DISSERTATION

DEVELOPING AND EVALUATING MANAGEMENT ZONES FOR VARIABLE RATE FERTILIZER APPLICATION

Submitted by

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WE HEREBY RECOMMEND THAT THE **DISSERTATION** PREPARED UNDER OUR SUPERVISION BY KIM FLEMING, ENTITLED DEVELOPING AND EVALUATING MANAGEMENT ZONES FOR VARIABLE RATE FERTILIZER APPLICATION, BE ACCEPTED AS FULFILLING IN PART REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY.

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ABSTRACT OF **DISSERTATION**

DEVELOPING AND EVALUATING MANAGEMENT ZONES FOR VARIABLE RATE FERTILIZER APPLICATIONS

Variable rate fertilizer application technology (VRT) can provide an opportunity to more efficiently utilize N fertilizer inputs, however accurate prescription maps are essential. Grid soil sampling has most frequently been used to develop these prescription maps. Research has shown this method has several technical and economic limitations. Defining management zones that characterize the spatial variability within a field may provide for a more effective use of VRT. Management zones can be defined as spatially homogeneous sub-regions within a field that have similar crop input needs

The initial objective of this dissertation was to evaluate management zones identified using soil color from aerial photographs and farmer experience. These farmer developed management zones were compared to soil nutrient levels, texture, apparent soil electrical conductivity readings, topography, and crop yields collected in 1997, 1998, 1999, and 2000 at two fields. Analysis indicates that this method can be useful in identifying different management zones. The soil and yield parameters followed the trends indicated by the management zones at field one with the highest values found in the high productivity zones and the lowest the low productivity zones. Significant differences were found among the management zones. At field two the low productivity

zone was significantly lower in the soil and crop parameters, however high and medium productivity zones were generally not significantly different. Further testing over a broader scope of fields and crop production systems can follow to confirm these results.

A second objective was to evaluate and compare the prescription maps using the management zones described above with prescription maps developed from grid soil sampling. To achieve this objective six N treatments were applied on three center pivot irrigated corn fields in northeast Colorado in 1999 and 2000. There were no significant differences in yield between the treatments developed from management zones and the treatments developed from grid soil sampling. These data indicate that management zone based variable rate application is at least equally effective as grid based application. However, the cost of implementing the management zone based VRT program is much less making it a profitable alternative to grid soil sampling.

The final objective for the dissertation was to compare and evaluate prescription maps developed from soil color and farmer experience with prescription maps developed from apparent soil electrical conductivity. Apparent soil electrical conductivity (EC_a) has proven to relate closely to other properties that often determine a field's productivity. Management zones based on EC_a were developed on two fields using a GPS equipped Veris® model 3100 conductivity sensor. These two methods of developing management zones were compared to soil nutrient levels, texture, and crop yields collected in 1997 and 1998. The soil and yield parameters followed the trends indicated by both management zone methods at field 1 with the highest values found in the high productivity zones and the lowest the low productivity zones. Significant differences were found among the management zones. However at field two the high and medium productivity zones were not significantly different using the soil color approach while the soil conductivity approach was effective in identifying three distinct management zones. Both methods of developing management zones seem to be identifying homogeneous subregions within fields.

Matching crop inputs to the variability that occurs in farm fields using precision farming technologies appears to have the potential to increase cropping efficiency. However, choosing the most effective methods to utilize these technologies is key in obtaining the benefits they may provide.

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CHAPTER 1

INTRODUCTION

There are ongoing economic pressures in production agriculture to increase crop yields. However, high grain yield production comes at a cost of applying significant quantities of various agricultural inputs, i.e. nutrients, pesticides and irrigation. In traditional farming systems, producers attempt to apply these inputs at a uniform rate across a given field. However, due to inherent spatial variability in fields, not all areas may require the same levels of input. When inputs are inexpensive relative to the value of the crop produced, farmers will logically apply inputs at a level to insure all areas of the field receives an adequate level of the input (Frasier et al.,1999). This results in various areas of the field receiving greater input than necessary. The significance of this is two-fold: (1) additional inputs add cost that may be unnecessary, and (2) excess input may be prone to offsite degradation of the environment through runoff or leaching.

Although the spatial and temporal variability of yield limiting factors has been recognized for a long time (Rennie and Clayton, 1960; Malo and Worcester, 1975; Robert et al., 1990), farmers continued to manage their fields uniformly because they lacked the technology to manage for variability. With the introduction of new precision farming technologies such as global positioning systems (GPS), geographic information systems (GIS), yield monitors and variable rate application technology (VRT) farmers now have the ability to manage their fields site specifically. Intuition suggests that precision farming and site-specific management of crop production inputs to match the variability that occurs in the field will solve many of the problems cited above. However, implementation of these practices has been slow.

As more producers become aware of precision farming technology they are asking how precision farming can improve their productivity and profitability. Variable rate nitrogen (N) fertilizer application is promoted by industry as a way to increase efficiency and improve production. Environmentally, it seems correct to vary the amount of N fertilizer in relation to crop need (Verhagen et al., 1995); however this will not appeal to farmers unless economic gain from VRT can be demonstrated. Producers have limited experience with this new technology and equipment and need unbiased information to determine whether VRT is a feasible option for their individual farming operations. There is a vast array of claims, beliefs, and testimony, yet little quantitative data exists to address these basic issues (Nowak, 1997).

Variable rate fertilizer application can provide an opportunity to more efficiently utilize N fertilizer inputs, however accurate prescription maps are essential. Grid soil sampling has most frequently been used to develop these prescription maps. Research has shown this method has several technical and economic limitations. Defining management zones that characterize the spatial variability within a field may provide for a more effective use of VRT. The opportunity for improved management using VRT is not only to obtain more information about a management zone within a field, but also to be able to improve management decisions for that zone. Precision farming is not just the use of high-tech equipment, but the acquisition and wise use of information obtained from that technology. The overall objective of this dissertation is to develop approaches for defining management zones for VRT N application prescription maps. Information from this research should aid in technology transfer efforts in precision farming and lead to greater adoption of VRT if it is economically viable.

Specific objectives include:

1. Evaluating management zones identified using soil color from aerial photographs and farmer experience.
2. Compare and evaluate VRT prescription maps for N fertilization developed from management zones with prescription maps developed from grid soil sampling.
3. Compare and evaluate VRT prescription maps developed from soil color and farmer experience with prescription maps developed from apparent soil electrical conductivity (ECa).

CHAPTER 2

COMPONENTS OF PRECISION FARMING

Precision farming is a management system based on the inherent variability in soil and microclimate conditions present in many fields. Although farmers have been aware that fields have variable conditions, conventional management has generally been uniform. Precision farming matches fertilizers, pesticides, crop varieties, and management practices with soil and microclimate characteristics. This has the potential of providing economic and environmental benefits due to the reduced waste in input application. For example the implementation of precision farming allows fertilizer and herbicides to be applied only where needed, avoiding over application and/or shorting nutrients on specific soils.

These new opportunities for replacing uniform application are derived from technological advances in several areas including:

1) improved microcomputer capabilities;
2) GIS-based models for data analysis and landscape management (Moore et al., 1993; Moraes et al., 2001; Nielsen et al., 1990);
3) global positioning systems (GPS) for field navigation (Larsen et al., 1994; Petersen 1991; Saunders et al., 1996);
4) yield mapping and variable rate chemical applications (Larsen and Robert, 1991; Sawyer, 1994; Stafford et al., 1998); and

5) decision support systems (DSS) for crop management (Petersen et al., 1993; Shearer et al., 2000).

The following sections will review the components of a precision farming system. The application of GPS and GIS technologies, precision farming data layers, decision support systems, modeling, profitability, and field applications of the technology will be discussed.

2.1 Application of GPS and GIS Technologies

Geographic information systems and GPS technology in agriculture are rapidly advancing. Applications in major non-agricultural markets have helped reduce development costs to agriculture. Global positioning systems and GIS technologies provide the means for georeferencing points where data are acquired and where treatments are applied using the digitized maps (Petersen et al., 1995). Determining position within a few centimeters is now a straight forward and easy process (Tyler, 1993).

Research on development of devices that sense soil, crop, and weed conditions is a major thrust in agricultural science and engineering. Precise GIS/GPS automated navigation systems will reduce skips and overlaps in tillage, amount of materials added, and seeding (Borgelt 1993; Larsen et al., 1991). Traffic lines can be precisely designated, thereby reducing compaction where crops grow. Cariou et al. (2001) found the maximum lateral deviation along a traffic line determined from an automated navigation system to be 18.4 cm with a bias of three cm and a standard deviation less than five cm. More efficient weed control is possible with GIS and GPS technology (Colliver et al., 1996). An example would be only treating sites mapped as weed infested rather than treating the whole field, and returning to these sites when weeds are vulnerable to treatment, but difficult to find by conventional methods.

Geographic information systems provide the framework for a comprehensive analysis tool for physical and economic factors affecting agricultural production and hence profitability and financial sustainability (Griffith, 1995). He proposed that this type of analysis within spatially aware systems will likely progress from simple two-dimensional maps, that are largely user generated and supported, to sophisticated three-dimensional maps driven by data suppled by someone other than the user. The evolution of farm level GIS for precision farming has been slow, progressing from simple mapping packages that are spatially aware to full-feature GIS programs for farm operations. The spatial management of data within GIS allows analysis of changes in profitability as production practices change due to increased understanding of how physical attributes affect the production process and impact profitability.

2.2 Precision Farming Data Layers

The initial phase of a precision farming management system are GIS data layers. This requires an inventory and map of the spatial data. Data from this initial phase can be applied to models for interpretation and predictions. The final and perhaps most important component in precision farming is a decision support system (DSS). The precision farming management plan is applied by soil sampling, tilling, planting, fertilizing, and controlling weeds according to the plan. The initial cycle of the precision farming management plan is completed when the resource conditions, crop yield, and pest distributions are monitored and recorded for use in the next cycle. All phases of the precision farming system from the inventory and processing of site-specific data, through modeling, DSS, and field application rely on the generation of digitized maps.

Using yield monitors on combines to create crop yield maps can be an accurate and relatively inexpensive mapping method (Stafford et al., 1998; Pierce, 1996). Mapping crop yield variability is an important closing link in the precision farming decision-making control loop, either by itself, or in combination with other spatial variability data (Colvin et al,. 1993). Evaluating the spatial distribution of crop yield can improve the understanding of soil productivity patterns within a field (Cambardella et al., 1996).

Soil attribute maps are needed for precision farming. These maps illustrate the variability of essential biological and environmental attributes needed for the development of management plans. Soil survey maps are readily available sources of estimated soil attributes but may be too coarse for precision farming (Robert, 1993). However, with terrain attribute data computed from fine resolution digital elevation models (DEMs), these sources may be enhanced. Moore et al. (1993) conducted a survey in north-central Montana using GPS to generate a DEM. The goal was to use the DEM in the analysis of autocorrelated terrain, soil, and crop varieties.

These GPS/GIS methods offer a promising, cost-effective means of creating the fine resolution (about 1:6000) scale) maps needed for precision farming. Moraes et al. (2001) used a DGPS in combination with spatial interpolation analysis to acquire precise altitude data and generate DEM. The DGPS was shown to be a fast and useful technique to acquire data for precision farming.

The conventional method of obtaining field information concerning soil attributes for precision farming is based on grid soil sampling. However, because of the cost and the labor intensity associated with grid soil sampling there is a trade off between the information attained and the cost involved (Gotway et al,. 1996). Research studies using grid soil sampling for variable-rate nutrient application have focused on the need to keep the number of samples to a minimum, while still attaining an acceptable level of accuracy. Hammond (1992) found that a 60 m grid was adequate for developing nutrient level maps, compared to distances of 30 and 120 m. Franzen and Peck (1994) found that a distance of 64.8 m between samples in a square grid was acceptably accurate.

In conjunction with the sampling density, the interpolation method used to produce soil attribute maps affects map accuracy. Wollenhaupt et al. (1994) compared several interpolation methods, including inverse-distance squared and kriging. The results of their study suggested that for data obtained on 31.8 m grid, maps produced using inverse-distance squared interpolation were more accurate than those obtained by kriging. Accuracy was determined by comparing residual values to actual sample values. For larger grid spacings, all of the mapping approaches in their study seemed to produce maps of equal accuracy. In a similar study in Nebraska, Gotway et al. (1996) used a prediction-validation approach to evaluate the accuracy of kriging and inverse-distance squared interpolation methods. Their results suggested that regardless of sampling density used the accuracy of interpolation methods depended on the coefficient of variation of the data. Overall the results of this study indicate that kriging is a relatively safe choice for all data sets similar to ones tested. The accuracy of predictions obtained from kriging was not as sensitive to higher coefficients of variation as the inverse distance method appears to be.

Mueller et al., (2001) indicated that a common commercial scale of grid sampling at 100 m was grossly inadequate and that sampling at greater intensities only modestly improved prediction accuracy that did not justify the increased sampling cost. Their data suggest that the use of the field average fertility values at their research field was not substantially worse than grid sampling. Schloeder et al. (2001) demonstrated that spatial interpolation of coarse-scaled limited surface soils data was mostly inappropriate. Whelan et al. (1996) reported that very simple geostatistical methods are appropriate in fields with less than 100 samples. In addition, the best geostatistical methods to use will depend on unique spatial properties in each field and cannot be predicted in advance (Kravchenko and Bullock, 1998). Clearly the technical and economic limitations associated with grid soil sampling suggests other methods are needed to assess soil attributes within a field for precision farming applications.

Microclimate attribute maps show within field variations in net solar radiation, temperature, and water supply as influenced by terrain position. Fine resolution microclimate attribute maps could be generated by modifying GIS climate database values (Nielsen et al., 1990) on the basis of local digital terrain models (Moore et al., 1993). These maps could be used to predict crop disease conditions that are influenced by microclimate on spatial basis (Shwartz, 2001).

Remote sensing has been routinely applied in agriculture to identify crops and to estimate crop potential over large regions (Anderson et al.,1993). Remote sensing has also been used to identify selected soil characteristics that differentiate soils from plants and to monitor soil properties related to plant growth (Dancy et al., 1986). Soil type, soil moisture, and soil organic matter (SOM) affect reflection and adsorption characteristics of soil surfaces. Soil characteristics that are expressed by color can easily be captured on either color or black and white film (Henderson et al., 1989). Soil color is largely indicative of SOM content. Fertile soils that are high in SOM are much darker than the relatively infertile sandy soils. These characteristics of SOM have been used by soil scientist to help classify soils and to generate soil survey maps across the U.S.A. In this process, soil series boundaries are usually superimposed on aerial photographs that show field boundaries, farmsteads, and fields. Seguin and Gray (1989) used LANDSAT TM digital images in six visible and IR bands to develop a polynomial model relating spectral responses to SOM in the topsoil. Lee et al. (1988) used a soil sensitive spectral region of TM images to classify soils by SOM content, where the rate of successful classification was above 65%. Using LANDSAT TM images, Bhatti et al. (1991) reported a SOM distribution highly correlated with the spatial distribution determined by grid sampling the surface soil ($r^2 = 0.88$). In addition the semivariograms for the two methods of determining SOM were similar. More importantly, the SOM content was significantly correlated to winter wheat yield ($r^2 = 0.81$). These data suggest that SOM determined by remote sensing may be used to determine site-specific crop yield potential and ultimately crop N requirements. Diker and Bausch (1998) demonstrated a method to estimate in-season soil N at various growth stages of irrigated corn. Soil N was estimated from plant N assessed through remote sensing. The nitrogen reflectance index was employed to estimate plant N. Regression analysis between soil N and plant N showed good relationships at various growth stages. Boydell and McBratney (1999) found that a number of consecutive years of remotely sensed cotton yield estimates will cluster to generate regions of similarity for management zones. Yang and Anderson (1996) demonstrated that aerial digital videography of grain sorghum fields is a useful tool for establishing within-field management zones. Multi spectral video was also useful modeling the spatial variability of yield. A significant negative correlation ($r^2 = 0.90$) was obtained between the red spectral band and crop yields.

2.3 Decision Support Systems

With these new opportunities for farm level monitoring, strategies must be developed for collecting, integrating, and interpreting the many types of information that are necessary for decision making. One evolving strategy is a decision support system (DSS).

A DSS can harness the power and memory of computers to assist farmers and consultants in integrating information from various sources for evaluation. A precision farming DSS could link site-specific attribute data with models and GIS technology (Petersen, 1995). A GPS/GIS driven DSS that includes models and record keeping systems would assist farmers in meeting their goals and maintaining records of their actions. The development of these types of DSS for precision farming poses a complex and challenging problem at this time. Without such a system many of the other components discussed will not reach their full potential.

2.4 Modeling

The value of modeling environmental systems has been widely recognized by scientist and policy makers. However, the integration of GIS with such models has only recently been demonstrated. For precision farming a deterministic model is needed, that utilizes variable soil conditions within fields rather than generalized capacity models on a regional basis. These models must have an integrated analysis of physical, biological, and chemical processes. GIS has the potential for conveniently handling the large quantities of spatial data needed for such models.

While the potential for integrating GIS and environmental modeling is becoming very common (Goodchild et al. 1992) there are significant incompatibilities preventing true integration (Kemp, 1992). Effective precision farming models must deal with dynamic and continuous factors while GIS manages static and discrete data. To effectively integrate them, the continuity of environmental models must be added to GIS, while incorporating spatial interaction to environmental models. Fraisse et al., (1998) evaluated a new version of the CERES-Maize model that was modified to improve the simulation of site specific crop development and yield. They found the modification improved the ability of the model to simulate site-specific crop development.

2.5 Precision Farming Profitability

Perhaps the greatest societal impact of precision application of agricultural chemicals will be in the maintenance and improvement of soil and water quality. However, the practice will not be widely accepted unless it is also profitable. Current research in precision farming does not consistently show increased profitability. Wollenhaupt and Buchholz (1993) discuss the limitations of precision farming but said they strongly feel variable rate fertilization shows promise as a practice that will be profitable. Watkins et al. (1998) showed a greater economic benefit from varying water application than from varying N application across the field. Killian et al. (2001) reported a higher profitability with reduced amounts of applied N using variable rate. Tiffany et al. (2000) found that despite low commodity prices, modest yield improvements from precision agriculture technologies can readily justify their cost. They found yield increases from 24% to 5.22% using precision farming tools with an average 10% rate of return on money spent for the tools. Lambert and Lowenberg-DeBoer (2000) summarized and organized the publicly available studies of the profitability of precision agriculture. They reported on 108 studies that reported economic figures. Of those studies 63% indicated positive net returns for a given PA technology, while 11% indicated negative returns. There were 27 articles indicating mixed results (26%). For all PA technology combinations identified, over 50% of the studies reported positive benefits, except for VRT-yield monitor systems which reported 43% positive benefits. About 60% of the studies of N or NPK VRT systems reported profits.

2.6 Field Applications

Variable rate technology that varies fertilizer applications rates across the field according to yield goals, soil fertility levels, and environmental constraints is now a commercially established practice. One service company in Illinois contracted 28,000 ha in 1992 for grid sampling and variable rate fertilizer application. (Mann, 1993).

An area in Missouri, threatened by nutrient and pesticide leaching from intensive cropping practices is the site of comprehensive precision farming applications. Some 3600 ha were grid sampled and 2500 ha fully processed for variable-rate fertilizer application. Phosphorus levels from <20 to >200 kg ha^{-1} and potassium levels from <100 to >400 kg ha^{-1} were not uncommon. Plans for this precision farming project included the expansion to 10,000 ha, use of GPS for locating soil sample sites and field boundaries, and bar-code readers for sample identification (Holmes, 1993).

A grain farmer in Indiana uses variable control mechanisms for the application of all materials. Estimated savings from reduced use of starter fertilizer, dry fertilizer, ammonia, other chemicals, and seed was \$33.78 ha^{-1} in 1991. Chemical inputs were reduced, especially where groundwater contamination might occur (Macy, 1993).

In a survey of Nebraska farmers 35% of the persons operating irrigated farms plan to adopt the use of yield monitors and 32% plan to adopt the use of variable rate application technology during the next five years (Miller and Suppalla, 1996).

In 1998 yield monitors were used on about 12% of the acreage in North America. In 1996 29% of farm retail dealers nationwide offered some grid soil sampling using GPS. By 1999, 45% offered this service. Controller driven variable rate application has experienced similar growth. In 1996, 13% of fertilizer dealers offered controller driven variable rate application. By 1999, the percentage was 37% (Lowerberg-DeBoer, 2000)

A fertilizer company in northeast Colorado has used farmer developed management zones to variably apply fertilizer on over 5000 ha yearly since 1996 (Fleming et al., 2001).

Precision farming will be the agricultural system of the 21st century. It has become a reality by the development of technologies such as microcomputers, positioning systems, and GIS. The major challenge in optimizing precision farming is the development of information systems and DSS based on GIS to efficiently merge field information databases and provide sound management recommendations to producers.

CHAPTER 3

EVALUATING FARMER-DEFINED MANAGEMENT ZONE MAPS

Literature Review

Accurate prescription maps are essential for effective VRT N fertilizer application (Sawyer,1994; Ferguson et al., 1996). The concept of using management zones to develop VRT prescription maps has received considerable attention. A management zone for VRT application can be defined as a sub-region of a field that expresses a homogeneous combination of yield limiting factors for which a single rate of a specific crop input is appropriate (Doerge, 1999). Researchers have long understood the value of dividing whole fields into smaller, homogeneous regions for fertility management. Earlier studies proposed the division of fields by soil type (Carr et al., 1991). Their work indicated that applying different fertilizer treatments to contrasting soils in a field can generate greater returns than applying a field average fertilizer treatment. Mausbach et al. (1993) concluded that the National Cooperative Soil Survey is not adequate for variable rate application. Soil surveys were not intended for precision farming and tend to map at scale too coarse to be effective for VRT. Franzen et al. (2002) compared Order one and Order two soil surveys with maps from grid sampling and topography based zone maps. Order two soil surveys were seldom useful in determining zones for site specific management of NO_3-N. Order one soil surveys were much more related to soil NO_3-N than Order two surveys, but their consistency was not as high as when topography based zones or maps from grid sampling were used. Landscape position has also been used to divide fields (Fiez et al., 1994). They found that landscape position alone was not effective in dividing fields into units for variable rate N management. However, Franzen et al. (2000) concluded that topography based zone soil sampling may be useful in semiarid environments. Long et al. (1998) proposed using the spatial variation in grain protein levels to identify N management zones in spring wheat. Currently, the procedure is applicable for dryland fields that are cropped annually to wheat. Practical implementation of this procedure requires that an appropriate sensor be made available to producers that can continuously read the protein concentration of grain from a combine harvester. Stafford et al. (1998) used yield maps to regionalize fields into management units. The clustering procedure they used recognized subregions of the fields with distinct patterns of season to season variation in yields. Boydell and McBratney (1999) found that a number of consecutive years of remotely sensed cotton yield estimates clustered to generate regions of similarity for management zones. Yang and Anderson (1996) demonstrated that aerial digital videography of grain sorghum fields is a useful tool for establishing within-field management zones. Multi spectral video was also useful in modeling the spatial variability of yield. A significant negative correlation ($r^2 = 0.90$) was obtained between the red spectral band and crop yields. Shatar and McBratney (2001) used a k-means cluster analysis on sorghum yields, soil organic C, and soil K to subdivide fields into homogeneous units. The algorithm presented shows some promise for identifying spatially contiguous zones which are more homogenous in soil properties than the whole field. Mulla and Bhatti (1997) concluded that spatial patterns in surface organic matter content and yield maps could be useful in delineating fertilizer management zones. Using fixed fertilizer costs and wheat prices their study suggests the economic return was greatest when the management zones were defined using organic matter. Ostergaard (1997) developed management zones for VRT N application based on soil type, yield, topography, aerial photos, and producer experience. Five fields were divided into 12 to 17 management zones. The zones were soil sampled to determine N rate. They found a \$15 to \$35 ha^{-1} economic advantage using variable rate N application. Fleming et al. (2001) describe the application of soil color in aerial photographs and farmer knowledge to define management zones for variable rate fertilizer application. Initial analysis indicates that this method is effective in identifying different management zones. However, ground truthing is needed to develop accurate VRT maps from the zones.

We defined our management zones based on the following relationships. The spectral properties of bare soil surfaces are largely governed by soil organic matter (SOM) and moisture (Schreier et al., 1988). The grey tones in black and white aerial photographs often correlate with these soil properties and may be linked to productivity (McCann et al., 1996). Chen, et al. (2000) found that remotely sensed imagery of a bare soil field could be quantified to describe the spatial variation of SOM. Predicted SOM was highly correlated with measured SOM (r =0 .97). The technology and methodology were simple and accurate enough to be of practical use in agricultural production fields. Using LANDSAT TM images, Bhatti et al. (1991) reported that SOM distribution was highly correlated with the spatial distribution determined by grid sampling the surface soil. In addition the semivariograms for the two methods of determining SOM were similar. More importantly, the SOM content was significantly correlated to winter wheat yield. These data suggest that SOM determined by aerial photographs or remote sensing may be used to determine site-specific management zones.

Scientists know that the experiences of farmers have been extremely important in the development of agriculture as we know it today (Crookston, 1996). If it were not for farmers experiential decision-making most of the modern agriculture that we take for granted today would be unknown. Dr. Crookston has spent several years working with agricultural researchers in the U.S. and developing countries. It was his observation that the family farm has been a valuable research enterprise ever since agriculture began. Each generation has studied its alternatives and made its decisions. Unfortunately the potential contributions of indigenous farmer knowledge to soil and crop research is not being fully utilized today. Farmers generally know which areas of a field produce high yields and which areas are low in production. It is logical that nutrient needs are different for these areas. This allows identification of different "management zones" in a field using farmer knowledge as one of the predictors.

Soil sampling and analysis has long been used to evaluate the productivity status of soils (Havlin et al., 1999; Peck and Melsted, 1973). Evaluating the spatial distribution of crop yield can improve the understanding of soil productivity patterns within a field (Cambardella et al., 1996). Yield mapping can provide a dense spatial data set at low cost (Stafford et al., 1998). Well designed and well calibrated yield mapping systems can produce high quality yield estimates (Pierce, 1996). Apparent soil electrical conductivity (ECa) is the ability of a material to transmit (conduct) an electrical current. Researchers have used soil ECa to measure or estimate many chemical and physical properties of soils. Williams and Hoey (1987) found that ECa strongly correlates to soil texture. In addition to its ability to identify variations in soil texture, ECa has proven to relate closely to other properties that often determine a field's productivity (Lund et al., 1999).

The objective of this chapter is to evaluate management zones developed using SOM determined by aerial photographs and farmer knowledge. The zones will be evaluated using soil sampling and analysis, yield maps, and ECa.

Materials and Methods

Aerial 35mm bare soil photographs obtained from USDA Farm Service Agency flights were used as an initial template in developing management zones. The photographs were geo-registered using AgriTrak Professional®. Initially the bare soil photographs were enhanced to contrast color differences using Adobe Photoshop 4.0. The farmers then drew vector lines on the photographs using AgriTrak Professional® to establish the individual management zones (high, medium, and low productivity areas) based on soil color, their knowledge of the topography and management experience on the field.

Field studies were conducted from 1997 to 2000 on two center pivot irrigated fields in northeastern Colorado to assess the technical and economic feasibility of precision farming (Appendix 1, Table 1). Data from 1997, 1998, 1999, and 2000 at these locations will be discussed in this chapter and used to evaluate the farmer-developed management zones. The area of field 1 was 71 ha while field 2 was 52 ha. Soils in both fields included a Valentine sand (sandy, mixed nonacid, mesic Typic Ustipsamment), a Bijou loamy sand (coarse loamy, mixed, mesic Mollic Haplargid), and a Truckton loamy sand (coarse loamy, mixed, mesic Udic Argiustoll) (Soil Taxonomy, 1996). The fields were in continuous corn (*Zea mays* L.) throughout the study. Each field has been managed and operated by the same two farmers since 1977. Irrigation strategy was based on experience, no formal scheduling program was used. Fertility management was based on soil sampling and experience (Table 3.1).

Table 3.1. Irrigation and fertilizer summary

Field	Irrigation H_2O	Preplant NO_3-N	Fertigation NO_3-N	Preplant P	Preplant K
	m^3	kg ha^{-1}	kg ha^{-1}	kg ha^{-1}	kg ha^{-1}
1-97	2672	140	151	45	45
2-97	2467	95	127	22	45
1-00	2776	62	213	50	56
2-00	2570	62	174	67	45

Soil sampling was completed in April 1997 and March 2000 on a 76 m grid over both fields. The surface 0-0.2 m was analyzed for NO_3, NH_4, P, K, Zn, pH, SOM, and texture (Table 3.2).

Table 3.2. Soil analysis procedure

Test	Procedure
NO_3-N	2M KCL extract, analyzed by cadmium reduction-sulfanilamide colorimetric (R.L. Mulvaney, 1996)
NH_4	2M KCL extract, analyzed by salicylate-nitroprusside colorimetric (R.L. Mulvaney, 1996)
P	0.5M $NaHCO_3$ extract, analyzed by ascorbic-molybdate colorimetric (S. KUO, 1996)
K	1.0M ammonium acetate, analyzed by ICP (Helmke and Sparks, 1996)
Zn	DTPA extract, analyzed by ICP (Reed and Martens, 1996)
pH	1:1 soil:water matrix (Thomas, 1996)
SOM	Loss-on-Ignition and regressed back to Walkley-Black (Nelson and Sommers, 1996)
Tex.	Hydrometer method (Day, 1965)

Subsoil samples from 0.3 to 0.6, 0.6 to 0.9, and 0.9 to 1.2 m increments were analyzed for NO_3-N. Texture analysis was not performed in 2000.

The Natural Resource Conservation Service assisted in surveying for a topographic map of both sites in March 1997. Two methods were used, a laser level to determine elevation along with GPS to generate position and Total Station which determines xyz data. Elevation and slope data were averaged within the same 76 m grids the fields were soil sampled on for analysis.

Two approaches were used to map soil ECa in the fields. The first used the Geonics EM38 ground conductivity meter (Geonics Limited, 1998). This device measures EC by transmitting electromagnetic energy into the soil. Then a sensor in the device measures the resulting electromagnetic field that this creates. The strength of the secondary electromagnetic field is directly proportional to the EC of the soil.

For field-scale mapping, a mobile EM measurement system was used. The EM38 was mounted to a 3 m long cart consisting of a wooden beam supported at the rear by two spoke-wheeled pneumatic tires. The wooden beam was necessary because the EM38 would respond strongly to metallic objects within approximately 1 m.. The tongue of this cart was attached to the rear of a second, similar cart, which was in turn attached to the rear hitch of a four-wheel all-terrain vehicle (ATV). The second cart was necessary to increase the distance between the EM38 and ATV, for eliminating the effects of ATV engine noise on the performance of the sensor. With this configuration, the EM38 was suspended approximately 24 cm (horizontal mode) to 28 cm (vertical mode) above the ground surface during data collection.

The ECa conductivity data were read into a laptop computer mounted in front of the ATV operator through an analog-to-digital converter module. Data obtained from a Trimble ag32 differential GPS (DGPS) receiver were integrated with the EM38 data to provide the coordinates of each measurement point with an accuracy in the range of 1-2 m. All the GPS positional data were based on the World Geodetic System of 1984 (WGS84).

The second method used the Veris Model 3100 sensor cart (Lund and Christy, 1998). The Veris system identifies soil variability by directly sensing ECa. As the cart is pulled through the field, a pair of coulter electrodes transmit an electrical current into the soil, while two other pairs of coulter electrodes measure the voltage drop. The measurement electrodes are configured to measure apparent conductivity over an approximate 0- to 30-cm depth (shallow reading) as well as a 0- to 90-cm depth (deep reading). The system georeferences the conductivity measurements using a Trimble ag32 DGPS receiver, and stores the resulting data in digital form.. All the GPS positional data were based on the World Geodetic System of 1984 (WGS84). The Veris system records data on a 1 s interval, and data density can be modified by the operator through changes in travel speed and/or spacing between measurement transects.

Data from both methods were collected on transects spaced approximately 10 m apart on a l-s interval, corresponding to a measurement every 3 to 5 m along the transects. This procedure resulted in a data density of 200 to 300 points per ha.

Highly correlated ECa measurements can be obtained from these two methods (Suddeth et al., 1998). The fields were mapped using both methods in 1997, in 1999 only the Veris method was used.

The fields were yield mapped during the 1997, 1998 and 1999 harvest with two Case IH®[1] Axial Flow combine harvesters equipped with Micro-Trak®[1] yield monitors. Data from 1997 and 1998 were evaluated at field 1 while data from 1997 and 1999 were evaluated at field 2. Location data were collected on a one second interval using an Ashtech Super C/A receiver GPS system in differential mode. The GPS system was a 12-channel receiver. All the GPS positional data were based on the World Geodetic System of 1984 (WGS84). The GPS data was differentially corrected with a base station set near the experimental field. The receiver at the base was identical to the rovers. Post-processing of the GPS data showed that the GPS accuracy was sub-meter. Yield data were processed and mapped using Farmers Software Harvest Mapping System®.

Cluster analyses of the soil data from both fields in 1997 and 2000 was performed to examine soil data patterns in relation to the producer defined management zones. The objective of cluster analysis is to statistically minimize the within-group variability while maximizing the among-group variability to produce homogeneous groups that are definitive from one another. Virtually all applications of cluster analysis in soil science literature have been hierarchal agglomerative methods (Young and Hammer, 2000). Langohr et al. (1976) used cluster analysis to develop methods for grouping soils. They found that similarities in particle size distribution approximated soil series. Webster and Oliver (1990) describe general agglomerative strategy and details of particular forms of it using soil data.

The soil attributes included in the analysis were SOM, NO_3-N, K, sand, silt, clay, and Veris deep and shallow ECa. For the cluster analysis, these data were standardized to a mean of 0 and standard deviation of 1 in order to bring all data to a standard measurement scale. The analyses were performed using Ward's Minimum Variance method using SAS statistical software (SAS Institute, 1990). This method is an agglomerative hierarchical clustering technique (initial clusters are formed from pairing of individual cases; subsequent clusters are formed from joining pairs of previous clusters and/or cases; clustering continues until all clusters/cases are joined into one cluster). Ward's method, as many clustering methods, is sensitive to outliers. Consequently, the algorithm was instructed to keep 10% of the most "different" cases out of clustering process. To facilitate the comparison of the cluster analysis with the management zones the data were divided into three clusters.

An analysis of variance (ANOVA) was performed on the soil, ECa, and yield data from the management zones using an ordinary least squares model (OLS) and a spatial auto regressive model (SPA) using S-PLUS statistical software (Mathsoft, 1995) when spatial autocorrelation between observations existed. Spatial autocorrelation was measured using Moran's I (Moran, 1950). The Moran's I is used to test for the presence of spatial autocorrelation in a two-dimensional plane. In this study, the null hypothesis is that the measurements of soil and yield data are independent of one another in space. Moran's I is a dimensionless statistic and can be interpreted as a Pearson product-moment correlation between variables x and y. The index generally ranges over the interval of -1+1, but can exceed these limits if an irregular pattern of weights has been used or extreme values are heavily weighted (Bonham and Reich, 1999). The spatial weight matrix used in the analysis was based on inverse distance. The null hypothesis of no significant differences between management zones was tested by the ANOVA model

$Y(ij) = y.. + a(i) + e(ij)$

where y.. is the grand mean of all observations, a(i) is the effect of the ith management zone, and e(ij) are independent random errors. Equality of means by management zone was tested with a restatement of the ANOVA model in the form of a regression model

$Y(ij) = y.. + b0 + b1 * a1 + b2 * a2 + e(ij)$

a1 = 1 if high productivity management zone
= 0 if medium productivity management zone
= -1 if low productivity management zone

a2 = 1 if medium productivity management zone
= 0 if high productivity management zone
= -1 if low productivity management zone

When spatial autocorrelation exists is a data set the assumption if independent observations in a classical model is violated. This can underestimate the standard errors, resulting in increased overall significance between individual parameters or overestimate the standard error resulting in an overall lack of significance when one exists (Bonham and Reich, 1999). All of the soil sample data points were spatially joined to their respective management zones for the analysis of variance. For the spatially dense yield and ECa data the points were averaged in 30m by 30m pixels and then spatially joined to their respective management zones. This was necessary for the spatial analysis in S+. The spatial algorithms are too complex to analyze very large data sets such as the complete yield and ECa on personal computers available at this time. Data pixels that fell into more than one management zone were dropped.

Results and Discussion

3.1 Prescription Maps

The management zone maps for fields 1 and 2 are presented below (Figures 3.1 and 3.2).

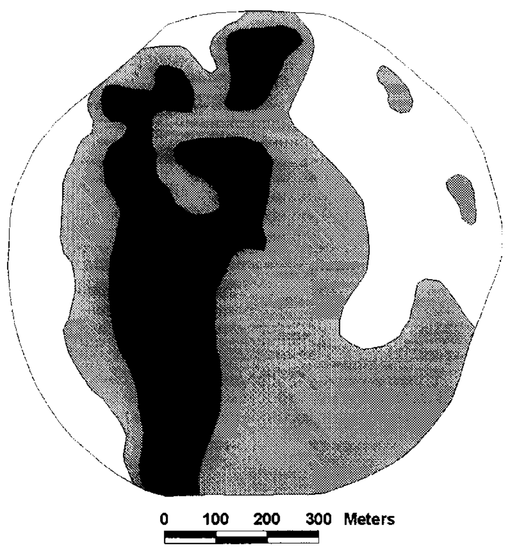


Figure 3.1. Field 1-farmer developed management zones; (low productivity = white, medium productivity = gray, high productivity = black).

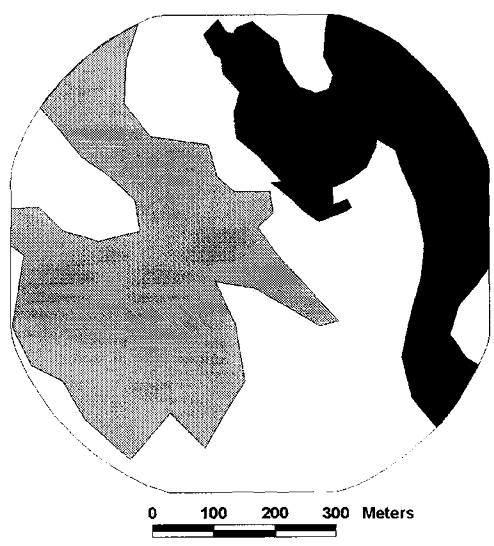


Figure 3.2. Field 2-farmer developed management zones; (low productivity = white, medium productivity = gray, high productivity = black).

3.2 Cluster Analysis

Soil and yield data were used to evaluate if the farmer-developed management zones representing areas of high, medium and low productivity have the potential for developing VRT prescription maps. Initially, cluster analysis was used to group soil sample points with similar patterns in soil attributes; the cluster analysis was then compared to the management zones.

The bar in the box and whisker plots (Figures 3.3, 3.4, 3.5, and 3.6) represents the median value in the data; the box represents the distribution of data in the 25 to 75th percentile; the whiskers show the range of data from the quartiles to the farthest observation not farther than 1.5 times the distance between the quartiles; and the lone points are extremes within the cluster's data. The number 3 clusters for each field are above average in SOM, clay, silt, Veris deep and shallow ECa, K, and NO_3-N and below average in sand. These soils are sandy and higher productivity in areas of lower sand and higher clay levels would be expected due to the higher water holding and cation exchange capacity of the higher clay content soils. In these non-saline soils, texture has probably the greatest influence on conductivity values with clay having the highest conductivity and sand the lowest. Areas with higher ECa values will be higher in clay and productivity. The number 2 clusters range from slightly above to slightly below average in SOM, clay, silt, Veris deep and shallow ECa, K and NO_3-N. The number 1 clusters are below average in SOM, clay, silt,, K, ECa, and NO_3-N and above average in sand content. Based on their relationships with the soil parameters discussed above, the number 3 clusters would be highest in productivity, the number 1 clusters would be lowest in productivity, the number 2 clusters would be intermediate in productivity.

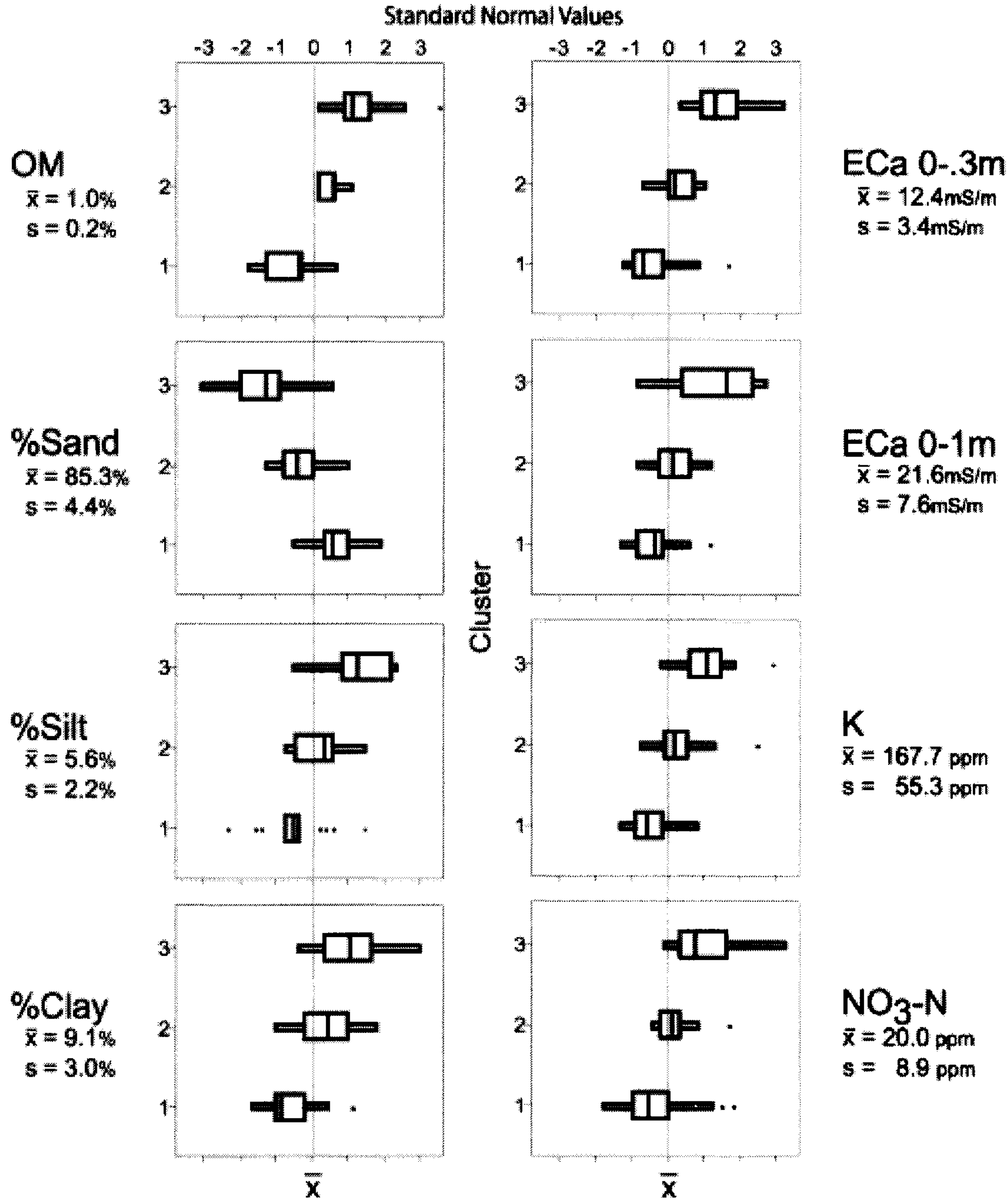


Figure 3.3. Soil attribute patterns over the three soil clusters at field 1-97.

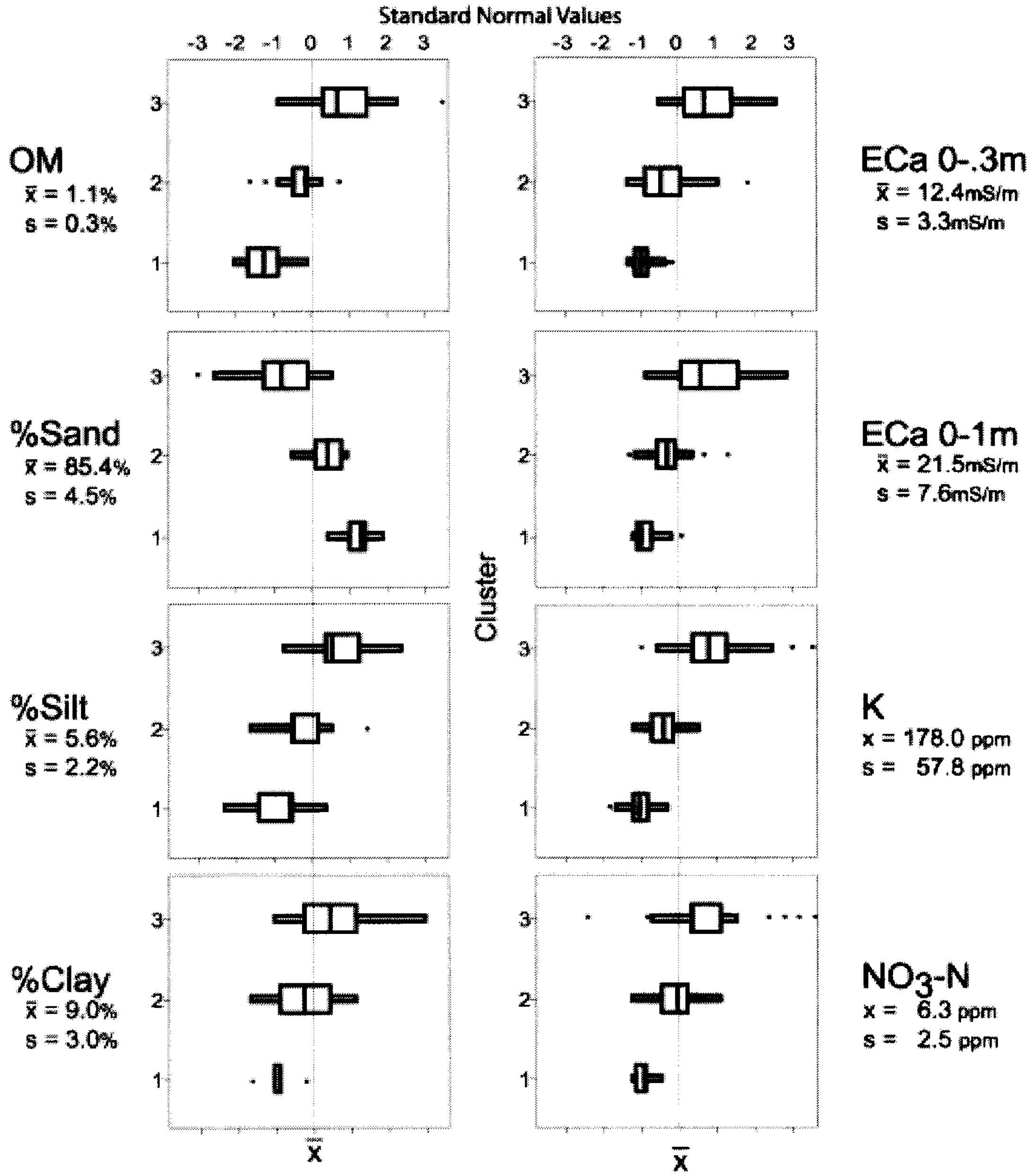


Figure 3.4. Soil attribute patterns over the three soil clusters at field 1-00.

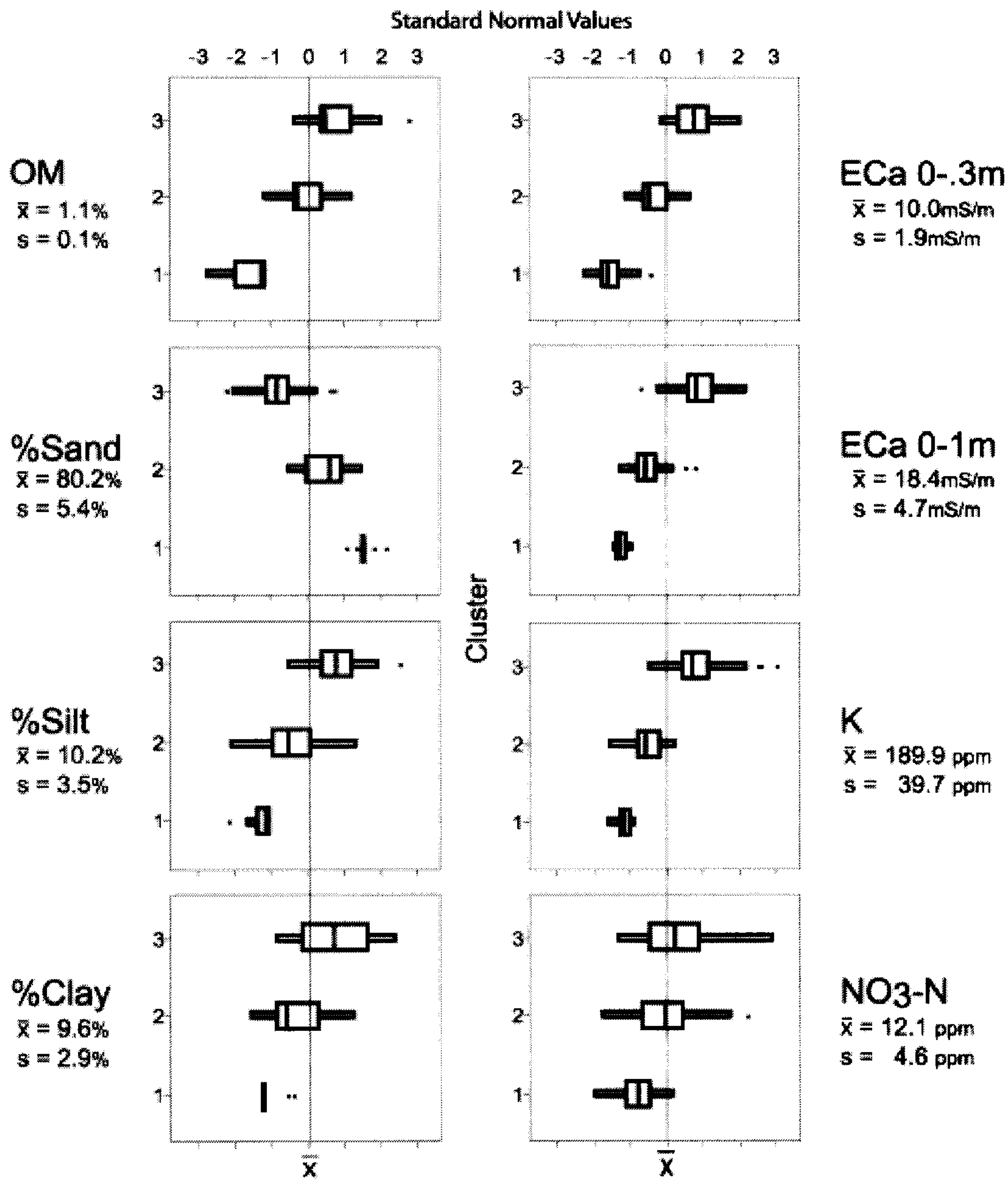


Figure 3.5. Soil attribute patterns over the three soil clusters at field 2-97.

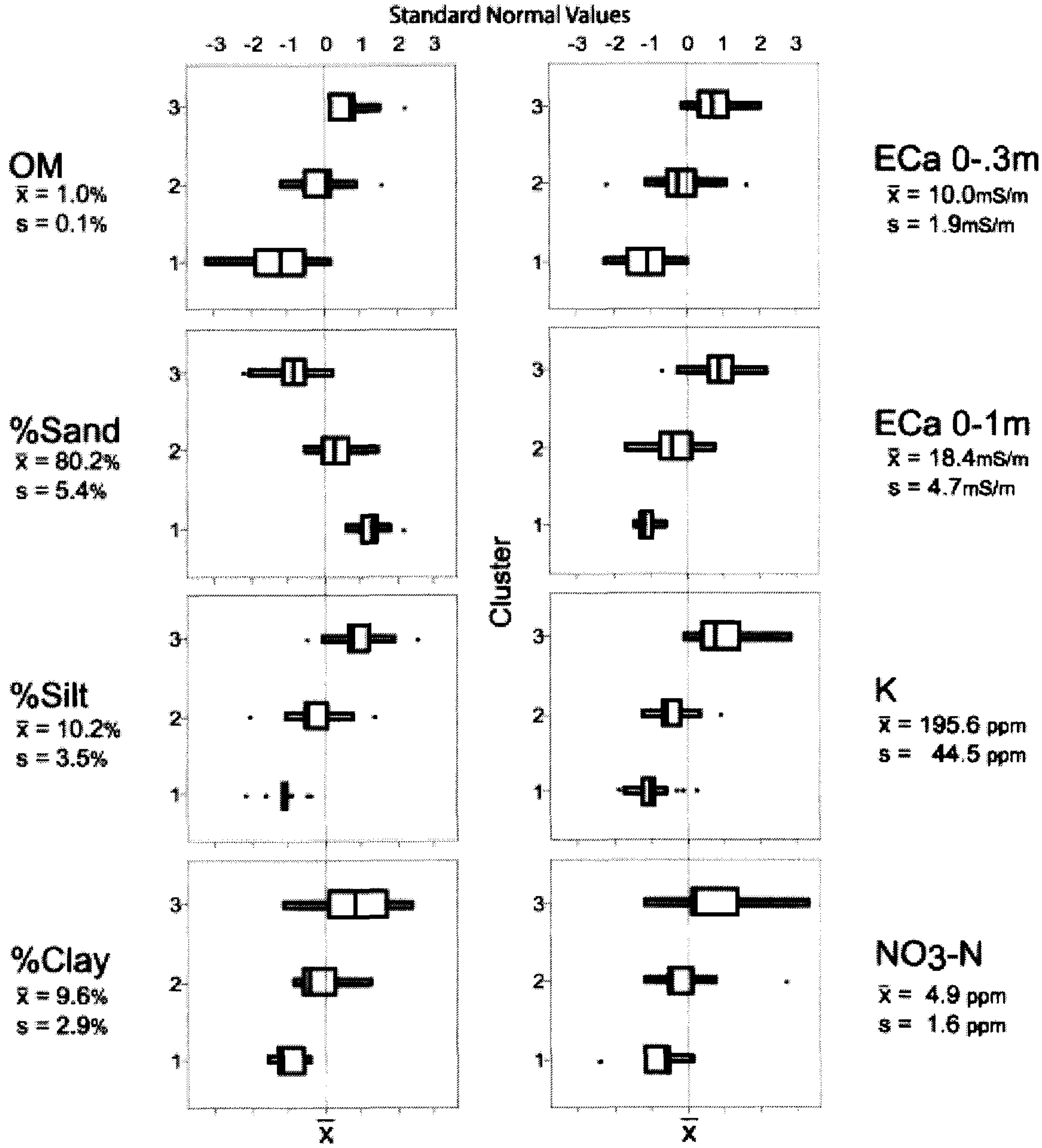


Figure 3.6. Soil attribute patterns over the three soil clusters at field 2-00.

Field 1-97 & 00

The majority of the sample points from field 1 associated with the high productivity cluster 3 (Figure3.7) were located within the farmer defined high productivity zone (79%) while the points associated with the medium productivity cluster 2 were mostly located within the farmer defined medium productivity zone (78%). The sample points associated with the low productivity cluster 1 were evenly divided among the low and medium farmer defined management zones.

At field 1-2000 the majority of the sample points associated with the high productivity cluster 3 (Figure 3.8) were located within the farmer defined high productivity zone (52%) while the points associated with the medium productivity cluster 2 were mostly located within the farmer defined medium productivity zone (56%). The majority of the sample points associated with the low productivity cluster 1 were located within the farmer defined low productivity management zones (62%).

The farmer-developed management zones at field 1 in 1997 and 2000 followed soil attribute patterns with areas of distinct soil patterns being recognized. Discrepancies between the delineation and soil patterns occurred mostly along zone boundaries. These results seem to indicate that on this field, with some exceptions, the management zones represent different suites of soil characteristics and thus have potential for VRT application maps.

Field 1

Management Zone

Cluster	Low	Medium	High
1	33	33	6
2	2	21	4
3	0	5	19

#Points/Zone

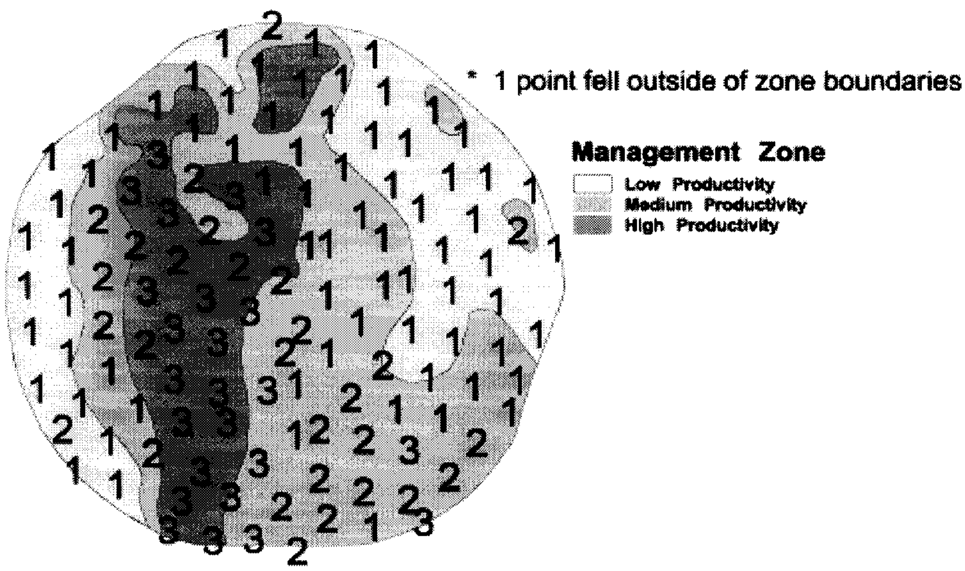


Figure 3.7. Relationship of cluster analysis to management zones (field 1-97).

Field 1

Management Zone

Cluster	Low	Medium	High
1	13	5	3
2	18	25	2
3	0	22	24

#Points/Zone

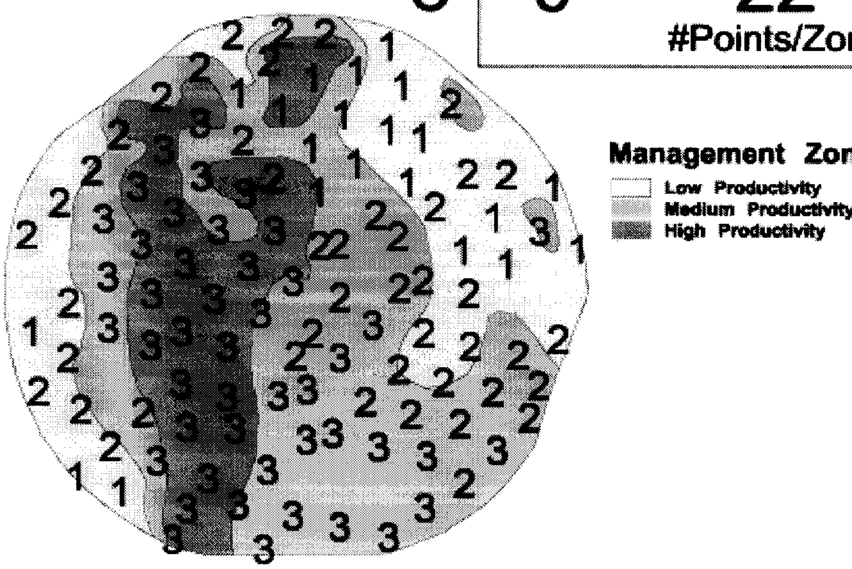


Figure 3.8. Relationship of cluster analysis to management zones (field 1-00)

Field 2-97 & 00

The cluster analysis on field 2 indicated that the management zones were effective in delineating homogeneous low productivity regions of the field. However, the analysis indicated that the high and medium zones were not defined as accurately as they were on Field 1. One hundred percent of the sample points associated with the low productivity clusters were located within the low productivity management zone in 1997 (Figure 3.9). However, the highest percentage of sample points associated with the high productivity clusters were located within the medium productivity zone (68%), while 63% of the points associated with the medium productivity clusters were located within the low productivity zone.

In 2000 100 % of the sample points associated with the low productivity clusters were located within the low productivity management zone (Figure 3.10). Similar to the 97 data the majority of the sample points associated with the medium productivity cluster 3 were located in the low productivity management zone and majority of the high productivity clusters were located in the medium productivity management zone

It seems at field 2 this method of defining management zones is effective at recognizing low productivity areas but less effective in delineating high and medium zones. Perhaps the method is only recognizing two management zones at field 2.

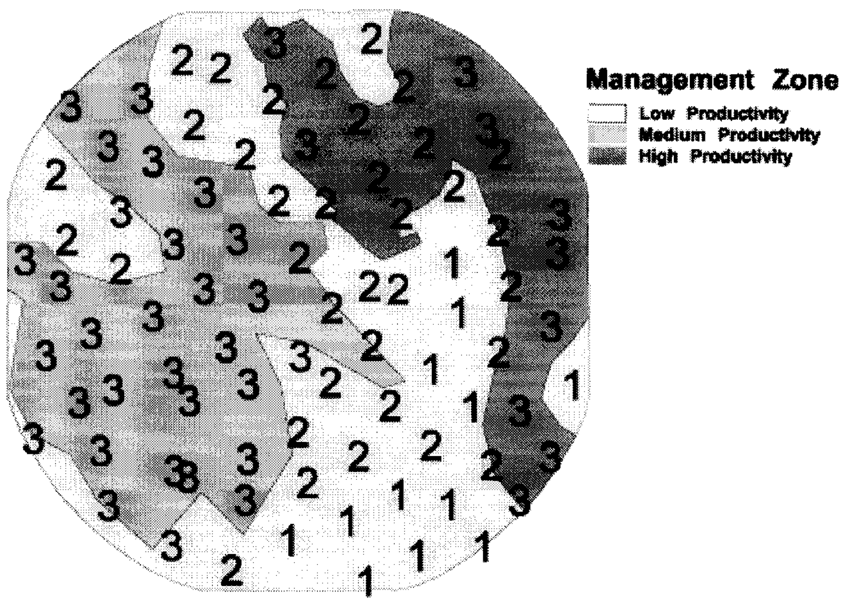
3.3 Analysis of Variance

A classical ordinary least squares (OLS) model was initially used on the soils and yield data based on management zone. When spatial autocorrelation among observations was indicated using Moran's I, a spatial auto regressive model (SPA) was used (Appendix 1, Tables 3 and 4).

Field 2
Management Zone

Cluster	Low	Medium	High
1	12	0	0
2	22	1	12
3	3	27	10

#Points/Zone



97

Figure 3.9. Relationship of cluster analysis to management zones (field 2-97)

Field 2
Management Zone

Cluster	Low	Medium	High
1	21	0	0
2	16	3	10
3	2	25	11

#Points/Zone

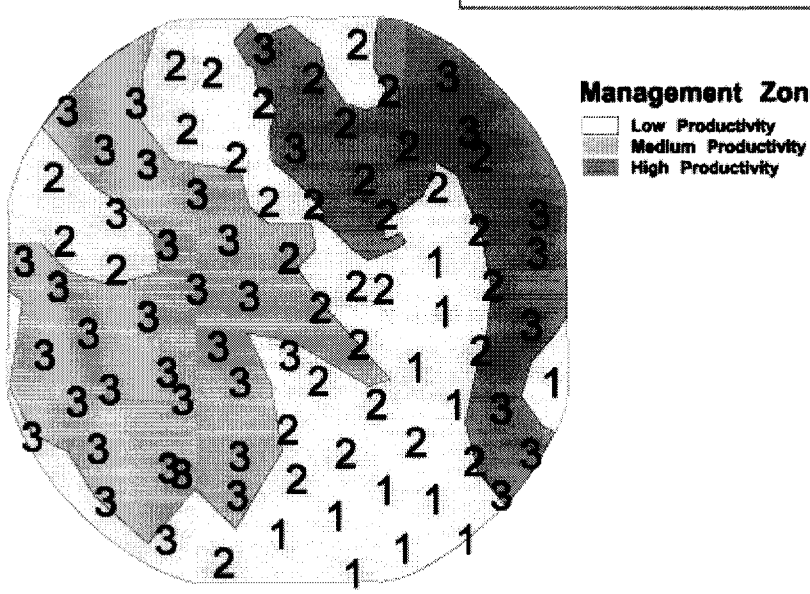


Figure 3.10. Relationship of cluster analysis to management zones (field 2-00)

Field 1-97

Soil organic matter, NO_3-N, K, Zn, and crop yield followed the trends indicated by the management zones with the highest nutrient levels and yield in the high productivity zones, intermediate levels in the medium zones, and lowest levels in the low productivity zones. Levels of SOM and crop yield were significantly different in all management zones (Tables 3 and 4). Statistically significant differences in a spatially dense data set such as yield data can be misleading. The very large N values can lead to statistical differences, however the differences may be insignificant agronomically. This appears to be the case here. Nitrate and K levels were significantly different between the high/low and high/medium zones while Zn levels were significantly different between the high and low productivity zones. Phosphorus did not follow the trends seen with the other nutrients, with higher levels seen in the lower productivity zones and lower levels in the high productivity zones. Perhaps the immobility of P would account for this. The lower productivity areas would remove less P resulting in a build up of the soil test P-level.

Soil texture showed similar trends to the data above (Table 3.5). Clay and silt levels were significantly higher in the high productivity zone, intermediate in the medium zones, and lowest in the low productivity zones while sand followed the opposite trend. As discussed earlier these soils are sandy and higher productivity in areas of lower sand and higher clay levels would be expected due to the higher water holding and cation exchange capacity of the higher clay content soils.

Table 3.3. Field 1-97 analysis of variance of SOM, NO_3-N, and P as a function of management zone (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity).

	SOM			NO_3-N			P		
MZ	n	%	SD	n	ppm	SD	n	ppm	SD
1	35	0.8a	0.03	35	18a	1.3	35	16a	0.9
2	57	1.0b	0.02	57	20a	1.1	57	11b	0.8
3	29	1.2c	0.03	29	25b	1.5	29	14a	1.1
Model		SPA			SPA			OLS	
Pr > F		0.0001			0.0001			0.001	

Means followed by different letters are significantly different at $p < 0.05$

Table 3.4. Field 1-97 analysis of variance of K, Zn, and yield as a function of management zone (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity).

	K			Zn			Yield		
MZ	n	ppm	SD	n	ppm	SD	n	Mg ha^{-1}	SD
1	35	142a	6.6	35	3.8a	0.2	639	9.8a	0.2
2	57	160a	5.2	57	4.1ab	0.1	963	10.7b	0.1
3	29	207b	7.2	29	4.4b	0.2	474	10.8c	0.2
Model		SPA			SPA			SPA	
Pr > F		0.0001			0.001			0.0001	

Means followed by different letters are significantly different at $p < 0.05$

Table 3.5. Field 1-97 - Analysis of variance of sand, silt, and clay as a function of management zone (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity).

	Sand			Silt			Clay		
MZ	n	%	SD	n	%	SD	n	%	SD
1	35	88a	0.009	35	4a	0.007	35	7a	0.008
2	57	85b	0.007	57	6b	0.006	57	9b	0.006
3	29	82c	0.010	29	9c	0.008	29	11c	0.009
Mode 1		OLS			OLS			OLS	
Pr > F		0.0001			0.0001			0.0001	

Means followed by different letters are significantly different at $p < 0.05$

It is well documented that variation in soil properties across landscapes affects soil productivity. In Nebraska increased corn (*Zea mays* C.) yields were reported on the upper and lower interfluve and footslope positions while decreased yields were seen on the upper and lower linear slopes (Jones et al., 1989). Greater crop yields were obtained in footslope positions compared to backslope and sideslope positions in western Iowa (Spomer and Piest, 1982). Increased yields at footslope positions were attributed to deposition of soil, organic matter, and nutrients from upslope positions and additional plant available water.

The elevation and slope data across management zones at field 1-97 had similar results to these studies. The highest elevation and greatest slopes were associated with the low productivity management zone while the lowest elevations and slopes were associated with the higher productivity zones (Table 3.6).

Table 3.6. Field 1-97 analysis of variance of elevation and slope data as a function of management zone (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity).

	Elevation			Slope		
MZ	n	m	SD	n	degrees	SD
1	35	1352.5a	0.09	35	2.3a	0.02
2	57	1351.9b	0.07	57	1.5b	0.01
3	29	1351.2c	0.11	29	0.9c	0.03
Model		SPA			OLS	
Pr > F		0.0001			0.0001	

Means followed by different letters are significantly different at $p < 0.05$

Apparent electrical conductivity values also followed the trends indicated by the management zones. Differences were significant across all management zones for both the EM38® and Veris® 3100 conductivity data (Table 3.7). As discussed earlier in these soils, texture has probably the greatest influence on conductivity values with clay having the highest conductivity and sand the lowest.

Table 3.7. Field 1-97 analysis of variance of EM38®, shallow Veris®, and deep Veris® conductivity data as a function of management zone (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity).

	EM38			Veris Shallow			Veris Deep		
MZ	n	mS m^{-1}	SD	n	mS m^{-1}	SD	n	mS m^{-1}	SD
1	593	20.8a	0.45	562	3.1a	0.11	562	22.6a	0.26
2	930	29.8b	0.36	899	5.5b	0.09	899	28.2b	0.21
3	454	37.1c	0.50	451	9.0c	0.13	451	39.9c	0.29
Model		SPA			SPA			SPA	
Pr > F		0.0001			0.0001			0.0001	

Means followed by different letters are significantly different at $p < 0.05$

Field 2-97

Results of the analysis of variance on field 2 indicated that the soil and crop parameters were different across the management zones, however similar to the cluster analysis, they did not follow the trends indicated by the farmer developed zones. The zone classified as medium in productivity was highest in SOM, K, clay, silt, yield, and Veris conductivity, while the high productivity zones had intermediate values for these parameters (Tables 3.8 - 3.11). Values for Zn, NO_3-N, P, and EM38 conductivity were nearly equal in the high and medium zones. Crop yields and Veris conductivity values were significantly different across all zones. No significant differences were detected between the high and medium productivity zones for SOM, K, clay, and silt. The low productivity zone had significantly lower values for the parameters listed above and were highest in sand.

Table 3.8. Field 2-97 analysis of variance of SOM, NO_3-N, and P as a function of management zone (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity).

		SOM			NO_3-N			P	
MZ	n	%	SD	n	ppm	SD	n	ppm	SD
1	38	0.96a	0.02	38	11a	0.7	38	11a	0.7
2	28	1.15b	0.02	28	14b	0.8	28	15b	0.9
3	22	1.09b	0.02	22	14b	0.8	22	15b	1.0
Model		OLS			SPA			OLS	
Pr > F		0.0001			0.0001			0.001	

Means followed by different letters are significantly different at $p < 0.05$

Table 3.9. Field 2-97 analysis of variance of K, Zn, and yield as a function of management zone (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity).

	K			Zn			Yield		
MZ	n	ppm	Sd	n	ppm	Sd	n	Mg ha^{-1}	SD
1	38	162a	5.1	35	2.2a	0.06	735	11.2a	0.2
2	28	219b	5.9	57	2.7b	0.08	500	14.1b	0.3
3	22	199b	6.7	29	2.7b	0.09	372	13.1c	0.3
Model		OLS			OLS			SPA	
Pr > F		0.0001			0.0001			0.0001	

Means followed by different letters are significantly different at $p < 0.05$

Table 3.10. Field 2-97 - Analysis of variance of sand, silt, and clay as a function of management zone (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity).

	Sand			Silt			Clay		
MZ	n	%	Sd	n	%	Sd	n	%	SD
1	38	84a	0.008	38	7a	.006	38	8a	0.007
2	28	75b	0.009	28	13b	.008	28	11b	0.008
3	22	79c	0.010	22	11b	.006	22	10ab	0.009
Model		OLS			OLS			OLS	
Pr > F		0.0001			0.0001			0.0001	

Means followed by different letters are significantly different at $p < 0.05$

The elevation and slope data from field 2-97 were somewhat mixed. As one would expect from past research slopes were significantly higher in the low productivity management zones (Table 3.12). However similar to the soil and yield data from this filed there was little difference in slopes between the medium and high zones. Elevation was significantly lower in the high productivity zones, there was little difference in elevation between the low and medium productivity zones.

Table 3.11. Field 2-97 analysis of variance of EM38®, shallow Veris®, and deep Veris® conductivity data as a function of management zone (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity).

	EM38			Veris Shallow			Veris Deep		
MZ	n	mS m^{-1}	SD	n	mS m^{-1}	SD	n	mS m^{-1}	SD
1	639	24.7a	0.20	674	7.3a	0.06	674	18.8a	0.16
2	465	30.8b	0.23	475	10.0b	0.07	475	26.3b	0.19
3	420	31.3b	0.25	339	8.6c	0.09	339	23.0c	0.22
Model		SPA			SPA			SPA	
Pr > F		0.0001			0.0001			0.0001	

Means followed by different letters are significantly different at $p < 0.05$

Table 3.12. Field 2-97 analysis of variance of elevation and slope data as a function of management zone (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity).

	Elevation			Slope		
MZ	n	m	SD	n	degrees	SD
1	38	1342.2a	0.18	38	1.3a	0.05
2	28	1342.6a	0.19	28	0.5b	0.99
3	22	1340.2b	0.23	22	0.7b	0.13
Model		SPA			OLS	

Means followed by different letters are significantly different at $p < 0.05$

The results from field 2 illustrate that this method is consistently identifying low productivity sub-regions within the field. While the data trends indicate the medium productivity zones should be classified as high productivity zones the differences are generally not significant. Perhaps only two zones are being recognized in this field. There may be inclusions in the medium, and high productivity zones that are not being identified using this method to define zones.

Field 1-00

Results from 2000 were nearly identical to 1997. Soil organic matter, NO_3-N, K, Zn, and crop yield followed the trends indicated by the management zones with the highest nutrient levels and yield in the high productivity zones, intermediate levels in the medium zones, and lowest levels in the low productivity zones. Levels of SOM, NO_3-N and crop yield were significantly different in all management zones (Tables 3.13 and 3.14). Potassium levels were significantly different between the high/low and high/medium zones. Zinc levels were not significantly different among the zones. Phosphorus did not follow the trends seen with the other nutrients, with higher levels seen in the lower productivity zones and lower levels in the high productivity zones. The immobility of P would account for this anomaly as discussed earlier. The lower productivity areas would remove less P resulting in a build up of the soil test P-level.

Table 3.13. Field 1-00 analysis of variance of SOM, NO_3-N, and P as a function of management zone (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity).

		SOM			NO_3-N			P	
MZ	n	%	SD	n	ppm	SD	n	ppm	SD
1	34	0.99a	0.04	34	5a	0.38	34	21a	1.4
2	53	1.1b	0.03	53	6b	0.30	53	15b	1.1
3	29	1.3c	0.04	29	8c	0.40	29	15b	1.5
Model		SPA			OLS			SPA	
Pr > F		0.0001			0.0001			0.001	

Means followed by different letters are significantly different at $p < 0.05$

Table 3.14. Field 1-00 analysis of variance of K, Zn, and yield as a function of management zone (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity).

	K			Zn			Yield		
MZ	n	ppm	SD	n	ppm	SD	n	Mg ha^{-1}	SD
1	34	151a	6.4	34	4.1a	0.2	639	10.1a	0.2
2	53	178b	5.1	53	4.3a	0.1	963	11.5b	0.2
3	29	221c	7.2	29	4.6a	0.2	474	12.4c	0.3
Model		SPA			SPA			SPA	
Pr > F		0.0001			0.001			0.0001	

Means followed by different letters are significantly different at $p < 0.05$

Conductivity values in 2000 also followed the trends indicated by the management zones. Again differences were significant across all management zones for the Veris® 3100 conductivity data (Table 3.15). In these soils, texture has probably the greatest influence on conductivity values with clay having the highest conductivity and sand the lowest.

Table 3.15. Field 1-00 analysis of variance of shallow Veris® and deep Veris® conductivity data as a function of management zone (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity).

	Veris Shallow			Veris Deep		
MZ	n	mS m^{-1}	SD	n	mS m^{-1}	SD
1	562	9.0a	0.16	562	15.4a	.19
2	899	13.0b	1.0	899	22.8b	1.6
3	451	19.1c	0.21	451	34.0c	2.1
Model		SPA			SPA	
Pr > F		0.0001			0.0001	

Means followed by different letters are significantly different at $p < 0.05$

Field 2-00

Results of the analysis of variance on field 2 were again similar to 1997. The data indicated that the soil and crop parameters were different across the management zones, however they did not follow the trends indicated by the farmer developed zones. The zone classified as medium in productivity was highest in SOM, K, yield, and Veris conductivity, while the high productivity zones had intermediate values for these parameters (Tables 3.16, 3.17, and 3.18). Values for NO_3-N, P, K, and Zn were not significantly different in the high and medium zones. Crop yields, SOM, and Veris conductivity values were significantly different across all zones.

Table 3.16. Field 2-00 analysis of variance of SOM, NO_3-N, and P as a function of management zone (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity).

	SOM			NO_3-N			P		
MZ	n	%	SD	n	ppm	SD	n	ppm	SD
1	43	0.87a	0.02	43	4a	0.2	43	9a	1.0
2	29	1.1b	0.02	29	5b	0.3	29	13b	1.2
3	22	1.0c	0.02	22	5b	0.8	22	13b	1.0
Model		OLS			OLS			OLS	
Pr > F		0.0001			0.0004			0.03	

Means followed by a different letters are significantly different at $p < 0.05$

Table 3.17. Field 2-00 analysis of variance of K, Zn, and yield as a function of management zone (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity).

	K			Zn			Yield	
MZ	n	mean	SD	n	mean	SD	n	Mg ha^{-1}	SD
1	43	168a	5.5	43	1.9a	0.12	735	12.1a	0.3
2	29	226b	6.7	29	2.4ab	0.14	500	13.4b	0.4
3	22	212b	6.7	22	2.6b	0.17	372	13.0c	0.4
Model		OLS			OLS			SPA	
Pr > F		0.0001			0.006			0.0001	

Means followed by different letters are significantly different at $p < 0.05$

Table 3.18. Field 2-00 analysis of variance of shallow Veris® and deep Veris® conductivity data (mS $^{-1}$) as a function of management zone (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity).

	Veris Shallow			Veris Deep		
MZ	n	mS $^{-1}$	SD	n	mS $^{-1}$	SD
1	674	13.7a	.09	674	22.2a	.18
2	475	20.1b	1.2	475	27.3b	.23
3	339	17.2c	1.6	339	22.8c	.28
Model		SPA			SPA	
Pr > F		0.0001			0.0001	

Means followed by different letters are significantly different at $p < 0.05$

The results from field 2-00 again illustrate that this method is consistently identifying different low productivity sub-regions within the field. However, medium and high zones are not being clearly distinguished.

3.4 Conclusions

Farmer developed management zones based on soil color and farmer experience were compared to soil nutrient levels, texture, ECa readings, and crop yields for two fields managed by two different farmers over two years. Cluster analysis indicated that the management zones do represent different suites of soil characteristics. A spatial analysis of variance showed that the soil and crop parameters followed the trends indicated by the management zones for field one. The zone designated as medium by the farmer in field two had the highest soil and crop parameters however, the medium and high productivity zones tended to be similar at field two. Our analysis indicates that the farmer assigned zones may be useful. These results are similar to the findings of Mulla and Bhatte (1997). They concluded that in terms of practicality organic matter estimated from bare soil images offer the best feasibility in dividing fields into management zones. Yang and Anderson (1996) also had success using digital video images of sorghum fields to classify management zones. Their analysis of variance showed that plant biomass and yield differed significantly among their management zones.

Differences in the effectiveness of farmer identified management zones between fields may be due to the selective skills of the different farmers in recognizing zone boundaries. Further testing over a broader scope of fields, farmers, and crop production systems is needed to confirm these results.

CHAPTER 4

EVALUATING MANAGEMENT ZONE TECHNOLOGY AND GRID SOIL SAMPLING FOR VARIABLE RATE NITROGEN APPLICATION

Literature Review

Field level studies have shown that organic C, total N, and NO_3-N have spatial dependance and variation (Cambardella et al., 1994). Using the ratio of nugget to total semi variance to classify spatial dependance, organic C and total N were strongly spatially dependent while NO_3-N was moderately spatially dependent. Other studies have concluded that N uptake and crop response to N varies spatially within fields (Malzer, 1996; Dampney and Goodlass, 1997). Welsh et al. (1999) reported significant yield increases where 30% more additional N was applied to historically higher yielding parts of the field. Kachanoski et al. (1996) showed that optimal levels of N fertilization have spatial variability. The maximum yield increase and the economic yield increase over the check yield with no N applied were both strongly correlated with spatially optimal economic return of N (r=0.70 to 0.88). Baxter et al. (2001) found the variation in mineral N is not uniform and too noisy to manage with variable rate application. Variable rate application technologies enable farmers to adjust N rates to reflect these variations. Accurate prescription maps are essential for effective VRT N fertilizer application (Sawyer,1994; Ferguson et al., 1996). Grid soil sampling has most frequently been used to develop these prescription maps (Mueller et al., 2001). Past research has indicated several technical and economic limitations associated with this approach. There is a need to keep the number of samples to a minimum while still allowing a reasonable level of map quality. However, Gotway et al. (1996) found that the optimum grid density may depend on the coefficient of variation. In many cases, where the spatial distribution is rather complex, much finer grid densities than those currently used commercially are required to produce accurate prescription maps. Mueller et al. (2001) indicated that a common commercial grid sampling scale of 100 m was grossly inadequate and that sampling at greater intensities only modestly improved prediction accuracy that would not justify the increase in sampling cost. Their data suggest that the use of the field average fertility values at their research field was not substantially worse than grid sampling. Schloeder et al. (2001) demonstrated that spatial interpolation of data with limited sample size (n = 46) on coarse-scaled (1188 ha) surface soils data was mostly inappropriate. For most of their data sets the inability to predict, could be attributed to either spatially independent data, limited data, sample spacing, extreme values, or erratic behavior. Whelan et al. (1996) reported that in fields with less than 100 samples only very simple geostatistical methods such as inverse distance are appropriate. Sample sizes of 100 to 500 are needed for geostatistical methods such as kriging. Kravchenko and Bullock, (1998) studied several interpolation techniques, such as ordinary kriging, lognormal kriging, and inverse distance weighting, and found the best geostatistical methods to use depended on unique spatial properties in each field and could not be predicted in advance. Hammond (1992) found that a 60 m grid was adequate for developing prescription maps, compared to distances of 30 and 20 m. Franzen and Peck (1994) found that a distance of 65 m between samples in a square grid improved the probability for returns by better identifying areas which would benefit from variable rate application compared to a distance of 25 m, and was preferable to a grid distance of 98 m. McBratney and Pringle (1999) reported that grid sampling at 20 to 30 m is generally needed when applying site specific management at a resolution of 20 by 20 m.

As can be seen, no one grid size adequately describes the variability that exists in fields of a diverse population. If one fails to sample at a fine enough resolution to capture the spatial correlation in crop nutrient data, the interpolation methods and application maps developed from those methods will not be valid or accurate (Reich, 2000). However, the cost associated with grid sampling to the intensity required for accurate maps may be prohibitive in many cases. Ferguson et al., (2002) used grid soil sampling and the University of Nebraska N algorithm to create VRT N application maps. There was no significant difference in the total N applied using VRT (142 kg N ha^{-1}) and uniform application (142 kg N ha^{-1}). Corn yield means ranged from 4.5 to 13.9 Mg ha^{-1} and were influenced relatively little by uniform and VRT treatments. They concluded the University of Nebraska algorithm may not be sensitive enough to localized differences in soil N supply and crop N demand within fields to be used for VRT N application.

Due to the limitations associated with grid soil sampling to develop VRT prescription maps, the concept of management zones has received considerable attention. Researchers have understood the value of dividing whole fields into smaller, homogeneous regions for fertility management. Earlier studies proposed the division of fields by soil type (Carr et al., 1991). Their work indicated that applying different fertilizer treatments to contrasting soils in a field can generate greater returns than applying a field average fertilizer treatment. Mausbach et al. (1993) concluded that the

National Cooperative Soil Survey is not adequate for variable rate application. Soil surveys were not intended for precision farming and tend to be mapped at scales too coarse to be effective. Franzen et al. (2002) compared Order 1 and Order 2 soil surveys with maps from grid sampling and topography based zone maps. Order 2 soil surveys were seldom useful in determining zones for site specific management of NO_3-N Order 1 soil surveys were more related to soil NO_3-N than Order 2 surveys, but its consistency was not as high as when topography based zones or maps from grid sampling were used. Landscape position also has been used to divide fields (Fiez et al., 1994). They found that landscape position alone was not effective in dividing fields into units for variable rate N management. However Franzen et al. (2000) concluded that topography based zone soil sampling may be useful in semiarid environments. Long et al. (1998) proposed using the spatial variation in grain protein levels to identify N management zones in spring wheat. Currently, the procedure is applicable for dryland fields that are cropped annually to wheat. Practical implementation of this procedure requires that an appropriate sensor be made available to producers that can continuously read the protein concentration of grain from the combine harvester. Stafford et al. (1998) used yield maps to regionalize fields into management units. The clustering procedure they used recognized subregions of the fields with distinct patterns of season to season variation in yields. Boydell and McBratney (1999) found that a number of consecutive years of remotely sensed cotton yield estimates will cluster to generate regions of similarity for management zones. Yang and Anderson (1996) demonstrated that aerial digital videography of grain sorghum fields is a useful tool for establishing within-field management zones. Multi spectral video was also instrumental in modeling the spatial variability of yield. A significant negative correlation ($r^2 = .90$) was obtained between the red spectral band and crop yields. Shatar and McBratney (2001) used a k-means cluster analysis on sorghum yields, soil organic C, and soil K to subdivide fields into homogeneous units. The algorithm they developed shows promise for identifying spatially contiguous zones which are more homogenous in soil properties than the whole field. Mulla and Bhatti (1997) concluded that spatial patterns in surface organic matter content and yield maps could be useful in delineating fertilizer management zones. Using fixed fertilizer costs and wheat prices their study suggests the economic return was greatest when the management zones were defined using organic matter. Ostergaard (1997) developed management zones for VRT N application based on soil type, yield, topography, aerial photos, and producer experience. Five fields were divided into 12 to 17 management zones. The zones were soil sampled to determine N rate. They found a $15 to $35 per ha economic advantage using variable rate N application. Fleming et al. (2001) described the application of soil color and farmer knowledge to define management zones for variable rate fertilizer application. Initial analysis indicates that this method is effective in identifying different management zones. A management zone for VRT application can be defined as a sub-region of a field that expresses a homogeneous combination of yield limiting factors for which a single rate of a specific crop input is appropriate (Doerge, 1999).

The spectral properties of bare soil surfaces is largely governed by soil organic matter (SOM) and moisture (Schreier et al., 1988). The grey tones in black and white aerial photographs often correlate with these soil properties and may be linked to productivity (McCann et al., 1996). Chen et al. (2000) found that remotely sensed imagery of a bare soil field could be quantified to describe the spatial variation of SOM. Predicted SOM was highly correlated with measured SOM (r = .97). The technology and methodology were simple and accurate enough to be of practical use in agricultural production fields. Using LANDSAT TM images Bhatti et al. (1991) reported that the SOM distribution was highly correlated with the spatial distribution determined by grid sampling the surface soil. In addition, the semivariograms for the two methods of determining SOM were similar. More importantly, the SOM content was significantly correlated to winter wheat yield. These data suggest that SOM determined by aerial photographs or remote sensing may be used to determine site-specific management zones.

Scientists know that the experiences of farmers have been extremely important in the development of agriculture as we know it today (Crookston, 1996). If it were not for farmers experiential decision-making, most of the modern agriculture that we take for granted today would be unknown. Dr. Crookston has spent several years working with agricultural researchers in the U.S. and developing countries. It was his observation that the family farm has been a valuable research enterprise ever since agriculture began. Each generation has studied its alternatives and made its decisions. Unfortunately the potential contributions of indigenous farmer knowledge to soil and crop research is not being fully utilized today. Farmers generally know which areas of a field produce high yields and which areas are low in production. It is logical that nutrient needs are different for these areas. This allows identification of different "management zones" in a field using farmer knowledge as one of the predictors.

The major objective of this chapter is to compare and evaluate prescription maps developed from farmer identified management zones with prescription maps developed from grid soil sampling. The management zones will also be evaluated to determine the optimum N rates in each zone. One management zone approach will assume that the lower productivity areas are inherently less fertile than the higher productivity areas and thus have higher fertilizer requirements. Higher amounts of fertilizer inputs are applied in the low productivity areas to bring the whole field up to optimum fertility levels. The other management zone approach will use a yield potential concept. This method assumes the lower productivity areas have a lower yield potential than the high productivity areas. Lower amounts of fertilizer are applied to the areas with less yield potential and higher amounts are applied to the high yield potential areas. Yield mapping data will be used to evaluate the prescription maps developed from the two methods of VRT and the two approaches of utilizing the management zones. Yield mapping can provide a dense spatial data set at low cost (Stafford et al., 1998). Well designed and well calibrated yield mapping systems can produce high quality yield estimates (Pierce, 1996).

Materials and Methods

Six N treatments were applied on three center pivot irrigated corn fields in northeast Colorado in 1999 and 2000. Field 1-99 and 1-00 in this study is the same field 1 reported on in chapter 3 while field 2-99 and 3-00 reported on in this chapter are different fields operated by the same farmer (Appendix 1, Table2). Field 1-99 contained 71 hectares, while field 2-99 contained 55 hectares and field 3-00 contained 61 hectares. Two VRT N treatments based on management zones and 1 VRT treatment based on grid soil sampling were evaluated. Three uniform N treatments (0 kg ha^{-1}, N-recommendation + 56 kg ha^{-1}, and N-recommendation - 56 kg ha^{-1}) were applied to assess if N was a limiting yield factor within management zones and to access the accuracy of the N recommendation algorithm used in the study for variable rate N application. Each field was predominantly planted to corn with occasional sugar beet (Beta vulgaris L.) rotations depending on market conditions. The fields had been in continuous corn for four years prior to the study. Soils present on the fields include a Valentine sand (sandy, mixed nonacid, mesic Typic Ustipsamment), a Bijou loamy sand (coarse loamy, mixed, mesic Mollic Haplargid), and a Truckton loamy sand (coarse loamy, mixed, mesic Udic Argiustoll).

All treatments received N credits for starter N applied and NO_3-N in the ground water. Ground water NO_3-N concentrations used for N credits in 1999 and 2000 were based on preseason water analysis and estimated irrigation amounts. Actual kg ha^{-1} NO_3-N amounts applied were determined from in season water analysis in 1999 and 2000 and actual irrigation amounts applied up to the tasseling growth stage. Actual kg ha^{-1} NO_3-N amounts applied were lower in 1999 and higher in 2000 (Table 4.1).

Table 4.1. Starter NO_3-N, irrigation H_2O, irrigation NO_3-N credits, and actual irrigation NO_3-N amounts

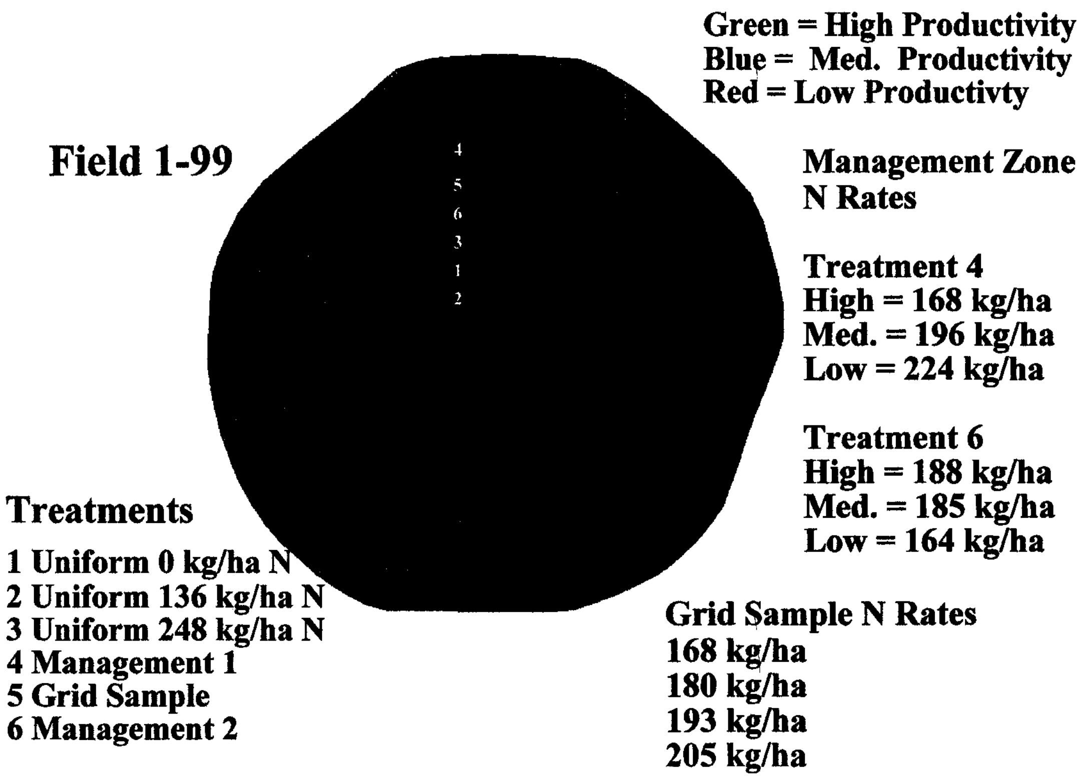
Field	Starter NO_3-N	Irrigation H_2O (total)[1]	Irrigation H_2O (tassel)[2]	Irrigation NO_3-N (credits)[3]	Irrigation NO_3-N (actual)[4]
	kg ha^{-1}	m^3	m^3	kg ha^{-1}	kg ha^{-1}
1-99	28	2415	1439	28	19
2-99	28	1850	1142	35	12
1-00.	28	2775	1562	28	44
3-00	28	2827	1809	28	54

1 Irrigation water applied during entire growing season
2 Irrigation water applied until tassel growth stage
3 Estimated NO_3-N credits
4 Actual NO_3-N credits

The experimental area at each location was sampled using a 0.4 hectare grid for the grid-based treatments (GSVRT). Sampling points were located randomly within the grids using Farm GPS software (Red Hen Systems, 1995) . Routine analysis was performed on the surface samples from 0 to 20 cm which included NO_3-N and organic matter; subsurface samples from 20 to 60 and 60 to 120 cm were analyzed for nitrate. Nitrate was extracted using 2M KCL and analyzed by cadmium reduction-sulfanilamide colorimetric (R.L. Mulvaney, 1996). Organic matter was estimated from Loss-on-Ignition and regressed to Walkley-Black (Nelson and Sommers, 1996). From this analysis an N recommendation was developed for each grid point using the University of Nebraska nitrogen algorithm (Hergert et al.,1995) with a common expected yield value of 12.5 Mg ha^{-1}. Using these data, an interpolated N recommendation surface was then generated for the VRT application map. The interpolated surface was developed using the Kriging Interpolator 3.1 extension in Arcview 3.1. Kriging procedures and parameters are presented in Appendix 2.

Aerial photographs were used as an initial template in developing the management zones. A gray scale image of a bare soil photograph was enhanced to contrast color differences. The farmer then drew vector lines using Agri Trak Professional®[1] to establish individual management zones (high, medium, and low productivity areas) based on soil color, topography, and his management experience on the field. One management zone treatment (M1VRT) approach assumes that the lower productivity areas are inherently less fertile than the higher productivity areas and thus have higher fertilizer requirements. Higher amounts of fertilizer inputs are applied in the low productivity areas to bring the whole field up to optimum fertility levels. This is the approach our cooperating farmer has used for VRT application. He determined rates from minimal soil test data from each zone using a constant expected yield. The other management zone treatment (M2VRT) uses a yield potential approach. This method assumes the lower productivity areas have a lower yield potential than the high productivity areas. Lower amounts of fertilizer are applied to the areas with less yield potential and higher amounts are applied to the high yield potential areas. Nitrate and SOM samples collected for the GSVRT treatment were averaged within each zone and rates were generated using the University of Nebraska N algorithm with variable expected yields for this treatment. Expected yields were 13.1 , 11.9 and 10.6 Mg ha^{-1} in the high, medium, and low productivity zones respectively. These rates were derived in consultation with the cooperators.

A whole field N recommendation was also generated from the grid soil sample data using the University of Nebraska N algorithm with a 12.5 Mg ha^{-1} expected yield to establish the N-recommendation + 56 kg ha^{-1}, and N-recommendation - 56 kg ha^{-1} treatments. The treatments were arranged in a randomized two factor cross design with nested replications within management zones. Each treatment was 24 meters (32 rows wide) corresponding to the applicator width and ran the length of the field (approximately 912 meters). Yield data were replicated within each treatment strip in 30 m increments. Each treatment crossed each of the management zones. Urea-ammonium nitrate was applied preplant to each treatment using a commercial Terrgator applicator equipped with a Raven controller and a Agritrak variable rate control system. The application system was evaluated in 1998 and 1999, N rates applied were spatially very accurate (Auglund, 1999). See Figures 4.1 and 4.2 for management zones, N rates and treatment strips.



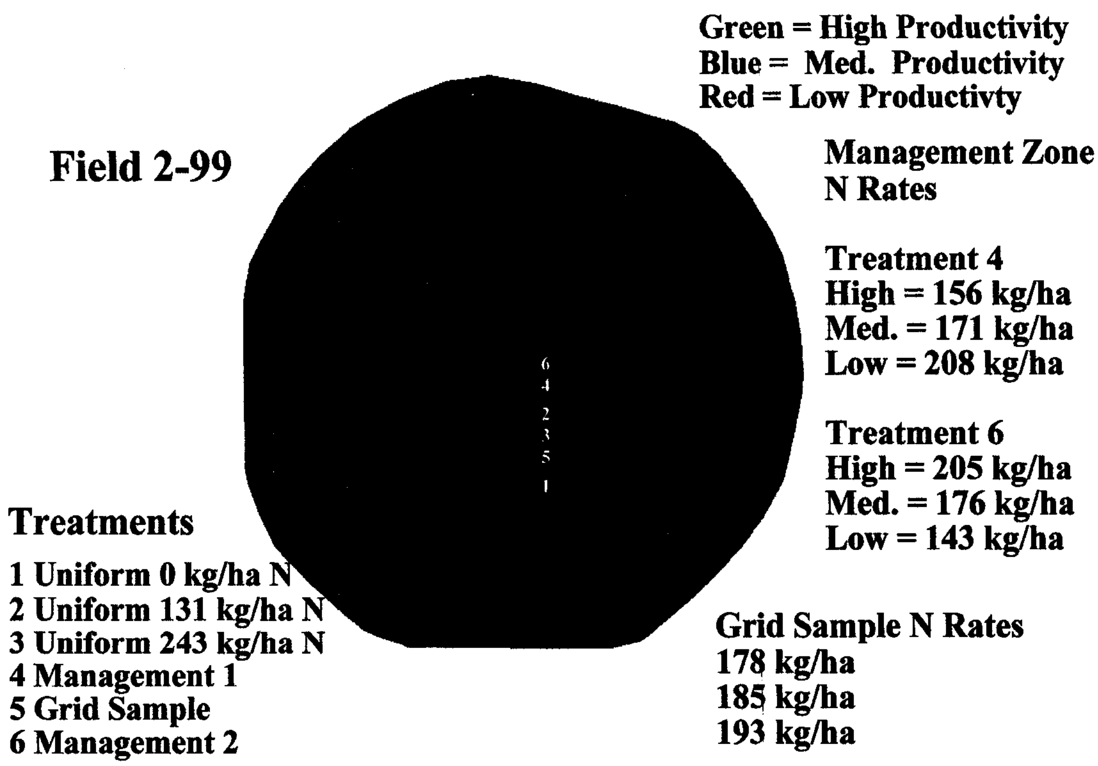
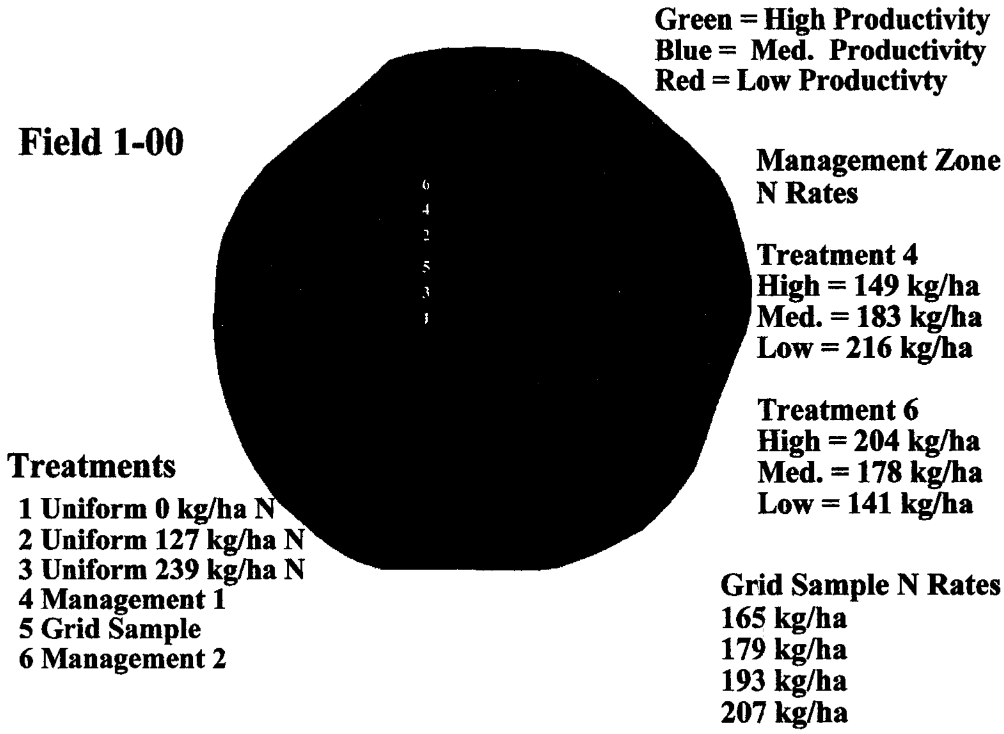


Figure 4.1. Farmer identified management zones, N rates, and treatment strips for fields 1-99 and 2-99



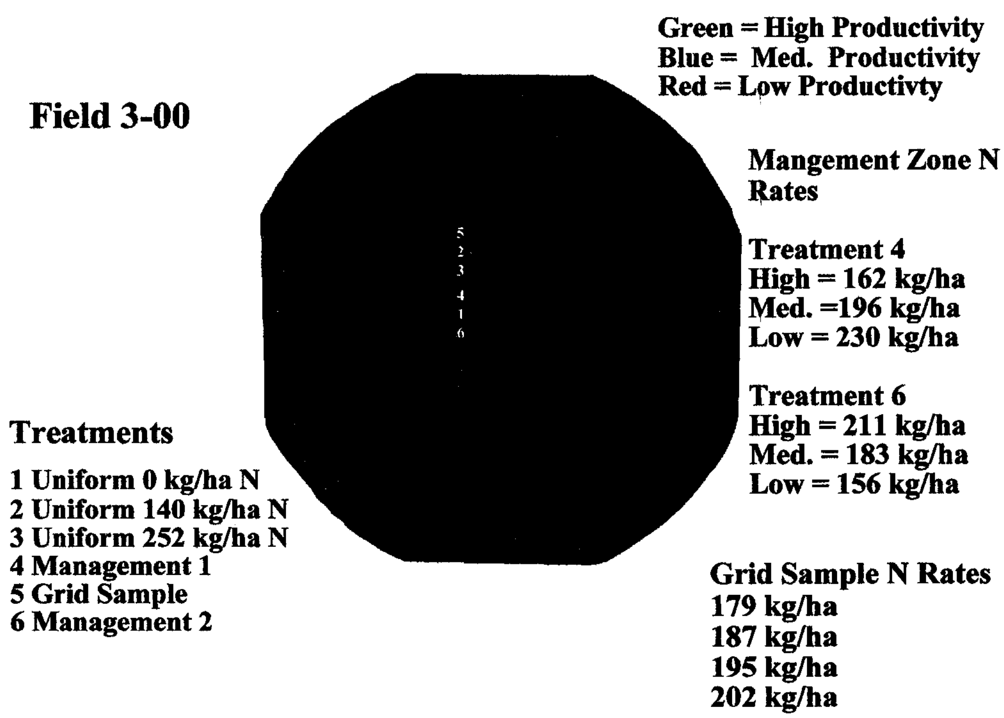


Figure 4.2. Farmer identified management zones, N rates, and treatment strips for fields 1-00 and 2-00

The following codes will be used when referring to management zones and treatments in the following text and tables:

Table 4.2. Codes for management zones and treatments

Code	Zones and Treatments
MZ1	low productivity zones
MZ1	medium productivity zones
MZ3	high productivity zones
Treatment 1	0 kg ha^{-1}
Treatment 2	N-recommendation - 56 kg ha^{-1}
Treatment 3	N-recommendation + 56 kg ha^{-1}
Treatment 4	M1VRT
Treatment 5	GSVRT (grid based approach)
Treatment 6	M2VRT

The fields were harvested and yield mapped with a Case IH®[1] Axial Flow combine equipped with a Micro-Trak®[1] yield monitor with Ashtech®[1] GPS receivers and a base station for differential correction described earlier. The center 16 rows of each treatment were used for yield evaluation. Yield data were processed and mapped using Farmers Software Harvest Mapping System®[1].

Nitrogen treatments were analyzed using the spatial auto regressive model described in Chapter 3. Spatial autocorrelation was measured using Moran's I (Moran, 1950). The Moran's I is used to test for the presence of spatial autocorrelation in a two-dimensional plane. In this study, the null hypothesis is that the measurements of yield data are independent of one another in space. Moran's I is a dimensionless statistic and can be interpreted as a Pearson product-moment correlation between variables x and y.

The index generally ranges over the interval of -1+1, but can exceed these limits if an irregular pattern of weights has been used or extreme values are heavily weighted (Bonham and Reich, 1999). The analysis of variance as a function of management zones consisted of a two factor cross design with nested replications within management zones. The spatial weight matrix used in the analysis was based on inverse distance. Yield observations were averaged in 30 m by 12 m replications in each management zone in each treatment strip for analysis. Data pixels that fell into more than one management zone were dropped. The null hypothesis of no significant differences between N treatments within a given management zone was tested by the ANOVA model.

$$Y(ijk) = y.. + a(i) + b(j) + e(ijk)$$

where y.. is the grand mean of all observations, a(i) the effect of the ith N treatment, b(j) the effects of the jth management zone, e(ij) are independent random errors. Equality of means by N treatment and management zone was tested with a restatement of the ANOVA model in the form of a regression model.

$$Y(ijk) = y..\ a1Xik1 + a2\,Xik2 + a3\,Xik3 + a4\,Xik4 + a5\,Xik5 + b1Zjk1 + b2Zjk2 + e(ij)$$

where

Xik1 = 1 if the observation was from treatment 1
-1 if the observation was from treatment 6
0 otherwise

Xik2 = 1 if the observation was from treatment 2
-1 if the observation was from treatment 6
0 otherwise

Xik3 = 1 if the observation was from treatment 3
-1 if the observation was from treatment 6
0 otherwise

Xik4 = 1 if the observation was from treatment 4
-1 if the observation was from treatment 6
0 otherwise

Xik5 = 1 if the observation was from treatment 5
-1 if the observation was from treatment 6
0 otherwise

Zik1 = 1 if the observation was from the low productivity zone
-1 if the observation was from the high productivity zone
0 otherwise

Zik2 = 1 if the observation was from the medium productivity zone
-1 if the observation was from the high productivity zone
0 otherwise

When spatial autocorrelation exists is a data set the assumption if independent observations in a classical model is violated. This can underestimate the standard errors, resulting in increased overall significance between individual parameters or overestimate the standard error resulting in an overall lack of significance when one exists (Bonham and Reich, 1999).

Results and Discussion

4.1 Spatial Analysis of Variance of Corn Yield

Field 1-99 Spatial analysis of variance of corn yield over N treatments as a function of management zones

The grain yield in treatment 1 was significantly lower than all other treatments across all zones indicating that N was a yield limiting factor (Table 4.3). The grain yield in treatment 2 was significantly lower than treatments 3, 4, and 6 in MZ 1, however there was no significant difference between treatments 3, 4, 5, and 6 in MZ1. There was no significant difference in yields between treatments 2, 3, 4, 5, and 6 in MZ 2 and there was no significant difference between treatments 2, 4, 5, and 6 in MZ 3. Management zone 1 seems to be more sensitive to lower N rates than zones 2 and 3. The check and recommended rate - 56 kg ha^{-1} were significantly lower than treatments 3, 4, and 6 where higher rates were applied. The N algorithm seems to be performing effectively in MZ1 with little additional yield response when the recommended rate + 56 kg ha^{-1} was applied at treatment 3. At MZ3 there was little yield response beyond the recommended rate - 56 kg ha^{-1}. The N algorithm seems to be over applying in the higher productivity soils at this field. The management zones followed the expected trends with the lowest yields in MZ1 and the highest yields in MZ3. There were significant differences across all management zones in treatments 1, 2, 5, and 6 while zone 1 & 3 and 2 & 3 were significantly different in treatments 3 and 4. This indicates the zones do represent homogeneous sub regions within the field. These results are similar to the results discussed in Chapter 2.

Table 4.3. Analysis of variance of grain yield on field 1-99 over N treatments as a function of management zone (MZ=Management Zone and TRT=Treatment)

MZ	Trt1	Trt2	Trt3		Trt4	Trt5	Trt6
	-------	------	---------	Mg ha^{-1}	------	--------	------
MZ1	A6.0a	B6.8a	C8.8a		C9.1a	BC8.0a	C8.3a
MZ2	A7.6b	B9.8b	B10.1b		B10.4b	B9.9b	B9.6b
MZ3	A10.5c	B11.1c	C12.1b		BC11.9b	BC11.4c	BC11.5c

TRT means preceded by a different higher case letter are significantly different at $p < 0.05$
MZ means followed by a different lower case letter are significantly different at $p < 0.05$

Field 2-99 Spatial analysis of variance of corn yield over N treatments as a function of management zones

The grain yields in treatment 1 was significantly lower than all other treatments and treatment 2 was significantly lower than treatment 3 across all zones (Table 4.4). There were no significant differences in yield between the VRT treatments, management zone VRT seems to be at least as effective as grid based VRT in maintaining corn yields in this field. The N algorithm seems to be performing reasonably well in MZ 2 and 3. Crop yields were not significantly higher in the recommended rate + 56 kg ha^{-1} treatment than the recommended rates in treatments 4, 5, and 6. However in MZ1 significantly higher yield response was seen with the recommended rate + 56 kg ha^{-1} treatment over the recommended rates in treatments 4, 5, and 6. In MZ1 the N algorithm seems to be under applying. The management zones followed the expected trends with the lowest yields in MZ1 and the highest yields in MZ3. There were significant differences between management zones in all treatments except treatment 1. The yields in management zones 1 & 2 and 1 & 3 were significantly different in treatments 2, 3, and 6 while zones 1 and 3 were significantly different in treatments 4 and 5. The data indicates distinct differences between management zone 1 and zones 2 and 3. However zones 2 and 3 are not significantly different. Perhaps only 2 management zones are being identified on this field.

Table 4.4. Analysis of variance of grain yield on field 2-99 over N treatments as a function of management zone (MZ=Management Zone and TRT=Treatment)

MZ	Trt1	Trt2	Trt3		Trt4	Trt5	Trt6
	-------	------	---------	Mg ha^{-1}	------	--------	------
MZ1	A4.3a	B7.9a	C9.5a		B8.8a	B8.3a	B8.4a
MZ2	A4.6a	B8.5b	C10.8b		CD10.1ab	BC9.7ab	CD10.4b
MZ3	A3.5a	B9.9b	C11.5b		CB10.4b	CB10.9b	CB10.7c

TRT means preceded by a different higher case letter are significantly different at $p< 0.05$
MZ means followed by a different lower case letter are significantly different at $p< 0.05$

Fields 1-00 and 3-00 Spatial analysis of variance of corn yield over N treatments as a function of management zones

At field 1-00, the grain yields in treatment 1 was significantly lower than all other treatments across all zones. At field 3-00, treatment 1 was significantly lower than all other treatments in management zones 1 and 2. However there was no significant difference in yields in treatments in management zone 3.

Grain yields followed the expected management zone trends at both fields with the highest yields in MZ3 and the lowest in MZ1 (Tables 4.5 and 4.6). Significant differences were observed across management zones at field 1-00. In treatments 1, 2, 4, and 5 management zones 1 & 2 and 1 & 3 were significantly different, in treatments 3 and 6 all three management zones were significantly different. The management zones continue to represent homogeneous sub-regions at this field in 2000. At field 3-00 management zones 1 and 3 were significantly different in treatments 1 and 4, all three zones were significantly different in treatment 6. While grain yields followed the expected trends in treatments 2, 3, and 4 differences were not significant at the .05 level.

Table 4.5. Analysis of variance of grain yield on field 1-00 over N treatments as a function of management zone (MZ=Management Zone and TRT=Treatment)

MZ	Trt1	Trt2	Trt3		Trt4	Trt5	Trt6
	-------	------	---------	Mg ha^{-1}	------	--------	------
MZ1	A7.0a	B10.1a	B9.6a		B9.7a	B9.8a	B9.6a
MZ2	A9.2b	B11.2ab	B12.9b		B12.0ab	B12.1b	B11.8b
MZ3	A11.0b	B12.5b	B13.6c		B12.6b	B12.4b	B12.7c

TRT means preceded by a different higher case letter are significantly different at p< 0.05
MZ means followed by a different lower case letter are significantly different at p< 0.05

Table 4.6. Analysis of variance of grain yield on field 3-00 over N treatments as a function of management zone (MZ=Management Zone and TRT=Treatment)

MZ	Trt1	Trt2	Trt3		Trt4	Trt5	Trt6
	-------	------	---------	Mg ha^{-1}	------	--------	------
MZ1	A8.2a	B11.9a	B12.6a		B12.6a	B11.9a	B11.4a
MZ2	A10.3ab	B14.0a	B13.7a		B14.2a	B13.7ab	B13.0b
MZ3	A12.4b	A14.4a	A13.9a		A14.6a	A14.8b	A14.5c

TRT means preceded by a different higher case letter are significantly different at $p < 0.05$
MZ means followed by a different lower case letter are significantly different at $p < 0.05$

The check treatment had significantly lower yields than all other treatments over all fields and years indicating N is a limiting factor at these sites. Moderately high N concentrations in the irrigation water and somewhat excessive irrigation rates at field 3-00 may be masking the treatment and management zone effects to a degree (Table 4.6). Excessive N application will be an ongoing concern and limitation with N studies in semiarid heavily irrigated systems where N is present is the ground water. It appears one should take care in developing N rates for these types of systems taking into account all possible irrigation scenarios.

The effectiveness of the N algorithm varied by management zone and fields. At field 1-97 the algorithm performed well in MZ1 but was less effective in the higher productivity zones 2 and 3. However at field 2-97 the algorithm was more effective in the higher productivity zones 2 and 3 and less effective in MZ1. At field 1-00 little yield response occurred beyond the recommended rate - 56 kg ha^{-1} across all zones. At field 1 in 2000 the N algorithm seems to be over applying across all zones.

Significant zone effects were noted across the uniform treatments at each site indicating that the management zones reflected distinct sub-regions within the field.

Other research on near by fields found similar results (Fleming et al., 2001). Soil organic matter and soil texture are probably the major factors defining the management zones. The high productivity zones were consistently highest in SOM and clay while the low productivity zones were lowest in SOM and highest in sand across both fields. Higher clay and SOM levels would lead to higher water holding capacity and cation exchange capacity resulting in higher productivity.

There were no significant differences across the VRT treatments. These data indicate that management zone based variable rate application is at least equally effective as grid based application. However, the cost of implementing the management zone based VRT program is less making it a profitable alternative to grid soil sampling. The majority of the cost advantage is due to the soil sampling and analysis cost associated with grid sampling. Total N applied was similar between the management zone and grid sample based treatments.

Additional studies are needed to better quantify the optimum N rate in each zone. Current recommendation algorithms may not be effective for VRT applications. Using a wider range of N rates, regression models may determine the economically optimum N rate in each zone. Due to the environmental dynamics of N in soils a reactive approach utilizing remote sensing technology may be more effective than predictive approaches.

Variable rate N application using management zones can involve increased risk. Management zone N response may not be consistent leading to problems in predicting the most effective rates across management zones. In season crop conditions such as unusually favorable growing conditions or yield limiting conditions such as pest infestation, pesticide injury, hail, frost or N losses from excessive rainfall or volatilization can contribute to temporal differences in N response. Increased management will be needed to fully realize VRT potential. Consistent best management practices for water and N application are needed to evaluate year to year management zone N response. Inconsistent management could also lead to temporal changes in N response. The opportunity for improved management using VRT is not only to obtain more data from a management zone within a field, but also to be able to interpret the data in order to make better management decisions that are most appropriate for that zone. Precision farming is not just the use of high-tech equipment, but the acquisition and wise use of information obtained from that technology.

CHAPTER 5

SOIL COLOR WITH FARMER INPUT VS. APPARENT SOIL CONDUCTIVITY: EVALUATING DIFFERENT APPROACHES TO DEVELOPING MANAGEMENT ZONES FOR VARIABLE RATE FERTILIZER APPLICATION

Literature Review

Accurate prescription maps are essential for effective VRT N fertilizer application (Sawyer,1994; Ferguson et al., 1996). Researchers have understood the value of dividing whole fields into smaller, homogeneous regions for fertility management. Earlier studies proposed the division of fields by soil type (Carr et al., 1991). There work indicated that applying different fertilizer treatments to contrasting soils in a field can generate greater returns than applying a field average fertilizer treatment. Mausbach et al. (1993) concluded National Cooperative Soil Survey is not adequate for variable rate application. Soil surveys were not intended for precision farming and tend to map at scale too coarse to be effective. Franzen et al. (2002) compared Order 1 and Order 2 soil surveys with maps from grid sampling and topography based zone maps. Order 2 soil surveys were seldom useful in determining zones for site specific management of NO_3-N. Order 1 soil surveys were more highly related to soil NO_3-N than Order 2 surveys, but their consistency was not as high as when topography based zones or maps from grid sampling were used. Landscape position also has been used to divide fields (Fiez et al., 1994). They found that landscape position alone was not effective in dividing fields into units for variable rate N management. However Franzen et al. (2000) concluded that topography based zone soil sampling may be useful in semiarid environments. Long et al. (1998) proposed using the spatial variation in grain protein levels to identify nitrogen management zones in spring wheat. Currently, the procedure is applicable for dryland fields that are cropped annually to wheat. Practical implementation of this procedure requires that an appropriate sensor be made available to producers that can continuously read the protein concentration of grain from combine harvester. Stafford et al. (1998) used yield maps to regionalize fields into management units. The clustering procedure they used recognized subregions of the fields with distinct patterns of season to season variation in yields. Boydell and McBratney (1999) found that a number of consecutive years of remotely sensed cotton yield estimates clustered to generate regions of similarity for management zones. Yang and Anderson (1996) demonstrated that aerial digital videography of grain sorghum fields is a useful tool for establishing within-field management zones. Multi spectral video was also useful in modeling the spatial variability of yield. A significant negative correlation (r^2=0 .90) was obtained between the red spectral band and crop yields. Shatar and McBratney (2001) used a k-means cluster analysis on sorghum yields, soil organic C, and soil K to subdivide fields into homogeneous units. The algorithm presented shows some promise for identifying spatially contiguous zones which are more homogenous in soil properties than the whole field. Mulla and Bhatti (1997) conclude that spatial patterns in surface organic matter content and yield maps could be useful in delineating fertilizer management zones. Using fixed fertilizer costs and wheat prices their study suggests the economic return was greatest when the management zones are defined using organic matter. Ostergaard (1997) developed management zones for VRT N application based on soil type, yield, topography, aerial photos, and producer experience. Five fields were divided into 12 to 17 management zones. The zones were soil sampled to determine N rate. They found a $15 to $35 per ha economic advantage using variable rate N application. Fleming et al., (2001) describe the application of soil color and farmer knowledge to define management zones for variable rate fertilizer application. Initial analysis indicates that this method is effective in identifying different management zones. However, ground truthing is needed to develop accurate VRT maps from the zones. A management zone for VRT application can be defined as a sub-region of a field that expresses a homogeneous combination of yield limiting factors for which a single rate of a specific crop input is appropriate (Doerge, 1999).

Developing Management Zones:

Method 1 - Soil Color with Farmer Input

The spectral properties of bare soil surfaces is largely governed by soil organic matter (SOM) and moisture (Schreier et al., 1988). The grey tone pattern in black and white aerial photographs is often a reflection of these soil properties and may be linked to productivity (McCann et al., 1996). Chen, et al. (2000) found that remotely sensed imagery of a bare soil field could be quantified to describe the spatial variation of SOM. Predicted SOM was highly correlated with measured SOM ($r = 0.97$). The technology and methodology were simple and accurate enough to be of practical use in agricultural production fields. Using LANDSAT TM images Bhatti et al. (1991) reported SOM distribution highly correlated with the spatial distribution determined by grid sampling the surface soil. In addition the semivariograms for the two methods of determining SOM were similar. More importantly, the SOM content was significantly correlated to winter wheat yield. These data suggest that SOM determined by aerial photographs or remote sensing may be used to determine site-specific management zones.

Scientists know that the experiences of farmers have been extremely important in the development of agriculture as we know it today (Crookston, 1996). If it were not for farmers experiential decision-making most of the modern agriculture that we take for granted today would be unknown. Dr. Crookston has spent several years working with agricultural researches in developing countries. It was his observation that the family farm has been a valuable research enterprise ever since agriculture began. Each generation has studied its alternatives and made its decisions. Unfortunately the potential contributions of indigenous farmer knowledge to soil and crop research is not being fully utilized today. Farmers generally know which areas of a field produce high yields and which areas are low in production. It is logical that nutrient needs are different for these areas. This allows identification of different "management zones" in a field using farmer knowledge as one of the predictors.

Method 2 - Soil Electrical Conductivity

Electrical conductivity (EC) is the ability of a material to transmit (conduct) an electrical current. Apparent electrical conductivity (ECa) mapping has been useful in locating saline seeps in the northern Great Plains (Halvorson and Rhoades, 1974) and for diagnosing salinity related problems in the irrigated Southwest (Rhoades and Corwin, 1981). Researchers also have used soil ECa to measure or estimate many other chemical and physical properties of non-saline soils. Williams and Hoey (1987) found that ECa strongly correlates to soil texture. In addition to its ability to identify variations in soil texture, electrical conductivity has proven to relate closely to other properties that often determine a field's productivity (Lund et al., 1999). These include water content (Kachanoski et al., 1988), cation exchange capacity and exchangeable Ca and Mg (McBride et al., 1990), depth to claypans (Kitchen et al., 1999), soil organic C (Jaynes et al., 1996) and herbicide behavior in soil (Jaynes et al., 1994). Sudduth et al. (1995) found strong correlations between ECa and depth to claypan and yield. Heermann et al. (1999) reported that ECa was the best predictor of crop yield when compared to many other common soil and crop parameters. Soil classification using ECa provides an effective basis for delineating interrelated physical, chemical, and biological soil attributes (Johnson et al., 2001). With the advent of GPS, practitioners can now place ECa measuring devices on GPS-equipped field vehicles and create ECa maps for all types of agricultural soils. These maps can be the basis for developing management zones for VRT. The objective of this chapter is to compare and evaluate prescription maps developed from soil color and farmer experience with prescription maps developed from ECa.

Materials and Methods

To develop the apparent electrical conductivity (ECa) management zones fields 1-97 and 2-97 described in chapter 3 (Appendix1, Table 3) were mapped using a GPS equipped Veris® model 3100 conductivity sensor (Lund and Christy, 1998). The area of field 1 was 71 ha while field 2 was 52 ha (Appendix1, Table 3). Soils in both fields included a Valentine sand (sandy, mixed nonacid, mesic Typic Ustipsamment), a Bijou loamy sand (coarse loamy, mixed, mesic Mollic Haplargid), and a Truckton loamy sand (coarse loamy, mixed, mesic Udic Argiustoll) (Soil Taxonomy, 1996). These are non-saline soils. The fields were in continuous corn (*Zea mays* L.) throughout the study.

Each field has been managed and operated by the same 2 farmers since 1977. Irrigation strategy was based on experience, no formal scheduling program was used. Fertility management was based on soil sampling and experience (Table 3.1, Chapter 3).

The Veris system identifies soil variability by directly sensing soil electrical conductivity. As the cart is pulled through the field, a pair of coulter electrodes transmit an electrical current into the soil, while two other pairs of coulter electrodes measure the voltage drop. The measurement electrodes are configured to measure ECa over an approximate 0- to 30-cm depth (shallow reading) as well as a 0- to 90-cm depth (deep reading). The system georeferences the ECa measurements using an external Trimble ag32 DGPS receiver, and stores the resulting data in digital form. The Veris sensor cart records data on a 1 s interval, and data density can be modified by the operator through changes in travel speed and/or spacing between measurement transects.

Data were collected in April 1998 on transects spaced approximately 10 m apart on a l-s interval, corresponding to a measurement every 3 to 5 m along the transects. This procedure resulted in a data density of 200 to 300 points per ha.

The shallow, deep, and difference between the shallow and deep ECa readings were clustered into three management zones using Ward's Minimum Variance technique in SAS (SAS Institute, 1990) described in chapter 3. Zones with the highest, intermediate, and lowest ECa values were defined as high, medium and low productivity zones respectively. The soil color with farmer input management zones (SC) were developed using the methods described in chapter 3. The soil nutrient levels, texture, and crop yields data from 1997 described in chapter 3 were used to evaluate the two methods of developing management zones.

The management zones were analyzed with an ordinary least squares model and a spatial ANOVA using a spatial auto regressive model in S+ to account for correlation between observations described in chapter 3.

Results and Discussion

5.1 Field 1-97

A classical ordinary least squares (OLS) model was initially used on the soils and yield data based on management zone. When spatial autocorrelation between observations were indicated using Moran's I, a spatial auto regressive model (SPA) was used. When comparing the two methods the management zones and results of the analysis of variance were somewhat similar on this field with the following common observations (Figure 5.1).

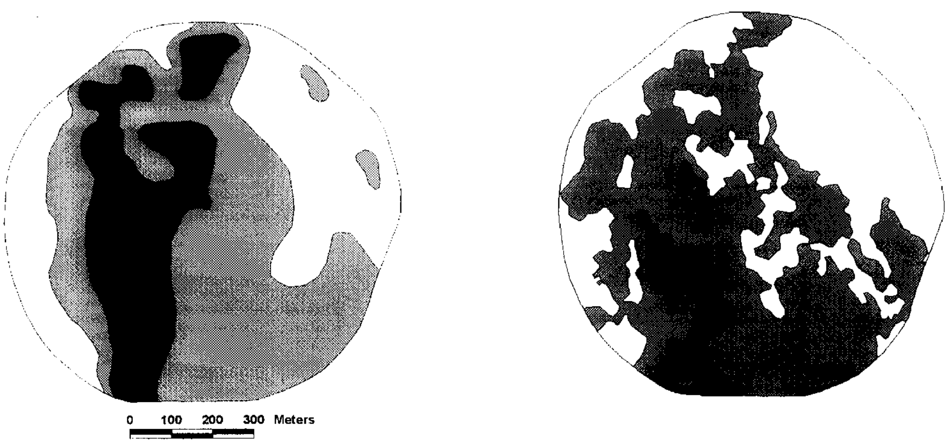


Figure 5.1. Field 1 management zones. Soil color with farmer input management zones on the left and ECa management zones on the right at field 1 (low productivity = white, medium productivity = gray, high productivity = black).

Levels of SOM and crop yield were significantly different in all management zones. Nitrate and K levels were significantly different between the high/low and high/medium zones while Zn levels were significantly different between the high and low productivity zones. Phosphorus did not follow the trends seen with the other nutrients, with higher levels seen in the lower productivity zones and lower levels in the high productivity zones.

Table 5.1. Soil color and conductivity-field 1-97 analysis of variance of SOM, NO_3-N, and P as a function of management zone (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity).

		SOM			NO_3-N			P	
				Soil Color					
MZ	n	%	SD	n	ppm	SD	n	ppm	SD
1	35	0.8a	0.03	35	18a	1.3	35	16a	0.9
2	57	1.0b	0.02	57	20a	1.1	57	11b	0.8
3	29	1.2c	0.03	29	25b	1.5	29	14a	1.1
Model		SPA			SPA			OLS	
Pr > F		0.0001			0.0001			0.001	
				Apparent Soil Conductivity					
1	52	0.85a	0.02	52	17a	1.1	52	13a	0.8
2	57	1.0b	0.02	57	20a	1.1	57	13a	0.8
3	13	1.2c	0.05	13	30b	2.2	13	13a	1.7
Model		SPA			OLS			SPA	
Pr > F		0.0001			0.0001			0.0001	

Means followed by different letters are significantly different at $p < 0.05$

Soil texture showed similar trends. Clay and silt levels were higher in the high productivity zone, intermediate in the medium zones, and lowest in the low productivity zones while sand followed the opposite trend using both methods (Table 5.3). Differences were significant between all texture classes with the soil color method; however differences were not significant between the high and medium zones using the conductivity method.

Table 5.2. Soil color and conductivity-field 1-97 analysis of variance of K, Zn, and yield as a function of management zone (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity).

	K			Zn			Yield	
				Soil Color				
MZ	n	ppm	SD	n	ppm	SD	n	Mg ha^{-1}	SD
1	35	142a	6.6	35	3.8a	0.2	639	9.8a	0.2
2	57	160a	5.2	57	4.1ab	0..1	963	10.7b	0.1
3	29	207b	7.2	29	4.4b	0.2	474	10.8c	0.2
Model		SPA			SPA			SPA	
Pr > F		0.0001			0.001			0.0001	
				Apparent Soil Conductivity					
1	52	148a	6.0	52	4.0a	0.1	926	9.8a	0.1
2	57	166a	5.7	57	4.1ab	0..1	1080	10.7b	0.1
3	13	224b	12.0	13	4.5b	0.3	168	10.8c	0.2
Model		SPA			OLS			SPA	
Pr > F		0.0001			0.01			0.0001	

Means followed by different letters are significantly different at $p < 0.05$

Table 5.3. Soil color and conductivity-field 1-97 Analysis of variance of sand, silt, and clay as a function of management zone (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity).

	Sand			Silt			Clay		
				Soil Color					
MZ	n	%	SD	n	%	SD	n	%	SD
1	35	88.4a	.009	35	4.2a	.007	35	7.4a	.008
2	57	85.2b	.007	57	5.6b	.006	57	9.2b	.006
3	29	81.8c	.010	29	9.4c	.008	29	10.8c	.009
Model		OLS			OLS			OLS	
Pr > F		0.0001			0.0001			0.0001	

Table 5.3 Continued.

		Sand			Silt			Clay	
				Apparent Soil Conductivity					
1	13	87.7a	.009	13	4.5a	.006	13	7.7a	.008
2	57	83.8b	.006	57	6.3b	.005	57	10.0b	.006
3	52	81.5b	.014	52	7.8c	.007	52	10.7b	.009
Model		SPA			OLS			SPA	
Pr > F		0.0001			0.0001			0.0001	

Means followed by different letters are significantly different at $p < 0.05$

Higher productivity in areas of lower sand and higher clay levels would be expected due to the higher water holding and cation exchange capacity of the soils higher in clay.

The Moran's I for the raw data was significant across all parameters indicating the data are spatially autocorrelated (Appendix 1, Tables 4 and 6). In general the spatial model had slightly lower standard error and higher r^2 using both management zone approaches. However the spatial model was not always significantly better than the OLS. With the SC method the Likelihood ratios were not significant for P, sand, silt, and clay while with the EC approach the Likelihood ratios were not significant for NO3, Zn, and silt. The Moran's I for the residuals of these parameters was also not significant indicating the management zones are accounting for the spatial autocorrelation in these parameters.

These results are similar to the findings of Mulla and Bhatte (1997). They concluded that in terms of practicality organic matter estimated from bare soil images offer the best feasibility in dividing fields into management zones. Yang and Anderson

(1996) also had success using digital video images of sorghum fields to classify management zones. In this study color infrared digital video images of two grain sorghum fields in south Texas were acquired and classified into management zones using unsupervised classification. Their analysis of variance showed that plant biomass and yield differed significantly among their management zones.

It is interesting how similar the SC management zones that were defined using a qualitative supervised classification with our cooperating farmers are to the EC management zones that were defined using a quantitative unsupervised computer classification. The two methods seem to be capturing similar information in this field.

5.2 Field 2-97

Results of the spatial analysis of variance for the SC method on field 2 indicated that the soil and crop parameters were different across the management zones; however they did not follow the trends indicated by the farmer developed zones. The zone classified as medium in productivity was highest in SOM, K, yield, and clay, while the high productivity zones had intermediate values for these parameters. The low productivity zone had the lowest values for the parameters listed above and were highest in sand. In addition no significant difference was detected between the high and medium productivity zones for the soil parameters discussed above. This would seem to indicate this method is only defining two zones in this field (Tables 5.4, 5.5 and 5.6).

Table 5.4. Soil color and conductivity-field 2-97 analysis of variance of SOM, NO_3-N, and P as a function of management zone (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity).

	SOM			NO_3-N			P		
				Soil Color					
MZ	n	%	SD	n	ppm	SD	n	ppm	SD
1	38	0.96a	0.02	38	11a	0.7	38	11a	0.7
2	28	1.15bc	0.02	28	14bc	0.8	28	15bc	0.9
3	22	1.09c	0.02	22	14c	0.8	22	15c	1.0
Model		OLS			SPA			OLS	
Pr > F		0.0001			0.0001			0.001	
				Apparent Soil Conductivity					
1	39	0.95a	0.01	39	11a	0.6	39	11a	0.8
2	27	1.13b	0.02	27	13b	0.8	27	15a	0.9
3	22	1.14b	0.02	22	15b	0.9	22	14.b	1.0
Model		OLS			SPA			OLS	
Pr > F		0.0001			0.0001			0.02	

Means followed by a different letters are significantly different at $p < 0.05$

Table 5.5. Soil color and conductivity-field 2-97 analysis of variance of K, Zn, and yield as a function of management zone (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity).

	K			Zn			Yield		
				Soil Color					
MZ	n	ppm	Sd	n	ppm	Sd	n	Mg ha^{-1}	SD
1	38	162a	5.1	35	2.2a	0.06	735	11.2a	0.2
2	28	218bc	5.9	57	2.7bc	0.08	500	14.1b	0.3
3	22	199c	6.7	29	2.7c	0.09	372	13.1c	0.3
Model		OLS			OLS			SPA	
Pr > F		0.0001			0.0001			0.0001	

Table 5.5 Continued.

		K			Zn			Yield	
				Apparent Soil Conductivity					
1	39	159a	4.5	39	2.2a	0.06	637	11.0a	0.2
2	27	203b	5.4	27	2.8b	0.08	605	13.4b	0.2
3	22	226c	6.0	22	2.7b	0.09	358	13.7c	0.3
Model		OLS			OLS			SPA	
Pr > F		0.0001			0.0001			0.0001	

Means followed by different letters are significantly different at $p < 0.05$

Table 5.6. Soil color and conductivity-field 2-97 Analysis of variance of sand, silt, and clay as a function of management zone (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity).

		Sand			Silt			Clay	
				Soil Color					
MZ	n	%	Sd	n	%	Sd	n	%	SD
1	38	84.4a	.008	38	7.3a	.006	38	8.3a	.007
2	28	75.4b	.009	28	13.3cb	.008	28	11.4b	.008
3	22	78.7c	.010	22	11.6c	.006	22	9.7ab	.009
Model		OLS			OLS			OLS	
Pr > F		0.0001			0.0001			0.0001	
				Apparent Soil Conductivity					
1	39	84.5a	.007	39	7.6a	.007	39	7.9a	.006
2	27	78.4b	.008	27	11.4b	.008	27	10.1b	.007
3	22	74.5c	.009	22	13.3c	.009	22	12.1c	.008
Model		SPA			OLS			OLS	
Pr > F		0.0001			0.0001			0.0001	

Means followed by different letters are significantly different at $p < 0.05$

The results from field 2 illustrate the SC method is consistently identifying different productivity sub-regions within the field, however it indicates the sub-regions need to be ground truthed to classify them as management zones. The management zones developed from EC indicate why the trends in the SC approach changed. The patterns of the zones from both methods are quite similar however the EC zones reveal significant inclusions of high productivity soils in the area that was defined as medium with the SC approach. There are also inclusions of medium productivity soils in the area defined as high in productivity with the soil color method (Figure 5.2).

Figure 5.2. Field 2 management zones. Soil color with farmer input management zones on the left and ECa management zones on the right at field 2 (low productivity = white, medium productivity = gray, high productivity = black).

All of the soil and crop parameters followed the trends indicated by the management zones. Crop yield, K, sand, silt, and clay were significantly different across all three zones using the clustered conductivity method (Tables 5.4, 5.5, and 5.6).

Other studies have also shown that clustering algorithms can be effective in developing management zones. Stafford et al. (1998) used yield maps to regionalize fields into management units. The clustering procedure they used recognized subregions of the fields with distinct patterns of season to season variation in yields. Boydell and McBratney (1999) found that a number of consecutive years of remotely sensed cotton yield estimates clustered to generate regions of similarity for management zones. Shatar and McBratney (2001) used a k-means cluster analysis on sorghum yields, soil organic C, and soil K to subdivide fields into homogeneous units. The algorithm presented showed some promise for identifying spatially contiguous zones which are more homogenous in soil properties than the whole field.

The results from the Moran's I analysis on the raw data was similar to field 1-97 with all of the parameters being spatially autocorrelated (Appendix 1, Table 4 and 6). However, the Moran's I for the residuals of most of the soil parameters was not significant indicating the management zones for the most part were accounting for the spatial correlation in the data in this field. The exceptions were NO_3 in both zone delineation methods and sand and clay with the ECa method. The Likelihood ratios were significant for these parameters indicating the spatial model was significantly better.

5.3 Conclusions

Both methods of developing management zones seem to be identifying homogeneous subregions within fields. However, in field 2-97 the EC_a approach was more effective in identifying three distinct management zones. The Moran's I analysis indicated the data were spatially autocorrelated. On field 1-97 the analysis was mixed with certain soil parameters the OLS model was adequate, with others a spatial auto regressive model was needed. On field 2-97 the OLS model was adequate; the MZ accounted for the spatial correlation for the most part in this field. This analysis has identified the large scale spatial variability between zones for each method. However, further analysis is needed to evaluate the small scale spatial variability within zones to determine which method is characterizing the fields most accurately. An intense small scale cluster sampling technique within each zone is needed to accomplish this. In the future methods using the information from both EC_a and soil color along with farmer knowledge may provide the most effective MZ.

CHAPTER 6

OVERVIEW SUMMARY

The overall objective of this dissertation is to develop and evaluate effective management zones for VRT N application prescription maps. Grid soil sampling has most frequently been used to develop these prescription maps, however, past research has indicated several technical and economic limitations associated with this approach. The initial objective to reach the overall objective stated above was to examine the concept of management zones as an alternative to grid soil sampling to develop prescription maps for VRT N application. To define the management zones two well documented relationships were used: i) Bare soil photographs indicating SOM levels, and ii) Farmer experience. These farmer developed management zones were compared to soil nutrient levels, texture, conductivity readings, topography, and crop yields collected in 1997, 1998, 1999, and 2000. Cluster analysis indicated that the management zones do represent different suites of soil characteristics. An analysis of variance showed that soil and crop parameters followed the trends indicated by the management zones on field 1-97,00. At field 2-97,00 the low productivity zone consistently had the lowest soil and crop parameter values however the medium and high zones were similar in most parameter values.

A second objective for the dissertation was to evaluate and compare the prescription maps using the management zones described above with prescription maps developed from grid soil sampling. To achieve this objective six N treatments were applied on three center pivot irrigated corn fields in northeast Colorado in 1999 and 2000. Field 1-99 and 1-00 in this study is the same field 1 reported on above while field 2-99 and 3-00 reported on here are different fields operated by the same farmer. Field 1-99 contained 71 hectares while field 2-99 contained 55 hectares and field 3-00 contained 61 hectares. Two VRT N treatments based on management zones and 1 VRT treatment based on grid soil sampling were evaluated. Three uniform N treatments (0 kg ha^{-1}, N-recommendation + 56 kg ha^{-1}, and N-recommendation - 56 kg ha^{-1}) were also applied to determine if N was a limiting yield factor within management zones and to access the accuracy of N recommendations used in the study.

Significant zone effects were found at each site indicating that the management zones reflected distinct sub-regions within the field. Other research on nearby fields found similar results (Fleming et al., 2001). Soil organic matter and soil texture were probably the major factors defining the management zones. The high and medium productivity zones were consistently highest in SOM and clay while the low productivity zones were lowest in SOM and highest in sand across both fields. Higher clay and SOM levels would lead to greater water holding capacity and cation exchange capacity resulting in increased productivity.

The check treatment had significantly lower yields than all other treatments over all fields and years indicating N is a limiting factor at these sites. There were no significant differences in the variable rate treatments across all sites and years. These data indicate that management zone based variable rate application is at least equally effective as grid based application. However, the cost of implementing the management zone based VRT program is much less making it a profitable alternative to grid soil sampling. The majority of the cost advantage was due to the soil sampling and analysis cost associated with grid sampling. Total N applied was similar between the management zone and grid sample based treatments. Additional studies are needed to better quantify the optimum N rate in each zone. Current N recommendation algorithms may not be effective for VRT applications. Using a wider range of N rates, regression models may determine the economically optimum N rate in each zone. Due to the environmental dynamics of N in soils a reactive approach utilizing remote sensing technology may be more effective the predictive approaches.

The final objective for the dissertation was to compare and evaluate prescription maps developed from soil color and farmer experience with prescription maps developed from apparent soil electrical conductivity. Apparent electrical conductivity has proven to relate closely to other properties that often determine a field's productivity.

The management zones were analyzed with an ordinary least squares model (OLS) and a spatial ANOVA using a spatial auto regressive model (SPA). Both methods of developing management zones seem to be identifying homogeneous subregions within fields. However, in field 2-97 the apparent soil conductivity approach was more effective in identifying three distinct management zones. The Moran's I analysis indicated the data was spatially autocorrelated. On field 1-97 the analysis was mixed with certain soil parameters the OLS model was adequate, with others a spatial auto regressive model was needed. On field 2-97 the OLS model was adequate; the management zones accounted for the spatial correlation for the most part in this field. This analysis has identified the large scale spatial variability between zones for each method. However, further analysis is needed to evaluate the small scale spatial variability within zones to determine which method is characterizing the fields most accurately. An intense small scale cluster sampling technique within each zone is needed to accomplish this. In the future, methods using the information from both apparent soil conductivity and color along with farmer knowledge may provide the most effective management zones.

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APPENDIX 1
FIELD INFORMATION AND STATISTICS TABLES

Appendix 1 Table 1 Chapter 3 field operation/management summary

Field	Year	Field #	Size	Soil Sampling Date	Grid size	Corn Hybrid	Planting Date	Harvest Date
1-97	1997	6	71 ha	4/24/97	76 m	Pioneer 3531	May 9-10	October 21-22
2-97	1997	39	52 ha	4/25/97	76 m	Pioneer 3559	May 5-6	November 1-3
1-00	2000	6	71 ha	3/16/00	76m	Pioneer 34G81	May 11-13	December 1-4
2-00	2000	39	52 ha	3/17/00	76m	Pioneer 34G81	May 3-4	October 13-15

Appendix 1 Table 2. Chapter 4 field operation/management summary

Field	Year	Field #	Size	Soil Sampling Date	Grid size	Starter-N	Irrigation-N	P	K	Corn Hybrid	Planting Date	Harvest Date
1-99	1999	6	71 ha	3/17/99	63 m	28 kg ha^{-1}	19 kg ha^{-1}	56 kg ha^{-1}	62 kg ha^{-1}	Pioneer 3414	May 9-10	November 2
2-99	1999	7	55 ha	3/18/99	63 m	28 kg ha^{-1}	12 kg ha^{-1}	34 kg ha^{-1}	45 kg ha^{-1}	Pioneer 3489	May 11-12	November 4
1-00	2000	6	71 ha	4/10/00	63m	28 kg ha^{-1}	44 kg ha^{-1}	50 kg ha^{-1}	56 kg ha^{-1}	Pioneer 34G81	May 11-13	December 4
3-00	2000	16	61 ha	4/6/00	63m	28 kg ha^{-1}	54 kg ha^{-1}	50 kg ha^{-1}	56 kg ha^{-1}	Pioneer 36B08	May 4-5	December 1

Appendix 1 Table 3 Chapter 5 operation/management field summary

Field	Year	Field #	Size	Soil Sampling Date	Grid size	Starter	Corn Hybrid	Planting Date	Harvest Date
1-97	1997	6	71 ha	4/24/97	76 m	28 kg ha^{-1}	Pioneer 3531	May 9-10	October 21-22
2-97	1997	39	52 ha	4/25/97	76 m	28 kg ha^{-1}	Pioneer 3559	May 5-6	November 1-3

Appendix 1 Table 4. Moran's I for the residuals and Likelihood Ratios for variables at fields 1-97 and 2-97

Field	Variable	Moran's I	Test Statistic	p-value	Likelihood Ratio	p-value
1-97	SOM - %	0.131	15.400	0.000	18.661	0.000
	NO_3-N - ppm	0.078	9.582	0.000	7.739	0.005
	P - ppm	0.023	1.624	0.119	1.961	0.161
	K - ppm	0.106	12.677	0.000	10.954	0.001
	Zn - ppm	0.044	5.769	0.000	4.389	0.036
	Yield - mg ha^{-1}	0.081	78.5635	0.000	622.527	0.000
	% Sand	0.006	1.017	0.309	0.138	0.711
	% Silt	0.001	0.706	0.481	0.001	0.973
	% Clay	0.009	1.249	0.212	0.325	0.569
	EM38	0.074	52.443	0.000	717.123	0.000
	Veris Shallow	0.065	40.887	0.000	516.820	0.000
	Veris Deep	0.078	48.119	0.000	622.523	0.000
2-97	SOM - %	0.009	1.241	0.215	0.425	0.515
	NO_3-N - ppm	0.069	6.716	0.000	5.850	0.016
	P - ppm	-0.004	0.923	0.356	1.509	0.219
	K - ppm	0.002	0.846	0.846	0.009	0.925
	Zn - ppm	0.006	1.081	0.280	0.138	0.711
	Yield - mg ha^{-1}	0.134	134.792	0.000	190.742	0.000
	% Sand	0.041	2.475	0.013	3.746	0.053
	% Silt	0.012	1.160	0.246	0.434	0.51
	% Clay	0.042	2.472	0.013	3.250	0.071
	EM38	0.091	121.1	0.000	246.123	0.000
	Veris Shallow	0.102	127.9	0.000	210.718	0.000
	Veris Deep	0.114	131.1	0.000	163.082	0.000

Appendix 1 Table 5. Moran's I for the residuals and Likelihood Ratios for variables at fields 1-00 and 2-00

Field	Variable	Moran's I	Test Statistic	p-value	Likelihood Ratio	p-value
1-00	SOM - %	0.104	11.868	0.000	13.3	0.000
	NO_3-N - ppm	0.006	1.073	0.283	0.171	0.679
	P - ppm	0.063	7.584	0.000	8.404	0.004
	K - ppm	0.115	13.036	0.000	9.407	0.002
	Zn - ppm	0.054	6.588	0.000	5.309	0.021
	Yield - mg ha^{-1}	0.073	65.228	0.000	210.086	0.000
	Veris Shallow	0.076	71.483	0.000	228.963	0.000
	Veris Deep	0.078	78.961	0.000	196.953	0.000
2-00	SOM - %	-0.009	0.329	0.742	1.015	0.314
	NO_3-N - ppm	0.003	0.914	0.361	0.029	0.863
	P - ppm	0.004	0.999	0.318	0.064	0.8
	K - ppm	0.002	0.876	0.381	0.017	0.896
	Zn - ppm	-0.004	0.597	0.597	0.017	0.896
	Yield - mg ha^{-1}	.140	141.882	0.000	341.945	0.000
	Veris Shallow	.913	129.016	0.000	267.957	0.000
	Veris Deep	.936	135.935	0.000	251.278	0.000

Appendix 1 Table 6. Moran's I for the residuals and Likelihood Ratios for variables at fields 1-97 and 2-97, conductivity developed management zones

Field	Variable	Moran's I	Test Statistic	p-value	Likelihood Ratio	p-value
1-97	SOM - %	0.132	15.749337	0.000	7.798	0.005
	NO_3-N - ppm	0.013	1.727	0.084	1.042	0.307
	P - ppm	0.038	5.192	0.000	4.338	0.037
	K - ppm	0.093	11.313	0.000	5.076	0.054
	Zn - ppm	0.015	1.842	0.066	1.199	0.273
	Yield - mg ha^{-1}	.128	88.973	0.000	423.573	0.000
	% Sand	0.135	16.027	0.000	8.901	0.003
	% Silt	0.019	2.162	0.051	2.127	0.144
	% Clay	0.125	14.903	0.000	13.023	0.000
2-97	SOM - %	0.015	1.399	0.162	0.649	0.421
	NO_3-N - ppm	0.069	6.716	0.000	4.761	0.029
	P - ppm	-0.001	0.929	0.353	0.834	0.361
	K - ppm	-0.006	0.360	0.719	0.155	0.694
	Zn - ppm	-0.002	0.552	0.581	0.021	0.886
	Yield - mg ha^{-1}	.143	122.083	0.000	348.265	0.000
	% Sand	0.134	12.084	0.000	6.613	0.010
	% Silt	0.041	2.678	0.007	3.158	0.076
	% Clay	0.0980	9.130	0.000	3.718	0.054

APPENDIX 2

DEVELOPING N-RECOMMENDATION POLYGONS

Steps Used in Developing N-Recommended Polygons - 1999

1. In Arcview 3.1, joined sample points data with sample values table containing N-Rec values.

2. Kriged point data for N-Rec values based on variograms and parameters as specified below. Kriging was performed in Arcview 3.1 using GWA SA Kriging Interpolator 3.1 extension in UTM-Zone 13-WGS84 projection.

   Parameters for 1-99 Kriging:
   - Selected Model = Gaussian
   - Lag = 20
   - Nearest Neighbors = 12
   - Search Distance = 500m

   Parameters for 2-99 Kriging:
   - Selected Model = Circular
   - Lag = 20
   - Nearest Neighbors = 12
   - Search Distance = 500m

3. Clipped kriged surface to boundaries of treatment strips.

4. Performed minor nearest neighbor smoothing (3 nearest neighbors, rectangular area) to eliminate small islands and sharp edges.

5. Converted grid surface to Arcview polygons using "Convert to shape file" option.

6. Converted Arcview polygon files to MapInfo polygon files using Universal Translator function in MapInfo.

7. Converted UTM-Zone 13-WGS84 projection to Lat/Long-WGS84 projection by using "Save Copy As" function in MapInfo.

Steps Used in Developing N-Recommended Polygons - 2000

1. In Arcview 3.1, joined sample points data with sample values table containing N-Rec values.

2. Kriged point data for N-Rec values based on variograms and parameters as specified below. Kriging was performed in Arcview 3.1 using GWA SA Kriging Interpolator 3.1 extension in UTM-Zone 13-WGS84 projection.

   Parameters for 1-00 Kriging:
   Selected Model = Linear with Silll
   Lag = 10
   Nearest Neighbors = 12
   Search Distance = 500m

   Parameters for 3-00 Kriging:
   Selected Model = Gaussian
   Lag = 17
   Nearest Neighbors = 12
   Search Distance = 500m

3. Clipped kriged surface to boundaries of treatment strips.

4. Performed minor nearest neighbor smoothing (3 nearest neighbors, rectangular area) to eliminate small islands and sharp edges.

5. Converted grid surface to Arcview polygons using "Convert to shape file" option.

6. Converted Arcview polygon files to Mapinfo polygon files using Universal Translator function in MapInfo.

7. Converted UTM-Zone 13-WGS84 projection to Lat/Long-WGS84 projection by using "Save Copy As" function in MapInfo.

APPENDIX 3

SPATIAL ANALYSIS OF NITROGEN REFLECTANCE INDEX OVER N TREATMENTS

Introduction and Literature Review

The major objective of this appendix is to compare and evaluate prescription maps developed from the management zones described earlier in the dissertation with prescription maps developed from grid soil sampling using remote sensing data. All locations and treatments are the same as described in chapter 4 of the dissertation. A sub-objective of this appendix will be to evaluate the most appropriate method of selecting a reference value when using the NRI to evaluate plant N status over different sub-regions of a field.

Remote sensing can be used to evaluate the plant N status (McMurtrey et al., 1994; and Blackmer et al., 1994). Bausch and Duke (1996) introduced the Nitrogen Reflectance Index (NRI) to estimate the plant N status of corn. The index is calculated from a ratio of NIR/GREEN reflectance of an area of interest to NIR/GREEN reflectance of a reference, i.e. N stress free corn. This technique provides a very fast spatial and temporal estimate of plant N status. The NRI may help to spatially evaluate which VRT method most effectively maintains N stress free corn throughout the growing season.

Materials and Methods

Corn canopy radiance and incoming irradiance were measured simultaneously with a mobile data acquisition system (Bausch et al., 1990). This system consisted of an instrument platform with two Exotech 100BX four-channel radiometers mounted on a boom carried on a high-clearance tractor as shown in. The radiometer height was 10 m above ground. The Exotech 100BX radiometer is a compact, lightweight, rugged and entirely self-contained instrument designed for use in the field environment. The 100 BX is supplied with adapters for each channel to obtain a 1°, 15°, or a 180° field of view. An important feature of this instrument is that each of the four independent channels has separate gain controls. This feature aids in measurement accuracy in cases where there is a large difference in radiance in the four spectral bands (Exotech Incorporated).

One of the two radiometers on the instrument platform measured target radiance. The radiometer was fitted with 15° circular field of view (FOV) optics. It was pointed perpendicular to the target (nadir view angle), and the viewed spot on the ground was 2.6m in diameter. The other radiometer looked upward to measure irradiance with a 180° FOV.

Radiant energy was measured in the green (520 nm – 600 nm), red (630 nm – 690 nm) and near-infrared (760 nm – 900 nm) wavebands. An Campbell Scientific, Inc. datalogger (model 23X) was used to sample voltages from the radiometers and log the data.

Location data were collected by using an Ashtech Super C/A receiver GPS system in differential mode. The GPS system was a 12 channel receiver. All the GPS positional data were based on the World Geodetic System of 1984 (WGS84). GPS data was differentially corrected with a base station set near the experimental field. The receiver at the base was identical to the rovers. Post-processing of the GPS data showed that the GPS accuracy was sub-meter.

A data point was collected and stored every 2 s. Traveling 1.7 m s^{-1}, the distance between centers was approximately 3.6 m. Transects were collected through each treatment with the tractor to measure canopy reflectance. To determine in-season N status, reflectance data was collected on each of the fields at various growth stages in the study (Table 1).

Appendix 3 Table 1 NRI data collection date and growth stage

Field	Date	Growth Stage
1-99	7-1	V8
	8-13	R2
	8-18	R3
2-99	7-8	V11
	8-18	R3
1-00	7-5	V10
	7-19	V16
	7-26	VT
	8-14	R2
3-00	7-11	V12
	8-8	R3

Bausch and Duke (1996) introduced the Nitrogen Reflectance Index (NRI) to estimate the plant N status of corn. The index is calculated by a ratio of NIR/GREEN reflectance of an area of interest to NIR/GREEN reflectance of a reference or N stress free corn. An NRI value was calculated for each reflectance data point collected. This technique provides a fast estimate of plant N status and its spatial variability. An NRI value of 0.95 appears to be the critical values for optimum plant nitrogen status (Diker, 1998).

The NRI was calculated using 2 different methods. In method 1 (NRIHI) the reference was calculated by averaging the NRI values from the highest N rate (N-recommendation + 56 kg ha^{-1}) in the high productivity management zone. Method 2 (NRIMZ) used a management zone specific reference. In this method the reference was calculated by averaging the NRI values from the high N rate in each of the three management zones.

Nitrogen treatments were analyzed using the spatial auto regressive model described in chapter 3. Spatial autocorrelation was measured using Moran's I (Moran, 1950). The analysis of variance as a function of management zones consisted of a two factor cross design with nested replecations within management zones. The null hypothesis of no significant differences between N treatments within a given management zone was tested by the ANOVA model.

Y (ijk) = y.. + a(i) + b(j) + e(ijk)

where y.. is a constant common to all observation, a(i) the effect of the ith N treatment, b(j) the effects of the jth management zone, e(ij) are independent random errors. Equality of means by N treatment and management zone was tested with a restatement of the ANOVA model in the form of a regression model.

Y(ijk) = y.. a1Xik1+ a2 Xik2 + a3 Xik3 + a4 Xik4 + a5 Xik5 + b1Zjk1 + b2Zjk2 + e(ij)

where

Xik1 = 1 if the observation was from treatment 1
-1 if the observation was from treatment 6
0 otherwise

Xik2 = 1 if the observation was from treatment 2
-1 if the observation was from treatment 6
0 otherwise

Xik3 = 1 if the observation was from treatment 3
-1 if the observation was from treatment 6
0 otherwise

Xik4 = 1 if the observation was from treatment 4
-1 if the observation was from treatment 6
0 otherwise

Xik5 = 1 if the observation was from treatment 5
-1 if the observation was from treatment 6
0 otherwise

Zik1 = 1 if the observation was from the low productivity zone
-1 if the observation was from the high productivity zone
0 otherwise

Zik2 = 1 if the observation was from the medium productivity zone
-1 if the observation was from the high productivity zone
0 otherwise

The spatial weight matrix used in the analysis was based on inverse distance. In general, the presence of spatial autocorrelation between observations can underestimate the standard errors when using a classical model, resulting in increased overall significance between individual parameters or overestimate the standard error resulting in an overall lack of significance when one exists. Yield observations were averaged in 30 m by 12 m replications in each management zone in each treatment strip for analysis. Data pixels that fell into more than one management zone were dropped.

Results and Discussion

Spatial Analysis of NRI over N treatments

The two methods of determining reference values for the NRI data were based on different concepts of NRI potential. The NRIHI method assumes the highest N rate in the highest productivity management zone represents N stress free corn. All corn that had NRI values less than 0.95 based on this reference would be assumed at some level of N stress. The NRIMZ methods assumes that corn in the medium and low productivity management zones may not have the potential to reach the NRI N stress free levels of the high productivity management zones. Based on this assumption references were established in the high N rate in each management zone. This allows for a management zone specific NRI level.

Correlation coefficients were calculated for N application rates and NRI values across all fields and years. The coefficients from the early season data (V7 thru V17) were generally low and or not significant (Tables 7, 8, 9, and 10 at end of Appendix 3). Field 2-99 was an exception, higher significant coefficients were seen at V11 at this site. Reflectance data may be predominately influenced by residual NO_3-N and soil background at earlier growth stages. However, at the VT to R3 growth stages coefficients were higher and for the most part significant. Crop yield and NRI were also significantly correlated for the most part at the later growth stages. This was true across both methods of calculating NRI. This indicates the NRI is influenced by N rate and is an indicator of N stress and resulting yield in the crop.

The following codes will be used when referring to management zones and treatments in the following text and tables:

Appendix 3 Table 2 Codes for management zones and treatments

Code	Zones and Treatments
MZ1	low productivity zones
MZ1	medium productivity zones
MZ3	high productivity zones
Treatment 1	0 kg ha^{-1}
Treatment 2	N-recommendation - 56 kg ha^{-1}
Treatment 3	N-recommendation + 56 kg ha^{-1}
Treatment 4	M1VRT
Treatment 5	GSVRT
Treatment 6	M1VRT

Field 1-99
V8 Growth Stage
NRIMZ Reference

At V8, no significant differences in NRI values were noted between the check and the other uniform and variable rate treatments (Table 3). The NRI values are greater than 0.95 across all treatments and management zones. The NRI data seems to indicate little response to N application at this stage. This along with the lack of correlation between the NRI values and N rates at this growth stage would indicate residual and starter N is adequate to maintain N stress free corn. Soil background will also influence reflectance at early growth stages.

NRIHI

The trends in these data across treatments are very similar to the results from the NRIMZ data (Table 3). However using this single, non-management zone specific reference indicates N stress in management zones 1 and 2. With starter N applications, N stress would not be expected at this early growth stage, the N stress indicated here is probably misleading. The NRIMZ approach seems most appropriate for interpreting this data. However the NRIHI approach does allow one to observe differences across management zones that is masked using a management zone specific reference. The NRI data follow the trends one would expect across all treatments with the highest readings in MZ 3 and the lowest in MZ 1. There are significant differences across all management zones in treatments 1 and 6 while zones 1 & 3 and 2 & 3 were significantly different in the remaining treatments. Soil background is influencing these differences also.

Field 1-99
R2 and R3 Growth Stage
NRIMZ Reference

At the R2 and R3 growth stage the check treatment was significantly lower than the other treatments (Table 3). Considerable N stress is seen in treatment 1 at both R2 and R3. An NRI response to applied N at these growth stages is clearly evident. The significant correlation coefficients between N application rate and NRI values discussed earlier also indicate NRI response. There are significant differences between treatments 4 and 5 in MZ2 at R2 and some N stress is indicated in treatment 5 in zones 1 and 3, while the corn remained N stress free in treatments 4 and 6 indicating some advantage to management zones over grid sampling in this case. In treatment 2 at R2 and R3, MZ1 has N stress while zones 2 and 3 remain N stress free. In MZ1 treatment 2 was also significantly lower than treatments 3, 4, 5, and 6 at R2 and treatments 3 and 4 at R3. This indicates in this field higher N rates are needed to achieve optimum NRI values on the low productivity management zone soils while somewhat lower rates are sufficient on medium and high productivity management zone soils. It appears that rates of approximately 179 kg ha^{-1} are adequate in zones 2 and 3, however higher rates are needed in zone 1 for optimum NRI values. In addition at R2 and R3, treatment 4 remained N stress free across all zones. In treatment 6 where lower rates than treatments 3 and 4 were applied to zone 1, mild N stress is detected in zone 1 while zone 1 in treatments 3 and 4 are N stress free. Based on NRI values the approach of applying higher N rates on the lower productivity soils seems most appropriate on this field in 1999. Levels of N stress in the check treatment were lowest in MZ3 and highest in MZ1. As discussed in chapter 3, MZ1 is higher in sand and lower in clay than MZ3. This may be leading to higher N leaching rates in MZ1 resulting in more N stress. It is interesting to note that even though a zone specific reference is used significant differences between zones are seen in treatments 1 and 2. In addition the NRI values were higher in MZ3 and lowest in MZ1 in treatment 1. This indicates a strong management zone effect at low N application rates.

Field 1-99
R2 and R3 Growth Stage
NRIHI Reference

The trends in the data across treatments observed here is again very similar to the results from the NRIMZ data. Based on our experience at earlier growth stages these lower NRI values in zones 1 and 2 are misleading. A zone specific reference does a better job of characterizing NRI N stress. As at the earlier growth stage, zone effects are evident and the data follows the management zones with the highest values in MZ3 and the lowest in MZ1 (Table 3).

Appendix 3 Table 3 Analysis of variance of NRI values on field 1-99 over N treatments as a function of management zones using 2 reference methods at various growth stages (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity)

MZ	NRI Method	Growth Stage	*Trt1	Trt2	Trt3	Trt4	Trt5	Trt6
MZ1	NRIMZ	V8	1.0a	1.1a	1.1a	1.1a	0.98a	1.0a
MZ2			1.1a	1.2a	1.0a	1.1a	0.98a	.99a
MZ3			1.0a	1.0a	1.1a	1.0a	0.94a	.97a
MZ1		R2	0.68a	0.76a	0.98a	1.0a	0.92a	0.93a
MZ2			0.85b	1.1b	1.0a	1.1a	0.98a	1.0a
MZ3			0.90b	0.95b	0.99a	0.98a	0.92a	0.97a
MZ1		R3	0.66a	0.76a	0.97a	0.98a	0.92a	0.90a
MZ2			0.82b	1.1b	1.0a	1.1a	0.98a	0.99a
MZ3			0.91b	0.98b	1.0a	1.0a	0.95a	0.98a
MZ1	NRIHI	V8	0.71a	0.71a	0.75a	0.79a	0.69a	0.72a
MZ2			0.85b	0.97a	0.79a	0.87a	0.76a	.79b
MZ3			1.1c	1.1b	1.2b	1.1b	1.0b	1.1c
MZ1		R2	0.59a	0.65a	0.84a	0.89a	0.78a	0.81a
MZ2			0.69b	0.84a	0.79b	0.88b	0.77b	0.82a
MZ3			0.89b	0.93b	0.97b	0.95b	0.91b	0.96b
MZ1		R3	0.58a	0.67a	0.85a	0.79a	0.80a	0.88a
MZ2			0.69b	0.87a	0.82a	0.80a	0.79a	0.88ab
MZ3			0.89b	0.96b	0.98b	0.97b	0.93b	0.96a

* Trt1 = check, Trt1 = Treatment 2 = N-recommendation - 56 kg ha^{-1}, Trt3 = N-recommendation + 56 kg ha^{-1}, Trt4 = M1VRT, Trt5 = GSVRT, and Trt6 = M2VRT
MZ means followed by a different lower case letter are significantly different at $p < 0.05$

Field 2-99
V11 growth stage
NRIMZ Reference

At V11, in field 2-99, the check treatment is significantly lower than treatments 3 and 4 in zone 1 and treatments 3 and 5 in zones 2 and 3 (Table 4). The NRI values were less than 0.95 over all treatments and management zones. The lowest NRI values are in treatments 1 and 2, the lowest applied N rates. The NRI and N rate correlation coefficients were also high and significant at this date. Based on NRI values it appears there is early season N stress and a NRI response to N rate that was not seen on field 1-99. However there is no significant difference across the variable rate treatments.

Field 2-99
V11 growth stage
NRIHI Reference

The NRI values indicate high levels of N stress in the NRIHI data set (Table 4). Management zone effects are seen in this data set with the highest NRI values in MZ 3 and lowest in MZ 1 across all treatments. Management zones 1 & 2 and 1 & 3 are significantly different in treatments 2, 3, 4, and 5.

Field 2-99
R2 Growth Stage
NRIMZ Reference

Treatment 1 is significantly lower than all other treatments across all management zones at this date (Table 4). Treatment 5 is significantly lower than treatments 4 and 6 in zones 1 and 2 indicating an advantage to management zones over grid based applications in the low and medium productivity soils. The NRI values have increased over all treatments from the V11 growth stage except the check treatment. This indicates a continued NRI response to applied N on this field. There is N stress indicated in all the treatments except the highest N rate , treatment 3 and MZ 1 in treatments 4 and 6. On this field it appears N stress free NRI values are obtained with approximately 179 kg ha^{-1} N in the low productivity management zone soils, while higher rates are needed in higher productivity management zone soils to achieve stress free NRI values. The NRI response to N application rates by management zone appears to be field specific with the opposite responses in fields 1-99 and 2-99

Field 2-99
R2 Growth Stage
NRIHI

Management zone effects are again evident in this data set with NRI values following the expected trends with highest values in MZ3 and the lowest in MZ1 (Table 3). Treatment 1 continued to be significantly lower than all other treatments across all management zones.

Field 1-00
V10 Growth Stage
NRIMZ Reference

At this early growth stage NRI response to N rate is not evident, because there were no significant differences between treatments. The NRI N rate correlation coefficients were also low at V10. Early season N stress was expressed throughout all treatments in both the NRIMZ and NRIHI data (Table 5). Differences in N stress levels across treatments at this growth stage are probably due to random variation in residual soil N. Management zone effects are clear in the NRIHI data with the highest values in MZ3 and the lowest in MZ1.

NRIHI Reference

The NRI values are very low in MZ1 and 2. These are not realistic values at this early growth stage. This indicates the management zone specific reference is a better approach. Management zone effects are clear in the NRIHI data with the highest values in MZ3 and the lowest in MZ1.

Appendix 3 Table 4 Analysis of variance of NRI values on field 2-99 over N treatments as a function of management zones using 2 reference methods at various growth stages (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity)

MZ	NRI Method	Growth Stage	*Trt1	Trt2	Trt3	Trt4	Trt5	Trt6
MZ1	NRIMZ	V11	0.82a	0.87ab	0.94a	0.93a	0.89a	0.86a
MZ2			0.71b	0.76a	0.86a	0.80b	0.86b	0.75b
MZ3			0.67ab	0.83b	0.89b	0.85ab	0.89ab	0.78ab
MZ1		R2	0.67a	0.87a	0.98a	1.0a	0.90a	0.96a
MZ2			0.61b	0.83a	0.95a	0.90a	0.88b	0.90b
MZ3			0.54b	0.89a	0.98a	0.90a	0.94b	0.91b
MZ1	NRIHI	V11	0.62a	0.66a	0.70a	0.71a	0.68a	0.66a
MZ2			0.71b	0.77b	0.86b	0.81b	0.86b	0.77ab
MZ3			0.69ab	0.84b	.90b	0.84b	0.91b	0.80b
MZ1		R2	0.63a	0.81a	0.91a	0.95a	0.84a	0.89a
MZ2			0.64a	0.87b	1.0b	0.95b	0.93a	0.94b
MZ3			0.57a	0.92b	1.0b	0.94b	0.98a	0.95b

* Trtl = check, Trt2 = Treatment 2 = N-recommendation - 56 kg ha^{-1}, Trt3 = N-recommendation + 56 kg ha^{-1}, Trt4 = M1VRT, Trt5 = GSVRT, and Trt6 = M2VRT
MZ means followed by a different lower case letter are significantly different at $p < 0.05$

Field 1-00
V16 Growth Stage
NRIMZ Reference

The NRI values increased from the levels seen at V10. For the most part all treatments reflect N stress free corn. Treatment 6 was the exception where N stress was apparent across all management zones (Table 5). Correlation coefficients for N rate and NRI were low at this growth stage and there is little evidence of N rate influence on NRI in zones 2 and 3. Increases in NRI values from V10 may be due to increased mineralization. Some treatment effect is beginning to show in zone 1 where treatment 3 is significantly higher than all other treatments. Nitrogen stress was evident across all treatments in zone1 also.

NRIHI Reference

Nitrogen stress is indicated across all zones and treatments. These data are again misleading due to the use of a single reference value. Management zone effects are again evident in the NRIHI data with the highest NRI values in MZ3 and the lowest in MZ1 (Table 5).

Field 1-00
VT Growth Stage
NRIMZ and NRIHI Reference

At VT the corn remained N stress free in treatments 3, 4, 5,and 6. In treatment 2 zone 3 did show N stress while zones 1 and 2 remained N stress free in the NRIMZ data. Nitrogen stress was seen in treatment 1 indicating that NRI values are beginning to reflect N application rates (Table 5). Correlation coefficients between NRI values and N application rate were higher and significant at this growth stage. No significant differences were seen between the VRT treatments. The NRIHI data indicated N stress across all zones and treatments except treatments 5 and 6 in zone 3. Based on observations at earlier growth stages the single reference value is exaggerating N stress in zones 1 and 2. The typical management zone effects were again evident in the NRIIHI data (Table 5).

Appendix 3 Table 5 Analysis of variance of NRI values on field 1-00 over N treatments as a function of management zone using 2 reference methods at various growth stages (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity)

MZ	NRI Method	Growth Stage	*Trt1	Trt2	Trt3	Trt4	Trt5	Trt6
MZ1	NRIMZ	V10	0.85a	0.89a	0.86a	087a	0.86a	0.75a
MZ2			0.92a	0.91a	0.96a	0.89a	0.86a	0.86a
MZ3			0.88a	0.85a	0.90a	0.82a	0.84a	0.83a
MZ1		V16	0.88a	0.87a	0.95a	0.87a	0.85a	0.82a
MZ2			0.97a	0.97a	0.98a	0.99a	0.95a	0.86a
MZ3			1.0a	0.97b	0.93a	1.0a	1.0a	0.83a
MZ1		VT	0.88a	0.97a	0.97a	0.97a	0.98a	0.95a
MZ2			0.92a	0.98a	0.99b	1.0a	.99a	0.98a
MZ3			0.86a	0.89a	0.95a	0.94a	0.97a	0.96a
MZ1		R2	0.81a	1.0a	0.97a	1.0a	0.97a	0.95a
MZ2			0.87a	1.0a	1.0a	1.0a	0.99a	0.97a
MZ3			0.83a	0.94a	0.97a	0.93a	0.96a	0.95a
MZ1	NRIHI	V10	0.65a	0.55a	0.53a	0.37a	0.54a	0.46a
MZ2			0.77a	0.67a	0.65b	0.65a	0.75a	0.57b
MZ3			0.93b	0.83b	0.93c	0.80b	0.98b	0.73c
MZ1		V16	0.65a	0.62a	0.60a	0.65a	0.70a	0.52a
MZ2			0.76b	0.76b	0.78b	0.78b	0.84a	0.67a
MZ3			0.88c	0.86c	0.94c	0.87c	0.94c	0.82c
MZ1		VT	0.66a	0.73a	0.73a	0.73a	0.77a	0.76a
MZ2			0.76b	0.81a	0.81a	0.85a	0.86b	0.85b
MZ3			0.86c	0.89b	0.94b	0.93b	0.96c	0.95c
MZ1		R2	0.63a	0.77a	0.76a	0.78a	0.80a	0.72a
MZ2			0.72b	0.85a	0.85a	0.85a	0.86a	0.82b
MZ3			0.82c	0.93b	0.97b	0.91b	0.95b	0.93c

* Trt1 = check, Trt2 = Treatment 2 = N-recommendation - 56 kg ha^{-1}, Trt3 = N-recommendation + 56 kg ha^{-1}, Trt4 = M1VRT, Trt5 = GSVRT, and Trt6 = M2VRT
MZ means followed by a different lower case letter are significantly different at $p < 0.05$

Field 1-00
R2 Growth Stage
NRIMZ and NRIHI Reference

Significant N stress and treatment effects are seen in the NRI data at this growth stage (Table 5). Treatment 1 is significantly lower than all other treatments across all management zones. There is no significant differences between the VRT treatments. There is mild N stress in zone 3 in treatments 2 and 4 while zones 1 and 2 are N stress free. Somewhat higher rates may be needed in the higher productivity soils to obtain optimum NRI levels. Typical management zone effects are again seen in the NRIHI data. (Table 5).

Field 3-00
V12 Growth Stage
NRIMZ and NRIHI reference

At V12, treatment 1 in zones 1 and 2 showed N stress and was significantly lower than all other treatments (Table 6). All other zones and treatments were N stress free. There were no significant differences among the variable rate treatments. Nitrogen application rate was only influencing the NRI at lower rates in the low productivity zones. Correlation coefficients between NRI and N rate were only significant in zones 1. Typical management zone effects were seen in the NRIHI data (Table 6).

Field 3-00
R3 Growth Stage
NRIMZ and NRIHI reference

At R3, only treatment 1 in zone 1 was significantly lower than the other treatments. There were no other significant differences between treatments (Table 6). At this growth stage in field 3-00 excessive irrigation and moderate N levels in the irrigation water tend to mask the treatments and reference method effects. Fifty to 55 pounds of additional N was applied through the irrigation system at this growth stage. With the starter fertilizer, irrigation water N , and applied N even the N recommendation -56 kg ha^{-1} had 221 kg ha^{-1} applied. Management zone effects were seen in the NRIHI data with the NRI values following the same trends described in all the previous data sets (Table 6).

Appendix 3 Table 6 Analysis of variance of NRI values on field 3-00 over N treatments as a function of management zone using 2 reference methods at various growth stages (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity)

MZ	NRI Method	Growth Stage	*Trt1	Trt2	Trt3	Trt4	Trt5	Trt6
MZ1	NRIMZ	V12	.80a	1.0a	1.1a	1.0a	1.1a	0.96a
MZ2			0.85b	1.1a	0.98a	0.98a	1.0a	0.95a
MZ3			1.0b	1.0b	1.0a	1.1a	1.1a	1.1a
MZ1		R3	0.88a	1.0a	1.1a	1.1a	1.1a	1.0a
MZ2			0.92a	1.0a	1.0a	1.0a	1.1a	0.98a
MZ3			1.0a	1.1a	1.1a	1.1a	1.1a	1.1a
MZ1	NRIHI	V12	0.67a	0.87a	0.93a	0.88a	0.92a	0.83a
MZ2			0.84b	1.0b	0.98ab	0.98a	1.0b	0.94ab
MZ3			1.0b	1.0c	1.1b	1.1b	1.1b	1.1b
MZ1		R3	0.75a	0.85a	0.95a	0.93a	0.97a	0.89a
MZ2			0.91ab	1.0b	1.0ab	1.0ab	1.1b	0.98ab
MZ3			1.0b	1.1b	1.1b	1.1b	1.1b	1.1b

* Trt1 = check, Trt2 = Treatment 2 = N-recommendation - 56 kg ha^{-1}, Trt3 = N-recommendation + 56 kg ha^{-1}, Trt4 = M1VRT, Trt5 = GSVRT, and Trt6 = M2VRT
MZ means followed by a different lower case letter are significantly different at $p < 0.05$

Conclusions

The early season (V6 to V10) NRI data are not very useful in evaluating different N treatments. Soil background can bias the data causing excessive variability not related to crop reflectance thereby reducing correlation between NRI and N rate. At later growth stages after canopy closure, NRI values are highly correlated with N rate and crop yield.

At these times in the growing season NRI is more valuable in evaluating N status across treatments.

Using a management zone specific reference to calculate NRI values appears to be the best approach to evaluate N stress levels based on NRI levels. The NRIHI method indicates excessive N stress at early season growth stages when N stress would not be expected when using starter fertilizer. Based on the early season NRI values the level of N stress indicated at the later sample dates is probably also misleading with the NRIHI approach. The corn in management zones 1 and 2 does not have the potential to reach the NRI values in the highest N rate in zone 3. Using a single reference can lead to identifying N stress when it does not exist. This concept could have implications when interpreting any N status indicators that utilize a reference value. This in itself may indicate a need for defining in field management zones beyond their use for VRT. Using a within field specific reference may be needed when interpreting remote sensing data for crop health related evaluations.

Another factor that may be influencing the difference in reference approaches is the timing of the reference measurements. The site specific reference is measured nearer the same time the value of interest is measured. This avoids discrepancies that can arise from differences in sun angle through the sampling period.

On fields 1-99, 1-00, and 3-00 early season (pretasseling) NRI values seemed to be mostly influenced by residual and starter applied NO_3-N. Correlation coefficients for NRI values and N rate were low and NRI values mostly reflected N stress free corn early in the season. On field 2-99 N application rate influenced NRI values earlier in the season with higher N rate NRI value correlation coefficients at V11. Early season N stress was also detected at this field. Nitrate concentrations in the irrigation water may be influencing these results. Nitrate concentration levels were lowest at field 2-99 and higher at the other fields. Early season irrigation application rates were also somewhat lower on field 2-99 leading to earlier N stress.

There is some evidence of an advantage for management zone VRT over grid based VRT if field 1-99 at the R2 growth stage. Treatment 4 has significantly higher NRI values than treatment 5 in MZ2. However, at other growth stages and in other zones there were no significant differences between the variable treatments. No significant differences were noted between the management zone based applications and the grid based applications in fields 2-99, 1-00 and 2-00. These data would indicate management zone based VRT is as effective as grid based application in maintaining N stress free corn.

On field 1-99 lower rates in treatment 2 resulted in N stress in zone 1 while these rates achieved stress free NRI values in zones 2 and 3 at the later growth stages. In addition, at treatment 4, where higher rates relative to the other zones were applied on the MZ1 the corn remained N stress free across all zones. Treatment 6 reflected N stress in zone 1 where lower rates were applied. The approach of applying higher N rates on the low productivity zone soils seems most appropriate on this field in 1999. Lower rates at field 2-99 resulted in N stress in treatment 2 and the lower application rates in treatment 4 in zones 2 and 3 at the R2 growth stage. On treatment 6 a lower N rate achieved stress free NRI values in zone 1 while higher rates resulted in N stress NRI values in zones 2 and 3. In this field it seems an approach of applying higher rates to the high productivity zones is most appropriate.

On field 1-00 N stress was expressed in zone 3 on treatments 2 and 4 while zones 1 and 2 were N stress free. Field 1-00 seems to indicate a need for higher rates in the high productivity zones. We observed the opposite trend in 1999 on this field described above. It appears NRI response to N rates by management zones can vary temporally. All N application rates were higher in 2000 than 1999 due to higher NO_3-N concentrations in the irrigation water and somewhat higher irrigation rates. This may be leading to the temporal variation on this field. With lower initial N rates in 1999, increased N immobilization may be occurring in the low productivity zones leading to increased NRI response at higher N rate applications. Higher initial N rates in 2000 led to less immobilization and less NRI response at higher N rates. Similar response to applied N was seen in corn grain yield described later in this chapter. Volatilization may be another factor for temporal differences in NRI response to applied N in the low producitvity management zone soils. Volatilization can be significant with broadcast application of urea-ammonium nitrate on these somewhat calcareous soils. Lower buffer capacity in sandy, low organic matter soils in the low productivity zones can also enhance volatilization (Havlin et al., 1999). Perhaps somewhat different management practices led to temporal differences in volatilization rates in these soils. Timing and depth differences in spring tillage may have resulted in higher residue levels in 1999 leading to higher volatilization rates. There also may have been differences in the timing and effectiveness of incorporation practices from year to year. Differences in environmental conditions such as soil moisture and temperature could also influence temporal differences in volatilization rates. Application rates beyond the check treatment were generally high enough to obtain N stress free NRI levels at all growth stages on field 2-00 in the study. Moderately high nitrate levels in the irrigation water and excessive water application tended to mask treatment effects at this field.

Appendix 3 Table 7 Field 1-99 correlation coefficients and p-values for NRI vs. N rate and NRI vs. yield

MZ	NRI Method	Growth Stage	CC-N	p-value-N	CC-YLD	p-value-YLD
MZ1	NRIMZ	V8	0.66	0.22	0.46	0.36
MZ2			-0.41	0.44	0.59	0.41
MZ3			0.47	0.42	0.55	0.40
MZ1		R2	0.92	0.02	0.98	0.003
MZ2			0.90	0.03	0.97	0.003
MZ3			0.93	0.02	0.88	0.04
MZ1		R3	0.92	0.008	0.96	0.009
MZ2			0.89	0.05	0.97	.003
MZ3			0.97	0.005	0.86	0.06
MZ1	NRIHI	V8	0.60	0.19	0.52	0.43
MZ2			-0.31	0.60	0.29	0.62
MZ3			0.60	0.28	0.49	0.59
MZ1		R2	0.90	0.03	0.98	0.003
MZ2			0.87	0.05	0.91	0.03
MZ3			0.99	0.0009	0.89	0.05
MZ1		R3	0.85	0.06	0.87	0.04
MZ2			0.87	0.05	0.86	0.05
MZ3			0.97	0.005	0.85	0.06

Appendix 3 Table 8 Field 2-99 correlation coefficients and p-values for NRI vs. N rate and NRI vs. yield

MZ	NRI Method	Growth Stage	CC-N	p-value-N	CC-YLD	p-value-YLD
MZ1	NRIMZ	V11	0.58	0.30	0.60	0.25
MZ2			0.87	0.05	0.66	0.22
MZ3			0.84	0.07	0.59	0.27
MZ1		R2	0.92	0.02	0.96	0.008
MZ2			0.98	0.002	0.99	0.0001
MZ3			0.94	0.02	0.99	0.0009
MZ1	NRIHI	V11	0.95	0.01	0.66	0.31
MZ2			0.92	0.030	0.71	0.22
MZ3			0.92	0.03	0.61	0.35
MZ1		R2	0.92	0.03	0.97	0.03
MZ2			0.98	0.003	0.99	0.0006
MZ3			0.94	0.02	0.99	0.0001

Appendix 3 Table 9 Field 1-00 correlation coefficients and p-values for NRI vs. N rate and NRI vs. yield

MZ	NRI Method	Growth Stage	CC-N	p-value-N	CC-YLD	p-value-YLD
MZ1	NRIMZ	V10	0.49	0.33	0.63	0.21
MZ2			0.51	0.37	0.61	0.25
MZ3			0.47	0.34	0.60	0.26
MZ1		V16	0.40	0.60	0.69	0.20
MZ2			0.93	0.06	0.55	0.28
MZ3			-.078	0.21	0.55	0.30
MZ1		VT	0.93	0.06	0.70	0.19
MZ2			0.92	0.07	0.72	0.15
MZ3			0.93	0.07	0.75	0.13
MZ1		R2	0.83	0.05	0.93	0.02
MZ2			0.88	0.05	0.95	0.01
MZ3			0.95	0.009	0.93	0.02
MZ1	NRIHI	V10	0.57	0.36	0.66	0.31
MZ2			0.53	0.41	0.71	0.22
MZ3			0.49	0.47	0.61	0.35
MZ1		V16	-0.33	0.67	0.71	0.20
MZ2			0.83	0.16	0.69	0.22
MZ3			0.71	0.29	0.73	0.17
MZ1		VT	0.89	0.11	0.75	0.15
MZ2			0.84	0.15	0.77	0.13
MZ3			0.89	0.11	0.78	0.12
MZ1		R2	0.81	0.05	0.97	0.006
MZ2			0.87	0.05	0.95	0.01
MZ3			0.95	0.01	0.95	0.01

Appendix 3 Table 10 Field 3-00 correlation coefficients and p-values for NRI vs. N rate and NRI vs. yield

MZ	NRI Method	Growth Stage	CC-N	p-value-N	CC-YLD	p-value-YLD
MZ1	NRIMZ	V12	0.80	0.17	0.63	0.21
MZ2			0.84	0.15	0.58	0.24
MZ3			0.76	0.24	0.55	0.30
MZ1		R3	0.99	0.001	0.93	0.02
MZ2			0.87	0.05	0.97	0.01
MZ3			0.79	0.11	0.97	0.007
MZ1	NRIHI	V12	0.79	0.09	0.55	0.32
MZ2			0.83	0.08	0.59	0.29
MZ3			0.75	0.24	0.61	0.27
MZ1		R3	0.98	0.002	0.93	0.02
MZ2			0.90	0.03	0.95	0.01
MZ3			0.89	0.04	0.96	0.007

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APPENDIX 4

A COMPARISON OF FARMER-DEVELOPED MANAGEMENT ZONES AND SOIL SURVEY

Introduction and Literature Review

Accurate prescription maps are essential for effective VRT N fertilizer application (Ferguson et al., 1996). The concept of using management zones to develop VRT prescription maps has received considerable attention. A management zone for VRT application can be defined as a sub-region of a field that expresses a homogeneous combination of yield limiting factors for which a single rate of a specific crop input is appropriate (Doerge,1999). Researchers have long understood the value of dividing whole fields into smaller, homogeneous regions for fertility management. Earlier studies proposed the division of fields by soil type (Carr et al., 1991). Their work indicated that applying different fertilizer treatments to contrasting soils in a field can generate greater returns than applying a field average fertilizer treatment. Mausbach et al. (1993) concluded that the National Cooperative Soil Survey is not adequate for variable rate application. Soil surveys were not intended for precision farming and tend to map at scale to coarse to be effective for VRT. Franzen et al. (2002) compared Order one and Order two soil surveys with maps from grid sampling and topography based zone maps. Order two soil surveys were seldom useful in determining zones for site specific management of NO_3-N. Order one soil surveys were much more related to soil NO_3-N than Order two surveys, but their consistency was not as high as when topography based zones or maps from grid sampling were used. The objective of this chapter is to compare farmer developed management zones for variable rate fertilizer application with Soil Survey.

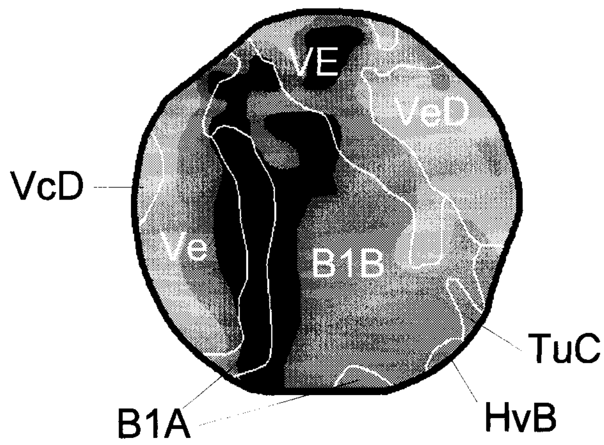
Materials and Methods

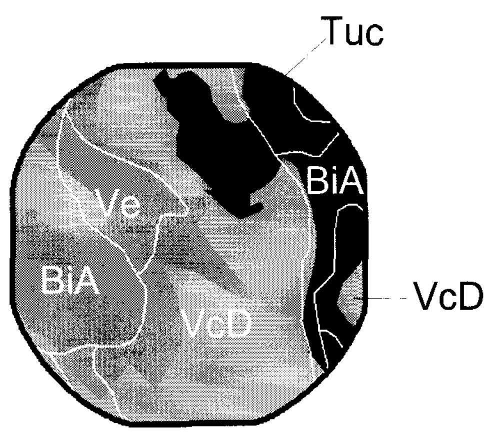
The Order two soil survey (Soil Taxonomy, 1996) for fields 1-97 and 2-97 were overlaid on the management zones on these fields developed and described in chapter 3. (Figures 1and 2). Table 1 provides codes for soil series and zones.

Appendix 4 Table 1 Codes for soil series and management zones

Soil Series and Zones	Code
Bijou loamy sand, 0 to 1 percent slopes	B1A
Bijou loamy sand, 1 to 3 percent slopes	B2A
Heldt sandy loan, 1 to 3 percent slopes	HvB
Truckton loamy sand 3 to 5 percent slopes	TuC
Valentine sand, hilly	VcD
Valentine-Dwyer sand , terrace	Ve
Low productivity zone	Light Gray
Medium productivity zone	Dark Gray
High productivity zone	Black

A raster analysis in Arc View was done to determine the percentage of each mapping unit in each the low, medium, and high productivity management zones (Tables 2 and 3).





Appendix 4 Figure 1. Field 1-97 (top) and 2-97 (bottom) soil survey overlaid on management zones

Appendix 4 Table 2. Field 1-97 Comparison of management zone and soil survey (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity).

MZ	B1A	B1B	HvB	Tuc	VcD	VE
	%	%	%	%	%	%
1	1.3	4.2	0	0	49.2	45.3
2	4.4	57.4	1.1	1.8	2.5	32.8
3	28.1	48.3	0	0	0	23.6

Appendix 4 Table 3. Field 2-97 Comparison of management zone and soil survey (MZ 1 = low productivity, MZ 2 = medium productivity, and MZ 3 = high productivity).

MZ	B1A	B1B	Tuc	VcD	VE
	%	%	%	%	%
1	12.4	2.5	0.8	81.8	2.5
2	41.4	3.4	0	32.8	22.5
3	28.6	2.1	19.2	50.1	0

Results and Discussion

At field 1-97 94.5% the low productivity zone consisted of Valentine sand hilly and Valentine-Dwyer sand terrace soil series. The medium productivity zone consisted of 68.8% Bijou loamy sand Bijou loamy sand zero to one and one to three percent slopes while the high productivity zone consisted of 76.4% of these two series. Thirty two percent of medium productivity zone and 2.6 percent of the high productivity zone consisted of Valentine-Dwyer sand soil series. The Valentine sand is a sandy, mixed nonacid, mesic Typic Ustipsamment. These are very sandy Entisols, the least develop soil order. They develop in these semi arid mesic soil temperature regimes with generally moist springs and long dry periods. These less developed sandy soils would generally be associated with lower productivity. In contrast the Bijou loamy sand is a coarse loamy, mixed, mesic Mollic Haplargid. These are Aridisols with characteristics associated with dry climates. They possess an Argillic (B_t) horizon indicating higher clay content than the Valentine soils. It also has Mollic colors (dark) indicating higher clay and organic matter content. The Truckton loamy sand is a coarse loamy, mixed, mesic Udic Argiustoll. These are Mollisols with thick dark base rich surface horizons mostly associated with sub-humid to semi arid prairie vegetation. These soils also possess an Argillic horizon, a higher clay content subsurface horizon. These Bijou and Truckton soils with higher clay and organic matter content would be associated with darker more productive soils. This is consistent with the data in chapter three that indicated the low productivity zone had the highest sand and lowest clay content and vice versa in the high productivity zone. The highest percentage of Bijou loamy sand zero to one percent slopes in the high productivity zones is similar to the results in chapter three also, the lowest slopes and elevation were found the high productivity zones.

The results at field 2-97 indicate 84.3% of the low productivity management zone consisted of Valentine sand hilly and Valentine-Dwyer sand terrace soil series. Results from the medium and high productivity zones were similar to the findings in chapter three in that the zones seem to be quite similar. Forty four percent of the medium zone and 50% of high productivity zone consisted of Bijou loamy sand and Truckton loamy sand series. Fifty five percent of the medium and 50% of the high zone consisted of Valentine sand hilly and Valentine-Dwyer sand terrace soil series.

With some exceptions it seems both the soil color-farmer input classification and Soil Survey are describing similar areas in this field. The soil color-farmer input seems to be effective in identifying the Mollic characteristics associated with the Bijou and

Truckton soils. Both classification methods would seem to have similar potential for defining management zones. The results in chapter four indicated farmer defined management zones are as effective as grid soil sampling for developing variable rate prescription maps, with the relationships described above one could assume similar results using Soil Survey. At these fields this would seem to differ from Mausbach et al. (1993) and Franzen et al., (2002) that indicated that Order two soil survey was not as useful as grid sampling in determining zones for site specific management. Perhaps the wide range in soil development at these fields is contributing to these differences. At fields with more uniform soil development, soil survey may be less effective in determining management zones.

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APPENDIX 5

UNIFORM VS. VARIABLE RATE N APPLICATION USING FARMER-DEVELOPED MANAGEMENT ZONES: AN ECONOMIC COMPARISON

Introduction and Literature Review

Agronomic recommendations have been developed for use on a field basis. However managing a field uniformly may be inappropriate. Field level studies have shown that organic carbon, total N, and NO_3-N, have spatial dependance and variation (Cambardella et al., 1994). Using the ratio of nugget to total simivariance to classify spatial dependance, organic carbon and total N were strongly spatially dependent while NO_3-N was moderately spatially dependent. Other studies have concluded that N uptake and crop response to N varies spatially within fields (Malzer, 1996, Dampney and Goodlass, 1998). Welsh et al. (1999) results indicated that where 30% more additional N was applied to historically higher yielding parts of the field, yield was significantly increased. Kachanoski et al., (1996) showed that optimal levels of N fertilization have spatial variability. The maximum yield increase and the economic yield increase over the check yield with no N applied were both strongly correlated with spatially optimal economic return of N (r=0.70 to 0.88). Baxter et al (2001) found the variation in mineral N is neither uniform or too noisy to manage with variable rate application. Fertilizing an entire field to meet the needs of the most deficient areas or basing fertilizer rates on the potential of the most productive areas can be expensive and lead to environmental contamination (Sawyer, 1994). Recent advances in technology allows us to simultaneously determine location in a field, store information about that location and variably apply the rate of fertilizer (VRT) to these locations.

Economic returns to site specific technology can be difficult to quantify (Snyder. 1996). They compared variable and uniform N-application strategies over a three year study on two sites. Correlation between variables were unique to each site, excluding relations between N over-application and yield. For every kilogram of N over-applied, yield decreased by 0.016 Mg/ha. The estimated amount of total N applied to fields was always less for VRT than for uniform application strategies. VRT profitability results were different for both sites and both years. Both sites enjoyed one year (out of two) with return from VRT management. The authors assume these results reflect differences in growing seasons Watkins et al., (1998) presented results that indicated a greater economic benefit from varying water application than from varying N application across the field. Killian et al. (2001) showed a higher profitability with reduced amounts of applied N using variable rate. Babcock and Paustch., (1998) randomly selected 240 sites from 20 locations representing 12 counties in Illinois. Using this information, a model was designed to analyze the environmental and economic costs and benefits absorbed by producers if they switched from single-rate N application to VRTN. Simulated results were generated after filtering data from 20 randomly selected sites representing 12 counties through the model. Findings suggest that 66% of the acreage farmed using single-rate N application would be oversupplied with nitrogen, 4% would be undersupplied, while 30% would receive optimal amounts. If farmers were to switch from single-rate technology to VRT, gross returns would increase $4.03 (range). When all counties were combined, returns over fertilizer cost were \$4.44/acre. Increases in returns were mainly due to decreases in N application. English et al. (1999) used 30-acre hypothetical fields to model and evaluate VRT. When simulated fields were composed of greater than 30% and less than 85% low-yielding land, returns from VRT were positive. The authors conclude that farmers will benefit from VRT where fields are typified by these low- and high-yielding land distribution ratios. The results are sensitive to changes in corn to nitrogen price ratios. Lambert and Lambert and Lowenberg-DeBoer (2000) summarized and organized the publicly available studies of the profitability of precision agriculture. They reported on 108 studies that reported economic figures. Of those studies 63% indicated positive net returns for a given PA technology, while 11% indicated negative returns. There were 27 articles indicating mixed results (26%). For all PA technology combinations identified, over 50% of the studies reported positive benefits. Sixty-three percent of the studies of N VRT systems reported profits while 15% were negative and 22% mixed. Ferguson et al. (2002) used grid soil sampling and the University of Nebraska N algorithm to create VRT N application maps. There was no significant difference in the total N applied using VRT (142 kg N ha^{-1}) and uniform application (142 kg N ha^{-1}). Treatment means ranged from 4.5 to 13.9 Mg ha^{-1} and were influenced relatively little by uniform and VRT treatments. They concluded the University of Nebraska algorithm may not be sensitive enough to localized differences in soil N supply and crop N demand within fields to be used for VRT N application. The objective of this chapter is to make an economic comparison of VRT N application using the management zones described in chapter 4 with uniform N application.

Materials and Methods

The management zone, N rate and yield data generated in chapter 4 were to be utilized to determine the economical optimum N rate in each management zone. The data collected provided 5 N rate and yield pairs at each management zone and field. Several non-linear regression models were developed including log normal, 1st and 2nd degree polynomial, and Spillman to determine the economical optimum N rate (Mathsoft, 1995). The management zone specific economical optimum N rates and yields were to be compared to economically optimum uniform whole field rates.

Results and Discussion

The sparse data sets made modeling the economically N rates problematic. The models lacked data points at both the lower and upper portions of the curve. This lack of knowledge of how the curves behaved in those areas resulted many times in poor fits and unrealistic predicted optimum N rates.

The polynomial curves indicated a drop in yields at unrealistic N rates of 200 to 250 lbs ac^{-1} (Figure 1). The log normal models indicated very high optimum N rates over 300 lbs ac^{-1} in many cases. The model did not indicate the lower marginal increase in yields one would expect at higher N rates (Figure 2). The Spillman model did force an asymptote in the data, however the model was insensitive to wide changes in N rate (Figure 3). Nitrogen rate increases over 100 lbs ac^{-1} resulted in less than 5 bu ac^{-1} increase in yield in some of the models.

Being able to model and predict management zone specific economical optimum rates is crucial to utilizing this technology effectively. Accurate models can begin to evaluate if our current N recommendation algorithms are adequate for site specific management. Our study was not designed to specifically address these issues. Further research is needed utilizing a wider range of N rates to adequately model N response by management zone.

To fully realize the economic potential for VRT farmers may need to establish on farm management zone N response trials over three to five years to determine if predictable response trends exist in their fields. These could be efficiently evaluated using yield monitor technology.

If predictable trends cannot be established due to variable and unexpected in season crop conditions a reactive strategy may be needed. This approach involves reacting to actual N levels in corn fields during the growing season. This can be done by monitoring crop N status near real time and applying mid season N only when and where needed. Remote sensed crop canopy imagery is needed for this approach.

Variable rate N application using management zones will involve increased risk. Initially management zone N response may not be reliable. In season crop conditions such as unusually favorable growing conditions or yield limiting conditions such as pest infestation, pesticide injury, hail, frost or N losses from excessive rainfall or volatilization can contribute to temporal differences in N response. Increased management will be needed to fully realize VRT potential. Consistent best management practice for water and N application are needed to evaluate year to year management zone N response. Inconsistent management could also lead to temporal changes in N response. The opportunity for improved management using VRT is not only to obtain more data from a management zone within a field, but also to be able to interpret the data in order to make better management decisions that are most appropriate for that zone. Precision farming is not just the use of high-tech equipment, but the acquisition and wise use of information obtained from that technology.

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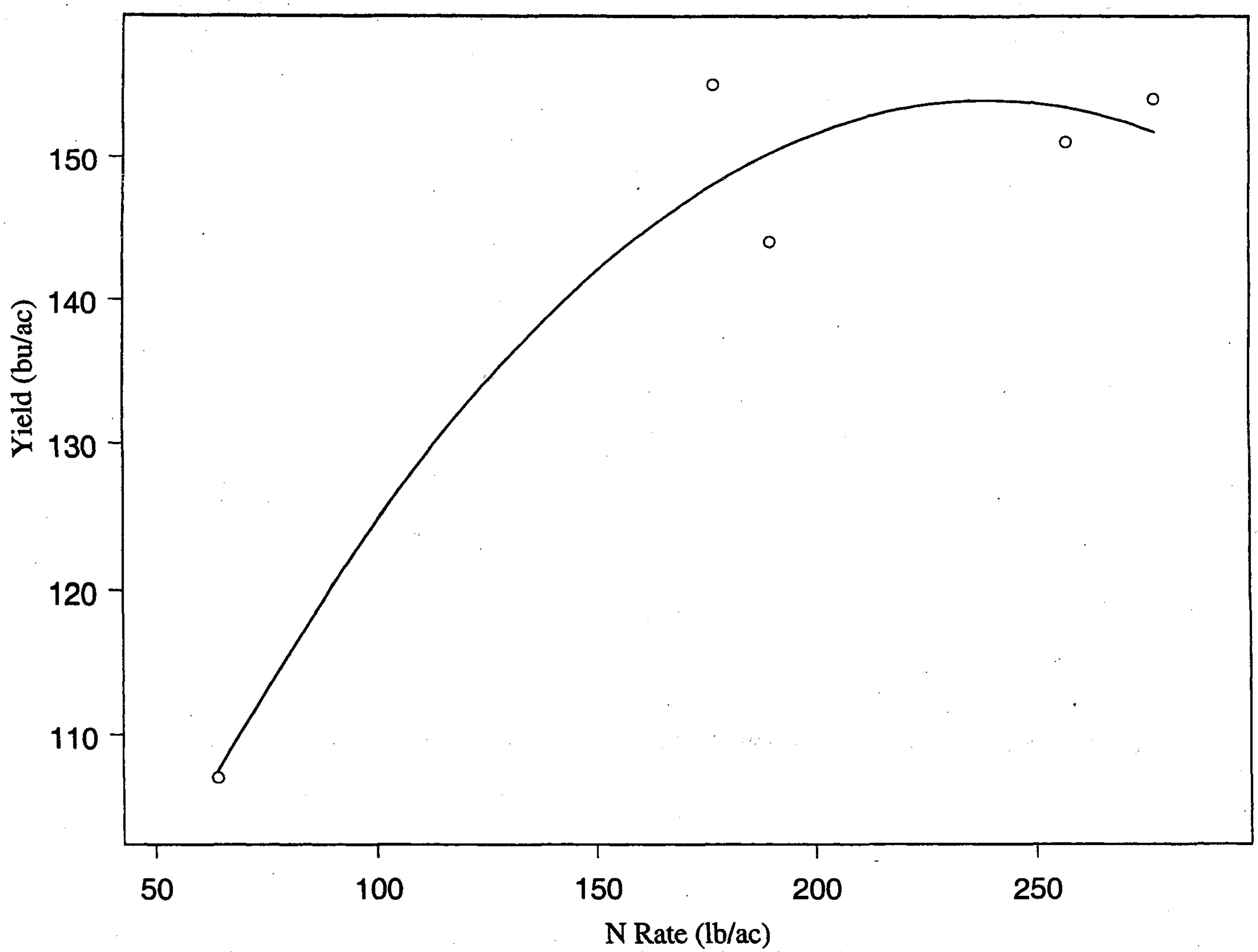

Figure 1. Field 1-00 low productivity management zone, second degree polynomial model

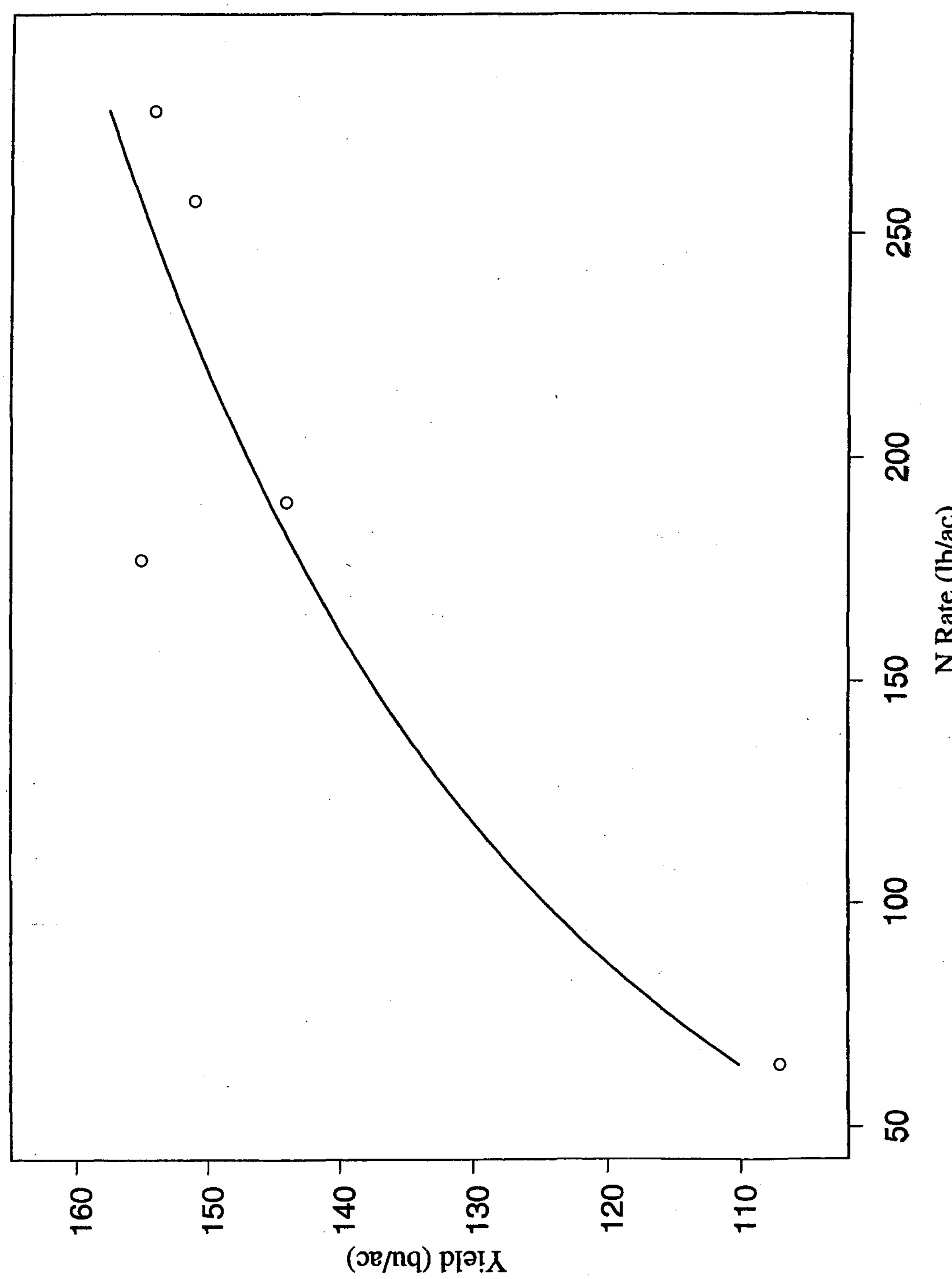

Figure2. Field 1-00 low productivity management zone, log normal model

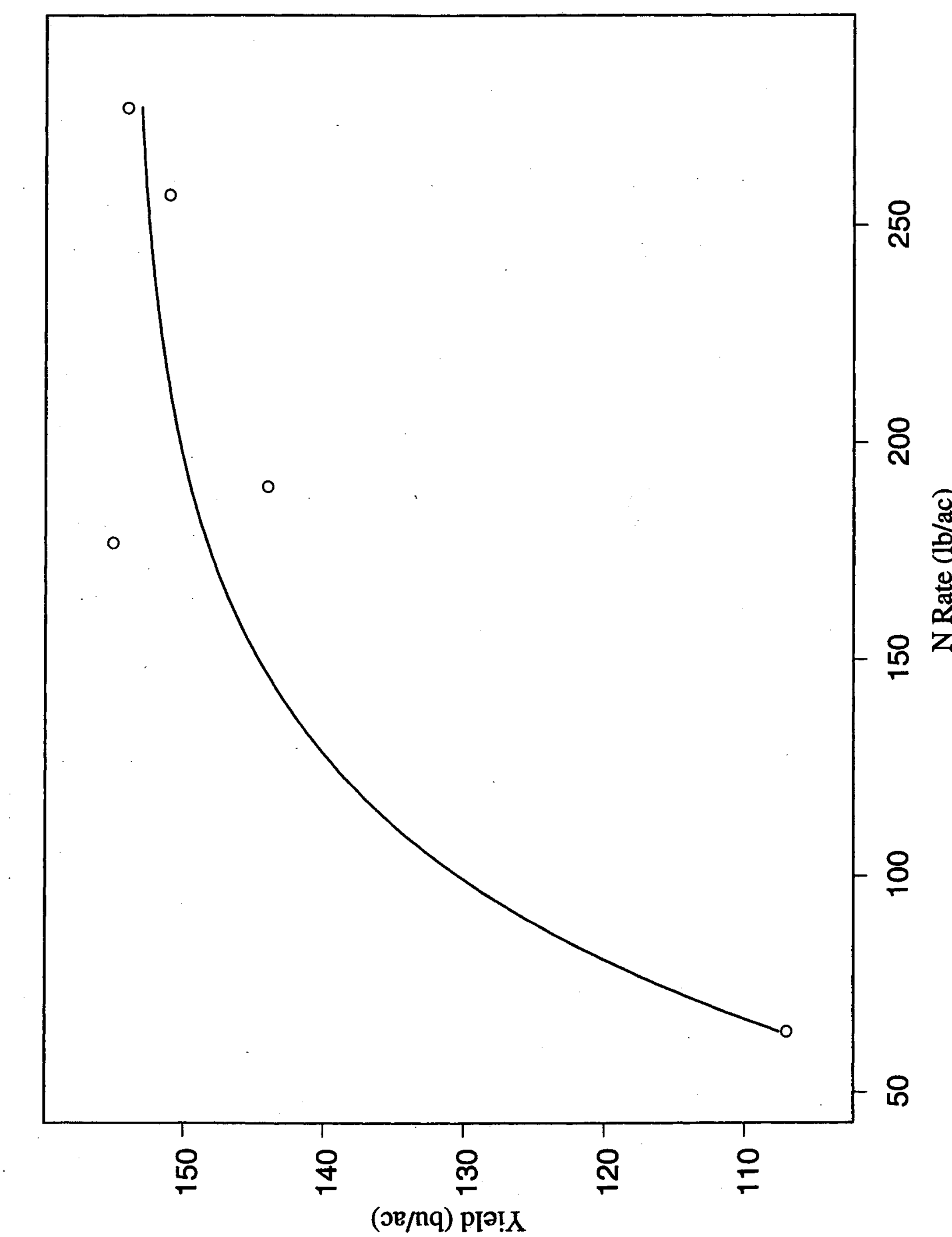

Figure 3. Field 1-00 low productivity management zone, Spillman model

APPENDIX 6

PRECISION FARMING - FROM TECHNOLOGY TO DECISIONS: A CASE STUDY

Introduction

In the Fall of 1995, Dan Wiens a fertilizer consultant in northeast Colorado was challenged by a customer. Earlier that year Larry Rothe, an area farmer tried a variable rate (VRT) fertilizer program based on grid soil sampling on 2.5 acre grids. He was disappointed with the application maps because he felt they failed to capture the hills and other areas in the fields where variable rate application was needed. In addition, the program did not provide the flexibility to modify the application map based on criteria beyond grid sampling. Larry needed some way to more accurately identify regions in his fields where variable rates were needed. During this same time much of the research in variable rate application was indicating the cost of grid sampling to the intensity needed to create accurate maps was prohibitive (Hammond, 1992, Franzen and Peck, 1995, Gotway et al., 1996). This was the motivation behind the development of Dan's VRT program.

Dan's Background

Dan grew up on a small cotton, alflafa, and corn farm near Madera, California. He graduated from Cal Poly with a B.S. in Ag Business Management in 1970 and earned his MBA from Golden Gate University in 1973, he also is a Certified Crop Advisor. He worked as a sales representative for Uniroyal Chemical from 1970 to 1977. In 1975 he was transferred to Fort Morgan, Colorado. In 1977 he started his own fertilizer business called Morgan Soil. During this time he purchased a 200 acre irrigated farm that he continues to manage today. He later sold the fertilizer business to Centennial Ag and has worked for them until now as a fertilizer consultant. Dan has always had a love for computers, buying his first one in 1980 an Apple II. Dan comments, "I've always wanted to tell computers what to do and not vice versa."

Larry's Background

Larry was raised on the family farm north of Greeley, Colorado. He graduated from Colorado State University in 1970 with a B.S. in Farm and Ranch Management. From 1970 to 1972 he worked for his father and uncles on the farm. In 1973 he took a position with First Western Bank in Sacramento, California. After a year he returned to Colorado and began farming near Wiggins. He now farms 3000 acres of irrigated corn, sugar beets, and onions. He bought his first computer in 1980 and learned how to program, developing a small database program. He saw the potential for field and crop management early on and has constantly been an early adopter of new technologies.

The Case

In early January 1996 as Dan discussed their dilemma with developing a viable VRT program with Larry, his eyes came to rest on an aerial photograph of Larry's farm. He had seen the photo many times before but this time saw it in a new context. As he studied the variability in soil color he asked Larry, "why can't we use this to develop our variable rate application maps?"

Later that spring Dan consulted with Dr. Dave Wagner a remote sensing specialist from Colorado State University. Dr. Wagner described the work he had been doing with bare soil aerial imagery. His work indicated bare soil photos could be effective in identifying areas of high and low soil organic matter (SOM). Other research also indicated the grey tone pattern in black and white aerial photos is often a reflection of properties that impact crop yield (McCann et al., 1996). Bhatti et al. (1992) found SOM can be effectively determined from remote sensing and is significantly correlated with yield. Dan later contracted with Dr. Wagner to photograph three of Larry's fields. Dr. Wagner introduced Dan to several types of image processing software to enhance, georeference, and analyze the aerial photos. Larry felt the photos could be very effective in identifying regions in his fields for variable rate application.

During the winter of 1997 Dan and Larry began examining ASCS photos to determine if they could be effective in identifying variation in soil color. They found that generally they were taken to late in the season to indicate differences in soil color. However, photos taken when the fields were in sugar beets tended to reveal the differences in soil color, due to their later canopy cover. After examining several years of photos they were able to identify effective images for most of Larry's farms.

Dan used Adobe Photoshop® to enhance and process the images, he then georeferenced the images in a GIS package. Using these images as a template Larry drew vector lines on the maps indicating areas of high, medium, and low productivity based on soil color, topography, and his past management experience on the fields. These early photos and regions represented their first attempt at generating farmer developed management zones for variable rate application.

During this same time frame Dan installed variable rate controller equipment on one of his company's Terragator® liquid fertilizer applicators and developed the software to vary rates based on the management zones. A single liquid fertilizer mix was formulated to fit each field and was variably applied. As much as 40% more was applied to the lightest color soils and 40% less on the dark color soils. Using this method Dan applied variable rate fertilizer on 2500 acres of corn, sugar beets, and onions on Larry's farm. Larry and Dan estimated an increase in net returns of about $15.00 to $20.00 per acre in some cases. However, since no formal trials or check treatments were applied this was only an estimate.

Beginning in the 1997 growing season Larry also became a cooperator on a field scale precision farming project with Colorado State University and the USDA ARS. Dan is very practical minded businessman and tends to cast a skeptical eye at much of the research being done in academia. He felt as some do, that industry is always one or two steps ahead of university research. Larry feels any advantage he can find will help position himself better for the major changes in agriculture expected over the next few years and having early access to the data being generated out of the project may be one more advantage on his side. Kim Fleming, project manager for the research group was intrigued by their work and asked if he could correlate the projects data with the management zones. Fleming felt that the application of precision farming technologies has raced ahead of research into its value and saw this as an excellent opportunity to work with industry in determining the value of the technologies. Although skeptical of their work, Dan felt this could give him additional information to validate the management zones. Many of the soil and crop parameters being measured in the project followed the trends indicted by the management zones.

Dan needed to decide what his next step was. The management zone concept showed promise, however there are still many questions remaining. These and other issues will have to be addressed to determine whether it will be prudent for his business to make a major investment to further develop this concept or invest in one of the grid soil sample based VRT programs already developed.

Teaching Note

Computers, GPS, and GIS technology are enabling farmers and agricultural professionals to enter a new era in farm management. The challenge facing everyone adopting these precision farming methods is turning the massive databases being collected into better management decisions. The objectives for this case are to: 1) Evaluate the different approaches to precision farming and variable rate technology of a farmer and fertilizer consultant; 2) Determine how each might improve their utilization of the new technology; and 3) Develop an understanding of the challenges facing agribusinesses in using variable rate technology. The case was developed for extension, university, and agricultural industry trainers.

Notes to Facilitators

Debate over the value of grid soil sampling and the intensity needed to develop accurate maps is expected. The key will be utilizing the synergy produced from differing viewpoints to develop constructive solutions to the complex problem Dan faces. Some key questions I would hope would be raised are:

1. How effective will other farmers be in developing the management zones based on their aerial photos and experience? Larry felt very comfortable with the process. Utilizing farmer input helps give him ownership and control of the program. However, Larry is an early adoptor, some producers may feel intimidated by the technology and prefer more of the control to be in the hands of the consultant.
2. How practical is it to get aerial photos of the quality needed to develop the management zones on a wide scale basis and train people to properly enhance, georeference, and analyze the photos?
3. The results from the analysis of the data generated from the research project look positive, however will the concepts apply to other fields and other parts of the country?
4. What has other research in this area indicated? The papers referenced in the case could be provided to the students and in some teaching environments a literature search may be an appropriate exercise.
5. What other types of remote sensed data may be effective in developing the zones?

An important component that is missing that Dan needs to use to make valid decisions are on farm trails comparing his management zones with grid soil sampling approaches to variable rate application. Developing the experimental design and protocol for such a trail could be another valuable outcome from using this case. Depending on the depth of analysis desired the discussion of the case could last from an hour to a full day.

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