EVALUATING SPATIAL EFFECTS INDUCED BY ALTERNATIVE ON-FARM TRIAL EXPERIMENTAL DESIGNS WITH CROSS-REGRESSIVE VARIABLES USING MONTE CARLO METHODS

T.W. Griffin

Department of Agricultural Economics and Agribusiness
University of Arkansas, Division of Agriculture, Cooperative Extension Service
Little Rock, Arkansas

R.J.G.M. Florax

Department of Agricultural Economics
Purdue University
West Lafayette, Indiana

J. Lowenberg-DeBoer

Department of Agricultural Economics
Purdue University
West Lafayette, Indiana

Abstract

The goal of this research was to adapt spatial regression methods to on-farm trials in a farm management context. Different experimental designs and statistical analysis methods are tested with site-specific data under a range of spatial autocorrelation levels using Monte Carlo simulation techniques. Simulations indicated that data usable for farm management decision making could be gathered from limited replication experimental designs if that data were analyzed with the appropriate spatial statistical model.

Keywords: spatial econometrics, yield data analysis, spatial analysis, spatial autocorrelation, spatial heterogeneity, spatial effects, on-farm research

Introduction

Many farmers conduct on-farm comparisons of new varieties and other categorical practices in large non-replicated blocks. Although these on-farm comparisons are not considered statistically valid from the perspective of traditional agronomic methods, farmers nevertheless continue to conduct these comparisons to provide information for farm management decisions. With precision agriculture technologies and spatial regression methods, new opportunities are created for design and analysis of on-farm experimentation. The general objective of this research was to determine if spatial econometrics can help farmers make better use of the limited replication data they currently collect with precision agriculture technologies. The specific objective of this research

was to determine if spatial statistical analysis can increase the probability of making the correct decision from split-field, paired-field and other limited replication large block experimental designs. A simulation approach was used to accomplish these objectives.

Background and Literature Review

Prior research has used simulation to evaluate the performance of estimators used on spatial and aspatial models (Das et al., 2002; Florax and Folmer, 1991; Florax et al., 2002). These studies evaluating estimators for spatial models indicated models explicitly modeling spatial autocorrelation were more efficient than aspatial models, thus estimators used on aspatial models with spatial data lead to unreliable inference. Previous agricultural simulation studies using spatial analyses focused on plant breeding programs (Singh et al., 2003; Baird and Mead, 1991), a comparison of statistical models (Brownie and Gumpertz, 1997), suggestions for theoretical models (Cullis and Gleeson, 1991), at least one study on a Bayesian approach (Besag and Higdon, 1999), and comparisons of field-scale experimental designs for agriculture (Lowenberg-DeBoer et al. 2003; Griffin et al., 2005b).

Lowenberg-DeBoer et al. (2003) evaluated the performance of aspatial and spatial error process models for two experimental designs and two levels of spatial autocorrelation. They compared a non-replicated design to a randomized five block experimental design under moderate (λ=0.5) and high (λ=0.9) levels of spatial autocorrelation. Lowenberg-DeBoer et al. (2003) assigned four homogeneous zones mimicking the seminal field-scale spatial econometric work reported in Anselin et al. (2004) and Bongiovanni (2002) in a 15 by 15 grid and used the estimated coefficients from the Anselin et al. (2004) study as the true treatment effects for variable rate nitrogen application. Griffin et al. (2005b) evaluated the bias, mean squared error, and percent of correct decisions of spatial and aspatial models for four field-scale experimental designs under six levels of positive spatial autocorrelation. Griffin et al. (2005b) used non replicated, two, four, and eight block designs with eight blocks mimicking field-length strip-trials. Designs were evaluated under spatial autocorrelation levels ranging from independent errors (λ=0.0) to high levels (λ=0.72) including λ=0.8. 0.24, 0.40, and 0.56. Griffin et al. (2005b) used a 16 by 16 grid with equal proportions of four homogenous zones with two categorical treatments. Unlike Lowenberg-DeBoer et al. (2003) which used a discrete neighbor specification of a spatial weights matrix in the data generating process (DGP), Griffin et al. (2005b) used a continuous Gaussian semivariogram. Although Brownie and Gumpertz (1997) performed similar field-scale simulations as Lowenberg-DeBoer et al. (2003) and Griffin et al. (2005), they randomly assigned plot yields and treatment assignments with each Monte Carlo dataset. Lowenberg-DeBoer et al. (2003) and Griffin et al. (2005) concluded that on-farm trial data from non-replicated single block experimental designs were as useful as traditional randomized block and field-length strip-trial designs if that data is analyzed with the appropriate statistical methods explicitly modeling spatial autocorrelation.

This research builds upon the field-scale on-farm trial work of Lowenberg-DeBoer et al. (2003) and Griffin et al. (2005) by evaluating spatial and aspatial

model performance under differing levels of spatial autocorrelation and differing field-scale experimental design blocking scenarios. Previous simulation studies have generated data by one of two approaches. One approach uses a discrete specification of the spatial correlation structure by means of a spatial weight matrix in the DGP. The other approach uses a semivariogram to generate the two-dimensional surface. This research expands the work of Lowenberg-DeBoer et al. (2003) and Griffin et al. (2005) by conducting simulations with the R Software using the discrete spatial process as the DGP under a range of spatial autocorrelation levels and experimental designs. This chapter built upon two of the future research suggestions of Lowenberg-DeBoer et al. (2003) including 1) conducting more simulation runs of each scenario with automated computer routines and 2) evaluating experimental designs farmers tend to conduct including, side-by-side non-replicated split-field single blocks and field-length strip-trial designs along with intermediate blocking designs.

Methodology

Monte Carlo simulation methodology was used for crop production under a range of field replications and positive spatial autocorrelation levels evaluated with aspatial and spatial models (Griffin et al., 2005b; Lowenberg-DeBoer et al., 2003; Robert and Casella, 2004). Spatial autocorrelation ranged from zero to high levels found in field-scale precision agriculture datasets. Simulation is required to determine the bias, variance, and mean squared error from estimators used in aspatial and spatial models. Simulation was also required to test alternative experimental designs on the same field in the same weather year, an almost impossible task to accomplish with real field-scale experiments. It is only with simulation that true parameters are known. Working null hypotheses include 1) field-scale treatment replication negates spatial autocorrelation, 2) aspatial statistical analysis offers inference equal to spatial analysis, and 3) there are no difference in farm management recommendations made from differing spatial techniques.

In this study, two broad regression methods were compared for analysis of simulated data. The first method was a standard aspatial model estimated using ordinary least squares (OLS). The second broad method were spatial models estimated using both Anselin's (1988) discrete approach and Cressie's (1993) direct representation continuous geostatistical approach.

Aspatial models assume spatial independence. If spatial autocorrelation does exist, OLS estimates remain unbiased but are inefficient (Cressie, 1993). When there is no spatial autocorrelation among observations, OLS is the best linear unbiased estimator (BLUE) of the data. When there is spatial autocorrelation, OLS is no longer BLUE. The matrix notation for the familiar linear model is $y = X\beta + \varepsilon$ where y is a vector of observations, X is a matrix of explanatory variable values, β is the vector of regression parameters, and ε is a vector of errors.

Theory and *a priori* information implies that field-scale precision agricultural datasets have spatially autocorrelated error terms rather than spatially autocorrelated dependent variables. To simulate these conditions, spatially

autocorrelated errors (ε_i's) were generated by a spatial autoregressive transformation of a random normal (0,3) uncorrelated iid errors (μ) using the simultaneous autoregressive random variables generator operator (invIrM) of the spdep contributed package (Bivand, 2006) to R (R Development Core Team, 2006) as described by Anselin (2005) ($\varepsilon_n = (I - \lambda W)^{-1}\mu$). Six levels of spatial autocorrelation (λ = 0%, 20%, 50%, 70%, and 90%) were imposed on the uncorrelated random error term (μ) of a 16 x 16 structure (N=256) using the first order queen contiguity spatial weights matrix. The dependent observation variable was constructed by adding the spatially autocorrelated error term, ε, to the Xβ vector. Explanatory variables included homogenous zones and treatment binary variables plus interaction terms between zones and treatments. Homogenous zones and treatment binary variables were restricted to sum to zero so that the coefficients including intercept are interpreted as the difference from mean field response. In this scenario the dependent variable was constructed and could be regressed upon a matrix of explanatory variables without an omitted variable problem.

Four experimental designs were developed to compare the effects of two treatments: single non-replicated block, and two, four, and eight blocks (Figure 1). The single non-replicated block may be analogous to the side-by-side non-replicated split-field experimental design used by farmers. The two and four replicated block designs of this research may be similar to other field-scale experiments farmers conduct such as limited field-length replication, split-planter, and strip-trial experimental designs. The eight replication blocks of this research represents the ideal strip-trial designs derived from classical small-plot research in which treatment blocks, i.e. strips, are very narrow and no spatial autocorrelation exists in the treatment block.

Each block has two experimental units, or one each of two treatments. Figure 1 is a visual representation of the four experimental designs that differ in number of experimental blocks. The four horizontal areas labeled z_1, z_2, z_3, and z_4 are zones of homogeneous production potential areas (for example, topography, zones, and/or soils) that represent fixed effects. The shaded areas indicate where treatment 1 and treatment 2 are situated. The following model was estimated:

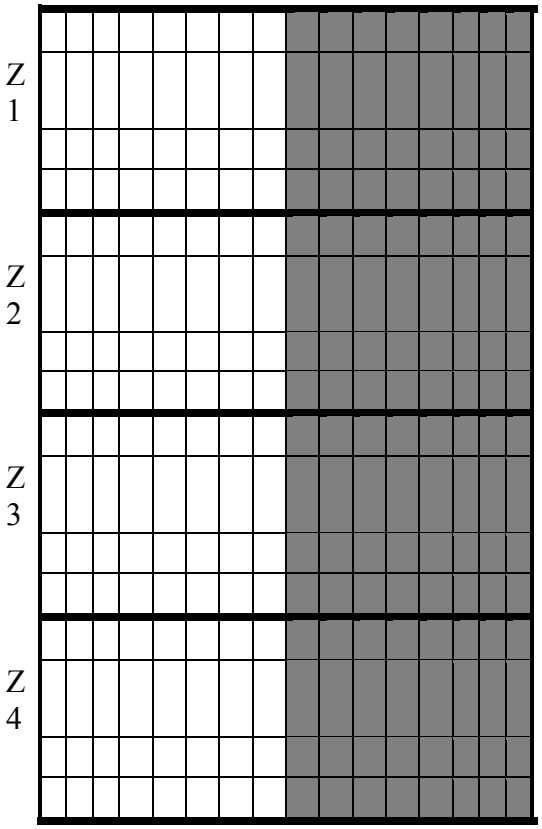
$$y_i = \mu + \tau_k T_k + \sum_{s=1}^{4} \delta_s z_s + \sum_{j=1}^{4} \gamma_j z_s T_k + \varepsilon_i \qquad (1)$$

where y_i is a response variable, $i \in [1,...,256]$;
τ_k is a treatment effect;
z_s is a site in a field with unique attributes, $s \in [1,...,4]$;
z_s is constrained as $\sum \delta_s = 0$;
T_k is treatment;
and ε_i is a random disturbance term.

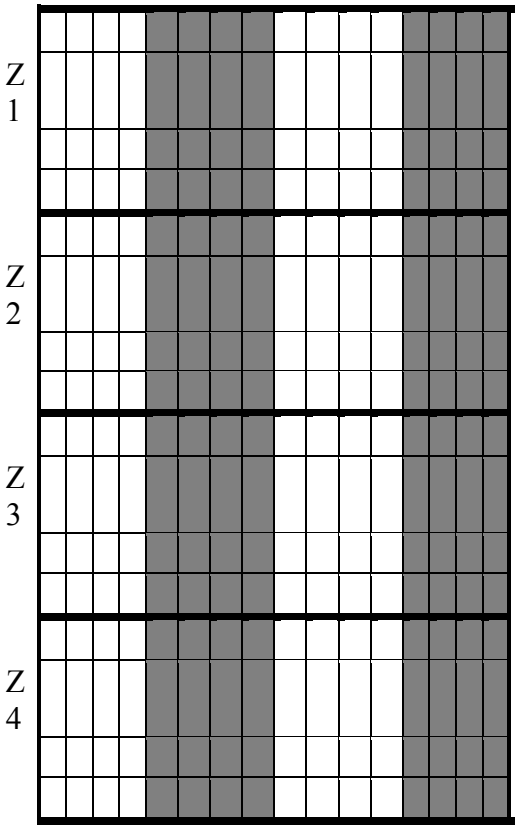
Starting with the parameters used by Griffin et al. (2005b), the simulated relationship between the dependent variable (y) and the explanatory variables is given in Equation (2):

$$y = 50 + 0.5*z_2 - 0.9*z_3 - 1.1*z_4 + 3.75*T + 1.2*T*z_2 - 1.8*T*z_3 + 0.10*T*z_4 + e \quad (2)$$

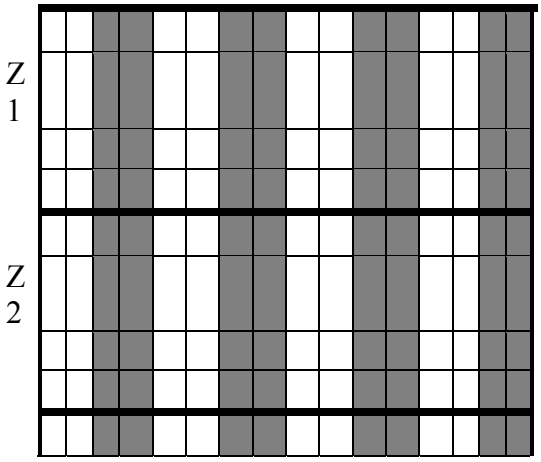
where z_2, z_3, and z_4 are areas with more homogeneous properties, T is the treatment, and interaction terms of T and the four zones. This relationship among treatments, zones and y may be thought of as a categorical agricultural experiment, i.e., tillage, herbicide, or variety across zones of soils, elevation, etc. These are the "true" parameter values of the model (Equation 2).

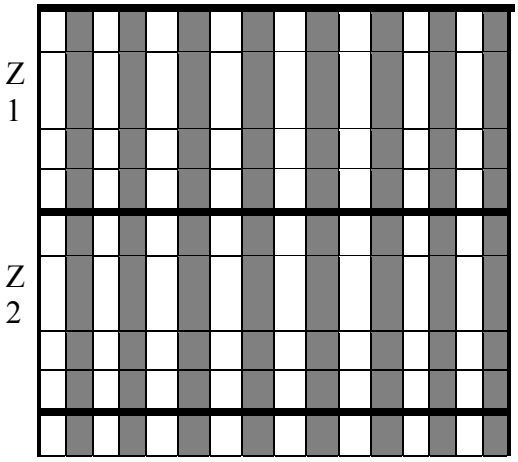


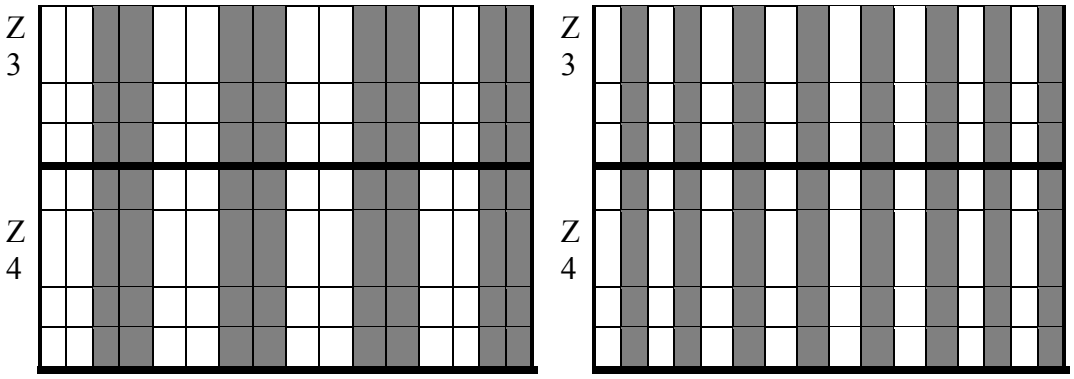
Single block, two treatments



2 blocks, 2 treatments







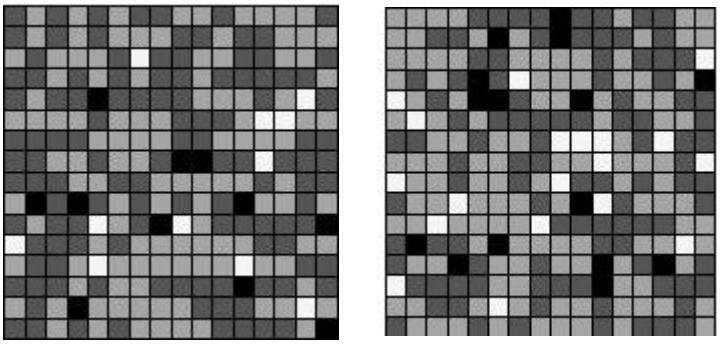
4 blocks, 2 treatments

8 blocks, 2 treatments

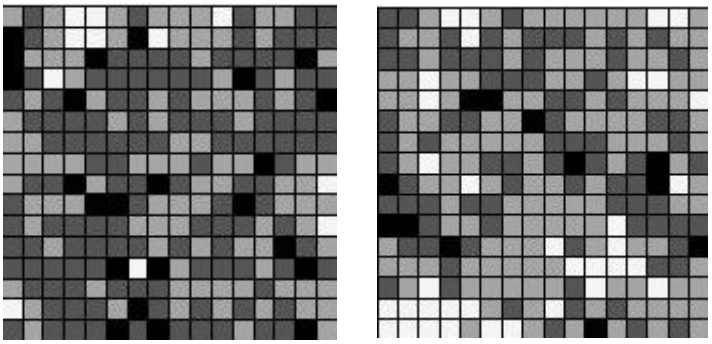
Shaded areas are treatments and z_1, z_2, z_3, *and* z_4 are homogeneous zones

Figure 1: Representations of Four Experimental Designs

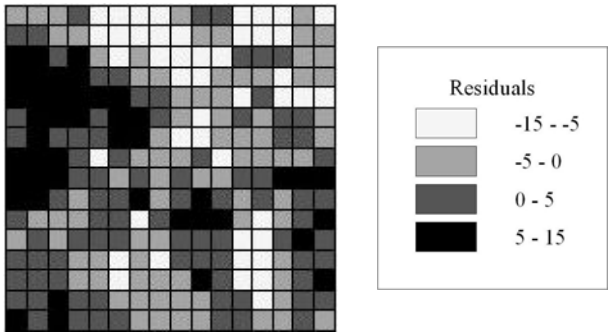
One Monte Carlo dataset from each of the five levels of spatially autocorrelated errors are represented with shaded areas as the random level sets of the simulated fields (Figure 2). Traditional analysis assumes the "ideal situation" of no spatial autocorrelation between experimental units is represented by the 0% spatial autocorrelation level. At $\lambda = 0$, values are randomly distributed across the grid. When spatial autocorrelation approaches 100%, correlation between observations becomes evident as grid cells cluster together. A grid cell with a given error value tends to cluster with other grid cells of similar value. In all, there were 20 experiments from five levels of spatial autocorrelation and four levels of blocking, each evaluated 1,000 times using aspatial and spatial analysis.



λ=0.0 Moran's I = 0.06 **λ=0.2 Moran's I = 0.10**



λ=0.5 Moran's I = 0.16 **λ=0.7 Moran's I = 0.34**



λ=0.9 Moran's I = 0.60

Figure 2: Representation of five spatially autocorrelated (λ) level sets

The spatial error process model was estimated using one of three row-standardized spatial weights matrices. The first matrix was specified as a first order queen, the same as used in the DGP. The second matrix was specified as a first order rook contiguity. The third matrix was specified as an inverse distance matrix with the distance band empirically determined at each iteration by the spatial range. The spatial range was determined by the spatial correlogram of the OLS residuals at the distance Moran's I becomes negative. Observations separated by distances greater than the distance band were not considered neighbors. The spatial error process model was estimated with ML as called by the errorsarlm function and with GM as called by the GMerrorsar function within spdep (Bivand, 2006) contributed package of R (R Development Core Team, 2006). Although the OLS estimator is expected to be unbiased when the spatial error model is appropriate, the variance of estimators may lead to wrong farm management decisions. In addition, some bias may be expected because of misspecification of spatial weights matrix.

Similar to the spatial error process models using inverse distance matrices, the geostatistical (GEO) approach estimates parameters at each iteration. The partial sill (σ^2) and range (φ) for a spherical semivariogram were estimated using the variog function and used by the likfit function in the geoR contributed package (Ribeiro and Diggle, 2001) for R. Spherical semivariogram functional forms have been used for field-scale agricultural studies (Adamchuk et al., 2004; Gotway and Harford, 1996; Solie et al., 1999) and is given by

$$\gamma(h)=\begin{cases}1.5\dfrac{h}{a}-0.5\left(\dfrac{h}{a}\right)^3 & \text{if } h \le a \\ 1 & \text{otherwise}\end{cases}$$

where a is the range (Isaaks and Srivastava, 1989). The partial sill is calculated as the difference between the sill and nugget (Isaaks and Srivastava, 1989). The sill is the value of the semivariogram at the plateau reached for larger distances and the nugget is the unexplained variance of the semivariogram model (Cressie, 1993; Isaaks and Srivastava, 1989). GEO model coefficients were estimated with restricted maximum likelihood (REML) (Cressie, 1993). The restriction is that estimators are "obtained by applying maximum likelihood to error contrasts rather than the data themselves" (Cressie, 1993, p. 92).

Measures of a good estimator include bias, variance, and mean squared error (MSE) (Casella and Berger, 2002). Bias is estimated as the difference between the expected value, i.e. mean estimated coefficient $\hat{\beta}$ across all simulation replications, and the true parameter value $\beta\left(bias = \sum_r \hat{\beta}_r / R - \beta \right)$. The MSE is used to gauge the performance of the regression estimators. An estimator with desired MSE properties has small combined variance and bias (Casella and Berger, 2002). In other words, desired MSE properties come from controlling both variance and bias $\left(MSE\left[\hat{\beta}\right] = (1/R)\sum_r \left(\hat{\beta}_r - \beta\right)^2 \right)$. Variance is a measure of how much the parameter estimates vary. MSE is equal to bias squared plus the variance. MSE is particularly useful in comparing biased estimators because for unbiased estimators, the MSE is equal to the variance.

To be certain that spatial autocorrelation was introduced into the simulated error term, a Moran's I test for global spatial autocorrelation was conducted on the estimated OLS residuals (not the simulated error terms) using the row-standardized first order queen continuity spatial weights matrix (Anselin, 1988). If the associated p-value for the Moran's I test statistic at an iteration was below the 10% level, then the null hypothesis of no spatial autocorrelation was rejected. In cases where spatial autocorrelation was greater than or equal to 0.5 ($\lambda \geq 0.5$), the Moran's I test null hypothesis was rejected more than 99% of the time for any experimental design, i.e. number of treatment blocks (Table 1). When λ=0.2, the Moran's I test statistic null hypothesis was rejected between 33% and 60% of the time. In the four cases where spatial autocorrelation was zero, the Moran's I test null hypothesis was rejected less than seven percent of the time. As the number of experimental blocks increased, the null hypothesis of no spatial autocorrelation was rejected more often similar to Lowenberg-DeBoer et al. (2003). Rather than the differing experimental designs inducing additional spatial autocorrelation into the data, the experimental designs may have induced spatial heteroskedasticity in the form of structural changes across the data. Since Moran's *I* has power over both spatial autocorrelation and spatial heteroskedasticity, the increased rejection of the null hypothesis with increased number of replicated blocks may be from the mistaken identity between the spatial effects.

Table 1: Moran's *I* Rejection Rate for Spatially Autocorrelated Residuals (p=0.10)

lambda	**0.0**	**0.2**	**0.5**	**0.7**	**0.9**
1 block	**0.01**	**0.33**	**0.99**	**1.00**	**1.00**
2 blocks	**0.02**	**0.38**	**0.99**	**1.00**	**1.00**
4 blocks	**0.04**	**0.48**	**1.00**	**1.00**	**1.00**
8 blocks	**0.07**	**0.60**	**1.00**	**1.00**	**1.00**

Results

Mean estimates of bias and MSE over 1,000 Monte Carlo trial runs for the aspatial and seven spatial models are presented in Table 2 and Table 3. The ML_Q and GM_Q models are the spatial error process models using a row-standardized first order queen contiguity matrix estimated with maximum likelihood and general moments, respectively. The ML_r and GM_r models are the spatial error process models using a row-standardized first order rook contiguity matrix estimated with maximum likelihood and general models, respectively. The ML_{IDW} and GM_{IDW} are spatial error process models using row-standardized inverse distance spatial weights matrices with empirically determined distance bands. The GEO model indicates the geostatistical model where the semivariogram priors of partial sill and range were estimated at each iteration and estimated with REML. The GEO, the ML_{IDW} and GM_{IDW} models are the three models expected to be used in real field-scale experimental analysis since the spatial interaction structure is empirically determined in an otherwise unknown DGP.

The bias and MSE were calculated from estimated parameter values for the treatment variable, T, from these models. The treatment variable, T, was used because it was the coefficient the farm manager would use to determine their decisions. Although the interaction terms between the treatment variable and soil zones would be used for site-specific decisions, the ultimate decision criteria would be based upon the treatment variable since it is interpreted as difference from mean field condition due to the specification of the binary variables. Parameter estimated treatment coefficients for all models were similar when spatial autocorrelation was zero for any block designs.

Simulation results confirmed the theoretical notion that OLS is unbiased relative to other estimators (Table 2). However, when spatial autocorrelation exists in the data ($\lambda>0.5$), the spatial models had lower bias than OLS although the spatial models with empirically determined spatial interaction structures had similar bias. In addition, the number of blocks and experimental design replications reduced the estimated bias when $\lambda>0$.

Table 2: Bias of Treatment Variable Estimator under Differing Experimental Designs and Spatial Autocorrelation Levels

	OLS	ML_Q	GM_Q	ML_r	GM_r	ML_{IDW}	GM_{IDW}	GEO
λ	1 block							
0.0	-0.0057	-0.0052	-0.0051	-0.0054	-0.0054	-0.0054	-0.0063	-0.0051
0.2	0.0156	0.0168	0.0164	0.0160	0.0160	0.0169	0.0157	0.0161
0.5	0.0109	0.0124	0.0123	0.0115	0.0116	0.0102	0.0105	0.0069
0.7	0.0432	0.0252	0.0275	0.0386	0.0376	0.0253	0.0244	0.0305
0.9	0.0198	0.0282	0.0227	0.0168	0.0154	0.0307	0.0390	-0.0127
	2 blocks							
0.0	0.0038	0.0037	0.0041	0.0034	0.0034	0.0035	0.0051	0.0032
0.2	-0.0131	-0.0126	-0.0134	-0.0130	-0.0130	-0.0130	-0.0111	-0.0123
0.5	-0.0059	-0.0018	-0.0022	-0.0041	-0.0042	-0.0015	-0.0012	-0.0048
0.7	0.0059	-0.0034	-0.0028	0.0001	0.0009	-0.0083	-0.0077	-0.0025

0.9	0.0151	0.0009	0.0001	0.0070	0.0021	0.0003	-0.0027	0.0027
	4 blocks							
0.0	0.0036	0.0032	0.0050	0.0034	0.0034	0.0038	0.0053	0.0035
0.2	-0.0002	-0.0006	0.0014	-0.0002	-0.0002	-0.0001	0.0045	-0.0005
0.5	-0.0148	-0.0138	-0.0138	-0.0144	-0.0144	-0.0138	-0.0146	-0.0148
0.7	0.0107	0.0064	0.0064	0.0099	0.0085	0.0052	0.0051	0.0074
0.9	0.0051	-0.0042	-0.0040	0.0230	-0.0017	-0.0019	-0.0040	-0.0047
	8 blocks							
0.0	-0.0038	-0.0044	-0.0050	-0.0039	-0.0039	-0.0038	-0.0039	-0.0039
0.2	0.0020	0.0019	0.0020	0.0020	0.0020	0.0020	0.0028	0.0019
0.5	-0.0068	-0.0060	-0.0060	-0.0067	-0.0067	-0.0061	-0.0062	-0.0072
0.7	0.0037	0.0006	0.0006	0.0008	0.0008	-0.0002	-0.0005	0.0000
0.9	-0.0001	-0.0041	-0.0040	-0.0032	-0.0034	-0.0033	-0.0041	-0.0038

GM_Q and ML_Q used first order queen weights matrix
GM_r and ML_r used first order rook contiguity weights matrix
ML_{IDW} and GM_{IDW} used IDW with distance band determined by spatial correlogram
GEO uses the REML estimator in a geostatistical model

As the number of blocks increased, MSE decreased for all estimators for every positive level of spatial autocorrelation. As the level of spatial autocorrelation increased, the difference in MSE between OLS and spatial models widened; however this gap closed as the number of blocks increased. Increased number of blocks and thus replications decreased MSE for all models and estimators.

When there were no spatial autocorrelation in the data, i.e. $\lambda = 0$, then there is virtually no effect of blocking on MSE (Table 2 and Table 3). However as spatial autocorrelation levels increased, MSE increased but at differing rates with respect to model and number of replication blocks (Table 3).

Table 3: MSE of Treatment Variable Estimator under Differing Experimental Designs and Spatial Autocorrelation Levels

	OLS	ML_Q	GM_Q	ML_r	GM_r	ML_{IDW}	GM_{IDW}	GEO
λ				1 block				
0.0	0.0330	0.0330	0.0333	0.0329	0.0329	0.0330	0.0336	0.0330
0.2	0.0531	0.0532	0.0536	0.0530	0.0530	0.0533	0.0550	0.0559
0.5	0.1297	0.1153	0.1162	0.1233	0.1239	0.1199	0.1204	0.1188
0.7	0.3140	0.2266	0.2286	0.2712	0.2773	0.2809	0.2983	0.2439
0.9	2.3741	0.4265	0.6026	1.0996	1.4549	0.7191	0.9738	0.6448
				2 blocks				
0.0	0.0356	0.0359	0.0360	0.0355	0.0355	0.0356	0.0372	0.0357
0.2	0.0489	0.0488	0.0493	0.0486	0.0486	0.0492	0.0544	0.0489

0.5	0.0960	0.0800	0.0804	0.0873	0.0880	0.0846	0.0880	0.0840
0.7	0.1980	0.1113	0.1141	0.1440	0.1509	0.1414	0.1392	0.1185
0.9	0.8839	0.1566	0.1746	0.2501	0.3818	0.4349	0.3900	0.1844
	4 blocks							
0.0	0.0344	0.0345	0.0437	0.0344	0.0344	0.0344	0.0449	0.0344
0.2	0.0424	0.0421	0.0498	0.0422	0.0422	0.0424	0.0529	0.0422
0.5	0.0542	0.0503	0.0503	0.0515	0.0516	0.0510	0.0517	0.0512
0.7	0.0716	0.0578	0.0579	0.0603	0.0609	0.0596	0.0597	0.0604
0.9	0.1723	0.0664	0.0665	0.0711	0.0984	0.0780	0.0779	0.0689
	8 blocks							
0.0	0.0339	0.0340	0.0343	0.0340	0.0340	0.0340	0.0341	0.0339
0.2	0.0283	0.0281	0.0281	0.0281	0.0281	0.0282	0.0286	0.0281
0.5	0.0222	0.0211	0.0211	0.0214	0.0215	0.0212	0.0211	0.0216
0.7	0.0229	0.0198	0.0198	0.0200	0.0201	0.0200	0.0201	0.0201
0.9	0.0404	0.0164	0.0164	0.0176	0.0180	0.0173	0.0174	0.0170

GM_Q and ML_Q used first order queen weights matrix
GM_r and ML_r used first order rook contiguity weights matrix
ML_{IDW} and GM_{IDW} used IDW with distance band determined by spatial correlogram
GEO uses the REML estimator in a geostatistical model

Although the estimators using empirically determined spatial interaction structures, e.g. GEO, ML_{IDW}, and GM_{IDW}, had higher MSE than the spatial models using a similar weights matrix as used to generate the data, these models had lower MSE than using traditional analysis methods with increased replication blocks. With real data, the true DGP is not known and spatial interaction structures must either be chosen *a priori* or empirically determined.

Looking at the relative changes in bias and MSE across the number of blocks indicates improved estimation precision from lower variance (Table 3). However, it is also important to account for the spatial structure of the data, and doing so may allow fewer blocks while achieving roughly the same level of precision. Farm managers would obtain more reliable information by applying spatial analysis to one and two block experimental designs when λ=0.7 and λ=0.9, respectively, than adding another experiment replication block. At lower levels of spatial autocorrelation $(\lambda \leq 0.5)$, an additional experimental design block was more useful than choice of statistical model; however it is unlikely that field scale datasets would have spatial autocorrelation levels in the vicinity.

Rather than examine the asymptotic properties of estimators and models, farm managers are more concerned with how often the statistical results will lead to farm management recommendations for the right decision. The estimated treatment coefficients of each statistical model were examined at each iteration to determine if the farm management recommendation was the same as the true treatment effect. The treatment variable was the only coefficient evaluated

because the specification of the binary variable, i.e. $\Sigma d_i = 0$, allowed the coefficient to be interpreted as the difference from the mean condition. The coefficients were evaluated based upon if statistically significantly greater than zero.

This criterion uses the classical t-test to test whether the estimated coefficient was greater than zero at the 10% confidence level. Since the farm management recommendation would be to choose the treatment that had the highest average for the field, i.e. the highest average from all four zones, a statistically significant strictly positive estimated coefficient provided a farm management recommendation consistent with the true treatment effect.

In situations of a categorical treatment, the farm manager may be concerned with whether one treatment outperformed another. At each iteration the null hypothesis that the estimated coefficient was greater than zero was evaluated at the 10% confidence level and enumerated to determine the percent incorrect decisions (Table 4). In the non-replicated single block design, the spatial models outperformed the aspatial model however the spatial models did not always lead to correct decisions. The ML_Q model had the lowest percent incorrect decisions however the specification of W was similar to the DGP. The three models that empirically estimated parameters for the spatial interaction structure were similar however the geostatistical model dominated the spatial error process models.

Under conditions when the observations were independent (i.e. spatial autoregressive parameter equaled zero), farm management recommendations based upon statistical inference were similar for all models. However, when positive spatial autocorrelation existed in the data, differences between models existed. When no spatial autocorrelation, the aspatial model estimated as OLS appropriately estimated the model parameters for any amount of replications tested. Under these "ideal" conditions, farm management recommendations based on this model would have been inappropriately made less than 5% of the time (Table 4). When spatial autocorrelation increased to levels expected at field scales, i.e. $\lambda \geq 0.7$, the aspatial model did not accurately estimate the model parameters as well as at lower levels of spatial autocorrelation. The farm management recommendation would have been incorrectly made more than 23% and 40% of the time when λ=0.7 and λ=0.9, respectively (Table 4).

Table 4: Percent Incorrect Decisions for Treatment Variable

λ=	0	0.2	0.5	0.7	0.9
1 block					
OLS	0.02	0.05	0.14	0.23	0.40
ML_Q	0.02	0.04	0.12	0.21	0.27
ML_{IDW}	0.02	0.05	0.13	0.23	0.33
GM_{IDW}	0.02	0.05	0.13	0.22	0.38
GEO	0.02	0.05	0.13	0.21	0.32
2 blocks					
OLS	0.03	0.06	0.12	0.20	0.33

ML_Q	0.02	0.06	0.11	0.13	0.18
ML_{IDW}	0.03	0.06	0.10	0.17	0.29
GM_{IDW}	0.03	0.06	0.11	0.16	0.27
GEO	0.03	0.06	0.10	0.13	0.19
4 blocks					
OLS	0.02	0.04	0.06	0.08	0.19
ML_Q	0.02	0.04	0.05	0.05	0.08
ML_{IDW}	0.02	0.04	0.05	0.06	0.10
GM_{IDW}	0.03	0.05	0.05	0.06	0.09
GEO	0.02	0.04	0.06	0.06	0.08
8 blocks					
OLS	0.02	0.01	0.01	0.01	0.04
ML_Q	0.02	0.01	0.00	0.00	0.00
ML_{IDW}	0.02	0.01	0.00	0.01	0.00
GM_{IDW}	0.03	0.01	0.00	0.00	0.00
GEO	0.02	0.01	0.01	0.00	0.00

ML_Q used first order queen weights matrix
ML_{IDW}, GM_{IDW} used IDW with distance band determined by spatial correlogram
GEO uses the REML estimator in a geostatistical model

When replications were included in the experimental design, the accuracy of the farm management recommendation increased to levels similar to the ideal condition of zero spatial autocorrelation for eight replication blocks which mimics condition of very narrow field-length strip-trials. The use of four replicated experimental design blocks was unable to achieve the same accuracy as eight blocks. The farm management recommendation was made incorrectly more than 8% and 19% of the time with the four replicated blocks for λ=0.7 and λ=0.9, respectively, the spatial autocorrelation expected at field scales (Table 4).

From the farm manager point of view, the spatial models performed better relative to the aspatial model estimated with OLS in the presence of positive spatial autocorrelation but were not perfect under the conditions of this simulation. As expected, the spatial model with the lowest percent incorrect decisions rate was the ML_Q. In order to mimic real conditions where the true DGP is unknown, spatial models empirically estimating the spatial interaction structure were compared. All three models, i.e. ML_{IDW}, $GM_{IDW,}$ and GEO, performed similarly although the GEO had slightly lower percent incorrect decisions for any level of blocking and level of spatial autocorrelation. Increasing the number of treatment blocks improves the percent of correct decisions for all models.

When the second experimental design block was considered, the OLS model had similar percent incorrect decisions as the single block design data analyzed with the spatial models. This indicates that the farm manager would be as well

off to use spatial analysis with single block designs as using aspatial analysis with two blocks. When the four block experimental designs were considered, the decision became less clear. The percent incorrect decisions for the OLS model under four blocks was similar to the percent incorrect decisions for GEO under two block designs while decisions based upon the other candidate spatial models were less accurate. Once an eight block experimental design was used, the percent incorrect decisions were controlled for any statistical model. An eight block experimental design in this analysis does not necessarily represent any eights block field-scale experiment designs but rather a situation of field-length narrow strips such that no spatial autocorrelation exists in the width of the strip. The use of real on-farm trial with eight replicated blocks may be more closely represented by the two or four blocks of this study with respect to spatial autocorrelation and independence of observations.

Although this research indicated similar results as previous studies, the magnitudes of the percent incorrect decisions differed from Lowenberg-DeBoer et al. (2003) and Griffin et al. (2005b). These differences can be explained by the statistical test to determine the percent incorrect decisions of the model, the underlying DGP, and the choice of semivariogram priors used in the model estimation of the estimated coefficients.

Griffin et al. (2005b) reported the percent incorrect decisions for their spatial model was below the 6% level for any level of spatial autocorrelation or number of replication blocks while their aspatial model had very high percent incorrect decisions for any strictly positive level of spatial autocorrelation regardless of the number of replication blocks. Not only was the spatial models of the current research unable to reproduce the low percent incorrect decisions of Griffin et al. (2005b), the aspatial results were relatively better than those that they suggested. One limitation of the Griffin et al. (2005b) study that explains this difference was the perfect knowledge of the DGP when estimating treatment response. The level of the percent incorrect decisions for their spatial model was most likely the random process of the DGP since the semivariogram used to estimate the coefficients were exactly the same as the one used in the DGP. The DGP for the spatial correlation structure of each simulated field of the current research was not directly used during estimation of coefficients but were estimated using techniques that spatial analysts may choose. Although the first order queen spatial weights matrix was used in the DGP, it was not row-standardized like the matrix used in the spatial error process models. Furthermore, the spatial error process models using the inverse distance weights matrices and the GEO model all estimated the spatial correlation structure, i.e. inverse distance weights matrix distance band and semivariogram parameters, at each iteration without prior knowledge of the DGP.

The differences between aspatial model results from the three studies are the result of choice of statistical test. The F-test used by Griffin et al. (2005b) jointly tested all estimated coefficients and rejected the null hypothesis too often relative to the treatment variable. The MSE associated with the higher levels of spatial autocorrelation ($\lambda \geq 0.5$) from the current research and Griffin et al. (2005b) were within the same ranges. The MSE of the treatment variable estimated by the aspatial model from the non-replicated design in Griffin et al. (2005b) was 1.57 and 4.4 for λ=0.40 and λ=0.72, respectively. The MSE of the current research

was 0.13, 0.31, and 2.37 for λ=0.5, 0.7, and 0.9, respectively, for the single block design using OLS. When the eight replicated block designs were evaluated, Griffin et al. (2005b) reported MSE of 0.05 and 0.07 for λ=0.40 and λ=0.72, respectively, when the treatment variable estimated with OLS. The current research indicated that MSE was 0.22, 0.23 and 0.040 when λ=0.5, 0.7, and 0.9, respectively, for eight blocks and OLS. The MSE for Griffin et al. (2005b) treatment coefficient tended to be smaller than the MSE for other variables in their study, and was always larger than the corresponding MSE of the spatial model.

Griffin et al. (2005b) reported the percent incorrect decisions as the F-test that jointly tested all estimated coefficients were different from the true parameter value. While the F-test was a statistically valid test, it was inappropriate for determining the percent incorrect decisions of the model. The true decision and percent incorrect decisions would be based on the treatment coefficient since the binary explanatory variables were restricted to sum to zero, i.e. $\Sigma d_i = 0$. Therefore, a difference in the statistical test used and choice of estimated coefficient to test lead to differences in the magnitude of results, especially for aspatial models.

The higher percent incorrect decisions in Griffin et al. (2005b) were likely from inappropriate use of the F-test to jointly test all estimated coefficients. Although the same F-test was used on their spatial regression coefficients, very low percent incorrect decisions resulted from the estimation using the same spatial structure as the DGP.

Summary

Large block comparisons are the types of experiments farmers want to conduct. With yield monitor data and spatial statistical methods, more reliable comparisons can be made with limited replication designs. This study has shown that spatial econometric methods such as Anselin's discrete and Cressie's continuous approach provide unbiased and efficient parameter estimates regardless of variability or number of replicates. These results indicate that replication reduces variance and MSE, but reducing MSE via limited replication experimental designs is not as useful as modeling spatial autocorrelation at the levels found in field-scale precision agriculture datasets. Hence, farmers using split-field large-block comparisons of categorical inputs obtain reliable results with spatial analysis and precision agriculture data.

This study has shown that farmers who prefer not to replicate can obtain useful results by performing spatial statistical analysis on limited replication data rather than adding a replicate and using traditional analysis under the levels of spatial autocorrelation expected at field-scales. In essence, the farmer has the choice of trading management time and effort during on-farm trial implementation with advanced spatial analysis of the resulting data, which can often be conducted at non-intensive times or outsourced.

These results indicate that spatial models dominate the addition of another replicate when considering starting at one and two block designs. When the DGP was unknown, geostatistical models dominated the spatial error process models

using empirically determined specification of the spatial weights matrices. There are many factors that plague analysis of field-scale data, and this study examined only spatially autocorrelated errors. The large sample sizes of precision agriculture datasets may be examined to determine the ramification of using differing models and estimators. Other econometric failures and assumption violations may give indication of which spatial models dominate on-farm trial analysis. At the farm level, many factors affecting crop growth and treatment effects are unmeasured and subsequently omitted from the dataset inducing an omitted variable problem. Precision agriculture data are often measured with systematic and random errors in both the dependent and independent variables. Yield monitor data has both erroneously measured observations that lead to errors in variables and improper locational attributes leading to spatial effects. The spatial effects not evaluated in this study may include spatial heteroskedasticity that may be induced by experimental design.

References

Adamchuk, V.I., Morgan, M.T., and Lowenberg-DeBoer, J.M. 2004. A Model for Agro-Economic Analysis of Soil pH Mapping. Precision Agriculture, 5, 111–129, 2004

Anselin 2005. Spatial Regression Analysis in R: A Workbook. Available online at: http://sal.uiuc.edu/. Last accessed September 4, 2006.

Anselin, L. 2002. Under the Hood. Issues in the Specification and Interpretation of Spatial Regression Models. Available on-line at: http://sal.uiuc.edu/users/anselin/papers/hood.pdf Accessed March 1, 2006.

Anselin, L. 2001. Spatial Effects in Econometric Practice in Environmental and Resource Economics. American Journal of Agricultural Economics 83(3) August 2001: 705-710.

Anselin, L. 1995. Local Indicators of Spatial Association - LISA. Geographical Analysis, 27, 93-115.

Anselin. L. 1992. SpaceStat Tutorial: a Workbook for Using SpaceStat in the Analysis of Spatial Data. Available on-line at: http://www.terraseer.com/products/spacestat/docs/spacestat_tutorial.pdf. Accessed September 26, 2006.

Anselin, L. 1988. Spatial Econometrics: Methods and Models, Kluwer Academic Publishers, Drodrecht, Netherlands.

Anselin, L., R. Bongiovanni, and J. Lowenberg-DeBoer. Forthcoming 2004. A Spatial Econometric Approach to The Economics Of Site-Specific Nitrogen Management In Corn Production. American Journal of Agricultural Economics.

Anselin, L. and Griffith, D.A. 1988. Do Spatial Effects Really Matter in Regression Analysis? Papers of the Regional Science Association Vol 65 pp 11-34.

Anselin, L. and Moreno, R. 2002. Properties of Tests for Spatial Error Components. October 22, 2002. Available on-line at: http://sal.uiuc.edu/users/anselin/papers/am_revised.pdf. Accessed September 26, 2006.

Baird, D., and Mead, R. 1991. The Empirical Efficiency and Validity of Two Neighbour Models. Biometrics, Vol. 47, No. 4, pp. 1473-1487.

Besag, J. and Higdon, D. 1999. Bayesian Analysis of Agricultural Field Experiments. Journal of Royal Statistical Society B, 61 Part 4, pp. 691-746.

Bivand, R. with contributions by Luc Anselin, Olaf Berke, Andrew Bernat, Marilia Carvalho, Yongwan Chun, Carsten Dormann, Stéphane Dray, Rein Halbersma, Nicholas Lewin-Koh, Hisaji Ono, Pedro Peres-Neto, Michael Tiefelsdorf and and Danlin Yu. 2006. spdep: Spatial Dependence: Weighting Schemes, Statistics and Models. R package version 0.3-30. Available on-line: http://cran.r-project.org/doc/packages/spdep.pdf Accessed: August 21, 2006.

Bongiovanni, R. 2002. A Spatial Econometric Approach to the Economics of Site-Specific Nitrogen Management in Corn Production. PhD Dissertation. Purdue University, West Lafayette, IN.

Brownie, C., and Gumpertz, M.L. 1997. Validity of Spatial Analyses for Large Field Trials. Journal of Agricultural, Biological, and Environmental Statistics, Vol. 2, No. 1. pp. 1-23.

Casella, G. and Berger, R.L. 2002. Statistical Inference. 2nd ed. Duxbury, Pacific Grove, CA.

Cressie, N. A.C. 1993. Statistics for Spatial Data. John Wiley & Sons: New York.

Cullis, B.R., and Gleeson, A.C. 1991. Spatial Analysis of Field Experiments – An Extension to Two Dimensions. Biometrics, Vol. 47, No. 4. pp. 1449-1460.

Das, D., Kelejian, H.H., and Prucha, I.R. 2003. Finite Sample Properties of Estimators of Spatial Autoregressive Models with Autoregressive Disturbances. Papers in Regional Science 82, 1-26.

Florax, R. and Folmer, H. 1992. Specification and Estimation of Spatial Linear Regression Models: Monte Carlo Evaluation of Pre-Test Estimators. Regional Science and Urban Economics, 22:405–432.

Florax, R.J.G.M., Voortman, R.L., and Brouwer, J. 2002. Spatial Dimensions of Precision Agriculture: A Spatial Econometric Analysis of Millet Yield on Sahelian Coversands. Agricultural Economics. 27(2002) p. 425.

Gotway, C.A. and Harford, A.H. 1996. Geostatistical Methods for Incorporating Auxiliary Information in the Prediction of Spatial Variables. Journal of Agricultural, Biological, and Environmental Statistics, Vol. 1, No. 1 pp. 17-39

Griffin, T.W., Dobbins, C.L., and Lowenberg-DeBoer, J. 2006. Whole Farm Profitability Impact from Implementing and Harvesting On-farm Trials: A Linear Programming Model. Site Specific Management Center Newsletter, August, Available on-line at: www.purdue.edu/ssmc

Griffin, T.W., Brown, J.P., and Lowenberg-DeBoer, J. 2005a. Yield Monitor Data Analysis: Data Acquisition, Management, and Analysis Protocol. Available on-line at: http://www.purdue.edu/ssmc

Griffin, T.W., Lambert, D.M., and Lowenberg-DeBoer, J. 2005b. Testing Appropriate On-Farm Trial Designs and Statistical Methods for Precision Farming: A Simulation Approach. Proceedings of the 7th International Conference on Precision Agriculture and Other Precision Resources Management, ASA/SSSA/CSSA, Madison, WI.

Griffin, T.W., J.M. Lowenberg-DeBoer, D.M. Lambert, J. Peone, T. Payne and S.J. Daberkow. 2004. Precision Farming: Adoption, Profitability, and Making Better Use of Data. Paper presented at the 2004 Triennial North Central Farm Management Conference, July 14-16, 2004, Lexington, Kentucky.

Isaaks, E. H. and Srivastava, R. M. 1989. An Introduction to Applied Geostatistics. Oxford Univ. Press, New York, Oxford.

Lambert, D.M., Lowenberg-DeBoer, J. and Bongiovanni, R. 2004. A Comparison of Four Spatial Regression Models for Yield Monitor Data: A Case Study from Argentina. Precision Agriculture 5 pp. 579-600.

Lambert, D., Lowenberg-DeBoer, J., and R. Bongiovanni. 2002. Spatial Regression, an Alternative Statistical Analysis for Landscape Scale On-farm trials: Case Study of Variable Rate N Application in Argentina. P.C. Robert et al., ed. In: Proceedings of the 6th International Conference on Precision Agriculture. ASA/CSSA/SSSA Madison, WI.

Lowenberg-DeBoer, J. 2002a. Blocks vs. Strips for On-Farm Experimentation, Site Specific Management Center Newsletter, June, (www.purdue.edu/ssmc)

Lowenberg-DeBoer, J. 2002b. Zero Rates in Site-Specific On-Farm Trials, Site Specific Management Center Newsletter, September, (www.purdue.edu/ssmc)

Lowenberg-DeBoer, J., D. Lambert, and R. Bongiovanni. 2003. Appropriate On-Farm Trial Designs for Precision Farming. Proceedings of the 4th European Conference on Precision Agriculture, J. Stafford & A. Werner, editors, Wageningen Academic Publishers, Netherlands, 2003.

Lowenberg-DeBoer, J. and H. Urcola. 2003. How Should Yield Monitor Data Be Combined With Other Information Sources In Choosing Hybrids And Varieties? Jan 2003 SSMC newsletter, (www.purdue.edu/ssmc)

R Development Core Team 2006. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL http://www.R-project.org.

Ribeiro, P. J. Jr and Diggle, P. J. 2001. geoR: A Package For Geostatistical Analysis R-NEWS, 1(2):15-18. June, 2001.

Singh, M., Malhotra, R.S., Ceccarelli, S., Sarker, A., Grando, S., and Erskine, W. 2003. Spatial Variability Models to Improve Dryland Field Trials. Experimental Agriculture Vol 39, pp. 151-160.

Solie, J.B., Raun, W.R., and Stone, M.L. 1999. Submeter Spatial Variability of Selected Soil and Bermudagrass Production Variables. Soil Science Society of America Journal 63:1724-1733