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Spatial Approaches to Panel Data in Site-Specific Nematode Management in Cotton Production

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ABSTRACT

Root-knot nematode infestations tend to be spatially clustered within agricultural fields and result in crop yield penalties. Site-specific nematode management provides the opportunity for producers to maximize profit while maintaining acceptable yield and reducing overuse of product. This paper determines the potential of site-specific nematicide application by using spatial econometric analyses of on-farm experiments panel data to estimate cotton yield response functions with respect to environmental factors and treatment applications. The results suggest that yield response for nematicide application differs by soil texture. The nematode populations at bloom season and nematicide treatment are significant factors in explaining yield variability. Spatial spillovers from neighboring plots also significantly impact yield estimates. The results can be used to provide practical recommendations for effectively controlling nematodes via site-specific management.

Keywords: Site-specific nematode management, spatial autocorrelation, spatial panel econometrics.

Introduction

Nematode infestations tend to be spatially clustered within agricultural fields and result in crop yield penalties. Each year about 10% of all U.S. cotton production is lost to nematodes (Blasingame and Patel, 2005; Koenning et al., 1999) and yield losses in individual fields may reach 50%. Nematode control is primarily dependent on the application of nematicides (Koenning et al., 2004). The cost of nematicide is currently higher than other pesticides and also has potential negative environmental effect. Site-specific nematode management provides the opportunity for producers to maximize profit while maintaining acceptable yield and reducing potential for pollution by overuse of product. This strategy relies upon applying nematicides at a single or variable rates across the field only in locations where economically justified.

Recent advances in precision agriculture technologies and spatial statistics allow realistic estimation of nematode damage to field crops, provide reasonable production recommendation, and deliver a practical method of site-specifically controlling nematodes. Specifically, spatial econometric theory applied to panel data provides the researcher the framework to control for both spatial and temporal heterogeneity and dependencies and obtain more reliable estimation. The overall objective of this study is to determine the potential of site-specific nematicide application by using spatial panel econometric analyses of on-farm experiments precision agriculture data collected in southeastern Arkansas. Spatial econometric methods for panel data were used to estimate the cotton yield response functions with respect to environmental factors and treatment applications while explicitly modeling spatial effects in cotton yield, nematode population, soil texture and nematicide application with controlling spatial and temporal heterogeneity and dependence. Specific objectives were: 1) to compare aspatial standard panel model, spatial autoregressive lag and spatial autoregressive error models with fixed and random

effects extensions for empirical on-farm trials panel data. 2) to determine the spatial effect of nematode population density, nematicide treatment, and soil texture on the yield of cotton based on the best fit model.

The remainder of the paper proceeds as follows. First some background is provided on the spatial technologies for nematode management and on field-scale agricultural experiments. It is followed by an overview of the spatial panel methods and data used in this study. Empirical results are presented next. Implications and conclusions are drawn out in the last section.

Background

When combined with other spatial technologies such as variable rate applicators and electrical conductivity sensors, farmers with yield monitors have a toolkit to determine the impact of nematode infestation and a practical method of economically controlling the pests.

Soils data have been used in precision agriculture modeling to account for environmental heterogeneity. The most commonly used soil data, soil mapping unit polygons such as those available for download at SSURGO, were only able to be used as categorical variables, i.e. heterogeneity between soils but not within a soil series. Site-specific sensors that measure soil electrical conductivity or electromagnetic induction provide continuous data over space such that models can be evaluated with a continuous covariate for soils rather than discrete categories.

Soil electrical conductivity is especially useful for site-specific nematode management since it is assumed that nematode crop yield penalties are a function of both the magnitude of infestation as well as the soil texture. Evidence indicates a given nematode population results in different yield penalties as soil texture changes (Monfort, et al. 2007). It is unclear as to the exact mechanism for this interaction although it logically follows that plants in more attractive growing environments are less likely to be adversely impacted by root damage compared to plants growing in soils that have limited water and/or nutrient availability (Mueller, et al. 2011). Soil electrical conductivity sensors have been correlated to soil texture (Griffin et al., 2005; Barnes et al., 2003).

Although yield monitor data have been widely used to evaluate crop varieties, nitrogen rates, and seeding rates at the farm level (Griffin et al., 2008), analysis problems exist with precision agriculture datasets. Precision agriculture datasets tend to have very few explanatory variables that lead to omitted variable problems or an underspecification of the model. Ordinary least square (OLS) estimates are biased and generally inconsistent under omitted variables (Wooldridge, 2003). OLS residuals are expected to be spatially correlated when an important omitted variable has spatial structure (Bell and Bockstael, 2000; Bockstael, 1996). Additional aspatial problems arise from measurement errors in attributes and location.

Yield monitor observation is correlated with its neighboring observation and result in spatial autocorrelation and heteroscedasticity. Spatial autocorrelation and heteroscedasticity has

traditionally been neutralized in agricultural field research by reducing experimental unit sizes until plot sizes could be assumed to be homogeneous (Montgomery, 2001). Replication, randomization, and blocking techniques are combined with small-plots to determine treatment differences. However, treatment effects are more efficiently estimated by modeling spatial autocorrelation via spatial econometric technique than the traditional approach of neutralizing spatial autocorrelation (Cressie 1993). The advanced development of site-specific measurements and spatial statistical computation allow for new approaches to statistically valid inference.

Methodology

Most agricultural data, such as site-specific crop yield data, are expected to be spatially structured i.e. autocorrelated and heteroscedastic, which violates the assumptions of classical statistics and failing to account for spatial autocorrelation results in OLS estimates inefficient and bias the test statistics (Anselin, et al 2004). Spatial econometric methods that adjust for spatial dependence should be chosen to obtain more accurate estimates.

Spatial panel data model occupies an emerging and promising position in spatial econometrics. Spatial panel data related to time series observations of a number of spatial units. Compared to purely cross-sectional data or time-series data, panel data offer researchers extended modeling possibilities due to its more informative, more variability, less collinearity among the variables, more degrees of freedom, and hence the more efficient estimates (Elhorst 2003, 2011). Panel data can also be better able to specify some complicated behavioral hypotheses which can not be identified and measured by pure cross-section or pure time-series data (Hsiao 2005). Panel data can also reduce the risk of obtaining bias estimates resulting from the omitted variables by controlling for individual heterogeneity which can not be dealt with in pure cross-section or pure time-series data (Moulton 1986, 1987).

Spatial dependence may be incorporated into the model as spatial error autocorrelation which is known as spatial autoregressive error model or as a spatially lagged dependent variable which is known as spatial autoregressive lag model, or a combination of both which constitute the specification of spatial Durbin model (Anselin and Hudak, 1992; LeSage and Pace, 2009). Both spatial error model and spatial lag model have been used with site-specific yield data (Anselin et al., 2004, Lambert et al., 2004, Griffin et al., 2008). The econometric techniques for spatial processes testing and estimation with panel data can be applied for both spatial lag and spatial error model (Baltagi et al, 2003; Elhorst, 2003; Elhorst et al. 2010). The standard panel data models---fixed effect (FE) and random effects (RE) can be tested in both a spatial autoregressive variable and a spatial autocorrelated error process.

The spatial fixed effect model treat unobservable spatial and/or time period effects fixed while spatial random effect model treat it as a random variable that has an iid distribution. Hausman's specification test and other substantive reasoning can be used to test and choose the spatial fixed effects specification against spatial random effects specification.

In this paper, we apply spatial lag and spatial error models using both fixed- and random-effects extensions to the panel data. We follow the model specification from Elhorst (2003). If we stack the observations as one equation for each cross-sectional at one point in time (e.g., T spatial series with N observations over space), the spatial error autocorrelation model with fixed effect extension (referred as the SEM-FE model) can be expressed as:

$$Y_t = X_t\beta + \mu + \varphi_t, \quad \phi_t = \delta W\varphi_t + \varepsilon_t, \quad E(\varepsilon_t) = 0, \quad E(\varepsilon_t\varepsilon_t') = \sigma^2 I_N \quad (1)$$

where $i=1,2,\dots, N$ refers to a spatial unit, $t=1,2,\dots,T$ to a given time period, $Y_t = (Y_{t1}, \dots, Y_{tN})'$ is a $N \times 1$ vector of dependent variable for specific location i at time period t . X is a $N \times K$ matrix of explanatory variables; μ is the fixed unknown parameter representing the effect of omitted variables that are specific to individual spatial unit i (some space specific time-invariant variables which can not measured or captured, like soil texture, weather availability, etc.). $\varphi_t = (\varphi_{t1}, \dots, \varphi_{tN})'$ capture the peculiar effects to the t -th time period which are constant over space. $\varepsilon_t = (\varepsilon_{t1}, \dots, \varepsilon_{tN})'$ is $N \times 1$ vector of independently and identically distributed (i.i.d.) error term with zero mean and variance σ^2 for location i at time period t . The weights matrix W is an $N \times N$ spatial weights matrix representing the interaction between the spatial units. W_{ij} is the (i,j) th element of W ($i,j = 1,2,\dots, N$), $W_{ij}=1$ if i and j are neighbors, and $=0$ otherwise. δ is the spatial autocorrelation coefficient.

The SEM-FE model has the following stacked form:

$$Y = (I_T \otimes X)\beta + (\tau_t \otimes I_N)\mu + \varphi \quad (2)$$

Where $Y = (Y_1, \dots, Y_T)'$, $\varphi = (\varphi_1, \dots, \varphi_T)'$. I_T is the identity matrix of size T ; τ_t is a $T \times 1$ vector of ones; I_N is the identity matrix of size N ; β is a $TK \times 1$ vector of coefficients, and \otimes denotes the Kronecker product operator.

The fixed effect extension to a spatial lag model (referred as the SAR-FE model) can be specified as:

$$Y_t = \delta WY_t + X_t\beta + \mu + \varepsilon_t, \quad E(\varepsilon_t) = 0, \quad E(\varepsilon_t\varepsilon_t') = \sigma^2 I_N \quad (3)$$

which can be written as stacked form as:

$$Y = [(I_T \otimes X)\beta + \varepsilon](I_T \otimes B) \quad (4)$$

Where $B = (I_N - \delta W)^{-1}$. δ is spatial autoregressive coefficient. The others are same as previously defined.

Anselin et al. (2006) point out that the potential problem is existed in the estimation approach of Elhorst (2003) for either spatial error or spatial lag model with fixed effects extension due to ignoring of demeaning the error term and suggest the use of a generalized inverse to remedy this potential problem.

Following Elhorst (2003), for the specification in (1), if we treat μ_i as a random variable which is assumed to be iid $\sim(0, \sigma_\mu^2)$, and $E(\mu_i, \mu_j) = \sigma_\mu^2$ if $i=j$ and zero otherwise. Then the spatial error model with random effects extension (referred as the SEM-RE model) can be specified as:

$$Y_t = X_t\beta + v, \quad v = (\tau_T \otimes I_N)\mu + [I_T \otimes (I_N - \delta W)^{-1}] \varepsilon \quad (5)$$

Where μ is random variable intercept which capture the effect of omitted variables that are specific to individual spatial unit i . The others are same as previously defined.

The spatial lag model with random effects extension (referred as SAR-RE) can be expressed as:

$$Y_t = \delta WY_t + X_t\beta + v, \quad v = (\tau_T \otimes I_N)\mu + (I_T \otimes I_N)\varepsilon \quad (6)$$

Related symbols are same as previously defined.

Spatial panel data models can be estimated both following the maximum likelihood (ML) and the generalized method of moments (GM) approach. To solve the computer capacity problem for the spatial data containing large number of spatial unit N , some extension of the generalized moment (GM) estimators were developed and applied for spatial panel data (Kelejian and Prucha 1999; Kapoor et al., 2007)

In this study, using on-farm trial experiments panel data, we conducted econometric estimation for the model across a range of aspatial and spatial estimators with fixed effect and random effect extension. The Results were compared and interpreted with respect to theoretical rationale and empirical indication was discussed.

Data and Empirical Model

The dataset used in this study come from field-scale on-farm trials conducted in a commercial cotton field (6.1 ha) in Ashley County located in southeastern Arkansas. This field had been planted in cotton each year for at least 10 years prior to initiation of the study and had been identified by the grower as a problem field due to *Meloidogyne incognita*, a root-knot nematode. The field was subdivided into 512 plots (32 plots wide \times 16 plots long) to facilitate sequential sampling across 5-yr period (2001-2004 and 2011). Each sampling plot approximately 0.012 ha with 3.6 m (four rows) wide and 30.5 m in length were established in March 2001. The geographic location of each plot was identified using a GPS receiver (Trimble, Sunnyvale, CA) and Site-Mate, a GPS mapping software (Farmworks, Hamilton Hamilton, IN). Yield was recorded by Ag Leader PF3000 yield monitor (Ag Leader

Technology, Ames, IA) mounted on a 4-row John Deere 9970 cotton picker and at least seven individual recordings for each plot.

Each plot was sampled for *M. incognita* prior to fumigation (Ppre), at planting (Pi), at peak bloom (Pm) and at harvest (Pf) for year 2001-2003. Soil texture (percent sand fraction) and the pre-plant soil fertility levels were determined from each plot. To ensure that a range of nematode population densities was available, 1,3 dichloropropene was applied in strips (3.9-m wide) at rates of 14.1, 29.2 and 42.2 liter/ha (128 plots each) each year 2 wk prior to planting. Nematicide treatments were replicated 8 times in 2001 and 2002 and 16 times in 2003 and stopped in 2004.

Data distribution and statistics can be found in the following figure and table. Figure1 shows the yield curve for five years (2001-2004, and 2011). Lint yield of 2011 when the nematicide application has been stopped for 8 years share both the lowest average value and most of lower peak values. The next lowest average value occurred in 2001 when the nematicide application was initiated. The lint yield reached both the highest mean value and peak value in 2002.

Table1 reports the definitions and statistics of the variables used in the analysis. As for the root-knot nematode population density, it was sampled prior to fumigation (Ppre), at planting (Pi), at peak bloom (Pm) and at harvest (Pf) for year of 2001-2003, but not for year 2004 and 2011. So we choose population at peak bloom (Pm) which shows the strongest significant effect on yield in cross-sectional regression representing the population density level for our panel data analysis. Since the spatial panel data model has problem to include time and space invariant variables due to perfect collinearity of such variables with the spatial or time dummies (Baltagi 2001; Elhorst 2003), we created some interaction variables to explore the potential relationship between soil properties, treatment application and yield. With the inclusion of these variables, the empirical model estimated can be specified as:

$$Yield = f (pop, pop * elevation, pop * zsand, telone, telone * zsand, yr01, yr02, yr03, yr04, pop * treatyr) \quad (7)$$

Where $yr01, \dots, yr04$ are dummy variables for the time period 2001-2004. $Treatyr$ is another dummy which is equal to 1 for year 2001,2002 and 2003 when the nematicide were applied in the field and equal to 0 for year 2004 and 2011 without treatment application.

Empirical Results

We estimated yield potential (penalty) as a function of nematode population, nematicide using rate, time dummies and other interaction variables as equation (7) using on farm field-scale trial experiment data in 2001, 2002, 2003, 2004 and 2011 in Ashley county, AR. The variation in the estimated effects that may occur across aspatial and spatial models were examined. The models were estimated in STATA 10. For spatial models we assume a queen contiguity matrix to define neighboring states in weight matrix W (Anselin, 2002).

The estimation results are summarized in Table 2. The first model is a standard panel model with fixed effects. The second column presents a standard panel model with random effects. The last four columns present results from the spatial panel estimations with fixed and random extension. The coefficients across all six models share the same sign although there are some difference for magnitude, and significance between the four spatial panel models. As expected, the spatial autoregressive parameter (*Rho*) in spatial lag models and the coefficient on the spatially correlated errors (*Lambda*) in spatial error models have positive effect and highly significant. It indicates that the spatial dependence inherently existed in our data, and spatial panel model is a better alternative to the aspatial standard panel model by accounting for the spatial dependence. Breusch and Pagan Lagrangian multiplier test for random effects model indicates the panel effect existed in the data and panel model is better fit than OLS regression.

The estimate results for SAR model and SEM model are similar except the magnitude of the estimates of coefficient are larger for SAR model. Theory and *a priori* information suggest that when crop yield is the dependent variable, spatially autocorrelated error terms are expected rather than the contagion existing in the dependent variables, suggesting that the spatial analyst would opt to use spatial error process models to address the spatial effects explicitly. AIC values also suggest that spatial error model may be a better fit on our yield monitor data. As for the choice between FE and RE extension, the Hausman (1978) test yield a $\chi^2(8) = 87.10$ statistic, which is highly significant at the 1% level. It indicates that the RE model is inconsistent. However, some literatures state that the Hausman test should not interpret a rejection as an choice of the FE model and a nonrejection as an choice of the RE model (Hsiao and Sun 2000; Baltagi 2001). The essential interpretation should be based on whether the units in the sample can be viewed as a population or random draw from some underlying population (Verbeek 2004). Since yield monitor data are random sample rather than a population, random effect model may be more appropriate for this study and we give more attention to the results based on SEM_RE model.

The nematode population density and nematicide using rate are significant determinants to explain the variation of cotton yield across aspatial and spatial models. The time effects from year 2001, 2002, 2003 and 2004 reveal a strong upturn in cotton yield relative to 2011. Nematode population interacted with nematicide application has significant effect on crop yield while nematode population interacted with elevation do not affect crop yield significantly.

Nematicide application interacted with soil texture (*telone_zsand*) significantly affect crop yield. It indicates that the effect of nematicide on yield is different for different values of percent sand fraction. This provides the potential to develop the site-specific nematode management strategy.

Conclusions

This research conducted spatial panel econometric analysis to determine the potential of site-specific nematicide application using on-farm field scale experiment data for cotton production in Ashley County, Arkansas. Aspatial standard panel model, spatial autoregressive error, spatial autoregressive lag model with fixed effect and random effect extension were used to estimate

crop yield response functions with respect to environmental factors and treatment applications. Test statistics indicate that spatial panel models are the proper alternative to aspatial panel models. The spatial error model with random effect extension may be the most appropriate model for this case study due to capturing spatial effects from nematode population, soil texture, and nematicide application rate with controlling spatial and temporal heterogeneity and dependence. Results suggest that nematode population at bloom season is significant factors in explaining yield variability. Yield response for nematicide application differs by soil texture. This finding provides evidence to support the potential of site-specific nematode management. Spatial spillovers of soil texture and nematode population from neighboring plots also significantly impact yield estimates. The results can be used to provide practical recommendations for effectively controlling nematodes via site-specific management.

Figure.1. Lint Yield Curve

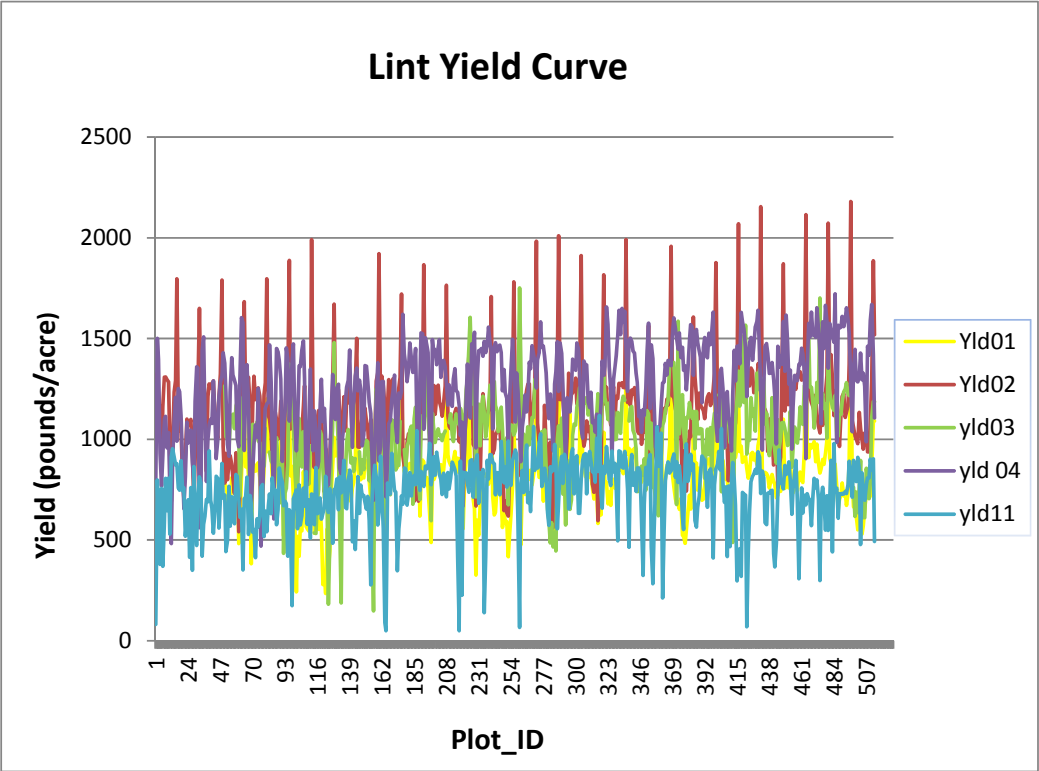


Table 1. Descriptive Statistics for Variables Used in the Analysis

Variable	Mean	Std. Dev.	Min	Max	Definition
elevation	128.52	12.62	88.55	142.03	elevation (feet) for the plot
yield	1012.13	298.01	48.87	2179.32	Cotton yield (pounds/acre)
pop	806.37	1643.94	0	22045	M. incognita population density (juveniles/500 cm ³ of soil)
telone	1.25	1.63	0	4.5	nematicide application rate (gallon/acre)
zsand	46.36	11.03	21.66	82.96	the percent sand fraction of the soil

Table 2. Regression Results from a Variety of Panel Specifications

	Panel_FE Coef. (Std.Err.)	Panel_RE Coef. (Std.Err.)	SAR_FE Coef. (Std.Err.)	SAR_RE Coef. (Std.Err.)	SEM_FE Coef. (Std.Err.)	SEM_RE Coef. (Std.Err.)
pop	0.143*** (0.028)	0.206*** (0.025)	0.139*** (0.030)	0.200*** (0.026)	0.114* (0.028)	0.170*** (0.026)
pop_elev	0.0002 (0.00018)	1.54E-05 (0.0002)	0.0003* (0.0002)	0.0001 (0.0002)	0.0004* (0.0002)	0.0002 (0.0002)
pop_zsand	-0.0005** (0.00024)	-0.001*** (0.0002)	-0.0004 (0.0003)	-0.001*** (0.0002)	-0.0003 (0.0002)	-0.001*** (0.0002)
telone	40.321*** (11.686)	87.501*** (9.648)	42.419*** (12.830)	90.010*** (10.010)	36.050*** (12.643)	95.0427*** (9.833)
telone_zsand	-0.201 (0.239)	-1.231*** (0.195)	-0.161 (0.263)	-1.335*** (0.202)	-0.087 (0.263)	-1.379*** (0.197)
yr01	52.110*** (15.461)	50.394*** (14.915)	57.600*** (16.975)	68.228*** (16.214)	54.571*** (14.839)	53.612*** (14.778)
yr02	363.780*** (16.987)	363.350*** (16.342)	416.399*** (18.650)	428.558*** (17.737)	364.794*** (16.155)	364.121*** (15.998)
yr03	292.855*** (14.274)	291.127*** (14.010)	352.039*** (15.672)	362.459*** (15.308)	292.211*** (13.436)	291.599*** (13.458)
yr04	493.876*** (12.083)	492.075*** (12.260)	566.648*** (13.267)	569.366*** (13.525)	495.763*** (11.610)	496.431*** (11.818)
pop_treatyr	-0.158*** (0.013)	-0.162*** (0.012)	-0.175*** (0.014)	-0.165*** (0.013)	-0.157*** (0.013)	-0.152*** (0.012)
_cons	722.110*** (8.432)	721.777*** (9.321)	113.289*** (9.257)	97.155*** (9.802)	318.961*** (5.119)	307.874*** (5.730)
AIC			34016.12		33940.54	
Rho			0.558719***	0.57438***		
Lambda					0.55872***	0.574379***
N=2560						
T=5						

Notes: Significance is at the 1, 5, and 10% level as noted by, ***, **, and *, respectively.

Reference

Anselin, L. 1988. *Spatial econometrics: methods and models*. Dordrecht, The Netherlands: Kluwer.

Anselin, L., Hudak, S. (1992). Spatial econometrics in practice: a review of software options. *Regional science and urban economics* 22: 509–536

Anselin, L. 2002. Under the Hood Issues in the Specification and Interpretation of Spatial Regression Models, *Agricultural Economics*, 27, 247–267.

Anselin, L., Bongiovanni, R., & Lowenberg-DeBoer, J. 2004. A spatial econometric approach to the economics of site-specific nitrogen management in corn production. *American Journal of Agricultural Economics* 86, 675–687.

Baltagi, B. (2001). *Econometric analysis of panel data*. J. Wiley & Sons Ltd. England
Barnes, Edward M., Kenneth A Sudduth, John W Hummel, Scott M Lesch, Dennis L Corwin, Chenghai Yang, Craig S. T. Daughtry , and Walter C. Bausch. 2003. Remote- and Ground-Based Sensor Techniques to Map Soil Properties. *Photogrammetric Engineering Remote Sensing*. Volume: 69, Issue: 6, 619-630

Bell, K. P., & Bockstael, N. E. 2000. Applying the generalized-moment estimation approach to spatial problems involving micro level data. *The Review of Economics and Statistics*, 82, 72–82.

Blasingame D, Patel MV (2005) Cotton disease loss estimate committee report. 2005. Proceedingd of the Beltwide Cotton Conference, National Cotton Council of America, Memphis.

Bockstael, N. E. 1996. Modeling economics and ecology: the importance of a spatial perspective. *American Journal of Agricultural Economics* 78, 1168–1180.

Byrd, Jr., D. W., Barker, K. R., Ferris, H., Nusbaum, C. J., Griffin, W. E., Small, R. H., and Stone, C. A. 1976. Two semi-automatic elutriators for extracting nematodes and certain fungi from soil. *Journal of Nematology* 8:206–212.

Cressie, N. A. C. 1993. *Statistics for spatial data* (Revised ed.). New York: Wiley.

Elhorst, P. (2003) Specification and estimation of spatial panel models, *International Regional Science Review* 26: 244–268

Florax, R. J. G. M., Voortman, R. L., & Brouwer, J. 2002. Spatial dimensions of precision agriculture: a spatial econometric analysis of millet yield on Sahelian coversands. *Agricultural Economics*, 27, 425–443.

- Gee, G. W., and Bauder, J. W. 1979. Particle size analysis by hydrometer: A simplified method for routine textural analysis and a sensitivity test of measurement parameters. *Soil Science Society of America Journal* 43:1004–1007.
- Griffin, T. W., & Lowenberg-DeBoer, J. 2005. Worldwide adoption and profitability of precision agriculture: Implications for Brazil. *Revista de Política Agrícola*, 14, 20–37.
- Griffin, T. W., Dobbins, C. L., Vyn, T., Florax, R. J. G. M., & Lowenberg-DeBoer, J. 2008. Spatial analysis of yield monitor data: case studies of on-farm trials and farm management decision-making. *Precision Agriculture*, 9, 269–283.
- Hsiao C .2005. Why panel data? University of Southern California, IEPR working paper. 05.33
- Kapoor, M., H.H. Kelejian, and I.R. Prucha. 2007. ‘‘Panel Data Model with Spatially Correlated Error Components.’’ *Journal of Econometrics* 140,1:97–130.
- Kelejian, H.H., and I.R. Prucha. 1999. A Generalized Moments Estimator for the Autoregressive Parameter in a Spatial Model.’’ *International Economic Review* 40:509–33.
- Koenning SR, Overstreet C, Noling JW et al. 1999. Survey of crop losses in response to phytoparasitic nematodes in the United States for 1994. *J Nematol* 31(Suppl):587–618
- Koenning SR, Kirkpatrick TL, Starr JL et al. 2004. Plant-parasitic nematodes attacking cotton in the United States: old and emerging production challenges. *Plant Dis* 88:101–113
- Jenkins, W. R. 1964. A rapid centrifugal-flotation technique for separating nematodes from soil. *Plant Disease Reporter* 48:692.
- Lambert, D. M., Lowenberg-DeBoer, J., & Bongiovanni, R. 2004. A comparison of four spatial regression models for yield monitor data: a case study from Argentina. *Precision Agriculture* 5, 579–600.
- LeSage, James P. and R. Kelley Pace. (2009) *Introduction to Spatial Econometrics*. CRC Press, Taylor and Francis Group.
- Monfort, W.S., Kirkpatrick, T.L., Rothrock, C.S., Mauromoustakos, A. 2007. Potential for Site-specific Management of *Meloidogyne incognita* in Cotton Using Soil Textural Zones. *Journal of Nematology*, March 2007, 39 (1): 1-8.
- Montgomery, D. C. Design and analysis of experiments (5th ed.). New York, NY: John Wiley & Sons, Inc., 2001.
- Mueller, J.D., Khalilian, A., Monfort, W., Davis, R.F., Kirkpatrick, T.L., Ortiz, B.B., Henderson, W.G. 2011. Site-Specific Detection and Management of Nematodes. In: Oerke, E.C., Gerhards R., Menz G., Sikora, R.A., editors. *Precision Crop Protection-the challenge and use of Heterogeneity*. Berlin, Germany: Springer. p. 385-402.