Spatial Econometric Issues for Bio-Economic and Land-Use Modeling

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SPATIAL ECONOMETRIC ISSUES FOR BIO-ECONOMIC AND LAND-USE MODELING

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Abstract

We survey the literature on spatial bio-economic and land-use modelling and review thematic developments. Unobserved site-specific heterogeneity is common in almost all of the surveyed works. Heterogeneity appears also to be a significant catalyst engendering significant methodological innovation. To better equip prototypes to adequately incorporate heterogeneity, we consider a smorgasbord of extensions. We highlight some problems arising with their application; provide Bayesian solutions to some; and conjecture solutions for others. (70 words)

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1. Introduction

The objectives of this paper are three. First, we survey recent literature using spatial econometric techniques, with emphases on bio-economic and land-use modelling. Second, we highlight thematic developments in the literature. Third, we discuss limitations and propose potentially fruitful directions for future research, focussing attentions on one issue that seems particularly problematic within this literature.

The start point for the investigation is the Special Issue of Agricultural Economics (2002). The goal of that Special Issue was “to introduce agricultural economists to new analytical approaches involving spatial data…” (Nelson, 2002, p.197). The papers reported there fall into two basic categories: those that explicitly use spatial econometric methods and those that use GIS techniques (broadly defined).[1] By and large, the spatial-econometric contributions in that Special Issue generate inferences in the context of a prototypical regression framework, which we represent symbolically as

$$\mathbf{z} = \rho\mathbf{W}\mathbf{z} + \mathbf{X}b + u\,,$$

$$u = \lambda\mathbf{W} + e\,, \qquad (1)$$

$$e \sim f^{MN}(e\,|\mathbf{0_N},\sigma^2\mathbf{I_N}),$$

where $\mathbf{z} \equiv (z_1, z_2, .., z_N)'$ denotes an N-vector of responses of interest; ρ depicts correlation across the responses; $\mathbf{W}$ denotes an N-dimensional spatial weight matrix; $\mathbf{X} \equiv (\mathbf{x}_1, \mathbf{x}_2, .., \mathbf{x}_N)'$, $\mathbf{x}_1 \equiv (x_{11}, x_{12}, .., x_{1K})'$, $\mathbf{x}_2 \equiv (x_{21}, x_{22}, .., x_{2K})'$, .., $\mathbf{x}_N \equiv (x_{N1}, x_{N2}, .., x_{NK})'$ denotes observations on the covariates; $b \equiv (\beta_1, \beta_2, .., \beta_K)'$ denotes the corresponding K-vector of response coefficients; $u \equiv (\upsilon_1, \upsilon_2, .., \upsilon_N)'$ denotes a N-vector of random disturbances; λ depicts correlation across the disturbances; $e \equiv (\varepsilon_1, \varepsilon_2, .., \varepsilon_N)'$ denotes another N-vector of random disturbances; and $f^{MN}(e\,|\mathbf{0_N},\sigma^2\mathbf{I_N})$ denotes the multivariate normal probability distribution function defined over the vector e, with mean $\mathbf{0_N}$ and covariance $\sigma^2\mathbf{I_N}$. In some contexts, the response variable $\mathbf{z}$ will be observed, in which case $\mathbf{z} \equiv \mathbf{y} \equiv (y_1, y_2, .., y_N)'$, an N-vector of observable quantities. In other contexts $\mathbf{z}$ will be latent and will relate in some way to the observed data $\mathbf{y}$. In either case, one feature of the setup in (1) that is fundamental to the analysis is that the indices defining the subunits in question, $\{i\}_{i=1}^{N}$, contain spatial information. The investigator observes data **X**, **W** and **y** and makes inferences about the unobserved parameters $q \equiv (b', \rho, \lambda, \sigma)'$.

The majority of the papers that we survey employ particular specializations of this setup and it is therefore useful to present it as a point of reference. For example, Holloway, Shankar and Rahman (2001) observe adoption behaviour among Bangladeshi rice producers using farm-level data. Parameter λ is constrained a priori to equal zero; parameter σ is constrained to equal one; the observed $\mathbf{y} \equiv (y_1, y_2, .., y_N)'$ are binary values, equalling one if the farmer adopted a high-yielding-variety rice technology and equalling zero otherwise; and the elements of **z** are latent responses constrained to be non-negative if adoption occurs and constrained to be negative otherwise.

Early work with spatial regression commenced with Cliff and Ord (1975). The methodological literature has witnessed many advances since then, with important collections of these advances in Anselin (1988, 1999, 2003) LeSage (1999, 2000, 2002) and Smith and LeSage (2004).

2. Environmental Resources, Forestry and Conservation

An early application of spatial regression techniques in ecology is Pinel-Alloul et al. (1988) who examine the effects of body size, depth, and sampling scale on the spatial heterogeneity of zooplankton in Lake Cromwell, Quebec, Canada. The importance of incorporating spatial information into statistical analyses of conservation biology is a recurrent theme in the literature re-emphasized by Carroll and Pearson (1999). Modern methodological advances, especially the Gibbs sampler and the advent of more general MCMC methods permit Hertzberg et al. (2000) to study the effects of spatial habitat configuration on recruitment growth and population structure of arctic Collembola. Their Bayesian methodology employs a finite-mixture distribution (Lavine and West, 1992; Diebolt and Robert, 1994) to model heterogeneity in densities of the species in question. Dennis et al. (2002) employ the Getis-Ord distance-statistic to calculate the smallest distance ensuring that each sample point of upland beetles has at least one neighbour. They make inferences about how patterns of habitat heterogeneity affect the distribution of representative ground and rove beetles sampled at an upland site of varied landform. The complex spatial heterogeneity of ecological systems is a common theme in the respective applications of Newbold and Eadie (2004), Polasky et al. (2005), Rangel et al. (2006) and Shi et al. (2006). These contributions are also linked by their overriding theme which is "predicting the probability of persistence of a species given a land-use pattern (Polasky et al., 2005)." Claessens et al. (2006) investigate the problem of incorporating spatial autocorrelation among a sample of kauri using logistic regression. They discover that thresholds are significant in explaining the age distribution and the geographic dispersion and ecology of the kauri species in the Waitakere ranges of New Zealand. Laband and Nieswiadomy (2006) also use spatial autocorrelation techniques to examine the impact of environmental and political factors affecting the risk of extinction of species in 49 US states. Finally, two contributions to the conservation literature deserving special mention are Newburn et al. (2006) and McPherson and Nieswiadomy (2005). In the former spatial autocorrelation techniques are used to derive inferences about targeting strategies for land conservation in the presence of heterogeneous land costs and heterogeneous probabilities of land-use conversion. In the latter, spatial autocorrelation techniques are applied on a global scale to measure the (Grossman and Krueger, 1995) conjecture of a Kuznets-type (approximately U-shaped) relationship between threatened bird and mammal species and the level of per-capita income in 113 countries at various stages of development. They find that significant spatial autocorrelation exists, with shocks spilling over, geographically, into neighbouring countries.

Heterogeneity is, again, an overriding theme in the conservation literature focused on genetic resources. Early work that is noteworthy for its methodological contributions are Epperson (1990) and Epperson (1993), both of which focus on the geographic distribution of genetic variation in plants. In the former a spatial-autorregressive regression (SAR) is used and in the latter a STAR (space-time autoregressive) model is employed. In Bjørnstad et al. (1995) population genetic drift and genetic mappings are assessed taking explicit account of the fact that both the genetic makeup and the environmental conditions of a population are spatially correlated. And in He et al. (2000)

spatial autocorrelation is used to study the spatial distribution of genotypes and gene frequencies at in three stands of the a tropical rainforestendangered perennial in Southwest China.

Contributions related to forestry can be broadly classified into two categories: those that employ a spatial regression model as the main focus of the work (Pattanayak and Butry, 2005; Mena et al., 2006) and those works (Roberts et al., 2000; Kohlin and Parks, 2001), in which the spatial regression is ancillary. The target focus is reducing rates of fragmentation and deforestation of naturally forested areas. Frequently, the deforestation rate is the observed dependent variable. With the exception of Mena et al. (2006), who use a spatial lag regression model, the SAR model predominates.

Kerr et al. (2003) employ classical and Bayesian spatial regression techniques to make predictions of land use and carbon storage on a large geographic and temporal scale. On a smaller scale, spatial correlation among heavy-metal contaminated soil sites is at issue in Schnabel and Tieje (2003). Kim et al. (2003) improve the methodology for estimating hedonic price functions in the presence of spatial dependence. They apply a spatial-hedonic housing-price model to the Seoul metropolitan area and measure the marginal value of improvements in concentrations of sulphur dioxide and nitrogen dioxide. Diagnostics suggest that the spatial-lag, rather than the spatial autocorrelation model, is preferred. Finally, an innovative methodology combing both the spatial lag and spatial aurotcorrelation models (as in (1) above) is presented in Atasoy et al. (2006). Using panel data they relate the density of residential development and the change in residential land use to three measures of water quality.

Deserving special attention is the contribution by Assunção (2003), which develops innovative alternatives to the traditional framework in (1), above. At issue is the notion that regression covariate coefficients may vary as they would in a traditional random-coefficients framework (Hildreth and Houck, 1968), with two peculiarities. First, the variation arises in response to variation in space. Second, the differences across regions is not discrete but, rather, varies smoothly as a function of the area location. The model is implemented using Gibbs and Metropolis-Hastings sampling and is highlighted in applications to the adoption of new technologies by Brazilian farmers; the diffusion of a zoonotic disease in Bel Horizonte, a large Brazilian metropolitan area; and the study of women's fertility statuses in Minas Gerais, a Brazilian state.

Additional works employing explicitly spatial statistical techniques are available from the survey articles Vaughn (1994), Bateman et al. (2002), Nilsson et al. (2003) and Batabayal and Nijkamp (2004).

3. Marine Resources

Recent contributions in marine resources were given impetus by the commissioning of a Special Issue devoted to Spatial Modelling in Fisheries Economics. The works presented there (Holland et al., 2004; Wilen, 2004; Holland, 2004; Sanchirico, 2004, Dalton and Ralston, 2004; Smith and Wilen, 2004; Hicks et al., 2004; Curtis and McConnell, 2004; and Strand, 2004) cover an eclectic range of issues, all related in some way to the spatial organization of marine resources. Topics include making use of increasingly abundant spatial information to enhance the efficiency of management of coastal fisheries; designing cost-effective marine reserves; analysing the effects of spatial closures in a fishery; enhancing realism in bio-economic models by endogenizing port choice; assessing the welfare losses arising from spa tial set asides; modelling fishermen's spatial decisions; and comparing estimates of fishermen's risk preferences between spatially aggregated and spatially disaggregated models. Five of the nine papers appearing in the Issue are inherently empirical, wit h formal econometric procedures being applied. Surprisingly, formal <u>spatial</u> econometric modelling of the type espoused in (1) is absent.

Another collection of papers devoted to Spatial Models in Fisheries Economics contains four papers devoted to the topic of developing formally spatial econometric models of fisheries. Mistiaen and Strand (2000) develop and test a short-run, expected-utility maximizing model of fishermen's location choices. Using the random-parameters logit model in their empirics, they are able to incorporate heterogeneity in risk preferences across subunits of the sample. Curtis and Hicks (2000) investigate the cost of area closures mandated by regulations designed to conserve sea turtle populations. Their empirical application is the Hawaiian pelagic longline fishery and they implement their site-choice analysis using the logit specification. Smith (2000) discusses aspects of modelling information processing by fishermen, including the choice between structural and reduced-form models, decay in information transmission during search, and complexities encountered in modelling spatial search and information sharing. Fleming (2000) emphasizes the significance of spatial heterogeneity in fisheries and compares the utility of discrete-choice models of fishermen's site preferences with alternative techniques. Once again, formal spatial econometric models of the type engendered in (1) are absent.

Of the remaining papers surveyed in this category, two (Sanchirico and Wilen, 2004; Sanchirico, 2005) are conceptual. Broadly speaking, they relate to the spatial management of renewable resources in general and the management of marine reserves in particular. In contrast, an additional two works are empirical and are deserving special attention. Smith (2002) presents two econometric approaches for predicting the spatial behaviour of renewable resource harvesters and assesses empirically spatial patterns of exploitation in the California sea urchin fishery. At issue is the desire to understand how the magnitude and the spatial distribution of fishing effort respond to biological, economic and oceanographic factors. Two models are investigated. One, which is macro in nature, and combines count-data and seemingly unrelated regression techniques; and another, which is micro in orientation, and employs discrete-choice techniques to model fishermen's site preferences. The macro-model, by its very structure, incorporates correlation across space; the micro-model, a nested-logit regression, does not. Significantly, in the context of present attentions, the former "outperforms" the latter (Smith, 2002, p. 524).

Finally, in this section, Su et al. (2004) present an innovative methodology for modelling stock recruitment of pink salmon in the Northeast Pacific ocean. Specifically, they model the number of adult recruits produced per spawner (the survival rate) from a specific stock in a given brood year. Their objective is to improve the understanding of the effects of environmental factors on spawner-to-recruit survival rates. For this purpose they construct alternative spatial hierarchical Bayesian models and compare them. Hierarchical modelling, which has roots in the early work of Lindley and Smith (1972) and is now commonplace in many fields, has, perhaps, enjoyed less frequent application in the bio-economic and agricultural-economic sciences. We conjecture that the Bayesian hierarchical methodology offers enormous scope for enhancing the dexterity with which to model spatial heterogeneity. In this regard, one important contribution of Su et al. (2004) is the introduction of distance-based, spatially-correlated prior distributions for stock-specific parameters. Significantly, they find that the spatial hierarchical Bayesian methodology produces more consistent and precise estimates of the effects of sea-surface-temperature on productivity than does a conventional single-stock approach.

4. Agricultural Resources and The Land

More than other categories, agricultural-resource and land studies witness the most intensive use of the prototypical spatial econometric structures. Examples include studies of the spatial organization of commodities (see, for examples Roe et al., 2002; Isik, 2002), in which the spatial lag model is employed, as well as studies of spatial relationships between commodity prices (see, for example, Florkowski and Sarmiento, 2005), in which the spatial autocorrelation model sees frequent employment. Beyond the studies examining the geographic make-up of industry, two collections dominate this group, namely studies examining crop yield and studies examining land-use. Each of eight studies surveyed relating generally to spatial yield prediction (Voortman, et al., 2004; Anselin et al., 2004; Lambert and Lowenberg-DeBoer, 2004; Dark, 2004; Persson, et al., 2005; Miller, 2005; Wang et al., 2005; Yiu et al., 2006) contain explicit use of one, and in most cases two, of the prototypes in (1). A general theme emerges. This theme is improving inferences about yield and crop response in the presence of site-specific heterogeneity.

Irwin and Geoghegan (2001) survey the literature on spatially-explicit land-use change prior to 2000 and Parker et al. (2003) survey the literature on multi-agent-system models of land-use change. In contrast to the crop-yield studies, many studies of land use and land-use change use methods alternative to those in the standard spatial frameworks. Pelkey et al. (2000) consider vegetation change in Tanzania using a large-data sample that prohibits inversion of an N-by-N matrix required to implement the Gibbs sampler. Nelson et al. (2004) study infrastructural congestion and deforestation using multinomial-, nested- and random-parameters logit techniques that preclude spatial-weights matrices. Cho and Newman (2004) extend a two-stage discrete-choice modelling procedure (Bockstael and Bell, 1998) to permit estimation of land development densities. Robertson et al. (2006) use spatial regression tree analysis to reference water quality within streams. The remaining articles surveyed in the land-use category (Walker et al., 1999; Crocker and D'Souza, 2002; Munroe et al., 2004; and Polsky, 2004) exemplify the versatility of the spatial lag and spatial autocorrelation frameworks in a wide and broader set of circumstances, including studies of the relationship between climate change and land-use classification change in the central and eastern United States and in western Honduras. Finally within this category, Verburg et al. (2004) survey methodologies employed in land-use-change studies. In assessing progress and looking to the future they propose development of models that "better address the multi-scale characteristics of the land-use system, implement new techniques to identify neighbourhood effects, explicitly deal with temporal dynamics and achieve a higher level of integration between disciplinary approaches and between models studying urban and rural land-use change (p. 309)."

Other papers in this general category provide further examples of the spatial autocorrelation and spatial lag models to unifying the mathematical foundations of regional science (Griffith, 1999), better implementing integrated regional econometric and input-output modelling (Rey, 2000), improving understanding of farm-land values decomposition (Plantinga et al., 2002; and Huang et al., 2006) and better understanding the drivers of change in the relationship between environmental amenities and human settlement patterns in the rural-urban fringe in the midwestern United States (Gustafson et al., 2005).

In closing this section, it is relevant to comment on the use of discrete-choice technologies used extensively in location-choice studies. Without exception the surveyed works employ classical statistical procedures. They rely almost exclusively on variations of logit methodology. Likely this arises due to computational problems encountered in classical estimation of the multinomial probit. However, the logit methodology suffers a significant disadvantage because it prohibits explicit spatial regression analysis. Such is not the case with probit estimation, and incorporation of explicit spatial weight matrices and associated correlation parameters follows naturally from the binary- or multinomial-probit specifications. Fleming (2004) surveys techniques for estimating spatially dependent discrete-choice models; Bayesian estimation of multinomial probit models and comparisons with classical methodology are reviewed in Geweke et al. (1994); and Autant-Bernard et al. (2006) model spatial dependence explicitly in the multinomial probit.

5. Thematic Developments and Extensions

Because spatial econometric modelling in the bio-economic and land-use categories is eclectic, it is only with difficulty that thematic developments emerge. Yet closer inspection reveals some fairly clear orientations and preoccupations. Broadly described, an over-arching theme in this diverse literature appears to be loosening the constraints of our prototype models in order to engender added realism to the modelling environment. In this way research aims to close the gap between the realities of the data-generating environment and the modelling context that the research employs to depict it. 'Heterogeneity' is ever-present. It overarches and underpins each of the literary divisions we have chosen. For example, in the contexts of forming site-specific yield predictions, (Voortman et al., 2004; Anselin et al., 2004), utilising satellite imagery of the Ngorogoro crater (Pelkey et al., 2000), or mapping appropriate covariates to conservation biology measures (Claessens et al., 2006; Shi et al., 2006), the researcher confronts the problem of better incorporating heterogeneous, site-specific factors that have a fundamental impact on the biological- and natural-resource process. In Anselin et al. (2004) heterogeneity arrives in the form of the unobserved nutrient status of a yield site; in Pelkey et al. (1999) it is present in the unobserved behaviour of predatory mammals and migratory species; and in Shi et al. (2006) it arises due to the unobserved complex spatial heterogeneity of ecological systems. In each case heterogeneity is fundamental to the data generating environment. In this context it is not surprising that many of the innovative developments in spatial-econometric methodology arise as direct responses to the desire and the need to better incorporate heterogeneity in the biological, agricultural or land-use process. Therefore, in suggesting extensions and potentially fruitful directions for new research we focus attentions on heterogeneity in the modelling of bio-economic and land-use resources.

Several directions identify themselves from the innovative methodologies in Assunção (2003) and Su et al. (2004). These studies make efficient use of the Bayesian hierarchical methodology. Hierarchical modelling of processes in order to adequately represent heterogeneity is common in Bayesian inference. Koop and Tobias (2004), for example, illustrate the methodology's advantages in the context of modelling returns to schooling. Tsionas (2002) proposes a stochastic frontier model with random coefficients to separate technical inefficiency from technological differences across firms, and free the frontier model from the restrictive assumption that all firms must share exactly the same technological possibilities. Other examples can be found in the literature, particularly in the medical sciences. In the context of our spatial prototypes in (1), above, a natural question arising is the type of modification required in order to adequately incorporate heterogeneity in the bio-economic and land-use process. Where it is observable among covariates we are able to condition inferences by simply including the relevant covariate information in the econometric exercise. This point is important. Only unobserved heterogeneity is problematic. Unobserved, heterogeneous factors that impact the modelling environment may be present in any of the parameters about which we make inferences. Thus, heterogeneity may impact the regression coefficients, b, or the sampling standard error, σ. However, because it delimits so many methodological differences over a standard regression framework, in the space that remains we focus attentions only on the spatial weights matrix, $\mathbf{W}$, and the parameter depicting correlation among contiguous geographic units, ρ. Durlauf (2004) surveys the settings in which phenomena give rise to spatial dependence, termed 'neighbourhood effects.' Many of the settings he surveys differ markedly from the one depicted in (1), which is a homogeneous set of correlations between contiguous regions within the sample. The many assumptions embedded in this overly simplistic framework beg some obvious questions. The hierarchical extension of the basic spatial relationship posits a distributional assumption across subsets of the sample, say, i = 1, 2, .., N, concomitantly replacing '$\rho\mathbf{W}$' in (1) with alternative assumptions '$\rho_1\mathbf{W_1}$', '$\rho_2\mathbf{W_2}$', .., '$\rho_N\mathbf{W_N}$' across subsets and assuming, simultaneously, that ρ_1, ρ_2, .., ρ_N are linked as draws from some common distribution, $f(\rho_1, \rho_2, .., \rho_N|\rho)$ with 'ρ' the over-arching 'hyperparameter' depicting correlation throughout the sample. Notwithstanding its attractiveness, non-hierarchical alternatives exist.

A first question about the relationship '$\rho\mathbf{W}$' is the <u>magnitude of the geographic space</u> within which dependence exists. When there is good reason to question the size, but not the pattern, of contiguity in the sample it is natural to combine contiguous regions forming successively larger neighbourhoods in which spatial dependence might exist. Subsequently one can test for the neighbourhood size that is most appropriate among the given alternatives. Holloway and Lapar (in press) implement this modification to a model of northern-Philippino smallholders and determine that, across the twelve geographic units comprising the sample, a significant, positive, neighbourhood effect exists and that it spans a three-unit radius. Despite its attractions, one potential shortcoming of this approach is that the model selection procedures required to implement it (Chib, 1995; Chib and Jeliazkov, 2001) are computationally intensive and may be prohibitive when the number of geographic units is large.

Second, the assumption that the relationship '$\rho\mathbf{W}$' is homogeneous across the entire sample can be relaxed. Alternatively, one may posit a relationship that is additive and of the form '$\sum\rho_i\mathbf{W_i}$', for an exhaustive set of subunits, i = 1, 2, .., N, across the sample. Using '$\sum\rho_i\mathbf{W_i}$' in place of '$\rho\mathbf{W}$' is appropriate when there is reasonable belief that intrinsic factors within the data-generating environment give rise to heterogeneous neighbourhood effects. Moreover, despite its complications, implementation follows easily and naturally by extending the basic Gibbs algorithm in the standard spatial regression (LeSage, 2002). Experiments (available upon request) suggest that the extended Gibbs-sampling algorithm works extremely well, predicting accurately upwards of ten correlation components in a sample of only one-hundred observations. Nevertheless, the procedure suffers from drawbacks. The most significant drawback is that the researcher must know a priori the division of respective subunits across the sample, which are implied by the weight matrices '$\mathbf{W_1}$, $\mathbf{W_2}$,.., $\mathbf{W_N}$.'

A third modification designed to overcome the informational demands of the former procedure is a mixture-modelling approach based on Bayesian classification and discrimination. Bayesian implementation of finite mixtures (Lavine and West, 1992; Diebolt and Robert, 2004) is simple, intuitive and attractive. And when the number of components within the mixture is unknown, a modification (Richardson and Green, 1997) facilitates inference. Mixture modelling is attractive in the context of (1) because it allows the data itself to sample select and designate observations into the most appropriate classification, namely the one corresponding to a particular form of spatial dependence. Work is currently underway to implement such a model in a sample of US congressional votes on proposed agricultural legislation.

Finally, depicting dependence of the correlation parameter on possible sets of covariates offers potential for better understanding the relationship between spatial dependence and observable factors upon which the investigator may condition inferences. To our knowledge such work has not yet been attempted. Nevertheless, it is conceivable that one could implement such a model by extension of generalized linear model methodology (Dellaportas and Smith, 1993) and that such extension offers considerable scope for improving our understanding of the nature of the forces effecting spatial dependence in bio-economic and land-use modelling.

6. Conclusions

Despite some 'embarrassment of riches' in the burgeoning and innovative literature that we survey, considerable scope appears to exist for improving the robustness of inferences derived from spatial models of bio-economic and land-use change.

Footnotes

[1] This survey reports the research of a subset of papers from a broader search that, tangentially, relates to agriculture, the land, land-use, and bio-economic and natural-resource modelling. Space

prohibits reports of papers from omitted sections entitled 'Public Choice Toward the Environment, the Land and Agricultural Trade;' 'Housing, the Economics of Real Estate, and the Rural-Urban Fringe;' and papers contained in the Special Issue of Agricultural Economics showcasing Spatial Analysis for Agricultural Economists. An extended version of the paper containing these reports is available upon request.

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