Spatial Approaches to Panel Data in Agricultural Economics: A Climate Change Application

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Panel data are used in almost all subfields of the agricultural economics profession. Furthermore, many research areas have an important spatial dimension. This article discusses some of the recent contributions made in the evolving theoretical and empirical literature on spatial econometric methods for panel data. We then illustrate some of these tools within a climate change application using a hedonic model of farmland values and panel data. Estimates for the model are provided across a range of nonspatial and spatial estimators, including spatial error and spatial lag models with fixed and random effects extensions. Given the importance of location and extensive use of panel data in many subfields of agricultural economics, these recently developed spatial panel methods hold great potential for applied researchers.

Panel data are used in almost all areas of agricultural economics. From price analysis to conservation to nutrition, identification often comes from differences over both time and cross-section, making panel data a vital component of analyses in these fields. Furthermore, many of these same research topics have an important spatial dimension. Particularly in agricultural economics, in which land is immobile, weather events impact decisions and resulting outcomes, policies are set at a myriad of levels defined by regional political boundaries, and information is often regionally explicit—location matters. The recent development of spatial econometric theory applied to panel data provides agricultural economists the ability to control for both spatial and temporal dependencies.

Explicit econometric techniques for testing for spatial processes and estimation with panel data in the presence of both a spatial lag and a spatial error have just recently been developed (Baltagi, Song, and Koh, 2003, 2007c; Elhorst, 2003, 2009; Lee, 2003; Baltagi, Egger, and Pfafermayer, 2007a; Baltagi, Kelejian, and Prucha, 2007b; Kapoor, Kelejian, and Prucha, 2007; Baltagi, 2008; Baltagi and Liu, 2008; Lee and Yu, 2009a, 2009b, 2010; Elhorst, Piras, and Arbia, 2010; Yu and Lee, 2010). Many of these programs are now available as a package in the R language (Millo and Piras, 2009a, 2009b; Piras, 2010; R Development Core Team, 2010). Among other things, these subroutines give analysts the ability to use the standard fixed vs. random effects in the presence of both a spatial autoregressive variable

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and a spatial autocorrelated error process. Different error specifications are possible with individual effects that may or may not be spatially correlated. Methods are also currently being developed to account for spatial processes in simultaneous equations estimations (Kelejian and Prucha, 2004; Baltagi and Pirotte, 2011).

Spatial heterogeneity also frequently complicates panel regressions. Various non- and semi-parametric methods have been developed for controlling for heterogeneity in cross-sectional data and are currently in the process of being expanded to panel data. Each of these methods relies on specific assumptions and data requirements. In this article, we briefly review the recent theoretical advances in spatial econometrics and their applications to panel data and discuss its potential for application across a wide range of fields within agricultural economics.

To demonstrate the effect of these spatial panel methods, we tap into a recent debate in the agriculture and resource economics literature about the effect of climate change on agricultural profitability and land values. As an alternative to detailed crop yield simulations, Mendelsohn, Nordhaus, and Shaw (1994) estimate a cross-section of county farmland values as a function of local climate, finding potentially positive effects of climate change on U.S. agriculture. Later work finds very different estimates for irrigated and nonirrigated areas and, when considering only the rain-fed regions and using multiple years of data, find significantly negative estimated effects of climate change (Schlenker, Hanemann, and Fisher, 2005). Most recently, Deschenes and Greenstone (2007) use time-series variation and find positive effects of climate change. Although the two more recent articles make an attempt to correct for spatial correlation among the error terms, none use formal spatial panel methodology. Thus, we believe it is interesting and informative to explore these different approaches using a county-level panel data set while formally controlling for both a spatial lag and a spatial error correlation.

Using a hedonic land value framework, we incorporate spatial effects across a variety of spatial panel estimators combining spatial lag and spatial error techniques within fixed- and random-effects frameworks. The differences in underlying assumptions and implementation procedures are discussed, whereas the variation in estimation results that may be obtained across the available estimators is illustrated within the context of an applied example.

Spatial Panel Methods Theory

Spatial models are an important tool in agricultural economics as well as the related disciplines of regional sciences, geography, urban and real estate economics, economic geography, public economics, and local public finance (Baltagi, Song, and Koh, 2007c). Spatial panel data models are an emerging and promising topic within the spatial econometrics literature. Recent contributions include, among others, Baltagi, Song, and Koh (2003, 2007c), Elhorst (2003, 2009), Baltagi, Egger, and Pfafermayr (2007a, 2009), Baltagi, Kelejian, and Prucha (2007b), Kapoor, Kelejian, and Prucha (2007), Pesaran and Tosetti (2007), Anselin, Le Gallo, and Jayet (2008), Baltagi and Liu (2008), Lee and Yu (2009a, 2009b, 2010), and Millo and Piras (2009a, 2009b).

Panel data relate to a cross-section of observations such as individuals, groups, countries, or regions repeated over several time periods. Spatial panels relate to repeated observations associated with a particular position in space. Data can be observed at specific point locations (e.g., housing data) or aggregated over regular or irregular geographic areas (e.g., countries, regions, or states).

The structure of the interactions between the spatial units is represented by means of a spatial weights matrix. The spatial weights matrix W is a $N \times N$ positive matrix. Each observation appears both in rows and columns. Hence the nonzero elements on each row of the matrix define the "neighborhood" of the corresponding spatial unit. The element w_{ij} expresses the intensity of the interaction between locations i and j. The simplest specification follows a binary scheme where $w_{ij} = 1$ when i and j are neighbors and zero otherwise. The decision of how to classify what constitutes a neighbor can vary, but the most common definition is simply one of contiguity: if two units share a common border, they are neighbors. Another common

approach is to define neighbors as the "k" nearest units to observation i. This latter approach is the one we take in this article. In particular, we calculate a 10-nearest-neighbors spatial weights matrix in which distance is measured in kilometers. By convention, the diagonal elements of the spatial weights matrix w_{ij} are all set to zero. Thus, a unit is not a neighbor of itself.

Although the original weights are generally symmetric, the matrix is often used in a row-standardized form, leading to a matrix that is no longer symmetric. Unless based on a formal theoretical model, the specification of the spatial weights matrix is often ad hoc and the choice is typically driven by geographic criteria. Furthermore, in a panel data context, weights are assumed to remain constant over time.

In a panel data framework, a large number of combinations of spatial heterogeneity and spatial dependence is possible but some of them are particularly difficult to implement in practice. As for the cross-sectional case, spatial panel data models can be estimated both following the maximum likelihood (ML) and the generalized method of moments (GM) approach. Given the large number of cross-sectional units in many panel data, the ML estimation may be cumbersome in terms of computing capacity. Motivated by this shortcoming, Kelejian and Prucha (1999) suggest an alternative estimation procedure for these models, which remains computationally feasible even for large sample sizes. Later, Kapoor, Kelejian, and Prucha (2007) extend this procedure to panel data models involving a first-order spatially autoregressive disturbance term, in which the innovations have the following error component structure:

$$u_{it} = \rho(I_T \otimes W_N)u_{it} + \varepsilon_{it},$$

where W_N is a spatial weights matrix and ρ is a spatial autoregressive parameter, and

$$\varepsilon_{it} = \mu_i + \nu_{it}$$

where μ_i is the region-specific, time-invariant portion of the error, and ν_{it} is the region and time-specific error. Contrary to other approaches, the disturbances are allowed to be correlated over time and across spatial units. In other words, the model allows for spatial interactions that involve not only the residual error components, but also the location-specific error components.

Kapoor, Kelejian, and Prucha (2007) maintain the assumption that the error components ν_{it} are identically and independently distributed with mean zero and variance σ_ν^2. The error components μ_i are also identically and independently distributed with mean zero and variance σ_μ^2. Furthermore, the two processes are assumed to be independent of each other. Under some additional assumptions, the variance covariance matrix of ε_N can be expressed as

$$\Omega_\varepsilon = \sigma_\nu^2 Q_0 + \sigma_1^2 Q_1,$$

where $\sigma_1^2 = \sigma_\nu^2 + T\sigma_\mu^2$, $Q_0 = \left(I_T - \dfrac{J_T}{T}\right) \otimes I_N$,

$$Q_1 = \frac{J_T}{T} \otimes I_N \text{ and } J_T = \iota_T \iota_T'.$$

Furthermore, using the properties of Q_0 and Q_1, its inverse takes the form

$$\Omega_\varepsilon^{-1} = \sigma_\nu^{-2} Q_0 + \sigma_1^{-2} Q_1.$$

The estimation procedure makes use of this inverse to calculate a feasible GLS estimator of the parameter vector. To estimate the spatial autoregressive parameter and the variance components, Kapoor, Kelejian, and Prucha (2007) propose an extension of the generalized moment estimator developed in Kelejian and Prucha (1999). Specifically, they define three sets of GM estimators based on the six moment conditions

$$\Gamma_N = \begin{bmatrix} \gamma_{11}^0 & \gamma_{12}^0 & \gamma_{13}^0 & 0 \\ \gamma_{21}^0 & \gamma_{22}^0 & \gamma_{23}^0 & 0 \\ \gamma_{31}^0 & \gamma_{32}^0 & \gamma_{33}^0 & 0 \\ \gamma_{11}^1 & \gamma_{12}^1 & 0 & \gamma_{13}^1 \\ \gamma_{21}^1 & \gamma_{22}^1 & 0 & \gamma_{23}^1 \\ \gamma_{31}^1 & \gamma_{32}^1 & 0 & \gamma_{33}^1 \end{bmatrix}, \gamma_N = \begin{bmatrix} \gamma_1^0 \\ \gamma_2^0 \\ \gamma_3^0 \\ \gamma_1^1 \\ \gamma_2^1 \\ \gamma_3^1 \end{bmatrix},$$

where, for $i = 0,1$:

$$\gamma_{11}^i = \frac{2}{N(T-1)^{1-i}} E u_{N'} Q_i \bar{u}_N,$$

$$\gamma_{12}^i = \frac{-1}{N(T-1)^{1-i}} E \bar{u}_{N'} Q_i \bar{u}_N,$$

$$\gamma_{21}^i = \frac{2}{N(T-1)^{1-i}} E \bar{\bar{u}}_{N'} Q_i \bar{u}_N,$$

$$\gamma_{22}^i = \frac{-1}{N(T-1)^{1-i}} E \bar{\bar{u}}_{N'} Q_i \bar{\bar{u}}_N,$$

$$\gamma_{31}^i = \frac{1}{N(T-1)^{1-i}} E(u_{N'} Q_i \bar{\bar{u}}_N + \bar{u}_{N'} Q_i \bar{u}_N),$$

$$\gamma_{32}^i = \frac{-1}{N(T-1)^{1-i}} E\bar{u}_{N'} Q_i \bar{\bar{u}}_N,$$

$$\gamma_{13}^i = 1, \gamma_{23}^i = \frac{1}{N} tr(W'W),$$

$$\gamma_{33}^i = 0, \gamma_1^i = \frac{1}{N(T-1)^{1-i}} E u_{N'} Q_i u_N,$$

$$\gamma_2^i = \frac{1}{N(T-1)^{1-i}} E\bar{u}_{N'} Q_i \bar{u}_N, \text{ and}$$

$$\gamma_3^i = \frac{1}{N(T-1)^{1-i}} E u_{N'} Q_i \bar{u}_N.$$

The first set of GM estimators is based only on a subset of the moment conditions (the first three equations) and assigns equal weights to each of them. This first set of estimators should be therefore used as initial estimators.

From the theory of GM estimators, we know that the ideal weighting matrix for asymptotic efficiency is the inverse of the variance–covariance matrix of the sample moments at the true parameter values. The second set of GM estimators uses all moment conditions and an optimal weighting scheme. Kapoor, Kelejian, and Prucha (2007) derive the weighting matrix under the assumption of normally distributed innovations. They point out that, although the use of such a matrix is not strictly optimal in the absence of normality, it can be viewed as a reasonable approximation of the true and more complex variance–covariance matrix.

The third set of GM estimators is motivated by difficulties related to the computation of the elements of the asymptotic variance–covariance matrix of the sample moments. Although one could take advantage of the particular structure of *W*, the computation of such a matrix can still be difficult in many cases. The third set of GM estimators still uses all moment conditions but weights them with a simplified scheme.

Using any of the previously defined estimators for the spatial coefficient and the variance components, an FGLS estimator can be generated based on a spatial Cochrane-Orcutt-type transformation of the original model. Following the classic error component literature, a convenient way of calculating the estimator is to further transform the already spatially transformed model premultiplying it by $I_{NT} - \theta Q_1$, where $\theta = 1 - \sigma_v/\sigma_1$. The FGLS estimator is then identical

to an OLS estimator calculated on the "doubly" transformed model.

There are a few straightforward extensions of the estimation methodology discussed previously (see also Mutl and Pfaffermayr, 2008). First, when it is unlikely that the time-invariant errors μ_i are independently distributed, a fixed-effects specification can be estimated using a subset of the moment conditions (i.e., those assuming that the variance of the error components is zero). Second, when a spatially lagged dependent variable is included in the regression equation, the model can be estimated using a two-stage least-squares procedure. We implement both extensions in our empirical analysis.

An interpretation issue arises when a spatially lagged dependent variable is included in the model. As LeSage and Pace (2009) point out, a marginal change in a single observation will not only affect the observation itself (direct effect), but also potentially influence all other observations in the sample (indirect effect), implying that the marginal effect of a variable is no longer simply its coefficient. In a cross-sectional framework, LeSage and Pace (2009) define the average total impact (*TI*), the average direct impact (*DI*), and the average indirect impact (*IM*) from changes in the model variable X_k as

$$DI = n^{-1} tr(S_k(W))$$

$$TI = n^{-1} \imath^T S_k(W) \imath$$

$$IM = TI - DI,$$

where $S_k(W) = (I - \lambda W)^{-1} \beta_k$, $\imath$ is a vector of ones and $tr()$ denotes the trace operator. They also discuss how to calculate measures of dispersion for inference regarding the statistical significance of these effects. In the context of our particular model specification, effects estimates (for each time period) assume expressions that are identical to the cross-sectional case reported previously. Therefore, the theory presented in LeSage and Pace (2009) applies to our application.

Although we concentrate on *static* spatial panel data models that do not include time-lagged dependent variables in the regression equation, there has been a growing interest in the *dynamic* case. Anselin, Le Gallo, and Jayet (2008) present a taxonomy for spatial dynamic

models and classify them into four categories: 1) *pure space recursive* in which the dependence pertains only to neighboring locations in a previous period; 2) *time–space recursive* when both time and space–time lags are included; 3) *time–space simultaneous* when the model includes a time lag and a contemporaneous spatial lag; and 4) *time–space dynamic* when all forms of dependence are included. Recently, several of these models have been more formally developed. Parent and LeSage (2010) consider a time–space dynamic model that relates commuting time to highway expenditure. Korniotis (2010) estimates a time–space recursive model with fixed effects. Elhorst (2003) proposes an unconditional maximum likelihood estimator for dynamic panels. Yu and Lee (2010) study a model in which multiple dynamic effects are included.

Applications in Agricultural Economics

Spatial dependencies enter into nearly all subfields of agricultural economics. We provide a brief discussion of potential or actual applications in four major areas of the profession with references to recent examples where applicable. None of these reviews should be considered a complete or comprehensive listing. For earlier reviews of spatial econometric methods, see Anselin (2001, 2002) and Nelson (2002).

Finance and Risk Management

The finance and risk management literatures commonly deal with a number of issues that may be considered from a spatial perspective. We focus on potential applications of spatial panel methods to portfolio style analysis of credit and insurance markets. Although analyses at the individual level are required to calculate actuarially fair insurance rates and make accurate loan application and pricing decisions, how individual loans and insurance policies are aggregated into a bank or company portfolio depends on the interactions among the individual contracts. These interactions can be thought of as inherently spatial in nature attributable to systemic factors such as weather, which may create financial stress or insurance losses over a widespread geographic region. Furthermore, analyses of such issues

generally involve the use of credit or insurance market performance data over time. Although explicit spatial panel methods have yet to be introduced to these areas, recent applications of spatial techniques include analyses of historic U.S. crop insurance program losses (Popp, Rudstrom, and Manning, 2005; Woodard et al., 2011).

Production and Land Economics

Spatial methods have also been widely adopted in the production and land economics literature. To examine the determinants of land values and rent levels, one would ideally use data observed over both time and space. Recent research has incorporated spatial as well as temporal effects into analyzing the factors which impact cash rent levels and land values in the corn belt (Huang et al., 2006; Du, Hennessy, and Edwards, 2007; Woodard et al., 2010).

Crop yield modeling is another area in the production literature in which spatial factors have been explicitly modeled. Anselin, Bongiovanni, and Lowenber-DeBoer (2004) use spatial methods in examining the potential for variable rate technologies in fertilizer application to improve crop yields. The spatial nature of weather events also provides potential for incorporating spatial methodologies into crop yield–weather models.

Development Economics

Spatial econometric techniques in general are somewhat newer to development economics than in other fields in agricultural and applied economics. Spatial methods have largely entered development economics through the analysis of technology adoption. In an early application of a spatial probit, Holloway, Shankar, and Rahmanb (2002) consider how neighbors affect the adoption of a high-yielding variety of rice in Bangladesh. As an example of more recent work, Langyintuo and Mekuria (2008) apply a spatial tobit estimator to technology adoption of improved maize varieties in Mozambique. As researchers increasingly return to interview households to add a time dimension to their data, we predict spatial panel methods may become more prevalent in this literature.

In very recent work, spatial lag models have been applied as a means to estimate peer effects (Bramoulle, Djebbari, and Fortin, 2009; Helmers and Patnam, 2010). To estimate the decision by a person influenced by the actions and attitudes of their social network, one needs to take into account the problem that their peers are simultaneously choosing their actions or attitudes in response to them. To surmount this reflection problem, Bramoulle, Djebbari, and Fortin (2009) propose applying a spatial lag model. Helmers and Patnam (2010) take a similar approach to estimating the peer effects on child skill acquisition in India. They further control for spatial errors and heteroskedasticity using the spatial HAC proposed by Kelejian and Prucha (2007). To our knowledge, the one area where formal spatial panel methods have been used in development is a recent article that uses county-level panel data from Mexico to consider the distributional effects of NAFTA (Baylis, Garduno-Rivera, and Piras, 2010).

Environmental Economics

Perhaps because of its association with urban economics, geography, and the locational attributes of many pollutants, environmental economics were an early adopter of spatial methods. One of the more frequent applications has occurred in hedonic models of house prices used to estimate the value of pollution (e.g., Leggetta and Bockstael, 2000; Kim, Phipps, and Anselin, 2003; Anselin and Lozano-Gracia, 2008; Cohen and Coughlin, 2008). Although to our knowledge no article has yet used formal spatial panel methods in environmental economics, Anselin and Lozano-Gracia (2008) use a spatial heteroskedasticity autocorrelation correction in their estimation of the effect of air pollution on Los Angeles housing prices. In a later article, Anselin and Lozano-Gracia (2010) apply the same methodology to value access to water in one major city in India.

Other applications have occurred in the conservation literature, in which the benefits of land conservation are clearly affected by location through location-specific characteristics, development pressure, and the conservation state of neighboring parcels (e.g., Mertens et al., 2002;

Müller and Zeller, 2002; Munroe, Southworth, and Tucker, 2002; Newburn, Berck, and Merenlender, 2006; Albers, Ando, and Chen, 2008; Honey-Roses, Baylis, and Ramirez, forthcoming). Because much of environmental economics uses panel data, we foresee great potential for the use of spatial panel methods in this literature. One research area that has used panel data and made some attempts to correct for spatial processes is in the estimations of the costs and benefits of climate change.

Climate Change and Agriculture Applications

We explore these spatial panel methods using a recent academic debate about the effect of climate change on American agriculture. Much of the early literature estimating the effect of climate change on agriculture takes an agronomic or production function approach that uses detailed crop growth models to simulate how different crop yields will respond to changes in climate. Articles using this methodology include Callaway et al. (1982), Adams et al. (1988, 1990, 1995), Adams (1989), Rozenzweig and Parry (1994), and Rind et al. (2002). Good surveys of the earlier work are cited in Mendelsohn, Nordhaus, and Shaw (1994) and include the National Research Council (1983), Smith and Tirpak (1989), and Cline (1992).

An alternative approach to this literature is suggested by Mendelsohn, Nordhaus, and Shaw (1994) who use a hedonic model to estimate a cross-section of farmland prices to estimate the effect of temperature and precipitation on agricultural productivity. In contrast to the earlier production function method, the hedonic approach has the benefit of being parsimonious while also incorporating the effects of crop choice and other behavioral responses to changing climate. The intuition comes from a Ricardian model of farmland values, in which those values capture discounted expected future profits associated with that land. Thus, farmland values inherently reflect the benefits of local climate on agricultural productivity.

Using 1982 county-level data for the lower 48 states, Mendelsohn, Nordhaus, and Shaw (1994) find that a 5-degree increase in surface

temperature and accompanying 8% increase in precipitation may actually aid agriculture when the observations are weighted by crop revenue. They contrast their findings to the earlier agronomic approaches, which generally found substantial damages from climate change.

Schlenker, Hanemann, and Fisher (2005) argue that the Mendelsohn, Nordhaus, and Shaw (1994) approach will overstate the benefits for agriculture from climate change because they aggregate irrigated and nonirrigated areas. Those warmer areas that are associated with higher crop revenue often also benefit from highly subsidized irrigation systems. Schlenker, Hanemann, and Fisher (2005, 2006) also note that it is inappropriate to assume that increasing temperatures will make farmland in the northern Great Plains look like the Central Valley in California. They address this concern by restricting themselves to counties east of the 100th meridian, where farming is possible without irrigation. They also make a number of innovations in terms of how to treat temperature and precipitation variables whose effects are highly nonlinear. Third, they estimate the effects of climate using both cross-sectional and pooled data that span 15 years. Lastly, they also transform their data to take into account spatial correlation in their error terms. Using this approach, they find that climate change is likely to negatively impact nonirrigated U.S. agriculture.

A third recent contribution to this debate comes from Deschenes and Greenstone (2007) who make use of time-series variation in weather to predict changes in agricultural profit from climate change. They argue that unobservables associated with location likely drive much of the results found in Schlenker, Hanemann, and Fisher (2005) and therefore use county fixed effects to control for these unobservable factors. They also use state-by-year fixed effects so that their identification comes off of how county weather in year *t* differs from the average county weather controlling for statewide annual shocks. They then estimate agricultural profit as a function of temperature and precipitation and find that warmer, wetter weather as predicted by climate change will increase agricultural profits by 4% per year.

Deschenes and Greenstone (2007) argue that their approach allows them to estimate the effect of weather on agricultural productivity and from that duce the potential effect of climate change. If anything, because it does not allow for the full range of behavioral responses to changes in climate, the authors argue that this model will provide a lower bound on the effect of climate change. A criticism of this approach has been that weather variation may have very different effects on agriculture than an expected long-run change in climate. Fisher et al. (forthcoming) also note concerns with the data and the need for a spatial error correction in the Deschenes and Greenstone (2007) model. Furthermore, these studies are subject to the assumption that adjustments are not made in response to climate change outside of the United States. The extent to which climate change impacts agriculture in other areas could also impact land values. This caveat also applies to the empirical illustration we provide subsequently.

Data and Approach

In this article, we explore the hedonic approach and examine variation in the estimated effects that may occur across nonspatial and spatial models. Using the same panel data used in Schlenker, Hanemann, and Fisher (2006), we use the spatial panel estimators discussed previously to estimate the effect of temperature and precipitation variables on the log of farmland values. We largely follow the model specification from Schlenker, Hanemann, and Fisher (2006) using county-level data from the continental United States and restricted to the counties east of the 100th meridian to control for nonirrigated agriculture.

We also use their formulation of the climate data, in which the temperature information is converted into nonlinear measures of degree-days. Specifically, we use 30-year rolling averages of degree days over 8°C from April to September with a second variable of degree days over 34°C to control for excessive heat. We regret that we do not have access to their detailed time-variant soil quality measures, so we follow the specification by Mendelsohn, Nordhaus, and Shaw (1994), using their data from 1982 on soil composition, erodability (K-factor), moisture capacity, and permeability. Lastly, like Schlenker, Hanemann,

and Fisher (2006), we include county average income per capita and population density to control for demand for land for nonagricultural uses. Summary statistics for our data are reported in Table 1.

Note that this discussion is for demonstration purposes only with a focus on illustrating the impact that the incorporation of spatial considerations may have on the estimates and interpretation of those results. We do not claim that our results reflect the effects of climate change on U.S. agriculture nor should they be compared with the results of the previously discussed climate change studies. For example, unlike all three previous articles, we present simple, unweighted results that use agricultural land area, agricultural value, and other measures of the accuracy of county land values to weight their observations. Thus, we do not recommend that readers use our results to predict the effect of climate change. We only hope that by illustrating some key differences between the approaches, we can demonstrate the value of spatial panel methods and perhaps shed some light on the debate.

Land values are spatially correlated. Along with reflecting potentially unobservable soil characteristics, agricultural land markets are highly localized with many buyers being farmers looking to add fields near to their existing operation. Like with house prices, one might also expect increased prices in one region to directly increase prices in the neighboring region, resulting in a spatial lag process. We apply spatial lag and spatial error models using both fixed- and random-effects extensions to the panel. We therefore extend the work by Schlenker, Hanemann, and Fisher (2005, 2006) to include a formal spatial panel framework.

Results

Specifically, we estimate seven models, all of which are presented in Table 2. The first three models do not control for spatial characteristics of the data. The first model is a simple pooled model with fixed effects by state. The second model, in column 2, is a standard panel model with county-level fixed effects. Note that the use of fixed effects drops the coefficients on our time-invariant characteristics such as latitude and soil type. The third column presents a standard panel model with random effects.

The last four columns present results from the spatial panel estimations. The fourth column

Table 1. Summary Statistics for Counties Included in the Analysis

Variables	Minimum	Median	Mean	Maximum	Standard Deviation
Farmland Value 1982	104	981	1136	8056	649.06
Farmland Value 1987	140	837	1013	7008	735
Farmland Value 1992	139	995	1262	14,530	1143.87
Farmland Value 1997	150	1327	1592	13,870	1154.75
Farmland Value 2002	205	1792	2183	22,850	1900.94
Degree-days (8–32°C)	1.03	2.3	2.3	3.42	0.5
Degree-days^2 (8–32°C)	1.07	5.27	5.53	11.70	2.28
Degree-days (34°C)	0.00	1.22	1.63	7.85	1.50
Precipitation (cm)	25.54	61.61	61.48	102.1	10.01
Precipitation^2 (cm^2)	652.4	3795	3881	10,430	1270.42
Latitude	−12.16	−0.51	−0.71	10.45	4.58
Income per capita	6133	16080	16770	57,110	6418.62
Population density	0.00	0.07	0.2	8.84	0.46
Population density squared	0.00	0.01	0.26	78.15	2.1
Clay	−0.14	−0.14	0.00	0.86	0.35
Permeability	−3053	−1235	−157.7	65,710	3612.47
Moisture capacity	−259.2	−122.5	−9.64	1707	269.23
Soil erosion	−0.19	0.01	0.00	0.19	0.07

Note: Farmland values are measured in 1997 U.S. dollars.

Table 2. Regression Results from a Variety of Panel Specifications

	Pooled OLS	County Fixed Effects	Random Effects with State Dummies	Spatial Error Fixed Effects	Spatial Error Random Effects	Spatial Lag Fixed Effects	Spatial Lag Random Effects
Constant	230.35		357.65		416.98		53.22
	(16.54)		(27.07)		(31.88)		(22.49)
Degree-days (8–32°C)	193.82	125.09	106.36	87.01	164.72	48.01	57.62
	(11.11)	(63.06)	(18.78)	(48.01)	(22.64)	(30.69)	(15.38)
Degree-days^2 (8–32°C)	−35.66	−35.51	−24.72	−21.2	−32.81	−11.22	−11.16
	(2.32)	(13.03)	(3.93)	(9.85)	(4.81)	(6.43)	(3.24)
Square root degree-days (34°C)	−44.66	77.36	1.1	9.43	−14.69	9.64	−3.26
	(1.81)	(3.61)	(2.53)	(4.36)	(2.94)	(4.48)	(2.04)
Precipitation	4.94	−0.48	3.72	1.19	1.56	−0.03	0.33
	(0.39)	(0.93)	(0.59)	(0.98)	(0.62)	(0.41)	(0.46)
Precipitation^2	−0.0326	0.0074	−0.0221	−0.0086	−0.0094	0.0006	−0.0015
	(0.003)	(0.0072)	(0.0045)	(0.0075)	(0.0048)	(0.0032)	(0.0035)
Latitude	−2.59		−3.63		−1.45		−0.41
	(0.43)		(0.71)		(0.88)		(0.57)
Income per capita	0.004	0.0041	0.0039	0.0022	0.0022	0.0004	0.0009
	(5.4e–5)	(4.5e–5)	(4.1e–5)	(8.9e–5)	(8.3e–5)	(0.0002)	(7.4e–5)
Population density	53.59	56.06	60.15	3.13	39.54	31.59	42.54
	(1.44)	(8.92)	(2.46)	(6.67)	(1.83)	(5.69)	(1.61)
Population density^2	−5.49	−15.45	−6.89	−4.39	−4.07	−8.11	−4.6
	(0.29)	(1.95)	(0.51)	(1.24)	(0.34)	(1.39)	(0.32)
Clay	2.35		4.49		0.18		−0.45
	(1.09)		(1.95)		(1.57)		(1.36)
Permeability	−0.001		−0.0014		0.0002		0.0002
	(0.0001)		(0.0002)		(0.0002)		(0.0002)
Moisture capacity	0.0373		0.0324		0.017		0.0158
	(0.0023)		(0.0042)		(0.0035)		(0.003)
Soil erosion	−46.22		−32.32		7.41		2.7
	(8.35)		(14.93)		(14.32)		(11.21)
State fixed effects	Yes	No	Yes	No	Yes	No	Yes
Number of observations	11,395	11,395	11,395	11,395	11,395	11,395	11,395
Spatial lag coefficient						0.895	0.776
						(0.005)	(0.002)
Spatial error coefficient				0.8055	0.8262	−0.4444	0.4239

Note: Standard errors are reported in parentheses below the coefficient estimates.

illustrates the spatial error model with fixed effects, whereas the fifth column uses random effects. The sixth and seventh columns present the same models including a spatial lag. First, note that the estimates of the spatial lag are highly significant in both fixed- and random-effects models. Similarly, both spatial error models show strong evidence of spatial correlation.

In all models, degree-days have a positive effect on land values, whereas squared degree-days have a negative effect. The estimated effect of increased excessive heat, as measured by the square root of degree-days over 34°C, is negative and significant for the pooled model and the two spatial models with random effects but appears to be significantly positive for the fixed-effects models. When we calculate simple marginal effects of an increase in degree-days above 8°C, but below 34°C at the average, the effect is negative for most models but positive for the pooled model and the two spatial models with random effects. The effect of precipitation is largely positive with a negative squared term. That said, although not significant, the effect of precipitation reverses for two of the models using county-level fixed effects. In all models, the marginal effect of precipitation is positive at the county average.

Beyond the effect of fixed vs. random effects, controlling for the spatial nature of these panel data makes a difference. We observe substantial differences in the coefficient estimates on degree-days between the spatial and nonspatial panel estimates. The spatial error random effects model has a coefficient estimate with a substantially larger absolute value on both degree-days and degree-days squared than the nonspatial model with random effects. The fixed-effect estimates are also smaller in (absolute) magnitude for the spatial model as compared with the standard fixed-effect estimates.

The estimates of the positive linear effect of precipitation decrease dramatically with the spatial models, whereas the coefficient on the squared term also decreases. This leaves the marginal effect of precipitation calculated at the average to be positive for all models but much smaller for all four spatial panel models. Again, although we caution against the use of our estimates to draw conclusions about the impact of climate change on agriculture, these results indicate that the estimated effects of the climate variables on agricultural land values is smaller when spatial models are used.

Furthermore, as one might anticipate, the estimates of the coefficients are smaller in magnitude for the spatial lag models. This result is not surprising given that degree-days influence agricultural value not only directly, but through the agricultural value of neighboring counties. As stated previously, the coefficient estimates in the spatial lag models do not directly represent estimates of the marginal effects of those factors as in the spatial error models. Thus, the magnitudes of the coefficients should not be compared with assess the marginal effect estimates resulting from the spatial error and spatial lag models.

We present estimates of the direct, indirect, and total effects as defined by LeSage and Pace (2009) in Tables 3 and 4. To save space, we do not present results on the statistical significance of the effects; these results are available from the authors on request. As can be seen in Tables 3 and 4, the combined marginal effect of temperature and precipitation is actually larger with the spatial lag models than their counterparts.

Discussion and Conclusion

We see strong evidence of spatial effects in our estimation. Furthermore, incorporating spatial panel methods clearly affects the results. In our example, the spatial methods give rise to

Table 3. Direct, Indirect, and Total Marginal Effects for the Spatial Lag Model with Fixed Effects

Spatial Lag with Fixed Effects	Direct	Indirect	Total
Degree-days (8–32°C)	50.24	391.62	441.87
Degree-days^2 (8–32°C)	−11.74	−91.52	−103.26
Square root degree-days (34°C)	10.08	78.61	88.69
Precipitation	−0.028	−0.225	−0.251
Precipitation^2	0.0006	0.0049	0.0056
Income per capita	0.0004	0.0033	0.0037
Population density	33.07	257.74	290.81
Population density^2	−8.49	−66.18	−74.67

Table 4. Direct, Indirect, and Total Marginal Effects for the Spatial Lag Model with Random Effects

Spatial Lag with Random Effects	Direct	Indirect	Total
Degree-days (8–32°C)	59.01	198.52	257.53
Degree-days^2 (8–32°C)	−11.42	−38.44	−49.86
Square root degree-days (34°C)	−3.33	−11.23	−14.57
Precipitation	0.34	1.13	1.47
Precipitation^2	−0.0015	−0.0051	−0.0067
Latitude	−0.4191	−1.4098	−1.8289
Income per capita	0.0009	0.0030	0.0039
Population density	43.57	146.57	190.14
Population density^2	−4.70	−15.82	−20.52
Clay	−0.46	−1.56	−2.02
Permeability	0.00001	0.00004	0.00055
Moisture capacity	0.0161	0.0543	0.0705
Soil erosion	2.76	9.29	12.05

smaller marginal effects of both temperature and precipitation. Although this result is expected for the spatial lag model because covariates now have both a direct effect within the county and an indirect effect through the spatially lagged outcome variable, it is somewhat more surprising for coefficients in the spatial error model to vary as much as they do from the standard panel results.

As to the debate about fixed vs. random effects, we do observe that fixed effects appear to generate larger and/or positive coefficients associated with increased temperature and precipitation, whereas random effects appear to indicate negative effects associated with increased temperature although slightly larger positive effects associated with increased rainfall. That said, these results should be treated very cautiously, noting that we are not weighting our observations by any measure of importance of agriculture in the county.

Future research on farmland values or other measures of productivity need to carefully take space into account. Schlenker, Hanemann, and Fisher (2005) note the high degree of spatial heterogeneity resulting from comparing west with east, which they associate with subsidies to irrigation that are more prevalent west of the 100th meridian than in the eastern half of the country. Presumably, other forms of spatial heterogeneity exist and should be taken into consideration when estimating the effect of climate change. One might expect, for example, that climate change may have differential effects on land near the urban fringe compared with land with very low development pressure. Although allowing for a nonlinear effect of population density helps address this issue, it does not address the effect population density has on the coefficients on temperature or precipitation. A better understanding of the spatial process of yields, prices, and land markets would further aid work in this area. Finally, the estimation of dynamic space–time panel models would allow researchers to quantify dynamic responses over time and space as well as space–time diffusion impacts.

In conclusion, we argue that given the importance of location and extensive use of panel data in finance and risk, production economics, environmental economics, and increasingly in development economics, recently developed spatial panel methods hold great potential for applied researchers in these fields. We demonstrate the applicability of these methods using a large data set and illustrate that the appropriate incorporation of spatial effects can generate different results than nonspatial panel models or ex-post corrections for spatial error correlation. As future advances are made in terms of seemingly unrelated regressions for spatial panel data, spatial panel estimators for discrete choices, and others, we feel that these tools have great potential to benefit empirical research in the agricultural economics profession.

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