Regional variation in industry characteristics is used to build instruments. As Puga (2010) explains in some detail, the most direct way to estimate agglomeration effects would be to look at systematic variation in productivity across space (Puga 2010). Clearly, the development of firm level production data with precise spatial information for heavy industry is paying dividends.

Compare this to agriculture, which is central to environmental and resource economics. Most large scale agriculture surveys that collect detailed information on firm structure only provide approximate measures of location. In contrast to the large industrial operations discussed above, most spatial interactions in agriculture require knowledge of either the point or, preferably, field boundaries. The Census of Agriculture and Agriculture Resource Management Survey, both administered by the USDA, are two examples. Remotely sensed land cover data provide field level crop covers but typically cannot inform on production practices. One exception is the USDA-NASS June Agricultural Survey (JAS). The JAS is national in scale and does combine georeferenced field level points with extensive information on production practices. However, it has received only limited use in research (Barnard et al. 1997; Schlenker et al. 2007). Whether or not better spatial information can be integrated into these surveys will depend in part on privacy concerns from producers. The USDA created the Common Land Unit (CLU) data layer to establish a complete set of field boundaries, the smallest land unit over which farm production decisions are made. However, due in part to a lawsuit, Section 1619 of the 2008 Farm Bill eliminated public access to the CLU.

In terms of households, parcel level property tax data has been increasingly used in land use modeling in the last 10-15 years and the impact has been extraordinary. However, these data omit information about households, e.g., income, race, presence of children, education, and other variables that we know influence demands for locational attributes. Current work in using locational equilibrium models to estimate the structural parameters of household location decisions provides a good example of the utility of spatially delineated household micro data. By matching individual housing transaction sales with individual-level data on race, income, and gender, Bayer et al. (2010) are able to tract the buy-sell decisions of selected households in their San Francisco study region, which allows them to estimate a dynamic microeconomic model of demand for houses and neighborhoods.

While the strength of these and other microeconomic structural models is their focus on the microeconomic foundations of firm and household interaction processes, many of these models could do more to incorporate additional spatial effects, particularly at finer spatial scales. Household interactions, for example, are typically captured at an aggregate scale, e.g., with aggregate measures of population density (e.g., Bayer and Timmins 2007). We see great utility in the development and application of spatial models that can account more explicitly for these interactions in space. Doing so requires not only spatial micro data, but spatial micro data on the characteristics, decisions and interactions of households and firms. Researchers and granting agencies should think longer term about efforts to collect microeconomic data

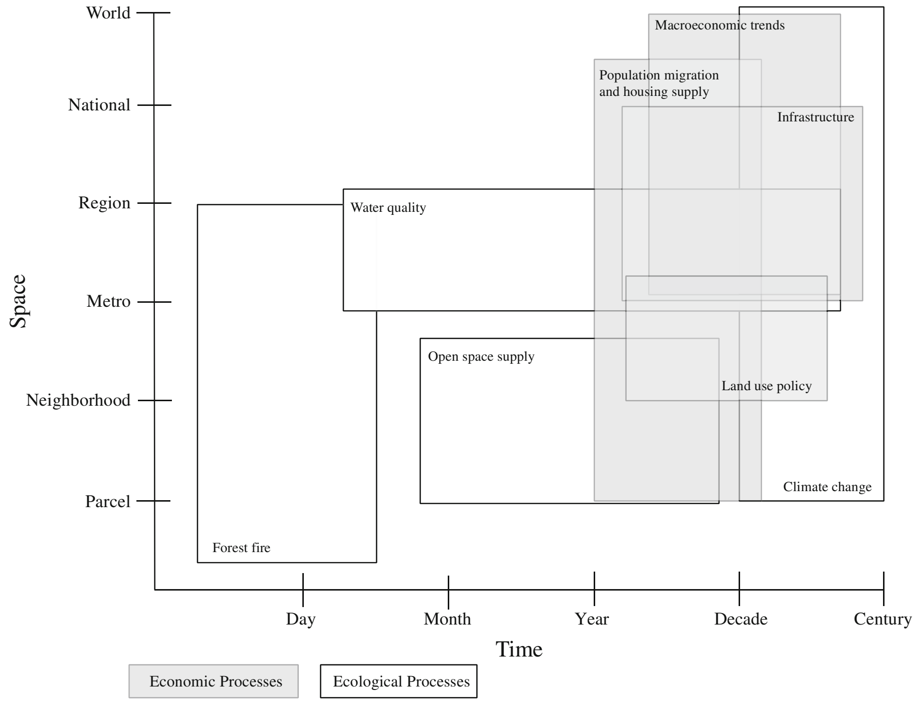

Fig. 1 Spatial and temporal dimensions of economic and ecological processes related to land use change

on firms and households that is expressly designed to model spatial effects. A useful precedent is the impact that longitudinal surveys had in turning labor economics from a fairly narrowly defined field into one that has produced many of the most important methodological advances in econometrics that have been applied to a wide array of applications.

5.2 Modeling Coupled Ecological-Economic Systems

Econometric spatial models have significantly improved the ability of environmental economists to understand how human driven land use change affects, and is affected, by a number of ecological factors, from environmental amenities to biophysical constraints. The early literature has progressed from using simple measures of neighboring land use to modeling the effect of development patterns on habitat fragmentation (Lewis and Plantinga 2007). More recently, greater consideration of biological and spatial complexity has been incorporated into land conservation models that seek to identify an optimal spatial arrangement of land use that maximizes ecological benefits, such as species and habitat conservation (Lewis et al. 2009; Nelson et al. 2008; Newburn and Berck 2006). These and other studies use a spatially explicit econometric model to estimate the reduced form parameters of a model of rural landowners' land use and conservation decisions and then use these estimated parameters to simulate conservation outcomes under alternative policy scenarios. While the modeling approach is rigorous and the results have generated useful insights, these models do not recover all the structural parameters of the decision making processes and thus are unable to fully model land use dynamics (Irwin 2010).

Finding ways to better represent the full scale and complexity of biophysical systems and the range of interactions among ecological and economic systems is an important challenge going forward. This is no small task. Figure 1 shows the relevant spatial and temporal extents for a common set of economic and ecological processes. Clearly the temporal and spatial scales vary depending on the process and, because both economic and ecological processes interact across scales, consideration of multiple scales and feedbacks across these scales is necessary. Such cross-scale interactions are common within economic systems, e.g., individual household choices that aggregate up to determine spatial migration flows and other aggregates, which in turn generate feedbacks that influence individual choices. These coupled linkages also occur across ecological and economic systems. For example, amenity-driven migration can degrade the very ecological resources that are valued as amenities; endogenous policy responses to protect degraded resources can induce greater demand for the resource. Spatial spillovers, e.g., in the demand for amenities across regions, and temporal lags that allow feedbacks to accumulate over time, are additional dynamics not depicted explicitly in Fig. 1 that, in addition to the multiple scales and interactions across scales, imply a tremendous amount of spatial and temporal complexity in the processes that underlie land use change.

Integrating richer representations of ecological systems into spatial economic models of land use change is important for a number of reasons. First, it is necessary to more accurately model land use change where there are feedbacks between human and environmental systems. In many cases, these feedbacks are spatially explicit because ecological functioning and the provisioning of ecosystem services are often spatially explicit. Second, policy for addressing environmental externalities should consider how to link to the human system that is the source of the externality to the affected environmental system to provide incentives to curb environmental damage to close the market failure. Third, as discussed above, multi-scale land use interactions can create complex dynamic paths through interactions that occur at different levels.

Within environmental and resource economics, bioeconomic models of fisheries have made important advances in considering greater complexity of spatial dynamics within economic models of decision making (see Smith et al. 2009 for a recent review). An alternative approach that has been pursued largely by geographers, as well as a few but growing number of economists, are agent-based models in which market trades and non-market interactions among heterogeneous agents (e.g., households, firms, land developers, landowners) are explicitly modeled. Rather than studying the long run steady state equilibrium or equilibria of the system, the focus is on the transitional dynamics that arise from individual-level decisions and interactions and the emergence of complex dynamics, including thresholds and other non-linearities. A key departure of agent-based economic models is the lack of any aggregate equilibrium constraints to close the model in a conventional way: given the initial specifications of the economic system, which may include detailed information about the institutional arrangements, initial number and types of consumers and firms, their endowments and behavioral rules, etc., agents carry out trades and other individual decisions. The transitional dynamics are driven solely by agent interactions (e.g., trades, externalities), which are modeled using computational methods that simulate these individual interactions across a simulated landscape. This approach has been applied to modeling spatial land use dynamics with ecological feedbacks. While agent-based models have often lacked economic fundamentals, promising work on agent-based models of land markets that model endogenous prices has begun (e.g., Filatova et al. 2009; Magliocca et al. 2009; Chen et al. 2010).[3] Work on empirically specifying these models is underway (e.g., see Brown et al. 2008 for an example and Robinson et al. 2007 for a discussion of empirical methods applied to agent based models), but more work is needed. Towards this end, we see great utility in using some of the spatial econometric modeling approaches discussed here to quantify spatial structure and space-time relationships, specify functional forms and identify the relevant ranges of key parameter values.

6 Conclusions

Spatial econometric models, including SAR, SEM, and their panel data and discrete choice counterparts, have been usefully applied to modeling land markets and land use change. In addition, more flexible approaches that either loosen the spatial structure imposed by $\boldsymbol{W}$ or take a different approach to modeling spatial dependence have provided important insights as well. Taken together, these models and methods have greatly benefited the empirical investigation of spatial effects in econometric models of land markets and land use change. Looking forward, we see a multiplicity of approaches emerging as more fully structural and dynamic models are developed. Significant progress in firm and household location choice modeling has come from combining spatial data on location and land use with spatially explicit data on the underlying economic mechanisms, including the individual firms and households themselves. These models demonstrate the benefits of richer spatial microeconomic data sets, something that we view as critical to the further development of structural models of land use. New spatial simulation models, including agent-based models, provide a means of representing complex dynamics and heterogeneity that characterize land use processes, but more work is needed in combining these powerful new computational methods with empirical methods to guide model specification. Taken together, the combination of these various modeling approaches are sure to produce exciting advances as well as new challenges in the further development of spatial economic models of land use.

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[3] See Parker et al. (2003) for a review of agent-based land use modeling. See Irwin (2010) for a discussion of the advantages and challenges of this using this approach to develop spatial dynamic models of land use in economics. See Parker and Filatova (2010) for an extensive discussion of the challenges that arise in agent-based models of land markets.

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