

## Field-Scale Experimental Designs and Spatial Econometric Methods for Precision Farming: Strip-Trial Designs for Rice Production Decision Making

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### Abstract

Site-specific data is spatially variable, precluding traditional econometric analysis. Some field-scale experimental designs present logistical, operational and mathematical problems in estimating treatment differences, specifically when adjacent observations are of different treatments such as with strip-trial designs. A modified spatial interaction structure is presented to analyze strip-trial designs with spatial econometrics.

Keywords: spatial analysis, on-farm research, yield monitor data, spatial interaction structure, spatial weights matrix, strip trials, split planter trials

# Field-Scale Experimental Designs and Spatial Econometric Methods for Precision Farming: Strip-Trial Designs for Rice Production Decision Making

## Introduction

This provisional paper evaluates a common field-scale experimental design and presents a spatial econometric analysis technique to address associated on-farm trial design limitations. Precision farming technologies have created a resurgence of interest in on-farm research because of the ease of collecting low-cost production data.

Researchers conducting field-scale experiments have expressed interest in using precision technologies for measurement and modeling spatial effects. Spatial effects can be measured and explicitly modeled rather than the conventional attempt to negate it, providing more reliable inference from on-farm trials.

Farmers conducting field-scale experiments typically utilize some sort of rudimentary analysis such as simple treatment averages by predefined management zones or some arbitrary grid, whether the analysis was conducted at the farm-level or outsourced. Precision farming technology has reduced the cost of intense data collection, but appropriate spatial analysis methods are not widely available or understood at the farmer, agricultural industry, or university outreach levels. In addition, some field-scale on-farm trial designs present complication when analyzing precision agriculture data.

To demonstrate how spatial analysis methods apply to field-scale strip-trial experimental designs, this paper reports on the use of spatial statistical methods to analyze on-farm rice *{Oryza sativa, L.}* trials. The most appropriate econometric analysis methods common to the precision agriculture literature are presented.

Precision agriculture has sparked the interest of farmers and researchers to revisit field-scale research. Instantaneous yield monitors have provided opportunities for this type of research to be implemented without interfering with other field operations. Farmers tend to conduct their own on-farm research using designs including strip-trials. Strip-trial designs are particularly inadequate for some inputs specific to rice, such as midseason applications of herbicides and fertilizers applied with aerial applicators. A key problem with site-specific field-scale data is the occurrence of spatial effects (dependence and heterogeneity), which precludes the usage of straightforward classical statistical approaches. In addition, strip-trial designs disrupt the measurement of spatial variability due to overriding spatial edge effects at treatment borders.

We present the idea of the “neighboring observation problem” which is a phenomenon in spatial analysis. In spatial analysis, characteristics of neighboring observations are used in the statistical model. When research questions are imposed upon geographic areas in which spatial variability is present such as field-scale agricultural research, some percentage of neighboring observations are of a different treatment due to treatment edges being adjacent to one another. These spatial spillover effects influence the power in estimating treatment differences. Spatial spillovers are an externality affecting the statistical model via the spatial interaction structure which defines which observations are neighbors. One potential solution is to create a modified spatial interaction structure such that neighbors are defined both on location and treatment criteria in a “hybrid” spatial weights matrix.

The overall objective of this paper is to demonstrate if strip-trial designs are appropriate for field-scale research data collected with yield monitors. Specific

objectives of this paper are 1) to evaluate the feasibility of field-scale split-planter experimental designs on rice production and 2) to determine the most appropriate analysis technique by conducting a series of spatial econometric diagnostics and analysis methods including a specialized spatial weights matrix that imposes a modified spatial interaction structure such that observations of a different treatments cannot be neighbors regardless of location, and referred to as the hybrid matrix  $W_h$ .

## **Background and Literature Review**

Several publications have described on-farm comparison and field-scale research in mechanized agriculture (Anderson and Honeyman, 1999; Bramley et al., 1999; Knighton, 2001; Nafziger, 2003; Whelan et al., 2003; Wittig and Wicks, 2001) and the economic ramifications when replications, treatments, or site years are reduced (Young et al., 2004). These methodologies for on-farm trials were derived from small plot designs developed in the early twentieth century for the technology available at that time. Concurrent publications recommend designs such as strip or split planter trials to accommodate variability across the field. Some studies have taken on-farm trials a step further by integrating precision agriculture technologies to measure variability and record yield data (Adams and Cook, 2000; Anselin et al., 2004; Brouder and Nielsen, 2000; Doerge and Gardner, 2001; Griffin et al., 2004; Knight and Pettitt, 2003; Lark and Wheeler, 2003; Liu et al., 2005; Lowenberg-DeBoer, 2002a,b; Lowenberg-DeBoer et al., 2003; Lyle et al., 2003; Nafziger, 2001; Nielsen, 2000; Whelan et al., 2003). Anselin et al. (2004), Florax et al. (2002), Griffin et al. (2005a), Lambert et al. (2004), Lambert (2005), and Liu et al. (2005) used spatial econometric models to analyze precision

agriculture data. This paper builds upon the earlier work of Florax et al. (2002), Griffin et al. (2005a), Lowenberg-DeBoer et al. (2003), Hurley et al. (2001), Lambert et al. (2004), Liu et al. (2005), and Anselin et al. (2004) by applying spatial statistical and spatial econometric techniques to rice. Griffin et al. (2005) used a Euclidean distance weights matrix and Liu et al. (2005) used an inverse distance weights matrix while the others used a first-order queen contiguity weights matrix. Although the first-order queen matrix was most likely the appropriate spatial interaction structure for those particular datasets, it is not universally the most appropriate.

#### *Benefits of strip trials*

Strip-trial designs have been popular on-farm trial designs and even promoted by the agricultural industry. Strip-trial designs were derived from classical small-plot statistical experimental designs with the advantage of having no spatial variability in the width of the treatment block, or strip, which were replicated with every planter pass. With many replications and no spatial variability assumed in the width of the plot, these designs were readily accepted by farm managers and field-scale researchers.

#### *Disadvantages of strip trails*

Field operations associated with planting and harvesting are the most critical to the success of the farm operation, causing the value of farmer's management time and labor to be at a premium, thus discouraging implementation of classical complete block experimental designs. Familiar experimental designs are often costly and cumbersome, interfering with production logistics (Lowenberg-DeBoer, 2002). Even though designs such as strip-trials or split-planter trials that were derived from small plot statistics reduce time requirements compared to randomized complete block designs, the perceived

benefits of research may still not overcome resource and time costs (Lowenberg-DeBoer et al., 2003). For instance, there are logistical problems associated with strip-trials. For split-planter or “split-grain drill” trials, filling a section of the grain drill or every so many planter boxes with a different variety or other treatment potentially leads to human error. With larger farms, the person planning may not be the person planting, potentially leading to communication and coordination problems. From the viewpoint of the analyst, it is a complex and tedious task to keep treatments and harvester passes in line.

Other problems with strip-trial designs arise from agronomic treatment interactions. If for instance the treatments are hybrid or varieties, taller varieties may dominate yields of shorter varieties due to competition such as shading and not the phenotypic response, possibly masking true yield differences. Other strip-trial phenomena include disease breaks from susceptible and resistant varieties. When one variety is susceptible to a pathogen, the resistant variety may act as a buffer zone. Strips of resistant varieties may not allow the pathogen to spread across the field as it normally would in a monoculture environment. Sometimes resistant varieties are adversely affected by intense exposure to the pathogen. Treatments such as herbicides or fertilizers may drift or otherwise move out of intended experimental plots and interfere with other treatments when strips are narrow.

## **Data and Methods**

The dataset comes from a farmer-managed on-farm field-scale experiment in Northeast Arkansas under a flood irrigated monoculture zero-grade practice. The farmer has five years experience using yield monitors on the combine harvester and collects the

data for future farm management decision-making. The farmer expected Hybrid 1 to dominate Hybrid 2 from industry claims and felt that rudimentary analysis with standard farm-level mapping software confirms the prior expectations. The farmer is considered to be innovative from farmer-peers as well as university researchers, being credited for developing and perfecting continuous rice production on zero-grade.

The farmer's research question deals with which rice hybrid dominates for both agronomic yield and economics to make better farm-management decisions in future years. The split-planter experimental design was implemented with a 20-foot grain drill with alleys in between, which allow labor to rogue noxious weeds and in particular red rice *{Oryza sativa, L.}* (Figure 1a). Each side of the drill had a different hybrid such that the center portion of the field had 20 feet of each hybrid. The combine header width is 25 feet which is disparate from the 20 foot grain drill; however with the alleys between treatments, this was of no consequence.

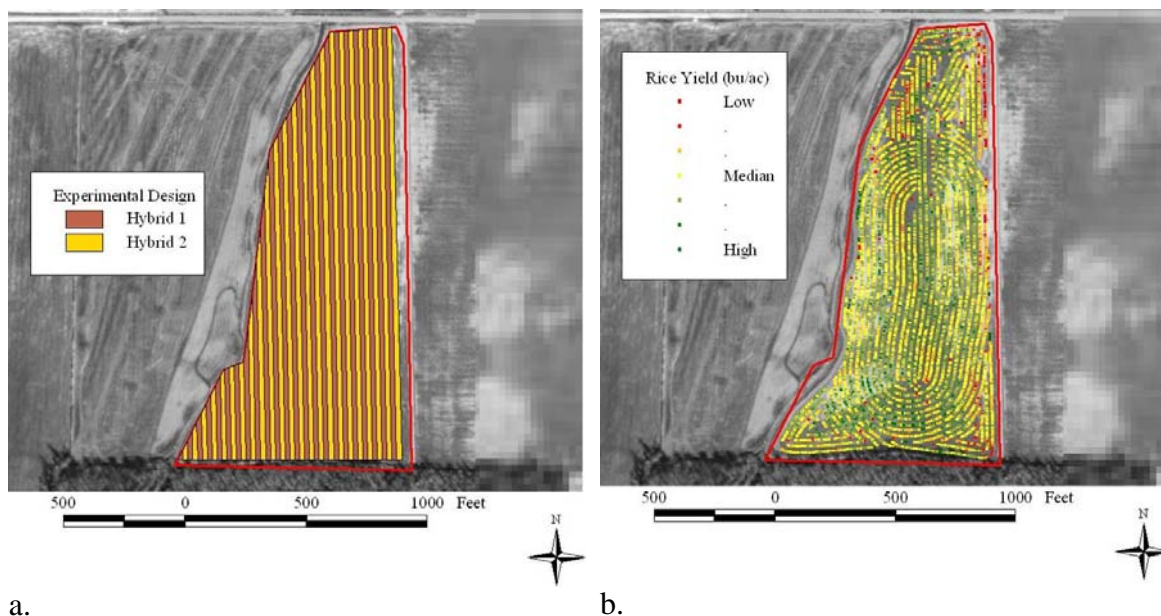


Figure 1. Strip-trial experimental design and filtered yield monitor data

Raw yield monitor data was exported by the farmer from AgLeader SMS software using the default filtering procedures of the software. The exported data from SMS was imported into Yield Editor Software (Drummond, 2004) and subjected to a filtering procedure as described by Griffin et al. (2005b) with the parameters and number of deleted points in Table 1 and presented in Figure 1b.

**Table 1. Parameters, criteria, and number of points deleted in yield data filtering**

<b>Filtering parameter</b>	<b>Parameter value</b>	<b>Number of deleted points<sup>b</sup></b>
Maximum velocity (mph)	4	8
Minimum velocity (mph)	1	114
Smooth velocity	0.2	88
Maximum yield (bu ac <sup>-1</sup> )	310	25
Minimum yield (bu ac <sup>-1</sup> )	55	55
Standard deviation filter	3	224
*Flow delay (s)	12	NA <sup>a</sup>
*Start pass delay (s)	4	NA
*End pass delay (s)	4	NA

\*Flow delay, start and end pass delays were conducted during importing raw data into SMS by the farmer.

<sup>a</sup> Points deleted are not cumulative, i.e. the “same” point can be deleted by multiple criteria.

<sup>b</sup> Not applicable.

Combine passes not parallel to grain drill passes such as curved or diagonal harvester passes caused uncertainty regarding which hybrid was harvested and whether the yield monitor measurement was from a single hybrid or a combination of treatments. Due to the harvest pattern, only the north-south subset of passes parallel to the treatment blocks was eligible to be included in the final dataset (Figure 2a). Any yield observation 1) within 1 meter of the treatment edge or 2) was not on a north-south transect did not meet this analysis criteria and subsequently omitted from analysis. The resulting yield data is presented in Figure 2b and summarized in Table 2.

#### *Selecting Appropriate Spatial Interaction Structure and Model*

The resulting final dataset was subjected to an exploratory spatial data analysis (ESDA) to ascertain 1) the level of spatial dependence within the data, 2) which spatial



econometric model was most appropriate and 3) the most appropriate spatial interaction structure. A series of spatial interaction structures, or so-called spatial weights matrices, were constructed by varying distance cutoff bands and type of weighting matrix. The distance band ranged from 16 meters, the minimum distance such that each observation has at least one neighbor when the restriction that only observations of the same treatment can be neighbors, to 175 meters, a distance large enough so that observations were expected to not be correlated from *a priori* information in increments of 25 meters starting with the 25 meter distance band. Additional matrices were created for 40 and 60 meters to iterate around the approximate appropriate distance from previous diagnostics. All spatial weights matrices were inverse distance, where the non-zero elements of the weight matrix were  $\frac{1}{d_{ij}}$  where  $d$  is distance between points  $i$  and  $j$ . Each matrix was constructed such that neighbors were assigned by location as well as by treatment. The first set of matrices allowed any observation to be a neighbor of any other observation based upon location criteria only and referred to as traditional matrices,  $W$ . The second set of matrices imposed a treatment restriction in addition to the location criteria to address the “neighboring observation problem” and referred to as “hybrid” matrices,  $W_h$  (see Appendix A for operational suggestions for creating hybrid matrices).

Table 2. Descriptive statistics for variables.

	Descriptive Statistics				Wald test on normality		Randomization Assumption		
	Mean	S.D.	Min	Max	Wald	Prob	Moran's I	z-value	S.D.
	YIELD bu ac <sup>-1</sup>	200.352	17.222	124.4	266.0	40.58	0.0000	0.1955	40.20
HYB	0.457	0.498	0.0	1.0	226.23	0.0000	1.0000	204.80	0.0049
SOIL	0.532	0.499	0.0	1.0	226.19	0.0000	0.8231	168.61	0.0049
BI	145.425	73.329	0.0	254.0	107.38	0.0000	0.0507	10.54	0.0049

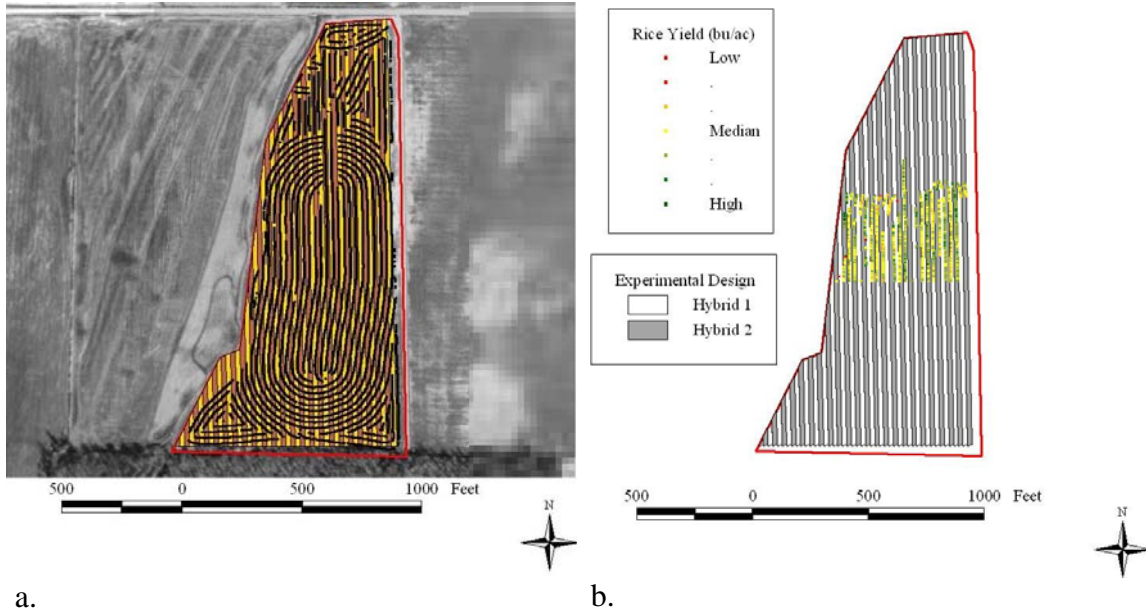


Figure 2. Yield data relative to strip-trial experimental design and resulting dataset

The first ESDA measure we use is Moran's I (Cliff and Ord, 1981) and can be utilized in the variable itself or in the OLS residuals. The Moran's I for a variable is given by:

$$I = \frac{n}{S_o} \frac{\mathbf{x}'\mathbf{W}\mathbf{x}}{\mathbf{x}'\mathbf{x}} \quad \text{eq. 1}$$

where  $\mathbf{x}$  is a  $n \times 1$  vector of observations as deviations from the mean,  $\mathbf{W}$  is an  $n \times n$  spatial weights matrix, and  $S_o$  is the sum of elements of  $\mathbf{W}$  (Cliff and Ord, 1981; Anselin, 1988). Moran's I can be thought of as a spatial correlation coefficient. Relatively high positive values of Moran's I is interpreted as high (low) values having neighbors of high (low) values, whereas a negative Moran's I signifies high and low value observations occur as neighbors. Site-specific yield data tends to be strongly positively spatially autocorrelated at the density in which yield monitor data is collected. A Moran's I value of 0.196 indicates that spatial autocorrelation was present in the data (Table 2).

The full econometric model is YIELD regressed on treatment, soil dummy, and a continuous covariate derived from aerial imagery:

$$y = trt_i + soil_i + BI \quad \text{eq. 2}$$

where  $y$  is yield,  $trt_i$  is treatment dummy for HYBRID,  $soil_i$  is dummy variable for soil zone, and BI is a brightness index derived from bare soil aerial imagery. The yield data was supplied by the farmer, the soils data available from USDA-NRCS, and the aerial imagery were black and white USGS images distributed via TerraServer. The value of the image pixel closest to the yield data point was appended to the dataset.

The Moran's  $I$  test for regression residuals is asymptotically normally distributed under the null hypothesis of no spatial dependence, and given by:

$$I = \frac{n}{S_0} \frac{\mathbf{e}'\mathbf{W}\mathbf{e}}{\mathbf{e}'\mathbf{e}} \quad \text{eq. 3}$$

where  $\mathbf{e}$  is the  $(n \times 1)$  vector of OLS residuals,  $\mathbf{W}$  an  $(n \times n)$  spatial weights matrix, and  $S_0$  the sum of elements of  $\mathbf{W}$ .

The Moran's  $I$  for residuals for hybrid matrices were higher than for traditional weight matrices, although both were highly significant (Figure 3). Lagrange Multiplier (LM) and Robust LM (RLM) tests indicated that spatial autocorrelation was in both the dependent variable (LAG) and the error term (ERR) (Figures 4 and 5). The LM values were largest for ERR across both matrices, indicating that the spatial error model is the most appropriate model for this data.

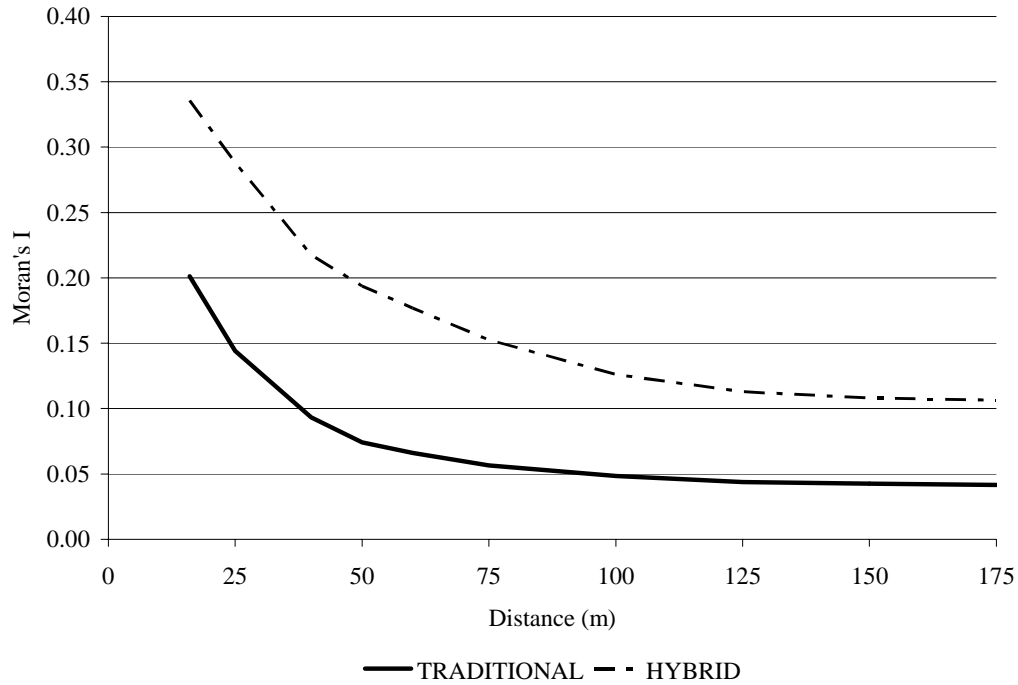


Figure 3. Moran's I tests for traditional and hybrid matrices

The ranking of RLMERR relative to the other LM tests dramatically differs between traditional and hybrid matrices. With traditional matrices LMLAG was higher than RLMERR and comparable to LMERR. With hybrid matrices, RLMERR was much higher than LMLAG and similar to LMERR. LM diagnostics of the hybrid matrices indicate that a 60-meter distance cutoff band was most appropriate for the data. Table 3 presents connectivity characteristics for the 60-meter inverse distance matrix in both a traditional and hybrid guise.

Table 3 Connectivity data for the 60-meter inverse distance spatial weights matrices.

	60 m inverse-distance traditional $W$	60 m inverse-distance hybrid $W_h$
Dimension	1,358	1,358
Nonzero links	684,634	346,810
Nonzero weights (%)	37.15	18.82
Average weight	0.00198	0.00392
Average number of links	504.149	255.383
Largest root (eigenvalue)	1	1
Smallest root (eigenvalue)	-0.1888	-0.2068

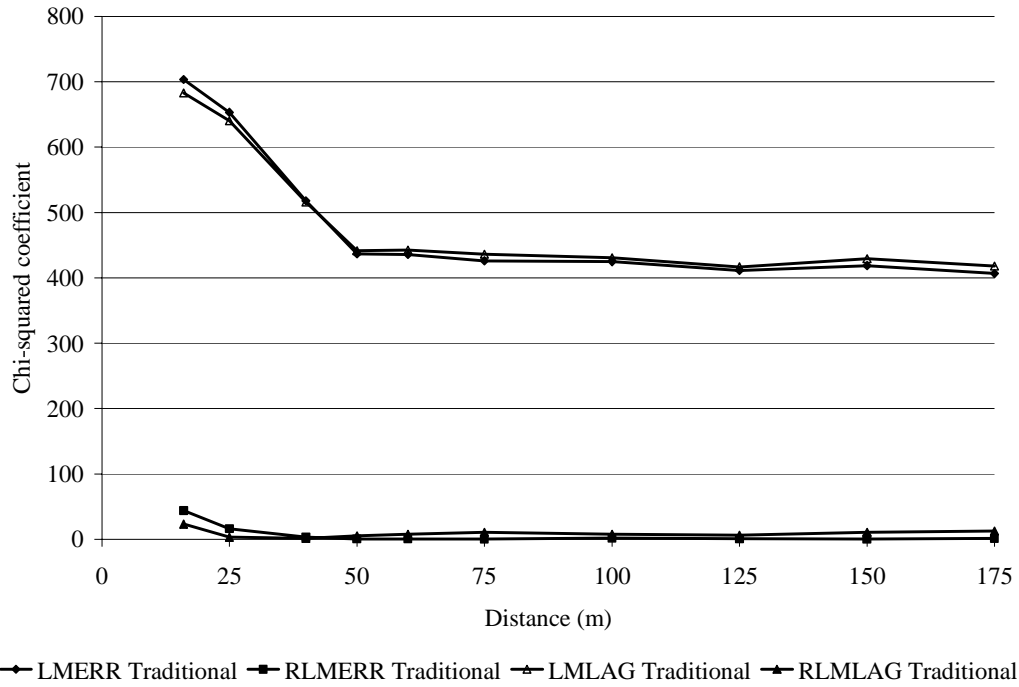


Figure 4. Lagrange Multiplier tests for spatial error and spatial lag in traditional matrices

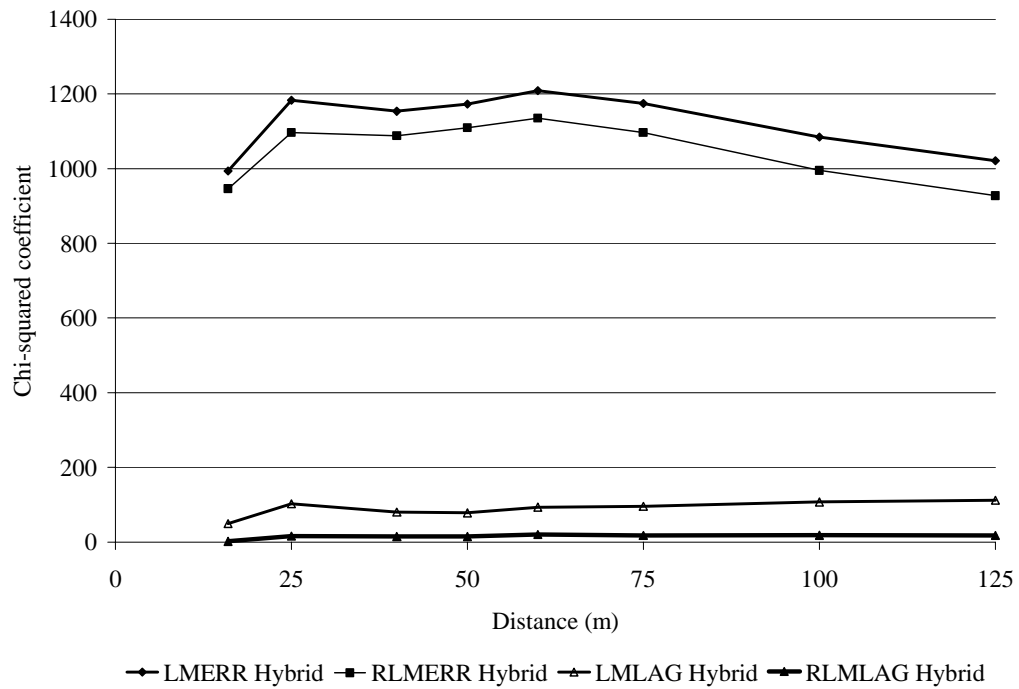


Figure 5. Lagrange Multiplier tests for spatial error and spatial lag in hybrid matrices

The spatial error model has spatially autocorrelated errors and is similar to the traditional OLS model with the exception that the error term  $\varepsilon$  is spatially autocorrelated and given as:

$$y = X\beta + \varepsilon \text{ where } \varepsilon = \lambda W\varepsilon + \mu \quad \text{eq. 4}$$

where  $y$  is a  $n \times 1$  vector of dependent variable,  $X$  is a  $n \times k$  matrix of explanatory variables,  $\beta$  a  $k \times 1$  vector of coefficients,  $\varepsilon$  a  $n \times 1$  vector of residuals,  $\lambda$  is the spatial autoregressive parameter, and  $\mu$  is the new vector of errors. The spatial error model more concisely written is:

$$y = X\beta + (I - \lambda W)^{-1} \mu \quad \text{eq. 5}$$

## Results

As previously stated, the full econometric model included yield as the dependent variable, a treatment dummy for hybrid, a soil dummy for soil zone, and a continuous covariate of the brightness index of an aerial image. Table 4 presents the estimated coefficients and z-values for spatial error models estimated with maximum likelihood (ML) for 60-meter inverse distance weights matrices with both a traditional and hybrid spatial interaction structure. The model using the traditional weights matrix indicates that HYBRID 1 significantly dominates HYBRID 2 by nearly four bushels while the alternative model using the hybrid matrix indicates there is no statistical difference in yield between treatments. Goodness of fit statistics indicates that the model using the hybrid matrix dominates the model using the traditional matrix.

Table 4. Estimated results for 60-meter inverse distance traditional and hybrid matrices..

ML Spatial Error		
Variable	Traditional	Hybrid
CONSTANT	193.73 (6.54) <sup>a*</sup>	195.43 (7.89)*
HYB	3.63 (3.72)*	-8.65 (-0.24)
SOIL	8.12 (2.83)*	7.47 (2.62)*
BI	0.01 (1.13)	0.00 (0.65)
LAMBDA	0.985 (96.48)*	0.978 (91.85)*
Log likelihood	-5704.78	-5605.73
AIC	11417.6	11219.5

<sup>a</sup>In parentheses z-values are reported for ML spatial models. Significance is indicated with \* for 1% levels.

## Conclusions

More information about local variations over the production surface is realized when spatial effects are explicitly modeled. Some experimental designs are more conducive for field-scale on-farm experimentation, but techniques for dealing with less desirable designs are being developed. A few obstacles of analyzing site-specific data from strip-trial designs have been demonstrated. It is our recommendation that larger treatment block designs such as split-fields are used for field-scale research for logistical reasons, as long as the appropriate spatial analysis is used. Split-field designs often have four or more harvester passes per treatment. If treatment block widths are sufficiently wide, then harvesting at any angle to the original experimental design would suffice, even at diagonals, perpendicular or in concentric circles. These large block designs offer reliable statistical inference with spatial analysis.

If a farmer wishes to use strip-trial designs, then we recommend harvesting with the treatment such that certainty exists about yield monitor measurements being of a single specific treatment. In addition we recommend spatial analysis that addresses the

“neighboring observation problem” by providing the appropriate spatial interaction structure. Although spatial statistical analysis dominates classical analysis when the data are spatially autocorrelated; more reliable analysis is obtained by implementing appropriate experimental designs. Without spatial econometric analysis, this dataset would be a total loss.

### **Future Work**

The level of confidence that the farm manager has in their on-farm trial results and associated decisions will be assessed to determine if spatial analysis has changed their discernment of results and decision-making process. Initial results indicate that farmer confidence levels are actually lower now that they feel they had a false confidence in previous rudimentary analysis.

Field studies of different crops and treatments across several regions are being assembled to ascertain commonalities and differences in appropriate spatial data analysis. These similarities will be shared with the agricultural software industry to encourage the development of a spatial decision support system in the form of farm-level software.



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## Appendix A

### Creating “Hybrid” Weight Matrices

In general, a weights matrix is constructed such that  $w_{ii}=0$ ,  $w_{ij} > 0$  for neighbors and  $w_{ij}=0$  for non-neighbors where  $ij$  denotes location information or matrix position for rows and columns. In the case of strip-trial designs, we impose the restriction that observations of differing treatments cannot be neighbors of one another, only observations from the same treatment. Other experimental designs also suffer from similar issues although to a lesser degree. In order for  $w_{ij} > 0$  in the normal case, the observation must meet the location criterion such as the first order contiguity or within some predetermined distance band. The hybrid matrix adds an additional criterion that the observation is of the same treatment, perhaps  $t=1$  if the observation is of the same treatment and  $t=0$  otherwise such that the criteria for a neighbor is now  $w_{iit}=0$ ,  $w_{ijt} > 0$  for neighbors and  $t=1$ , and  $w_{ijt}=0$  for non-neighbors and/or when  $t=0$ . Even though the observation may fit the location criterion, it is not considered a neighbor if it does not meet all the criteria.

Operationally, it is possible to create such a hybrid matrix, although it involves elaborate steps with multiple specialized software packages. To create the hybrid weights matrix ( $W_h$ ) such that observations of differing treatments are not neighbors, begin with the whole database in the SpaceStat (Anselin, 1992) format. The dataset must have been previously sorted by each treatment and then the unique identifier (TWG\_ID in my case) variable in sequential order. My preferred method is to export the whole database from ArcView GIS by using the SpaceStat Extension (Anselin, 1999). Once the database is in the SpaceStat format, create a distance matrix for the database (T-4-1). Create the inverse distance matrix from the distance matrix (T-4-6) for the appropriate distance cutoff band (it is my experience that a distance decay function makes the most intuitive sense when it comes to specifying a spatial interaction structure for precision agriculture data). Convert the inverse distance matrix to a sparse matrix, i.e. from a \*.FMT to a \*.GWT file format) (T-3-6; choose the inverse distance matrix created in the previous step, then assign a name for the new \*.GWT file). Assign a unique identifier from the original treatment database file (the one exported from ArcView GIS using SpaceStat Extension) (T-3-8; choose matrix created in previous step, assign name for new sparse matrix, chose original dataset with unique identifier exported from ArcView GIS using SpaceStat Extension, choose/assign unique identifier variable). Now the matrix must be separated into separate matrices for each treatment by selecting rows and columns that meet the treatment criteria. This is accomplished by either 1) selecting a range of unique identifiers that correspond to the treatment or 2) selecting the treatment dummy variable (D-2-7). Once the above procedure has been completed for each of the treatment datasets, the \*.GWT files can be opened with a text editor such as MS Notepad (my datasets exceed the row limitations of MS Excel). With the exception of the first row of each file, copy the data in the file with the highest unique identifier values and paste at the end of the text file with lower unique identifiers such that the first column of observations are in sequential order. The first line of the new text file should contain a numbers which is the summation of the number in all the \*.GWT files, which is the total number of observations. Save the new text file. Make sure the extension is \*.GWT. This is the hybrid matrix  $W_h$  which addressed the “neighboring observation problem.”