SPATIAL ECONOMETRIC APPROACHES TO DEVELOP SITE-SPECIFIC NEMATODE MANAGEMENT STRATEGIES 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 analysis of on-farm experiments 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 post-treatment nematode population at bloom season and percent sand fraction 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, nematicide application rate, soil texture, spatial 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. The overall objective of this study is to determine the potential of site-specific nematicide application by using spatial econometric analyses of on-farm experiments precision agriculture data. Spatial statistical techniques 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. Specific objectives were: 1) to compare aspatial classic model, spatial autoregressive error, spatial autoregressive lag and spatial Durbin models of for empirical on-farm trials 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. This is followed by an overview of the methodology and data use 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 are soil mapping unit polygons such as those available for download at SSURGO. However, these soil polygons 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 monitors 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. Replication allows for estimation of experimental error and to obtain a more precise estimate of treatment means (Montgomery, 2001). Randomization is a method to allow “observations (or errors) to be independently distributed random variables” (Montgomery, 2001; Yates, 1936). Blocking improves the precision of comparisons among treatments by reducing variability from nuisance factors (Montgomery, 2001). Treatment effects are more efficiently estimated by modeling spatial autocorrelation via spatial econometric technique than the traditional approach of neutralizing spatial autocorrelation via randomization (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 such as independence of observations and homoscedastic error terms. To correct for spatial effects in the residuals from a linear model estimated by OLS, methods that adjust for spatial dependence and will give more accurate estimates should be chosen. The two most commonly used models for site-specific agricultural data are the spatial autoregressive error (error) and spatial autoregressive lag (lag) models; and either can be estimated by maximum likelihood (ML), general method of moments (GM), instrumental variables (IV), and other classic estimators. Another extended spatial model labeled spatial Durbin model, which is motivated by concern over omitted variables, also occupies an interesting position in spatial econometrics.

The spatial error model is given as $y = X\beta + \varepsilon,\ \varepsilon = \lambda W\varepsilon + \mu$ or in reduced form as $y = X\beta + (I - \lambda W)^{-1}\mu$ where y is a n x 1 vector of dependent variables, X a n x k matrix of explanatory variables, β a *k* x *1* vector of regression coefficients,

ε an n x 1 vector of residuals, λ a spatial autoregressive parameter, W is an n x n spatial weights matrix, and μ a well behaved, non-heteroskedastic uncorrelated error term (Anselin, 1988). When the spatial autoregressive term, λ=0, the spatial error model reverts to the aspatial model. The spatial error process can be characterized by the autoregressive (AR) or the moving average (MA) error process resulting in global and local spillovers, respectively. The spatial error model has no substantive economic interpretation. When the spatial error model is appropriate, OLS estimates remain unbiased but are inefficient.

The spatial lag model is given as $y = \rho Wy + X\beta + \mu$ or in reduced form $y = (I - \rho W)^{-1}[X\beta + \mu]$ where ρ is the spatial autoregressive parameter and the others as previously defined (Anselin, 1988). Similar to the spatial error model, the spatial lag model reverts to the aspatial model when the spatial autoregressive term, ρ, is 0. Spatial lags result in global spillovers and have a substantive economic interpretation. Spatial lag models are sensitive to localized shocks influencing the whole system through the spatial multiplier, $(I - \rho W)^{-1}$. The OLS estimator is inconsistent for purely spatial autoregressive processes (Lee, 2002).

Another model can be used when we are concerned about omitted variables for site-specific agricultural data is spatial Durbin model. It is equivalent to a mixed autoregressive model on a specification which includes spatially lagged dependent and exogenous variables. The spatial Durbin model is given by $y = X\beta + \eta,\ \ \eta = \rho W\eta + \varepsilon,\ \ \varepsilon = X\gamma + u$ or in reduced form $y = (I - \rho W)^{-1}[X\beta + WX\gamma + u]$ where η is an N □1 vector of a spatially correlated omitted variable following a spatial autoregressive process with autoregressive parameter ρ, and u is an N □1 vector of well-behaved i.i.d. random error terms. The omitted variable is correlated with X when $\gamma \neq 0$. The others are same as previously defined. The spatial Durbin model allows the interested variable for each region depends on its own-region factors from the matrix X , plus the same factors averaged over the neighboring regions, WX while consider the omitted variable not included in the model specifications.

Both spatial error model and spatial lag model have been used with site-specific yield data. Anselin et al. (2004), Lambert et al. (2004), and Griffin et al. (2008) used the spatial error process model in their analyses, whereas Florax et al. (2002) used the spatial lag process 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. When a pathogen such as nematode infestation is the dependent variable, spatial contagion is expected to exist in the dependent variable thus the spatial lag process model would be most appropriate. For the site-specific nematode management case, the crop yield is more likely to be affected by the omitted variables, local nematode density and also neighborhood nematode population, the spatial Durbin model may be a better fit statistical model to address the crop yield response function.

In this study, using on-farm trial experiments data, we conducted econometric estimation for the model across a range of aspatial and spatial estimators, including standard OLS, spatial autoregressive error, spatial autoregressive lag and spatial Durbin models. The best fit model with respect to theoretical rationale and empirical indication was discussed.

DATA

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*. The field was subdivided into 512 plots (32 plots wide × 16 plots long) to facilitate sequential sampling over the 4-yr period (2001-2004). 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). The individual plot size was established to accommodate collecting yield using an Ag Leader PF3000 yield monitor (Ag Leader Technology, Ames, IA) that recorded yield once per second mounted on a 4-row John Deere 9970 cotton picker. The 30.5 m length ensured that each plot had at least seven individual yield recordings.

The nematicide 1,3-dichloropropene (Telone II, Dow Agrosciences, Indianapolis, IN) was applied 2 wk prior to planting at variable rate to ensure that there were differences in nematode population densities across the field. The application rate is 0, 14.1, 29.2 or 42.2 liter/ha in 2001 and 2002 and 0 and 29.2 liter/ha in 488 m × 3.7 m (16 plots long × 1 plot wide) strips in a randomized complete block design across the entire research plot area. Nematicide treatments were replicated 8 times in 2001 and 2002 and 16 times in 2003 and stopped in 2004.

All plots were sampled for *M. incognita* each year prior to nematicide application (Pre), at the time of planting and representing the initial population after fumigation (Pi), approximately 70 day after planting (Pm) peak bloom and at harvest (Pf). Soil samples were taken from each grid in April (planting) and October (harvest) each year from 2001 through 2003, and a final sample was collected in April 2004. Each sample consisted of a composite of 16 soil cores collected from the root zone (bed) to a depth of 30 cm in the center two rows of each grid. Nematodes were extracted from the composite samples using the semi-automatic elutriator (Byrd et al., 1976) followed by centrifugal flotation (Jenkins, 1964), and nematodes were identified and quantified with a stereoscope at 340 to 360 magnification. Soil texture (percent sand fraction) was also assessed for each grid plot utilizing hydrometer particle-size analysis (Gee and Bauder, 1979).

Cotton was grown in the field each year of the study under a reduced-tillage system. Stoneville 4892 BR, a glyphosate-tolerant cotton cultivar, was planted each year. Crop fertilization, irrigation (centerpivot) and insect/weed management were performed by the grower according to his normal farming practices. Yield was recorded each year at crop maturity using a four-row John Deere cotton picker equipped with an AgLeader PF3000 cotton yield monitor (Ag Leader Technology, Ames, IA) equipped with a GPS receiver. The yield was determined for each plot utilizing a spatial overlay tool for averaging point data by polygon or plot within the geographic information system SSToolbox (SST Development Group, Inc., Stillwater, OK). Lint yield was calculated based on a 35% gin turnout of seed cotton.

Data distribution and statistics can be found in the following figures and table. Figure1 shows the yield trend in the 4-yr period (2001-2004). Yield 2001 shares the lowest mean value when the nematicide application was initiated. Yield 2004 has the highest mean value while Yield 2002 hit the most peak values. However, the yields from 2001 to 2004 are not monotonically increasing.

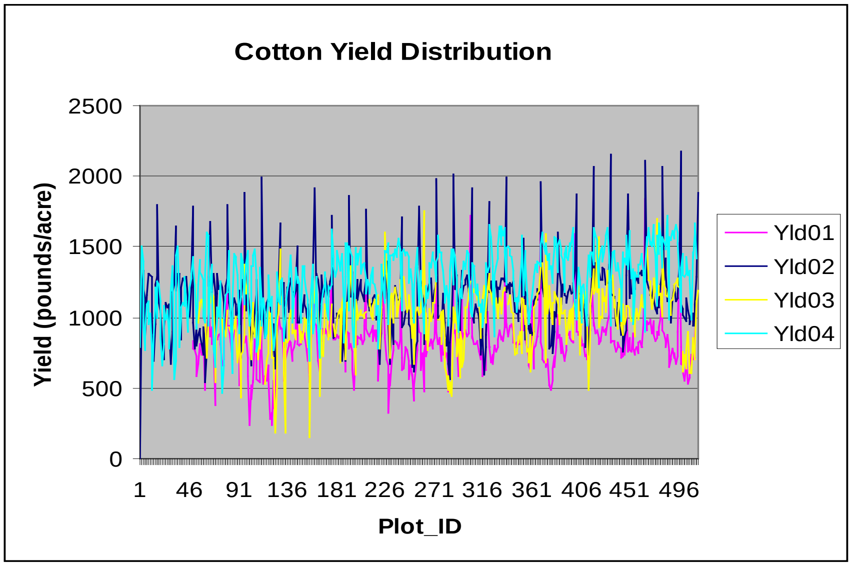

Fig.1.Distribution of cotton yield

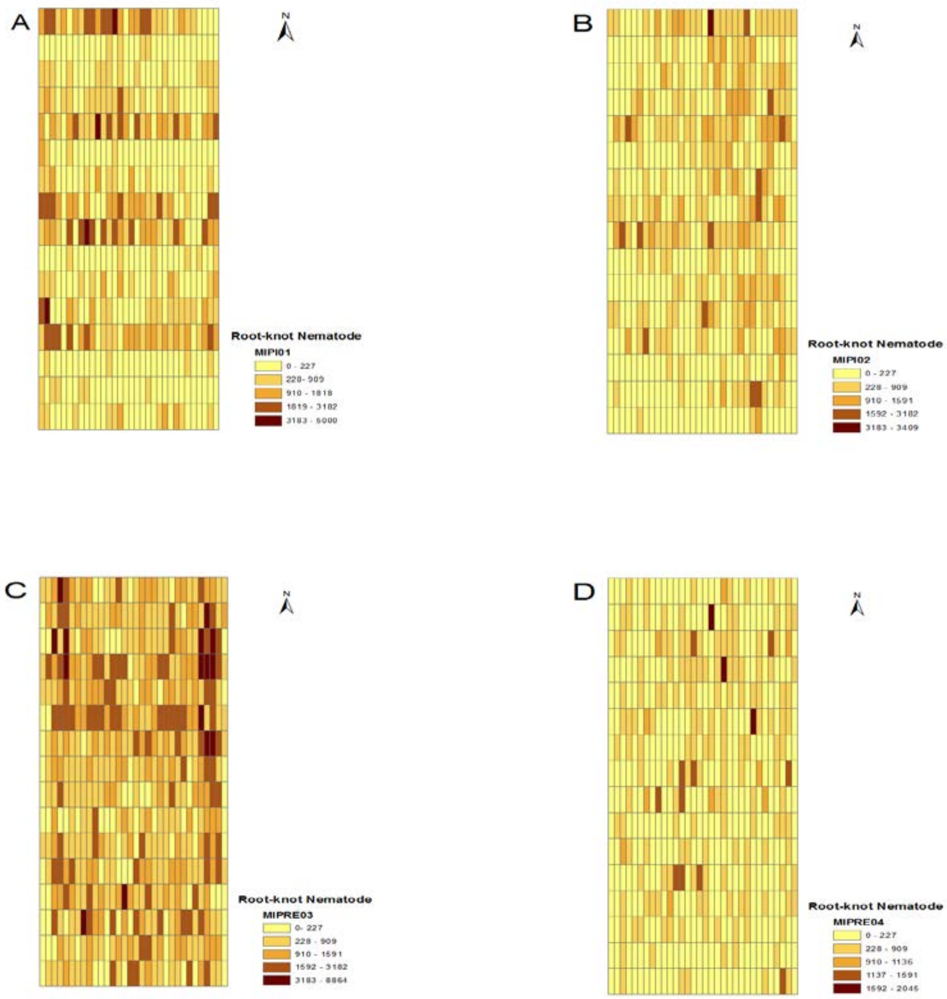

Fig. 2. Spatial distribution maps of root-knot nematode (*Meloidogyne incognita*) in a 6.1 ha cotton field in southeastern Arkansas in May 2001 (Fig. 2A), May 2002 (Fig. 2B), Mar 2003 (Fig. 2C), and Mar 2004 (Fig.2D). Spatial distribution maps were constructed utilizing the Latitude/Longitude coordinates of each plot in the GIS software ArcMap10. *M. incognita* nematode population densities represent number of adults and juveniles per 500 cm^3 soil.

Figure2 and Figure3 visibly indicate the spatial-temporal nematode population distribution. From Figure2, the population patch of *Meloidogyne incognita* contracted from 2002 and hit a significant reduction in 2004 although got a rebound at the spring 2003 before applying nematicide. Figure3 shows in the year of 2002, the population patch contracted most at the planting time in May after nematicide application (fumigation) in March while rebounded at the peak bloom time in July and the harvest time in October. The rebound reached a highest level at the peak bloom time.

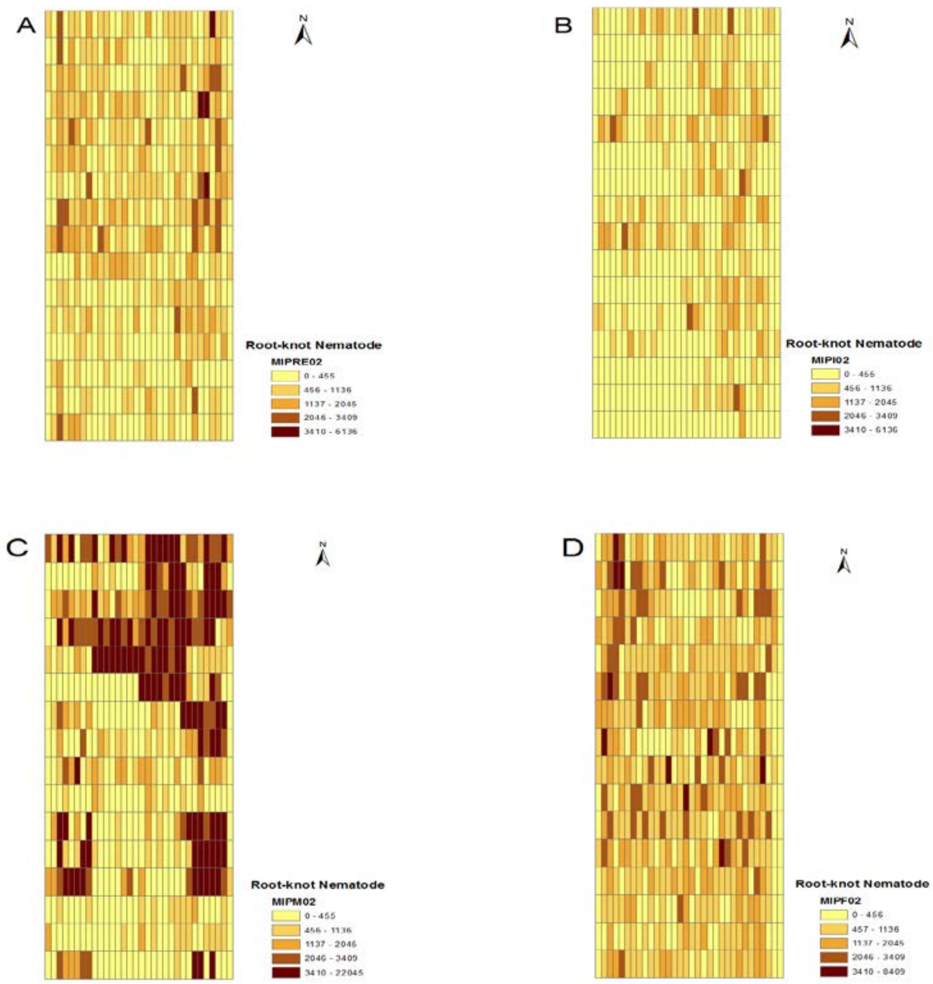

Fig 3. Spatial distribution maps of root-knot nematode (*Meloidogyne incognita*) in a 6.1 ha cotton field in southeastern Arkansas in Mar 2002 (Fig. 2A), May 2002 (Fig. 2B), July 2002 (Fig. 2C), and Oct 2002 (Fig.2D). Spatial distribution maps were constructed utilizing the Latitude/Longitude coordinates of each plot in the GIS software ArcMap 10. *M. incognita* nematode population densities represent number of adults and juveniles per 500 cm^3 soil.

The data we used for spatial econometric analysis is the sub- dataset for the 2002 crop season. Table1 reports the definitions and statistics of the variables used in the analysis. Consistent with the distribution map, the root-knot nematode population has the highest mean value with high standard deviation at the bloom season (Pm) while the initial population after fumigation treatment (Pi) shares the lowest average number.

Table1. Statistics of variables

Variable	Mean	Std.Dev.	Minimum	Maximum	Definition
YLD02	1136.58	252.24	541.34	2179.32	Cotton yield (pounds/acre) in 2002
MIPI02	473.68	559.01	0	3409.00	M. incognita population at planting
MIPM02	1999.19	2754.19	0	22045.00	M. incognita population at peak bloom
MIPF02	1181.46	946.39	0	8409.00	M. incognita population at harvest
TELONE	2.29	1.69	0	4.50	nematicide application rate (gallon/acre)
ZSAND	46.36	11.04	21.66	82.96	the percent sand fraction of the soil

We created some interaction variables to explore the potential relationship between soil properties, treatment application and yield. Quadratic term in nematode population was also included to assess non-linearity. With the inclusion of these variables, the specification estimated reads as:

$$Yield = f(Mipi02, Mipi02\_sq, Mipm02, Mipf02, Zland, Telone, Zland : Telone, Mipi02 : Zland, Mipm02 : Zland, Mipf02 : Zland) \quad (1)$$

EMPIRICAL RESULTS

We estimated yield potential (penalty) as a function of nematode population, soil texture, and other interaction variables as equation (1) using on farm field-scale trial experiment data in 2002 in Ashley county, AR. The focus is on the model comparison between standard regimes model that is estimated by OLS and spatial regimes models, which include spatial autoregressive error model (SERROR), spatial autoregressive lag model (SLAG) and spatial Durbin model (SDM). The models were estimated in R 2.14.2 using the *spdep* package. 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 coefficients from all four models are similar in sign, magnitude, and significance although there are some significance level differences for variable *Mipm, Mipf, Telone* and *Mipf:Zland.* The percent sand fraction of soil (*Zsand*), the nematode population at planting (*Mipi*), Telone interacted with soil texture (*Telone:Zsand*) are significant determinants to explain the variation of cotton yield across all four models, especially soil texture (*Zsand*) shows strong significance level at 1% in both aspatial and spatial models.

Table 2. Coefficient Estimates and Diagnostic Statistics

	OLS		SLAG		SERROR		SDM	
Variables	Estimate	Pr(>|t|)	Estimate	Pr(>|z|)	Estimate	Pr(>|z|)	Estimate	Pr(>|z|)
(Intercept)	1942***	0.00	812.69***	0.00	1924.3***	0.00	361.36	0.26
Mipi02	-0.229**	0.03	-0.187**	0.04	-0.171*	0.05	-0.15228*	0.08
Mipi02_sq	0.00	0.14	0.00	0.13	0.00	0.30	0.00	0.32
Mipm02	-0.02	0.37	-0.032**	0.04	-0.052***	0.00	-0.043***	0.01
Mipf02	-0.1134**	0.02	-0.06	0.18	-0.03	0.45	-0.04	0.35
			-		-		-	
Zsand	-16.4***	0.00	12.433***	0.00	15.322***	0.00	13.398***	0.00
Telone	-33.61	0.19	-31.00	0.15	-41.451**	0.03	-23.57	0.28
Zsand:Telone	1.012*	0.06	1.0839**	0.02	1.4248***	0.00	1.0447**	0.02
Mipi02:Zsand	0.00	0.41	0.00	0.33	0.00	0.23	0.00	0.30
Mipm02:Zsand	0.00	0.46	0.0006*	0.08	0.0009***	0.00	0.0007**	0.02
Mipf02:Zsand	0.00219**	0.04	0.00	0.25	0.00	0.49	0.00	0.33
lag.Mipi02							0.05	0.87
lag.Mipi02_sq							0.00	0.29
lag.Mipm02							0.148***	0.00
lag.Mipf02							-0.328***	0.01
lag.Zsand							15.804**	0.01
lag.Telone							156.19*	0.07
							-	
lag.Zsand:Telone							5.1571***	0.00
lag.Mipi02:Zsand							-0.01	0.24
lag.Mipm02:Zsand							-0.003***	0.00
lag.Mipf02:Zsand							0.007**	0.01
Lambda	N/A				0.90	0.00		
Rho	N/A		0.82	0.00			0.83	0.00
Log likelihood			-3289.24		-3283.48		-3256.82	
AIC	6730.49		6604.50		6592.90		6559.60	

Table 2. Coefficient Estimates and Diagnostic Statistics (Continued)

	OLS		SLAG		SERROR		SDM	
Variables	Estimate	Pr(>|t|)	Estimate	Pr(>|z|)	Estimate	Pr(>|z|)	Estimate	Pr(>|z|)
Diagnostic tests								
The Likelihood Ratio test (LR)			128.02	0.00	139.54	0.00	107.87	0.00
Hausman test					66.35	0.00		

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

As expected, the spatial autoregressive parameter (*Rho*) in spatial lag model has a positive effect and highly significant. It indicates that the spatial dependence inherently existed in our data, and spatial model is a better alternative to the aspatial standard model by accounting for the spatial dependence. The Likelihood Ratio test (LR) on this parameter is also highly significant, which means although the introduction of spatial lag term improved the model fit, it didn't make the spatial effects go away. As for the results for the spatial error model, the coefficient on the spatially correlated errors (*Lambda*) has a positive effect and it is highly significant. Compared to spatial lag model, the general model fit improved, as indicated in higher Log likelihood and lower AIC value. The spatial Hausman test indicate that the regression coefficients of a spatial error model significantly differ from those of the underlying linear model assuming $\square\square \neq 0$. Both spatial lag and spatial error model yield improvement to the original OLS model. Therefore, we should conclude that controlling spatial dependence will improve our model performance. If we continue to explore the relative model fit by comparing log likelihood and AIC values, we see that the spatial Durbin model differs clearly from the aspatial standard model, spatial lag model, spatial error model, and fits our on-farm trial data best with the highest log likelihood and lowest AIC value.

We present estimates of the direct, indirect, and total marginal effects for the spatial Durbin model shown as in Table 3. The direct effect is the effect of changes in the *i*-th observation of *xk* on *yi*. Indirect effect, which constitutes feedback effects through neighbors. The total effect represents the effect on each observation from changing the *k*-th explanatory by the one unit across all observations. The increase of nematode population at a specific plot at harvest time will decrease the crop yield of this plot, the spillover on neighboring has a stronger negative effect on the local yield, thus the total effect from the increase of nematode population on the yield penalty get strengthened. Soil texture of local plot significantly affects the crop yield of local plot. However, the spillover effect from the soil texture of neighboring plot will affect the total effect on the local plot. Treatment alone does not explain yield differences while it is significant for yield when interacted with soil texture, which means the effect of nematicide on yield is different for different values of percent sand fraction. When interacted with soil texture, the indirect (spillover) effect from the nematode population of neighbor plot at the bloom season and harvest time has significant effect on the local plot yield.

Table 3. Marginal Effect Estimates for Spatial Durbin Model

	Direct	Indirect	Total
Mipi02	-0.16*	-0.43	-0.59
Mipi02_sq	0.00	0.00	0.00
Mipm02	-0.03*	0.66**	0.63**
Mipf02	-0.08*	-2.09**	-2.17**
Zsand	-12.85***	27.09	14.24
Telone	-7.60	792.11	784.51
Zsand:Telone	0.54	-24.87*	-24.33*
Mipi02:Zsand	0.00	-0.03	-0.03
Mipm02:Zsand	0.00	-0.01**	-0.01**
Mipf02:Zsand	0.002*	0.04*	0.05**

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

CONCLUSIONS

This research conducted spatial 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 model, spatial autoregressive error, spatial autoregressive lag and spatial Durbin models were used to estimate crop yield response functions with respect to environmental factors and treatment applications. Test statistics indicate that spatial models are the proper alternative to aspatial classic models and the spatial Durbin model is the most appropriate model for our case study due to capturing spillover effects from nematode population, soil texture, and nematicide application rate. Results suggest that post-treatment nematode population at bloom season and percent sand fraction are significant factors in explaining yield variability. Yield response for nematicide application differs by soil texture. Nematicide application rate alone does not explain yield differences however when evaluating interaction between nematicide rate and soil texture, statistically significant coefficients are estimated. 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.

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