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Is Site-Specific Nematode Management Profitable: Evidence from Spatial Econometric Analysis

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Abstract

Nematode management in cotton has eluded farmers and researchers for decades. Control strategies have typically relied upon highly toxic nematicide application. Site-specific management provides opportunity to improve profitability while maintaining environmental stewardship; and can be based on yield penalty functions estimated from empirical data. A 4-year field-scale experiment was implemented in a commercial Arkansas cotton field known to exhibit crop yield loss due to nematodes. Root-knot nematode population was measured at four times within each plot each year: 1) prior to nematicide application, 2) at planting, 3) at peak bloom, and 4) at harvest. Due to spatial effects, spatial econometric models were estimated to obtain reliable yield response coefficients. Site-specific cotton yield response to treatment, soil texture, and nematode population were evaluated using a spatial error process model. Specific objectives were to estimate cotton yield response to environmental and treatment factors then conduct profitability analyses for site-specific nematicide application. The results support the potential of site-specific nematicide application including management zone delineation. Profitability analysis of variable rate nematicide application provides an initial insight into the potential of site-specific nematode management.

Keywords: spatial econometrics, yield monitor, nematodes, site-specific application

QEL codes: R3 C1 C93

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Introduction

Similar to other agricultural pests, nematode infestations are likely spatially clustered within agricultural fields and result in reduction in crop yield. Almost 10% of all U.S. cotton production is lost annually to nematode infestations with individual field yield losses reaching 50% (Koenning et al., 2004). Nematode control is primarily dependent on the application of nematicides (Starr et. al., 2007). The cost of nematicide application is currently higher than for most other pesticides and over-use has a potentially negative effect on the environment. Site-specific nematode management provides the opportunity for producers to maximize profit while reducing potential over-use of product. This strategy relies upon delivering nematicides at single or variable rates across the field at locations where it is economically justified. To use the strategy at the farm level, an estimate of profitability of site-specific management should be conducted and should be based on the clear establishment and reliable estimation of yield potential (penalty) function. Recent advances in precision agriculture technologies and spatial econometric approaches that account for spatial dependence enable more accurate estimation of yield potential (penalty) functions associated with nematode damage. These estimates can, in turn, be used to optimize nematicide placement strategies and to estimate the profit from site-specific nematicide application. The objective of this study was to determine the potential of site-specific nematicide application by using spatial econometric analyses of precision agriculture data from on-farm experiments. We build upon the spatial statistical methodologies presented by Liu et al. (2014) and the agronomic results presented b Liu et al. (forthcoming) to evaluate profitability of cotton yield response functions with respect to treatment application and environmental factors while explicitly modeling the spatial spillovers on cotton yield, nematode population, soil texture and nematicide application. The results provide evidence to support the potential of a site-specific approach to nematicide application and contribute to developing site-specific nematode management strategies for an on-the-go algorithm.

Background

When combined with spatial technologies such as variable-rate applicators and electrical conductivity sensors, farmers with yield monitors can assess the current impact of nematode infestations from the variation in yield and can then use this information practically to economically mitigate adverse effects of the pests in following growing seasons. Using soil data as an explanatory variable in the analysis of yield monitor data improves inference on treatment variables. The most commonly used soil data are polygons at the soil mapping unit level such as those that are freely available from the Soil Survey Geographic (SSURGO)

Database (NRCS, 2014). However, SSURGO soil polygons can only be used as discrete categorical variables that assume homogeneity within each patch of soil but improves flexibility of estimated model by allowing each soil mapping unit to have its own intercept and slope coefficients. Sensors that measure site-specific soil characteristics, such as apparent electrical conductivity, provide continuous data over space such that statistical models can be estimated with a continuous rather than discrete explanatory variable.

Soil electrical conductivity has been correlated to several factors that affect crop yield such as soil texture (Barnes et al., 2003). Soil electrical conductivity is especially useful for site-specific nematode management given how crop yield loss from nematode varies as soil texture changes (Montfort et al., 2007). It is unclear as to the exact mechanism for this interaction although it follows logically that plants in more suitable growing environments are less likely to be adversely affected by root damage compared to plants growing in soils that have limited water and (or) nutrient availability (Mueller et al., 2011).

Although yield monitor data have been used to estimate the yield response to crop varieties, nitrogen rates and seeding rates at landscape scales (Griffin et al., 2008), problems exist with data analysis in precision agriculture. The datasets for precision agriculture tend to have few explanatory variables, such as site-specific soil nutrients or other yield impacting factors, which may lead to some omitted variables or bias. The omitted variable problem occurs when the model specification incorrectly omits one or more important factors. Bias appears in the regression parameter estimates when the assumed model specification does not include an independent variable that is correlated with both the dependent variable and one or more of the included independent variables. Ordinary least squares (OLS) estimates are biased and generally inconsistent when important variables are omitted from model specification (Wooldridge, 2003). Moreover, when the omitted variable is spatially correlated or has its own spatial structure, residuals from OLS estimation are expected to be spatially correlated, leading to inefficient estimated coefficients or biased standard errors (Bell and Bockstael, 2000; Bockstael, 1996). Since agricultural plots may differ in some important characteristics (e.g. soil texture, elevation, etc.), spatial heteroscedasticity, which is the lack of constant variance for random regression errors across all spatial units, may exist in the data. The OLS estimates are inefficient under this situation due to the violation of the homoscedasticity assumption in classical statistics (Anselin, et al., 2004). Alternatively, if spatial autocorrelation is present in the dependent variable, parameter estimates by OLS will be biased and inconsistent.

Yield monitor observations are correlated with neighboring observations, resulting in spatial autocorrelation and heteroscedasticity. Spatial autocorrelation and heteroscedasticity have traditionally been neutralized in agricultural field research by reducing the size of experimental units to plots that could be assumed to be homogeneous (Montgomery, 2012). Replication, randomization and blocking techniques are combined with small-plots to determine treatment differences. However, treatment effects are estimated more precisely by modeling spatial autocorrelation by spatial econometric techniques than by the traditional

approach of neutralizing spatial autocorrelation by randomization. These techniques mask the spatial nature of the data and so part of the interesting or important information is disregarded (Cressie 1993). The advanced development of site-specific measurements and spatial statistical computation provides new approaches for statistically valid inference.

Methodology

Site-specific crop yield data, like most agricultural data, are expected to be spatially structured i.e. autocorrelated and heteroscedastic, which violates the assumptions of independence of observations and homoscedastic error terms. Aspatial estimators such as the standard OLS approach may result in inefficient parameter estimates when data have a spatial structure, so methods that explicitly account for these spatial effects need to be chosen for more reliable estimates.

The two most commonly used spatial econometric models are the spatial autoregressive error model and spatial autoregressive lag model. If the true data-generating process exhibits spatial dependence in the residuals, the spatial error model should be considered in order to obtain efficient estimates. If the true data-generating process exhibits spatial correlation in the dependent variable, the spatial lag model should be considered instead.

Both the spatial error model and the spatial lag model have been used with site-specific yield data (Anselin et al. 2004; Delbecq et al 2012; Florax et al. 2002). Theory and *a priori* information suggest that when crop yield is the dependent variable, the spatial effect on the local yield level comes through the spatially autocorrelated error term rather than the crop yield level of the neighboring regions. In this situation, the spatial error model is preferred. When the dependent variable is a pathogen such as nematode infestation, spatial contagion is expected to exist in the dependent variable and thus the spatial lag model is a better alternative. For research of site-specific nematode management, we assume crop yield is a function of nematode population, soil texture and other explanatory factors. However, the spatially autocorrelated-variables omitted, such as some geographic and environmental factors, may be correlated with explanatory variables such as nematode population. Thus, site-specific crop yield is explained not only by the explanatory variables of local plot, but also by the spatial explanatory variables of the neighborhood, such as neighborhood nematode population.

Following Anselin (1988), the expression of the spatial error model is given as

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}, \;\; \boldsymbol{\varepsilon} = \lambda \mathbf{W}\boldsymbol{\varepsilon} + \boldsymbol{\mu} \qquad (1)$$

or in reduced form as

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + (\mathbf{I} - \lambda \mathbf{W})^{-1}\boldsymbol{\mu} \qquad (2)$$

where $\mathbf{y}$ is an $n \times 1$ vector of the dependent variable, $\mathbf{X}$ an $n \times k$ matrix of explanatory variables, $\boldsymbol{\beta}$ an $k \times 1$ vector of regression coefficients, $\boldsymbol{\varepsilon}$ an $n \times 1$ vector of residuals, λ the spatial autoregressive parameter, $\mathbf{W}$ an $n \times n$ spatial weights matrix, $\boldsymbol{\mu}$ is an $n \times 1$ vector of independent identically distributed (i.i.d.) random error terms and $\mathbf{I}$ is an identity matrix. The spatial autoregression parameter, λ, has no substantive economic interpretation and, when λ is zero, the spatial error model reverts to the aspatial model. When spatial error dependence is present, the ordinary least squares (OLS) estimates are unbiased but are inefficient due to violation of the assumption of uncorrelated error terms and the non-diagonal structure of the disturbance variance matrix (Anselin, 1988).

The standard OLS and spatial error process model (SEM) were estimated for data from an on-farm experiment. Model fit and diagnostics are discussed and the spatial effects in cotton yield, nematode population, soil texture and nematicide application rate are addressed based on the regression results from the most appropriate model. All statistical models were estimated in R 2.14.2 (R Core Team, 2013) using the *spdep* (Bivand, 2013) contributed package. The interaction of spatial neighborhood structure was defined using first-order queen contiguity (Anselin, 2002). Observations were defined as neighboring regions if they shared either a common border or vertex with the region of interest.

Data

The data used in this study are from field-scale on-farm trials conducted in a commercial cotton field (6.1 ha) in Ashley County in southeastern Arkansas, USA. The general soil series for the trial field is a Rilla silt loam soil (fine-silty, mixed, thermic Typic Hapludalfs) (Soil Survey Staff, 2014). The field had been planted continuously in cotton for 10 years prior to the study and had been identified as a problem field by the producer due to an infestation of root-knot (*Meloidogyne incognita*) nematode. There were 512 plots in the field (32 plots wide × 16 plots long) and each plot was approximately 0.012 ha (3.6 m (four rows) wide and 30.5 m long). A GPS receiver (Trimble, Sunnyvale, CA, USA) accompanied by GPS mapping software (Site-Mate, Farm Works, Hamilton, IN, USA) were used to determine the geographic location of each plot. An Ag Leader PF3000 yield monitor (Ag Leader Technology, Ames, IA, USA) was used to record yield. At least seven individual yield monitor measurements were recorded for each plot over four sequential years (2001-2004).

The nematicide, 1,3-dichloropropene (Telone II, Dow Agrosciences, Indianapolis, IN, USA), was applied two weeks prior to planting in strips at rates of 0, 14.1, 29.2 or 42.2 l ha^{-1} in 2001 and 2002 and 0 or 29.2 l ha^{-1} in 2003, and arranged in a randomized complete block design across the field. The treatments were replicated eight times in 2001 and 2002, sixteen times in 2003 and no nematicide applied in 2004.

Soil samples for the detection of root-knot nematodes were taken from each plot at four stages each year: prior to nematicide application (Pre), at

planting and therefore representing the initial population after treatment (Pi), at peak bloom of the crop (maximum flowering stage at approximately 70 days after planting) (Pm) and at harvest (Pf). Each sample was a composite of 16 soil cores collected from the root zone to a depth of 300 mm in the center two rows of each plot. Nematodes were extracted from the samples using the semi-automatic elutriator (Byrd et al., 1976) followed by centrifugal flotation (Jenkins, 1964). Soil texture (percent sand, silt and clay fractions) of each individual plot was determined using hydrometer particle-size analysis (Gee and Bauder, 1979).

Cotton was grown in the field during the study period under a reduced-tillage system. Stoneville 4892 BR, a glyphosate-tolerant cotton cultivar, was planted each year under the producer's normal farming practices. A spatial overlay tool was used to determine the yield for each plot by averaging point data by polygon or plot within SSToolbox (SST Development Group, Inc., Stillwater, OK, USA). Lint yield was calculated based on a 35% gin turnout of seed cotton.

Data distribution and statistics are given in the following figures. The chloropleth maps were constructed from the georeferenced co-ordinates of each plot in the GIS software ESRI ArcMap10. Figure 1 shows the yield map for each year in the four-year study period (2001-2004). The smallest mean values of crop yield were observed in 2001, the year when nematicide application was initiated. The largest mean yield values occurred in 2004, whereas the maximum yield was observed in 2002. The yields from 2001 to 2004 were not monotonically increasing.

The spatial distribution of the nematode population over the four years is shown in Fig. 2 and throughout the 2002 season is shown in Fig. 3. From Fig. 2, the population density of *M. incognita* (representing the number of second-stage juveniles per 500 cm^3 soil) appeared to diminish from 2001 onwards with a significant reduction in 2004 although with a patch expansion in spring 2003. Figure3 shows that in 2002 the area of the greatest patch contraction occurred at planting in May (after nematicide application in March), but expanded further at peak flowering growth stage in July and at harvest time in October, with the greatest level at peak bloom time.

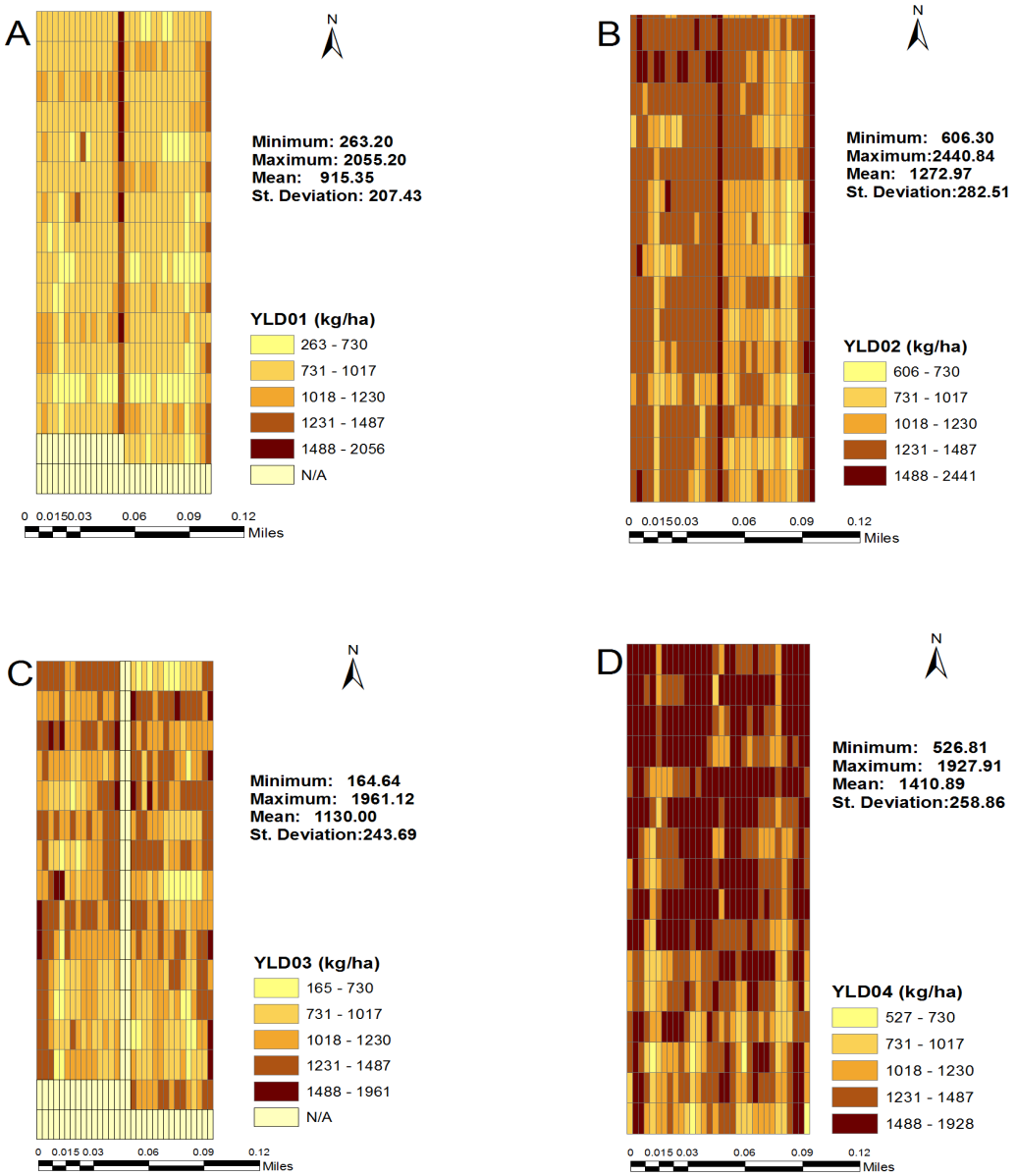

Fig. 1 Cotton yield maps in a 6.1 ha cotton field in southeastern Arkansas for A. 2001, B. 2002, C. 2003, and D. 2004.

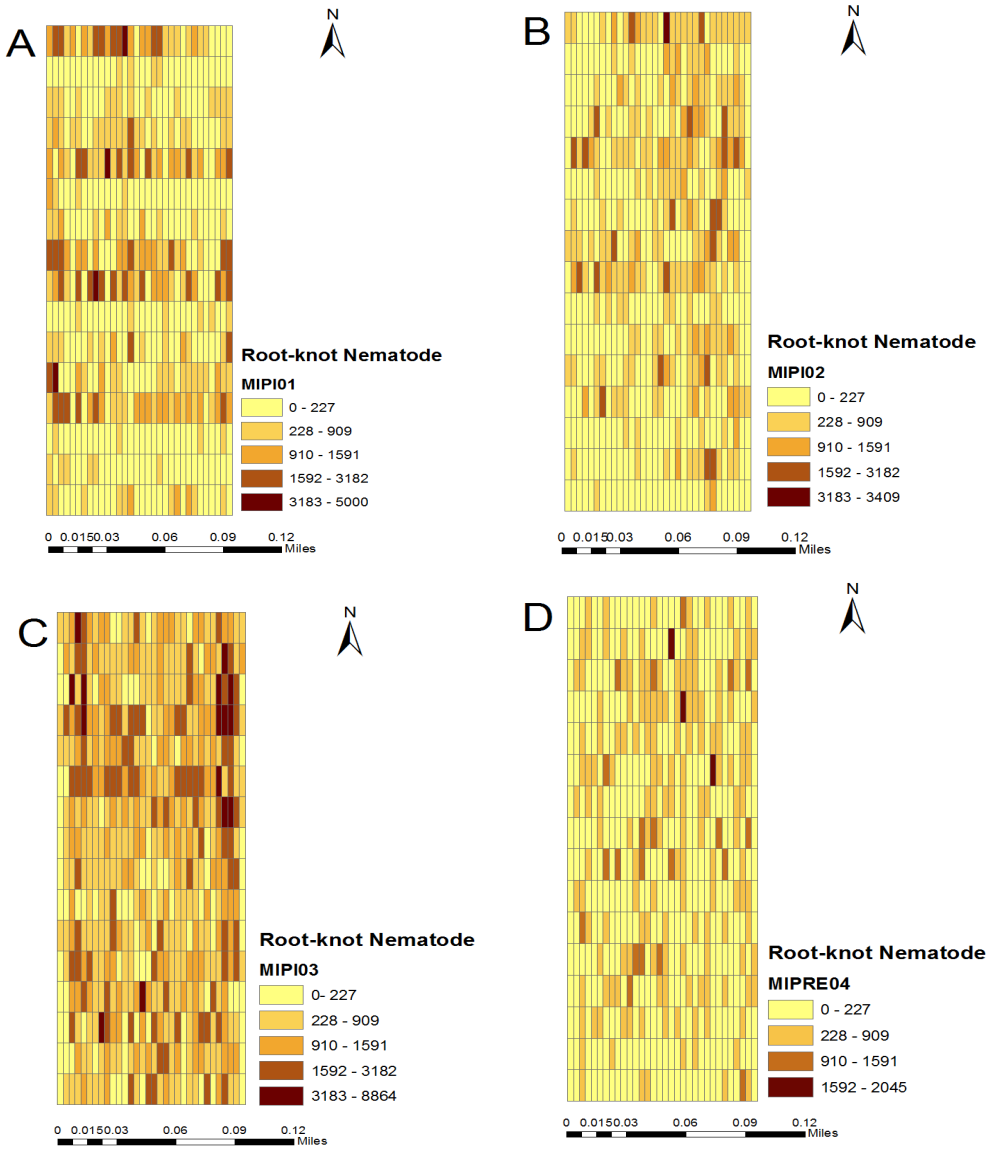

Fig. 2 Spatial distribution maps of root-knot nematode (*Meloidogyne incognita,* MI) intensity in a 6.1 ha cotton field in southeastern Arkansas in A. May 2001(at planting, MIPI01), B. May 2002(at planting, MIPI02), C. May 2003(at planting, MIPI03), and D. April 2004 (prior to treatment, MIPRE04). Nematode counts are the number of second-stage juveniles per 500 cm^3 of soil.

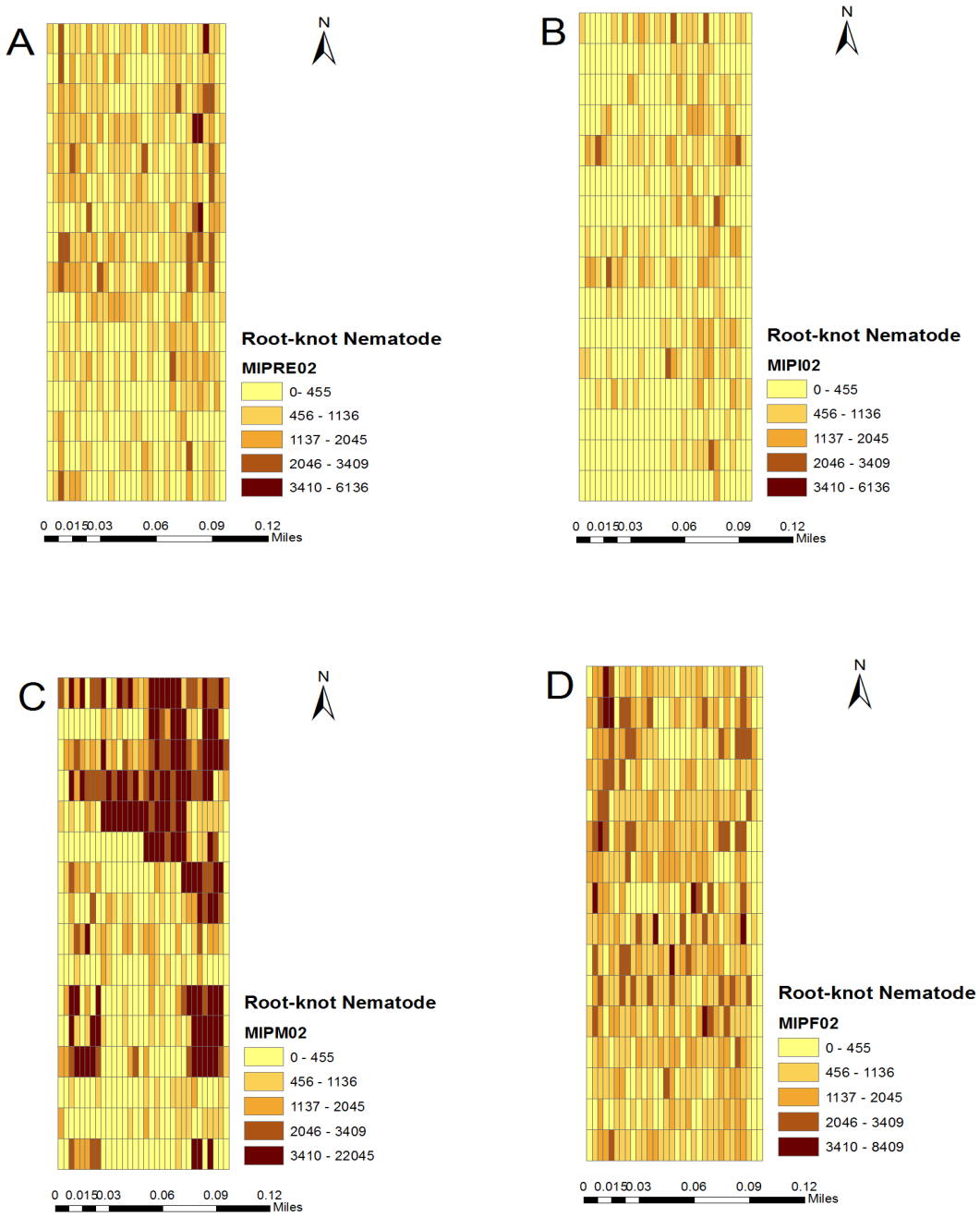

Fig. 3 Spatial distribution maps of root-knot nematode (*Meloidogyne incognita,* MI) intensity in a 6.1 ha cotton field in southeastern Arkansas in A. March 2002 (prior to treatment, MIPRE02), B. May 2002 (at planting, MIPI02), C. July 2002 (at peak bloom, MIPM02), and D. October 2002 (at harvest, MIPF02). Nematode counts are the number of second-stage juveniles per 500 cm^3 of soil.

The data that were used for the spatial econometric analysis were the sub-dataset for the 2002 crop season. Table 1 reports the definitions and descriptive statistics of the variables used in the analysis. Consistent with the distribution map, the root-knot nematode population density reached the largest mean value with a large standard deviation at peak bloom (Mipm02), whereas the initial population density after fumigation (Mipi02) had the smallest mean value.

Table 1. Descriptive statistics of variables

Variable	Mean	Std.Dev.	Minimum	Maximum	Definition
Yld02	1272.97	282.51	606.30	2440.84	Cotton yield (kg/ha) in 2002
Mipi02	473.68	559.01	0	3409	*M. incognita* population (Mi) (number of second-stage juveniles per 500 cm^3 soil) at planting (Pi) in 2002
Mipm02	1999.19	2754.19	0	22045	*M. incognita* population(Mi) (number of second-stage juveniles per 500 cm^3 soil) at peak bloom (pm) in 2002
Mipf02	1181.46	946.39	0	8409	*M. incognita* population (Mi) (number of second-stage juveniles per 500 cm^3 soil) at harvest (pf) in 2002
Telone	21.38	15.85	0	42.09	nematicide application rate (l/ha)
Sand	46.36	11.04	21.66	82.96	percent(%) soil sand fraction

In addition to nematode population, soil texture (% sand fraction) and nematicide (Telone II) application rate, some interaction variables were used to explore the potential relationship between soil properties, treatments and cotton yield. With the inclusion of these variables, the empirical model was:

$$\text{Yld02} = f(\text{Mipi02}, \text{Mipm02}, \text{Mipf02}, \text{Sand}, \text{Telone}, \text{Sand} : \text{Telone}, \text{Mipi02} : \text{Sand}, \text{Mipm02} : \text{Sand}, \text{Mipf02} : \text{Sand}) \quad (7)$$

Results

We estimated yield potential as a function of nematode population, soil texture, and other interaction variables using on-farm field-scale trial experiment data collected in 2002 in Ashley County, AR, USA. The estimation results are summarized in Table 2. The coefficients from all four models were similar in sign, magnitude and significance although some substantial differences existed for some variables. Soil sand fraction (*Sand*) and the interaction of Telone II and soil texture (*Telone: Sand*) are significant determinants to explain the variation in

cotton yield across all four models. In particular, soil texture (*Sand*) showed strong significance at the 1% level in both aspatial and spatial models.

Table 2. Coefficient estimates and diagnostic statistics

Variables	OLS	SEM
(Intercept)	2161.000***	2151.800***
Mipi02	-0.187*	-0.152*
Mipm02	-0.019	-0.058***
Mipf02	-0.134**	-0.038
Sand	-18.350***	-17.187***
Telone	-3.810	-4.855**
Sand:Telone	0.118*	0.169***
Mipi02:Sand	0.002	0.002
Mipm02:Sand	0.0003	0.0011***
Mipf02:Sand	0.003**	0.001
Lambda		0.902***
Measures of fit		
Log likelihood		-3340
AIC	6843	6704
Diagnostic tests	d.f.	Prob
Lagrange multiplier (error)	1	0.000
Robust LM (error)	1	0.000
Lagrange multiplier (lag)	1	0.000
Robust LM (lag)	1	0.002
Hausman test	10	0.000

Notes: Significance is at the 1%, 5%, and 10% levels, as indicated by ***, ** and * respectively. The Hausman test for the spatial error model (SEM) proposed by LeSage and Pace (2009) tests for significant difference between the SEM and OLS estimates.

Estimated coefficients from the best fitting model were selected based on the results of the diagnostic statistics. First, the spatial autoregressive parameter λ (Lambda) in the spatial error model was highly significant at the 1% significance level, indicating that spatial dependence existed inherently in the data, and that the spatial model is a better alternative to the non-spatial standard model (OLS) because it accounts for the spatial dependence. Furthermore, the sign on the autoregressive parameter indicated positive spatial effects. In general, this implies that plots with high (low) levels of nematode infestations have neighboring plots with high (low) levels of infestation. The diagnostic tests against the presence of

spatial autocorrelation reinforced the above conclusion. Both the Lagrange multiplier (LM) error test and the LM lag test rejected the null hypothesis of no spatial autocorrelation strongly at small significance levels ($p < 0.001$). Although robust LM tests suggested a spatial error model as the proper alternative rather than a spatial lag model, the spatial Hausman (Hausman, 1978) test rejected the null hypothesis and suggested that bias from omitted variables might be a problem (LeSage and Pace, 2009). From a theoretical perspective in this site-specific nematode management study, spatially autocorrelated omitted variables such as the geographic characteristics of the plot may influence the explanatory variables that are included such as nematode population.

Economic analyses

Given the lack of straightforward interpretation of the spatial lag process and spatial Durbin models, economic analyses were based on the spatial error process model. The percent sand fraction is the important variable to base application decisions. When percent sand was greater than 30%, agronomic benefit existed in applying nematicide. At the expected price ratios, application of nematicide was profitable when percent sand fraction was greater than 65%. In addition, site specific rates were constrained to be either 0X or 1X rate, the so-called "on-off" application method.

Conclusions

This research used spatial econometric analysis to determine the potential of site-specific nematicide application using field-scale, on-farm experimental data from cotton production in Ashley County, Arkansas, USA. Aspatial standard, spatial autoregressive error, spatial autoregressive lag and spatial Durbin models were used to estimate crop yield response functions with respect to treatment applications and environmental factors. Test statistics indicated that spatial models were the proper alternative to classic aspatial linear models. Results suggest that post-treatment nematode population density at maximum flowering stage and percent sand fraction of the soil are significant factors in explaining the variation in yield. Yield response to nematicide application differed across the spectrum of soil texture values. Nematicide application rate alone did not explain the variation in yield. However, when evaluating the interaction between nematicide rate and soil texture, statistically significant coefficients were estimated. Spatial spillovers of nematode population density from neighboring plots also affected yield estimates markedly. These findings provide evidence to support the potential of site-specific nematode management. Results from profitability analyses of site-specific nematicide application indicate practical recommendations are effectively for controlling nematodes via site-specific management. Results indicated that when percent sand fraction was greater than 65% then a site-specific "on-off" application rate is feasible.

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