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PRECISION AGRICULTURAL PRACTICES FOR OPTIMAL USE OF PHOSPHOROUS

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Abstract

This study analyzes the economics of variable rate phosphorus application for cotton production in the Texas High Plains. Specifically, we evaluate the economic implications of a variable rate phosphorus application program that is based on management zones delineated using a spatial statistics approach. Using experimental data from Lamesa, TX, we found that a management zone-based variable rate phosphorus program results in higher cotton yields and higher profits, on average, relative to a uniform rate phosphorus application.

Introduction

Phosphorus is an important fertilizer input used in cotton production. As such, there has been long standing interest in developing techniques to more accurately apply this fertilizer input in cotton production. A precision agriculture technique like variable rate phosphorus application is seen as a potential approach to achieve more accurate fertilizer applications, which can consequently reduce fertilizer costs and improve profitability of cotton producers.

In light of the potential profit enhancement associated with variable rate application, there has been a number of studies that develop variable rate fertilizer application programs based on "management zones" (See Franzen, Halvorson, and Hofman; Nolan, Goddard, Lohstraeter, and Coen). 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. These zones then serve as the basis for more precise variable rate application of fertilizer inputs.

Note, however, that in most of these studies management zones were delineated by using traditional clustering techniques or simply by visually inspecting a generated map for a particular field characteristic (i.e. yield, soil nutrient levels, etc.). These techniques do not take into account the underlying spatial autocorrelation in the data to optimally delineate management zones. Proper incorporation of spatial autocorrelation in management zone delineation procedures will yield better insights into spatial patterns and more effectively suggest zones for use as management units. In this regard, spatial statistics techniques, such as Exploratory Spatial Data Analysis (ESDA), have recently been developed that allows for identification of local clusters of similar values and also takes into account the spatial autocorrelation in the data (Messner and Anselin).

Therefore, the objectives of this study are: (1) to develop an ESDA-based management zone delineation procedure to establish a variable rate phosphorus program for cotton; and (2) to evaluate the economic impact of this variable rate approach relative to a uniform rate application. The second objective above is important because the eventual use of the variable rate approach developed here hinges upon its economic viability relative to the more traditional uniform rate application. There are previous studies that looked at the economics of various variable rate application programs (See Thirkwala et al., 1998; Dillon, 2002). But to our knowledge, there has been no study that has explicitly looked at the economics of a management zone-based variable rate phosphorus application program for cotton production in the High Plains of Texas. In addition, this is the first study that uses an ESDA approach for delineating management zones that can be used for more precise phosphorus application.

The ESDA Approach for Management Zone Delineation

The data used to establish management zones is based on a 2000 crop year agronomic cotton experiment designed to study phosphorus (P) use for cotton production in the Southern High Plains of Texas (Figure 1). The experiment is a randomized complete block design with three replicates and each replicate was within a center pivot irrigation span. There were three P treatments – variable-rate P, blanket-rate P and zero P – and there were three defined landscape positions – south-facing side slope, bottom slope, and north-facing side slope.

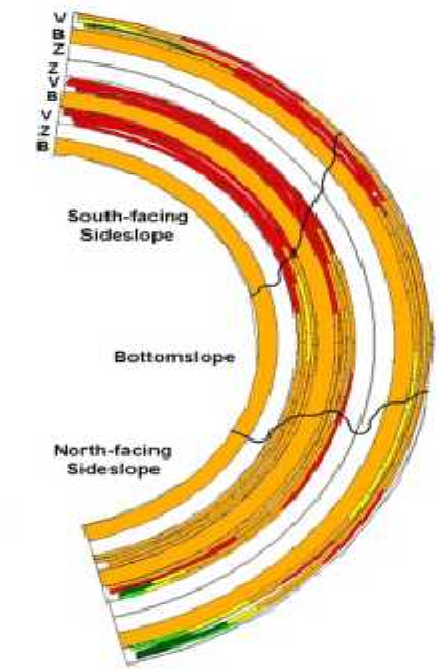


Figure 1. Experimental Design for Analysis of P use in Cotton (Lamesa, Texas).

Note that the data set was initially represented as point data for different locations in the field and it includes such variables as yield, soil P levels, water levels, etc. However, the spatial layout of this initial "raw" data is such that the points lay close to each other within the same row rather than between the rows. As such, this kind of design is not balanced. Therefore, to obtain a more balanced design for analysis, the points were spatially averaged and then converted to grids using the SSToolbox® geographic information system (GIS) software (Figure 2). The conversion of the data into grids also has the advantage of allowing us to delineate more compact zones.

As mentioned above, we use the ESDA approach as the main procedure for establishing management zones using the yield data collected. Yield data is being used as the main criterion for establishing management zones because phosphorus recommendations are typically based on this information. The ESDA approach can be defined as a method that combines different techniques to visualize spatial distributions (of yields, in this case), identify patterns of different locations, and identify patterns of association between these locations. 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 points with similar values of a specific characteristic (i.e. yield) are near in space. This means that, in the presence of positive spatial autocorrelation, certain points located close to each other share similar characteristics (Messner and Anselin, 2002, p. 10).

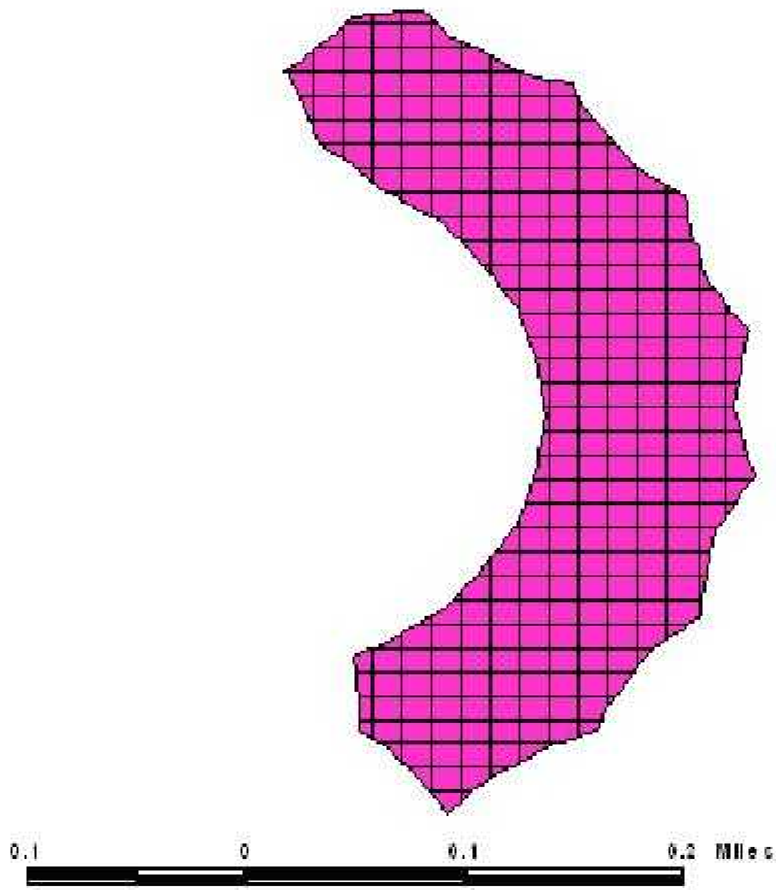


Figure 2. Conversion of Points Structure to Grids

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’ for each grid. This allows us to assess if there are any spatial relationships between these grids, which can then serve as the basis for management zones. According to Bivand (1998), neighborhood for each grid (or point) data 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/point. Another possible approach is to draw bands at different distances of the center of the grids. From the experimental data, we could see that the grids can be delineated by different level curves described by the center pivot irrigation span. Therefore, we could take advantage of the areas defined by the pivot as a means to develop the neighborhood structure of each grid. Taking the center pivot as a reference, we first delineate circles with different radius. The points between the level curves are then set as the neighbors of the grids within the curve.

Once, we defined the neighborhood structure, the contiguity relations of each grid within a neighborhood must be characterized using a weight matrix (Bivand, 1998). The four nearest-neighbor criterion is used here to establish the contiguity relations within each neighborhood. This weights matrix is then used to test for the presence of spatial autocorrelation in the yield data. The Moran’s I statistic is used to test for the presence of spatial autocorrelation. 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. That is, the data exhibits spatial randomness. The alternative is that the values of the neighboring sites are statistically similar. This means that there is a departure from spatial randomness and there are sites that tend to “cluster” together. *A priori,* we chose the handpicked lint yield (lbs/acre) as the main variable to serve as the basis for establishing management zones. The computed Moran's I statistic, based on the neighborhood structure and weights matrix defined above, is 0.7738 and it has a p-value of <0.001. This indicates that null hypothesis is rejected and that there is positive spatial autocorrelation in the yield data. Based on this result, a Moran scatterplot is created and compact 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), management zone 2 (MZ2), and management zone 3 (MZ3). MZ1 is the zone where low yields are clustered together (i.e. a grid with low yield is close to neighboring grids with low yields). MZ2 is the zone where high yields are clustered together (i.e. a grid with high yield is close to neighboring grids with high yields). MZ3 is where the grids with low yields are near grids with high yields (or vice-versa). The spatial layout of the delineated management zones is seen in Figure 3.

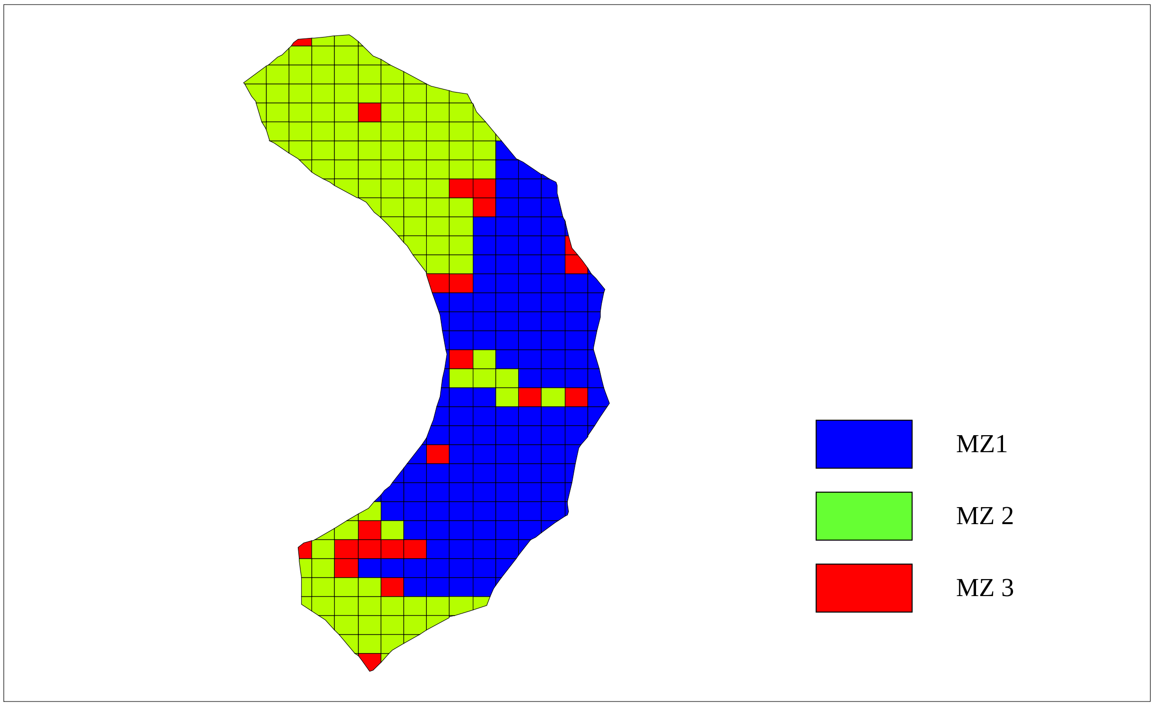


Figure 3. Management Zones Delineation

Economic Evaluation of Management Zone-Based Variable Rate Phosphorus Application

The framework to assess the economic implications of a management zone-based variable rate P application is based on a mathematical programming model for spatial profit (or net return) maximization. This approach is consistent with economic (or profitability) analysis of variable rate 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 rate P application based on an economic optimum, and (2) a variable rate P application based on the economic optimum for each of the management zones established above. Hence, our economic analysis evaluates the economic impact of a variable rate approach to P application versus relative to a uniform rate application.

Cotton Yield Response Estimation

To implement the mathematical programming model, one must first estimate a cotton yield response function for phosphorus. In our case, cotton yield response functions that are appropriate for a uniform rate P application and a variable rate P application must be established. Having these response functions allows us to calculate the economically optimal P application in both methods and, consequently, enables us to assess the profit impact of these technologies.

For the uniform rate P application, the traditional ordinary least squares (OLS) procedure is used to estimate a single cotton yield response equation for the whole field. The cotton yield response function estimated is specified as a quadratic function that can be expressed as follows:

$$Yield = \beta_0 + \beta_1 P + \beta_2 P^2 + \varepsilon, \qquad (1)$$

where *Yield* is the cotton yield per acre (handpicked cotton yield after ginning), *P* is the phosphorus rate per acre , β's are the parameters, and ε is the error term. This equation represents the average cotton yield response to P without regards to the heterogeneity of the field (that was evidenced by the three distinct management zones discussed in the previous section). The estimated parameters for this uniform rate case are given in Table 1.

Table 1. OLS estimates of the Cotton Yield Response Function: Uniform Rate

Variable	Coefficient	St. Error	t-statistic	P-value
Constant	430.16	40.4766	10.627	0.000
P	17.7972	4.83917	3.6777	0.000
P^2	-0.299837	0.140989	-2.126	0.034

For the variable rate P application, we used OLS estimation techniques but we explicitly take into account the spatial heterogeneity of the field (i.e. the management zones). Management zones were taken into account in the cotton yield response equation by using dummy variables for each zone and interaction terms of each zone to each P term in equation (1). Therefore, the cotton yield response function for the variable rate application of P can be written as follows:

$$\begin{aligned} Yield = {} & \beta_0 + \beta_1 P + \beta_2 P^2 + \beta_3 MZ1 + \beta_4 MZ2 + \beta_5 MZ3 + \beta_6 MZ1 \cdot P + \beta_7 MZ2 \cdot P + \beta_8 MZ3 \cdot P \\ & + \beta_9 MZ1 \cdot P^2 + \beta_{10} MZ2 \cdot P^2 + \beta_{11} MZ3 \cdot P^2 + \varepsilon. \qquad (2) \end{aligned}$$

Ordinarily, one out of the three dummy variables for the management zones is dropped from an equation to avoid perfect collinearity in OLS estimation. However, in this study we also want to determine 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. The coefficient for the dropped variable is then calculated in a supplementary regression, dropping another dummy variable. Therefore, in this approach the management zone dummies and interaction terms allows us to calculate the zone-specific response functions. The OLS estimates for the variable rate case are given in Table 2 below.

From Table 2, notice that only the parameters associated with MZ1 are significant at the 1% level. This suggests that cotton yield response would be highest where low yields are clustered together and P application in this zone must be treated differently than other zones. Also note that the parameters for MZ2 and MZ3 are not as well behaved as the MZ1.

Table 2. OLS estimates of the Cotton Yield Response Function: Variable Rate

Variable	Coefficient	St. Error	t-statistic	P-value
Constant	616.412	34.776	17.725	0.0000
P	-0.83735	4.0278	-0.2078	0.8354
P^2	0.0808	0.1126	0.7178	0.4734
MZ1	-240.713	43.253	-5.5651	0.0000
MZ2	116.795	45.9156	2.54368	0.0114
MZ3	123.918	57.423	2.157834	0.031753
*P*MZ1*	25.5401	5.2852	4.8323	0.000002
*P*MZ2*	-12.589	5.1904	-2.4255	0.015889
*P*MZ3*	-12.9505	6.5401	-1.98015	0.048622
P^2*MZ1	-0.7848	0.1567	-5.0074	0.000001
P^2*MZ2	0.51088	0.14281	3.57724	0.000406
P^2*MZ3	0.27395	0.177035	1.547441	0.122836

Profitability Analysis: Mathematical Programming Results

Once the parameters of the cotton yield response function 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. For the case of variable rate application we include a fixed fee, which reflects the short-run fixed application cost taken from the study of Roberts and English (1999). It covers such items as the cost of a consultant visit and the cost of the first yield map. 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 P 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:

$$\text{Max } \pi = \sum_{i=1}^{m} \left(\omega_i \left[A \left(\left(P_c(\beta_i + \gamma_i P_i + \alpha_i P_i^2) + \lambda_i P_s (\beta_i + \gamma_i P_i + \alpha_i P_i^2) \right) - r P_i - P\Phi \right) \right] \right) \quad (3)$$

Subject to: $P_i \le Max$

where:

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

A = Total land area (2,200 acres)

ω_i = Proportion of total land area allocated to management unit *i* (zone 1= 43.19728%, zone 2= 49.3197%, zone 3= 7.48299%)

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).

P_c = Price of cotton lint ($0.42 per lb)

P_s = Price of cotton seed ($0.05 per lb)

λ_i = Proportion of yield that corresponds to the total amount of cotton seed produced (61.5385%)

P_i = Quantity of P applied in management unit *i* (in lbs/acre)

r = Price of P fertilizer applied ($0.265/lb)

P_{tg} = Sum of the Price of Stripping and Ginning ($0.035/lb)

Φ = Fixed fee for variable rate phosphorus application ($3.00/per acre)

MaxP = Maximum level of P.

The mathematical programming model in equation (3) does not incorporate price risk for cotton lint and seed prices. As is well know, cotton producers are operating in an environment of price uncertainty and, therefore, price risk should be taken into account in any input application decision. Using cotton lint and seed prices in the previous five years, we calculated the average price over this period ($0.42 per lb for lint and $0.05 per lb for seed), as well as the prices one standard deviation above and below this mean. The average cotton lint and seed price are the ones used above and are considered the "normal" or "average" price situation. The prices one standard deviation above and below the mean price are the "high" and "low" price situations, respectively. The actual "low" price situation calculated are $0.22 per lb for cotton lint and $0.00 per lb for cotton seed. On the other hand, the actual "high" situation prices calculated are $0.62 per lb for cotton lint and $0.13 per lb for cotton seed.

To incorporate the risk of having below average or above average output prices in the model, we assign discrete probability values for each price situation and build four scenarios to analyze. The first scenario (Scenario 1) is where all the three price situations are equally likely to occur. That is, the probability of having low, average, and high price is set at 33.33%. The second scenario (Scenario 2) is where the probability of having a low price situation is 60%, while the probability of having an average and high price situation is both at 20%. The third scenario (Scenario 3) is where the probability of having an average price is 60%, while the probability of having a low and high price situation is both at 20%. Lastly, the fourth scenario (Scenario 4) is where the probability of having a high price is 60%, while the probability of having an average and low price situation is both at 20%.

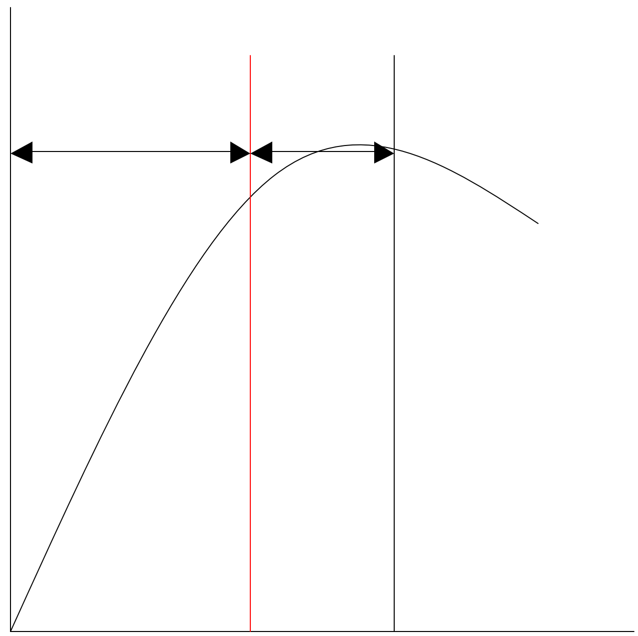
The mathematical modeling results that accounts for price risk are presented in Table 3. The first issue to note in these results is the P application difference between the UR and VR application methods. As suggested in the previous section, MZ1 is where the yield response is the highest. Hence, it is reasonable to expect that a lower amount of P would be required in this zone relative to the other zones (to get a comparable yield response). In fact, this is the case in Table 3 for all scenarios.

Table 3. Profitability of Uniform Rate (UR) vs. Variable Rate (VR) P Application: Four Price Risk Scenarios

	P application (lbs/acre)			Yield(lbs/Acre)	Expected Profit ($/acre)	Profit Differential (VR-UR)
	MZ1	MZ2	MZ3			
Scenario 1						
UR	28.83	28.83	28.83	694.06	$352.00	$8.23
VR	16.70	28.83	0	725.69	$360.23	
Scenario 2						
UR	28.57	28.57	28.57	693.91	$268.83	$3.66
VR	16.45	28.57	0	789.62	$272.49	
Scenario 3						
UR	28.82	28.82	28.83	694.06	$346.77	$7.96
VR	16.69	28.82	0	793.78	$354.73	
Scenario 4						
UR	28.99	28.99	28.99	694.14	$438.31	$13.06
VR	16.87	28.99	0	797.05	$451.37	

Given the lower P application in MZ1 for the VR approach, the "leftover" or "unused" P that would have been used in a UR was reallocated to MZ2. Since MZ2 is the zone that is characterized by a high yield cluster, it would need more P in this zone to have a comparable yield response to other zones. Of course this assumes a concave response function (see Figure 4). For MZ1 and MZ2, therefore, average P application is the same for both UR and VR approaches, but the amount applied for each zone was variable. For the case of MZ3, the P rate used was zero since this is the zone of "uncertainty" and the estimated response function for this zone is such that a unreasonable amount of P would be needed to get even a marginal yield response. Hence, the model optimally picked a zero application rate for this zone. For MZ2, the optimal P level is the same as the uniform rate. On the other hand, zero P level application is indicated for MZ3 because in this region it takes a very high level of P to get even a marginal yield response.

Based on the P levels chosen for the UR and VR approaches, the corresponding yields and profits for each approach are then calculated. As seen in Table 3, the VR approach had higher yields and expected profits for all scenarios. If the risk of having low, average, and high cotton output prices is equally likely, then the expected profit differential between a VR approach and a UR approach is $8.23/acre. When the average output prices are expected to occur (Scenario 3), the expected profit differential is very similar to the "equally" likely case. If lower prices are more likely to occur, a lower profit differential results (as expected). On the other hand, when high cotton prices are more likely, a higher profit differential between VR and UR is observed.



*L-L- Low Low Yield Area
** H-H- High High Yield area

Figure 4 Concave Cotton Yield Response Function

Conclusions

This study develops a spatial statistics-based approach for delineating management zones that can be used for a variable rate P application program. The spatial statistics approach to management zone delineation is a simple method that could serve as a guide for producers to recognize relevant spatial patterns in their field and manage it more effectively. An optimization/mathematical programming model is then utilized to evaluate the economic impact of a variable rate P fertilization strategy (based on the management zones delineated) versus the more traditional method of using a uniform rate for the whole field. Note that this mathematical programming model incorporates the output price risk for cotton lint and seed to account for the uncertainty that producers face in terms of these prices. The results of the model suggest that applying variable P rates based on the different response function for each management zone would result in higher yields and net returns relative to the traditional uniform rate application. Furthermore, this boost in net returns and yields is achieved with lower levels of applied P per acre, on average. Hence, more precise management of P based on the management zones delineated using a spatial statistics approach may also have potential implications for reduction of fertilizer runoff and non-point source pollution.

Even with these interesting insights, however, we must emphasize that the results presented above are preliminary. For example, the yield response function for both the traditional uniform rate and variable rate approaches was only estimated using OLS procedures. As Anselin, Bongiovanni, and Lowenberg-DeBoer suggests, this simple estimation procedure does not take into account the spatial autocorrelation in the data. Not taking this spatial autocorrelation into account may result in incorrect inferences and may likely affect our results. Hence, further study needs to be done with regards to more advance econometric techniques for estimating the yield response functions. Another aspect of the study that could be improved is the incorporation of risk into the optimization model. Instead of discrete probability categories, a model with continuous probability distribution functions for the output prices may be more desirable.

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