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

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Selected Paper prepared for presentation at the Southern Agricultural Economics Association's 2015 Annual Meeting, Atlanta, Georgia, January 31-February 3, 2015

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Abstract

Nematode management for cotton production has eluded farmers and researchers. Control strategies typically rely upon highly toxic nematicide application. Site-specific management provides opportunity to improve profitability while maintaining environmental stewardship. This paper determined the potential for site-specific nematicide application by using spatial econometric analyses of on-farm experimental data to estimate cotton yield response functions with respect to environmental factors and treatment applications. Results suggest that crop yield response for a given nematode infestation level or nematicide application rate differs by soil texture, providing evidence to support the potential of site-specific nematicide application and management zone delineation. The profitability analysis related is useful to provide practical recommendations for effectively controlling nematodes via site-specific management.

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

JEL: R3 C93 Q16 Q15

Introduction

Nematode infestations tend to be spatially clustered within agricultural fields and result in reduction in crop yield. Nematode control in cotton is primarily dependent on the application of nematicides because of a lack of effective resistant cultivars (Koenning et al., 2004). 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. It 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. Spatial statistical techniques were used to estimate cotton yield response functions with respect to treatment application and environmental factors while explicitly modeling the spatial effects 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.

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. Soil electrical conductivity is especially useful for site-specific nematode management since it is assumed that crop yield loss from nematode varies as soil texture changes (Montfort et al., 2007).

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. 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). Moreover, yield monitor observations are correlated with neighboring observations, resulting in spatial autocorrelation and heteroscedasticity which 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). However, these techniques mask the spatial nature of the data and so part of the interesting or important information is disregarded (Cressie 1993). Spatial econometric technique combined with the advanced development of site-specific measurements 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.

Following Anselin (1988), the expression of 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 $n \times 1$ vector of the dependent variable, **X** a $n \times k$ matrix of explanatory variables, **β** a $k \times 1$ vector of regression coefficients, **ε** an $n \times 1$ vector of residuals, λ the spatial autoregressive parameter, **W** an $n \times n$ spatial weights matrix, and μ a well behaved, independent identically distributed (i.i.d.) random error term. **I** is an identity matrix. The spatial autoregression parameter, λ, has no substantive economic interpretation and when λ is equal to 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 inefficient due to the violation of the assumption of uncorrelated error terms and the nondiagonal structure of the disturbance variance matrix (Anselin, 1988).

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).

An extended spatial model, referred to as the spatial Durbin model (SDM), is motivated by concern over omitted variables which may correlate with explanatory variables. It is similar to the spatial autoregressive model but with the addition of spatially weighted independent variables. The expression of the spatial Durbin model is given by $y = \rho Wy + X\beta + WX\gamma + u$ or in reduced form $y = (I - \rho W)^{-1}\left[X\beta + WX\gamma + \mu\right]$, where ρ is a spatial autoregressive parameter, γ is a spatial autoregressive parameter, and μ is an $n \times 1$ vector of well-behaved independent, identically distributed (i.i.d.) random error term. The omitted variable is correlated with **X** when $\gamma \neq 0$ .The other notations are the same as previously defined. The spatial Durbin model assumes that the dependent variable for each region is not only affected by the local factors (through the matrix **X**), but also by the same factors weighted and averaged over the neighboring regions (through the matrix product **WX**) while accounting for the influence of the variables erroneously omitted from the model.

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. The spatial error model is preferred in this situation. 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 the 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. Some combined spatial-autoregressive model with spatially weighted explanatory variables, such as the spatial Durbin model, may be appropriate in this situation (LeSage and Pace, 2009)

In this paper, a standard OLS, spatial error process (SEM), spatial lag process (SAR), and spatial Durbin model (SDM) were estimated for data from an on-farm experiment. The interaction of spatial neighborhood structure was defined using first-order queen contiguity (Anselin, 2002). Model fit and diagnostics was discussed and the spatial effects in cotton yield, nematode population, soil texture and nematicide application rate was addressed based on the regression results from the best fit model. All statistical models were estimated in R 2.14.2 (R Core Team, 2013) using the *spdep* (Bivand, 2013) contributed package.

Data

The data used in this study are from the field-scale on-farm trials conducted in a commercial cotton field (6.1 ha) known to exhibit crop yield loss due to an infestation of root-knot (*Meloidogyne incognita*) nematodes in Ashley County in southeastern Arkansas, USA. The field was subdivided into 512 plots (32 plots wide × 16 plots long). Each plot was approximately 0.012 ha consisting of four 30.5-m long rows (30.5 × 3.9 m). The geographic location of each plot was determined with a differential global position system (GPS) receiver (Trimble, Sunnyvale, CA, USA) accompanied by a GPS mapping software (Site-Mate, Farmworks, Hamilton, IN, USA). 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 and arranged in a randomized complete block design across the field. The treatments were replicated eight times.

All plots were sampled for root-knot nematode (*Meloidogyne incognita*) population density each year prior to nematicide application (*Mipre*), at the time of planting (representing the initial population after fumigation) (*Mipi*)), at peak bloom (maximum flowering stage at approximately 70 days after planting) (*Mipm*) and at harvest (*Mipf*). Cotton was grown in the field during the study period under a reduced-tillage system. 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.

Yield files include data-point information about yields, latitude, longitude which were used to generate a geopositioned data file, and also soil texture (% sand fraction) and nematicide (Telone II) application rate. 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. 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.

In addition to nematode population, soil texture (% sand fraction) and nematicide application rate and 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 expressed as:

$$Yld02 = f(Mipi02, Mipm02, Mipf02, Sand, Telone, Sand:Telone,$$
$$Mipi02:Sand, Mipm02:Sand, Mipf02:Sand)$$

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.

Estimated coefficients from the best fitting model were selected based on the results of the diagnostic statistics. The spatial autoregressive parameter λ (Lambda) in the spatial error model and ρ (Rho) in the spatial lag model and spatial Durbin model were all highly significant at the 1% significance level. It indicated 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 these autoregressive parameters 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 and should be corrected with the spatial Durbin model (LeSage and Pace, 2009). Application of the spatial Durbin model resulted in an improved model fit by having the largest log likelihood and smallest Akaike information criterion (AIC) values (Akaike, 1974). 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. Consequently, the local crop yield may not depend simply on local determinants, but also on the neighboring plot's determinants. Thus, the choice of spatial Durbin model as the best fitting model was supported by both empirical statistical diagnostics and theoretical considerations.

The signs of the coefficient estimates in Spatial Durbin model are the same as in the standard OLS model, with the exception of the significance level for some variables. The nematode populations at planting time (*Mipi*) and at harvest time (*Mipf*) are significant determinants for the cotton yield in the OLS model while the population density at the bloom time (*Mipm*) is highly significant for the yield variability suggested by the regression results from spatial Durbin model. The soil texture (percent sand fraction, *Sand*) has significant impact on the crop yield across spatial and aspatial models. The rate of nematicide applied did not explain yield differences alone although the interaction between *Sand* and *Telone* (*Sand: Telone*) was a significant determinant for yield variation. This suggests that the yield response to nematicide treatment varies with soil texture. The yield response for a given nematode population density is also different depending upon soil texture (*Mipm02: Sand*). The spillover effects of some explanatory variables from neighboring plots also significantly influence the local crop yield (*lag.Mipm02, lag.Mipf02, lag.Sand, lag.Telone, lag.Sand: Telone, lag.Mipm02: Sand, lag.Mipf02: Sand*) although some of the coefficient signs are different from the local effect signs since the spillover effects in the spatial Durbin model extend throughout the whole spatial system.

Since the autoregressive parameter (ρ) interacted with the explanatory variables, the magnitude of coefficients of the spatial Durbin model could not be interpreted directly. To interpret the magnitude of the coefficient, the marginal effects of a particular explanatory variable need to be derived. It can be decomposed into direct, indirect, and total effects as illustrated by LeSage and Pace (2009).

Since the coefficient estimates suggested that the crop yield response for a given nematode infestation level or nematicide application rate differs by soil texture, site-specific nematicide application may be modestly profitable. The delineation of management zones for nematicide application decisions within fields can be evaluated based on nematode density and soil texture. In this study, since soil texture was the most useful factor for explaining yield variation, management zone can be delineated based on soil texture categories: i) 0 to 30% sand, ii) 30 to 45% sand, iii) 45 to 65% sand, and iv) 65 to 100% sand. The average return for the field was estimated as the weighted sum of returns in each management area, where the weights are the proportion of the area. Maximization of expected profit from variable rate application can be expressed as:

$$MaxE[\pi] = \sum_{i=1}^{4} Area_i * E[P_C * E(Yield) - P_T * T_i]$$

Where E = expectation operator

π= total net returns over site-specific nematicide application (\$ ha^{-1})

$Area_i$ = proportion of management area i (i =1,...,4)

Pc = price of cotton (\$ kg^{-1})

E (Yield) = expected yield estimate from the yield response function estimated with spatial Durbin model (kg/ha)

P_T = price of nematicide (\$ kg^{-1})

Ti = quantity of nematicide applied in area i

The expected net return from uniform rate application can be calculated. The difference of the net return from the variable rate application and uniform rate application can be viewed as the breakeven variable rate (VR) fee. The VR application cost, which may include the equipment costs, staff training cost, etc, can be estimated. If the breakeven VR fee can cover the estimated VR application cost, site-specific nematicide application would be profitable. This economic analysis provides an initial insight into the potential of site-specific nematode management.

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 and the spatial Durbin model was the most appropriate model for this study since it captured the spatial effects of nematode population density, soil texture and nematicide application rate for both local plot and neighboring plots. 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. The crop yield response for a given nematode infestation level or nematicide application rate differs by soil texture. These findings provide evidences to support the potential of site-specific nematicide application and management zone delineation. The profitability analysis related is useful to provide practical recommendations for effectively controlling nematodes via site-specific management.

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

Table 2. Coefficient estimates and diagnostic statistics

Variables	OLS	SAR	SEM	SDM
(Intercept)	2161.000***	897.580***	2151.800***	348.560
Mipi02	-0.187*	-0.151*	-0.152*	-0.139
Mipm02	-0.019	-0.036**	-0.058***	-0.048***
Mipf02	-0.134**	-0.068	-0.038	-0.046
Sand	-18.350***	-13.909***	-17.187***	-15.053***
Telone	-3.810	-3.531	-4.855**	-2.620
Sand:Telone	0.118*	0.127**	0.169***	0.121**
Mipi02:Sand	0.002	0.002	0.002	0.002
Mipm02:Sand	0.0003	0.0006*	0.0011***	0.0008**
Mipf02:Sand	0.003**	0.001	0.001	0.001
lag.Mipi02				0.167
lag.Mipm02				0.166***
lag.Mipf02				-0.382***
lag.Sand				18.212**
lag.Telone				19.651*
lag.Sand:Telone				-0.631**
lag.Mipi02:Sand				-0.008
lag.Mipm02:Sand				-0.003***
lag.Mipf02:Sand				0.008***
Rho		0.818***		0.833***
Lambda			0.902***	
Measures of fit				
Log likelihood		-3346	-3340	-3314
AIC	6843	6717	6704	6670
Diagnostic tests	d.f.	Value	Prob	
Lagrange multiplier (error)	1	164.832	0.000	
Robust LM (error)	1	12.545	0.000	
Lagrange multiplier (lag)	1	162.133	0.000	
Robust LM (lag)	1	9.846	0.002	
Hausman test	10	93.748	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.

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