YIELD RESPONSE AND ECONOMIC IMPACT OF VARIABLE-RATE NITROGEN APPLICATIONS IN GRAIN SORGHUM

by

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B.S., Kansas State University, 2008

A THESIS

submitted in partial fulfillment of the requirements for the degree

MASTER OF SCIENCE

Department of Agronomy
College of Agriculture

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2012

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Abstract

Variable-rate (VR) nitrogen (N) applications have the potential to improve efficiency of grain sorghum production. Field experiments were conducted in 2010 and 2011 in Stockton and Manhattan, KS. Four VR-N prescriptions were generated using various combinations of grid soil sampling data, soil electrical conductivity (EC) data, and yield maps, and were compared in the field with a uniform application based on a composite soil sample and whole field average yield goal. Soil EC data were used to create management zones that were individually soil sampled. Prescriptions were applied before planting and grain sorghum was harvested and recorded with a yield monitor in the fall. Grain sorghum yields responded to N at both sites with a higher response in 2010 due to more precipitation during the growing season. At Stockton in both years, greatest yields and returns were realized with prescription 4, a combination of management zone soil data and spatially-variable yield goal, while the smallest yields were realized with prescription 2 based on management zone soil data and field average yield goal. Prescription 5, which used grid-soil sampling and a spatially-variable yield goal, and prescription 2 resulted in the lowest returns in both years. At Manhattan in both years, greatest yields and returns were realized with prescription 3, combining a composite soil sample with spatially-variable yield goal. Prescription 5 was among the lowest returning treatments in both years. At Stockton, there was no correlation between yield and soil EC during the 2010 growing season, however there was a significant correlation between yield and shallow EC during the drier 2011 season. At Manhattan, yield was correlated to deep EC in 2010 and to shallow EC in 2011. Overall, increasing spatial intensity of data to develop the prescriptions did not necessarily result in an increased yield response to the application. Prescriptions that included a variable yield goal component tended to perform better across both sites and years.

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Acknowledgements

I would like to thank my major professor, Dr. Anita Dille, for all of the help she has given me throughout my project and for the opportunity to become involved with the Agronomy Learning Farm. I would also like to thank my other committee members Dr. Kevin Dhuyvetter, Dr. Scott Staggenborg, and Dr. David Mengel, for their insight and support during this project. I would also like to give a special thanks to everyone that took time out of their schedules to share their expertise and technology with me including Dr. Randy Price and Darrel Oard for the use of the VR sprayer and guidance systems, Eric Lund and Paul Drummond from Veris Technologies for the use of their EC equipment, and Lucas Haag for the assistance with data analysis. I would also like to thank my family at Riffel Farms for providing me with the acres and equipment for my research at Stockton and for getting my rows planted straight. Finally, thanks to all of my family and friends for their support and encouragement during my graduate studies at K-State.

Chapter 1 - Review of Literature

Kansas has the greatest production of grain sorghum (*Sorghum bicolor* (L.) Moench) in the United States, with almost 810,000 hectares being harvested in 2011 to produce 2.8 million Mg of grain. This accounts for over 50% of the grain sorghum produced in the United States (NASS 2012). Much of this is due to the favorable growing conditions for sorghum in western Kansas. According to the 2010 Kansas county estimates nearly 95% of the state's grain sorghum was grown in the western two-thirds of the state (NASS 2011) where limited rainfall and high temperatures can make it difficult for other crops to perform. Grain sorghum is considered a relatively drought tolerant C_4 plant, capable of performing better than other crops such as corn (*Zea mays* L.) and soybeans (*Glycine max* L. Merr.) when growing in moisture limited and high temperature conditions (Stahlman and Wicks 2000).

In Kansas, grain sorghum is often substituted for corn in crop rotations and like corn, grain sorghum can require large amounts of nitrogen (N) fertilizer to achieve high yields. Nitrogen is one of the most essential and extensively applied nutrients in grain sorghum (Buah et al. 1998) and often the most expensive input for the crop. When managing N fertility, it is important to understand that spatial variability exists and that under- and over-applications of N will cause either N deficiencies in the crop or N losses due to leaching or runoff (Koch et al. 2004). Both of these situations will have an economic impact for farmers and the N losses can cause environmental concerns for the general public (Buah et al. 1998). One solution to the under- and over-applications of N fertilizer is to use variable-rate (VR) application methods. However, very little research has been done pertaining to VR-N application in grain sorghum.

Soil fertility can vary significantly within a field so the traditional nutrient management strategy of applying a single rate of fertilizer could be considered a misapplication (Thrikawala et al. 1999). Other variables in the field including soil texture, slope, and yield potential can also cause a similar result of mismanaged N fertilizer. Many of these field variables can be measured, recorded, and manipulated to be used in VR fertilizer prescription development. However, not only does the usefulness of this information need to be studied, but the economics behind collecting it and implementing it also need to be analyzed.

There are many methods of generating VR-N prescriptions with more new methods surfacing each year (Anglund and Ayers 2003). Creating a VR-N prescription is based on some type of variability within the field. Soil fertility, soil texture, soil depth, slope, water infiltration, yield potential, or elevation can all be variables upon which the prescription is based. Unfortunately, many of the new methods and technology being used have entered the market without scientific verification of accuracy or efficacy (Anglund and Ayers 2003). In order for a prescription to work well, the variables being used should have an influence on yield potential, soil N content, or some factor that is either going to spatially boost yields, or reduce inputs.

With the cost of N increasing and the cost of VR technology and equipment decreasing, it is becoming more economical to implement the technology. But for some smaller or less productive farms the cost to implement the technology and services for VR still may outweigh the savings on inputs. The potential for improved profitability due to VR-N application depends on identifying areas in the field where additional N inputs will increase revenue on a scale that is greater than the added costs and /or identifying areas where reducing N inputs will decrease costs on a scale that is greater than potential revenue reduction associated with lower grain yield (Snyder et al. 1999). In order for the returns to outweigh the costs, the fields involved need to have a sufficient amount of spatial variability. Assessing field variability can be done using various sampling methods such as grid-soil sampling or by mapping field measurements such as soil electrical conductivity (EC), yield, topography, or soil type. Once the field variability is assessed, an N prescription must be created. This step can be expensive to implement depending on the approach. The profitability potential of VR-N management is significantly enhanced if the initial means of preparing the prescription maps are less expensive (Koch et al. 2004).

Nitrogen Recommendations

Generating nitrogen recommendations in Kansas is typically done by using the Kansas State University nitrogen recommendation equation (Leikam et al. 2003):

N recommendation for grain sorghum (lbs acre^{-1}) = (Yield Goal (bu acre^{-1}) × 1.6) – (OM (%) × 20) – (Sample Depth (inch) × Profile N (ppm) × 0.3) – Manure N – Other N Adjustments + Previous Crop Adjustments [1]

The metric equivalent of the equation is:

N recommendation for grain sorghum (kg ha^{-1}) = (Yield Goal (Mg ha^{-1}) × 28.5) – (OM (g kg^{-1}) × 2.2) – (Sample Depth (cm) × Profile N (mg kg^{-1}) × 0.13) – Manure N – Other N Adjustments + Previous Crop Adjustments [2]

Yield goal is typically either estimated by the farmer's past experiences with the field or from yield monitor data. Soil organic matter content (OM) is measured by extracting 15-cm depth soil samples and having a soil testing lab perform an OM analysis. The Profile N portion of the equation is found by extracting 60-cm depth soil samples and having a soil testing lab analyze them for NO_3 content. Manure N accounts for the nitrate content of any manure that is applied to the field. Other N Adjustments would include any nitrates in irrigation water that may have been applied. Previous Crop Adjustments would credit the field for having a legume planted previously. This N credit could be anywhere from 22 to 134 kg N ha^{-1} depending on the quality of the legume crop and whether the crop was terminated and left on the surface or incorporated using tillage (Leikam et al. 2003). Because each part of the equation has an effect on the recommended amount of N to be applied, the methods for collecting the data to input as well as spatial resolution of that data will generate different results. The challenge is selecting which data to use based on economic feasibility of the approach.

Grid Soil Sampling

One approach for site-specific N studies is the use of grid soil sampling as the primary method of developing VR-N prescriptions. The trouble is that grid soil sampling is time consuming and labor intensive (Koch et al. 2004). With nutrients such as P and K, crop removal values can be used to estimate how much nutrient was removed by the previous crop based on its yield. This cannot be done with N, due to denitrification and its potential to leach.

Yield Monitoring

Previous crop yields should be considered when generating N prescriptions as one of the main components of an N recommendation equation is the yield goal of the crop. Yield monitors generate spatially dense data at a relatively low cost, potentially allowing characterization of the spatial and temporal yield variability (Dobermann 2003). These data can be used to generate yield potential for individual locations in a field by analyzing data from years past. However, as more yield monitors are used and multiple years of yield data accumulate, there is an increasing concern about how to process and interpret these data. This is due to the fact that the analysis and interpretation of yield map data has lagged behind yield monitor adoption by farmers (Dobermann 2003).

When calibrated properly, yield monitors perform quite well. One research project reported that when compared to certified scales, yield monitors were accurate to within 2 to 5% (Dobermann 2003). Before using the yield monitor data to make site-specific management decisions it is necessary to clean the data by removing points where: the combine header was raised, no grain flow was detected, values exceeded minimum and maximum biological yield limits, or the point was a local neighborhood outlier or a co-located point (Simbahan et al. 2004). This will improve the quality of the yield maps and allow them to be a more accurate assessment of yield.

Topography

A major portion of field variability is credited to topography. Topography affects yield by influencing water availability and the redistribution of soil particles, OM, and soil nutrients with resulting changes in physical and chemical properties of uphill and downhill soils (Kravchenko and Bullock 2000). Topography also plays a large part in the traditional management of many fields by giving a reason to terrace side-hills and plant with the contour. For site-specific management, knowing elevation and slope throughout a field can be most helpful for delineating areas where crop yields are more sensitive to extreme conditions, such as erosion on hillsides and flooding in low areas (Kravchenko and Bullock 2000).

Soil Type

Creating nutrient management zones by soil type is another way to approach field management in a site-specific manner. Using soil surveys is a great way of determining soil types throughout a field, but often these surveys are created on a scale that is not accurate enough to be used in site-specific management. Order 2 surveys are those seen in most county soil survey publications and have a scale from 1:12,000 to 1:31,680. These were developed for agriculture requiring detailed soils information for general planning purposes (Franzen et al. 2002). Order 1 surveys are needed for applications requiring very detailed soils information and usually have a scale larger than 1:15,840. The order 1 survey is much more related to soil NO_3 and would be more useful for determining nutrient management zones (Franzen et al. 2002).

Remote Sensing

Remote sensing is an increasingly popular source of data for site-specific crop management. Defined as the process of acquiring information about objects from remote platforms such as a boom, aircraft, or satellite, remote sensing provides important spatial and temporal data (Shanahan et al. 2001). Nitrogen is the most limiting nutrient in production of non-leguminous crops in the Great Plains (Osborne et al. 2002). However, with the use of remote sensing plant N concentration can be predicted to help determine if the N content is limiting the crop. One study shows that plant N concentration was best predicted using reflectance in the red and green regions of the spectrum, while grain yield was estimated using reflectance in the near-infrared (NIR) region (Osborne et al. 2002). Another study used green and near-infrared reflectance to calculate an N reflectance index. This index was highly correlated to a Nitrogen sufficiency index calculated from SPAD chlorophyll meter data and provided a quick assessment of plant N (Hatfield et al. 2008). There are a number of additional vegetative indices that are used for detecting crop health. One of the more commonly used indices is the normalized difference vegetative index (NDVI), where NDVI= (NIR-Red) / (NIR + Red), where NIR is near infrared reflectance and Red is red light reflectance (Shanahan et al. 2001). The NDVI is used to assess the health and condition of a growing crop or natural cover. Some research has shown that NDVI data could have issues due to soil background effects on the imagery (Shanahan et al. 2001). Using remote sensing to detect plant health or measure N concentration requires the crop to be growing, therefore it is not practical for pre-plant fertilizer applications. However, it can be used as a follow-up to determine general crop health and whether fertility was assessed correctly. Remote sensing is used more to direct topdressing, side-dressing, and split applications of N fertilizer.

Soil Electrical Conductivity

Soil EC is a field mapping option that shows promise for site-specific management. Depending on the strength of the relationship between EC and the soil's characteristics, EC may function as a direct or indirect indicator of numerous parameters such as soil moisture and clay content (Johnson et al. 2003). However, the practical utility of EC remains elusive due to its complex interactions between soil chemical and physical properties. Research has shown that the spatial patterns in EC are more correlated with clay, sand, organic matter components, subsoil structure, and exchange cations than the transient properties of soil water and temperature (Farahani and Buchleiter 2004).

Collecting EC data is fast, inexpensive, and the data do not need to be collected yearly, which is ideal for keeping input costs low. Soil EC is usually measured at two depths: a shallow reading (0-30 cm) and a deep reading (0-90 cm) (Johnson et al. 2003). The temporal stability of the deep readings will usually be greater than the shallow readings however it is dependent on the type of soil (sand vs clay) (Farahani and Buchleiter 2004). Determining which depth correlates to yield the best can depend on the field and the subsoil structure. Generally, shallow EC has been shown to be highly correlated with soil moisture, organic matter, and N content (Johnson et al. 2003). Deep EC has been shown to be correlated to claypan topsoil thickness and water holding capacity (Farahani and Buchleiter 2004).

The typical usage of EC data was to create management zones based on spatial patterns in EC. These zones will have similar characteristics which usually include OM, N content, salinity, percent clay, and bulk density (Johnson et al. 2003). Soil EC has been recognized as being a less expensive method for creating field management zones. Other means of determining field management zones based on soil parameters include grid-soil sampling, which can be costly and therefore economically unfeasible, particularly in dryland, low input farms (McCann et al. 1996).

Economic Considerations

Grid-soil sample-based field management is a tedious process and an intensive management strategy, however it is still feasible to manage some fields using a grid layout. As long as the increases in gross revenue or decreases in N input costs outweigh the added cost of technologies or services needed for VR, the management practice is sufficient (Koch et al. 2004). This is usually the case when a field is highly productive and highly variable. Changes in soil properties over time will affect the frequency of sampling when considering temporal variability. Often, crop rotations and intensity will have an influence on how often soil sampling needs to occur and can range from being performed annually, biannually, or even less frequently. This will have a large impact on the economic analysis of any type of sampling taking place. There has been research conducted regarding the economics behind VR-N application (Thrikiwala et al. 1999; Roberts et al. 2000) however, most was done using crop modeling or hypothetical scenarios in corn. Using a theoretical model, Roberts et al. (2000) found that yield would most likely increase 0 to 125 kg ha^{-1} on average using VR-N application compared to a uniform N application. This indicated that a significant reduction in N input was required in order to see an economical advantage from VR-N technology. Thrikiwala et al. (1999) found that a uniform N application was likely to be more economical when field areas were small and when there was little spatial variability in soil properties. Variable rate N applications can potentially improve yields and reduce inputs enough to be economically advantageous in fields with moderate to high variability. Ideally, economic analysis should be done on a field to field basis due to differences in spatial variability among individual fields (Roberts et al. 2000).

Site-specific management zones (SSMZ) is one way of classifying field regions with similar characteristics. By creating SSMZ a producer will have subfields that will be treated homogenously rather than treating the whole field in this manner. With similar productivity potential, fertilizer can be variably applied in accordance with the nutrient needs of each zone (Hornung et al. 2006). The purpose of using SSMZ was to capture the variabilty throughout a field while allowing the field management to remain economically feasible. Creating SSMZ can be approached in numerous ways involving many different types of data, such as soil surveys, topographic maps, remote images, soil EC, yield maps, and others (Hornung et al. 2006). There are multiple ways to combine these data to make SSMZ. One effective way was to combine topography and EC data (Fraisse et al. 2001). Another method was to use yield data and create yield region maps (Flowers et al. 2005). However, the appropriateness of management zones was based on the particular field and location of the area of interest (Schepers et al. 2004).

The objective of this study was to develop, apply, and evaluate five different N fertilizer prescriptions for grain sorghum. The prescriptions were generated by using different levels of input information intensity. The prescriptions included the use of site-specific data such as grid soil sampling, soil EC, and historical yield monitor data in multiple combinations. Prescriptions build upon each other, each one adding more intensity to the input data than the previous one. The first prescription begins with a traditional fertilization method with a consistent, uniform N rate. The second prescription adds EC management zones into the generation process and the third prescription uses spatially-variable yield data. The fourth prescription combines prescriptions 2 and 3 while prescription 5 brings the most intensity by adding grid-soil sampling data with spatially-variable yield data. The prescriptions were applied in the field at two locations over two years (four site-years) and compared based on yield response to N, prescription yield performance compared to historic yields, correlations of variables to yield, prescription revenues, prescription input expenses, and returns over N prescription costs. The hypothesis was that increasing the amount of spatially-variable data input into the N recommendation equation may boost yields while lowering the N fertilizer required thus improving returns in grain sorghum in Kansas.

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Chapter 2 - Generating Variable-Rate Nitrogen Prescriptions Using Yield Data, Soil Electrical Conductivity, and Grid-Soil Sampling

ABSTRACT

Variable-rate (VR) technology has been developed to capture and manage spatial variability within fields. A major uncertainty, however, is how to take advantage of and document this in-field variability. Although VR nitrogen (N) management can reduce inputs and potentially boost yields, it also requires an investment in technology and information. The purpose of this study was to create multiple VR-N fertilizer prescriptions based on various sets of data collected from four different fields. Fields were in Stockton and Manhattan, KS in 2010 and 2011 where grid soil sampling data, soil electrical conductivity (EC) data, and historic yield maps were used in different combinations to generate four VR-N prescriptions and one uniform N prescription to be used in grain sorghum. One prescription involved combining yield map data with grid soil sampling data to provide spatially-variable yield goals, profile N tests, and soil organic matter (OM) tests across the fields. Another prescription used yield map data and soil EC data to provide spatially-variable yield goals and EC zones that were sampled for profile N and OM. The other prescriptions used historic yield data for a spatially-variable yield goal with a field-composite soil test, used grid soil samples with a fixed overall yield goal, and used a field-composite soil test and fixed overall yield goal. Each prescription offered a different level of data intensity with respect to the inputs involved in creating it. All prescriptions were generated using EASi Suite GIS software and the KSU nitrogen recommendation equation for grain sorghum. The prescriptions were compared based on the variability of soil test data, EC, and yield goals. The variability and range of the input data had little effect on the total N

required to apply the prescription across the whole field. Typically, as prescription input data became more intense, more spatial-variability was captured by that prescription, as expected. The next step will be to field test the prescriptions and collect yield data to determine which prescriptions were more accurate and whether those requiring less or more N to fulfill the recommendations were under- or over-applying N.

INTRODUCTION

As the era of precision agriculture expands, the use and understanding of field data being collected must also expand. Understanding how the data can be gleaned and manipulated to be used in decision making process is widely undervalued. One aspect of precision agriculture that requires the use of these field data is variable-rate (VR) fertilizer applications. When it comes to managing the most essential crop nutrients, such as nitrogen (N), it is important to realize that spatial variability exists and that over- and under-applications of N occur using traditional management (Koch et al. 2004). Soil fertility can vary significantly within a field so the typical nutrient management strategy of applying a single rate of fertilizer could be considered a misapplication (Thrikawala et al. 1999). Other spatially-variable field properties, including soil texture, water holding capacity, and yield potential can also cause a misapplication of N.

Even with an understanding that spatial variability exists within a field, a challenge still presents itself: building prescriptions. There are many methods of generating a VR-N prescription with more new methods surfacing each year. Unfortunately, many of the new methods and technologies have entered the market without scientific verification of accuracy or efficacy (Anglund and Ayers 2003). Regardless of the method being used, it is important to use some form of N recommendation equation to be sure all N sources and field variables are accounted for. The Kansas State University N recommendation equation accounts for the yield goal of the field to initially set the total N required. In-field N sources such as profile NO_3, organic matter (OM), legume crop residue, and manure are taken into account and subtracted from the total N required to provide the producer with a recommended N fertilizer value (Leikam et al. 2003). Using an equation such as this, a producer can account for the variables that affect N fertilizer requirements for a crop and reduce over- or under-applications of N. The equation used for grain sorghum (*Sorghum bicolor* (L.) Moench) suggests that each bushel of grain produced will need 1.6 lbs of N (1 kg of grain needs 28.5 g N) to be taken up by the plant. This value is based on N use efficiency (NUE) of 50% (Leikam et al. 2003). Depending on the soil and the year, NUE can fluctuate drastically, but if NUE is consistently higher or lower, then the 1.6 lbs of N can be adjusted.

In 2011, Kansas produced over 50% of the grain sorghum in the United States (NASS 2012). Much of this is due to the favorable growing conditions for sorghum in western Kansas. Grain sorghum is considered a relatively drought tolerant C_4 plant, capable of performing better than other crops such as corn (*Zea mays* L.) and soybeans (*Glycine max* L. Merr.) when growing in moisture-limited and high temperature conditions (Stahlman and Wicks 2000). Very little research has been done pertaining to VR-N application in grain sorghum, even though grain sorghum is often substituted for corn in crop rotations in Kansas.

The objective of this study was to use multiple methods to generate five different N fertilizer prescriptions. The prescriptions will include the usage of site-specific data such as grid soil sampling, soil electrical conductivity (EC), and yields in multiple combinations. Prescriptions build upon each other, each one adding more spatiall-intense input data than the previous. The first prescription consists of a more traditional method by recommending a constant, uniform N rate across the field. The second prescription adds EC management zones into the generation process and the third prescription uses spatially-variable yield data. The fourth prescription combines prescriptions 2 and 3 while prescription 5 brings the most intensity by adding grid soil sampling to yield data. The hypothesis was that as input data increases in intensity, more field variability will be captured, and therefore, the N recommendation output will become more variable and fine-tuned.

MATERIALS AND METHODS

Nitrogen fertilizer recommendations were generated for two grain sorghum production fields in 2010 and in adjacent fields at the same farms in 2011. The first farm was a farmer-owned and operated production field in Stockton, KS and the second farm was located at the Kansas State University Department of Agronomy North Farm in Manhattan, KS. The Stockton fields were larger tracts than those used in Manhattan with the 2010 field being 38 ha and the 2011 field being 17.8 ha, both with a Holdrege silt loam soil, as compared with the Manhattan fields which were 8.9 ha and 7.3 ha in 2010 and 2011, respectively. Manhattan fields were a Smolan silt loam soil with partial inclusions of Wymore silty clay.

Prior to each growing season, soil samples were taken in a grid pattern. Due to the small scale of the experiments, Stockton sites were sampled on a 0.4 ha grid while the Manhattan sites were sampled on a 0.2 ha grid. Each sample included a 15 cm surface depth to acquire pH, OM, potassium, phosphorus, and surface NO_3 measurements accompanied with a 15 to 46 cm profile depth used to provide profile NO_3 measurements. Samples were submitted to the Kansas State University Soil Testing lab for analysis.

Prescriptions were generated with the software package EASi Suite version 2009.01 (Mapshots Inc., Cumming, GA). Using this software all soil sample data were imported for each field, interpolated using inverse distance weighting (IDW), and saved as a layer. When creating these layers, polygons were used to create the surface of the field. Each polygon was fitted with its own set of data estimated via interpolation. In this case, dimensions of the polygons were directly related to the width of the fertilizer application equipment to be used in each field. The applicator width was 10.7 m for Stockton, therefore interpolation was done in 10.7 by 10.7 m polygons. The applicator width for Manhattan was 4.6 m, therefore interpolation was done in 4.6 by 4.6 m polygons.

Soil EC measurements were taken at each site using a Veris 3100 EC cart (Veris Technologies, Salina, KS). In 2010, Stockton field was measured on May 17 and the Manhattan field was measured on May 24. In 2011, the Stockton field was measured on May 6 and Manhattan field was measured on May 4. The Veris cart measures EC at two depths, Shallow (30cm) and Deep (90cm), by inducing an electrical current into the soil through two coulter electrodes and measuring the voltage drop across two pairs of coulters (Lund et al. 2000).

Soil EC data were imported into EASi Suite where it was interpolated using IDW and saved as a layer. In order to use the soil EC data to generate the prescriptions, the layer was grouped into site-specific management zones that possess similar EC measurement values thus creating zones with similar soil properties that may include clay content, soil water content, salinity, bulk density, depth of conductive soil layers, and OM (Johnson et al. 2003; Kitchen et al. 2003). Management zones were developed using a format similar to a contour map where division lines were drawn between clusters of similar data. Management zones were based on the shallow EC measurements. Shallow EC has been reported be correlate to soil water, organic matter content, and total N (Johnson et al. 2001). Both Stockton fields were divided into five management zones while the Manhattan fields were divided into six zones in 2010 and five zones in 2011. These zones were treated as homogenous regions and the grid-soil sample data from within each zone were averaged to give soil test values for each zone (Table 2.2). This layer was used in generating prescriptions 2 and 4.

Stockton fields had historical yield data from three previous growing seasons available while Manhattan fields had yield data from six growing seasons. It was important to have an adequate number of growing seasons of yield data in order to represent spatial yield performance in each field. Historic yield data were subsequently used to establish a spatially-variable yield potential, or yield goal, in the fields. Historical yield data were imported into the software, filtered, and cleaned using the ARS yield editor add-on within EASi Suite. This removed erroneous data caused by rapid harvester speed changes, flow delays, and simple harvester machine dynamics (Griffin et al. 2007). Once the skewed and inaccurate data were removed, the yield data from each year were interpolated using IDW and saved as a layer. Each year's layer then had to go through a process called normalization. This converted each yield data polygon into an annual relative yield that lies on a scale between -1 and 1 and allowed for comparison of multiple years of yield data when different crops were in the rotation. This calculation was called annual relative difference (ARD) and was performed within the EASi Suite option IntelliCalc. The calculation of ARD for each polygon was:

$$\text{ARD} = (\text{Yield} - \text{Average Yield}) / \text{Average Yield} \qquad [1]$$

where Yield (kg ha^{-1}) is the measured yield in given polygon and Average Yield (kg ha^{-1}) is the observed field average.

Before the ARDs can be used to create a yield goal component it was important to compare among years to ensure that the field highs and lows were correlated to each other. If the multiple crops in the rotation were not all correlated, it was acceptable to exclude those with low correlations. All ARDs were highly correlated for all locations and years (data not shown). This allowed the ARDs for each field to be averaged into one layer labeled mean relative difference (MRD) by placing each layer on top of another and averaging the values that were "skewered" through each polygon (Figure 2.1). This estimates a MRD for each polygon in the field and indicated whether the polygon had high, medium, or low performance based on average yields. The calculation for MRD was:

$$\text{MRD} = (\text{ARD}_1 + \text{ARD}_2 \ldots\ldots \text{ARD}_X) / X \qquad [2]$$

where x is the years of yield data available. The MRD layer was then used to calculate the grain sorghum yield goal for each individual polygon in the field. Yield Goal was calculated for each field using:

$$\text{Yield Goal} = [(\text{MRD} + 1) \times \text{Field Average Yield}] \times 1.1 \qquad [3]$$

where the Field Average Yield is the expected grain sorghum yield for that field based on past records or experience. This calculation used the past yield data to weigh in with each polygon's relative potential while using a producer's field average yield to set the basis for yield prediction. The last term in equation 3 provides a 10% increase over field average yield as yield goals are usually aimed at achieving above average yields. Table 2.3 indicates the range in yield goals for all four fields. This yield goal layer was used in the process of generating prescriptions 3 and 5.

Five different N fertilizer prescriptions were generated for each grain sorghum crop using data collected from each field. Each prescription was created using the Kansas State University Nitrogen Recommendation Equation:

$$\text{N (lbs/acre)} = (\text{YIELD GOAL} \times 1.6) - (\%\ \text{OM} \times 20) - (0.3 \times 18'' \times \text{PROFILE NO}_3) \quad [4]$$

where YIELD GOAL (bu/ac), OM (%), and PROFILE NO_3 (ppm) were the three input variables used to generate the five prescriptions.

Prescription 1 used a field composite soil test to provide the PROFILE NO_3 and OM input values and a fixed YIELD GOAL to generate a uniform N prescription. The field composite soil sample was used as a whole field representation and was generated by averaging together several grid sample points from across the field to simulate the field composite soil sample. The fixed yield goal was determined by using an estimated field average for grain sorghum yield.

Prescription 2 used the soil EC measurements to create management zones which were individually soil sampled to create zone-composite soil tests. These soil data provided the PROFILE NO_3 and OM input values and together with the fixed YIELD GOAL, a VR-N prescription was generated.

Prescription 3 used the yield data from previous cropping seasons to create a spatially-variable YIELD GOAL that was combined with a field composite soil sample to provide the PROFILE NO_3 and OM input values to generate a VR-N prescription.

Prescription 4 combined the spatially-variable YIELD GOAL component from prescription 3 with the soil EC management zone approach from prescription 2 to provide the PROFILE NO_3 and OM values and create a VR-N prescription.

Prescription 5 combined the spatially-variable YIELD GOAL component from prescription 3 with PROFILE NO_3 and OM input values based on grid soil samples rather than field composite or EC management zone soil samples to generate a VR-N prescription.

Prescriptions 2, 3, 4, and 5 were all VR-N prescriptions, due to one or more components being spatially variable and needed to be prepared using IntelliCalc. Prescription 1 did not have any spatially-variable inputs and therefore could be calculated using only the KSU N recommendation equation (Leikam et al 2003). The four fields were compared using average, minimum, and maximum values of the historical yields and soil properties measured. Prescriptions for each field were compared based on the variability in yield goal, NO_3, and OM that each one captured and used to generate a N recommendation. Comparisons were also based on average, minimum, and maximum N rates to be applied among prescriptions and the total N required by each prescription to fertilize the entire field area.

RESULTS AND DISCUSSION

Data intensity increased from prescription 1 through prescription 5 with regards to extent of spatial variability of input data and the variability in the N rate to be applied. Tables 2.2 through 2.4 indicate the large ranges in the measurements of yield goal, NO_3, and OM as the prescription number increases in Stockton 2010 and 2011 and Manhattan 2010. Manhattan 2011 had a yield goal range of over 6000 kg ha^{-1} in prescriptions 3 through 5, whereas prescriptions 1 and 2 have no range in yield goal (Table 2.5). The variability of profile soil NO_3 was much greater for prescription 5 than it was for prescriptions 2 and 4, again due to the density of sampling for the input data (Tables 2.2 to 2.5). Prescriptions 1 and 3 have no variability in profile soil NO_3 test data, as those data came from the field composite soil sample. Prescription 5 had the most range in yield goal, NO_3, and OM in all fields due to the high density of data from grid soil sampling. The result of capturing more variability often allowed prescription 5 to decrease the total N required (Tables 2.6 to 2.9). Prescriptions 3 and 4, although more intensive, often had higher total N requirements than the lower intensity treatments, but this varied from field to field. Prescription 3 had the highest average N rate recommended to be applied across all four fields yet it did not always have the highest maximum N rate or the widest range of N rates (Tables 2.6 to 2.9). This was a result of the yield goal component having such a large influence on the outcome of the N recommendation equation.

The degree of N rate variability shown in Tables 2.6 through 2.9 is an indicator of how differently these prescriptions captured variability in the field. The total N required to fulfill each prescription also shows how variability was captured differently. For example, a range of

170 kg of total N was required to fertilize across the different prescriptions in Manhattan 2010 compared to a range of 1405 kg of total N required to fertilize across the five prescriptions in Stockton 2010.

Mallarino and Wittry (2004) found that more intensive grid sampling approaches uncovered more variability than zone sampling approaches which agrees with our results. However, adoption of an intensive grid-soil sampling approach may not be practical due to the increased costs associated with the approach and the possibility that increases in variability uncovered may not result in a crop response. Another approach to mapping in-field soil variability was zone sampling. Shaner et al. (2008) found that soil EC effectively assisted in developing management zones that provided soil fertility information comparable to grid soil sampling without the large number of samples and high cost. Soil EC also provided more valuable information towards generating zones than Order 2 soil surveys and topography maps in some fields (Shaner et al. 2008; Kitchen et al. 2003). Yields were also variable across the field and were captured using yield monitors. Using yield monitor data from previous years can be an improved way of determining yield goals on a spatial basis (Taylor 1998). Spatial yield goals have been reported to be beneficial and should be used when making management zones and fertility recommendations (Chang et al. 2004). Due to the differences in spatial variability captured across fields, it is important to understand which variables might drive the yield potential for any given field. This may allow for a starting point, if not some conclusive reasoning for selecting VR-N prescription generation methods.

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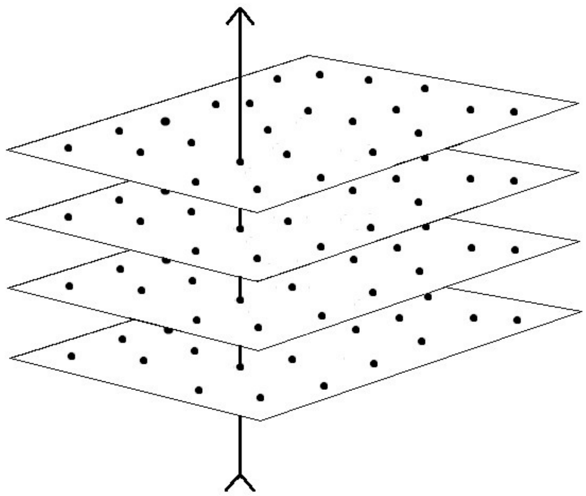

Figure 2.1 Illustration of the "skewering" effect on a polygon in a field through multiple layers of data. This example shows how annual relative difference (ARD) layers of multiple years (2006, 2007, 2008, and 2009) were combined.

Table 2.1 Average, CV, minimum, and maximum values for variables measured in each field.

Field	Statistic	$EC_{Shallow}$	EC_{Deep}	YG	NO_3	OM	P	K	pH
		------mS m^{-1}------		kg ha^{-1}	mg kg^{-1}	g kg^{-1}	mg kg^{-1}	mg kg^{-1}	
Stockton 2010	Average	77.0	70.1	6903	6.9	1.9	14.9	587	6.4
	CV	15.4	5.5	13.0	24.5	17.3	46.8	5.8	7.6
	Minimum	41.0	50.0	4393	4.5	1.2	7.2	528	5.7
	Maximum	106.0	98.7	9249	11.5	2.6	33.2	672	7.7
Stockton 2011	Average	28.0	-	6777	10.0	1.7	13.6	536	5.9
	CV	10.7	-	6.0	29.0	20.1	23.6	6.7	3.2
	Minimum	15.0	-	4769	5.0	1.0	9.0	464	5.6
	Maximum	40.0	-	9249	19.0	2.0	22.0	679	6.4
Manhattan 2010	Average	88.0	67.2	7154	7.7	2.2	26.1	294	6.5
	CV	8.8	3.8	7.9	15.9	16.4	75.4	6.0	9.5
	Minimum	64.0	58.9	3972	6.5	1.6	4.3	196	5.8
	Maximum	115.0	76.0	8333	9.0	3.1	70.4	351	7.8
Manhattan 2011	Average	32.0	-	7593	13.2	2.3	15.0	394	5.7
	CV	21.2	-	13.6	12.6	14.7	85.0	13.9	8.4
	Minimum	16.0	-	3796	8.8	1.7	5.3	337	5.2
	Maximum	55.0	-	10228	17.8	2.9	117.0	570	7.0

$EC_{shallow}$ - 30-cm soil electrical conductivity, EC_{deep} - 100-cm soil electrical conductivity, YG – yield goal based on normalized yield, NO_3 – 45-cm nitrate content, OM – 15-cm organic matter content, P – 15-cm phosphorus content, K – 15-cm potassium content

Table 2.2 Average, minimum, and maximum input values used in generating prescriptions for Stockton 2010.

Prescription	Yield Goal			NO_3			Organic Matter		
	Average	Minimum	Maximum	Average	Minimum	Maximum	Average	Minimum	Maximum
	-------------- kg ha^{-1} --------------			-------------- mg kg^{-1} --------------			-------------- g kg^{-1} --------------		
1	6903	6903	6903	16.3	16.3	16.3	2.1	2.1	2.1
2	6903	6903	6903	16.0	10.9	27.3	1.9	1.7	2.0
3	6903	4393	9249	16.3	16.3	16.3	2.1	2.1	2.1
4	6903	4393	9249	16.0	10.9	27.3	1.9	1.7	2.0
5	6903	4393	9249	22.7	8.5	34.2	1.9	2.7	2.4

Table 2.3 Average, minimum, and maximum input values used in generating prescriptions for Stockton 2011.

Prescription	Yield Goal			NO_3			Organic Matter		
	Average	Minimum	Maximum	Average	Minimum	Maximum	Average	Minimum	Maximum
	-------------- kg ha^{-1} --------------			-------------- mg kg^{-1} --------------			-------------- g kg^{-1} --------------		
1	6777	6777	6777	27.3	27.3	27.3	1.7	1.7	1.7
2	6777	6777	6777	23.4	18.9	40.5	1.7	1.0	2.1
3	6777	4769	9989	27.3	27.3	27.3	1.7	1.7	1.7
4	6777	4769	9989	23.4	18.9	40.5	1.7	1.0	2.1
5	6777	4769	9989	23.2	12.1	47.9	1.7	0.9	2.3

Table 2.4 Average, minimum, and maximum input values used in generating prescriptions for Manhattan 2010.

Prescription	Yield Goal			NO_3			Organic Matter		
	Average	Minimum	Maximum	Average	Minimum	Maximum	Average	Minimum	Maximum
	---------------kg ha^{-1}---------------			---------------mg kg^{-1}---------------			---------------g kg^{-1}---------------		
1	6087	6087	6087	10.0	10.0	10.0	2.1	2.1	2.1
2	6087	6087	6087	9.0	4.9	21.4	1.8	2.0	2.5
3	6087	3972	8333	10.0	10.0	10.0	2.1	2.1	2.1
4	6087	3972	8333	9.0	4.9	21.4	1.8	2.0	2.5
5	6087	3972	8333	10.8	4.8	25.9	2.2	1.6	3.1

Table 2.5 Average, minimum, and maximum input values used in generating prescriptions for Manhattan 2011.

Prescription	Yield Goal			NO_3			Organic Matter		
	Average	Minimum	Maximum	Average	Minimum	Maximum	Average	Minimum	Maximum
	---------------kg ha^{-1}---------------			---------------mg kg^{-1}---------------			---------------g kg^{-1}---------------		
1	6903	6903	6903	38.5	38.5	38.5	2.4	2.4	2.4
2	6903	6903	6903	34.9	30.8	41.2	2.3	2.0	2.6
3	6903	3796	10228	38.5	38.5	38.5	2.4	2.4	2.4
4	6903	3796	10228	34.9	30.8	41.2	2.3	2.0	2.6
5	6903	3796	10228	35.5	22.9	47.5	2.4	1.7	2.9

Table 2.6 Average, minimum, and maximum prescribed N rates for each prescription in Stockton 2010.

Prescription	N rate Average	Minimum	Maximum	Total N Required
	--------------------------kg ha^{-1}			----------------------------
1	106	106	106	4043
2	88	80	112	3362
3	125	54	189	4767
4	122	99	142	4639
5	105	32	187	4001

Table 2.7 Average, minimum, and maximum prescribed N rates for each prescription in Stockton 2011.

Prescription	N rate Average	Minimum	Maximum	Total N Required
	--------------------------kg ha^{-1}			----------------------------
1	132	132	132	2352
2	132	108	149	2352
3	142	114	197	2532
4	139	109	168	2472
5	141	113	181	2512

Table 2.8 Average, minimum, and maximum prescribed N rates for each prescription in Manhattan 2010.

Prescription	N rate			Total N Required
	Average	Minimum	Maximum	
	---------------------------kg ha^{-1}	----------------------------		
1	131	131	131	1166
2	123	103	231	1096
3	138	57	171	1226
4	131	83	188	1166
5	127	32	185	1126

Table 2.9 Average, minimum, and maximum prescribed N rates for each prescription in Manhattan 2011.

Prescription	N rate			Total N Required
	Average	Minimum	Maximum	
	---------------------------kg ha^{-1}	----------------------------		
1	116	116	116	850
2	128	122	225	932
3	148	80	223	1079
4	146	82	243	1063
5	124	62	209	908

Chapter 3 - Grain Sorghum Yield Response to Variable-Rate Nitrogen Applications

ABSTRACT

Variable-rate (VR) nitrogen (N) applications have the potential to improve efficiency of grain sorghum production. Field experiments were conducted in 2010 and 2011 in Stockton and Manhattan, KS. Four VR-N prescriptions were generated using various combinations of grid soil sampling data, soil electrical conductivity (EC) data, and yield maps, and were compared in the field with a uniform application based on a composite soil sample and whole field average yield goal. Soil EC data were used to create management zones that were individually soil sampled. Prescriptions were applied before planting and grain sorghum was harvested with a combine equipped with a yield monitor in the fall. Both sites had good yield responses to N with a higher response in 2010 due to more precipitation during the growing season. At Stockton in both years, greatest yields were realized with prescription 4, a combination of management zone soil data and spatially-variable yield goal, while the smallest yields were realized with prescription 2 based on management zone soil data and field average yield goal. At Manhattan in both years, greatest yields were realized with prescription 3, combining a composite soil sample with spatially-variable yield goal. At Stockton, there was no correlation between yield and soil EC during the 2010 growing season, however there was a significant correlation between yield and shallow EC during the drier 2011 season. At Manhattan, yield was correlated to deep EC in 2010 and to shallow EC in 2011. Overall, increasing spatial intensity of data to develop the prescriptions did not necessarily result in an increased yield response to the application. Prescriptions that included a variable yield goal component tended to perform better across both sites and years.

INTRODUCTION

In 2011, Kansas produced over 50% of the grain sorghum (*Sorghum bicolor* (L.) Moench) in the United States (NASS 2012). Much of this is due to the favorable growing conditions for grain sorghum in western Kansas. Grain sorghum is considered a relatively drought tolerant C_4 plant, capable of performing better than other crops such as corn (*Zea mays* L.) and soybeans (*Glycine max* L. Merr.) when growing in moisture-limited and high temperature conditions (Stahlman and Wicks 2000). In Kansas, grain sorghum is often substituted for corn in crop rotations, and like corn, grain sorghum can require large amounts of nitrogen (N) fertilizer to achieve high yields. Nitrogen is one of the most essential and extensively applied nutrients in grain sorghum (Buah et al. 1998). It is also very mobile in the soil and is transported in soil water. A majority of N taken up by plants is actually in water and taken up by mass flow. This means that when moisture is limited, N uptake in plants becomes limited as well.

When managing N fertility, it is important to understand that spatial variability across a field exists. This can be as simple as variation in profile N concentration or a more complex series of soil characteristics that determine how much N the crop will require, such as soil organic matter (OM) or soil texture. Failure to realize variation in N requirements across a field can lead to under- and over-applications of N that will cause either N deficiencies in the crop or N losses due to leaching or runoff (Koch and Khosla 2004). Both of these situations will have a negative economic impact for farmers and the N losses can cause environmental concerns for the general public (Buah et al. 1998). A solution to the under- and over-application of N fertilizer is to use variable-rate (VR) application methods. However, very little research has been conducted pertaining to VR-N application in grain sorghum.

There have been numerous VR-N studies in corn including one by Roberts et al. (2000) which found that yield would most likely increase 0 to 125 kg ha^{-1} on average using VR-N application rather than a uniform application. This study, like many others, was performed using crop modeling rather than field research. Koch et al. (2004) reported that simulated VR-N applications increased the average N rate applied by up to 30% when compared to uniform N application. However, Snyder et al. (1999) reported that simulated VR-N applications reduced average N rates by 10% when compared to a uniform N application. This indicated that the response of VR-N applications can vary greatly from field to field.

Five prescriptions for N application in grain sorghum were developed with increasing levels of intensity of input data. The first prescription was a constant, uniform rate of N based on field average yield goal. The second prescription used soil electrical conductivity (EC) management zone-based soil sample data with field average yield goal, while the third prescription used a composite soil sample and spatially-variable yield goal. Prescription four combined EC management zone-based soil sample with spatially-variable yield goal and prescription five used grid-based soil sample data with spatially-variable yield goal. The hypothesis was that by increasing the amount of spatially-variable data input into the N recommendation equation, grain sorghum yields will increase while lowering N fertilizer required. The specific objective was to apply these five prescriptions to grain sorghum in the field and evaluate their performance based on yield response to N applied, relative performance compared to historical yields, and correlations between yield and measured soil variables.

MATERIALS AND METHODS

Field experiments were established during the spring of 2010, one at a farmer-owned and operated production field in Stockton, KS and the other at the Kansas State University

Department of Agronomy North Farm in Manhattan, KS. These studies were repeated in 2011 in different but adjacent fields at both locations. In each year, the experimental area at Stockton was 10.5 ha consisting of a Holdrege silt loam soil while the experimental area at Manhattan was 2.8 ha consisting of a Smolan silt loam soil and partial inclusions of Wymore silty clay soil. The previous crop for all sites was winter wheat (*Triticum aestivum* L.). The experimental design consisted of six treatments arranged in parallel strips with two replications. Each treatment was applied down the length of the field with each plot width equal to one pass of the fertilizer applicator available, and was 10.7 m in Stockton and 4.6 m in Manhattan. The six treatments were the four VR-N prescriptions (see Chapter 2), a uniform N rate prescription, and treatment 6 which was a series of N test strips that ramped from 0 kg N ha^{-1} to 224 kg N ha^{-1} and back to 0 kg N ha^{-1} repeatedly across the length of the field. Increments of 22.4 kg N ha^{-1} were used within the test strip, which allowed each rate to be applied over a 27 m length for a total of 10 rates over 270 m. This distribution of numerous N test strips across the plot area provided a measure of grain sorghum yield response to N in different areas of the field. All prescriptions were decreased by 5.3 kg N ha^{-1} before being applied to account for application of starter fertilizer at planting. Table 3.1 summarizes the treatments and the components involved to create them.

Treatments at Stockton were applied each year with a 10.7 m wide custom-made, anhydrous knife-injector applicator with a Raven AccuFlow control system (Raven Industries, Sioux Falls, SD). A handheld GPS unit with Farm Site Mate software (version 11.40, CTN Data Service, Inc., Hamilton, IN) was used to communicate all of the N prescriptions to the Raven controller by reading the treatments that had been imported into Site Mate. An EZ Guide 500 GPS guidance system (Trimble, Sunnyvale, CA) was used to guide the application equipment and provide a 5 Hz GPS signal for quicker data logging. At Manhattan in 2010, liquid UAN (28-

0-0) was applied using a 4.6 m wide, three-point mounted sprayer equipped with surface banding nozzles. The application was controlled by using a Raven 440 controller (Raven Industries, Sioux Falls, SD) and pulse-width modulating nozzles to accurately and quickly change rates. The treatments were communicated to the controller through a handheld GPS unit equipped with Farm Site Mate software and application guidance was provided by an EZ Guide 500. In 2011, the Manhattan site was fertilized with liquid UAN using a 4.6 m wide, custom-made, three-point mounted coulter injector. This applicator was controlled using a Trimble EZ Boom in conjunction with an EZ Guide 500 guidance system to provide guidance and GPS signal. The treatments were capable of being directly imported into the EZ Guide 500 to bypass needing a handheld GPS unit.

After prescriptions were applied, atrazine + s-metolachlor (Bicep II Magnum, Syngenta Crop Protection, Greenboro, NC) herbicide was applied preplant, followed by no-till planting grain sorghum in 0.76-m rows. A starter fertilizer (10-34-0) was applied with the planter which provided 5.3 kg ha^{-1} of additional N and 18 kg ha^{-1} of P to provide sufficient P levels in the soil. Grain sorghum was combine harvested in the fall using the respective equipment at each location (Table 3.2). Yield data from all sites were filtered and cleaned using the ARS Yield Editor and compiled using EASi Suite software (version 2009.00.01, Mapshots Inc., Cumming, GA).

Grain sorghum yield response to N applied was determined using the test strips that made up treatment 6. The analysis was conducted by exporting raw yield data and N application data into a spreadsheet and estimating response curves. The biological optimum N rate (BONR) was the maximum N rate for which a yield response was observed and this was calculated by setting the first derivative of the response equation equal to zero and solving for N.

In order to look at within-plot variability, historical yield data were used to categorize the field area where treatment 6 was applied into three stable yield levels: low, medium, and high, based on annual relative difference (ARD) values from all three years (Stockton) or six years (Manhattan) of yield data available. Only the polygons in the field that had a consistent ARD from year to year were included in the stable categories. Polygons that were temporally variable regarding ARD values were considered instable, did not fit into these categories, and were left out of the analysis. The categorization was accomplished by exporting the raw ARD data for each year of historical yield data in each individual polygon in the fields (10.7 m by 10.7 m in Stockton and 4.6 m by 4.6 m in Manhattan). A mean ARD value and standard deviation was then calculated for the multi-year set of data in each polygon. Using the means, the polygons were sorted from lowest to highest and divided into low, middle, and high categories by using the lowest 25% of the polygons as the low category and the highest 25% of the polygons as the high category. The middle category contained the 25% that most closely surrounded a zero mean. This left 12.5% of the polygons between each category as a buffer to ensure the categories were not too alike. The polygons in each stable yield category were then sorted from low to high based on the standard deviations. The top 50% of the polygons (smallest deviation) were accepted as stable polygons in each stable yield category. Yield data and N application data from each stable polygon were fitted with a quadratic N response curve in each category in each field.

To compare among theprescriptions, yield data by treatment were extracted from EASi Suite and compared to each other based on average yield per prescription. Prescription yield performance was also compared in each stable yield category by using the raw yield data that were extracted from EASi Suite. Using the same stable yield categories developed for the N response analysis, prescription yields were compared to historic yields in each category to determine the change in yield (Δ yield). The Δ yield is the difference between the observed yield and the yield goal (based on normalized historical yield) at any given polygon in the field. This allowed for an assessment of within-plot variability of yields and a basis on which to compare prescriptions on performance at multiple yield potentials. Results were analyzed using PROC GLM at $P \leq 0.15$ in SAS version 9.2 (SAS Institute Inc., Cary, NC).

Soil EC datasets were typically large and generated a "data cloud" when plotted. A boundary-line analysis was used to describe the relationship between soil EC (shallow and deep) and either historical yields or observed yield. Creating the boundary-line was accomplished by using yield polygons above the 95th percentile for each 100 point increment of EC data along the x-axis. Boundary-line analysis puts the focus on the upper boundaries of the values within a scatter plot. This makes the examination less confusing when looking at large "clouds" of data with hundreds or thousands of data points plotted (Kitchen et al. 2003). When observing these scatter plots it must be understood that the upper boundary represents the maximum possible yield response to soil EC. The points below the boundary-line were assumed to have been influenced by other factors that limited the response of yield relative to soil EC.

Pearson correlation coefficients were calculated between all of the spatial data that were collected in each field using PROC CORR at $P \leq 0.05$ in SAS. The elevation data used in the correlation were collected using the yield monitor, which provided relative elevation values in each field.

RESULTS AND DISCUSSION

Yield Response to Nitrogen

Overall, the field in Stockton 2010 had the greatest yield response to N with the BONR being at 250 kg N applied ha^{-1} (Figure 3.1). The field in Manhattan 2010 had the second highest BONR at 205 kg N applied ha^{-1} (Figure 3.2). The Stockton 2011 field had a BONR of 177 kg N applied ha^{-1} which was much lower than that observed in 2010 (Figure 3.3). The yield response to N at Manhattan in 2011 was erratic and, therefore, misleading. Based on the results from the test strips, the response curve was a flat line (Figure 3.4). Nitrogen response varied between locations and years, which was expected due to the varying weather conditions and the fact that none of the fields were irrigated. Rainfall was more abundant in 2010 with 719 mm of precipitation in Stockton and 524 mm in Manhattan throughout the growing season compared to 593 mm in Stockton and 401 mm in Manhattan throughout the 2011 growing season. These Stockton fields were in close proximity to each other and had a similar soil type but precipitation varied between growing seasons. This caused grain sorghum in Stockton 2011 to grow under more stressful conditions, which likely explains the different N responses. Manhattan growing conditions were much less favorable in 2011 than 2010 due to only receiving 60% of the average rainfall during the 2011 growing season (Weather Data Library, Kansas State University).

The multiple test strips in treatment 6 provided data to evaluate the yield response to N inputs and to determine the yield response at three different yield-potential categories (low, medium, and high). The objective of this was to determine whether it was more practical to focus on applying more N to historically high yielding portions of the field to take advantage of the high performance potential or applying higher N rates to the historically low yielding portions of the field in an attempt to increase these yields to achieve a more uniform yielding field. At Stockton in 2010, BONR increased from 90 to 142 to 161 kg N ha^{-1} as stable yield category increased from low to medium to high (Figure 3.5). In 2011, Stockton BONR increased from 147 to 192 kg N ha^{-1} between the low and medium stable yield categories then decreased to 101 kg N ha^{-1} in the stable high yield category (Figure 3.6). The different N response between the two growing seasons was most likely influenced by the lack of rainfall later in the season during 2011. Differences in soil properties, such as infiltration rate, water holding capacity, and texture will influence how quickly moisture stress will affect N uptake and N mobility in different portions of the field. At Manhattan in 2010, the BONR increased from 0 to 91 kg N ha^{-1} between the low and medium stable yield categories, then increased to 215 kg N ha^{-1} in the high stable yield category (Figure 3.7). The Manhattan 2011 field had very erratic yield response to N in all stable yield categories due to the very dry growing conditions experienced in 2011. Therefore, very few conclusions could be drawn from the N response data (data not shown). Overall, these N responses indicate that the stable low yield category typically reached maximum yields at lower N rates than either the medium or the high stable yield category. Also, the stable high yield category did not always respond to higher N rates than the stable medium category. This suggests that the focus should be on applying appropriate N rates for each yield category rather than trying to have a uniform field or improving already high performing areas.

Comparison of N Applied and Yields across Prescriptions

In Stockton, average N applied (kg ha^{-1}) was greatest for prescriptions 3 and 4 in 2010 and for prescription 5 in 2011 (Table 3.3). In Manhattan, average N applied was greatest for prescription 3 in 2010 and for prescriptions 3 and 4 in 2011. Amounts of N applied for each prescription varied because of different levels of spatial variability inherent in each strip. Correspondingly, the greatest average yield (kg ha^{-1}) in Stockton 2010 was obtained with prescription 4 but it was not different from prescriptions 3 or the uniform application (prescription 1). In 2011, the greatest average yield (kg ha^{-1}) was achieved with prescriptions 4 and 5, although not different from prescriptions 1 and 3 (Table 3.3). In Manhattan 2010, the greatest average yield was obtained with prescription 3, while in 2011 no differences were obtained among prescriptions (Table 3.3). Overall, prescriptions 3, 4, and 5 tended to be the higher yielding treatments. Most likely this was due to the spatially-variable yield goal component included in these prescriptions. Prescriptions 1 and 2 used a fixed yield goal for the entire field and therefore did not capture the yield variability.

It was important to investigate whether each prescription performed adequately at all yield levels in the field. In order to do so, the prescriptions were compared to each other within each stable yield category of the field based on the change in yield (Δ yield) relative to the historical average spatial yields. At Stockton in 2010, Δ yield values were positive among all prescriptions within the stable low yield category, while the stable medium and stable high categories were mostly positive values with the exception of prescription 2 in the medium category and prescriptions 2 and 3 in the high category (Figure 3.8). In 2011, all Stockton prescriptions had positive Δ yield values in all stable yield categories (Figure 3.9). This was a result of sufficient rainfall during a majority of the growing season. At Manhattan in 2010, nearly all Δ yield values were negative among all prescriptions within the low and medium stable yield categories with the exceptions of prescriptions 1 and 5 in the low category and prescription 5 in the medium category, while the stable high category had all negative Δ yield values (Figure 3.10). The primary reason for so many negative Δ yield values was the lack of precipitation for the season partnered with greater historical yields rather than the ill-performing N prescriptions applied in 2010. Manhattan 2011 had mostly positive Δ yield values in the stable low yield category with only prescriptions 4 and 5 being negative. The stable medium yield category only had a positive Δ yield value for prescription 3, while the stable high yield category had all negative Δ yield values (Figure 3.11).

At Stockton in 2010, prescription 4 generated the greatest Δ yield across categories but it was not different from prescription 5 in low or in high stable yield categories (Figure 3.8). Both prescriptions used variable yield goal with some level of variable soil test. In Stockton 2011, there were no differences among prescriptions in any of the stable yield categories (Figure 3.9). At Manhattan in 2010, Δ yield values of prescriptions 5 and 1 were not different from zero in all categories and were greater than most other prescriptions within each category. In Manhattan 2011, there were no differences among the Δ yield values of treatments in the low or high stable yield categories (Figure 3.11). In the stable medium yield category prescription 3 had the greatest Δ yield value although it was not different from prescriptions 1, 2, and 5. Prescription 4 had a lower Δ yield value than prescription 3. These results all indicate that there were little or no differences between prescription performances in many stable yield categories. There were often little or no differences between the VR-N applications and the uniform N application (prescription 1) as well indicating that VR-N did not have much advantage within a stable yield category.

Relating EC to Yield

Using boundary-line analysis, it was determined that historical yield and shallow EC at Stockton 2010 had a slightly negative though significant linear relationship such that historic yield decreased as EC increased (Figure 3.12). The 2010 observed yield data had a negative quadratic relationship to shallow EC rather than linear (Figure 3.13). Due to the high correlation between shallow and deep EC, the historical yield had a slight negative quadratic relationship to deep EC (Figure 3.14). The 2010 observed yield also had a negative quadratic relationship to deep EC (Figure 3.15). In Stockton 2011, the historical yield had a negative linear relationship to shallow EC (Figure 3.16). The 2011 observed yield also had a negative quadratic relationship (Figure 3.17). This indicated that, on average, EC has a negative correlation to yield but it may not be as evident on a yearly basis. The shallow EC relationship with yield was more likely to change on a yearly basis, not only due to yield variation but also due to the temporal variability that existed with shallow EC due to the exposure of the soil surface to the environment. Correlation coefficients between shallow EC, deep EC, and yield for Stockton in 2010 and 2011 are shown in Table 3.4.

Soil EC relationships to historic and observed yields in Manhattan were quite different from those observed in Stockton. The historical yield responded negatively to an increase in shallow EC and a quadratic model was fit to those data at Manhattan 2010 (Figure 3.18). The 2010 yield did not respond quite the same to shallow EC as the normalized yield (Figure 3.19) as yield responded positively to increasing soil EC which gave a positive quadratic relationship. The historical yield and the 2010 yield had positive quadratic relationships with deep EC in Manhattan 2010 (Figures 3.20 and 3.21). The 2011 Manhattan boundary-line analysis had similar responses to those seen in the 2010 field (Figure 3.22). The historical yield responded negatively as shallow EC increased and a quadratic model was best fit to these data. The 2011 yield had a positive linear response to increases in shallow EC (Figure 3.23). Both Manhattan fields showed that shallow EC was more vulnerable to temporal changes, as the seasonal yield relationships to EC both opposed the long term average relationships. Also, both seasons in Manhattan, especially 2011, produced lower than average yields due to hot, dry weather. This had a large influence on the yield to EC relationship due to the high correlation between EC and soil water holding capacity.

Correlation Analysis

Understanding which variables influenced yield was important when determining how to create a VR-N prescription for any field. Not all variables can be accounted for or predicted, such as environmental conditions. Environmental conditions will not only influence yield, but how soil characteristics and fertility interact to affect yield. In 2010, grain sorghum yield in Stockton had the highest correlation to elevation with a Pearson correlation coefficient of 0.31 (Table 3.4). The next best correlations were to N rate, phosphorus, and OM content. In Stockton 2011, the highest correlation to yield was shallow EC with a negative Pearson correlation coefficient of -0.31. Elevation and OM had the next best correlations to grain sorghum yield. In Manhattan 2010, grain sorghum yield had the greatest positive correlation to phosphorus with a coefficient of 0.57 (Table 3.5). There was also a high correlation between yield and potassium, OM, and deep EC. Correlation in Manhattan 2011 was the greatest between yield and shallow nitrate with a Pearson correlation coefficient of 0.51. The next greatest correlations to yield were phosphorus, elevation, and potassium. In general, greatest correlations to yield were soil fertility elements, but elevation was also strongly correlated at most locations. This was most likely due to either precipitation accumulation in low lying areas or topsoil accumulation in low lying areas from erosion of hillsides over time.

CONCLUSIONS

Overall, grain sorghum yields did not consistently increase as the intensity of input data for the VR-N prescription increased, however the type of input data being used in each prescription did have a direct effect on yield outcome. Between both Stockton fields, prescription 4 (management zones and variable yield goal) was consistently the highest yielding and prescription 2 (EC zones and field average yield goal) was the lowest yielding. In

Manhattan, both fields recorded highest yields from prescription 3 (composite soil test and variable yield goal). The common input between these results was the use of historical yield data to create a spatially-variable yield goal. This indicated that a variable yield goal was a valuable tool in creating VR-N prescriptions at both Stockton and Manhattan. Another common observation between fields was that EC management zones used alone resulted in poor yields at all locations except 2011 Manhattan, which performed poorly overall. This indicated that EC management zones alone were not a good fertility management approach in these fields. However, when partnered with a variable yield goal (prescription 4), EC management zones can perform very well. The yield responses to N applied in the stable yield categories suggests that the VR-N applications should focus on applying appropriate N rates for each yield category rather than trying to improve already high performing areas in the field or trying to create a uniform field by improving the low yielding areas. The Δ yield analysis concluded that there were very few differences among treatments in a majority of the stable yield categories, although some prescriptions were consistently among the top performing treatments throughout categories at most locations (prescription 4). The uniform prescription (prescription 1) also performed quite well at times, bringing into question whether VR-N applications were beneficial within the stable yield categories. Based on the correlation analysis it could be beneficial to use a few other inputs for prescription generation, such as elevation, phosphorus, and potassium.

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Table 3.1 Descriptive breakdown of the six N prescriptions.

Prescription	Uniform or VR application	Variable Yield Goal	Soil Sampling Approach
1	Uniform	NO	Composite Sample
2	VR	NO	EC Zones
3	VR	YES	Composite Sample
4	VR	YES	EC Zones
5	VR	YES	Grid Samples
6	TEST STRIP APPLICATION		

Table 3.2 Fertilization and planting details for all fields.

	Stockton		Manhattan	
	2010	2011	2010	2011
Date of Fertilization	18-May	11-May	7-Jun	7-Jun
Nitrogen Source	NH_3	NH_3	UAN	UAN
Date of Planting	2-Jun	5-Jun	19-Jun	8-Jun
Seeding Rate (seeds ha^{-1})	148,000	148,000	156,000	156,000
Sorghum Variety	DKS42-20	DKS37-07	DKS42-20	DKS44-20
Harvest Date	7-Nov	26-Oct	9-Nov	1-Nov
Harvesting Equipment	Case IH 2588	Case IH 2388	Gleaner F3	Gleaner F3
Yield Monitor System	AFS Pro 600	Ag Leader Edge	Ag leader PF 3000	Ag Leader PF 3000

Table 3.3 Average N rates applied and grain sorghum yields observed in each prescription in Stockton and Manhattan, 2010 and 2011.

		N Applied		Yield	
	Prescription	2010	2011	2010	2011
		kg ha^{-1}			
Stockton	1	106.4 c	122.2 c	7683 ab	7383 ab
	2	87.5 d	134.2 b	7133 b	7260 b
	3	125.3 a	118.5 c	7378 ab	7370 ab
	4	123.0 a	130.2 b	7909 a	7526 a
	5	110.6 b	143.9 a	7192 b	7529 a
	LSD ≤ 0.15	3.0	7.4	643	181
Manhattan	1	131.4 b	106.6 c	5671 b	3478 ab
	2	122.6 c	121.3 bc	5654 b	3441 ab
	3	140.1 a	140.1 a	6189 a	3966 ab
	4	130.9 b	134.0 ab	5818 b	2991 b
	5	128.9 b	113.2 c	5698 b	3275 ab
	LSD ≤ 0.15	6.2	15.5	206	772

Table 3.4 Pearson correlation coefficients between EC, soil test values, N rate applied, and grain sorghum yield within each 10.7 by 10.7 m polygon at Stockton, KS in 2010 and 2011.

	Elevation	$EC_{Shallow}$	EC_{deep}	$NO_{3\ Shallow}$	$NO_{3\ Deep}$	P	K	OM	N Rate
	---------------------------- Pearson correlation coefficient, r -------------------------------								
2010									
$EC_{Shallow}$	**-0.258**								
EC_{deep}	**-0.240**	**0.686**							
$NO_{3\ Shallow}$	**-0.221**	**-0.082**	**-0.198**						
$NO_{3\ Deep}$	**0.260**	**-0.210**	**-0.144**	**0.542**					
P	**0.257**	**-0.300**	**-0.286**	**0.230**	**0.485**				
K	**0.093**	**-0.400**	**-0.165**	**-0.348**	**-0.391**	**0.408**			
OM	**-0.440**	**-0.089**	0.004	**-0.090**	**0.145**	**-0.289**	-0.023		
N Rate	**0.494**	**-0.301**	**-0.197**	**-0.225**	-0.098	**0.279**	**0.287**	**-0.257**	
Yield	**0.311**	0.016	**-0.087**	-0.007	**0.114**	**0.238**	-0.023	**-0.232**	**0.236**
2011									
$EC_{Shallow}$	**-0.188**								
$NO_{3\ Shallow}$	**0.306**	**-0.661**							
$NO_{3\ Deep}$	**0.300**	**-0.370**	--	**0.498**					
P	**0.369**	**-0.499**	--	**0.872**	**0.453**				
K	0.075	**-0.337**	--	-0.097	**-0.328**	**0.567**			
OM	**0.697**	**-0.506**	--	**0.584**	**0.380**	**0.558**	-0.176		
N Rate	-0.045	0.103	--	**-0.227**	-0.038	-0.142	0.220	-0.079	
Yield	**0.313**	**-0.315**	--	**0.162**	-0.024	0.130	-0.018	**0.278**	**0.187**

$EC_{shallow}$ - 30-cm soil electrical conductivity, EC_{deep} - 100-cm soil electrical conductivity, $NO_{3\ shallow}$ – 15-cm nitrate content, $NO_{3\ deep}$ – 45-cm nitrate content, P – 15-cm phosphorus content, K – 15-cm potassium content, OM – 15-cm organic matter content, N Rate – N fertilizer applied, Yield – observed yield.

Numbers in bold indicate significance $\alpha \leq 0.05$.

-- no data collected

Table 3.5 Pearson correlation coefficients between EC, soil test values, N rate applied, and grain sorghum yield within each 4.6 by 4.6 m polygon at Manhattan in 2010 and 2011.

	Elevation	$EC_{Shallow}$	EC_{deep}	$NO_{3\ Shallow}$	$NO_{3\ Deep}$	P	K	OM	N Rate
	---------------------------- Pearson correlation coefficient, r ------------------------------								
2010									
$EC_{Shallow}$	**-0.343**								
EC_{deep}	0.092	**0.446**							
$NO_{3\ Shallow}$	**-0.102**	0.084	**0.178**						
$NO_{3\ Deep}$	**0.454**	**-0.549**	**0.238**	**0.234**					
P	**0.259**	**-0.195**	**0.535**	**-0.167**	**0.378**				
K	**0.209**	**-0.117**	**0.633**	**0.170**	**0.388**	**0.649**			
OM	**0.281**	**-0.278**	**0.451**	**0.201**	**0.658**	**0.458**	**0.888**		
N Rate	0.079	**0.224**	**0.282**	-0.066	**0.134**	**0.224**	**0.105**	0.014	
Yield	**0.145**	-0.093	**0.367**	-0.030	0.084	**0.566**	**0.547**	**0.407**	**0.329**
2011									
$EC_{Shallow}$	**0.105**								
$NO_{3\ Shallow}$	**0.264**	**-0.063**							
$NO_{3\ Deep}$	**0.430**	**-0.750**	--	**0.115**					
P	**0.095**	**-0.294**	--	**-0.432**	**0.481**				
K	**0.252**	**-0.225**	--	**-0.429**	**0.435**	**0.892**			
OM	**-0.072**	**-0.788**	--	**-0.156**	**0.787**	**0.511**	**0.502**		
N Rate	**0.088**	0.017	--	**-0.103**	**0.112**	**0.249**	**0.228**	**0.078**	
Yield	**-0.425**	**-0.206**	--	**-0.510**	0.071	**0.432**	**0.333**	**0.323**	**0.083**

$EC_{shallow}$ - 30-cm soil electrical conductivity, EC_{deep} - 100-cm soil electrical conductivity, $NO_{3\ shallow}$ – 15-cm nitrate content, $NO_{3\ deep}$– 45-cm nitrate content, P – 15-cm phosphorus content, K – 15-cm potassium content, OM – 15-cm organic matter content, N Rate – N fertilizer applied, Yield – observed yield.

Numbers in bold indicate significance $\alpha \leq 0.05$.

-- EC_{Deep} was not recorded properly in 2011.

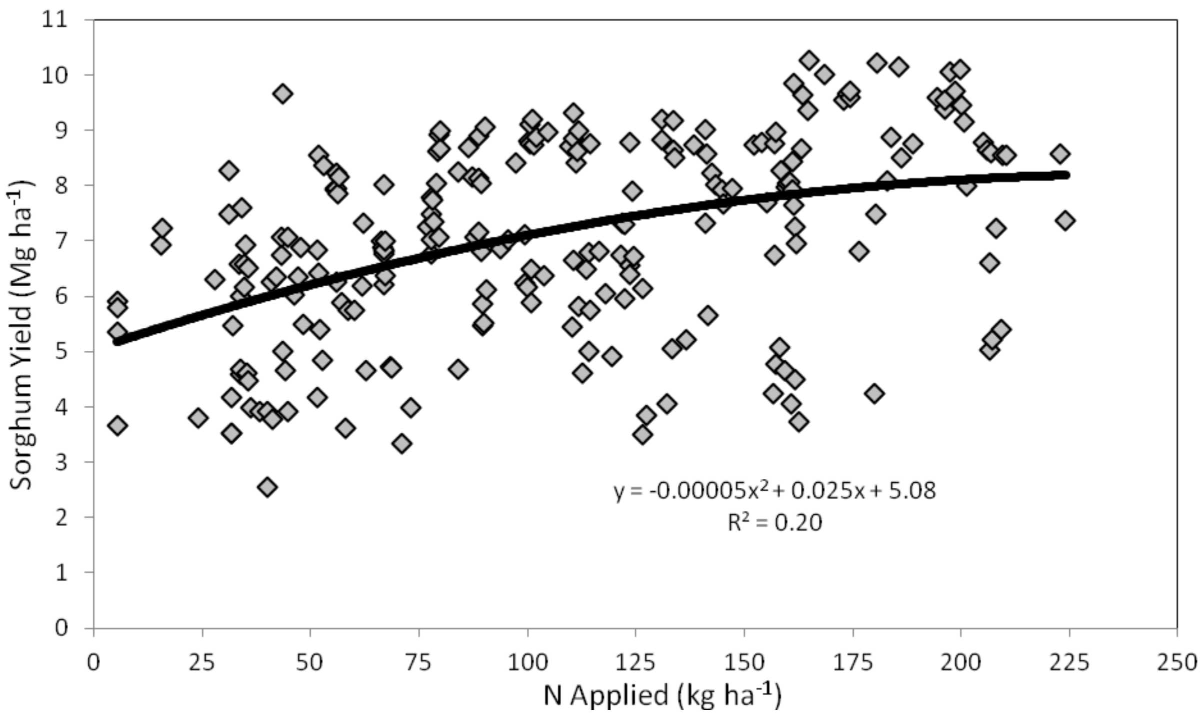

Figure 3.1 Grain sorghum yield (Mg ha^{-1}) in response to increasing N applied (kg ha^{-1}) across treatment 6 N test strips in Stockton 2010 (n=231).

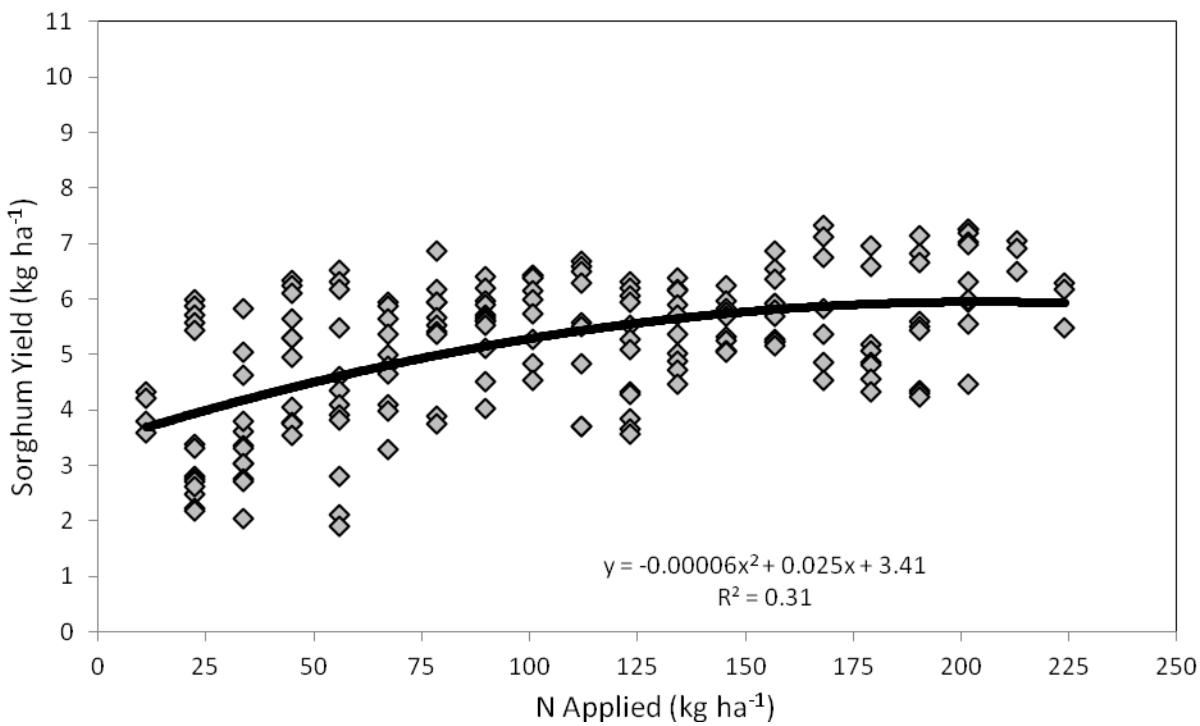

Figure 3.2 Grain sorghum yield (Mg ha^{-1}) in response to increasing N applied (kg ha^{-1}) across treatment 6 N test strips in Manhattan 2010 (n=188).

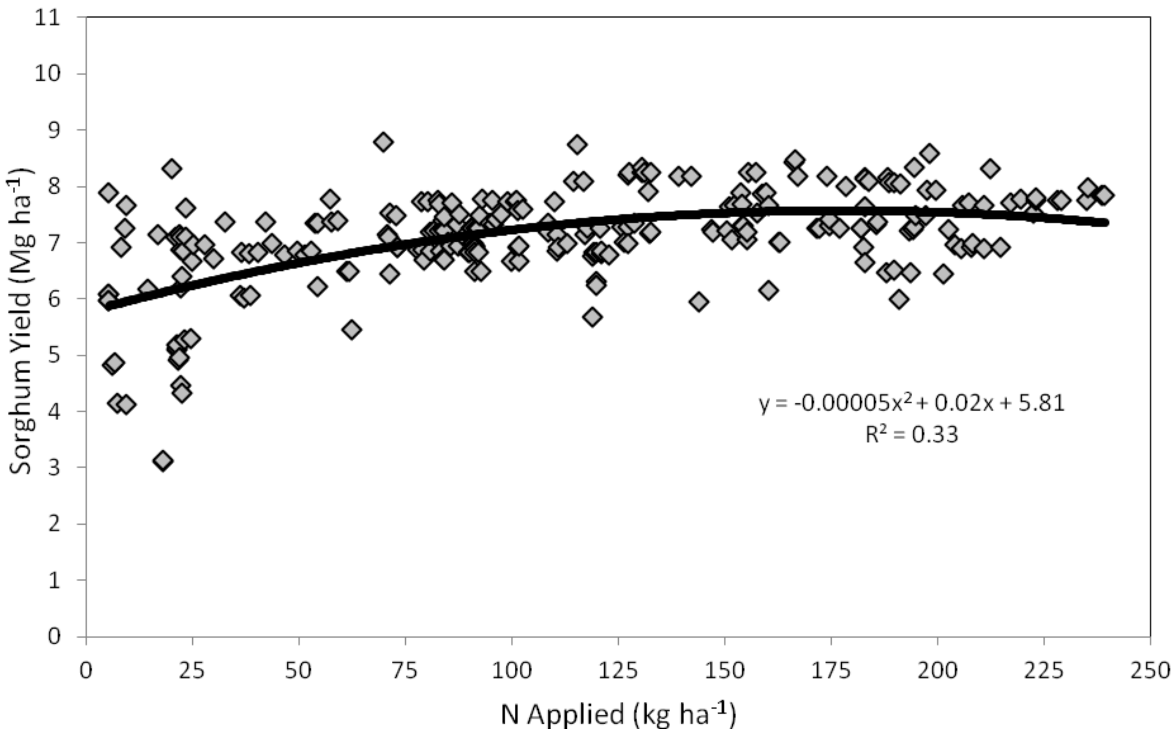

Figure 3.3 Grain sorghum yield (Mg ha^{-1}) in response to increasing N applied (kg ha^{-1}) across treatment 6 N test strips in Stockton 2011 (n=250).

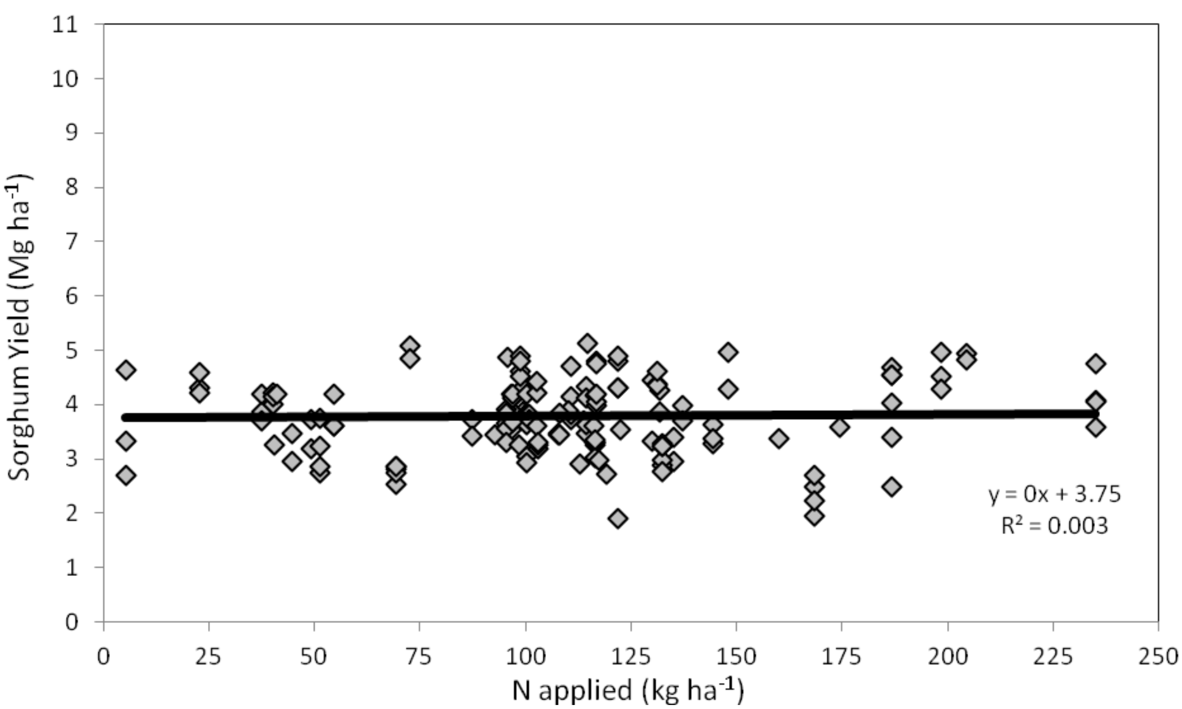

Figure 3.4 Grain sorghum yield (Mg ha^{-1}) in response to increasing N applied (kg ha^{-1}) across treatment 6 N test strips in Manhattan 2011 (n=148).

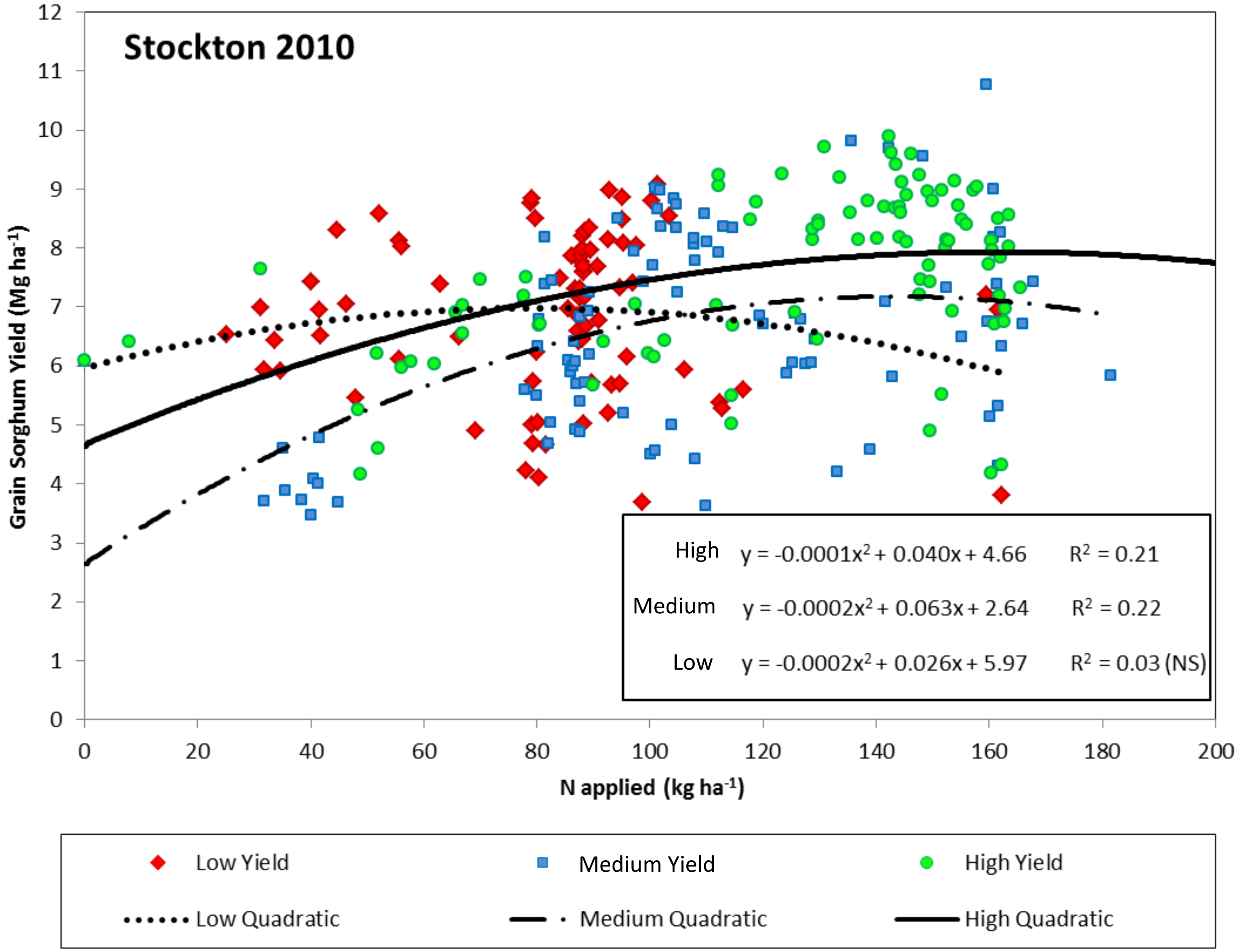

Figure 3.5 Grain sorghum yield response to applied N across three stable yield categories: low, average, and high - in Stockton 2010.

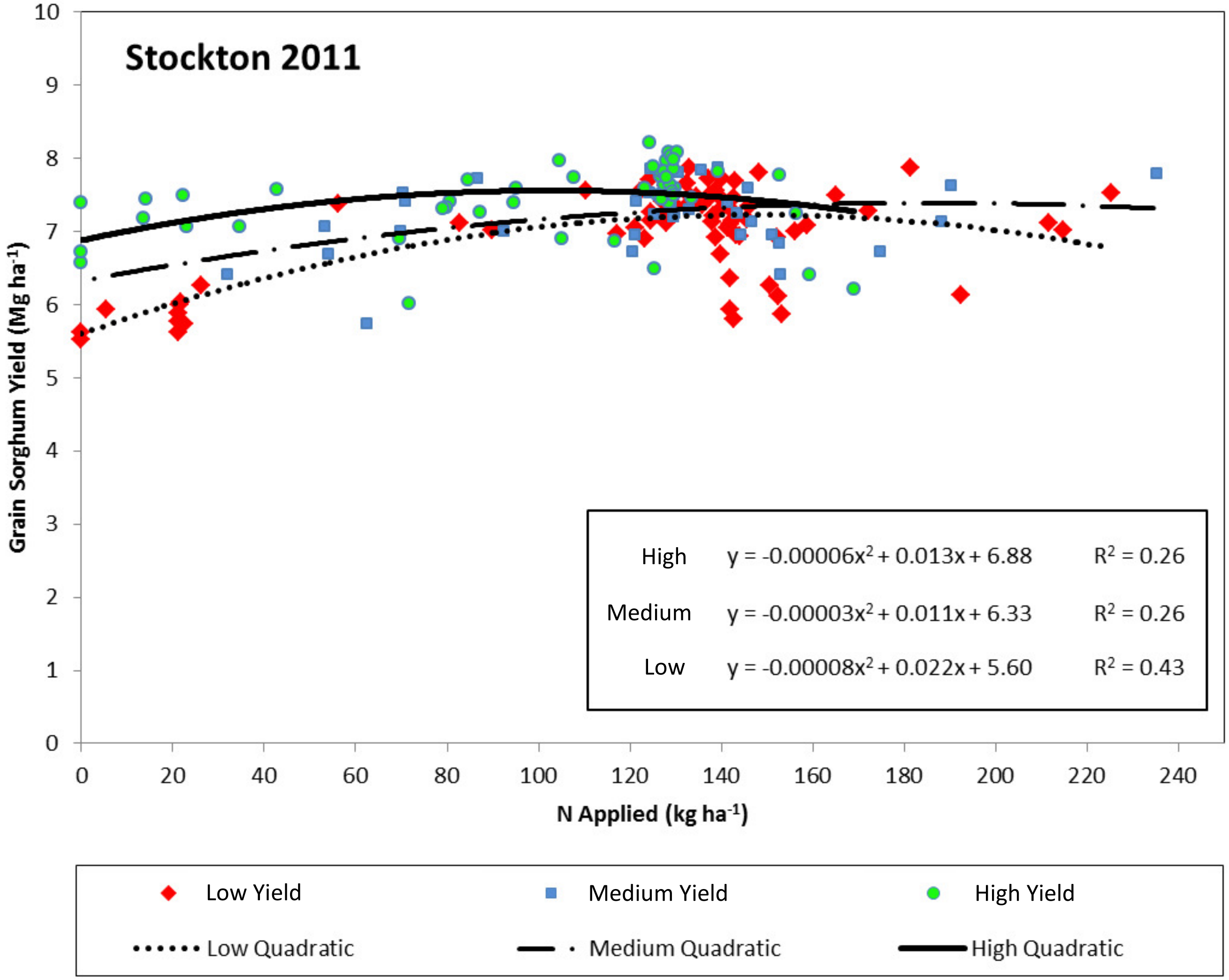

Figure 3.6 Grain sorghum yield response to applied N across three stable yield categories: low, average, and high - in Stockton 2011.

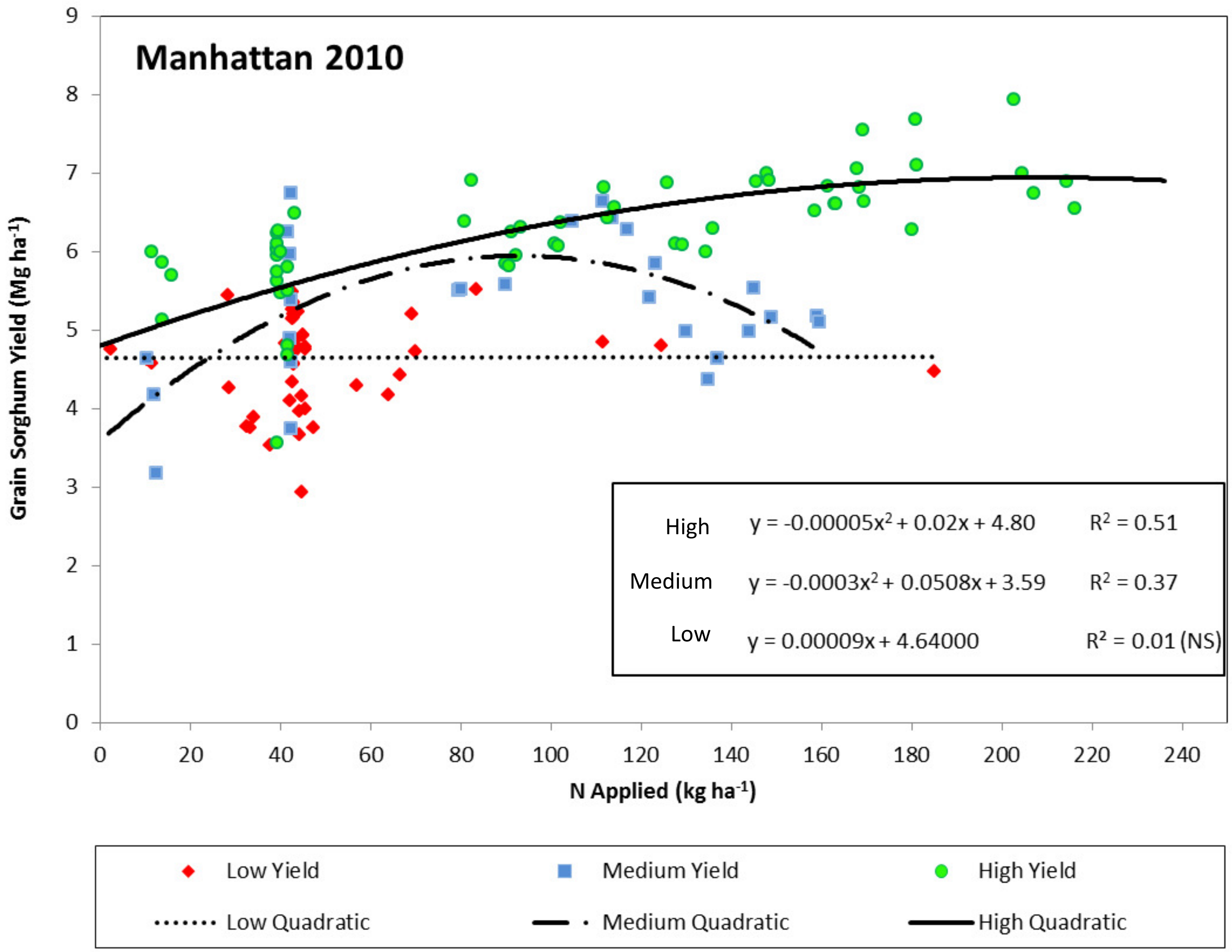

Figure 3.7 Grain sorghum yield response to applied N across three stable yield categories: low, average, and high - in Manhattan 2010.

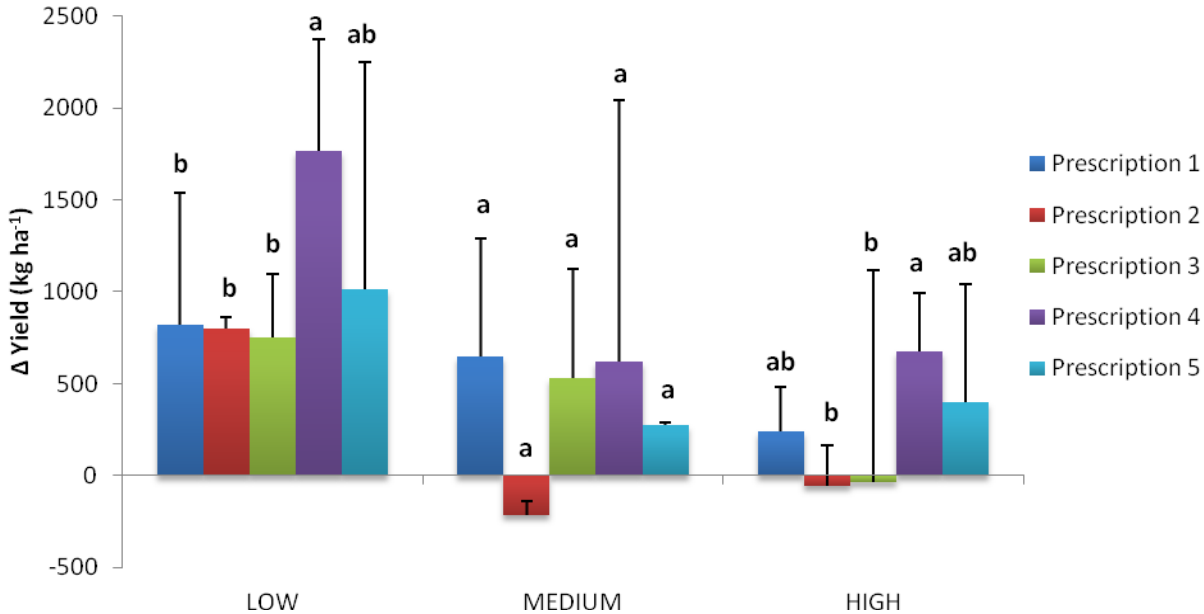

Figure 3.8 Delta yield values comparing treatments in the stable yield categories: low, medium, and high for Stockton 2010. Error bars represent standard error.

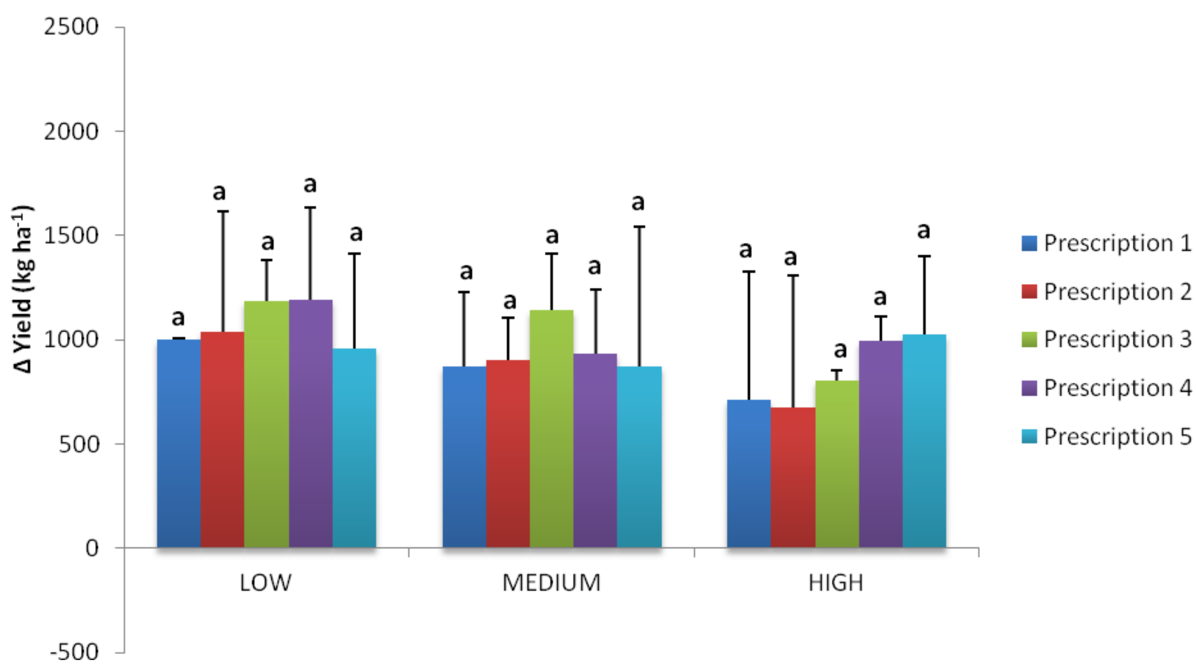

Figure 3.9 Delta yield values comparing treatments in the stable yield categories: low, medium, and high for Stockton 2011. Error bars represent standard error.

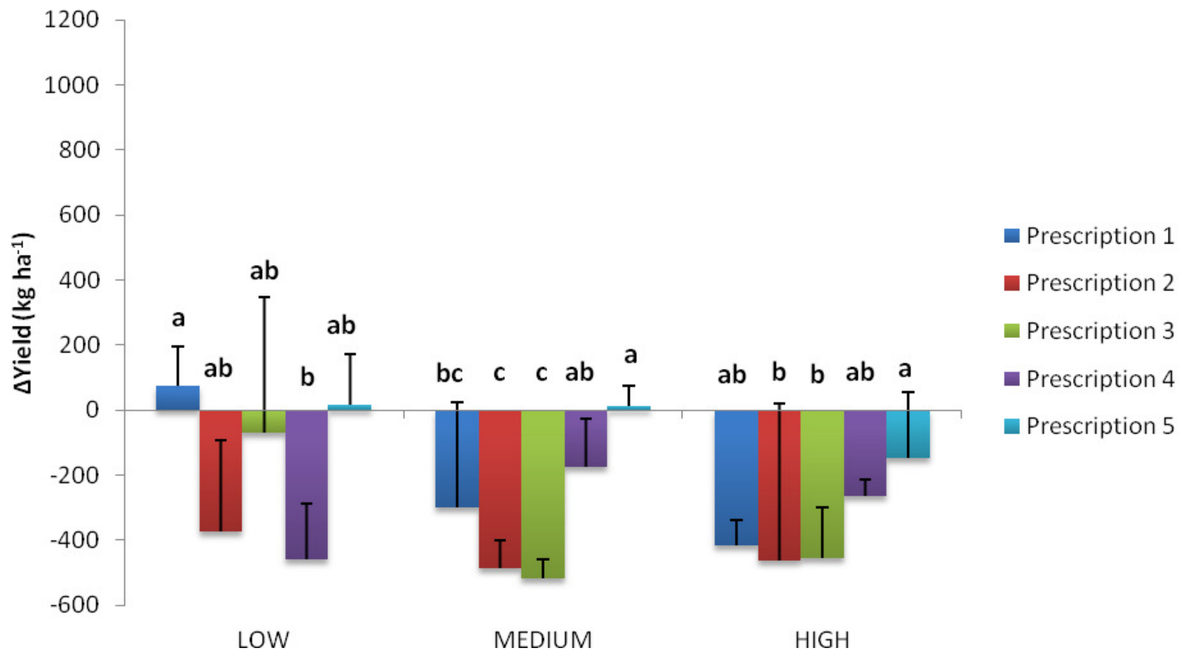

Figure 3.10 Delta yield values comparing treatments in the stable yield categories: low, medium, and high for Manhattan 2010. Error bars represent standard error.

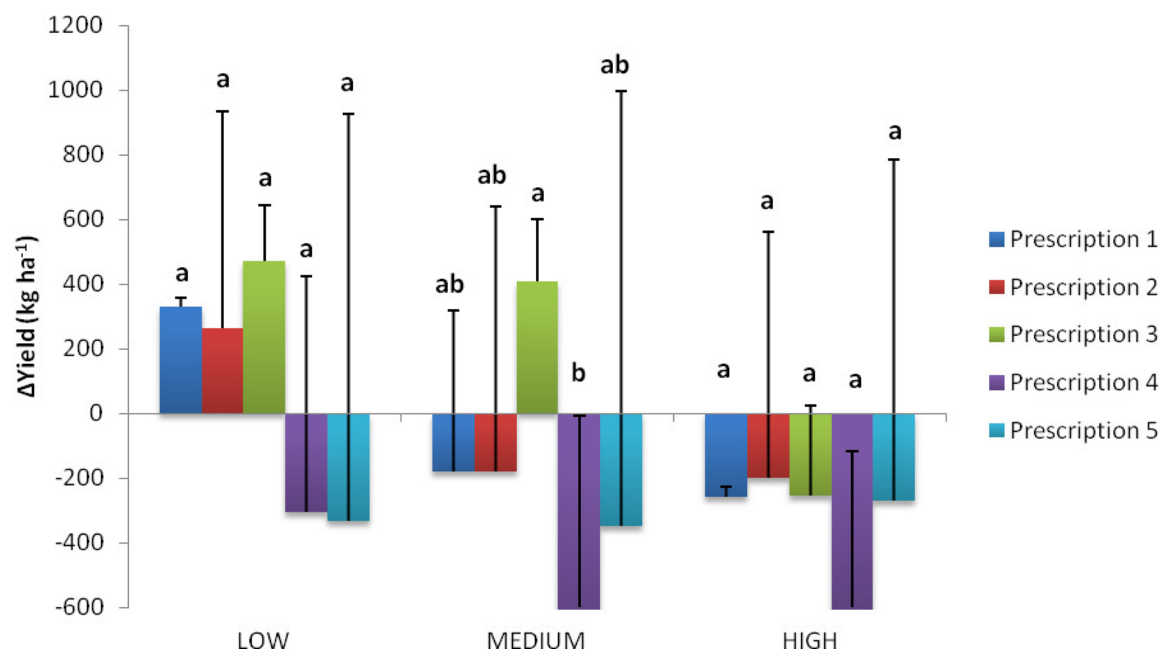

Figure 3.11 Delta yield values comparing treatments in the stable yield categories: low, medium, and high for Manhattan 2011. Error bars represent standard error.

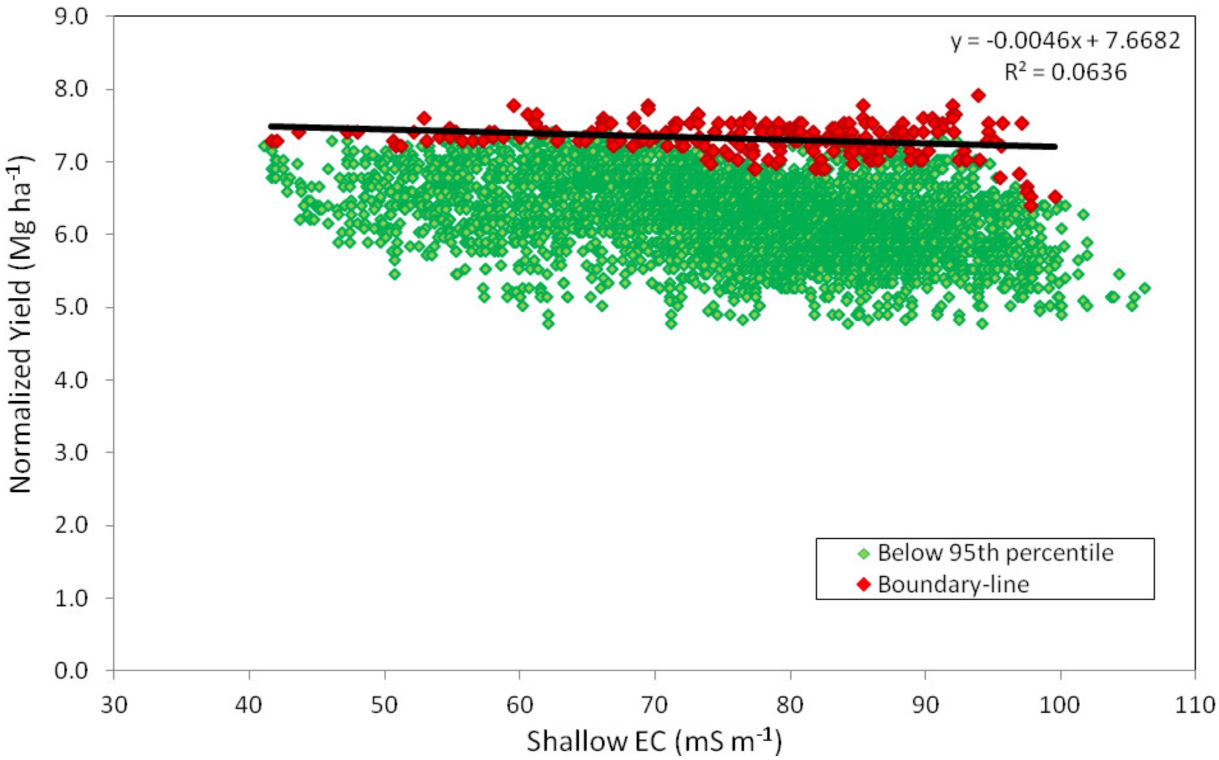

Figure 3.12 Boundary-line analysis of historical yield vs. shallow EC for Stockton 2010.

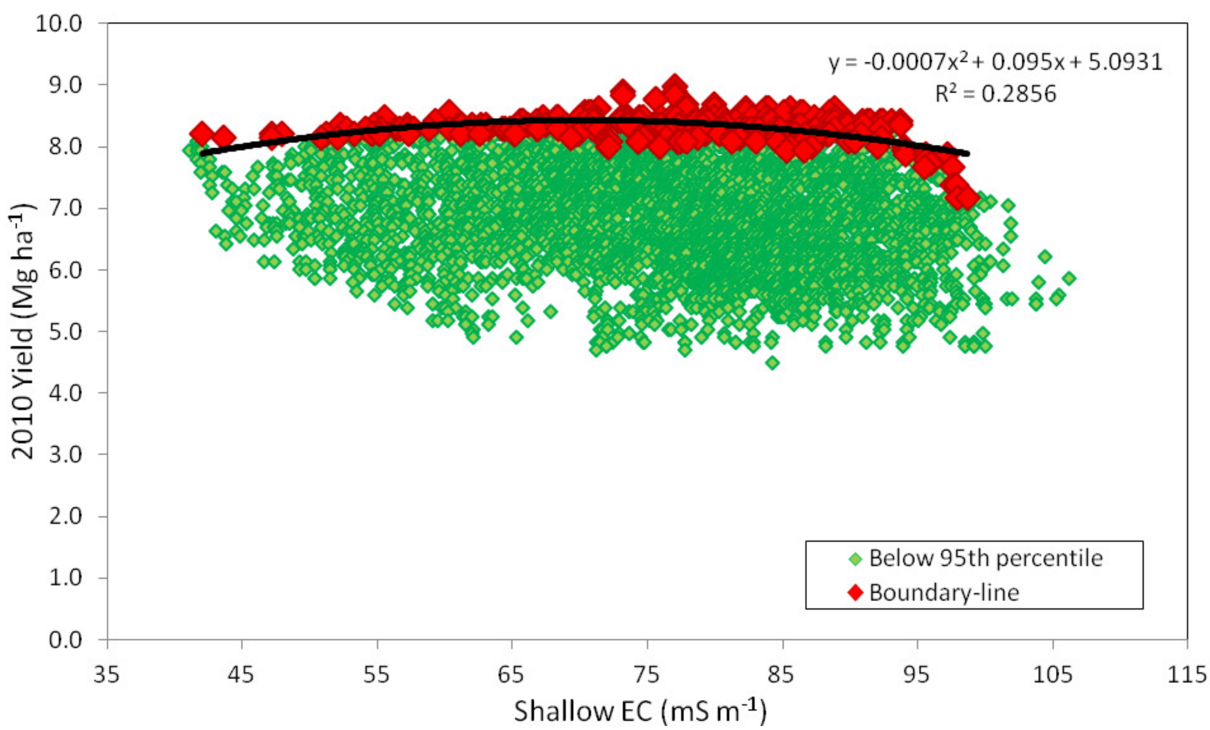

Figure 3.13 Boundary-line analysis of 2010 yield vs. shallow EC for Stockton 2010.

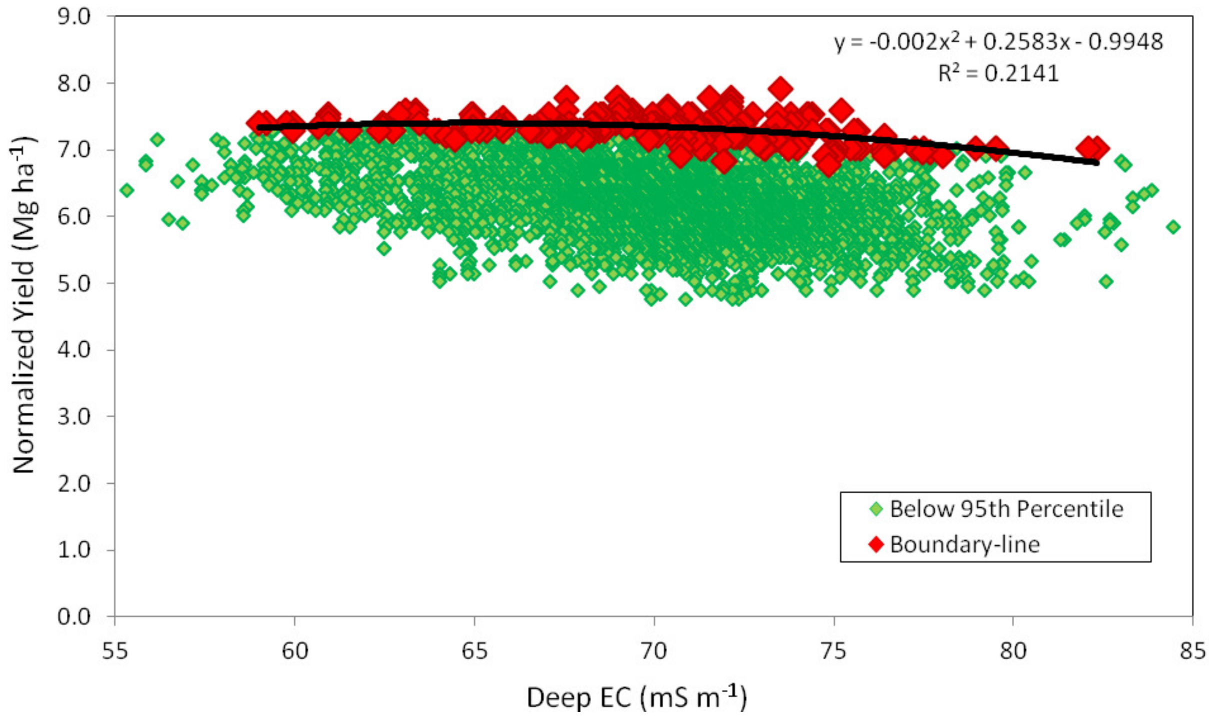

Figure 3.14 Boundary-line analysis of historical yield vs. deep EC for Stockton 2010.

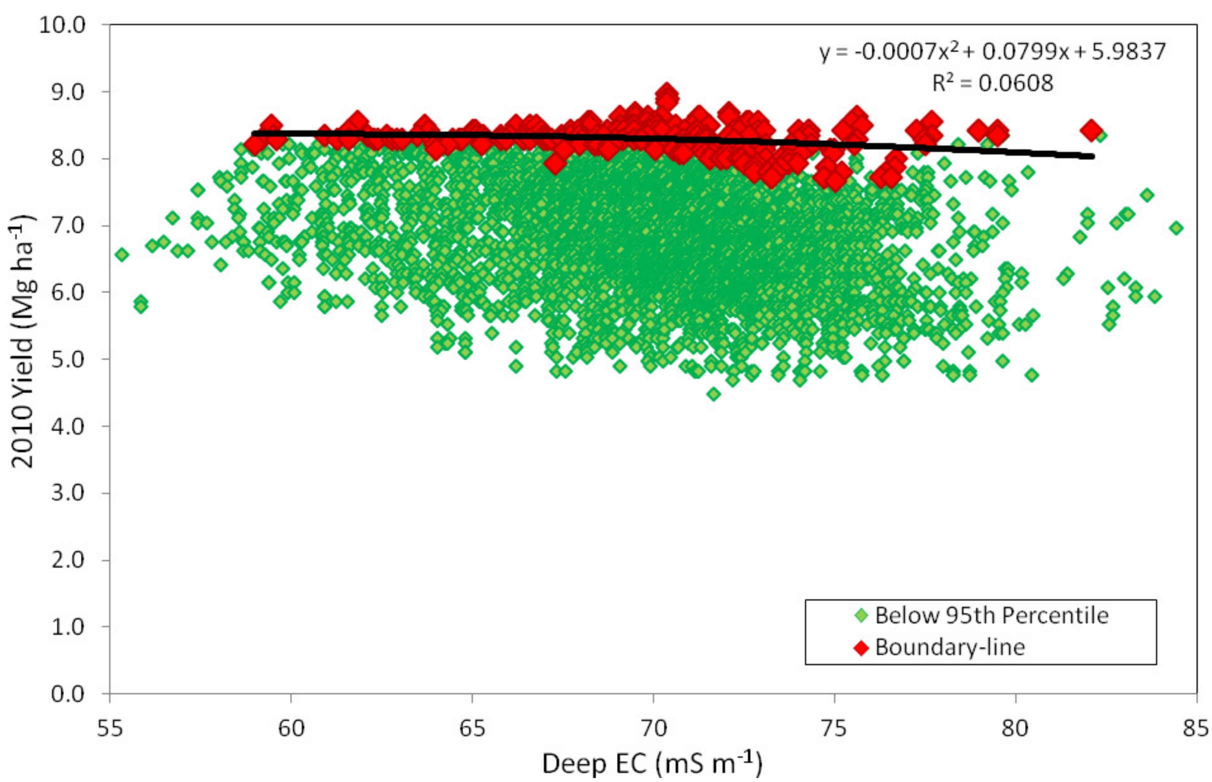

Figure 3.15 Boundary-line analysis of 2010 yield vs. deep EC for Stockton 2010.

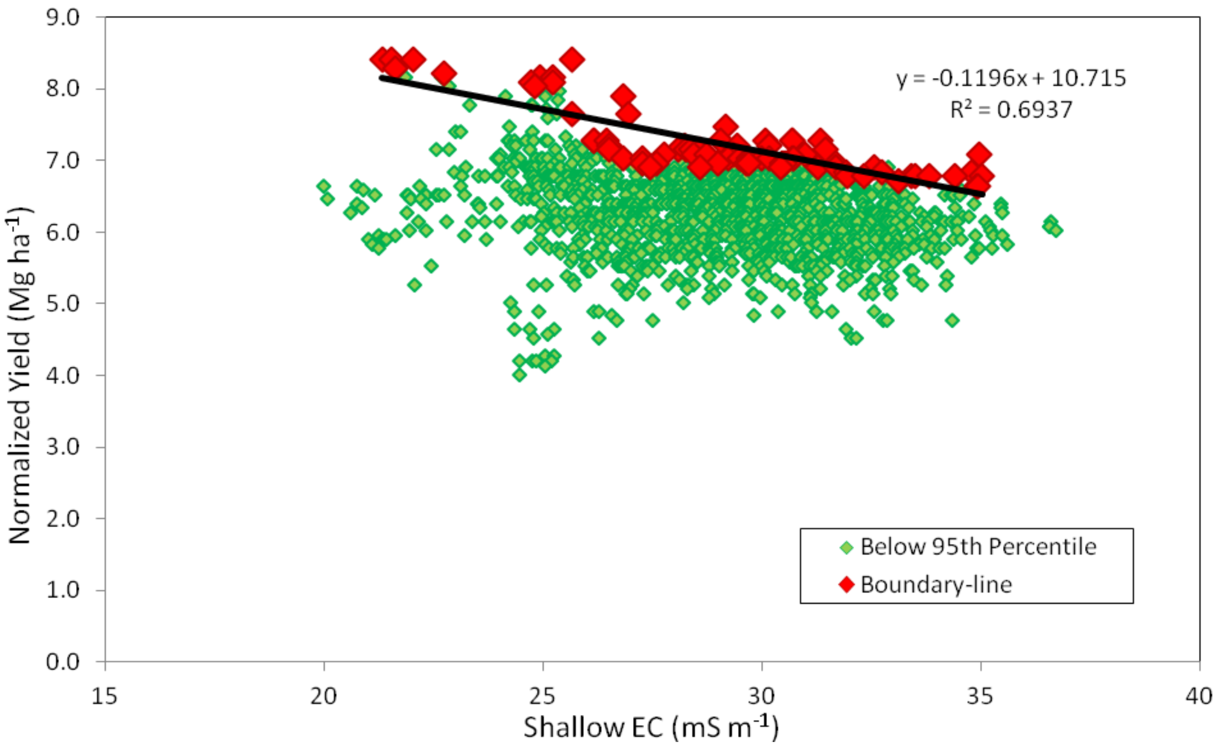

Figure 3.16 Boundary-line analysis of historical yield vs. shallow EC for Stockton 2011.

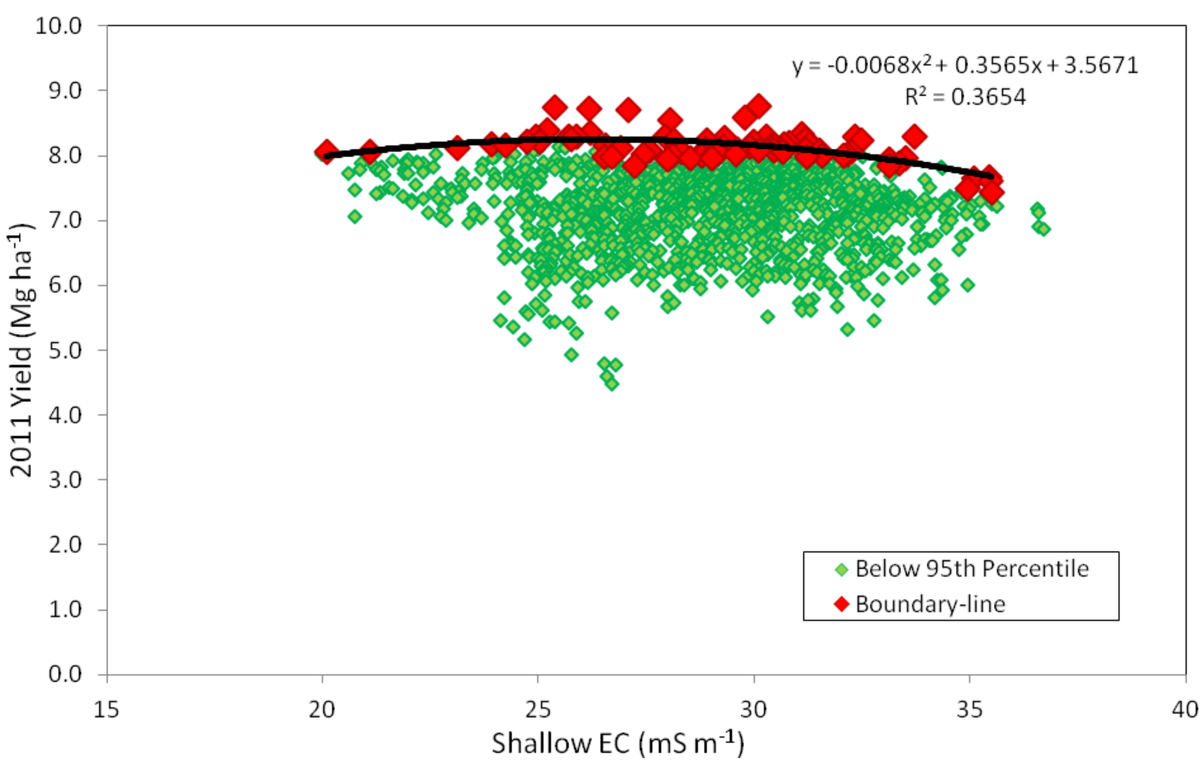

Figure 3.17 Boundary-line analysis of 2011 yield vs. shallow EC for Stockton 2011.

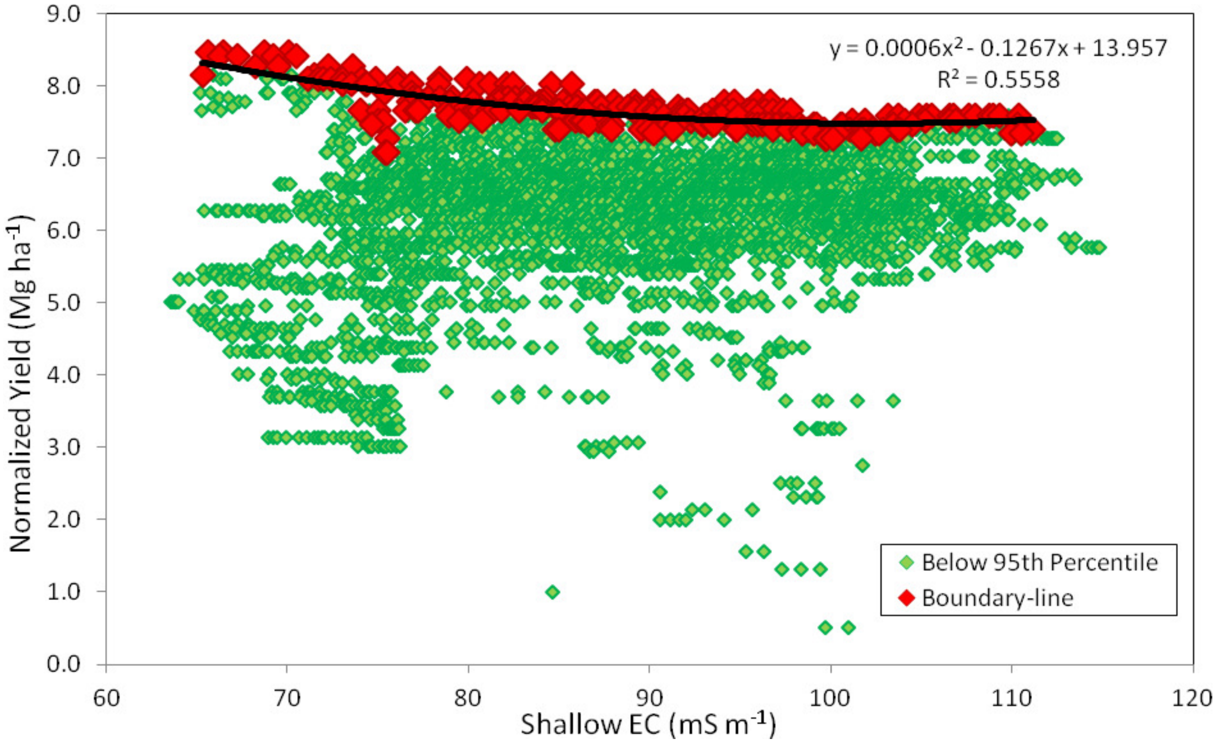

Figure 3.18 Boundary-line analysis of historical yield vs. shallow EC for Manhattan 2010.

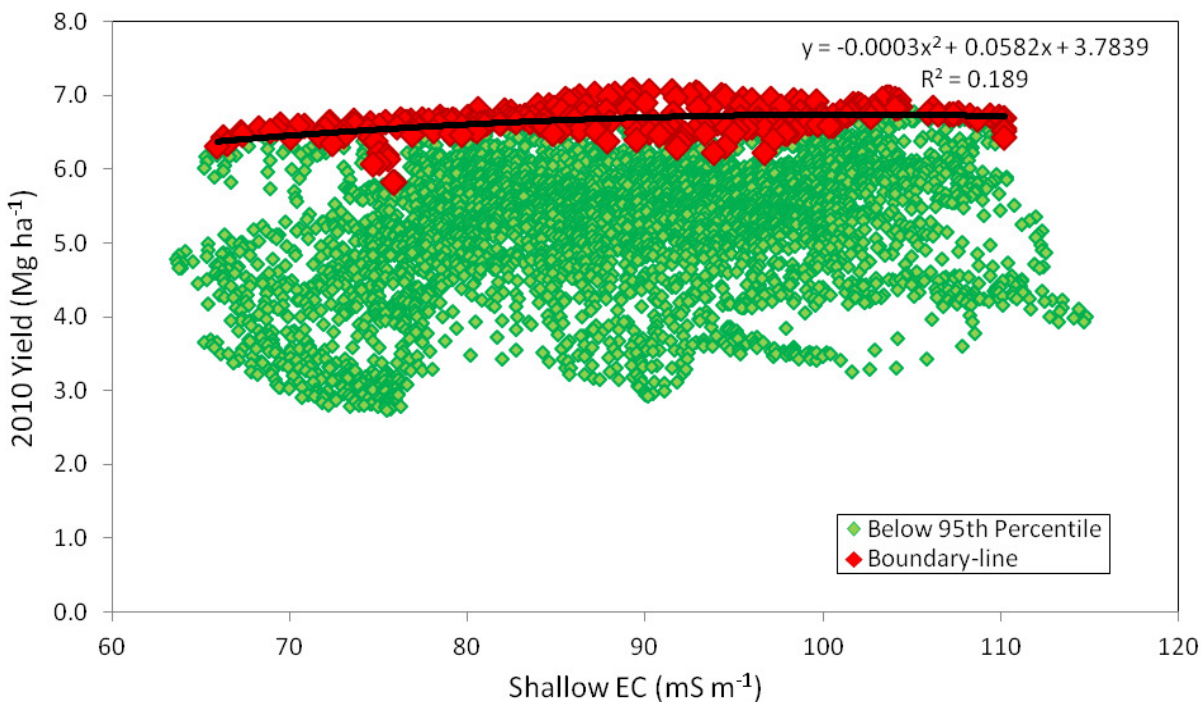

Figure 3.19 Boundary-line analysis of 2010 yield vs. shallow EC for Manhattan 2010.

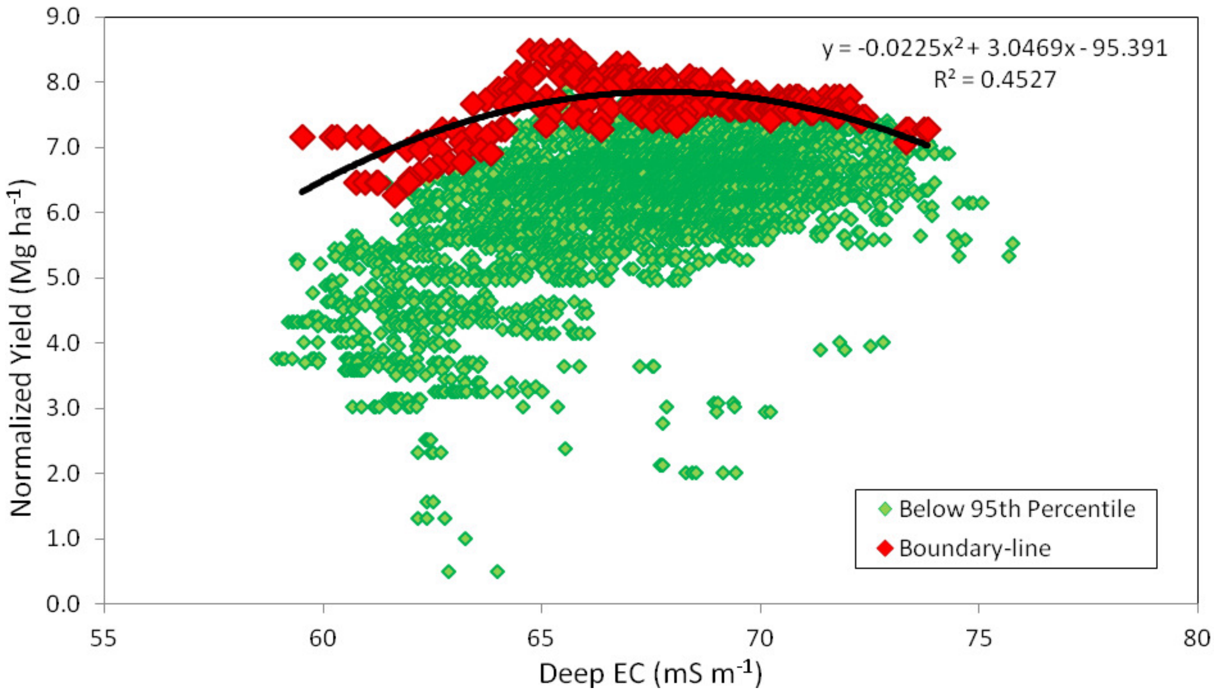

Figure 3.20 Boundary-line analysis of historical yield vs. deep EC for Manhattan 2010.

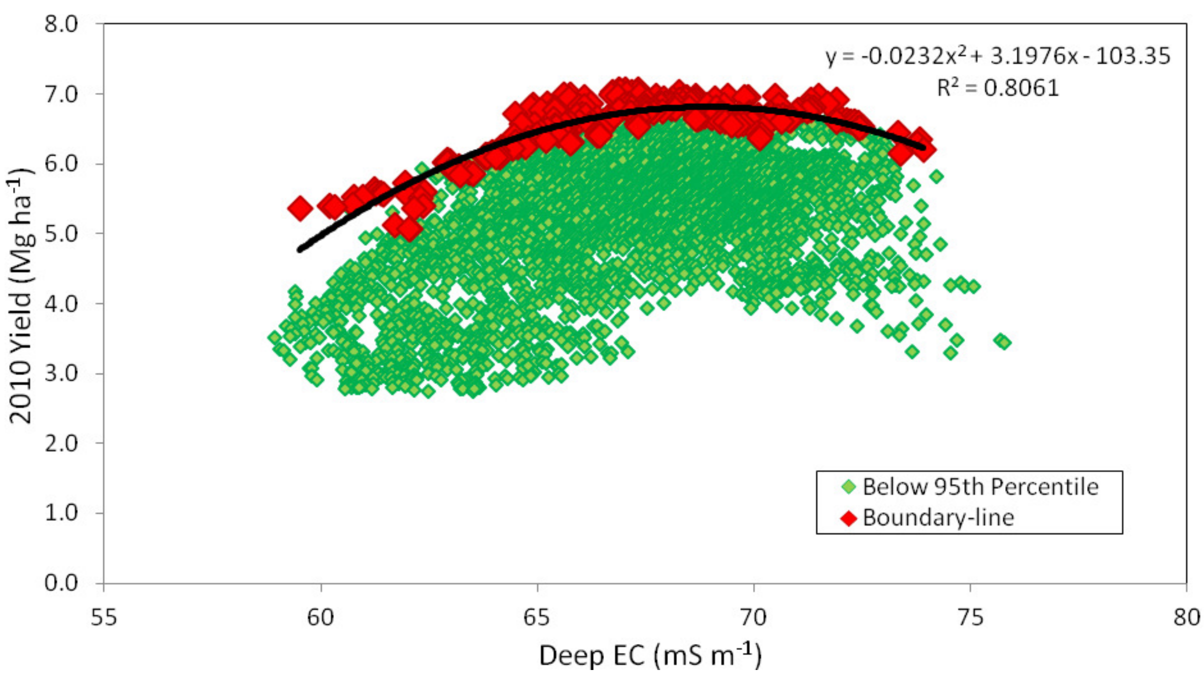

Figure 3.21 Boundary-line analysis of 2010 yield vs. deep EC for Manhattan 2010.

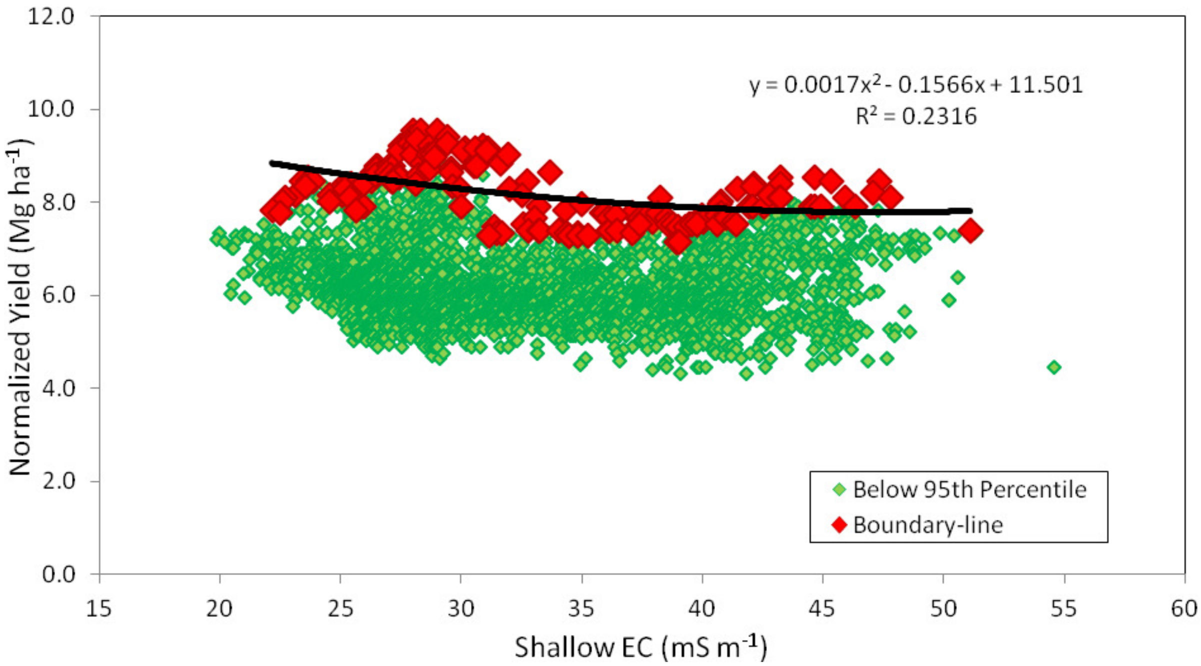

Figure 3.22 Boundary-line analysis of historical yield vs. shallow EC for Manhattan 2011.

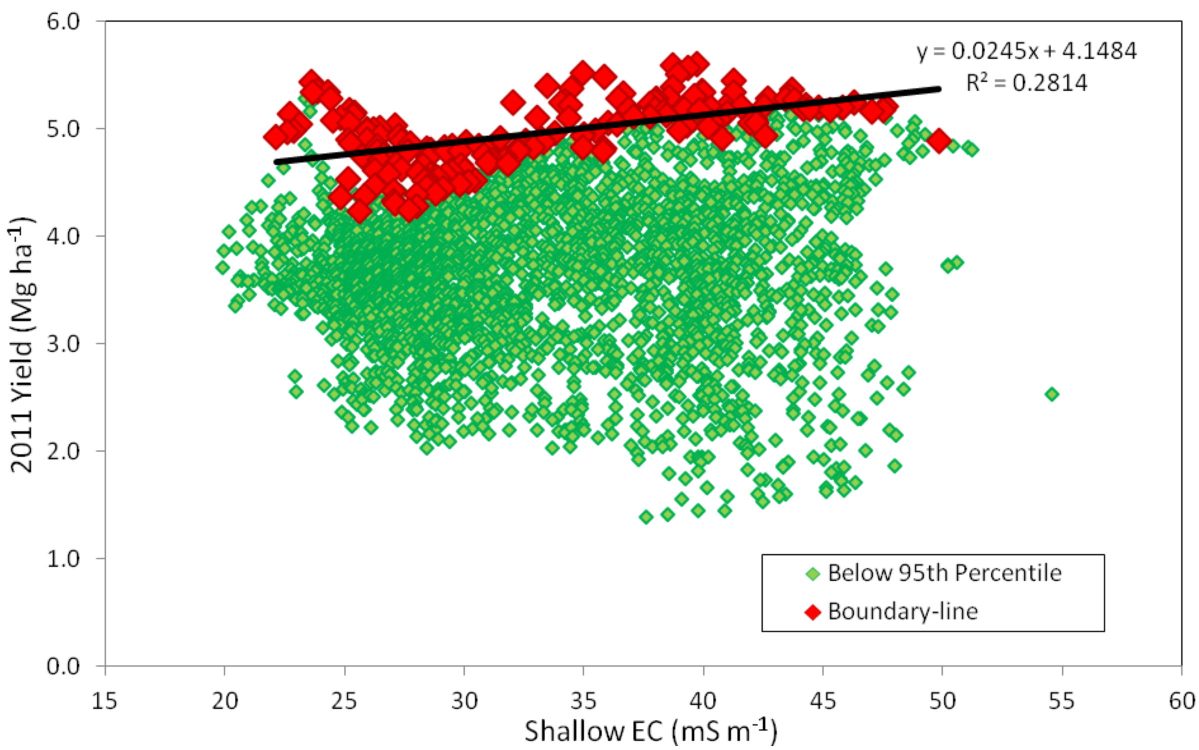

Figure 3.23 Boundary-line analysis of 2011 yield vs. shallow EC for Manhattan 2011.

Chapter 4 - Economic Analysis of Variable-Rate Nitrogen Applications

ABSTRACT

Demonstrating the economic benefits of variable-rate (VR) nitrogen (N) application in grain sorghum would increase its appeal to producers. Field experiments were conducted in 2010 and 2011 in Stockton and Manhattan, KS to evaluate the performance of four different VR-N prescriptions. Grid soil sampling data, soil electrical conductivity (EC) data, and yield data maps were used in different combinations to generate four VR-N prescriptions and one uniform N prescription to be applied in grain sorghum. Prescriptions were applied as treatments before planting and harvested for grain in the fall. Yield was recorded using yield monitor-equipped harvesters. Prescription expenses and returns were compared for each field. Soil sampling based on grids was the most expensive method at \$24.71 ha^{-1}, while sampling based on EC zones were less expensive at \$5.56 ha^{-1} followed by field composite samples that cost \$0.37 ha^{-1}. Stockton sites recorded highest returns from prescription 4 (EC zones and variable yield goal) and the lowest returns from both prescriptions 2 (EC zones and fixed yield goal) and 5 (grid soil samples and variable yield goal). Prescription 2 failed to capture the appropriate N requirements of the field, resulting in low yields. As for the other prescriptions, the cost of different input data was the driving factor that allowed some prescriptions to have higher returns than others. Manhattan sites recorded highest yields and returns from prescription 3 (composite soil sample and variable yield goal). Prescription 5 was among the lowest returning prescriptions as a result of the high cost of prescription input data (grid sampling), similar to Stockton sites. Overall, increasing intensity of data input in a prescription did not necessarily result in a revenue increase from the application. Increasing prescription intensity, while keeping input expenses low, such as using

EC zones, did result in improved returns. Increased revenue did not outweigh the costs associated with prescription 5, the most data intensive treatment. Prescriptions that included a variable yield goal component tended to have higher returns across all sites.

INTRODUCTION

Kansas produced nearly 2.8 million Mg of grain sorghum (*Sorghum bicolor* (L.) Moench) in 2011, which was equivalent to more than 50% of the US grain sorghum production (NASS 2012). Grain sorghum is considered a relatively drought tolerant C_4 plant, capable of performing better than other crops such as corn (*Zea mays* L.) and soybeans (*Glycine max* L. Merr.) when growing in moisture-limited and high temperature conditions such as those found in western Kansas (Stahlman and Wicks 2000). In Kansas, grain sorghum is often substituted for corn in crop rotations and grain sorghum requires large amounts of nitrogen (N) fertilizer to achieve yields similar to corn production. Nitrogen is one of the most essential and extensively applied nutrients in grain sorghum (Buah et al. 1998) and often the most expensive input for this crop. When managing N fertility, it is important to understand that spatial variability exists and that under- and over-applications of N will cause either N deficiencies in the crop or N losses due to leaching or runoff (Koch et al. 2004). Both of these situations will have a negative economic impact for farmers and the N losses can cause environmental concerns for the general public (Buah et al. 1998). A solution to the under- and over-applications of N fertilizer is to use variable-rate (VR) application methods. However, very little research has been done pertaining to VR-N application and its potential economic benefits in grain sorghum.

Soil fertility can vary significantly within a field so that the traditional nutrient management strategy of applying a single rate of fertilizer across the whole field could be considered a misapplication (Thrikawala et al. 1999). Other spatially-variable field variables include soil texture, slope, and yield potential could also lead to mismanaged N fertilizer applications. Many of these field variables can be spatially measured, recorded, and manipulated to be used in VR fertilizer prescription development. The usefulness of this information needs to be studied and the tradeoffs to collecting and implementing the data relative to the savings in N applied and yield gained needs to be evaluated. In order for a prescription to work well, the variables being used should have an influence on yield potential, N content, or some factor that is either going to spatially boost yields or reduce inputs.

One of the original methods of assessing field variability was grid-based soil sampling (Koch et al. 2004). Field management based on grid soil samples is a tedious process and an intensive management strategy, but it may be feasible for some fields to manage fertility using a grid layout if it increases gross revenue or decreases N input costs such that they outweigh the added cost of technologies or services needed for VR management (Koch et al. 2004). Temporal changes in soil properties and fertility will affect the frequency of sampling. Often, crop rotations and cropping intensity also influence how often soil sampling may take place, such as annually, biannually, or even less frequently. This will have a large impact on the economic analysis of any type of sampling taking place. In principle, grid sampling-based N application seems logical, but economically there are limitations. Minimal cost, yet effective approaches for managing spatial variability are needed (Koch et al. 2004).

Creating management zones is often a more effective and economical option compared to more detailed grid-based soil sampling (Fleming and Westfall 2000). There are numerous methods of defining management zones such as using variations in topography, soil color, and yield potential to group areas with similar characteristics. Another method is using soil electrical conductivity (EC), which may function as a direct or indirect indicator of numerous soil properties such as soil moisture and clay content (Johnson et al. 2003). Soil EC data are often used to create site-specific management zones (Johnson et al. 2003; Shaner et al. 2008). These zones are developed by spatially grouping sites in the field with similar EC measurements thus creating zones with similar soil properties that may include clay content, soil water content, salinity, bulk density, depth of conductive soil layers, and organic matter (OM) (Johnson et al. 2003; Kitchen et al. 2003). The EC zones are then used as soil sampling zones to make the process more strategic and cost effective than arbitrarily using a grid-based sampling procedure. Soil EC is usually measured at two depths: a shallow reading (0-30 cm) and a deep reading (0-90 cm) (Johnson et al. 2003). Deep EC has been correlated to claypan topsoil thickness and water holding capacity and has been found to have more temporal stability whereas shallow EC is more affected by transient soil properties such as solution concentration, topsoil water content, and soil temperature (Farahani and Buchleiter 2003). Due to the temporal stability of deep EC, a single EC mapping can suffice to define these zones without need for remapping. These findings justify EC measurements as an economical tool to create management zones that may benefit from varying inputs and practices (Farahani and Buchleiter 2003). Collecting EC data is fast, inexpensive, and the data do not need to be collected frequently while other means of determining the soils' parameters, such as grid-based soil sampling can be economically unfeasible, particularly in dryland, low input crop production (McCann 1996). It is important to keep in mind that the profit potential of VR-N management is significantly enhanced if the initial means of preparing prescription application maps are inexpensive (Koch and Khosla 2003).

Yield potential is a very useful tool when generating VR-N prescriptions. Whether the yield potential is being used to create a spatially-variable yield goal or to generate management zones it requires the use of a yield monitor. Determining if the investment in a yield monitor is economical can be difficult for some producers, especially if the producer does not know how to use yield data. This is not uncommon for the average producer. A major reason producers do not buy yield monitors is because the benefits are ill defined and are not realized initially after the purchase (Swinton and Ahmad 1997). The benefits realized from yield monitors by producers vary widely due to the range of use between producers. For example, one producer may not even download yield data from his monitor, while another producer uses the data to create VR fertilizer prescriptions. Generally, yield monitor benefits must be measured empirically on individual farms (Swinton and Ahmad 1997).

Today, most combines are equipped with a yield monitor when they are purchased and many used combines being traded are already equipped, which means many producers do not need to purchase a new yield monitor system. Economic studies can be difficult for yield monitors because it is difficult to separate costs and benefits of yield mapping from VR input management and other uses of yield data (Swinton and Lowenberg-Deboer 1998). It is also important to assess fixed costs, such as a yield monitor, over the entire area of farmland to calculate returns on a per hectare basis. Returns will increase as field area covered increases since fixed costs are spread over more hectares (Thrikawala et al. 1999). The same should apply for other fixed costs, such as the purchase of a VR fertilizer applicator.

Implementing VR-N application leads to the question of whether the potential increase in returns is sufficient to cover the cost of paying for services such as grid sampling, soil EC measurements, or the application itself (Roberts et al. 2000). The potential for improved profitability due to VR-N application depends on identifying areas in the field where additional N inputs will increase revenue on a scale that is greater than the added costs and/or identifying areas where reducing N inputs will decrease costs on a scale that is greater than potential revenue reduction associated with lower grain yield (Snyder et al. 1999). There are few analyses of revenues, costs, and returns associated with VR-N applications, and the results of the few existing analyses have not been communicated well to growers interested in practicing VR-N application (Koch et al. 2004).

The objective of this study was to economically analyze five different VR-N prescriptions applied in grain sorghum to determine the added value, if any, of using yield data, grid soil sampling, and soil EC data. Prescriptions build upon each other, each one adding more intensity to the input data than the previous one. The hypothesis was that increasing intensity of input data will allow for higher returns by decreasing the cost of N required, increasing revenue from yield, or a combination of both.

MATERIALS AND METHODS

Field experiments were established during the spring of 2010, one at a farmer-owned and operated production field in Stockton, KS and the other at the Kansas State University Department of Agronomy North Farm in Manhattan, KS. These studies were repeated in 2011 in different but adjacent fields at both locations. In each year, the experimental area at Stockton was 10.5 ha consisting of a Holdrege silt loam soil while the experimental area at Manhattan was 2.8 ha consisting of a Smolan silt loam soil and partial inclusions of Wymore silty clay soil. The previous crop for all sites was winter wheat (*Triticum aestivum* L.). The experimental design consisted of six treatments arranged in parallel strips with two replications. Each treatment was applied down the length of the field with each pass of the equipment being one plot. Plot width was based on the fertilizer applicator available and was 10.7 m in Stockton and 4.6 m in Manhattan. Development of the four VR-N prescriptions was described in chapter 2. Chapter 3 describes the application of these four prescriptions together with treatment 1, a uniform N rate across field, and treatment 6, a N test strip that increased N rates from 0 kg ha^{-1} to 224 kg ha^{-1} and then decreased rates back to 0 kg ha^{-1} repeatedly across the length of the field. After prescriptions were applied, atrazine + s-metolachlor (Bicep II Magnum, Syngenta Crop Protection, Greenboro, NC) herbicide was applied pre-plant followed by no-till planting grain sorghum in 0.76-m rows. A starter fertilizer (10-34-0) was applied with the planter which provided 5.3 kg ha^{-1} of additional N and 18 kg ha^{-1} of P to provide sufficient P levels in the soil. Grain sorghum was harvested in the fall using combines equipped with yield monitors. Yield data from all sites were filtered and cleaned using the ARS Yield Editor and compiled using EASi Suite software version 2009.00.01 (Mapshots Inc., Cumming, GA).

Economic Analysis

Treatments were compared based on returns from yield, cost of prescription inputs and N fertilizer, and returns over costs. The analysis was conducted using the 5-yr average prices for grain sorghum (\$156.71 Mg^{-1}), NH_3 fertilizer (\$0.86 kg^{-1} N), and UAN liquid fertilizer (\$1.28 kg^{-1} N) (NASS 2011). Several assumptions had to be made in order to analyze the data on a per hectare basis. The first assumption was that average field size was 32 ha. This allowed the cost of a field composite soil sample to be distributed across each hectare. The next assumption was that this 32-ha field could be divided into five EC management zones, each having 6.5 ha per zone. This allowed the cost of each composite soil sample for that zone to be distributed across each hectare of the management zone. The cost associated with analysis of each composite soil sample was \$12.00 (KSU soil testing lab). Cost of hiring a person to grid soil sample was \$24.71 ha^{-1} (Nathan Woydziak, Personal communication, Crop Quest). It was assumed that soil samples were taken annually. The cost for collecting EC data was assumed to be \$16.00 ha^{-1} and was spread out over five years using an 8% interest rate, thus costing \$4.03 ha^{-1} annually, and when including cost of analysis for each soil sample in the EC management zones, the total cost was \$5.56 ha^{-1}. No added cost was included for the yield monitor itself as it was assumed that the producer's combine was equipped with a yield monitor but the data that has been collected has not been utilized. Other variable input costs were not accounted for (such as seed, herbicide and/or other pesticides and fertilizers) and therefore, results were presented as returns over N prescription costs.

Grain sorghum yield response to N applied was determined using the test strips that make up treatment 6. The analysis was conducted by exporting raw yield data and N application data into a spreadsheet and estimating response curves. The biological optimum N rate (BONR) was determined as the maximum N rate for which a yield response was observed. It was calculated by setting the first derivative of the response equation equal to zero and solving for N. To calculate the economic optimum N rate (EONR) the response equation was set equal to the N: grain sorghum price ratio ($\$ kg^{-1}$ N): ($\$ kg^{-1}$ grain sorghum) and solved for N.

The economic analysis was performed using the 5-yr average prices for N and grain sorghum, but changes in this price ratio could lead to different results when comparing the returns of the treatments. Due to this possibility, a sensitivity analysis was completed to generate a range of prices to determine whether lower returning treatments would become more competitive at different price ratios. All sensitivity tables included grain sorghum prices ranging from \$78.57 Mg^{-1} to \$315 Mg^{-1} while Stockton N prices ranged from \$0.44 to \$1.32 kg^{-1} of N (using NH_3) and Manhattan N prices ranged from \$0.44 to \$2.21 $kg^{-1}$of N (using UAN).

RESULTS AND DISCUSSION

Economically optimum N rates (EONR) were always lower than the BONR across both fields and years. The BONR was the maximum N rate to which yield responded compared to the EONR, which was the N rate at which returns on yield over N costs were maximized. In 2010, the BONR for Stockton was 250 kg N applied ha^{-1} while the EONR was 197 kg N ha^{-1} (Figure

4.1). In 2011, the BONR was 177 kg ha^{-1} compared to the EONR of 140 kg N ha^{-1}. The difference between the two years was likely due to less precipitation received in 2011 across the region. As for Manhattan in 2010 the BONR was 205 kg N ha^{-1} compared with the EONR of 138 kg ha^{-1} (Figure 4.3). In 2011, there was a poor N response observed, therefore BONR and EONR were both equal to zero (Figure 4.4). At Manhattan, 2010 had below average rainfall for the region but not nearly as severe as the drought during the 2011 growing season. Soil water availability has a direct effect on N uptake into the plant and therefore influences how well the N is utilized.

Data from grid-based soil sampling was the most expensive to obtain for creating VR-N prescriptions. Grid-based soil sampling cost \$24.71 ha^{-1} compared to using soil EC management zones which cost \$5.56 ha^{-1} to implement, and the yield data were free (based on assumptions). The additional cost of developing the prescriptions depended on how many spatially-variable data sources were included (Table 4.2). Excluding the N fertilizer cost, it was evident that the uniform N prescription (prescription 1) would cost the same to develop as the spatially-variable yield goal prescription (prescription 3) and both were the least expensive with only the additional cost of a composite soil sample (\$0.37 ha^{-1}) for both prescriptions. The prescriptions using EC management zones (prescriptions 2 and 4) both cost \$5.56 ha^{-1} whether the variable yield goal was used or not. Using grid samples and a variable yield goal (prescription 5), the cost was \$24.71 ha^{-1}. The N fertilizer costs varied greatly across treatments and were not consistently reduced or increased by the more data intensive prescriptions at any locations. The N each prescription required varied from field to field and depended entirely on whether the prescription captured the variables that influenced yield at each field.

At all locations, prescriptions differed greatly when comparing the average expenditures, but few differences existed when comparing the average revenues generated with each prescription (Tables 4.3 and 4.4). Prescription 4 (management zones and variable yield goal) generated the greatest revenue from yield at Stockton in 2010 which allowed it to have the highest returns as well. Prescription 2 (management zones) generated the least revenue at Stockton 2010; however, it did have higher returns than prescription 5 (grid samples and variable yield goal), which had the greatest expenses across treatments and was the lowest returning prescription. In Stockton 2011, prescription 5 generated the greatest revenue from yield but because it was the most expensive prescription it resulted in returns next to lowest. Prescription 4 had the greatest returns across treatments in Stockton 2011. In Manhattan 2010, prescription 3 (variable yield goal) generated the greatest revenue from yield which allowed it to have the greatest returns across treatments. Prescription 5 was the most expensive treatment and generated the lowest revenue, which made it the lowest returning treatment in Manhattan 2010. In Manhattan 2011, prescription 3 generated the greatest revenue from yield, had the highest expenses, and the highest returns across treatments. Prescription 4 generated the lowest revenue which caused this treatment to have the lowest returns. Three of the four locations resulted in the highest average N rate coming from treatment 3. Both Manhattan locations also achieved the highest yields from prescription 3; however, it was lower performing at the Stockton sites. Prescription 5, which used grid-based soil sampling, was the least profitable at both Stockton and Manhattan in 2010 while it was nearly the least profitable in both fields in 2011. Prescription 1, the uniform rate treatment, was consistently in the middle regarding prescription returns and yields. The low expenses of this prescription often allowed it to outperform the more expensive, higher intensity prescriptions, such as prescription 5.

The economic analysis for the 2010 Stockton field shows that prescriptions 4 and 1 were significantly better than prescription 5. Using sensitivity tables, it was determined that no combination of grain sorghum and N prices allowed prescription 5 to improve returns to the level of prescriptions 4 or 1. The Stockton 2011 results indicated that prescription 4 had the highest returns of all treatments. Using sensitivity analysis, it was evident that realistically adjusting the price ratio would not make prescriptions 2 and 5 more competitive with prescription 4. However, a combination of high N costs and low grain sorghum value can allow prescriptions 1 and 3 to be indifferent from prescription 4 regarding returns (Tables 4.5 and 4.6).

Results for Manhattan 2010 indicated that prescription 3 had the highest returns of all prescriptions. Using sensitivity tables, it was determined that no other prescriptions can equal the returns of prescription 3. Manhattan 2011 results indicate that prescription 3 was the highest returning but only statistically higher than prescription 4. Sensitivity analysis indicates that no realistic price ratio could improve returns of prescription 4 to equal prescription 3.

CONCLUSIONS

Both Stockton sites saw highest returns from prescription 4 followed by prescription 3. Both prescriptions involved the use of a variable yield goal which indicated that using historic yield data was a beneficial tool in developing VR-N recommendations at Stockton. Prescription 4 also involved using EC management zones to guide the soil sampling process which proved to be very beneficial when paired with a variable yield goal. However, using EC management zones alone did not have the same high returning results (prescription 2) indicating soil EC may not be a good resource by itself when generating N prescriptions. Prescription 5 (grid sampling and variable yield goal) did not result in enough added revenue from yield to overcome the high costs of generating it, therefore this prescription was one of the lowest returning across treatments. Both Manhattan sites saw the highest returns from prescription 3 (composite soil sample and variable yield goal). Prescription 4 performed well in Manhattan 2010 with high returns but the high drought stress in 2011 caused poor yields and low returns across all prescriptions. The performance of these two prescriptions indicated that historic yield data was a very useful tool in prescription generation at Manhattan. The drought stricken season in Manhattan 2011 did not show advantages to having spatially variable soil tests, as the top two returning prescriptions (3 and 1) used a field composite soil testing method.

Revenue from yield was a much larger determining factor than expenses in determining returns over prescription costs. If a treatment had the lowest revenue from yield it was much more likely to have lowest returns regardless of the expenses involved. However, as prescription revenues became more comparable, the expenses became more influential on how the prescription returns ranked.

The VR-N prescriptions had an advantage in most fields in regards to yield and returns. However, on occasion the advantage over a uniform N rate was considered insignificant. Intensifying the input data for VR-N prescriptions did not allow for any consistent decrease or increase in N applied. Using yield monitor data to create a variable yield goal tended to provide a more strategic dispersal of N applied to allow for a yield advantage.

The results of this study suggest that grid-soil sampling is too intensive to be done yearly and see any economic benefit. It may not ever be an economically beneficial option for some cropping systems, but a one-time-only grid-sampling of a field could uncover underlying features or variability that would improve field management. Soil EC management zones were not a sufficient field management option, most likely due to the lower correlations between EC and yield. However, when an accurate yield goal component was introduced to the EC management zones, the yield performance was enhanced. In sloping fields, such as the sites in this study, elevation will most likely have a significant influence on yield due to soil erosion, depositing of topsoil, and water infiltration which are driven by elevation and slope. This suggests that topography could be useful as a field management tool.

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Table 4.1 Descriptive breakdown of the six N prescriptions.

Prescription	Uniform or VR application	Variable Yield Goal	Soil Sampling Approach
1	Uniform	NO	Composite Sample
2	VR	NO	EC Zones
3	VR	YES	Composite Sample
4	VR	YES	EC Zones
5	VR	YES	Grid Samples
6	TEST STRIP APPLICATION		

Table 4.2 Breakdown of the total expenses into soil sampling costs and N costs for each prescription in Stockton and Manhattan, 2010 and 2011.

	Prescription	Soil Sampling Cost	N Cost	Total Expenses
		------------------ $ ha^{-1}	--------------------	
Stockton 2010	1	0.37	91.43	91.80
	2	5.56	73.92	79.48
	3	0.37	107.72	108.09
	4	5.56	104.55	110.11
	5	24.71	95.42	120.13
	LSD $\leq$ 0.15			2.76
Stockton 2011	1	0.37	105.03	105.40
	2	5.56	114.20	119.76
	3	0.37	101.84	102.21
	4	5.56	110.77	116.33
	5	24.71	124.12	148.83
	LSD $\leq$ 0.15			6.05
Manhattan 2010	1	0.37	172.82	173.19
	2	5.56	161.45	167.01
	3	0.37	184.34	184.71
	4	5.56	171.04	176.60
	5	24.71	171.41	196.12
	LSD $\leq$ 0.15			9.64
Manhattan 2011	1	0.37	137.30	137.67
	2	5.56	155.09	160.65
	3	0.37	180.59	180.96
	4	5.56	171.54	177.10
	5	24.71	146.23	170.94
	LSD $\leq$ 0.15			19.98

Table 4.3 Treatment revenues, expenses, and returns in Stockton 2010 and 2011.

	Treatment	Revenues	Expenses	Returns over Prescription Costs
		--------------------------$ ha^{-1} --------------------------		
2010	1	1204.14 ab	91.80 c	1112.37 a
	2	1118.00 b	79.48 d	1038.51 ab
	3	1156.40 ab	108.09 b	1048.32 ab
	4	1239.60 a	110.11 b	1129.49 a
	5	1127.20 b	120.13 a	1007.08 b
	LSD ≤ 0.15	100.79	2.76	101.47
2011	1	1157.08 ab	105.40 c	1051.68 b
	2	1137.91 b	119.76 b	1018.15 d
	3	1155.03 ab	102.21 c	1052.82 b
	4	1179.56 a	116.33 b	1063.23 a
	5	1180.05 a	148.83 a	1031.22 c
	LSD ≤ 0.15	28.38	6.05	6.41

Table 4.4 Treatment revenues, expenses, and returns in Manhattan 2010 and 2011.

	Treatment	Revenues	Expenses	Returns over Prescription Costs
		--------------------------$ ha^{-1}	--------------------------	
2010	1	893.27 b	173.19 c	720.08 bc
	2	890.60 b	167.01 c	723.57 bc
	3	974.81 a	184.71 b	790.10 a
	4	916.49 b	176.60 bc	739.90 b
	5	897.52 b	196.12 a	701.39 c
	LSD ≤ 0.15	32.52	9.64	32.52
2011	1	545.03 ab	137.67 c	407.37 a
	2	539.30 ab	160.65 b	378.66 ab
	3	621.60 a	180.96 a	440.65 a
	4	468.80 b	177.10 ab	291.73 b
	5	513.25 ab	170.94 ab	342.33 ab
	LSD ≤ 0.15	121.02	19.98	112.28

Table 4.5 Difference in returns between prescription 4 (management zones and variable yield goal) and prescription 3 (composite sample and variable yield goal) across a series of price ratios for Stockton 2011.

		Grain Sorghum Market Price ($ Mg^{-1})												
		78.75	98.44	118.13	137.81	157.50	177.19	196.88	216.56	236.25	255.94	275.63	295.31	315.00
	0.44	1.91	4.99	8.08	11.16	14.24	17.32	20.41	23.49	26.57	29.65	32.74	35.82	38.90
	0.55	0.62	3.70	6.78	9.87	12.95	16.03	19.11	22.20	25.28	28.37	31.45	34.53	37.62
	0.66	-0.67	2.41	5.49	8.57	11.66	14.74	17.82	20.90	23.99	27.08	30.17	33.25	36.33
N cost	0.77	-1.97	1.12	4.20	7.28	10.36	13.45	16.53	19.61	22.69	25.80	28.88	31.96	35.05
($ kg^{-1})	0.88	-3.26	-0.18	2.91	5.99	9.07	12.15	15.24	18.32	21.40	24.51	27.60	30.68	33.76
	0.99	-4.55	-1.47	1.61	4.70	7.78	10.86	13.94	17.03	20.11	23.23	26.31	29.39	32.48
	1.10	-5.84	-2.76	0.32	3.40	6.49	9.57	12.65	15.73	18.82	21.94	25.03	28.11	31.19
	1.21	-7.14	-4.05	-0.97	2.11	5.19	8.28	11.36	14.44	17.52	20.66	23.74	26.82	29.91
	1.32	-8.43	-5.35	-2.26	0.82	3.90	6.98	10.07	13.15	16.23	19.37	22.46	25.54	28.62

Cells highlighted in yellow indicate when the returns from prescription 3 were equal or greater than returns from prescription 4.

Table 4.6 The difference in returns between prescription 4 (management zones and variable yield goal) and prescription 1 (uniform N) across a series of price ratios in Stockton 2011.

		Grain Sorghum Market Price ($ Mg^{-1})												
		78.75	98.44	118.13	137.81	157.50	177.19	196.88	216.56	236.25	255.94	275.63	295.31	315.00
	0.44	2.51	5.33	8.15	10.98	13.80	16.62	19.45	22.27	25.09	27.92	30.74	33.56	36.39
	0.55	1.62	4.45	7.27	10.09	12.92	15.74	18.56	21.39	24.21	27.03	29.85	32.67	35.50
	0.66	0.74	3.56	6.39	9.21	12.03	14.86	17.68	20.50	23.33	26.14	28.96	31.78	34.61
N cost	0.77	-0.14	2.68	5.50	8.33	11.15	13.97	16.80	19.62	22.44	25.25	28.07	30.89	33.72
($ kg^{-1})	0.88	-1.03	1.80	4.62	7.44	10.27	13.09	15.91	18.74	21.56	24.36	27.18	30.00	32.83
	0.99	-1.91	0.91	3.74	6.56	9.38	12.21	15.03	17.85	20.68	23.47	26.29	29.11	31.94
	1.10	-2.79	0.03	2.85	5.68	8.50	11.32	14.15	16.97	19.79	22.58	25.40	28.22	31.05
	1.21	-3.68	-0.85	1.97	4.79	7.62	10.44	13.26	16.09	18.91	21.69	24.51	27.34	30.16
	1.32	-4.56	-1.74	1.09	3.91	6.73	9.56	12.38	15.20	18.03	20.80	23.62	26.45	29.27

Cells highlighted in yellow indicate when the returns from prescription 1 were equal or greater than returns from prescription 4.

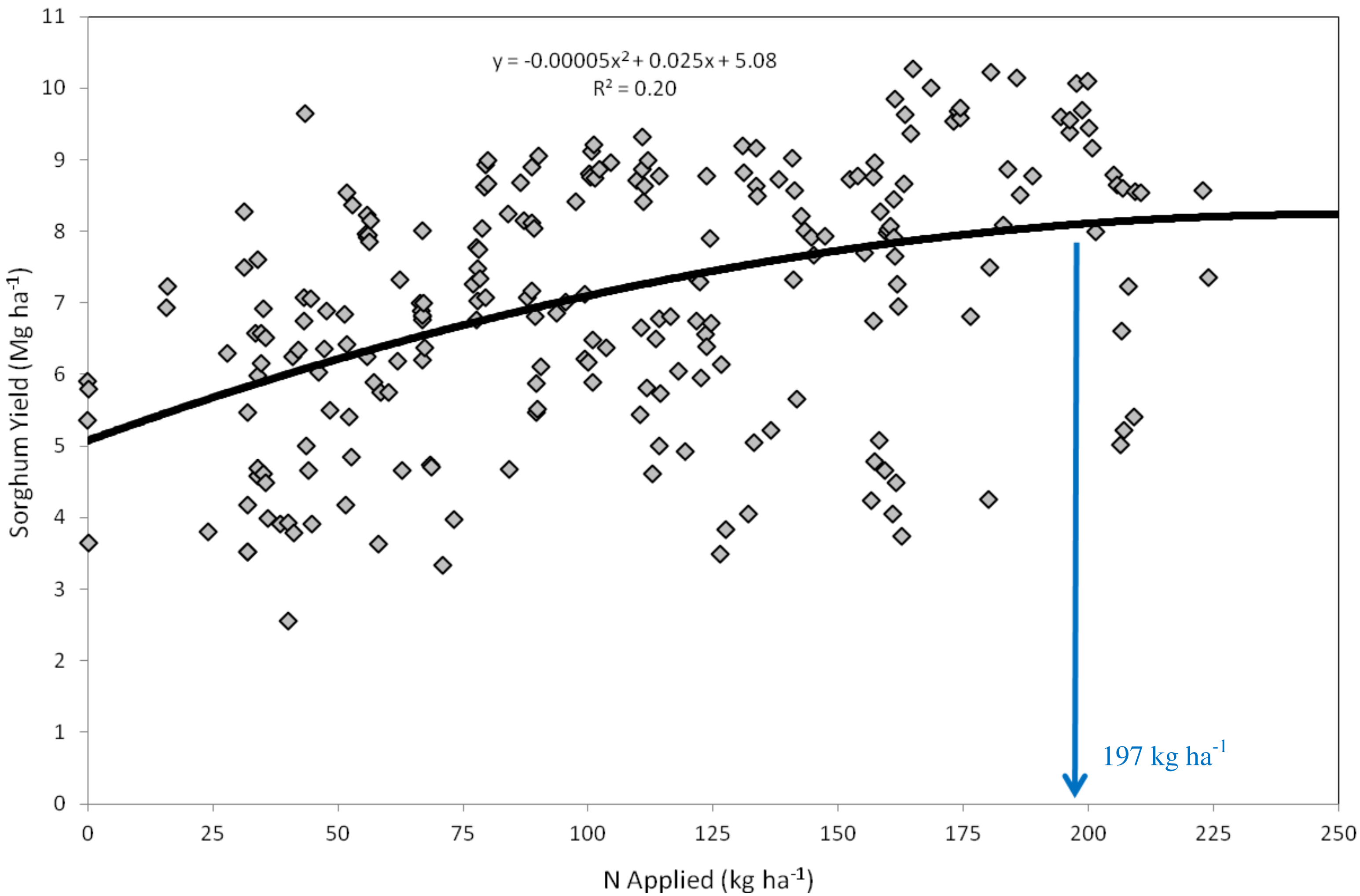


Figure 4.1 Grain sorghum yield (Mg ha^{-1}) response to N applied (kg ha^{-1}) across treatment 6 test strips in Stockton 2010. Blue line indicates economic optimum N rate at prices: sorghum = \$156.71 Mg^{-1}; NH_3 = \$0.86 kg^{-1}.

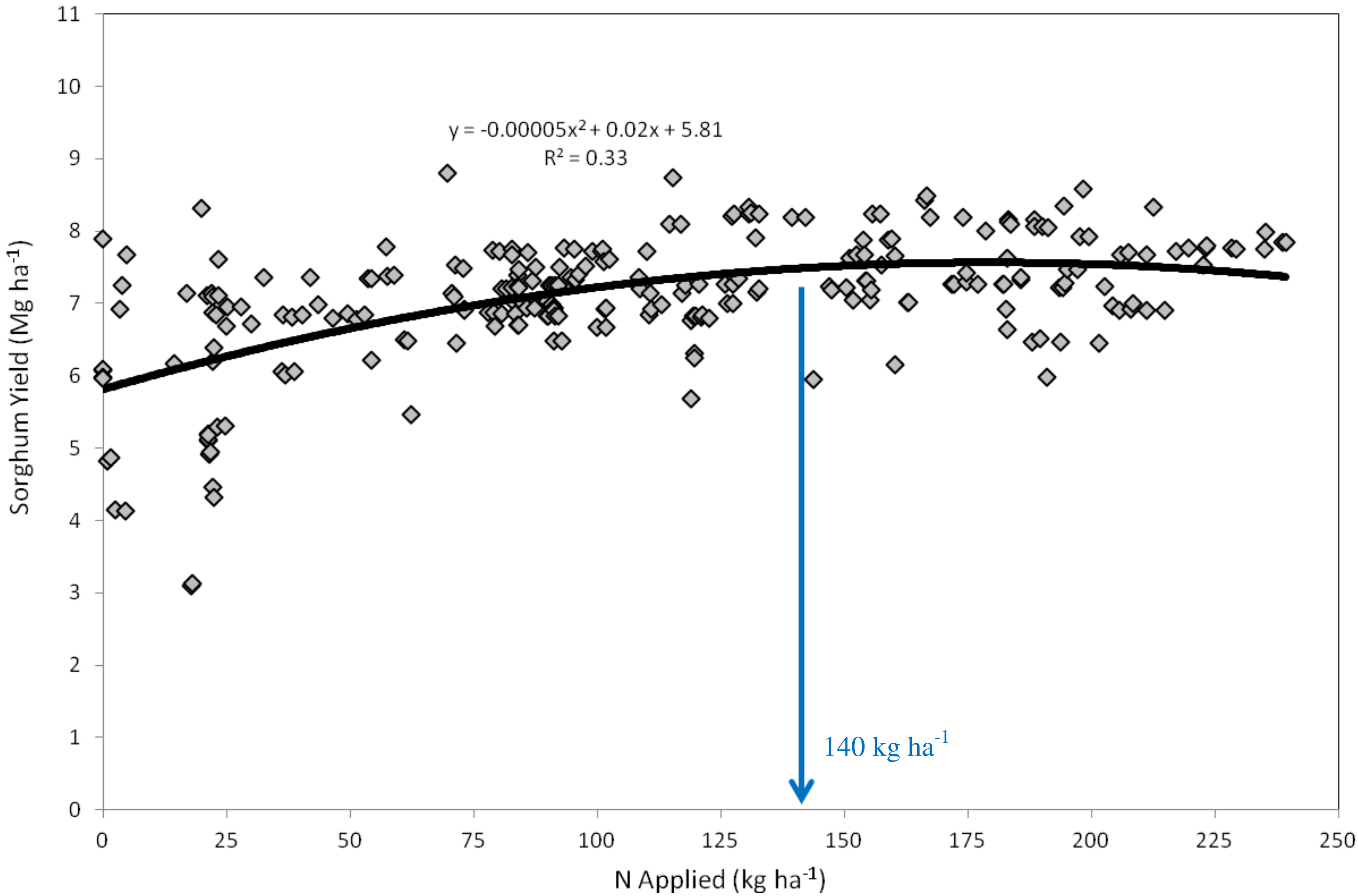


Figure 4.2 Grain sorghum yield (Mg ha^{-1}) response to N applied (kg ha^{-1}) across treatment 6 test strips in Stockton 2011. Blue line indicates economic optimum N rate at prices: sorghum = \$156.71 Mg^{-1}; NH_3 = \$0.86 kg^{-1}.

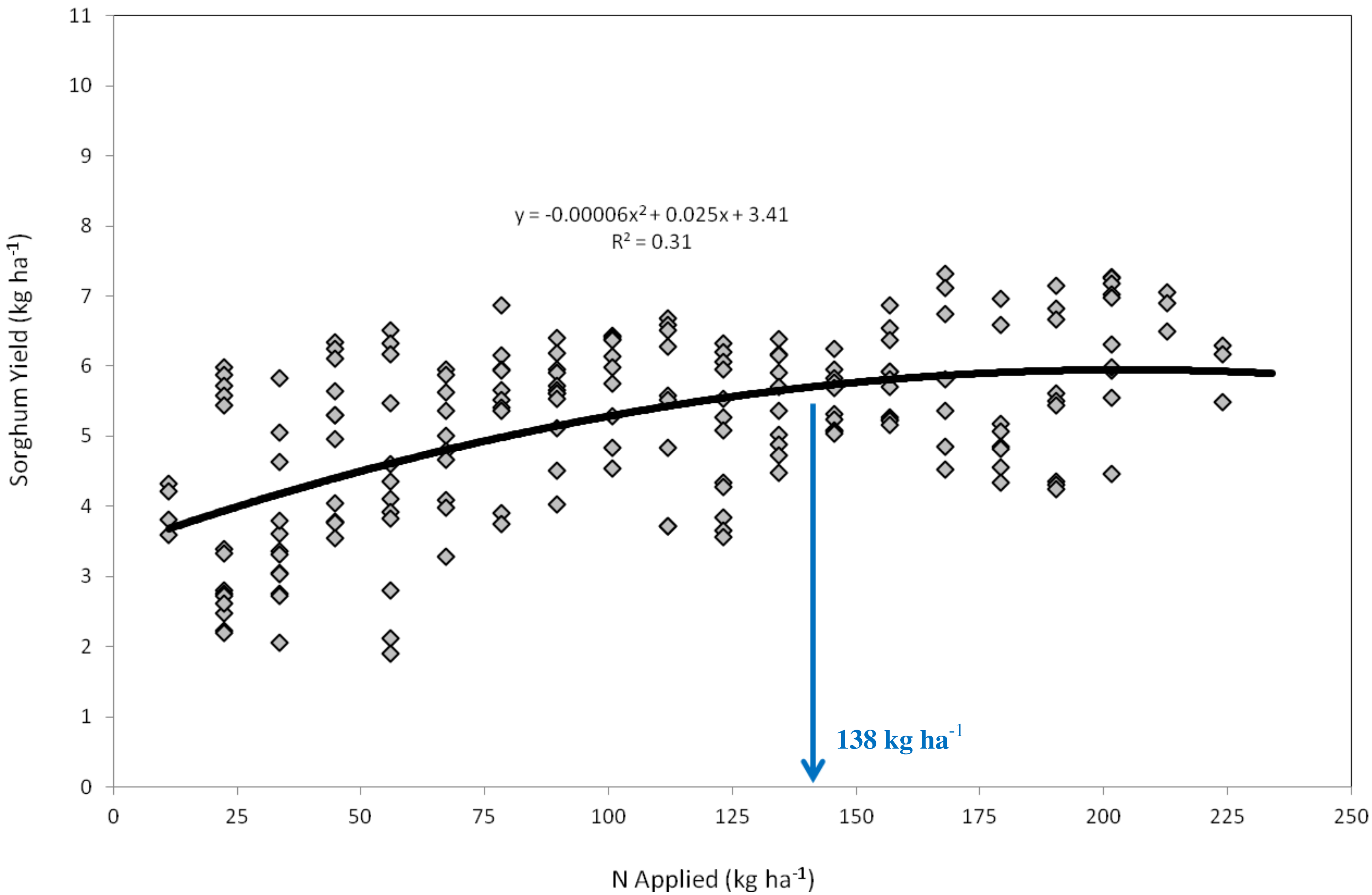


Figure 4.3 Grain sorghum yield (Mg ha^{-1}) response to N applied (kg ha^{-1}) across treatment 6 test strips in Manhattan 2010. Blue line indicates economic optimum N rate at prices: sorghum = \$156.71 Mg^{-1}; UAN = \$1.28 kg^{-1}.

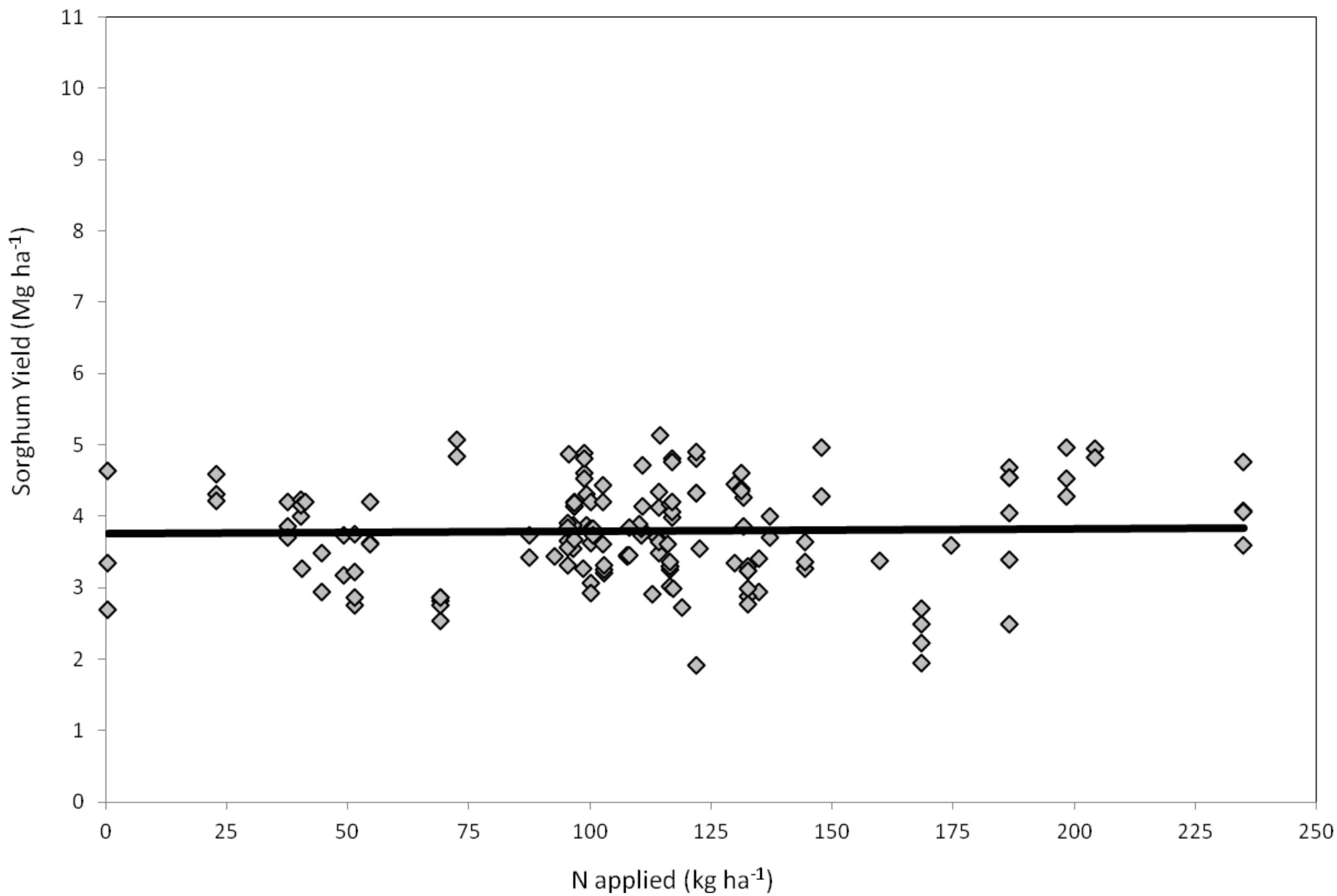


Figure 4.4 Grain sorghum yield (Mg ha^{-1}) response to N applied (kg ha^{-1}) across treatment 6 test strips in Manhattan 2011. Economic optimum N rate is equal to zero.

Appendix A - Weather Data

Table A.1 Weather data from growing seasons of 2010 and 2011 at Stockton and Manhattan.

	Stockton				Manhattan			
	2010		2011		2010		2011	
Month	GDD	Precipitation	GDD	Precipitation	GDD	Precipitation	GDD	Precipitation
	--°C day--	--mm--	--°C day--	--mm--	--°C day--	--mm--	--°C day--	--mm--
May	186.1	143.5	224.1	248.7	225.8	92.2	247.9	131.1
June	448.0	293.1	452.2	78.5	457.6	168.1	455.1	121.2
July	514.3	72.6	607.9	169.7	529.4	106.4	615.2	52.8
August	499.6	143.0	526.9	88.4	525.2	81.3	536.5	59.2
September	324.5	67.6	263.5	7.9	353.7	76.2	275.4	37.1
Total	1972.4	719.8	2074.7	593.1	2091.7	524.3	2130.1	401.3

Appendix B - Soil Sample Data

Table B.1 Grid Soil Sample Data for Stockton 2010.

Sample ID	pH	O.M.	P	K	NO_3 (15cm)	NO_3 (45cm)
		--%--	ppm			
1	7.7	1.6	15.0	617	4.3	7.4
2	6.8	1.1	25.9	595	3.4	7.4
3	6.0	2.0	9.7	607	2.7	5.3
4	6.1	1.8	11.0	566	4.0	6.7
5	6.2	2.1	9.1	627	3.2	6.5
6	6.4	1.8	11.5	592	3.8	6.2
7	7.4	1.6	16.6	608	4.3	6.8
8	6.3	2.1	11.5	550	4.2	6.0
9	6.2	2.1	9.8	564	3.2	5.3
10	6.1	1.8	7.2	568	4.1	7.2
11	5.7	2.1	22.7	672	3.0	5.6
12	6.1	2.2	8.8	550	4.3	7.1
13	6.2	1.8	11.2	528	3.8	6.8
14	6.6	1.8	17.1	578	5.3	7.3
15	6.3	2.0	10.3	562	6.4	7.5
16	6.5	1.7	22.4	641	4.5	6.9
17	6.4	1.8	24.0	576	5.8	5.7
18	6.6	1.4	23.0	549	5.9	7.9
19	7.6	2.3	33.2	628	3.5	6.2
20	6.2	1.6	7.7	588	3.0	6.4
21	6.3	1.9	10.6	566	2.7	5.9
22	6.2	1.9	9.0	594	3.8	5.1

Table B.2 Grid soil sample data for Manhattan 2010.

Sample ID	pH	O.M.	P	K	NO_3 (15cm)	NO_3 (45cm)
		--%--	---ppm---			
1	7.8	1.8	19.5	294	1.5	3.5
2	6.8	3.0	23.5	286	1.4	2.4
3	6.3	2.6	9.6	296	1.0	2.0
4	6.2	2.5	18.6	297	1.2	3.5
5	5.9	2.4	16.2	284	1.2	7.2
6	6.0	1.7	5.1	268	1.3	3.0
7	6.0	2.1	10.4	278	1.1	3.3
8	6.3	2.0	13.5	307	1.0	2.2
9	6.5	2.3	26.9	321	1.0	1.3
10	6.8	2.5	60.0	322	1.4	1.4
11	7.6	2.1	52.2	276	1.6	4.1
12	5.1	2.4	9.3	112	4.3	2.7
13	7.8	1.8	20.9	292	1.3	2.4
14	6.3	2.6	9.6	296	1.0	2.0
15	6.2	2.5	18.6	297	1.2	1.8
16	5.9	2.4	16.2	284	1.2	1.2
17	6.0	1.7	5.1	268	1.3	1.5
18	6.0	2.1	10.4	278	1.1	3.8
19	6.3	2.0	13.5	307	1.0	1.6
20	6.5	2.3	26.9	321	1.0	3.2
21	6.8	2.5	60.0	322	1.4	6.3
22	7.6	2.1	52.2	276	1.6	2.1

Table B.3 Grid soil sample data for Stockton 2011.

Sample ID	pH	OM	P	K	NO_3 (15cm)	NO_3 (45cm)
		--%--	----------ppm----------			
1	5.8	1.8	22.3	305	9.6	7.2
2	5.8	1.8	19.7	290	11.0	3.0
3	5.6	1.6	17.4	284	12.2	3.3
4	5.9	1.7	18.0	282	8.3	2.2
5	5.9	1.3	11.9	294	5.7	1.3
6	6.4	0.9	9.7	286	4.1	1.4
7	6.0	1.2	12.3	296	6.8	4.1
8	6.0	1.2	9.4	297	5.0	2.7
9	6.1	1.4	10.5	284	5.5	2.4
10	6.1	1.6	10.0	268	5.6	2.0
11	5.9	1.9	13.0	278	7.4	1.8
12	5.9	1.7	9.4	307	6.2	1.4
13	6.3	1.0	10.9	321	4.3	1.5
14	5.8	1.6	13.4	322	8.6	3.8
15	6.0	1.4	12.0	276	5.8	1.6
16	5.6	1.7	16.2	112	8.0	4.1
17	5.8	2.0	14.3	292	9.1	6.3
18	6.2	1.6	13.1	296	6.3	2.1
19	5.9	2.3	11.7	297	5.3	3.5
20	6.2	1.2	13.3	284	6.6	2.4
21	6.1	1.8	12.6	268	6.3	2.0
22	5.8	2.1	17.2	278	7.0	3.5
23	6.0	1.4	12.5	307	7.2	2.4
24	5.9	1.9	12.8	321	7.6	3.2
25	5.7	1.8	15.1	322	8.4	4.1
26	5.9	1.9	15.6	276	9.1	3.1

Table B.4 Grid soil sample data for Manhattan 2011.

Sample ID	pH	OM	P	K	NO_3 (15cm)	NO_3 (45cm)
		--%--	-----------------------	ppm	--------------------	
1	7.0	2.7	117.0	570	5.1	7.3
2	6.6	2.9	35.3	496	6.2	7.5
3	5.8	2.6	11.6	494	7.2	6.9
4	5.5	2.4	6.6	339	9.0	5.7
5	5.4	2.5	8.7	367	9.2	7.9
6	5.2	2.2	6.4	381	8.0	6.2
7	5.4	2.0	6.0	367	7.5	7.4
8	5.4	1.9	6.6	367	9.1	6.4
9	6.0	1.8	5.3	362	6.8	5.9
10	6.1	1.8	5.9	371	5.5	5.1
11	6.1	2.1	7.5	359	5.2	5.4
12	5.9	2.2	9.5	391	6.2	6.1
13	5.9	2.5	7.2	357	7.9	5.3
14	5.4	2.4	6.4	345	7.7	7.4
15	5.2	2.6	7.6	357	8.2	7.2
16	5.3	2.6	9.1	366	5.2	5.6
17	5.3	2.6	7.3	350	6.0	7.1
18	5.3	2.6	8.0	337	6.0	6.8
19	5.5	2.8	14.9	393	6.0	7.3
20	5.7	2.8	8.2	366	5.1	8.6
21	6.1	1.7	7.3	378	5.0	3.8
22	5.7	1.9	9.0	520	6.5	5.5
23	5.4	2.3	10.9	343	6.0	5.6
24	5.5	2.0	14.3	352	6.4	7.5
25	6.1	2.4	12.1	503	5.5	7.7

Appendix C - Field Images

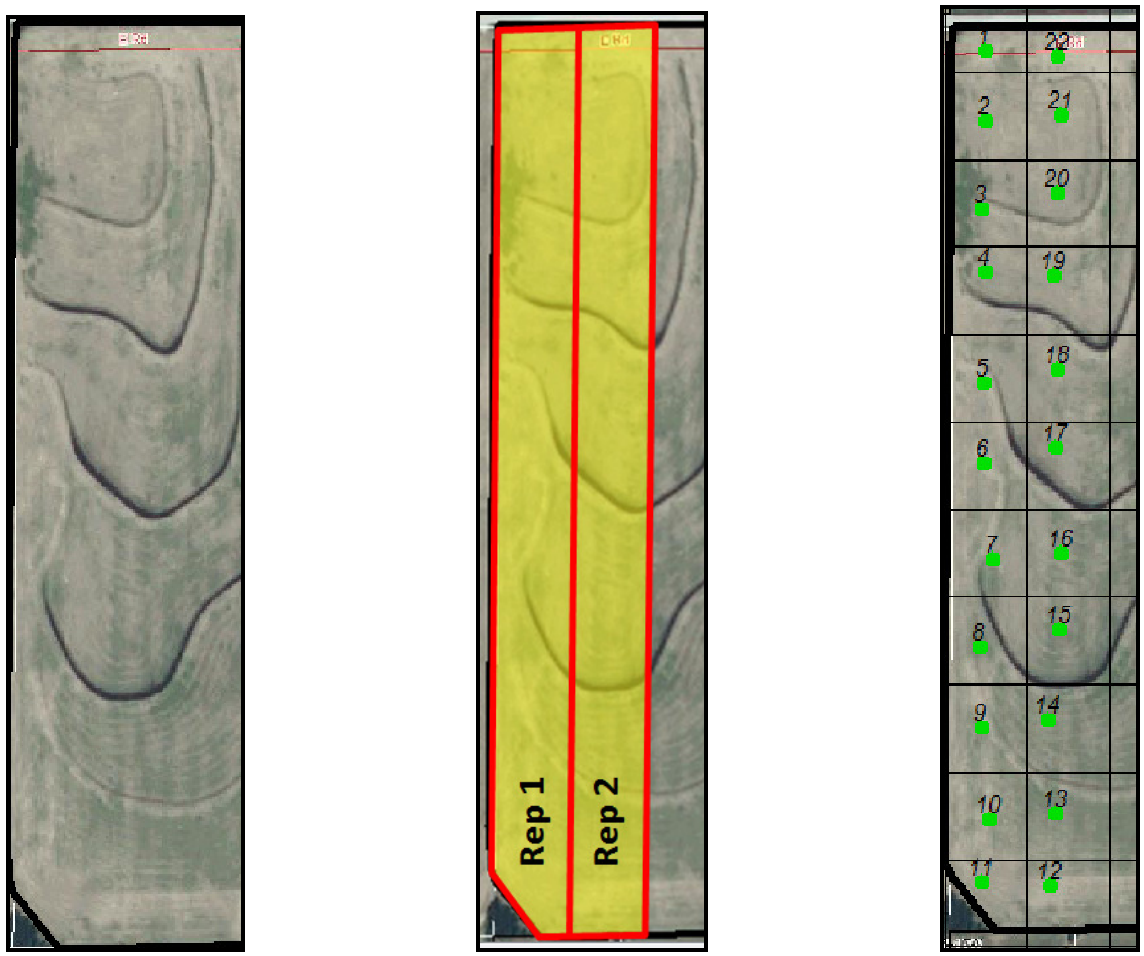


Figure C.1 Aerial field images show terraces (Left), plot layout (Center), and grid-layout with soil sample points (Right) in the Stockton 2010 field. The top of the images point north. Latitude: 39.50656, Longitude: -99.23899.

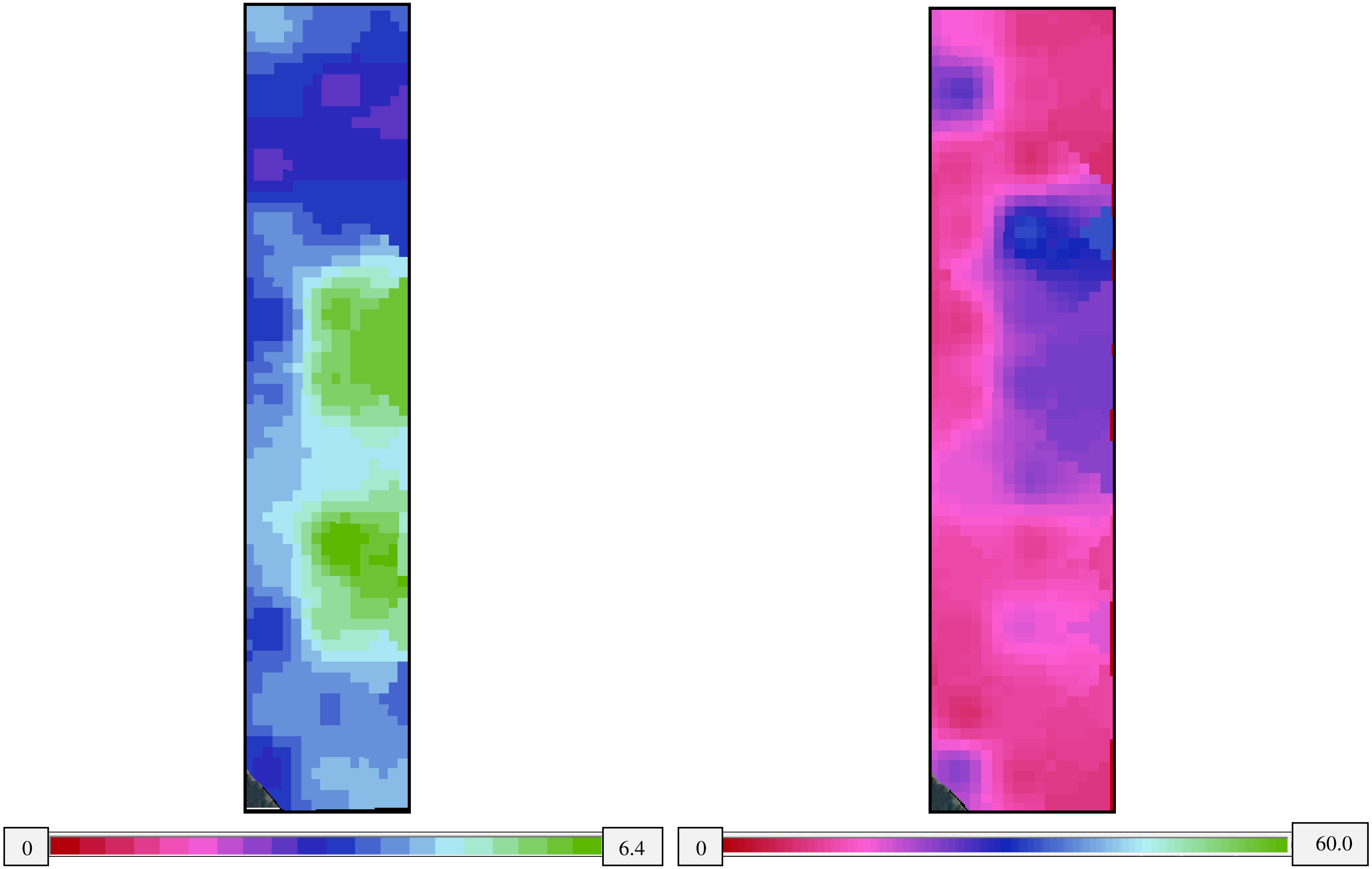


Figure C.2 Profile NO_3 (mg kg^{-1}) (Left) and the Phosphorus (mg kg^{-1}) (Right) layers of the Stockton 2010 field.

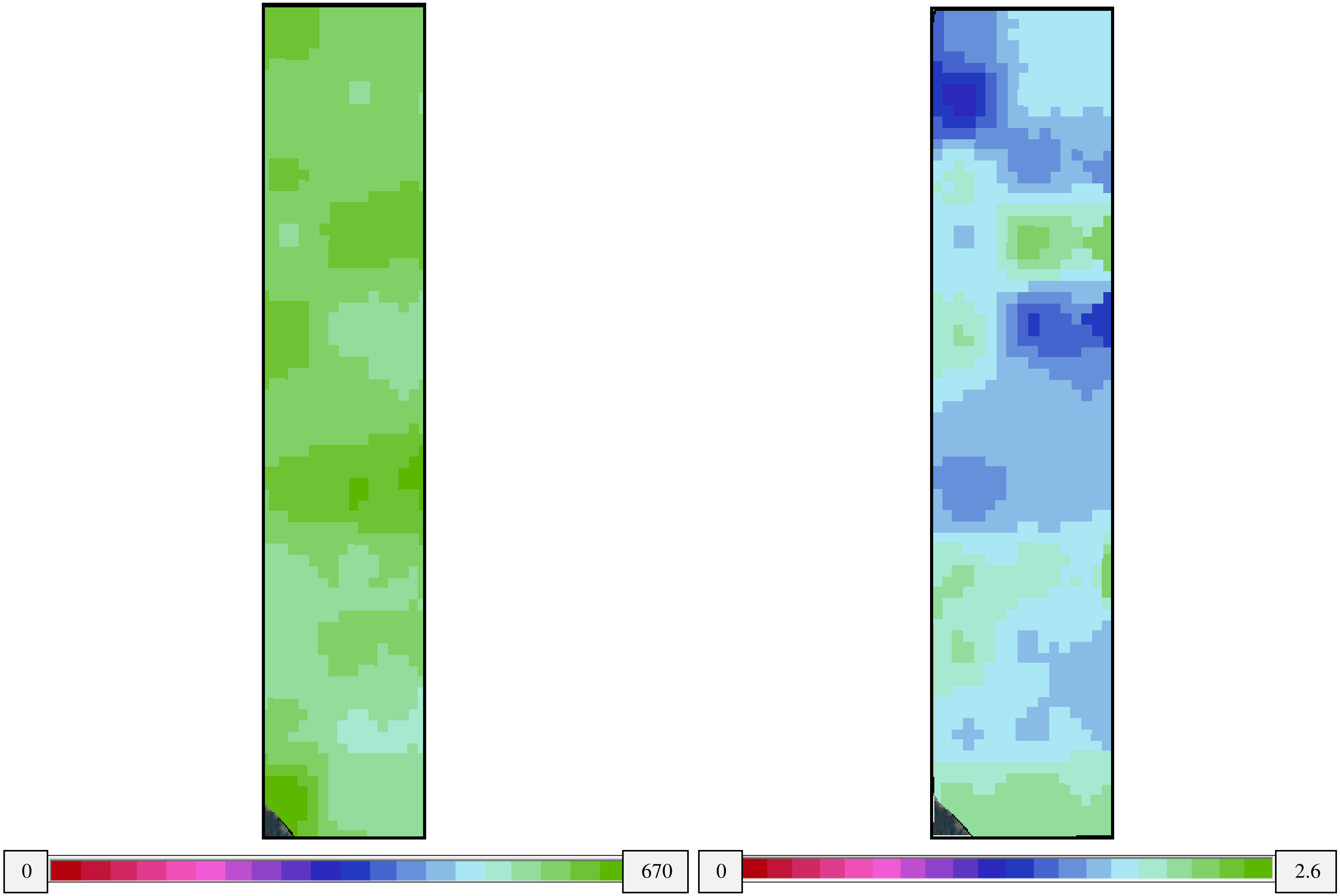


Figure C.3 Potassium content (mg kg^{-1}) (Left) and the OM content (g kg^{-1}) (Right) layers of the Stockton 2010 field.

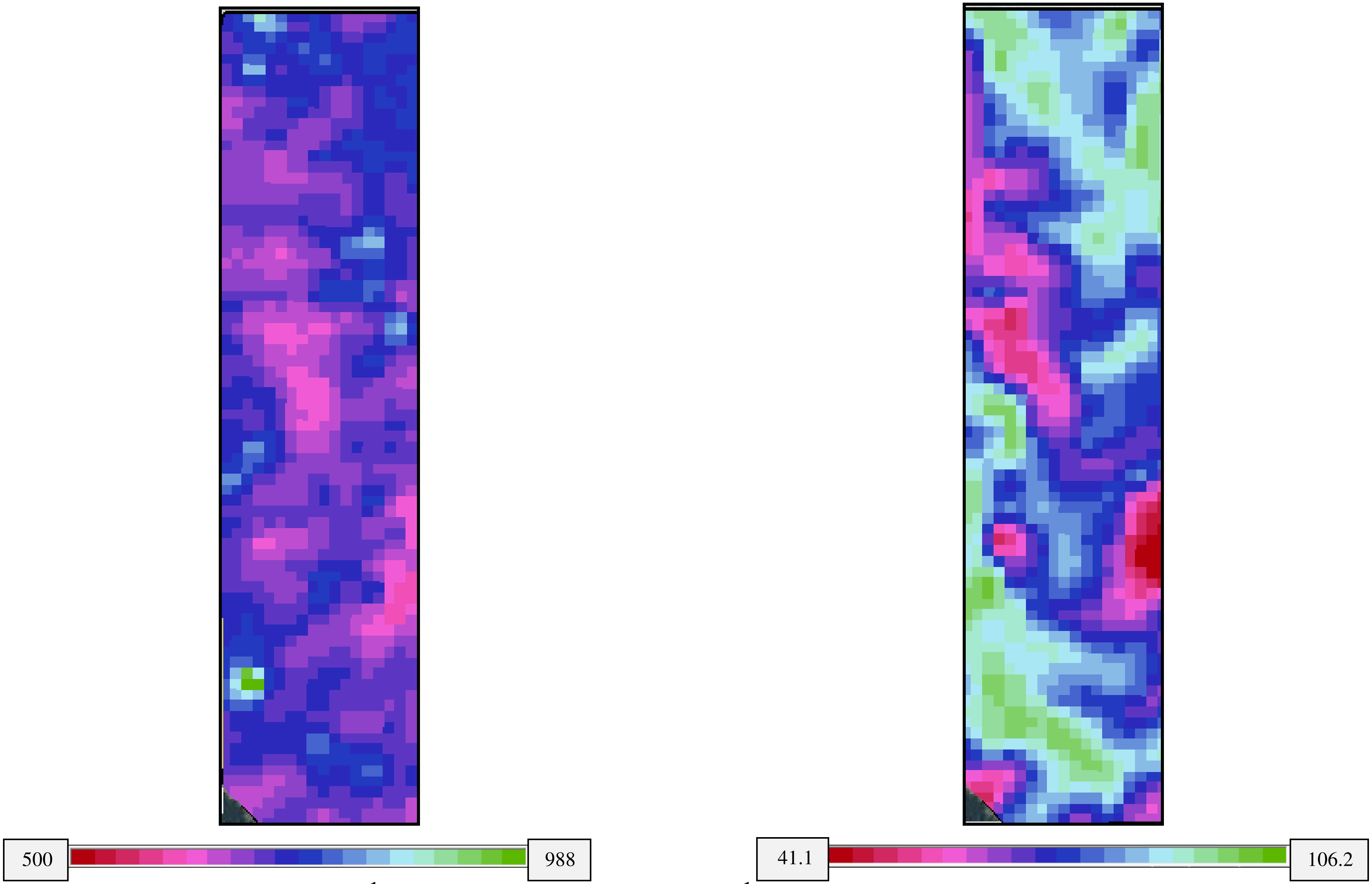
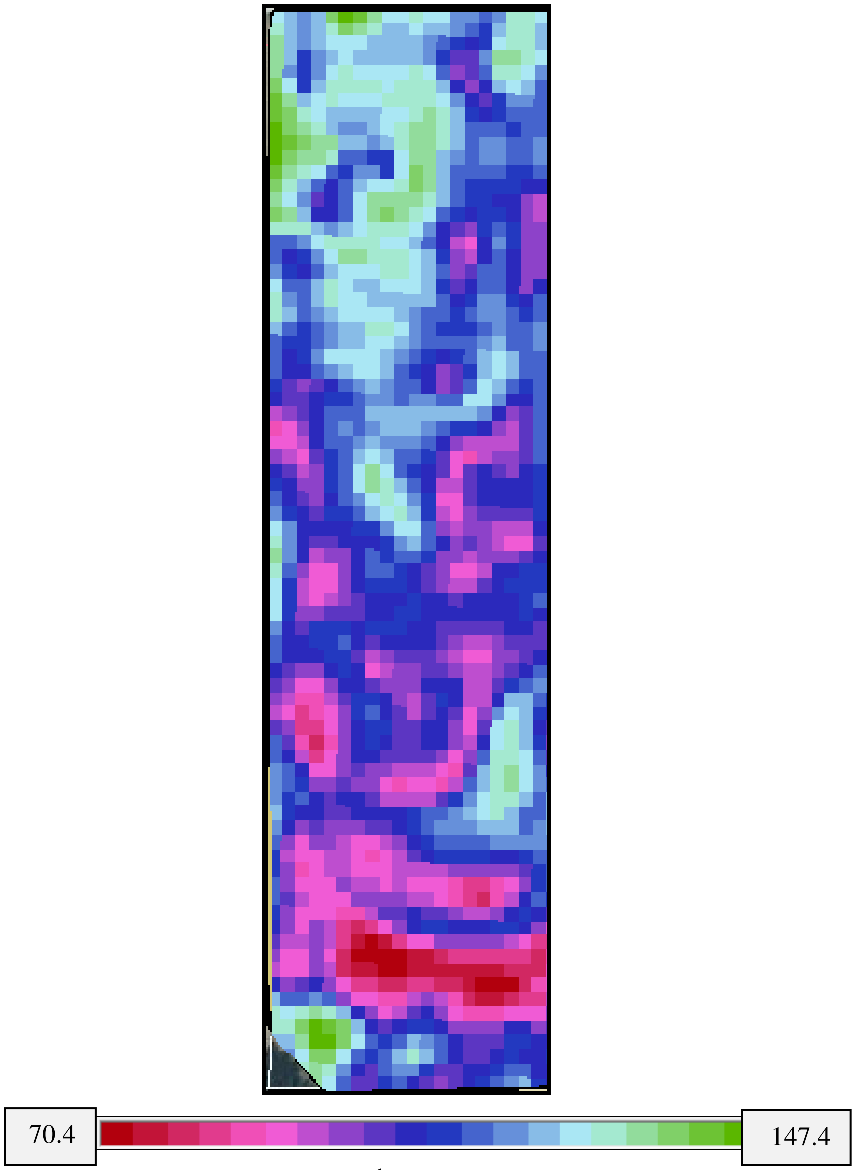


Figure C.4 Deep soil EC ($mS\ m^{-1}$) (Left) and shallow soil EC ($mS\ m^{-1}$) (Right) in the Stockton 2010 field.



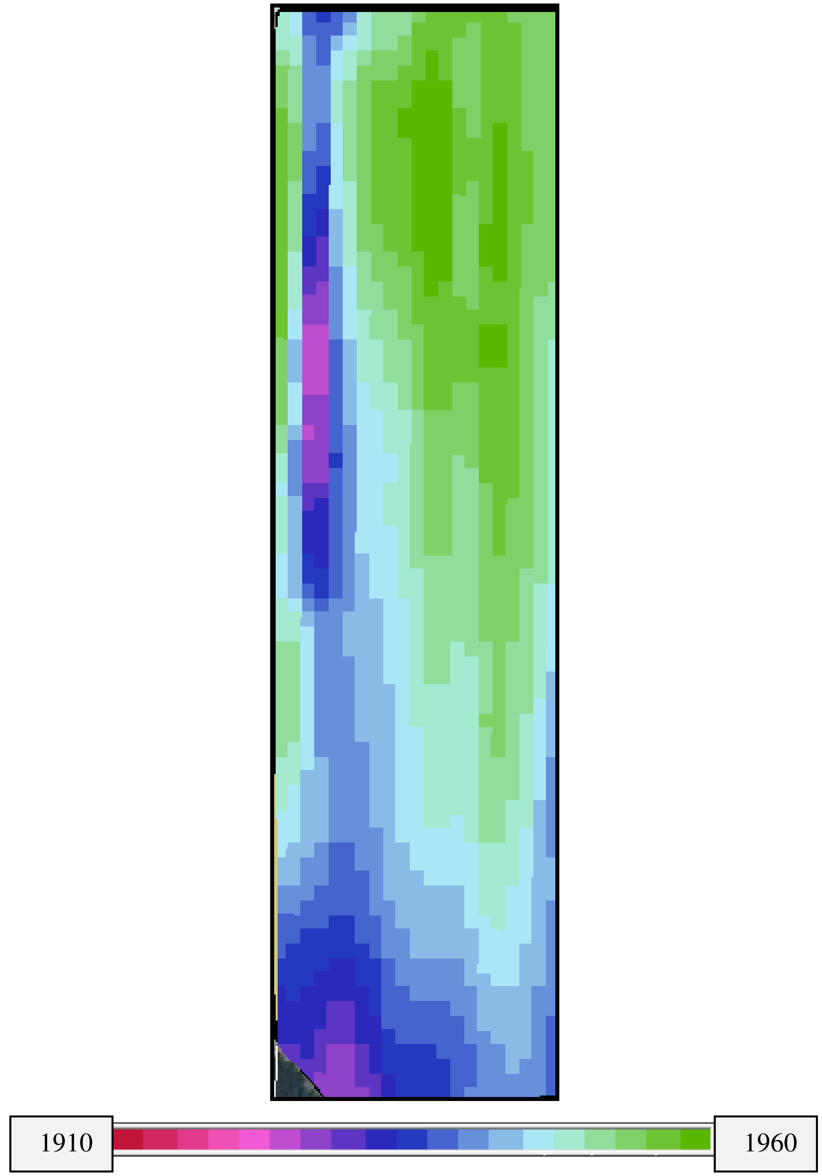


Figure C.5 Yield goal (bu ac^{-1}) (Left) and elevation (ft) (Right) of the Stockton 2010 field.

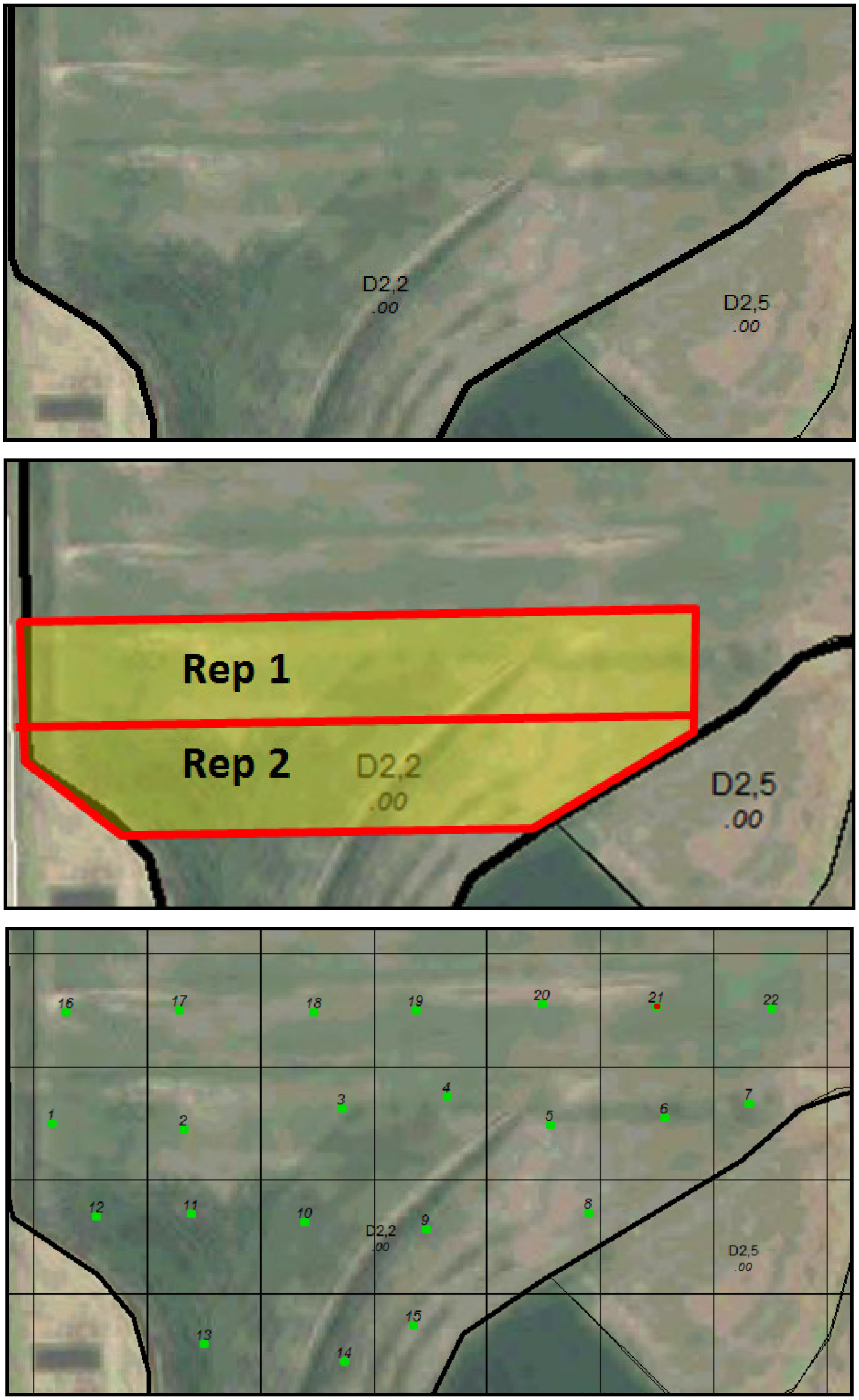


Figure C.6 Aerial image (Top), plot layout (Center), and grid-layout with soil sample points (Bottom) in the Manhattan 2010 field. The top of the images point north. Latitude: 39.21656, Longitude: -96.59678.

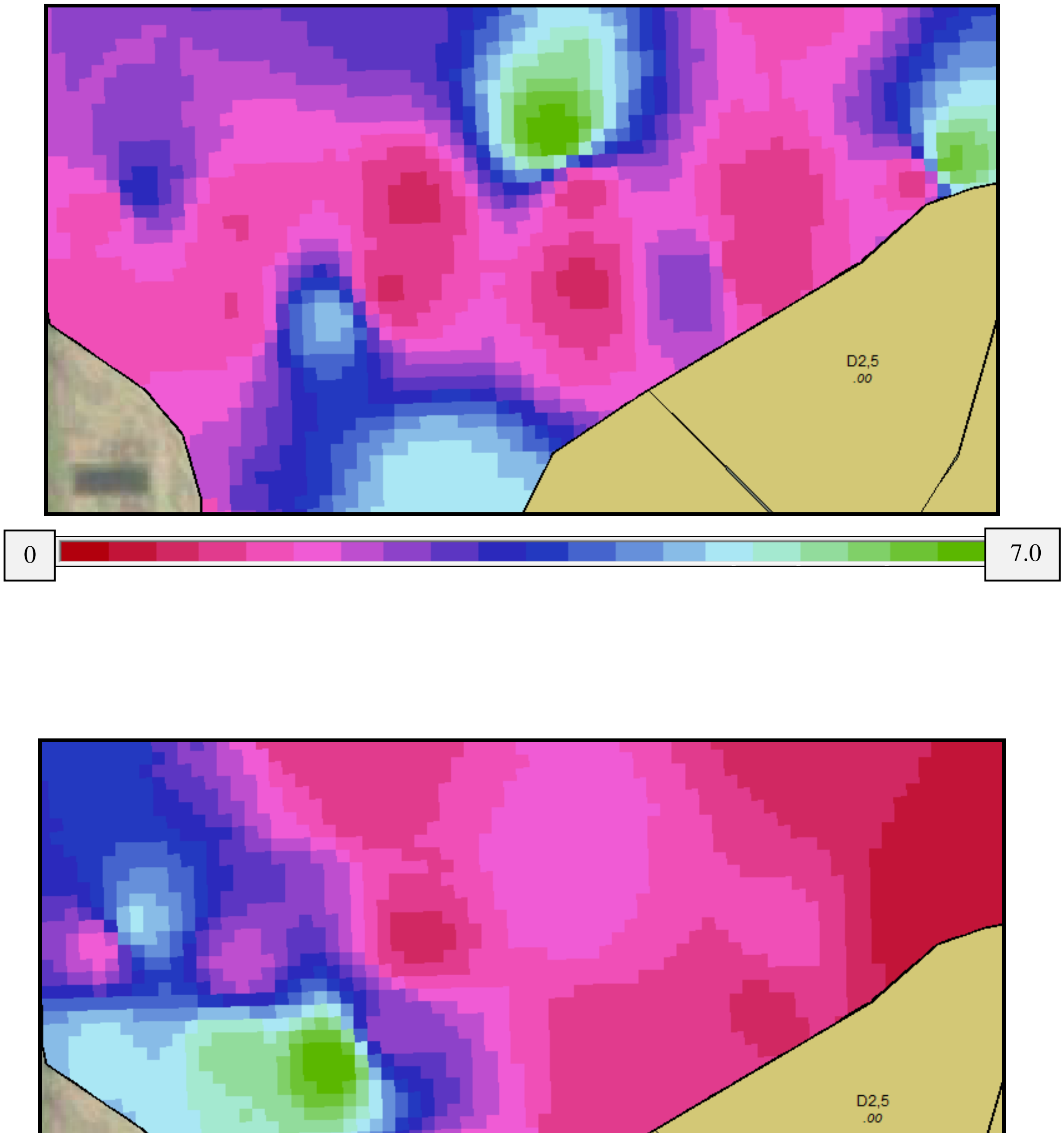


Figure C.7 Profile NO_3 (mg kg^{-1}) (Top) and Phosphorus (mg kg^{-1}) (Bottom) in the Manhattan 2010 field.

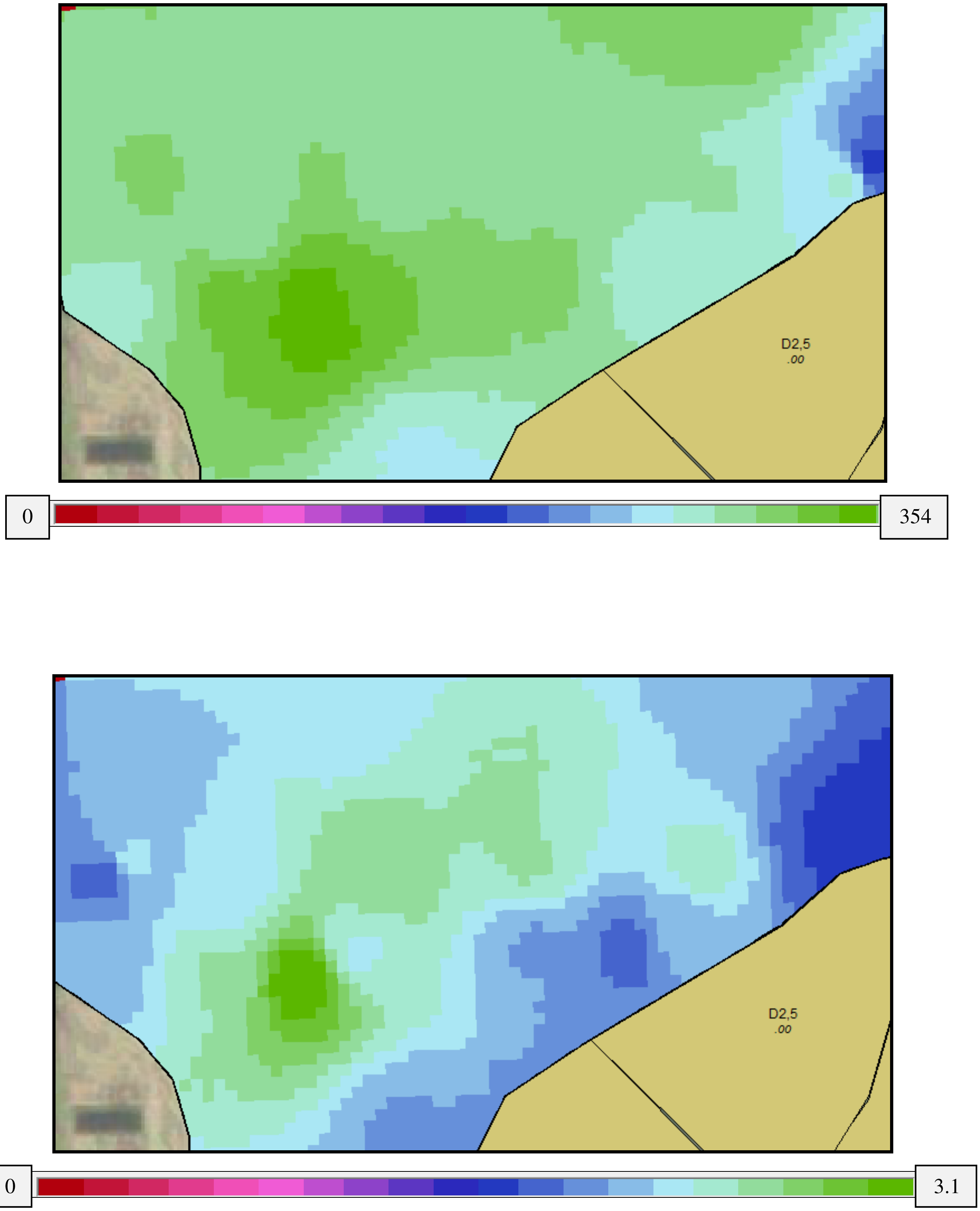


Figure C.8 Potassium content (mg kg^{-1}) (Top) and the OM content (g kg^{-1}) (Bottom) in the Manhattan 2010 field.

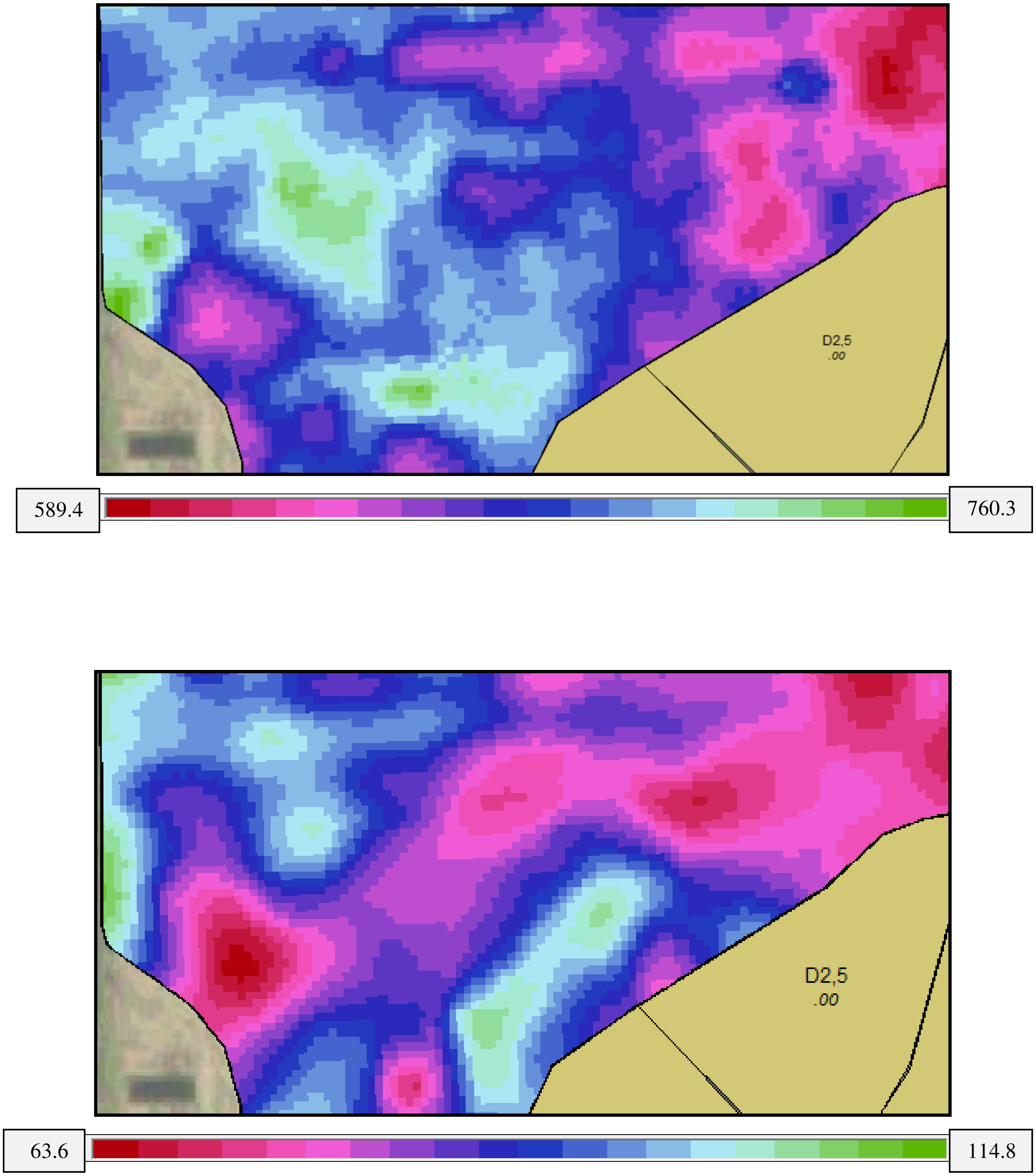
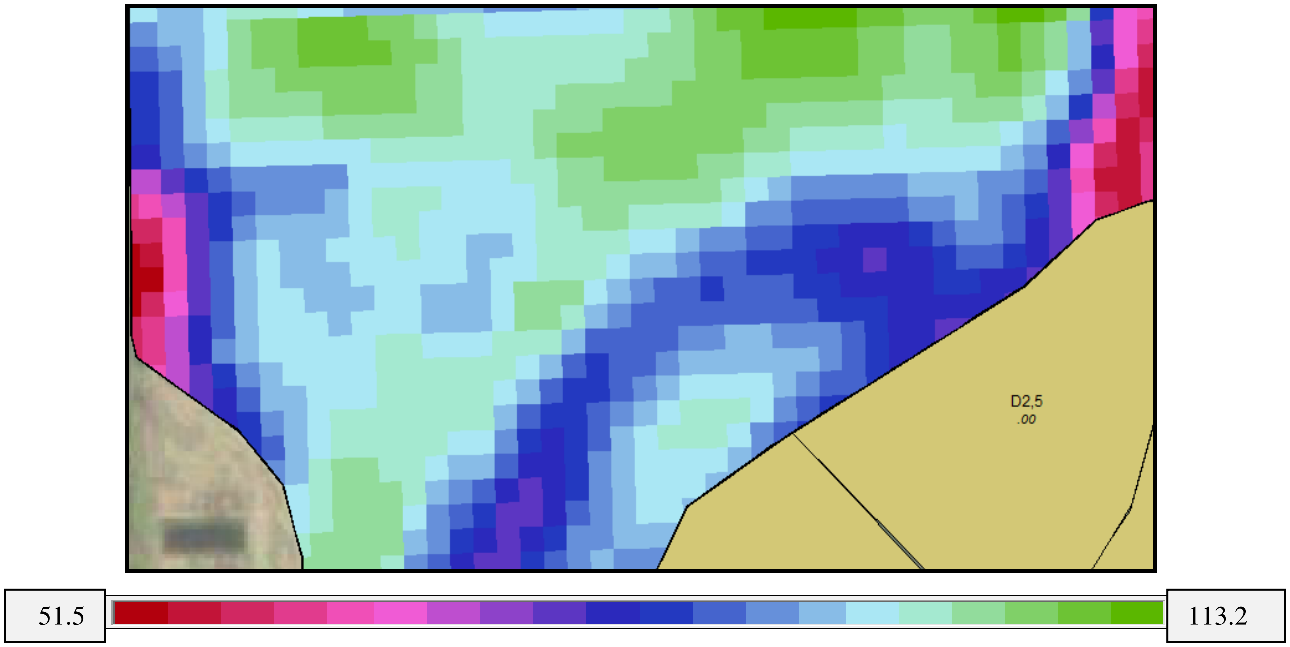


Figure C.9 Deep soil EC (mS m^{-1}) (Top) and shallow soil EC (mS m^{-1}) (Bottom) in the Manhattan 2010 field.



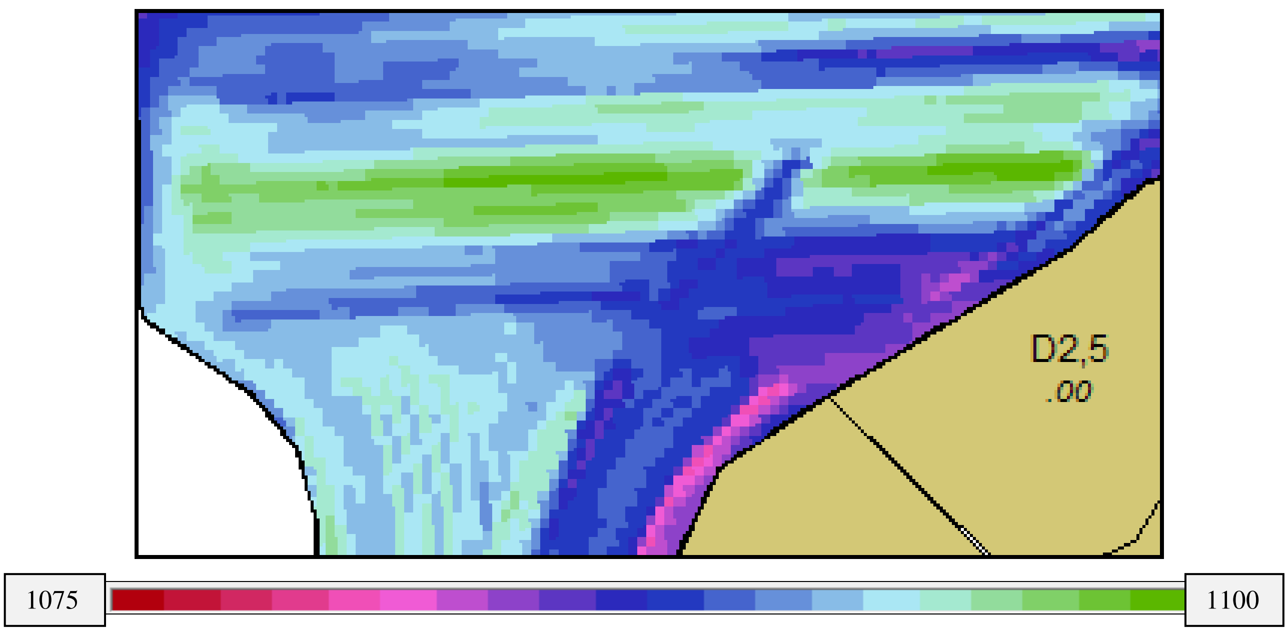


Figure C.10 Yield goal (bu ac^{-1}) (Top) and Elevation (ft) (Bottom) of the Manhattan 2010 field.

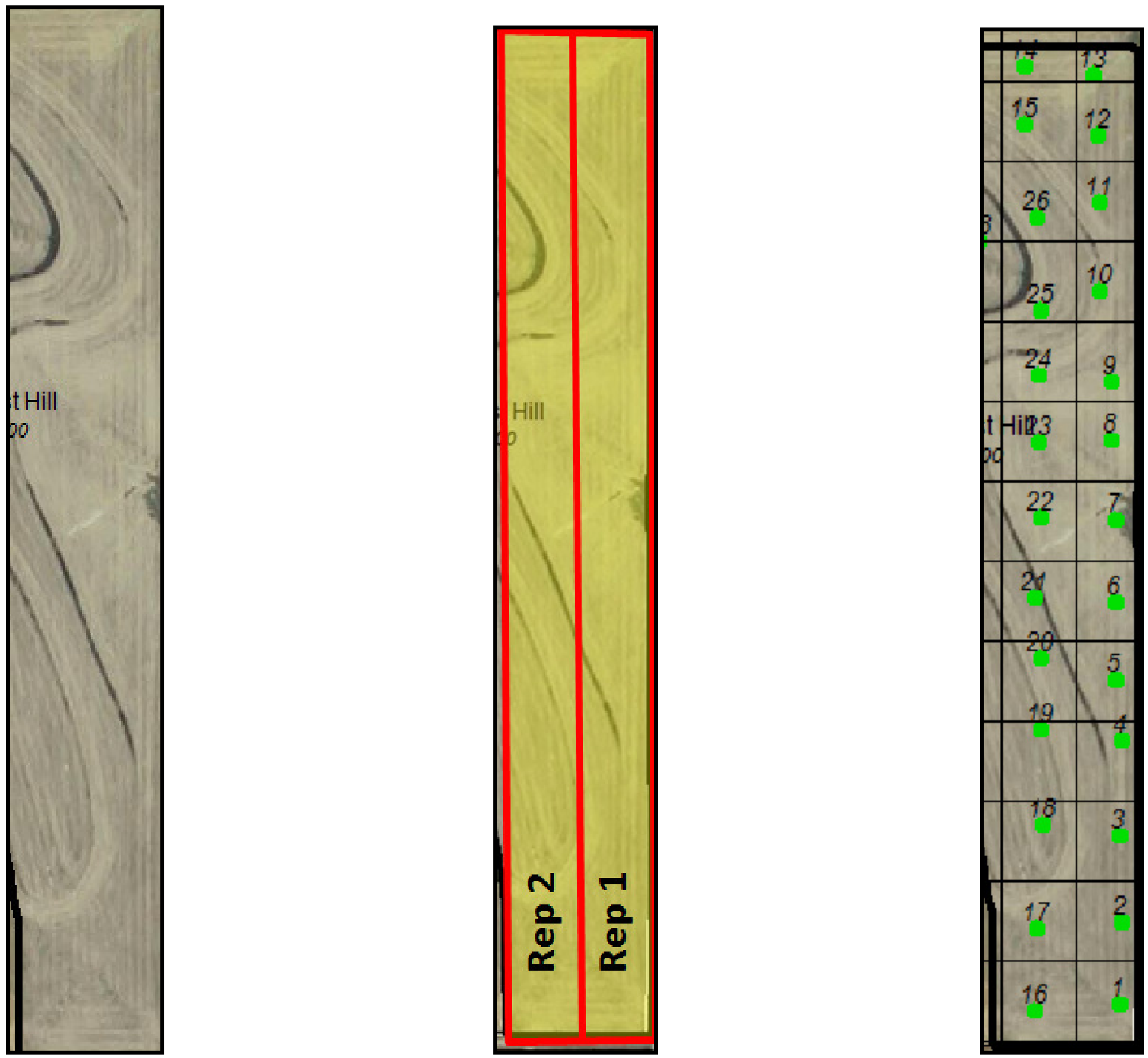


Figure C.11 Aerial image (Left), plot layout (Center), and grid-layout with soil sample points (Right) in the Stockton 2011 field. The top of the images point north. Latitude: 39.51245, Longitude: -99.19461.

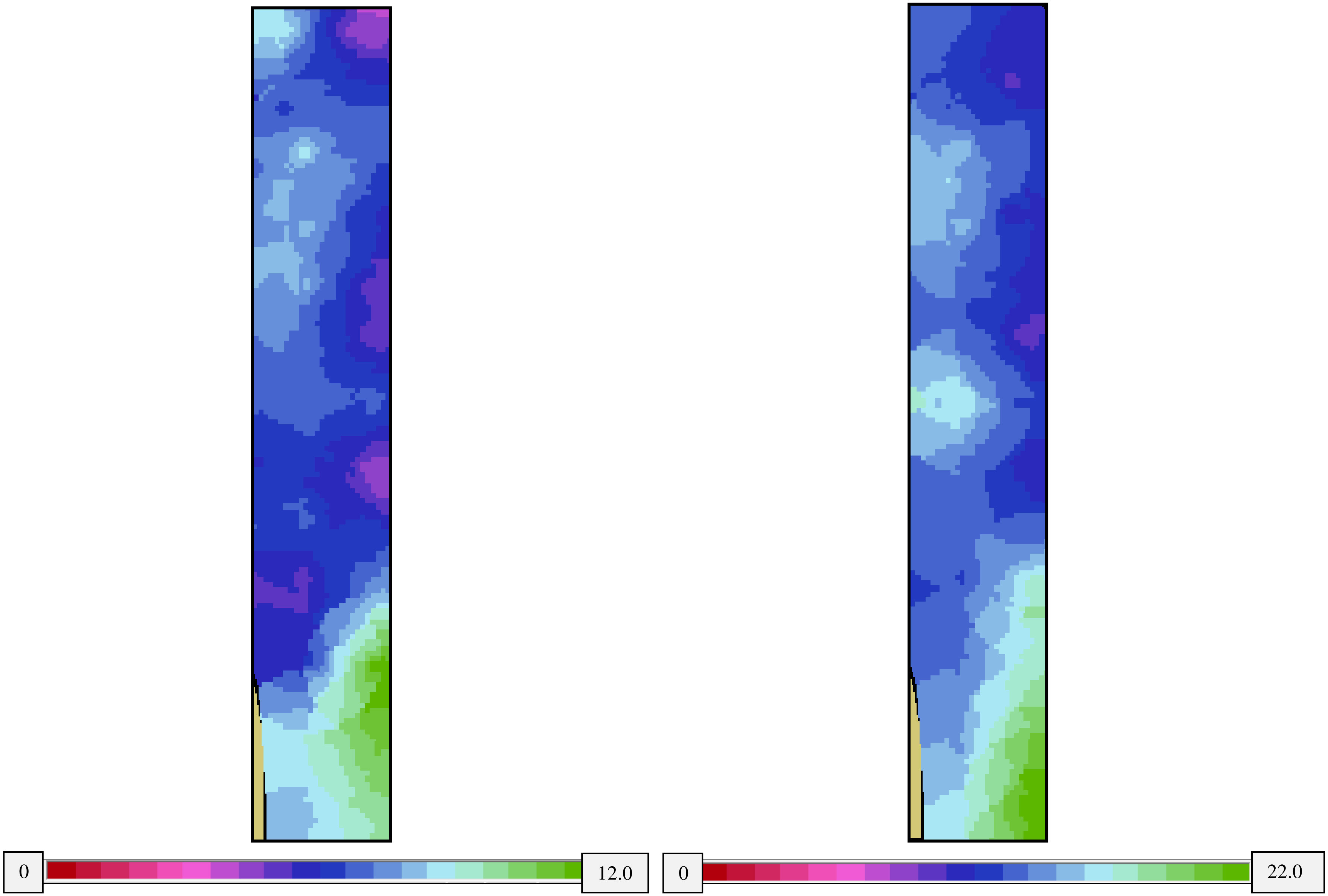


Figure C.12 Profile NO_3 (mg kg^{-1}) (Left) and phosphorus content (mg kg^{-1}) (Right) in the Stockton 2011 field.

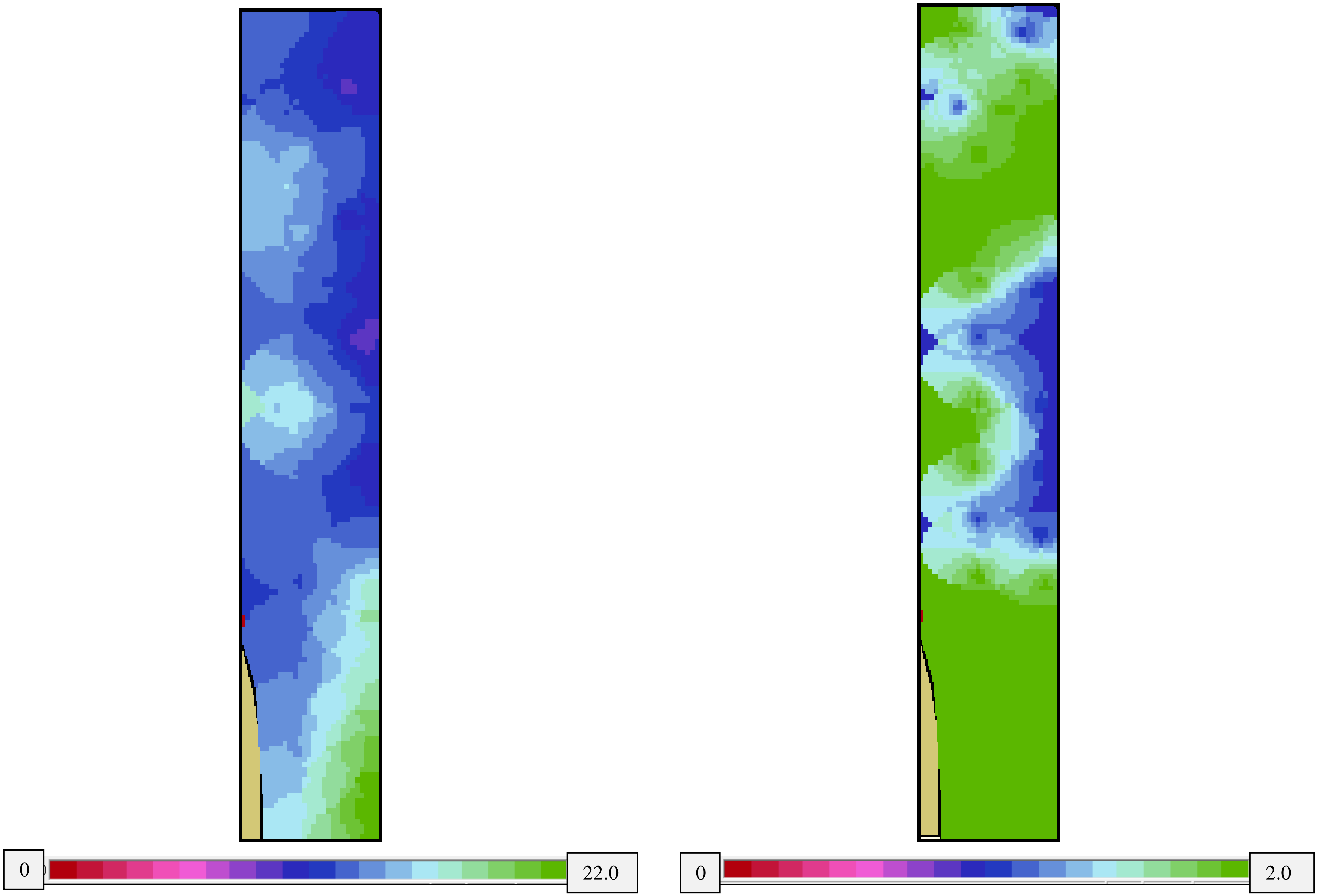


Figure C.13 Potassium content (mg kg^{-1}) (Left) and the OM content (g kg^{-1}) (Right) in the Stockton 2011 field.

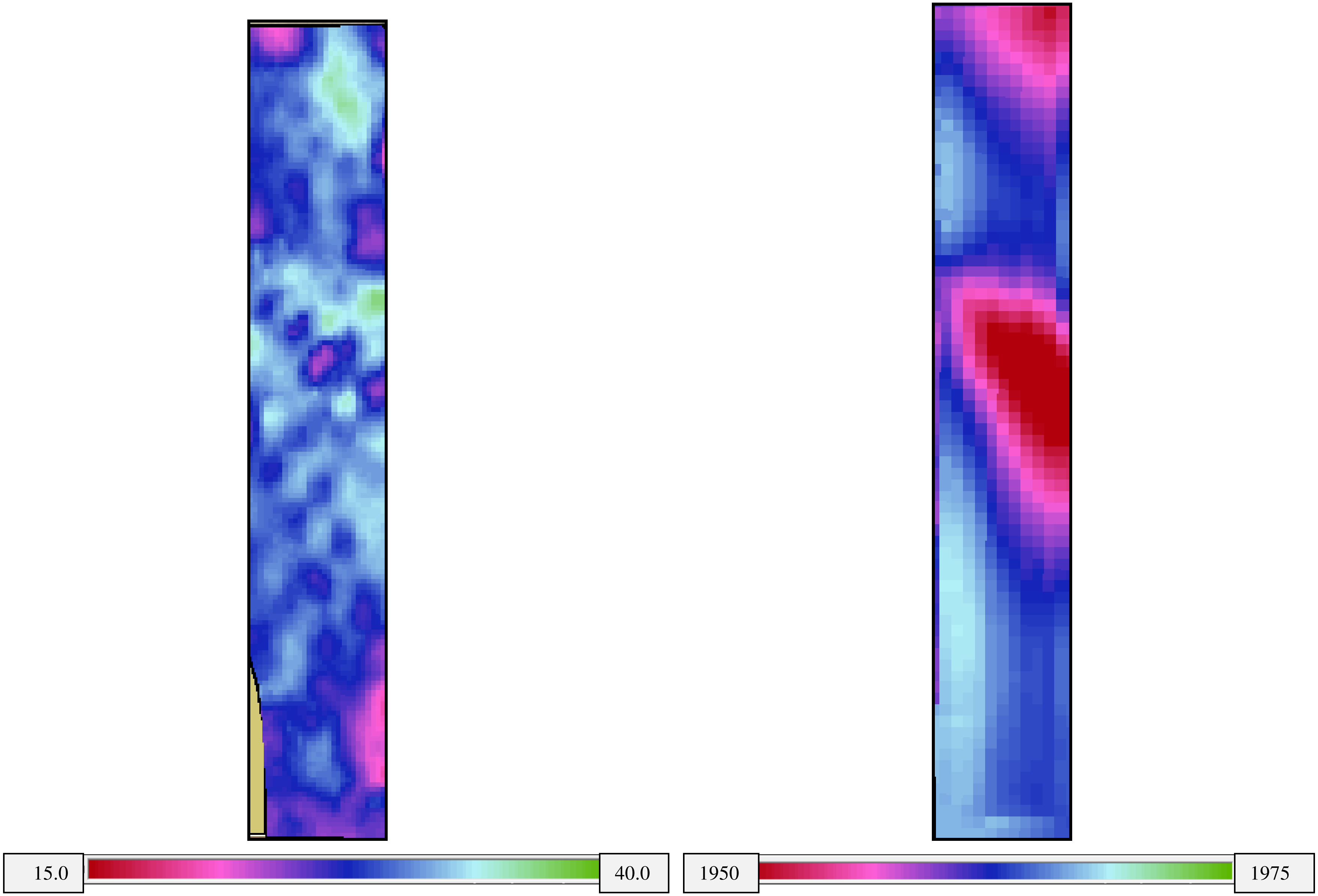


Figure C.14 Shallow soil EC (mS m^{-1}) (Left) and Elevation (ft) (Right) in the Stockton 2011 field.

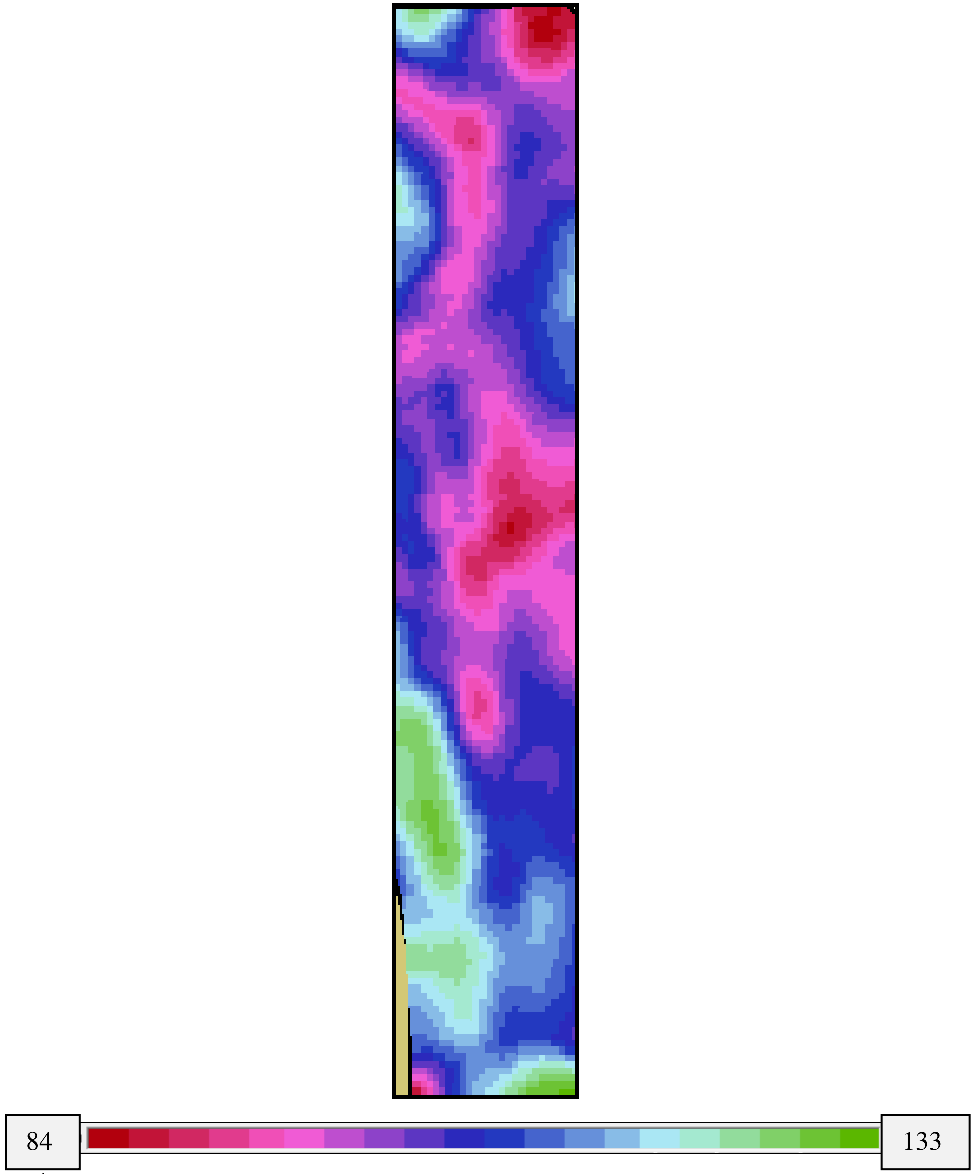


Figure C.15 Yield goal (bu ac^{-1}) of the Stockton 2011 field.

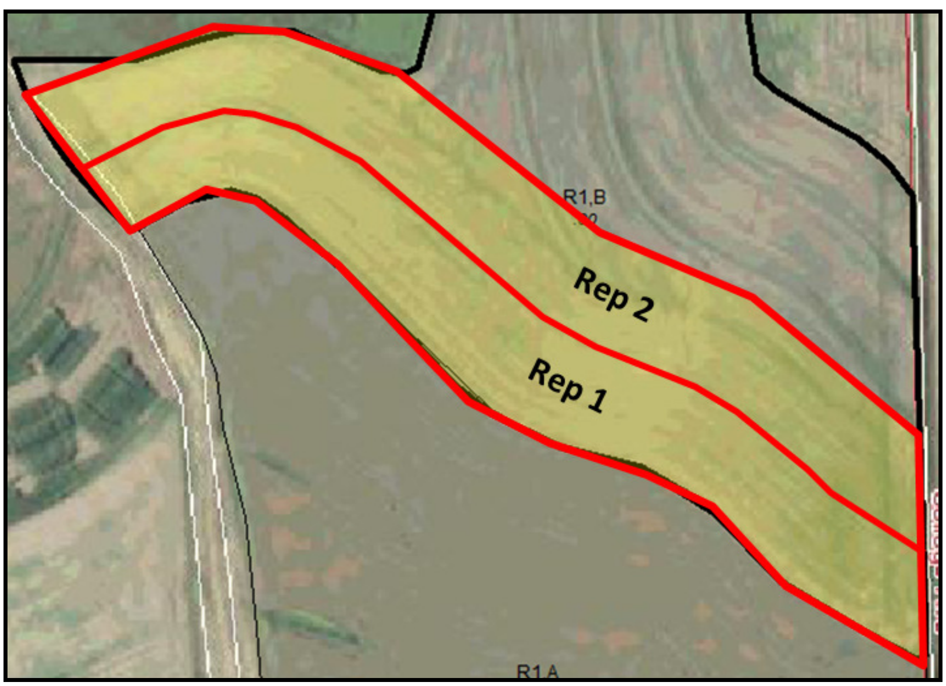


Figure C.16 Aerial image (Top) and plot layout (Bottom) of the Manhattan 2011 field. The top of the images point north. Latitude: 39.21656, Longitude: -96.59952.

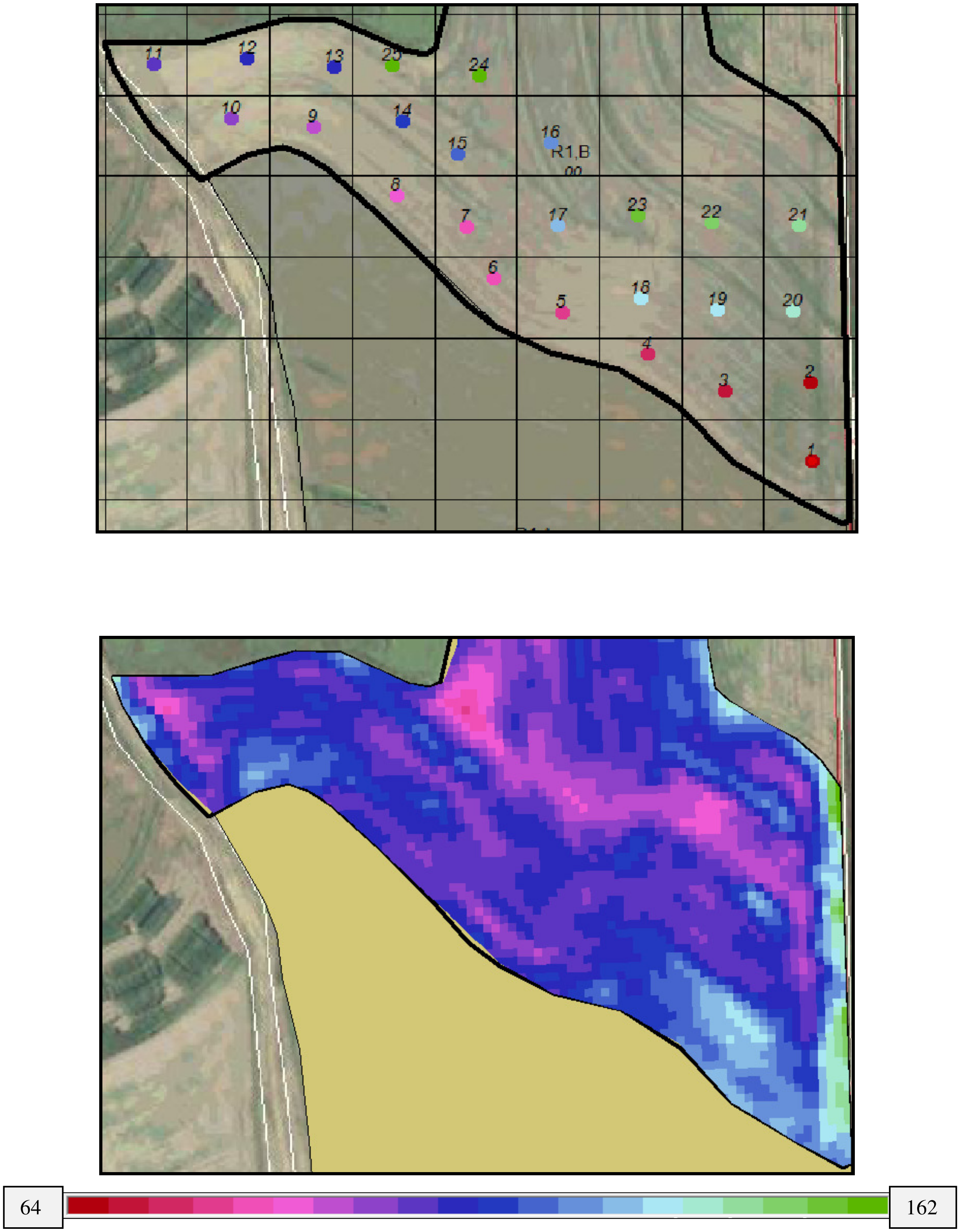


Figure C.17 Grid-layout with soil sample points (Top) and yield goal (bu ac^{-1}) (Bottom) of the Manhattan 2011 field.

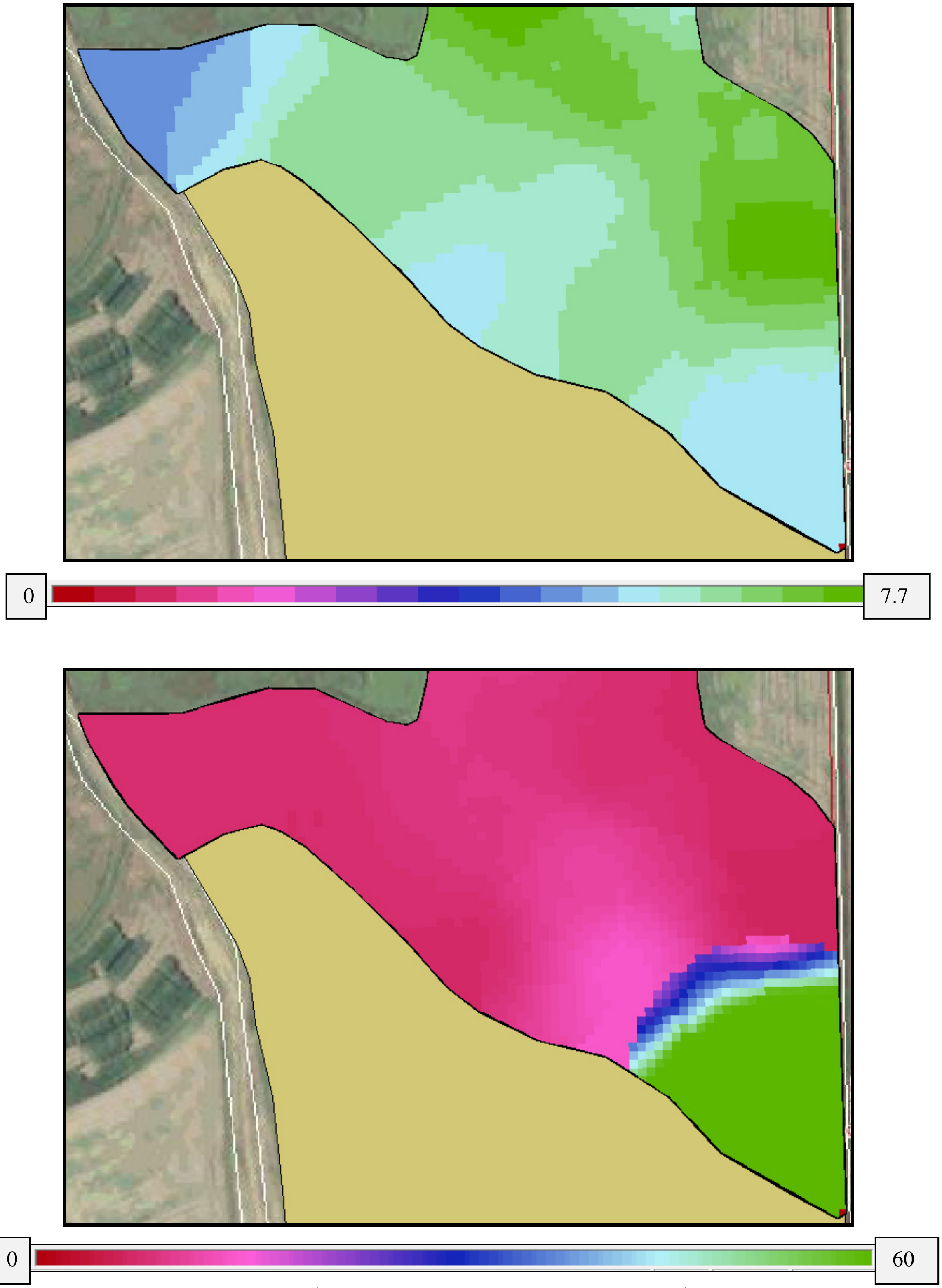


Figure C.18 Profile NO_3 (mg kg^{-1}) (Top) and Phosphorus (mg kg^{-1}) (Bottom) in the Manhattan 2011 field.

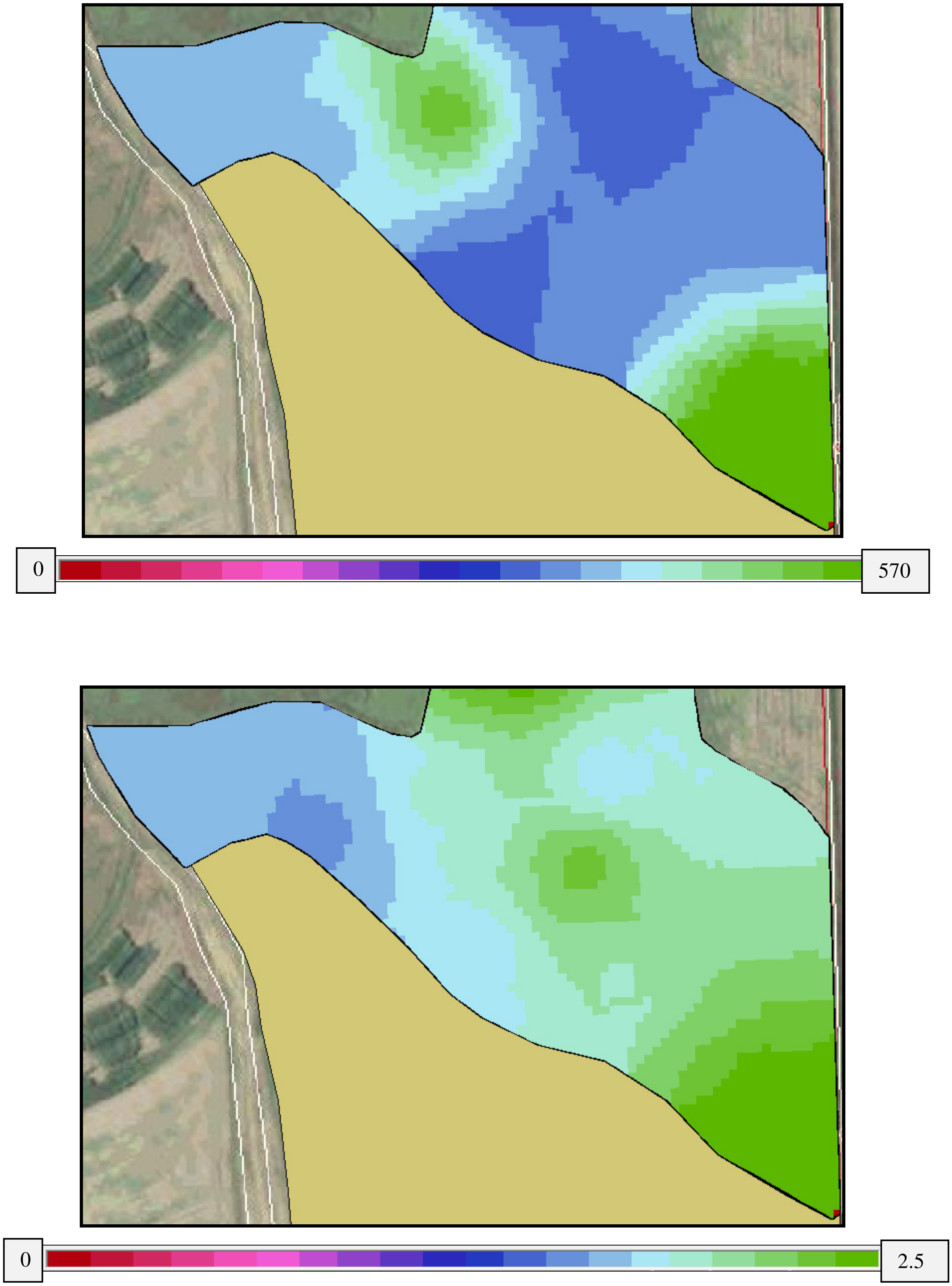
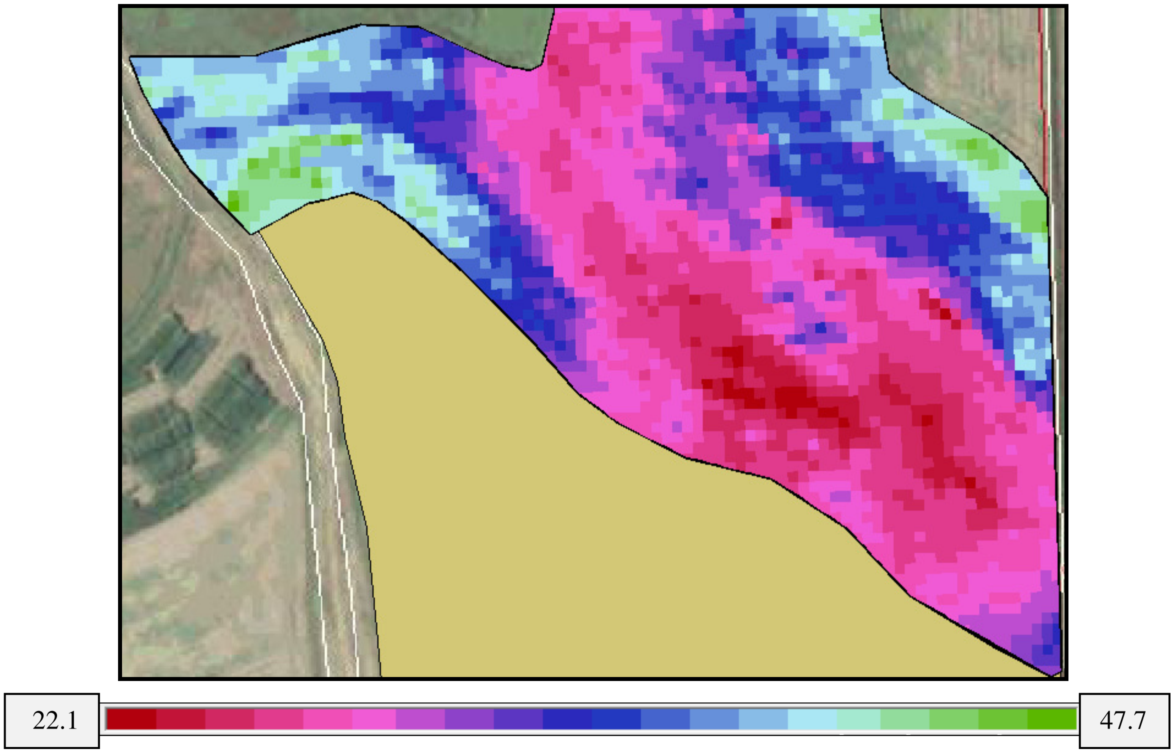


Figure C.19 Potassium content (mg kg^{-1}) (Top) and the OM content (g kg^{-1}) (Bottom) in the Manhattan 2011 field.



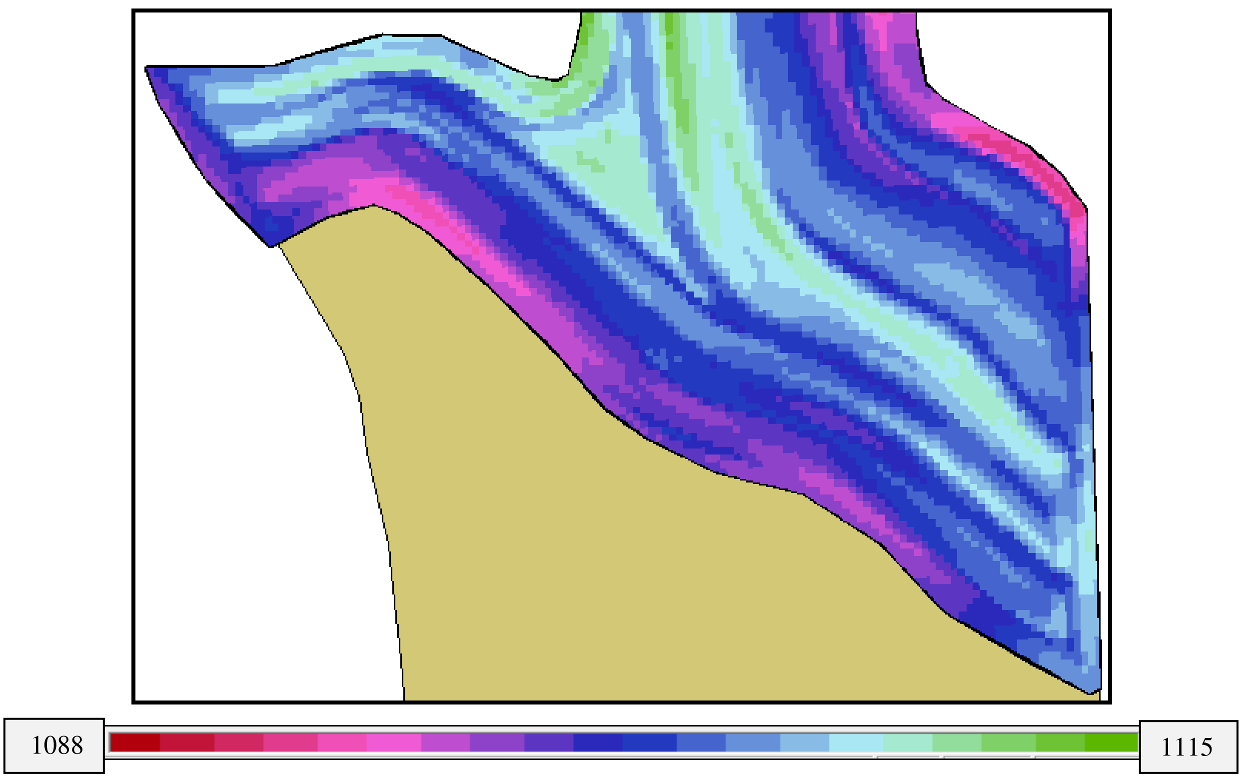


Figure C.20 Shallow soil EC (mS m^{-1}) (Top) and Elevation (Bottom) (ft) in the Manhattan 2010 field.