Economics of Management Zone Delineation in Cotton Precision Agriculture

Margarita Velandia[1], Roderick M. Rejesus[*], Eduardo Segarra[*], and Kevin Bronson[2]

Corresponding Author:

Roderick M. Rejesus

Department of Agricultural and Applied Economics

Texas Tech University

Box 42132

Lubbock, TX 79409-2132

Phone Number: (806)742-0261 ext. 253

FAX Number: (806)742-1099

E-Mail: roderick.rejesus@ttu.edu

January, 2006

Selected Paper prepared for presentation at the Southern Agriculture Economics Association Annual Meeting, Orlando, Florida, February4-8, 2006

[1] Margarita Velandia, Roderick M. Rejesus, and Eduardo Segarra are Graduate Research Assistant, Assistant Professor, and Professor, respectively, at the Department of Agricultural and Applied Economics, Texas Tech University, Lubbock, TX 79409

[2] Kevin Bronson is Associate Professor at the Texas Agricultural Experiment Station, Texas A&M University, Route 3, Box 219, Lubbock, TX 79401

Economics of Management Zone Delineation in Cotton Precision Agriculture

ABSTRACT

This paper develops a management zone delineation procedure based on a spatial statistics approach and evaluates its economic impact for the case of Texas cotton production. With the use of an optimization model that utilizes a yield response function estimated through spatial econometric methods, we found that applying variable N rates based on the management zones delineated would result in higher cotton yields and higher net returns, above Nitrogen cost, relative to uniformly applying a single N rate for the whole field. In addition, a variable rate N application using the delineated management zones produced higher net returns, above Nitrogen cost, relative to a variable N rate system where the zones are based solely on landscape position. This is indicative of the potential economic value of using a spatial statistics approach to management zone delineation.

Keywords: Management Zones, Exploratory Spatial Data Analysis, Site-Specific Nitrogen Management, Cotton Precision Agriculture.

JEL Classification: Q1, Q16.

Economics of Management Zone Delineation in Cotton Precision Agriculture

Introduction

Optimally configuring management zones for better management of farm inputs is one of the most fundamental issues in precision farming and variable rate application. Management zones are geographical areas that can be treated as homogenous, so that input application and decision-making can be treated separately for each zone, which will then lead to more precise management of the farm.

The objective of this paper is two-fold: (1) to develop a univariate management zone delineation procedure based on a specific ESDA (Exploratory Spatial Data Analysis) technique, and (2) to evaluate the potential economic impact of this management zone delineation procedure for the case of cotton production in the Texas High Plains.

This paper implements spatial econometric techniques and shows its importance in economically evaluating a particular management zone delineation procedure.

Empirical Methodology

Data and the ESDA Approach to Management Zone Delineation

The data used to establish management zones is based on a 2002 agronomic cotton experiment designed to study nitrogen (N) use for cotton production in the Southern High Plains of Texas. The experiment is a randomized complete block design with three replicates and each replicate was within a center pivot irrigation span. There were three N treatments – variable-rate N, blanket-rate N and zero N – and there were three defined landscape positions – south-facing side slope, bottom slope, and north-facing side slope. The data was originally collected as point data (135 data points). But we spatially averaged the data into 443 grids in order to obtain a balanced design and reduce measurement errors (Anselin, Bongiovanni, and Lowenberg-DeBoer, 2004). The original experimental design and the spatial structure of the yield data used in the analysis are presented in Figures 1 and 2, respectively.

As mentioned in the introductory section, we use an ESDA approach as the main procedure for establishing management zones. ESDA can be defined as a method that combines different techniques to visualize spatial distributions, identify patterns of different locations, and identify patterns of association between these locations (Anselin, 1998). This method is based on the concept of spatial autocorrelation, which is the relationship between spatial units, and makes use of the concept of distance between locations. Positive spatial autocorrelation is the idea that grids with similar values of a specific characteristic are near in space. This means that, in the presence of positive spatial autocorrelation, certain grids located close to each other share similar characteristics (Messner & Anselin, 2002, p. 10).

The step-by-step procedure for establishing the ESDA approach to management zone delineation can be described as follows: (1) Define the 'neighborhood' structure of each grid; (2) Establish a 'weight matrix'; (3) Test for the presence of spatial autocorrelation; (4) Graphically visualize the spatial correlation structure (if step (3) indicates there is spatial autocorrelation); and (5) Establish the management zones. The first step is to define the 'neighbors' of each grid. This allows us to assess if there are any spatial relationships between these points, which can then serve as the basis for management zones. According to Bivand (1998), the neighborhood for each grid can be set by any number of alternative methods. One approach is to set the neighbors by defining locations that share boundaries with each grid. Another possible approach is to draw bands at different distances of the grids. Since we have a grid-based data structure, we used a "rook" structure (four neighbors to each cell, north, south, east and west) to define the neighborhood in our management zone delineation procedure (Anselin, Bongiovanni, and Lowenberg-Deboer , 2004).[1]

Once, we defined the neighborhood structure, the contiguity relations of each grid within a neighborhood must be formally characterized using a spatial weights matrix (Bivand, 1998). A spatial weights matrix (**W**) is an NxN (where N regards to the number of observations), positive definite matrix with elements w_{ij} , where w_{ij} correspond to a pair of observations at locations *i* and *j*. By convention the diagonal elements of the weight matrix are set to be zero, implying that each location is not a neighbor of itself. Non-zero elements (w_{ij} =1) means that locations *i* and *j* are neighbors. Typically, the spatial weights matrices are also row-standardized to facilitate comparison of spatial characteristics across rows.

The spatial weights matrix is then used to test for the presence of spatial autocorrelation in the data. The Moran's I statistic is used to test for the presence of spatial autocorrelation (Anselin, 1988). Specifically, we use the global Moran's I calculated as follows:

(1) $$I = \frac{N\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} z_i z_j}{S_0 \sum_{i=1}^{n} z_i^2} ,$$

where N is the number of observations; $S_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}$; w_{ij} is the weight element from the spatial weights matrix; z_i and z_j are the deviations from the mean (i.e. $z_i = x_i - \mu$, where x_i is the value of the variable of interest in location *i* and μ is the mean of that variable for all locations). The null hypothesis of the test is that there is no association between the value observed at a location and the values observed at the neighboring sites. The alternative is that the values of the neighboring sites are statistically similar.

Yield data is often used in previous studies to delineate management zones due to the idea that yield captures all the variations in climate, soil and input interactions (as in Velandia et al., 2004 and Basnet et al., 2003). Therefore, yield may be a good variable to delineate management zones if these zones are meant to be the basis for the overall management of the field (i.e. for implementation of different management practices such N, P, K fertilization, water application, etc). However, if the management zones are meant specifically to improve N fertilization (which is the case here), then we believe that using soil nitrate as the basis for delineating management zones may be more appropriate. Hence, a priori, we chose nitrate in the soil (lbs/acre) as the main variable to serve as the basis for establishing management zones for more precise management of N fertilizer. This study also makes a contribution to the literature in this regard because this study is the first (as far as we know) to economically evaluate a management zone delineation procedure based on a spatial autocorrelation statistic for soil nitrate levels. Using soil nitrate as the variable of interest, the computed global Moran's I statistic, based on the "rook" neighborhood structure and weights matrix defined above, is 14.38 and this has a p-value of <0.001. This indicates that null hypothesis is rejected and that there is spatial autocorrelation in the data. Based on this result, a Moran scatterplot is created and management zones based on this scatterplot is then determined (Figure 3).

There are three management zones established based on our procedure. Management zone 1 (MZ1) represents high nitrate areas (i.e. grids with high nitrate levels have "neighbors" also with high nitrate levels). Management zone 2 (MZ2) represents low nitrate areas (i.e. grids with low nitrate levels have "neighbors" with low nitrate levels). Lastly, management zone 3 (MZ3) represents the area with a mix of high and low nitrate levels (i.e. grids with low nitrate levels have "neighbors" with high nitrate levels, and vice-versa).

Economic Model and Estimation Procedures

The economic model to assess the impact of the management zone delineation procedure is based on a mathematical programming model for spatial profit (or net return) maximization. This procedure is consistent with economic (or profitability) analysis of precision technologies conducted in the past (See, among others, Lowenberg- Deboer and Boehlje, 1996; Bongiovanni and Lowenberg- Deboer, 1998; Anselin, Bongiovanni, and Lowenberg-Deboer, 2001; Bullock, Lowenberg-DeBoer, and Swinton, 2002). In this framework, we compute the expected net returns from: (1) a uniform N rate application based on an agronomic optimum (URA), (2) a uniform N rate application based on an economic optimum (URE), and (3) a variable rate N application based on the economic optimum for each of the management zones established through our spatial procedure above (VRN). Hence, our economic analysis evaluates the economic impact of our management zone delineation procedure relative to the uniform N rate application based on the agronomically recommended rate and the economically optimum rate calculated from the model. In addition, we also compare the expected net returns from a variable rate N application that used landscape position (VRL) as the basis for the management zones versus a variable rate N system that is based on the management zone delineation procedure using our spatial approach.

For the uniform N application, we first use the agronomically recommended N rate and then calculate the corresponding net return based on the parameters of the profit maximization model below. This is the net returns calculated by simply plugging-in the agronomic N recommendation of 52 lbs/acre (See Bronson et al., 2003 for the agronomic basis of this recommendation). An economically optimal uniform N rate application is computed using the optimization framework below. We then compare the net return figures for the uniform rate case (for both the agronomic and economic optima) to the net returns, above Nitrogen cost, for the case of the variable rate N application using the delineated management zones (based on landscape position and the spatial approach). This calculation utilizes the optimization model, where the main component is a spatial cotton yield response function (for each management unit).

As mentioned above, there are studies that have examined the appropriate spatial econometric techniques for estimating spatial yield response functions using precision agriculture data (See, among others, Anselin, Bongiovanni, and Lowenberg-Deboer, 2001; Lambert, Lowenberg-Deboer, and Bongiovanni, 2004). For the case of variable rate N application, the typical procedure is to first start with standard ordinary least squares (OLS) regression of a response function specified with varying coefficients based on the management zones. Consistent with previous studies, we use the quadratic specification by management zone:

(2) $$Yield_{ij} = \alpha_i + \beta_i N_{ij} + \gamma_i N_{ij}^2 + \varepsilon_{ij}$$

where $Yield_{ij}$ is the cotton yield, N_{ij} is the N rate, *i* indexes management zone, and *j* is the location (in this case, the grids) within each management zone. This specification allows for the estimation of management zone effects on the levels α_i, as well as interaction effects between the management zones and the variables *N* and N^2. These management zone and interaction term coefficients are estimated using dummy variables.

Ordinarily, perfect collinearity due to a set of dummy variables is resolved by dropping a single dummy. However, because this analysis aims in part to investigate the difference in cotton yield response under uniform rate application (i.e. using an average N rate for the whole field) versus variable rate application, we wish to estimate management zone deviations from the mean yield, rather than deviations from the yield of an omitted management zone. The economic restriction required to do this is that the dummy variables for all the zones sum to zero. This condition is implemented by subtracting the management zone one dummy from the others, and then dropping management zone one from the data set. As a result, the constant coefficient estimate can be interpreted as the mean overall yield with zero applied N and the management zone dummies are the differences with respect to this overall mean. The coefficient for the dropped variable is then calculated in a supplementary regression, dropping another dummy variable. Consequently, the management zone dummies and interaction terms allows us to calculate the zone-specific response functions. Thus, the parameters of the yield response function that excludes the management zone dummies and the interaction terms represents our estimate of the uniform rate response function which reflects the "average" yield response for the whole field. This procedure allows us to estimate a single regression equation to generate the yield response function for both the uniform rate case and a particular variable rate case (either based on landscape or the spatial approach).

From the estimated regression of the yield response function, the presence of spatial autocorrelation in the residuals is then evaluated. If it is present, then appropriate spatial econometric techniques need to be implemented to account for the spatial autocorrelation in the residuals. As is well-known, ignoring such autocorrelation will yield OLS estimates that are inefficient and will bias the standard errors, t-test statistics and measures of fit, rendering statistical inference unreliable (Anselin, 1988).

Once the parameters of the cotton yield response functions are estimated, these estimates are used to formulate an optimization model to maximize profit for a representative farm. In this model, we maximize net returns over fertilizer cost using the yield response parameters and estimated prices/costs.

The net return for the farm is defined as the weighted sum of the net returns in each management zone (for the case of variable rate application), where the weights are the proportion of the area in the management zone. For the case of finding the economically optimum uniform N rate application, this weight is set to one and there is no management zone delineation. More formally, the mathematical programming model can be expressed as:

(3) $$\text{Max } E[\pi] = \sum_{i=1}^{m} (A\omega_i E[P_c(\alpha_i + \beta_i N_i + \gamma_i N_i^2) - r_N N_i]$$

where:

E = Expectation operator

π = Total net returns over N fertilizer and fixed cost ($)

A = Total land area (22,000 acres)

ω_i = Proportion of total land area allocated to management unit i (i.e. for the management zones based on the spatial approach, zone 1= 37%, zone 2= 48%, zone 3= 15%)

i = Management unit (either the whole field or the management zones)

m = Total number of management units (m = 1 for uniform rate application and m = 3 for variable rate based on the management zones delineated using the spatial approach).

P_c = Price of cotton ($0.47 per lb, see Bronson et. al, 2005)

N_i = Quantity of N applied in management unit i (in lbs/acre)

r_N = Price of N fertilizer applied ($0.21/lb, see Bronson et. al, 2005)

Results and Discussion

Response Function Estimation Results

The results of both the OLS and spatial error estimation procedures are presented in Table 1.[2] All the coefficients follow our a priori expectations and are all statistically significant (at the 10% level). Therefore, there are differences in the yield response for each management zone. Further, the magnitudes of the coefficients and standard errors are different in the spatial error model as compared to the traditional OLS. This suggests that economic inferences from these two models would be different and that incorrect decisions could be made when only traditional OLS techniques, rather than spatial econometric methods, are used in the yield response estimation.

Additionally, when the spatial error structure is modeled, the fit of the model improves as shown by the increase of the log likelihood and a decrease in Akaike Information Criteria (AIC). The improvement of the model was also to be expected because of the highly significant spatial error (lambda) coefficient.

Mathematical Programming Results: Yield, Nitrogen, and Profitability

Based on the estimated response function(s) and the optimization model described above, we estimated the yield, the N application levels, and the net returns over fertilizer cost for each of the different application techniques considered: URA, URE, VRN, and VRL. Each of these application scenarios was examined by using a yield response function estimated both by OLS and by using the spatial error model (SEM) estimated through a maximum likelihood technique (ML). This allows us to see the potential magnitude of inference or recommendation errors that could be committed when spatial autocorrelation is not properly accounted for in the yield response estimation.

A comparison of the returns for the different N rate application techniques is presented in Table 2. The OLS technique tends to overestimate the benefits from variable rate application relative to the uniform rate base on the agronomic recommendations, and OLS tends to underestimate the benefits from variable rate application relative to the uniform rate based on the economic optimization model. Note, that with the use of the spatial error model the variable rate application of N based on the management zones delineated tend to have a higher net return relative to the uniform rate base on the agronomic recommendations application, albeit smaller than if OLS was used. The spatial error model for the variable rate application of N based on the management zones delineated tend to have a higher net return relative to the uniform rate base on the economic optimization model, albeit higher than if OLS was used. Another notable comparison is the higher net return of VRN relative to VRL, once we correct the model for spatial autocorrelation. This shows that our spatial approach to management zone delineation has added value (in terms of variable rate application of N) relative to a management zone delineation technique based solely on landscape position.

The average N levels for the different application techniques are presented in Table 3. Our results show that, on average, the variable rate system using the delineated management zones based on the spatial approach tend to have higher yields than the uniform rate application techniques (Table 3). The VRN scenario also generated a higher average yield than the VRL scenario. With regards to N application levels, the variable rate scenario (VRN) tends to utilize more N (on average) than the URE technique (Table 4). But the variable rate scenario tends to have lower N levels relative to the URA scenario. Note, however, that the variable rate scenarios (VRN) tend to more efficiently utilize N because it applies less N in zones with high soil nitrate levels and more N in zones with low soil nitrate levels.[3] Therefore, even if N application is higher (on average) for the variable rate techniques, the more efficient use of the N fertilizer may possibly reduce nitrate run-off in the soil and, consequently, reduce non-point source pollution.

The results that regards to the net returns are based on an approach that does not take into account a fixed cost, given that this is a short run analysis. However, there is a fixed cost that regards to the nitrate soil test, which needs to be taking into account for the implementation of the variable rate technology. For the experiment consider in this analysis, the estimated cost for the nitrate soil analysis is $9.60/acre (Bronson et. al, 2005). If we consider this cost, then VRN is not more profitable than URA and URE anymore. The breakeven analysis, where the breakeven fee is simply calculate as the difference between net returns under VRN and net return under URA, shows that for VRN to be more profitable than URA and URE, the cost of the soil analysis needs to be less than $2.21/acre.

Sensitivity Analysis

The two important components that underlie the results presented above are the choice of neighborhood structure and the yield response estimation technique. The rook neighborhood structure is used as the basis for the spatial weights matrix in the delineation of the management zones and in modeling the error structure of the SEM yield response function. Standard OLS techniques and a ML approach to estimating the SEM yield response function are the estimation techniques used to produce the economic results above.

In order to check for the sensitivity of the economic results, we also examine the economic effect of using an alternative neighborhood structure and/or alternative estimation techniques (Table 4).

In general, we find that regardless of neighborhood structure or estimation technique VRN still tend to have higher net returns relative to the uniform rate approaches (URA and URE).

Conclusions

Based on an ESDA approach that utilizes a spatial autocorrelation statistic, we are able to develop a procedure for delineating management zones using precision agriculture data from cotton production in the Texas high plains.

The results of the optimization model suggest that applying variable N rates based on the management zones delineated (using the spatial approach developed), would result in higher yields and higher net returns over fertilizer cost relative to the traditional uniform rate application and relative to the variable rate application based on landscape position. Furthermore, the higher net returns and yields for the VRN application technique were achieved by more efficiently utilizing N for the whole field. Thus, more precise management of N based on the management zones delineated may have potential implications for fertilizer runoff and non-point source pollution in the soil. Furthermore, the results of our analysis also reinforce the observation in past studies that incorrectly estimating yield response functions without correcting for spatial dependence may lead to misleading inferences about the economic impact of variable rate technologies.

Footnotes:

[1] There are other contiguity-based neighborhood structures like the "queen" (eight neighbors to each cell) or the "bishop" (four neighbors with common vertex) structure. We also used these structures for defining management zones and found very similar results to the rook structure. The management zone delineation results for the alternative neighborhood structures are not reported here, but are available from the authors upon request.

[2] Note that the yield response function estimated in Table 1 is based on the management zones delineated using our spatial approach. Although not reported here, we also estimate the yield response function when the management zones are based on landscape position. This yield response function is used to evaluate the net returns from a variable rate N application based on management zones delineated by landscape position. This will allow us to see whether a variable rate application based on the management zone delineation procedure we develop generates higher net returns relative to a delineation procedure that is simply based on landscape position.

[3] In the interest of space, the exact figures for the applied N in each management zone are not explicitly reported here, but are available from the authors upon request.

References:

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

Anselin, L. "The Moran Scatterplot as an ESDA Tool to Assess Local Instability in Spatial Association." In: Fischer M., H. Scholten, and D. Unwin (eds), Spatial Analysis Perspectives on GIS. Taylor & Francis, Bristol, PA. pp. 111-125, 1998

Anselin L., Bongiovanni R. and Lowenberg-DeBoer J. "A spatial econometric approach to the economics of site-specific nitrogen management in corn production." American Journal of Agricultural Economics. 86 (August 2004): 675-687

Basnet, B., Kelly, R., Jensen, T., Strong, W., Apan, A. and Butler, D. "Delineation of Management Zones using Multiple Crop Yield Data." In International Soil Tillage Research Organization Conference, 16th Triennial Conference, pp. 69-75. 13 -18 July 2003. Brisbane, Australia: The University of Queensland.

Bivand, R. "A review of spatial statistical techniques for location studies." Online. Available at http://www.nhh.no/geo/gib/gib1998/gib98-3/lund.html. 1998. Retrieved October 2003.

Bongiovanni, R. and J. Lowenberg-DeBoer. "Economics of Variable Rate Lime in Indiana," pp. 1653-1666. Proceedings of the 4th International Conference on Precision Agriculture. St. Paul, MN, July 19-22, 1998.

Bronson, K.F., J. D. Booker, J.P. Bordovsky, J. W. Keeling, T.A. Wheeler, R.K. Boman, M.N. Parajulee, E. Segarra, M. Velandia-Parra, and R.L. Nichols. "Site-Specific Irrigation and Nitrogen Management for Cotton Production in the Southern High Plains," Working paper. April, 2005.

Bronson, K., Keeling, W., Booker, J.D., Chua, T., Wheeler, T., Boman, R., and Lascano, R. "Influence of Landscape Position, Soil Series, and Phosphorus Fertilizer on Cotton Lint Yield." Agronomy Journal 95(July-August 2003): 949–957.

Bullock, D. S., Lowenberg-Deboer, J. Swinton, S. "Adding value to spatially managed inputs by understanding site-specific yield response." Agricultural Economics 27(November 2002): 233- 245.

Lambert, D.M., Lowenberg-DeBoer, J., and Bongiovanni, R.M. "Spatial Regression Models for Yield Monitor Data: A Case Study for Argentina." Precision Agriculture. 5(December 2004): 579-600.

Lowenberg-DeBoer, J. and M. Boehlje. "Revolution, Evaluation or Deadend:Economic Perspectives on Precision Agriculture." In: Robert, P.; Rust, H. and R. Larson, eds. Proceedings of the 3rd International Conference on Precision Agriculture. Minneapolis, MN, June 23-26, 1996.

Messner, S. and Anselin, L. "Spatial analyses of homicide with aerial data." Working Paper, University of Illinois at Urbana-Champaign, 2002.

Velandia, M., R.M. Rejesus, E.Segarra, K. Bronson, and R. Kulkarni. "An Economic Analysis of a Spatial Statistics Approach to Management Zone Delineation in Precision Agriculture: The Case of Texas Cotton." In R.H. Rust and W.E. Larson (eds.), Proceedings of the Seventh International Conference on Precision Agriculture, Bloomington, MN (July 25-28, 2004).

Table 1. Parameter estimates of the cotton yield response function for the management zones delineated using the spatial approach

Variables	OLS (Ordinary Least Squares)		SEM (Spatial Error Model)	
	COEFF (lbs ac^{-1})	P-value	COEFF (lbs ac^{-1})	P-value
Constant	827.10	0.0000	916.26	0.0000
N	7.38	0.0000	2.71	0.0006
N^2	-0.10	0.0000	-0.03	0.0021
MZ1	806.09	0.0000	916.23	0.0000
MZ2	814.52	0.0000	893.64	0.1071
MZ3	860.70	0.0000	955.70	0.0369
N x MZ1	10.93	0.0000	2.69	0.0000
N x MZ2	6.59	0.0000	2.22	0.0074
N x MZ3	4.61	0.0002	2.88	0.2214
N^2 x MZ1	-0.19	0.0000	-0.06	0.0000
N^2 x MZ2	-0.06	0.0616	-0.01	0.0885
N^2 x MZ3	-0.055	0.0745	-0.034	0.0975
Lambda	NA	NA	0.64	0.0000

Measures of fit	OLS	SEM
Log Likelihood	-2675.32	-2536.82
AIC	5368.64	5091.65

Diagnostic tests	d.f.	Value	Value	P-value
Lagrange multiplier(error)	1	NA	147.71	0.0000
Robust LM(error)	1	NA	126.68	0.0000
Lagrange multiplier (lag)	1	NA	28.10	0.0000
Robust LM (lag)	1	NA	7.07	0.0781

Table 2. Net returns under different application methods and estimation procedures

	OLS	SEM	Difference (OLS-SEM)
	--- Net Returns (\$ $acre^{-1}$) ---		
Uniform rate, agronomic optimum (URA)	431.09	447.83	-16.73
Uniform rate, economic optimum (URE)	444.47	448.30	-3.83

Variable rate, spatial approach (VRN)	444.76	450.04	-5.28
Variable rate, landscape position (VRL)	445.46	447.45	-1.99
Differences across application techniques			
URE vs. URA (URE – URA)	13.38	0.47	12.9
VRN vs. URA (VRN – URA)	13.67	2.21	11.45
VRN vs. URE (VRN – URE)	0.29	1.74	-1.45
VRL vs. URA (VRL – URA)	14.37	-0.38	14.74
VRL vs. URE (VRL – URE)	0.99	-0.85	1.84
VRN vs. VRL (VRN – VRL)	-0.7	2.59	-3.29

Table 3. Nitrogen levels under different application methods and estimation procedures

	OLS	SEM	Difference (OLS-SEM)
	--- N level (lbs acre^{-1}) ---		
Uniform rate, agronomic optimum (URA)	52.00	52.00	0.00
Uniform rate, economic optimum (URE)	34.21	33.24	0.97
Variable rate, spatial approach (VRN)	34.71	42.66	-7.95
Variable rate, landscape position (VRL)	27.91	28.73	-0.82
Differences across application techniques			
URE vs. URA (URE – URA)	-17.79	-18.76	0.97
VRN vs. URA (VRN – URA)	-17.29	-9.34	-7.95
VRN vs. URE (VRN – URE)	0.5	9.42	-8.92
VRL vs. URA (VRL – URA)	-24.09	-23.27	-0.82
VRL vs. URE (VRL – URE)	-6.3	-4.51	-1.79
VRN vs. VRL (VRN – VRL)	6.8	13.93	-7.13

Table 4. Sensitivity of the differences in net returns under alternative neighborhood structure and estimation method assumptions

Neighborhood structure[1] Estimation Method[2]	Difference in net returns ($ acre^{-1}) across application techniques[3]					
	URE-URA	VRN-URA	VRN-URE	VRL-URA	VRL-URE	VRN-VRL
Rook Structure						
OLS	13.38	13.67	0.29	14.37	0.99	-0.7
SEM (ML)	0.47	2.21	1.74	-0.38	-0.85	2.59
SEM (GM-Two step)	6.25	9.70	3.45	5.61	-0.64	4.09
SEM (GM-Iterated)	5.49	6.76	1.26	4.03	-1.46	2.72
SEM (GM-GHET)	5.26	6.92	1.65	4.10	-1.17	2.82
Queen Structure						
OLS	16.65	20.50	3.85	17.35	0.70	3.15
SEM (ML)	4.66	6.76	2.10	4.25	-0.41	2.50
SEM (GM-Two step)	11.43	14.19	2.76	12.16	0.73	2.03
SEM (GM-Iterated)	11.43	13.28	1.86	11.45	0.03	1.83
SEM (GM-GHET)	10.87	11.61	0.74	9.80	-1.06	1.81

Note: (1) The neighborhood structures considered are rook and queen. Note that these structures are assumed both in the delineation of the management zones for the spatial approach and in specifying the error structure in the SEM model.

(2) The alternative estimation methods considered (aside from the traditional OLS and SEM (ML)) are: SEM using two stage general method of moments (GM-Two step), SEM using iterated general method of moments (GM-Iterated), and SEM using general method of moments that corrects for groupwise heteroskedasticity (GM-GHET).

(3) Application techniques are: uniform rate based on agronomic optimum (URA), uniform rate based on economic optimum (URE), variable rate based on the spatial approach (VRN), and variable rate based on landscape position (VRL).

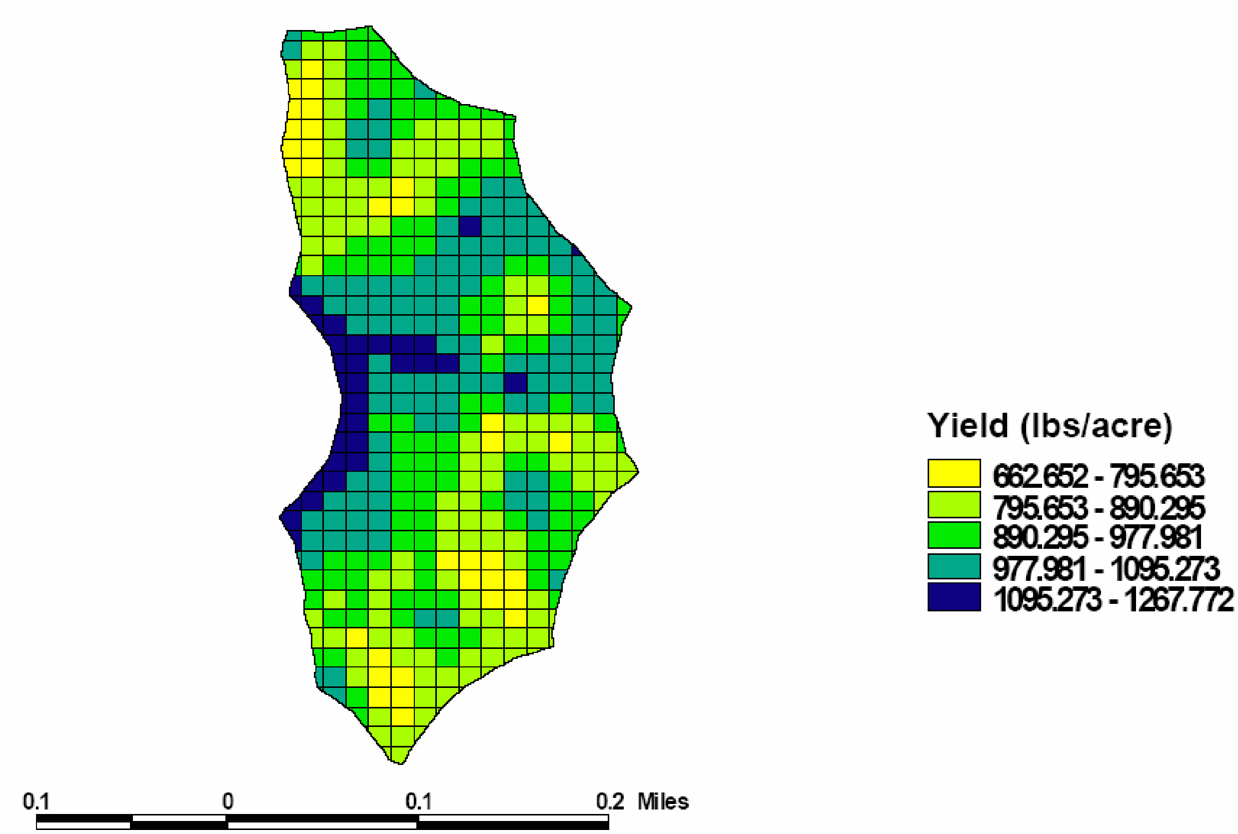

Figure 1. Digitized Grids for Cotton Yield (lbs/acre)

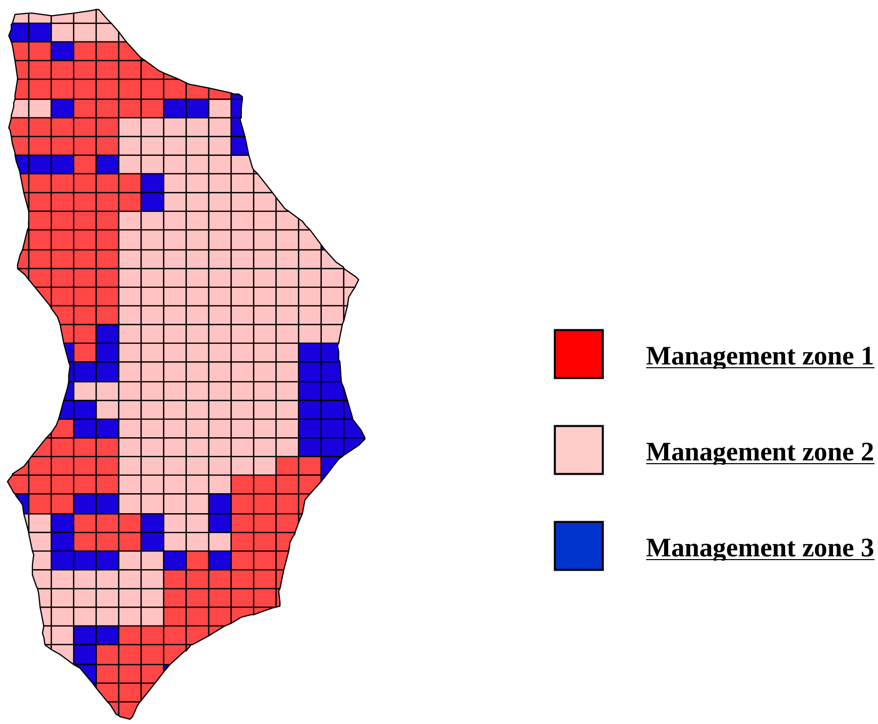

Figure 2. Delineated Management Zones from the ESDA Procedure