Precision Agriculture: Economics of Nitrogen Management in Corn Using Site-specific Crop Response Estimates from a Spatial Regression Model

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SUMMARY:

Adapting variable rate technology (VRT) to Argentine conditions requires methods that use inexpensive information and that focus on the inputs and variability common to Argentine maize and soybean growing areas. The goal of this study is to determine if spatial regression analysis of yield monitor data can be used to estimate the site-specific crop Nitrogen (N) response needed to fine tune variable rate fertilizer strategies. N has been chosen as the focus of this study because it is the most commonly used fertilizer by corn farmers in Argentina. The methodology uses yield monitor data from on-farm trials to estimate site-specific crop response functions. The design involves a strip trial with a uniform N rate along the strip and a randomized complete block design, with regression estimation of N response curves by landscape position. Spatial autocorrelation and spatial heterogeneity are taken into account using a spatial error model and a groupwise heteroskedasticity model. A partial budget is used to calculate uniform rate and VRT returns. First year data indicate that N response differs significantly by landscape position, and that VRA for N may be modestly profitable on some locations depending on the VRT fee level, compared to a uniform rate of urea of 80kg ha^{-1}. A more complete analysis will pool data over many farms and several years to determine if reliable differences exist in N response by landscape position or other type of management zone. The study is planned for four years. The purpose of this preliminary analysis is to show how spatial regression analysis of yield data could be used to fine tune input use.

Keywords: Economics, Precision agriculture, Argentina, corn, variable rate, nitrogen

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INTRODUCTION

Technologies based on computerized information and global positioning systems (GPS) are transforming large-scale commercial agriculture throughout the world. This technology is often labeled "precision agriculture" and is giving new life to the old idea of site-specific management by reducing the cost of crop information and variable rate input application.

The underlying concepts of site-specific management are transferable from place to place, but fine-tuning production systems are necessarily site-specific because soils, climate and economic conditions vary. Argentine producers and agribusiness companies face some special problems in adapting precision agriculture to their conditions. While yield monitoring in Argentina has followed a similar adoption path to that of North America, variable rate application of inputs has not been widely used because of the high cost of soil sampling and relatively low fertilizer use. Furthermore, management induced variability in Argentina is less than in the US or Canada (Lowenberg-DeBoer, 1999).

Commercial laboratory analysis of soil samples in Argentina ranges from \$40 to \$70 per sample, compared to the \$3 to \$8 charge for the basic analysis in the US. The cost of soil sampling makes the intensive grid or soil type sampling used in North America prohibitively expensive.

Adapting variable rate technology (VRT) to Argentine conditions will require methods that use inexpensive information, and that focus on the inputs and variability common to Argentine maize and soybean growing areas.

The objectives of this study are to:

1) determine if spatial regression analysis of yield monitor data can be used to estimate the site-specific crop N response needed to fine tune variable rate fertilizer strategies,
2) estimate the profits for site-specific N management using the crop responses estimated under objective (1), and
3) compare profits from site-specific N management using crop response functions with uniform rate management and proposed spatial management strategies.

N has been chosen as the focus of this study because it is the most commonly used fertilizer by corn farmers in Argentina. The methodology utilizes yield monitor data from a on-farm trial in southern Córdoba Province to estimate site-specific crop response functions with low cost independent variables such as landscape position, topography and soil color. Producers and crop consultants can use the site-specific crop response methodology to guide N application and increase profits.

The null hypotheses are:

1) There is not spatial autocorrelation or heteroskedasticity in corn yield response to N rates across landscape positions.
2) Maize N response does not vary by landscape position,
3) VRT N application is not profitable on average for VRT fees of \$6 ha^{-1}.

The main expected result would be information leading to improved N management throughout the maize and soybean growing areas of Argentina, especially those in Córdoba. From a methodological point of view, the results will show the consequences of ignoring spatial autocorrelation in a regression model when it is in fact present. The potential users are producers, crop consultants, and fertilizer dealers throughout the corn and soybean-growing areas of Argentina. Researchers in the area of precision agriculture will be pointed to the importance of spatial dependence in regression analysis models.

LITERATURE REVIEW

Site-specific fertilizer application is an old idea. In the US, the first extension recommendations on intensive soil sampling and variable rate fertilizer application appeared in 1929 (Linsley and Bauer, 1929). The recent resurgence of interest in the idea can be linked to the availability of GPS and information technology (IT) which lower information and VRT implementation costs dramatically. VRT fertilizer was the earliest commercially available precision agriculture service in the US. Currently, about 50% of the approximately 7500 retail fertilizer dealers in the US offer the service in the US (Akridge and Whipker, 1999). In contrast, only ten VRT fertilizer applicators were being used in Argentina in 1998 (Bragachini, 1999). In the US, VRT fertilizer is a common practice among producers of higher value field crops, such as sugar beets. Many US corn and soybean farmers have tried VRT fertilizer, but doubts remain about its profitability (Lowenberg-DeBoer and Swinton, 1997).

Swinton and Lowenberg-DeBoer (1998) review studies of the profitability of site-specific N, phosphorus (P) and potassium (K) fertilizer application based on intensive soil sampling, using either grids or soil type. They conclude that VRT fertilizer is often profitable for higher value field crops but seldom profitable for extensive dryland crops like wheat and barley. For maize and soybeans, VRT fertilizer often fails to cover the added costs of soil sampling and VRT application. Key methodological problems identified in these studies include: failure to charge soil sampling, analysis and VRT application fees, and use of simulation models which assumed target yields would be achieved. Lowenberg-DeBoer and Aghib (1999) use on-farm trial data from the eastern Corn Belt to show that VRT P & K just about covers costs as a stand-alone practice, and that it may have potential to reduce risks. Bongiovanni and Lowenberg-DeBoer (1998) show that VRT lime is modestly profitable in the Eastern Cornbelt. On-farm trials on the Sauder farm in central Illinois showed a 941 kg ha^{-1} yield increase for corn grown in an integrated site-specific management system which combined VRT NPK, lime, and plant population (Finck, 1998).

Many alternatives to intensive soil sampling have been proposed for N management, but no method has been widely accepted as better than uniform rate application. Pan et al. (1997) review studies of spatial variability of N in annual field crops. They note that current university and industry N recommendations in North America may not be very useful for site-specific management because they are broad compromises intended to be used regionally. Pan et al. also indicate that N available to the plant at any one location and time depends on many factors, including organic matter in the soil, previous crop, manure applications, recent temperature and rainfall patterns, and leaching losses. Because N is spatially and temporally dynamic, N soil tests, stalk nitrate tests, and leaf nitrate tests are not necessarily a good basis for making N fertilizer decisions, even when these tests are available and affordable.

Making better N management choices is not simply a case of understanding N dynamics, but also requires a decision support system that effectively uses relatively low cost data to predict yields and profits under alternatives. Many simulation and statistical models have been proposed (see various papers in Robert et al., 1994, 1996, 1998). The simulation process models have been calibrated to mimic spatial variability in specific fields, but it is not clear that this can be generalized. Most crop growth models currently lack many of the factors that drive spatial variability (e.g., topography, microclimate, water flow). Crop growth models are great research tools, but it is unlikely that producers and crop consultants will be willing to invest the time and resources to calibrate and validate the models for specific fields. Categorical models ranging from simple analysis of variance to clustering and fuzzy set analysis can be used to identify management areas, but leave the question of optimal N application unanswered.

Several researchers have used ordinary least squares (OLS) regression to help estimate crop responses, but with mixed results (e.g., Khakural et al., 1998; Coelho et al, 1998, Mallarino et al., 1996). Regression crop response functions have the advantage of fitting easily into the traditional crop production economics decision model (Heady and Dillon, 1961; Dillon and Anderson, 1990). Lowenberg-DeBoer and Boehlje (1996) show that the traditional uniform rate production economics decision framework can easily be modified for site-specific management. Software that combines regression and optimization could easily be developed using well-known algorithms. Annual updating of response coefficients to reflect genetic improvement and other management changes could be automated. These updates would reestimate the response with yield monitor data.

Kessler and Lowenberg-DeBoer (1998) show that spatial correlation of regression error is important in yield monitor data. Because of this spatial correlation, OLS regression gives biased coefficient estimates. Anselin (1988) outlines spatial regression models that adapt generalized least squares regression to spatial data. These spatial regression models have been used mainly for regional economics analysis. The authors do not know of any attempt to estimate spatial regression models with yield monitor data.

Spatial Econometrics. Anselin (1999a) defines spatial econometrics as a subfield of econometrics that deals with the treatment of spatial interaction *(spatial autocorrelation*n) and spatial structure *(spatial heterogeneit*y) in regression models for cross-sectional and panel data. Spatial econometrics is distinct from spatial statistics in the same ways that econometrics is distinct from statistics in general. These differences stem from the type of data being analyzed and the ways in which the results are used. A difference between geostatistics and spatial econometrics is the way in which the results are used. A primary concern of many studies in the geostatistics literature is with identifying and estimating spatial structure of a data set (Anselin, 1988). In short, geostatistics focuses on producing a better map. Spatial econometrics is concerned with estimating the relationships between variables that have spatial structure. Those estimated relationships are then used to calculate outcomes of economic interest (e.g., yields, profits, costs), which are in turn the basis for management decisions. When the data has spatial structure, spatial econometrics can produce more accurate estimates than conventional econometrics.

Spatial Autocorrelation. Spatial autocorrelation, or more generally, spatial dependence, is the situation where the dependent variable or error term at each location is correlated with observations on the dependent variable or values for the error term at other locations. The general case is formally: $E[y_i\, y_j] \neq 0$, or $E[\varepsilon_i\, \varepsilon_j] \neq 0$ for neighboring locations i and j, where i and j refer to individual observations (locations) and $y_{i(j)}$ is the value of a random variable of interest at that location. The form of the spatial dependence is given structure by means of a spatial weights matrix (W), which reduces the number of unknown parameters to one, i.e., the coefficient of spatial association in a spatial autoregressive or spatial moving average process (Anselin, 1992).

Spatial autocorrelation in yield data is present as the coincidence of value similarity with location similarity; i.e., high or low values for a random variable tend to be surrounded by neighbors with similar values. Since the values of yield factors at some point in the field depend on the values of other points in the field, the data from this field will present spatial autocorrelation. The presence of positive autocorrelation implies that a sample contains less information than an uncorrelated one. To carry out accurate statistical inference, this loss of information must be explicitly be taken into account in estimation and diagnosis tests. Therefore, classical statistical tests on spatial series must be combined with tests of spatial autocorrelation to assess the validity of drawing inferences (Anselin and Bera, 1998).

Spatial Regression Models. Anselin (1999a) outlines two important alternative models to deal with autocorrelation: the **spatial lag model** and the **spatial error model.** Since the estimates from the spatial regression model are going to be used in a decision model to measure costs, profits, etc., then accurate estimates are needed. This is the main role of an error model, whereas, in the lag model, the main role is to predict the spatial pattern. The preliminary analyses of the corn yield data point to autocorrelation in the variables that are not in the model. Obviously, there are other variables that influence yield, and these are very autocorrelated.

In the **spatial lag model**, the spatial autocorrelation pertains to the dependent variable, y. This alternative is formalized in a mixed regressive, spatial autoregressive model: $y = \rho Wy+X\beta+\varepsilon$, where y is the vector of yield points, ρ is the spatial autoregressive coefficient, Wy is a spatially lagged dependent variable, X is a matrix with observations on the explanatory variables, and β and $\varepsilon \sim (0, \sigma^2)$ are, respectively, the estimated coefficients and the normally distributed random error terms.

The **spatial error model**, or spatial dependence, is expressed by means of a spatial process for the error terms, either of an autoregressive or a moving average form. Such an autoregressive process can be expressed as: $y = X\beta + \varepsilon$. In the spatial error model, $\varepsilon = \lambda W\varepsilon + \mu$, where λ is the autoregressive coefficient for the spatial error term $W\varepsilon$. The error term μ is assumed to be normally distributed as $N(0,\sigma^2 I)$.

The consequences of ignoring spatial error dependence are that the OLS estimator remains unbiased, but is no longer efficient since it ignores the correlation between error terms. As a result, inference based on *t* and *F* statistics will be misleading, and indications of fit based on R^2 will be incorrect. Spatial autocorrelation inflates R^2, deflates standard errors for slope parameters, and overestimates the *t* values for inferential tests (Anselin, 1992).

Weights Matrix. One of the major distinguishing characteristics of spatial regression models is that the spatial arrangement of the observations is taken into account. This is formally expressed in a spatial weights matrix, W, with elements w_{ij}, where the ij index corresponds to each observation pair. The nonzero elements of the weights matrix reflect the potential spatial interaction between two observations. This may be expressed, for instance, as simple contiguity (having a common border), distance contiguity (having centroids within a critical distance band), or in function of the inverse distance (Anselin, 1992).

DATA

N response data was collected from strip trials on four farms in the Río Cuarto area, Córdoba Province, Argentina, in the 1998-99 crop season. This paper deals only with the yield data (8288 observations) from the farm "Las Rosas" located at 63º 50' 50" of longitude W and 33º 03' 04" of latitude S (Figure 1). The experimental design for the trials is a complete block strip trial that includes at least three different types of soils in terms of landscape (hilltop, slope, and low).

The complete, forthcoming study is projected for four crop seasons. Site-specific N response functions will be estimated for each farm. The site-specific N responses will be used to estimate the N application by landscape position that maximizes expected profits. Profits will be estimated for uniform application and for VRT N by landscape position.

The strips are wider or equal to the corn header width, with a zero N control and five other rates of elemental N: 29, 53, 66, 106 and 131.5 kg ha^{-1} of elemental N for the "Las Rosas" farm (Figure 2). The N rate is constant for the whole strip. Since the regression estimation procedure is flexible, N rates need not be the same from farm to farm. The highest N rate for each field is higher than the expected yield maximizing level. Each field has at least three blocks. Within each block, treatments are randomized. The treatments are the same and on the same location each time corn is grown in that field. The N source is either urea-ammonium nitrate solution (UAN), or urea.

Data was collected with a standard Ag Leader yield monitor. Yield files include data-point information about yields, latitude, longitude, elevation, and moisture. Since the raw data includes data points that are closer within the same row than between rows, these data yield points were averaged for a within-row distance equivalent to the between-rows distance, such that a distance weights matrix could be calculated. This was done in the GIS SSToolbox, creating 6.75 x 6.75 m grids over the observations, and rotating them by 10.5 degrees. Data points at the extremes were deleted. Finally, and after averaging the data within each grid, the 1772 observations were digitized as polygons (Figure 3).

METHODOLOGY

Response function estimation using spatial econometric techniques requires three steps: 1) Specification tests and diagnostics for the presence of spatial effects, 2) The formal specification of spatial effects in econometric models, and 3) The estimation of models that incorporate spatial effects.

Response estimates are made for the first year to obtain preliminary results, to show how yield data should be handled for economic analysis, and to elicit feedback from producers and crop consultants. After the fourth year's data is collected, the data will be pooled by farm and a single response function will be estimated. A quadratic response function will be tried first in all cases; alternative functional forms will be tested. The data will be analyzed using SpaceStat (Anselin, 1999b) and SSToolbox-GIS.

The **first hypothesis** was tested by running a classical OLS regression in SpaceStat with diagnostics tests. The corn response to N was estimated as quadratic for both the full pass data set and by landscape position: $Yield = \alpha_0 + \alpha_1 N_i + \alpha_2 N_i^2 + \varepsilon$, where: *Yield* = corn yield (from a yield monitor with GPS) and N_i = N rate. Five different topography areas were evaluated through dummy variables as Spatial Regimes in SpaceStat.

With Spatial Regimes, there is no constant for the general model, but a constant for each regression. In the yield model they are five separate regressions and only one R^2 for the whole model because the R^2 are computed on the residuals of the model. SpaceStat reports an observed value and a predicted value. The predicted value is a function of the variables and their coefficients in each of the separate regimes, so that the Spatial Regimes model works as a system of regressions. Regression coefficients for the five groups are estimated and reported separately. In the spatial econometric analysis, it is assumed that the error term has the same variance everywhere.

In the corn yield model under study, contiguity between spatial units is defined as a function of the distance that separates them. The relevant neighborhood is defined as all grid center points within 13.6 meters. The 13.6 meters are measured from the center point of the grid. All points in the neighborhood are of equal weight in the spatial weight matrix. For the estimation of spatial regression models, the spatial weights matrixes are row-standardized to yield a meaningful interpretation of the results. The row standardization consists of dividing each element in a row by the corresponding row sum. Each element in the new matrix thus becomes: $w_{ij} / \Sigma_j w_{ij}$. The resulting distance matrix provides more information about the observations, enabling the weights to capture the proximity of 11.3 neighbors on average.

The **second hypothesis** was tested by the Spatial Chow test –a test for structural instability in spatial regimes. Since the Spatial Regimes specification is treated as a standard regression model, the full range of estimation methods and specification diagnostics are carried out in SpaceStat. In addition, a test was implemented on the stability of the regression coefficients over the regimes. This was a test on the null hypothesis which states that the coefficients are the same in all regimes, e.g., for the two-regime case: $\boldsymbol{H_0}$: $\alpha_1 = \alpha_2$ and $\beta_1 = \beta_2$. This test is implemented for all coefficients jointly, as well as for each coefficient separately. In the classic regression model, this is the familiar Chow test on the stability of the regression coefficients. It has been extended to spatial models in SpaceStat in the form of a so-called spatial Chow test, and is based on an asymptotic *Wald Statistic*, distributed as χ^2 with $(M\text{-}1)K$ degrees of freedom (M as the number of regimes). SpaceStat lists the statistic, its degrees of freedom, and its associated probability level, for both the joint tests and the tests on each individual coefficient (Anselin, 1992).

In addition to the Spatial Chow test, a *t* test (*z* test in the spatial regression model) determined if the landscape and the slope interaction terms are significantly different from the mean. The dummy variable constraint was that the sum of dummy variable coefficients is equal to zero. Thus the coefficients are the difference between the intercept or slope for a given landscape position and the average slope or intercept. The coefficients represent *differences* from the base case, which for this analysis is topography zone 1 (Low East). It should be noted that the conventional 1% and 5% significance levels are useful benchmarks, but not magic.

The **third hypothesis** was tested by estimating one of the two Spatial Regression Models, either the spatial lag model or the spatial error model, taking into account heteroskedasticity, according to the interpretation of the diagnostics tests from the first hypothesis. The coefficients estimated through the Spatial Regression Model will be used to rank net returns over N fertilizer and VRT application costs for N by landscape positions, uniform applications, and other strategies. N will be optimized by landscape position using ordinary calculus (Dillon and Anderson, 1990). Net returns over fertilizer cost, VRT application fee, added non-N fertilizer costs for maintenance, and extra harvest and handling costs will be calculated each year. These are expected returns, so prices and costs should be the best estimate of future expected levels; often expected prices are best estimated at a three to five year average. Seed, weed control, and equipment costs are assumed to be the same everywhere in the field, so there is no reason to deduct them. The average return for the field will be estimated as the weighted sum of returns in each landscape area, where the weights are the proportion of area in that landscape position. The returns from site-specific management (SSM) by landscape position will be compared to the returns for uniform applications at the level recommended by INTA, at the level used by the producer for other fields and at the level recommended by other fertilization strategies for the area (e.g., Castillo et al., 1998). Hypothesis three will be supported if the returns for N by landscape position are on average higher than those of the commonly used uniform rate strategies. The economic analysis was performed using the partial budgeting tool, which determines whether the added benefits outweigh the added variable costs in a typical year.

RESULTS

Diagnostics tests for spatial dependence in the OLS model confirm that there is spatial autocorrelation in the data and that an error model should be used. There is also some presence of heteroskedasticity. The LM-error test for “Las Rosas” farm is 2762, while the LM-lag is 2380. The Robust LM-error test is 403, while the Robust LM-lag test is 21. The KB test is 71.7. All tests are significant at the 1% level. A higher LM test and/or robust LM test value point to the model that should be used. Therefore, a spatial autoregressive error (SAR) model has been used. It has been estimated by the Generalized Method of Moments (GMM), also accounting for groupwise heteroskedasticity (Anselin, 1999). Table 1 reports the regression coefficient estimates for the overall pass model (uniform rate) in the second column and then the estimates for each of the different spatial regions in the following columns. The estimated coefficients have the expected signs and maximum physical yields estimated with those coefficients are reasonable. The R^2 are quite good for on farm trial data.

In the SAR model, *z*-values are reported for the coefficient estimates, rather than *t*-values, i.e., in the spatial regression model inference is typically based on a standardized *z*-value. This is computed by subtracting the theoretical mean and dividing the result by the theoretical standard deviation: $z = (X - \mu) / \sigma$.

In the SAR model for the "Las Rosas" farm, the *z*-values for a significant response to N are significant at the 1% level for the Full Pass data and for each landscape position. The linear coefficient is significant at the 1% level for all estimates. The quadratic coefficient for the Full Pass and Low E are not significantly different from zero at any conventional significance level, the coefficients for Slope E and Hilltop are significant at the 1% level, and the coefficient for Slope W is significant at the 3% level.

In general, yields are highest in the Low area, but the response to N is greatest in the Hilltop (Figures 4 and 5). Optimal N rates are higher for Slope W and for Hilltop (Figure 6). The highest optimal N rates are for the Slope W (135 Kg ha^{-1}), which may be explained by the fact that Slope W is a lower quality soil. Low E, Slope E and Hilltop are type IIIes soils, while Slope W is type IVes. Soils type IIIes present excessive drainage, and are developed from sandy-loam materials. They have low water holding capacity, low structural stability, low organic matter content, important weather limitations, and moderate susceptibility to wind erosion. On the other hand, soils type IVes have even *higher* susceptibility to wind erosion, *lower* water holding capacity, *lower* organic matter content, and *very* low structural stability (Jarsun et al., 1993) characteristics that explain the high optimal N rate.

Given only one year of data, statistical tests are only indicative, but initial results indicate that autocorrelation and heteroskedasticity may bias N response, and that it differs significantly by landscape position. The value of the Chow statistic for "Las Rosas" is 234 in the OLS model and 153 in the SAR model. Chow test is significant at the 1% level, which indicates that maize N response varies by landscape position, therefore rejecting the hypothesis 2, that maize N response does not vary by landscape position. In addition to the Spatial Chow test, a *t* test (*z* test in the spatial autoregressive model) determined if the landscape and the slope interaction terms are statistically significantly different from the mean values (Table 2).

For the SAR model, all landscape positions are significantly different from the mean value (yield at the intercept) at the 2.5% significance level. The linear term, i.e., the marginal response to N, is significantly different from the mean at the 1% significance level only at the Low E and at the Hilltop topography zones. Slope W and Slope E are not significantly different from the mean. The quadratic term is significantly different from the mean only for the Low E topography zone at the 2% significance level, while the Hilltop is different from the mean only at the 13% significance level. It should be noted that for the OLS model, all landscape positions are significantly different from the mean value at the 1% significance level, but the linear and the quadratic terms are not significantly different from the mean at any conventional significance value, except for the linear term at the Hilltop, which is different at the 9% significance level.

Returns to N by landscape position. The profit maximizing (economic) response to N was obtained using a net price of corn of $6.85 per quintal, a cost of elemental N of $0.4348 per kg ($0.4674 per kg with a 15% annual interest rate), and a VRA application fee of $6 per hectare. Yield maximizing N rates, profit maximizing N rates, and profit (loss) from profit maximizing N application (compared to the no fertilizer strategy) are indicated in Table 3. Returns from N above fertilizer cost were calculated using marginal analysis, which states that when the value of the increased yield from added N equals the cost of applying one additional unit, profit is maximized; or when the marginal value product equals the marginal factor cost (MVP = MFC). Profit maximizing N rates were considered because it is the approach recommended in the production economics literature.

Returns to Uniform Rate and to Variable Rate N. Returns from N above fertilizer cost were estimated for two uniform application rates and for VRA by landscape position (Table 3). Two uniform rates were used to represent the range of N rates currently used in the Río Cuarto area. The higher uniform N rate was the profit-maximizing rate for the whole field analysis using the response function estimated with the Full Pass data (Table 1). The lower uniform N rate was 36.8 kg/ha recommended by Castillo et al. (1998). The estimated VRA assumed that N varied by landscape position according to the profit maximizing levels identified in Table 3 for that part of the topography. All three estimates use the response curves by landscape to estimate yield, which is weighted by the corresponding topography areas (21%, 20%, 32% & 26%).

Returns above fertilizer cost for a uniform rate of N, applied to the whole field (traditional fertilizer application), using the N fertilizer rate recommended by Castillo et al (1998) were estimated as follows:

$$\textit{Returns above fertilizer cost (\$/ha)} = \sum_{i=1}^{4} \left(P_c \left[a_i + b_i N_0 + c_i N_0^2 \right] - P_N N_0 \right) = \mathbf{\$399.75/ha}$$

where: P_c = Price of corn
i = Landscape area: 1=Low E, 2= Slope E, 3=Hilltop, 4=Slope W
N_0 = N rate for the whole field = 36.8 kg/ha (Castillo et al.,1998)
P_N = Price of N fertilizer, plus interest for 6 months at 15% annual interest rate

Returns above fertilizer cost for a uniform rate of N, applied to the whole field (traditional fertilizer application), using the whole field profit maximizing N rate from Table 2, were estimated as follows:

$$\textit{Returns above fertilizer cost (\$/ha)} = \sum_{i=1}^{4} \left(P_c \left[a_i + b_i N_0 + c_i N_0^2 \right] - P_N N_0 \right) = \mathbf{\$402.17/ha}$$

where: P_c = Price of corn
i = Landscape area: 1=Low E, 2= Slope E, 3=Hilltop, 4=Slope W
N_0 = Profit maximizing rate of N for the whole field = 46.35 kg/ha.
P_N = Price of N fertilizer, plus interest for 6 months at 15% annual interest rate

Returns above fertilizer cost for variable rate (VRA) of N were estimated as:

$$\textit{Returns above fertilizer cost (\$/ha)} = \sum_{i=1}^{4} \left(P_c \left[a_i + b_i N_i^* + c_i N_i^{*2} \right] - P_N N_i^* - F_{VRA} \right) = \mathbf{400.72}$$

where: P_c = Price of corn
i = Landscape area: 1=Low E, 2= Slope E, 3=Hilltop, 4=Slope W
N_i^* = Profit maximizing rate of N for each landscape area (see Table 2)
P_N = Price of N fertilizer, plus interest for 6 months at 15% annual interest rate
F_{VRA} = Variable rate application fee

Table 4 compares the results from using the OLS model and the SAR model. The breakeven for the variable rate fee charged by the service provider more than doubles in the SAR model, rendering it feasible for farmers, because the breakeven VRT fee is $0.97 higher than the market VRT fee of $6.00.

Implications. The spatial component reveals that there are patterns of interaction among yield points that are not accounted for in conventional models. The spatial model also shows how OLS estimates may be significantly biased when this interaction is not made explicit. The SAR model provides a better fit, which is important in economic analysis because it gives more accurate estimates. In this case, both models lead to the same conclusions, but in some cases OLS could be misleading. Nevertheless and for this specific case, an economic analysis based on OLS would discourage the adoption of VRT N fertilization, while a SAR model shows that a VRT fee of $6 is economically feasible.

CONCLUSIONS

The "Las Rosas" data for 1999 indicates that N response may differ significantly by landscape position, and that VRA for N may be modestly profitable at some fee levels. Data is needed for more farms over several years to determine how stable the differences in response are by landscape position. Data from three more farms in the 1998-99 growing season remain to be analyzed. Better estimates are needed for the cost of providing VRA services in Argentina. Efforts are ongoing to link the differences in response to measurable field characteristics (e.g., organic matter, water holding capacity).

The present analysis offers some preliminary evidence about the differences in N response and the econometric implications of those differences. It should be noted, however, that this is data from one farm for one season. A more complete analysis would pool data over many farms and several years to determine if reliable differences exist in N response by landscape position or other type of management zone. The study is planned for four years. The idea of this preliminary analysis is not to show conclusive results, but rather to show the methodology of how yield monitor data can be used for response estimation.

REFERENCES

Akridge, J., and L. Whipker. 1999. "Precision Agricultural Services and Enhanced Seed Dealership Survey Results," CAB, Purdue University, Staff Paper #99-6, June, 1999.

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

Anselin, L. 1992. SpaceStat Tutorial. A Workbook for Using SpaceStat in the Analysis of Spatial Data. Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign.

Anselin, L. 1999a. Spatial Econometrics. Staff Paper. Bruton Center School of Social Sciences University of Texas at Dallas, Richardson, TX.

Anselin, L. 1999b. SpaceStat. A Software Program for the Analysis of Spatial Data, Version 1.90 R26 (12/31/98), Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign.

Anselin, L. and A. Bera. 1998. Spatial Dependence in Linear Regression Models with an Introduction to Spatial Econometrics. In A. Ullah and D. Giles (eds.). Handbook of Applied Economic Statistics. New York: Marcel Dekker.

Bongiovanni, R. and J. Lowenberg-DeBoer. 1998. "Economics of Variable Rate Lime in Indiana," p. 1653-1666. *In Robert,P., Rust, R. and W. Larson, eds., Proceedings 4th Int. Conference on Precision Agriculture, 1998, St. Paul, MN. ASA/CSSA/SSSA.*

Bragachini, M. 1999. "Mercado Actual de Maquinaria Agrícola," INTA Manfredi, Argentina. January 1999.

Castillo, C., Espósito, G., Gesumaría, J., Tellería, G. and R. Balboa, 1998. "Respuesta a la fertilización del cultivo de maíz en siembra directa en Río Cuarto," Univ. Nac. Río Cuarto-CREA. AgroMercado Magazine, 1998, 5 p.

Coelho, A., Doran, J., and J. Schlepers. 1998. "Irrigated Corn Yield as Related to Spatial Variability of Selected Soil Properties," p. 441-452. *In Robert, P., Rust, R. and W. Larson, eds., Proceedings of the 4th International Conference on Precision Agriculture, 1998, St. Paul., MN. ASA/CSSA/SSSA.*

Dillon, J. and J. Anderson, 1990. The Analysis of Response in Crop and Livestock Production, Pergamon Press, New York.

Finck, C., 1998. "Precision Can Pay Its Way," Farm Journal, Mid-Jan., p. 10-13.

Heady, E., and J. Dillon, 1961. Agricultural Production Functions, ISU Press, Ames, IA.

Jarsun, B.; Lovera, E.; Bosnero, H.; and A. Romero. 1993. Carta de Suelos de la República Argentina, Hoja 3363-20. INTA-MAGyRR, Plan Mapa Suelos, Córdoba.

Kessler, M. and J. Lowenberg-DeBoer. 1998. "Regression Analysis of Yield Monitor Data and Its Use in Fine Tuning Crop Decisions," p. 821-828. *In Robert, P., Rust, R. and W. Larson, eds., Proceedings of the 4th International Conference on Precision Agriculture, 1998, St. Paul, MN. ASA/CSSA/SSSA.*

Khakural, B., Robert, P., and D. Huggins. 1998. "Variability of Soybean Yield and Soil/Landscape Properties across a Southwestern Minnesota Landscape," p. 573-580. *In Robert, P., Rust, R. and W. Larson, eds., 4th International Conference on Precision Agriculture, 1998, St. Paul, MN. ASA/CSSA/SSSA.*

Linsley, C., and F. Bauer, 1929. "Test Your Soil for Acidity," University of Illinois, College of Agriculture and Agricultural Experiment Station, Circular 346, Aug. 1929.

Lowenberg-DeBoer J. and S. Swinton. 1997. Economics of Site-Specific Management in Agronomic Crops, Chapter 16, p. 369-396. *In: Pierce, F., and E. Sadler, eds. The State of Site-Specific Management for Agriculture.*

Lowenberg-DeBoer, J. and M. Boehlje. 1996. "Revolution, Evaluation or Deadend: Economic Perspectives on Precision Agriculture." *In Robert, P., Rust, R. and W. Larson, eds., Precision Agriculture, Proceedings of the 3rd International Conference on Precision Agriculture, 1996, Madison, WI. SSSA.*

Lowenberg-DeBoer, J., 1999. "Precision Agriculture in Argentina," Earth Observation Magazine, June, 1999, p. MA13-MA15.

Lowenberg-DeBoer, J., and A. Aghib, 1999. "Average Returns and Risk Characteristics of Site-specific P and K Management: Eastern Cornbelt On-Farm Trial Results," Journal of Production Agriculture 12 (1999), p. 276-282.

Mallarino, A., Hinz, P. and E. Oyarzábal. 1996. "Multivariate Analysis as a Tool for Interpreting Relationships Between Site Variables and Crop Yields," p. 151-158. *In Robert, P., Rust, R. and W. Larson, eds., Proceedings of the 3rd International Conference on Precision Agriculture, 1996, Madison, WI. SSSA.*

Pan, W., Huggins, D., Malzer, G., Douglas, C. and J. Smith. 1997. "Field Heterogeneity in Soil-Plant Relationships: Implications for Site-specific Management," p. 81-99. *In The State of Site-specific Management for Agriculture, Pierce, F. and E. Sadler, eds., Madison, WI. ASA/SSSA/CSSA.*

Robert, P., Rust, R. and W. Larson, eds., 1992. Soil Specific Crop Management, Proceedings of 1st Workshop on Research and Development Issues, Madison, WI.

Robert, P., Rust, R. and W. Larson, eds., 1994. Site-specific Management for Agricultural Systems, Proceedings of the 2nd International Conference on Precision Agriculture, 1994, Madison, WI. ASA/CSSA/SSSA.

Robert, P., Rust, R. and W. Larson, eds., 1996. Precision Agriculture, Proceedings of the 3rd International Conference on Precision Agriculture, 1996, Madison, WI. SSSA

Robert, P., Rust, R. and W. Larson, eds., 1998. Proceedings of the 4th International Conference on Precision Agriculture, 1998, St. Paul., MN. ASA/CSSA/SSSA.

Swinton, S., and J. Lowenberg-DeBoer, 1998. "Evaluating the Profitability of Site-specific Farming," Journal of Production Agriculture 11, p. 439-446.

APPENDIX I: Figures

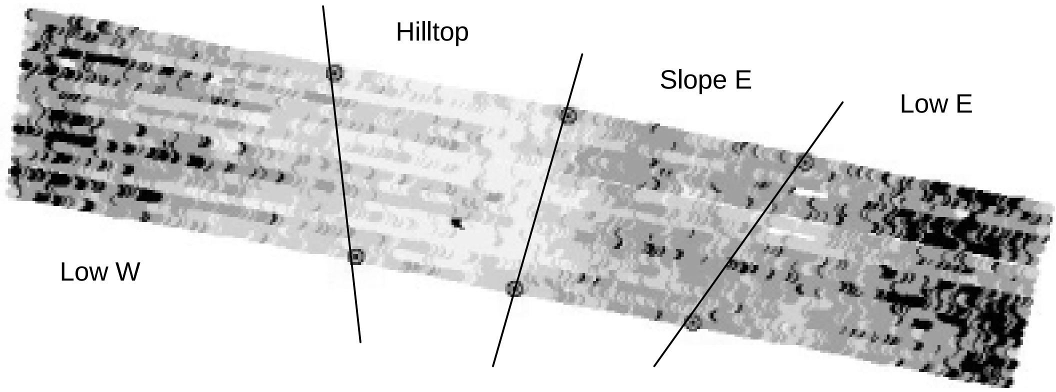

Figure 1. Raw yield data from the farm "Las Rosas", 1999 harvest season.

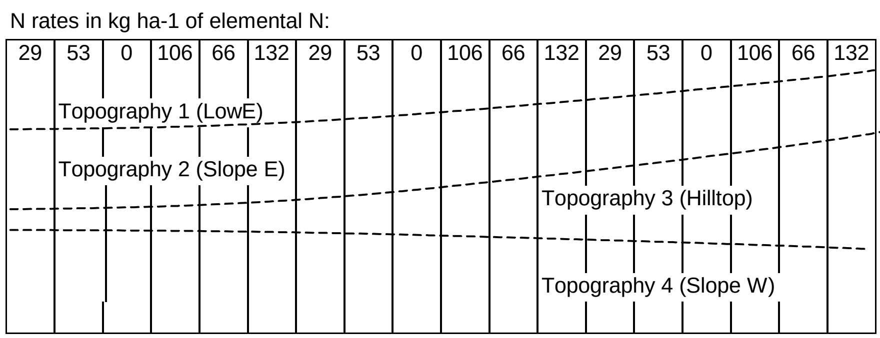

Figure 2. Diagram of the experimental design for the "Las Rosas" farm.

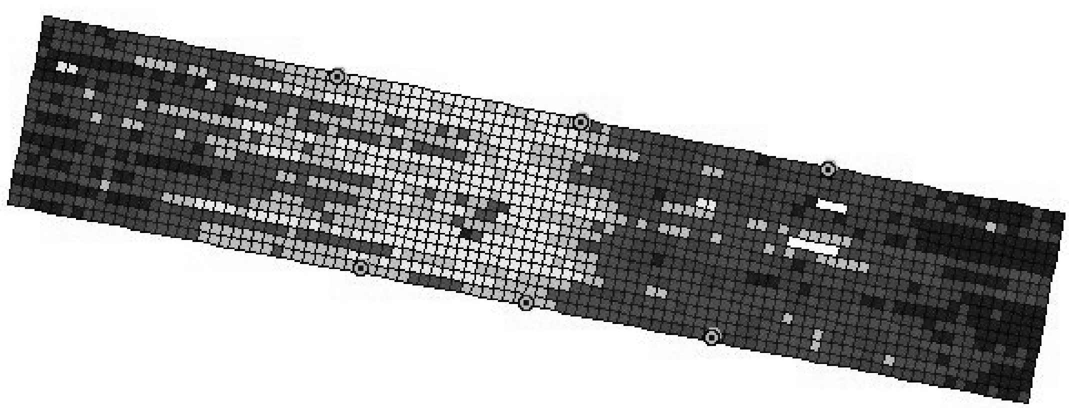

Figure 3. Digitized grids reflecting average yields within each grid.

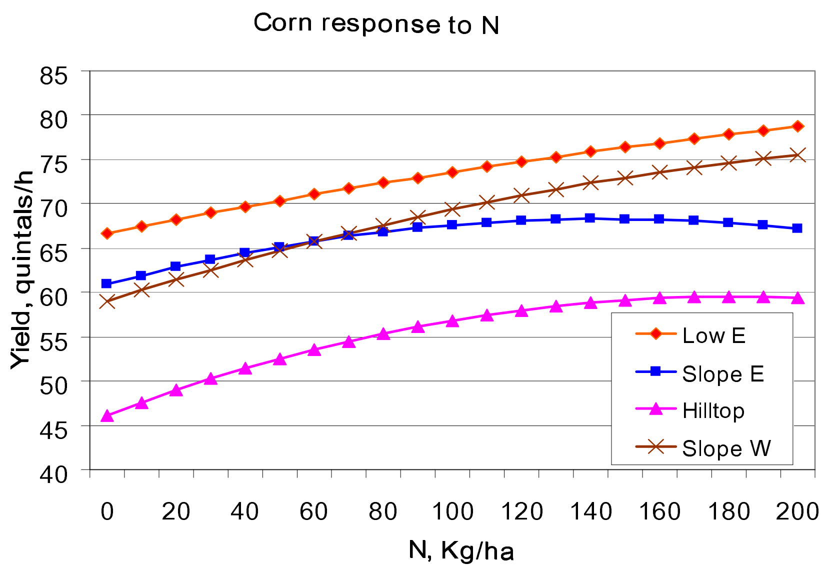

Figure 4. Crop response functions to N by landscape position, SAR model.

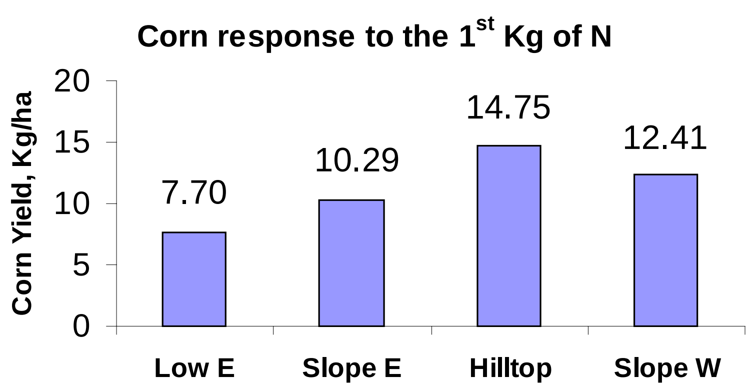

Figure 5: Corn Response to the First Kg of N

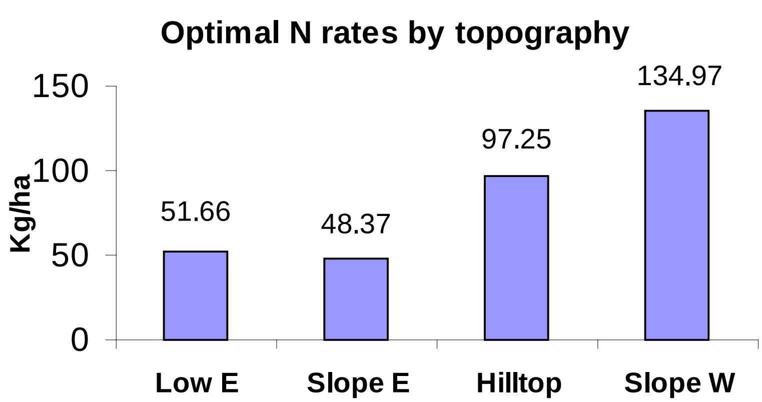

Figure 6: Optimal N Rates by Topography

APPENDIX II: Tables

Table 1. Regression estimates for the OLS and the SAR models for the Las Rosas farm.

OLS Regression Estimates for "Las Rosas"

Treatments:	Full Pass	Low East	Slope E	Hilltop	Slope W
Constant	67.1486	67.1486	60.6389	46.5788	60.1828
N	0.0873	0.0873	0.1047	0.1487	0.1208
t value	*4.25*	*4.25*	*4.54*	*6.35*	*6.42*
Probability	0.00	0.00	0.00	0.00	0.00
N^2	-0.00026	-0.00026	-0.00041	-0.00043	-0.00033
t value	*-1.76*	*-1.76*	*-2.50*	*-2.53*	*-2.49*
Probability	0.00	0.08	0.01	0.01	0.01
R^2	0.61	0.61	0.61	0.61	0.61

Spatial Error Model Regression Estimates for "Las Rosas"

Treatments:	Full Pass	Low East	Slope E	Hilltop	Slope W
Constant	63.1029	66.7195	60.9124	46.168	59.0072
N	0.0759	0.0770	0.1029	0.1475	0.1241
Z value	*5.85*	*5.81*	*7.66*	*8.19*	*9.00*
Probability	0.00	0.00	0.00	0.00	0.00
N^2	-7.5E-05	-0.00008	-0.00036	-0.00041	-0.00021
Z value	*-0.83*	*-0.91*	*-3.77*	*-3.18*	*-2.15*
Probability	0.40	0.36	0.00	0.00	0.03
R^2	0.22	0.67	0.67	0.67	0.67

Table 2. Regression estimates, standard deviations, t (z) values, and coefficient probabilities using *differences from the mean* for the OLS and the SAR models, Las Rosas farm.

	OLS Model				SAR Model			
VARIABLE	**COEFF**	**S.D.**	**t-value**	**Prob**	**COEFF**	**S.D.**	**z-value**	**Prob**
Constant	58.6373	0.3072	190.8817	0.0000	59.0662	0.7538	78.3621	0.0000
N	0.1154	0.0108	10.7160	0.0000	0.1126	0.0071	15.9661	0.0000
N^2	-0.0004	0.0001	-4.6396	0.0000	-0.0003	0.0000	-5.2468	0.0000
Low E	8.5113	0.5176	16.4431	0.0000	4.0367	0.8611	4.6877	0.0000
Slope E	2.0016	0.5565	3.5966	0.0003	2.0750	0.6906	3.0045	0.0027
Hilltop	-12.0585	0.5600	-21.5317	0.0000	-4.0874	0.8040	-5.0838	0.0000
Slope W	1.5455	0.4910	3.1476	0.0017	-2.0243	0.9038	-2.2398	0.0251
N x Low E	-0.0281	0.0181	-1.5512	0.1210	-0.0367	0.0115	-3.1823	0.0015
N x Slope E	-0.0107	0.0195	-0.5455	0.5855	-0.0081	0.0110	-0.7359	0.4618
N x Hilltop	0.0333	0.0197	1.6871	0.0918	0.0338	0.0138	2.4472	0.0144
N x Slope W	0.0054	0.0171	0.3156	0.7524	0.0110	0.0116	0.9476	0.3433
N^2 x Low E	0.0001	0.0001	0.7768	0.4374	0.0002	0.0001	2.2942	0.0218
N^2 x Slope E	-0.0001	0.0001	-0.3969	0.6915	-0.0001	0.0001	-1.2793	0.2008
N^2 x Hilltop	-0.0001	0.0001	-0.4835	0.6288	-0.0001	0.0001	-1.4971	0.1344
N^2 x Slope W	0.0000	0.0001	0.1971	0.8438	0.0001	0.0001	0.7435	0.4572

Table 3. Yield maximizing N rates, profit maximizing N rates and profit (loss) from N application.

Treatments:	**Full**	**Low E**	**Slope E**	**Hilltop**	**Slope W**
"Las Rosas" OLS					
Yield max. N rate (kg/ha)	169.54	169.54	126.67	174.36	180.98
Profit max. N rate (kg/ha)	37.08	37.08	44.15	94.36	78.75
Profits from N ($/ha)	2.43	2.43	5.52	26.01	14.18
"Las Rosas" SAR					
Yield max. N rate (kg/ha)	503.13	455.59	143.63	180.98	299.88
Profit max. N rate (kg/ha)	51.10	51.66	48.37	97.25	134.97
Profits from N ($/ha)	1.35	1.54	5.74	26.39	25.81

Table 4. Returns above fertilizer cost by treatment and by regression model.

Profits by treatment ($/ha)	**OLS**	**SAR**	Difference
"Las Rosas"			
Uniform profit maximizing N rate	$402.74	$399.75	$2.99
Urea dosis uniforme 80 kg/ha	$402.78	$402.17	$0.61
Variable rate N	$400.93	$400.72	$0.21
Breakeven VR fee	$3.07	$6.97	($3.90)