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SPATIAL AND TEMPORAL DYNAMICS OF NITROGEN-WATER INTERACTIONS IN CORN IN MICHIGAN

by

Mohamed E. M. Elwadie

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ABSTRACT

Spatial and Temporal Dynamics of Nitrogen-Water Interactions in Corn in Michigan

by
Mohamed E. M. Elwadie

This study was initiated to evaluate sensor-based nitrogen and water application for corn (*Zea mays L.*) in Michigan. Our hypothesis was that sensor-based N and water applications are more efficient for corn production than the current N fertilizer and irrigation practices based on mass balance recommendations. Chapter I evaluates the agronomic effects of N-water interactions in corn. The objectives were 1) to compare conventional mass balance N treatments to sensor-based N management strategies based on stress in plants, 2) compare dryland farming to irrigated corn, and 3) develop a crop coefficient for corn from remotely sensed data. Irrigation increased yield in 1999 but not without supplemental N application. Nitrogen effectively increased corn grain yield, but there was no significant difference between N applied at planting, or based on a pre-sidedress nitrate test (PSNT), or sensor-based application. A nitrogen x water interaction was present in the 1999 season, but was absent in the wet 2000 growing season. PSNT values were obtained at V6 and at silking (R1) growth stages. Earleaf N, stalk N, grain N, and postharvest residual soil profile N were determined. A reflectance-based crop coefficient (Kcr) from green normalized vegetation index (GNDVI) is introduced for estimating crop evapotranspiration. Chapter II evaluates the temporal dynamics and biophysical variables estimation of corn canopy in Michigan. High sensitivity to N centered around 560 and 810 nm spectral bands. These two wavelengths provided the

provided the best separation between different N treatments. Corn grain yield was correlated to different spectral vegetation indices (SVI) and chlorophyll meter readings. The highest correlation between SVI and corn grain yield was achieved at R2, R3, R4, and R5 growth stages. Green normalized vegetation index (GNDVI) performed better than all other SVI when correlated to chlorophyll meter readings ($R^2 = 0.98$). The results suggest that GNDVI could be used to substitute for chlorophyll meter readings in N scheduling. While NDVI and GNDVI reasonably estimated corn leaf area index (LAI), SAVI overestimated LAI. All SVI performed very well in estimating fractional cover (Fc) over the growing season. Chapter III assesses the spatial variability of selected soil properties and landscape attributes and their relationship to corn grain yield. Soil properties such as length of the horizon, bulk density, soil water content at - 10, - 33, and -1500 kPa, soil texture and landscape data such as elevation and slope magnitude were collected from a transect 224 meters long at the study site. Variability for all properties tested exhibited a strong spatial structure and 50 to 100 percent of the sample variance was spatially dependent and autocorrelated over a range of 5 to 224 m. Stepwise multiple regression analysis was applied to corn grain yields to identify the most important soil properties in Ap and Bt1 horizons affecting yield variation. Ap depth, Ap silt, Bt1 bulk density and Bt1 silt were the only significant factors in explaining yield variation. Corn grain yield and soil properties in Ap and Bt1 horizon exhibited a very strong spatial cross correlation. Fifty to 100 percent of the sample covariance was spatially dependent over a range of 26 to 212 m. Cumulative probability and Spearman rank correlation coefficient, the mean relative difference, and the standard deviation were used to characterize the temporal stability of spatial soil water content and water storage over the growing season.

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LIST OF ABBREVIATIONS

Etc	Potential evapotranspiration of the crop
Etp	Potential evapotranspiration
Fc	Fractional cover
GNDVI	Green normalized difference vegetation index
GRVI	Green ratio vegetation index
IRt	Infrared thermometer
Kcr	Reflectance based crop coefficient
KBS	W. K. Kellogg Biological Station
Kcb (Wright)	Wright basal crop coefficient
LAI	Leaf area index
NDVI	Normalized difference vegetation index
RVI	Ratio vegetation index
SAVI	Soil adjusted vegetation index
SVI	Spectral vegetation indices
TDR	Time Domain Reflectometry
δij	The relative difference in soil water content
$\gamma(h)$	Semivariance for interval distance class h

INTRODUCTION

This study was initiated to evaluate sensor-based nitrogen and water application for corn (*Zea mays L.*) in Michigan. The study has three main objectives relative to the understanding of temporal and spatial variability of processes and properties that regulate crop performance and crop yield within a field. First, this study tests the feasibility of stress-based N and water management for corn production in terms of crop yield, N leaching potential, and irrigation scheduling. Our hypothesis was that sensor-based N and water applications are more efficient for corn production than current fertilizer and irrigation practices based on mass balance recommendations. Therefore these sensor-based strategies must be site-specific, maximize corn yield and N and water use efficiency, and minimize N losses to the environment. Second, the study identifies wavelengths that are most sensitive to N deficiency and facilitate corn yield estimation. In addition, the investigation identifies the best growth stage for corn yield estimation and estimates biophysical variables of corn such as the leaf area index (LAI) and fractional cover (Fc) from multi-spectral data acquired over a corn canopy during the growing season. Finally, this study assesses the spatial variability of selected soil physical properties and landscape attributes and their relationship to corn grain yield.

Chapter I Overview

Current N fertilizer recommendations are based on yield response data averaged over a large landscape area resulting in a dilution of the accuracy of the response relationships (Buchholz, 1983). Nitrogen response and water distribution are field and season dependent and can vary greatly within the same field in the same season. Spatial variability within the same field makes it difficult to develop variable rate N and water recommendations for corn production that result in optimal N and water application and maximum economic returns.

Nitrogen management strategies for corn can be approached in two basic ways: mass balance strategies, whereby prescriptive applications of N inputs are made prior to or early in the N uptake phase of plant growth to avoid N deficiencies or as an interactive strategy, whereby N inputs are applied to meet N requirements as determined by the nutrient status of soils or plants during the rapid N uptake phase of corn.

Mass balance has been the most commonly used N management strategy. In this system fertilizer recommendations are usually based on a combination of yield goal, N requirement of the crop, residual soil N, and N mineralized from soil or plant residues and sometimes using soil organic matter as a proxy for N mineralization (Pierce and Novak, 1999). Interactive strategies include foliar fertilization, delayed N applications based on N content in plants, and chemigation strategies that assess crop needs based on tissue sampling, sensing plant reflectance, or crop simulation.

Schepers et al. (1996) suggested that strategies which sense the occurrence of N deficiencies in plants during the uptake phase may be better adapted to precision N management than strategies that use mass balance approaches that are, to a large extent, soil sampling based. The interactive N strategies are based on the fact that N deficiency in corn reduces chlorophyll content of leaves thereby increasing the amount of light transmitted through a leaf. The idea is to 1) monitor plant N concentration by monitoring plant or canopy reflectance of light or some measure of plant N content such as chlorophyll content, 2) estimate N fertilizer requirement using relationships between reflectance and plant N content, and then 3) fertilize the crop to the optimal N content for maximum economic yield. Often, a portion of a field is fertilized to optimal levels and the well-fertilized corn used as the standard for adjusting the N recommendations for the remainder of a field (Schepers et al., 1996). Bausch et al. (1996) estimated plant N using a previously developed index calculated from measured canopy reflectance

Water is essential to crop productivity since crop yields generally increase linearly with water transpired by a crop (Howell, 1990). Improved water management necessitates accurate estimation of a daily crop evapotranspiration (ETc). Improved water management is essential to optimize water relations for plants because it has a direct impact on the fate and transport of pollutants to surface and ground waters.

There are two areas of great interest in precision irrigation management. The major part of research has been made with variable rate irrigation systems, mainly with sprinkler irrigation provided by center pivot and linear move systems (Camp and Sadler, 1994; Evans et al., 1996; King et al., 1995; King et al., 1996; and McCann and Stark, 1993). The second part of variable rate irrigation research has been focused on developing irrigation scheduling programs based upon remote sensing vegetation indices obtained either from plant canopy reflectance and/or from canopy temperature. The introduction of a basal crop coefficient (Kcb) by Wright (1982) improved irrigation scheduling. The problem with the Wright basal crop coefficient is that it is dependent on time based parameters such as planting date and effective cover and the resistance to water movement from soil and plant surfaces. Neale et al. (1989) developed a reflectance-based crop coefficient (Kcr) from a normalized difference vegetation index (NDVI). The NDVI crop coefficient is independent of planting date and effective fractional cover since NDVI is a measure of the photosynthetic size of the plant canopy. Therefore, Kcr is a true representation of crop growth and development and is affected by nutrient and water stress, and diseases. Bausch et al. (1996) have developed a Kcr from a soil adjusted vegetation index (SAVI) to reduce the effect of soil background on canopy reflectance. Green normalized vegetation index (GNDVI) is another candidate parameter that could be used to develop crop coefficients from plant reflectance to be used for scheduling irrigation. The canopy temperature approach for variable rate irrigation obtains a measure of crop stress based on remotely sensed temperature differences between the surface and air temperatures. The most widely used indices are the crop water stress index (CWSI) which ranges from zero to one (Idso, 1982 and Jackson, 1982), and the water deficit index (WDI) (Moran et al., 1994). Both WDI and CWSI are commercially available to farmers and can be used as a basis for applying variable irrigation water based on water stress in corn rather than on the current basis of demand or weather-based water budgets which do not account for spatial variability within a field. More importantly, it is possible to remotely monitor water stress in plants and apply irrigation water based on the site-specific needs of corn within a field rather than uniformly applying irrigation water over a field as is the current practice.

Chapter II Overview

Optical remote sensing provides a powerful tool for monitoring changes in a crop over the growing season and can provide crop developmental information that is time-critical for site-specific crop management. Leaf chlorophyll is positively correlated with N concentration (Al-Abbas et al., 1974). Remote sensing has been used to characterize properties of vegetation, estimate yield, estimate total biomass, and to monitor plant health and plant stress (Jackson, 1986).

Many spectral vegetation indices (SVI) have been presented in the literature. Jackson and Huete (1991) interpreted some of the vegetation indices. Spectral vegetation indices (SVI) were used to measure the photosynthetic size of the plant canopy and to estimate yield (Wiegand et al., 1990). The most used indices are: ratio vegetation index (RVI), NDVI, and soil adjusted vegetation index (SAVI). A major advantage of the SVI is that they reduce multi-band observations into a single numerical index. Biophysical variables that are of great interest and can be estimated from remote sensing data are grain yield, leaf area index (LAI), and fractional cover (Fc).

Remote sensing has been used for yield estimation where grain yield was correlated to a single measurement of NDVI. Tucker et al. (1980) used NDVI as a time integral to estimate yield. Blackmer et al. (1996) correlated relative corn grain yield to reflective radiation from a photometric cell centered around 550 nm. They concluded that this wavelength was also more sensitive than other wavelengths to N stress in corn at dent time. Blackmer et al. (1996) analyzed aerial photos for N stress and found that black and white photos centered around 536 nm also predicted yield at the R5 growth stage. Therefore, identification of spectral wavelengths that are sensitive to N stress will aid in site-specific management of corn.

Leaf area index (LAI) is an important parameter for light interception by plants and is used extensively as an input to predict crop response in many simulation models. Remote sensing has been used to estimate biophysical variables such as LAI and Fc (fractional cover). There are three approaches as reported by Qi et al. (2000a) to estimate LAI. These include a simple regression that uses multi-band regression, a modeling approach, and a vegetation index approach. The vegetation index approach is associated with SVI such as NDVI. Here the LAI can be estimated using an empirical relationship. Fraction cover (Fc) is another very important property of vegetation. It has a direct role in daily agronomic decisions such as irrigation. Qi et al. (2000a) used an empirical approach to estimate LAI and Fc from imagery acquired from Landsat TM and from aircraft sensors.

Measurements of a canopy multi-spectral reflectance can provide a quick, cost effective , and non-destructive real time method of assessment of nutrient status and biophysical variable estimation of the whole field. Otherwise, the current methods of crop assessment are tedious, laborious, costly and time consuming.

Chapter III Overview

Precision Agriculture (PA) or site-specific crop management (SSCM) involves the management of spatially variable factors according to localized conditions (Larson and Robert, 1991). Precision agriculture is concerned with variability in the both space and time. Soil properties and processes that regulate corn production and environmental sensitivity vary in space and time (Lake et al., 1997; Pierce and Nowak, 1999; and Bell et al., 1995). Therefore, understanding the relationship between crop yield and environmental spatial variables is essential for SSCM.

Without variability, the concept of precision agriculture has no meaning. Mulla and Schepers (1997) suggested that the most important factors in variability include spatial patterns in pest infestations, plant available water, soil drainage, crop rooting depth, nutrient availability, soil texture, organic matter content and pH. The challenge for PA is to determine which major factors are responsible for variations in crop yield.

Spatial data do not comply with the assumptions of classical statistics, in particular independence. Tobler's first law of geography (Tobler, 1977) states that "everything is related to everything else, but near things are more related than distant things". Soil properties frequently exhibit spatial dependence, i.e., samples collected close to one another are often more similar in value than widely spaced samples (Trangmar et al., 1985). There are many geostatistical methods available that have been adopted for detecting the auto-correlation in environmental data for the characterization of spatial dependence of soil properties. The most widespread is the semivariance analysis. Semivariance analysis provides a versatile and unbiased means for examining autocorrelation in environmental data (Robertson and Gross, 1994). A semivariogram is basically a plot of dissimilarity (semi-variance) between samples against distance between samples (Issaks and Srivastava, 1989). The semi-variance ideally increases with distance between sample location, to a more or less constant value (the sill or total semi-variance or the population variance) at a given separation distance, called the range of the spatial dependence (Trangmar et al., 1985). Attributes separated by distances closer than the range are spatially related. Those separated by distances greater than the range are not spatially related. The semi-variance, when the distance of sample separation tends to zero, or y -intercept, is called the nugget variance or nugget effect (Webster, 1985). The nugget effect gives an indication of variability at scales less than the data spacing and/or due to analytical or random error. The difference between the sill and the nugget is the structural variance. Moreover, the semivariogram documents whether there are spatial components to the variability and how distinct the patterns may be. The semivariogram also reveals the spatial scale over which autocorrelation occurs.

Though variability may occur naturally as a result of complex geological and pedological or manmade processes, knowing the degree of spatial dependence and its extent is critical for evaluating its agricultural significance. Application of geostatistical techniques may provide more power for analyzing spatial variability and semivariance analysis gives a robust means for quantifying autocorrelation in spatial and temporal dimensions.

To characterize soil water content for precise variable rate irrigation application, the temporal stability of spatial soil water content variation has to be determined. Vachaud et al. (1985) used cumulative probability function and a mean relative difference technique to evaluate the temporal stability of spatial soil water storage. Cassel et al. (2000) applied the same technique to evaluate the temporal stability of soil spatial water content. The method uses the Spearman rank correlation coefficient as a criteria to evaluate the temporal stability of spatial soil water content.

CHAPTER I

PERFORMANCE OF SENSOR-BASED N AND WATER MANAGEMENT STRATEGIES FOR CORN IN MICHIGAN

ABSTRACT

This study was initiated to evaluate sensor-based nitrogen and water application for corn (*Zea mays L.*) in Michigan. Our hypothesis was that sensor-based N and water applications are more efficient for corn production than current fertilizer and irrigation practices based on mass balance recommendations. Therefore, these sensor-based strategies must be site-specific and maximize N and water use efficiency. The specific objectives were 1) comparing at-planting and pre-sidedress nitrate test (PSNT) N management with sensor-based N strategies based on stress in plants determined by leaf chlorophyll readings, 2) comparing dryland farming to irrigated corn, and 3) developing a crop coefficient from remotely sensed data that can be used in irrigation scheduling. Intervention N management strategies through PSNT and leaf chlorophyll sufficiency performed as well as at-planting N management strategies. There was a N x water interaction in the 1999 season but none in the wet 2000 season. Irrigation increased yield but not without N application. Nitrogen was the main factor determining yield in the wet 2000 season. We obtained PSNT values at V6 and at silking (R1) stages of growth, and earleaf N, stalk N, grain N, and postharvest soil profile N in the effective rooting depth. Canopy multispectral reflectance was measured in the visible and near infrared spectral bands. A real time reflectance-based crop coefficient (Kcr) from the green normalized vegetation index (GNDVI) is introduced for estimating crop evapotranspiration.

INTRODUCTION

Nitrogen Management Strategies

Current N fertilizer recommendations and practices are based on response data averaged over a large landscape area which dilutes the accuracy of response relationships (Buchholz, 1983). The N fertilizer recommendations that are based on an average response function and yield goal are poorly correlated with actual economically optimum N rates (Doerge, 2001). Nitrogen response and water distribution are field and season dependent and can vary greatly within the same field in the same season. Spatial variability within the same field makes it difficult to calculate variable rate N application rates and water recommendations for corn production for optimal application and maximal economic returns. Precision Agriculture (PA) was designed to target crop and soil inputs according to a specific field requirement to optimize profitability and protect the environment. Soil properties and processes that regulate corn production vary in both space and time (Lake et al., 1997, and Pierce and Nowak, 1999). There is an increasing interest in whether this variability implies that there could be an advantage in managing field crops in a spatially variable way instead of treating them according to average conditions (Robert et al., 1993). Therefore, understanding the relationship between crop yield and environmental spatial variables is essential for site-specific crop management (SSCM). Site-specific crop management involves the management of spatially variable factors according to their localized conditions (Larson and Robert, 1991, and Schueller, 1992). The ability to identify differences in crop N status within fields could lead to efficiencies in N fertilizer application (Blackmer et al., 1996). Therefore, it becomes essential to identify differences within the field for efficient variable rate N and water application.

Variable rate N recommendations started as a designated or a prescripted approach where N was applied at planting to prevent any nutrient deficiencies. Fields were divided into management zones and recommendations using prescribed methods were applied to individual zones. Ferguson et al. (1997) reported map units from grid soil sampling and Kitchen et al. (1995) suggested crop productivity zones. This prescription N management did not improve N use efficiency. The interactive N management approach relied heavily on remote sensing data and assessed crop needs based on tissue sampling and sensing plant reflectance. This approach depended on an interactive intervention of N management where N was applied to meet real time crop requirements depending on sensing N in plants. Schepers et al. (1992) delayed N applications based on N content in plants. They estimated N fertilizer requirements using relationships between reflectance and plant N content, and fertilized the crop to the optimal N content for maximum economic yield. Schepers et al. (1996) suggested that using strategies which sense the occurrence of N deficiencies in plants during the uptake phase may be better adapted to precision N management than strategies that use mass balance approaches that are based on soil sampling. The idea is to monitor plant N concentration through chlorophyll content in the plant by monitoring plant or canopy reflectance of light. Often, some portion of a field is fertilized to optimal levels and the well-fertilized corn used as the standard for adjusting the N recommendations for the remainder of a field (Schepers et al., 1996). Some researchers estimated plant N using a previously developed index calculated from measured canopy reflectance (Bausch et al., 1996). Blackmer et al. (1995) proposed that the images of canopy reflectance centered at 550 nm acquired late in the season could be used to detect portions of the field that were nitrogen deficient. Measuring light reflected from a plant canopy can be used to detect N deficiency in corn (Blackmer et al., 1996) and to trigger N fertilizer applications based on plant need.

From an energy balance viewpoint, all solar radiant flux incident upon any object is either reflected, transmitted, or absorbed. Vegetation is unique in the three-segment partitioning of solar irradiance. In the visible part of the spectrum (400 - 700 nm), reflectance is very low, transmittance is nearly zero, and absorption is high. The fundamental control of energy-matter interactions with vegetation in this part of the spectrum is plant pigmentation. In the longer wavelengths of the near-infrared portion of the spectrum (700 - 1350 nm), both reflectance and transmittance are high whereas absorption is very low. Intervention N strategies are based on the fact that N deficiency in corn reduces the chlorophyll content of leaves thereby increasing the amount of light transmitted through a leaf. A typical reflectance curve shows a peak at around 550 nm corresponding to green color due to reflection of light by chlorophyll and a dip in the plant spectral signature around 690 nm corresponding to a red color due primarily to chlorophyll absorption. Therefore, measuring multispectral reflectance of the plant canopy is a non-destructive method, a whole field approach, and a real time assessment of the crop.

Although technology is available to deliver variable N rates of fertilizer across fields, this practice in not yet economically beneficial in most cases and the potential cost savings are minimal (Doerge, 2001). Therefore, there is a need for a new N management strategy that fertilizes the crop to the optimal N content for maximum economic yield and protects the environment from nitrogen leaching.

Water Management Strategies

Water is critical to crop productivity since crop yields generally increase linearly with water transpired by a crop (Howell, 1990). Improved water management necessitates an accurate estimation of daily crop evapotranspiration. Water management is also critical to maintaining high water quality and to increasing water use efficiency. Techniques that optimize water relations for plants have a direct impact on the fate and transport of pollutants to surface and ground waters. Differences in water availability within a field are favored by 1) the occurrence of dissimilar soil types; 2) the presence of degradation processes (e.g., erosion, compaction, salinity); and 3) variation in the landscape which affects the horizontal distribution of water. Pierce et al. (1995) suggested that soil physical properties or landscapes (especially their effect on plant water relations) may be even more important than soil fertility in explaining yield variability.

There is a significant amount of research in the area of variable rate irrigation management with two, well-connected areas of interest in precision irrigation management. The major portion of research has focused on variable rate irrigation systems, mainly with sprinkler irrigation provided by center pivot and linear move machines (Camp and Sadler, 1994; Evans et al., 1996; King et al., 1995,1996; and McCann and Stark, 1993). The second part of variable rate irrigation research has focused on developing irrigation scheduling programs from remote sensing vegetation indices either from plant canopy reflectance or from canopy temperature.

The introduction of the basal crop coefficient (Kcb) by Wright (1982) successfully improved irrigation scheduling. The problem with the Wright basal crop coefficient is that it is dependent on time based parameters such as planting date and effective cover and the resistance to water movement from soil and plant surfaces. Specific crop evapotranspiration is a product of the crop coefficient and evapotranspiration rate from a reference crop. Neale et al. (1989) developed a reflectance-based crop coefficient (Kcr) from a normalized difference vegetation index (NDVI). They developed an equation of the form:

$$Kcr = a * NDVI + b \tag{1.1}$$

where: a = multiplier, and b = offset

$$a = (Kcb_{effective} - Kcb_{soil}) / (NDVI_{effective} - NDVI_{soil}) \tag{1.2}$$

Kcb effective = 0.93 at effective cover and Kcb_{soil} = 0.15 at dry soil conditions.

$$b = (Kcb_{soil} - a) * NDVI_{soil}) \tag{1.3}$$

Neale et al. (1989) reported two equations for two research sites:

$$Kcr = 1.092 * NDVI - 0.053 \tag{1.4}$$

$$Kcr = 1.181 * NDVI - 0.026 \tag{1.5}$$

The NDVI crop coefficient is independent of planting date and effective fractional cover since NDVI is the measure of photosynthetic size of plant canopy. Therefore, Kcr is a true representation of crop growth and development and is affected by nutrient and water stress, and diseases. The NDVI is computed by ratioing spectral reflectance of visible red light (R= 625 - 675 nm) and the near infrared light (NIR= 725 - 810 nm) as (NIR - R)/(NIR + R) and ranges from -1 to 1. Bausch (1993) used the soil adjusted vegetation index (SAVI) to predict evapotranspiration from a reflectance-based crop coefficient for corn that can be used as a basis for variable rate irrigation. Bausch et al. (1995) used the same form of the equation developed by Neale et al. (1989) and substituted SAVI for NDVI to reduce the effect of soil background on canopy reflectance. Green normalized vegetation index (GNDVI), which is the ratioing of the near infrared (NIR= 725 - 810 nm) and the green reflectance (560 nm) as (NIR - G)/(NIR + G) is another candidate that could be used to develop a crop coefficient for scheduling irrigation from plant reflectance data.

The canopy temperature approach to variable rate irrigation is accomplished by obtaining a measure of crop stress based on remotely sensed temperature differences between the surface and air temperatures. The most widely used index is the crop water stress index (CWSI) which ranges from 0 to 1 (Idso, 1982, and Jackson, 1982), and the water deficit index (WDI) (Moran et al., 1994). Both the WDI and CWSI indices are commercially available to farmers and can be used as a basis for applying variable rates of irrigation water based on water stress in corn rather than on the current basis of crop demand or weather-based water budgets which do not account for spatial variability within a field. More importantly, it is possible to remotely monitor water stress in plants and apply irrigation water based on site-specific needs of corn within a field rather than uniformly over a field as is the current practice.

Our hypothesis was that sensor-based N and water applications are more efficient for corn production than current fertilizer and irrigation practices based on mass balance recommendations. Therefore, sensor-based N and water management strategies can be site-specific and maximize corn yield and N and water use efficiency and minimize N losses to the environment.

Objectives

The overall objectives of this study were to determine if variable rate N fertilizer application based on plant chlorophyll sensing and variable irrigation based on vegetation indices such as NDVI, SAVI, and GNDVI are more efficient for corn production than the current fertilizer and irrigation practices based on mass balance recommendations.

The specific objectives of this study were:

- To compare the effectiveness of at-planting and PSNT N application strategies with intervention N management strategies based on stress in plants determined from remotely sensed chlorophyll measurements,
- To compare N fertilizer application strategies on dryland farming to irrigated corn, and
- To develop irrigation scheduling recommendations based on remotely sensed data.

MATERIALS AND METHODS

Site Description

The study was conducted at the W. K. Kellogg Biological Station (KBS), which is located in Southwest Michigan (85^0 24' W longitude, 42^0 24' N latitude) in the northern portion of the Midwest corn belt. The W. K. Kellogg Biological Station is on the pitted outwash plain of the morianic system left by the last retreat of the Wisconsin glaciation, about 12000 years ago (Robertson et al., 1997). Soils in the area were developed on the glacial outwash; soils at the site are Typic Hapludalfs, either fine-loamy, mixed, mesic Kalamazoo series or coarse-loamy, mixed, mesic Oshtemo series (Mokma and Doolittle, 1993). Mean annual temperature at KBS is 9.4^{0}C; precipitation is approximately 920 mm annually and spread evenly all throughout the year, and potential evaporation exceeds precipitation (30 years mean) for three months per year (Crum et al., 1990). These soils respond to irrigation in most years and are vulnerable to leaching because of the coarse textured soil materials and shallow depth of the groundwater. The experimental area is gently sloping, decreasing in elevation from west to north and decreasing from east to west. It is well known from previous studies that the soils are variable over short distances making it possible to conduct spatial variability studies (Francis J. Pierce, Personal communication).

Experimental Design

The experiment evaluated two irrigation and four N treatments in a split-plot experimental design. Irrigation was the main plot and N treatments were subplots with four replications. The irrigation treatments evaluated were 1) none (control), and 2) irrigation scheduled according to the Michigan irrigation scheduling program (Shayya et al., 1990). The four N fertilizer treatments evaluated included; 1) none (control), 2) N applied at planting, (200 and 145 kg/ha for irrigated and non-irrigated corn respectively), 3) N application based on PSNT levels plus yield at the V6 leaf stage of corn, and 4) stress based N applied in 70 kg/ha increments using remotely sensed chlorophyll measurements.

Measurements

Water was applied to N treatments using drip irrigation. Since N management and soil parameters affect corn growth and development, each N plot within the irrigation treatment was irrigated independently using a drip irrigation system devised to apply water between each row. The irrigation scheme used in the 1999 season consisted of applying 12.7 mm (0.5 inch) of water every 3 to 4 days; allowances were made for rainfall. Irrigation was scheduled in 1999 with the MSU SCHED program when 50% of plant available water was depleted from the crop root zone. The crop was exposed to water stress early in 1999 before irrigation lines were installed. A weather station at KBS provided input for irrigation scheduling calculations. A rain gauge was maintained at the site to ensure a site-specific rainfall record. Soil profile water content was measured weekly from planting to maturity using Time Domain Reflectometry (TDR). Time Domain Reflectometry access tubes were inserted in the middle of each plot prior to planting to a depth of 90 cm. A tube access probe with a mobile moisture meter (Trime Moisture Measuring System™) was used to measure volumetric soil water content at 18, 36, 53, 71, and 89 cm intervals on a weekly basis.

A multi-spectral ground based radiometer (CropScan, MSR87) was used to measure the green, red, and NIR spectral reflectance bands. The CropScan radiometer contains a set of eight narrow band filters, centered at:

460 nm, 510 nm , 560 nm, 610 nm, 660 nm, 710 nm, 760 nm, and 810 nm

The CropScan radiometer has a 28 degree field of view for reflected irradiation and the sensor was mounted on a 2.62 m pole above the canopy at nadir viewing and a cherry picker was used when the crop was very high. Two measurements per plot were taken for each sampling date in 1999 and three measurements per plot were taken in 2000 between the daylight hours of 10:30 am and 1:30 pm local time. The sensor was oriented parallel to the corn rows resulting in an oval ground area of about 1.53 m^2. Weekly multi-spectral measurements were taken using the CropScan radiometer from the V6 growth stage to the R5 (dent) growth stage. Leaf area was measured from V6 (2000 season only) to silking for each plot using the LAI-2000 plant canopy analyzer (Li Cor (R) leaf area meter).

All fertilizer N was applied as 28% solution using a precise liquid fertilizer applicator equipped with a capacity to apply N throughout the N uptake phase of corn growth and development. Fertilizer N recommendations for corn following corn was based on MSU fertilizer recommendations (N recommendation = -27 + 1.36* yield goal). For PSNT N treatment, N fertilizer rates were reduced based on the PSNT values of 6*ppm N in the surface 0- 30 cm (N recommendation = 27 + 1.36* yield goal - 6*ppm). Nitrogen applied at planting time was 145 kg/ha for a yield goal of 7,800 kg/ha for non-irrigated corn and 202 kg/ha was applied for a yield goal of 12,480 kg/ha for irrigated corn. Nitrogen was applied in 70 kg/ha increments from V6 to V14 for sensor-based N treatments based on leaf chlorophyll readings.

A Minolta SPAD-502 mobile chlorophyll meter (Spectrum Technologies Inc.) was used to measure red (690 nm) and NIR (940 nm) canopy absorption and transmittance in all plots. Leaf chlorophyll contents of 30 plants per plot were measured using a SPAD chlorophyll meter from V6 to V14 stages of growth to evaluate changes in sensor-based chlorophyll measurements. Nitrogen fertilizer application was triggered in the stress-based N treatment when reflectance of corn fell to 96% of the reflectance of well-fertilized corn as this level has been shown to maintain corn yield (Scheppers et al., 1996).

The soil was chisel plowed in the fall of 1998 and was fit with a field cultivator prior to planting in 1999 and in 2000. The site was mapped in the spring prior to planting for elevation and soil conductivity using commercial mapping procedures. These data were used in conjunction with soil profile measurements to establish the variability of soils and landscape parameters on the experimental site. Pioneer 3730 corn variety was planted on April 26, 1999 and April 29, 2000. The seeding rates were 64,250 seeds/ha for non-irrigated corn and 86,500 seeds/ha for irrigated corn. Crop measurements recorded included plant emergence, crop phenology, plant count and spacing, earleaf N at silking, stalk N, grain N, grain moisture, and grain yield. Soil measurements included water content at weekly intervals over the growing season using TDR, soil mineral N at V6 and silking (0 - 30 cm), and soil profile N after harvesting (0 - 90 cm). Corn grain yields were determined by harvesting two rows from each plot 9.84 m (30 ft) by 1.64 m (5 ft) for a total area of 16.1 m^2 (150 ft^2). Corn grain moisture was adjusted to 155 g/kg moisture.

Statistical Analysis

Analysis of variance (ANOVA) and covariance were performed using the SAS Mixed Procedure (SAS Institute, 2000). The Mixed Procedure in SAS uses a maximum restricted likelihood estimation of linear statistical models involving both fixed and random terms, such as the linear model underlying the split-plot analysis, and therefore is well suited to this task. The Tukey-Kramer test was used for comparison between different treatments at the 95% level of significance. Log transformations of the data were performed when there were outliers and then back transformation was performed on the original data.

RESULTS AND DISCUSSION

It is very clear from Figure 1.1 that evapotranspiration exceeded precipitation during the growing season and that supplemental irrigation was necessary for consistent high yield.

Chlorophyll meter readings were used to schedule sensor-based N treatment by calculating a N sufficiency index (NSI). The Nitrogen sufficiency index is the ratio of chlorophyl meter readings from different N treatments to the chlorophyl meter readings from a reference N treatment which had sufficient N. In this study the reference N treatment consisted of N applied at planting (145 kg/ha was applied for a yield goal of 7,800 kg/ha for non-irrigated corn and 202 kg/ha applied for a yield goal of 12,480 kg/ha for irrigated corn). The at-planting N treatment was the reference N treatment and was compared to different N treatments over the entire growing season. The nitrogen sufficiency index for both 1999 and 2000 growing seasons is illustrated in Figure 1.2a and Figure 1.2b. The control treatment showed a decline in leaf chlorophyll content as the season progressed. Early season drought in 1999 resulted in lower leaf chlorophyll content even after N was applied until irrigation or rainfall occurred in early July when leaf chlorophyll recovered as shown in Figure 1.2a. Figure 1.2b showed that leaf chlorophyll for sensor-based and PSNT N treatments for the 2000 growing season recovered immediately once the intervention management N was applied.

Interactive N management based upon the PSNT and leaf chlorophyll measurements performed as well as at-planting N management for corn grain yield. Irrigation increased corn grain yield but not without supplemental N application in 1999 (Figure 1.3a). There was a N x water interaction in the dry season of 1999 (P-value = 0.045). Figure 1.3a showed that under dryland farming conditions corn grain yield was not increased whether N was applied or not. Irrigation significantly increased corn grain yield over the control at all levels of N treatment. Sensor-based irrigation was not scheduled because acquisition of infrared thermometer (IRt) data was not available in the 1999 season. There was no N x water interaction for the wet 2000 season (P-value = 0.1677). Comparison of least square means shows that corn grain yield response to irrigation was not significant in the 2000 growing season. Figure 1.3b compares corn grain yield at different levels and strategies of N addition indicating that N is the main factor determining yield in the wet 2000 growing season. However, there was no significant difference in corn grain yield when N was applied at planting time as compared to application based on PSNT or sensor-based measurements. Table 1.1 shows the least square means for corn grain yields for the experiment in irrigated and non-irrigated N treatments in 1999 and during the wet 2000 growing season without irrigation. It is obvious from this least squares means analysis that irrigation doubled corn yield in 1999, however, an excellent 2000 yield without irrigation exceeded that of an irrigated 1999 for the same N treatments. The 1999 irrigated corn grain yield was lower than the 2000 corn grain yield because irrigation was not possible until late July of the 1999 season.

Table 1.2 shows total nitrogen fertilizer applied at different N treatments and least squares means for PSNT levels at V6 leaf, at silking, and after harvesting for the 2000 growing season. It is obvious that the at-planting N treatment had the highest nitrate-N levels at V6 on the first PSNT testing date (144.37 kg/ha), however, this high level decreased to 36.76 kg/ha when the PSNT was performed at the second sampling date at silking (7/23/2000). Therefore, much of the fertilizer applied at planting time was probably leached down through the soil profile and not used for plant nutrition. A starter N fertilizer was applied for PSNT N treatment and sensor-based N treatment at planting time. Then N fertilizer was applied for PSNT N treatments according to the MSU recommendation (N recommendation = -27 + 1.36* yield goal -6*ppm N in the 0 -30 cm depth). The recommended rate was calculated per PSNT N treatment at V6 and at silking when the PSNT was performed. For sensor-based N treatments, there was a weekly assessment of plant chlorophyll through chlorophyll meter readings that aided in the calculation of the N reference index. When the N reference index was less than 96% of the reference N treatment, N fertilizer was applied in 70 kg/ha increments from V6 to silking. Table 1.2 also shows that PSNT and sensor-based N treatment have N available for crop uptake at the rapid stage of growth at silking. Although the at-planting N treatment has the highest amount of N fertilizer applied, by the time of rapid N plant uptake there was significantly less soil NO_3-N in the at-planting N treatment compared to soil NO_3-N in the intervention N treatments that were applied based upon PSNT or on the sensor-based measurements. Therefore, intervention N management based upon PSNT and chlorophyll measurement resulted in less N fertilizer addition and less N leaching compared to at-planting N management. Table 1.3 illustrates the analysis of variance for the PSNT nitrate-N levels for 1999 and 2000 at two different dates (V6 and silking). Irrigation, irrigation x N, and irrigation x date were not significant in the PSNT N treatment. However, N, date, and N x date were significant (p-value = 0.001). The irrigation x N x date interaction was not significant in 1999 but was significant in the 2000 growing season. Although PSNT and sensor-based N treatments had smaller amounts of N fertilizer applied, adequate NO_3-N for crop nutrition was present at the two different PSNT dates for 1999 and 2000 as illustrated in Figures 1.4a and 1.4b. These results indicate that lower N addition based upon PSNT and sensor-based measurements can result in optimal corn grain yields while leading to less nitrate leaching potential when compared to the at-planting N treatment.

Table 1.4 shows the analysis of variance of KCl extract for soil profile NO_3-N after harvesting at three rooting depths for the two growing seasons. The rooting depth was 91 cm divided into 3 measuring depths of 0 -30 cm, 30 - 61 cm, and 61 - 91 cm. Figure1.5a illustrates that a dry 1999 irrigated season had a higher soil nitrate accumulation compared to the wet season of 2000. Although irrigation was only significant in the 2nd depth (30 - 61 cm), it is important to show the impact of irrigation on N leaching as summarized by least squares means (Table 1.5). Figure 1.5b shows the effect of the wet 2000 season without irrigation on soil nitrate leaching using the different N application strategies. Dryland farming has the highest accumulation of nitrate and a very high amount of NO_3-N was found in the first depth (0 - 30 cm) as compared to other depths in the irrigated 1999 season. The sensor-based N treatment had the highest residual accumulation of nitrate in the first depth in the 1999 irrigated season, probably due to the late N application that makes this interactive N application more appealing in reducing N potential for leaching to the ground water in theory. But, in a dry season like 1999, especially under dryland conditions and reduced growth and yield, the excess nitrate applied later in the season may still move beyond the rooting zone to groundwater after the crop is harvested. Therefore, sensor-based N application reduces nitrate leaching beyond the rooting zone when there is a normal growing season but may not be effective in dry years without irrigation. Nitrogen treatment based upon PSNT was the only N treatment with significant NO_3-N levels at the 30 - 61 cm depth in 2000 growing season. The NO_3-N accumulation at 30 - 61 cm is likely due to the application of the recommended dose that was not leached and yet was not taken up by the crop prior to maturity and harvest. The pre-sidedress nitrate test (PSNT) N treatment provides adequate N for crop production during a growing season but may be a source of nitrate leaching during dry seasons with irrigation as is the case with sensor-based N application.

Soil NO_3-N levels were not significantly different at the 61 - 91 cm depth regardless of N application or application strategy used.

Table 1.6 summarizes the analysis of variance for plant nitrogen (earleaf, stalk N, grain N, and corn grain yield). Irrigation was not significant in increasing earleaf N and there was no irrigation x N interaction. Although N application was significant in increasing earleaf N in 1999, it was not significant in 2000. Irrigation and N application were very significant when grain N was analyzed. While irrigation reduced grain N concentration probably due to a growth dilution effect, N application increased grain N concentration due to increased N uptake. There was an irrigation x N interaction in both seasons. Recent studies by Blackmer and Mallorino (1996) at Iowa State University (ISU) showed that N status of corn can be assessed by measuring nitrate concentration in the lower portion of cornstalks at the end of the season. Plants that have more N than needed will accumulate nitrate in the lower stalk at the end of the season. Corn plants that are deficient in N usually translocate N from lower cornstalks and leaves to grains during grain filling. While N fertilization has a significant impact on lower stalk N build up, irrigation reduced stalk N accumulation in the lower stalk and there was an irrigation x N interaction. According to the ISU publication, stalk nitrate concentration can be divided into four categories: low (<250 ppm), marginal (250 - 700 ppm), optimal (700 - 2000 ppm) and excess (>2000 ppm) NO_3-N. Table 1.7 shows the stalk NO_3-N levels with different irrigation and N management strategies. Optimal levels were found only in the at-planting N treatment. Sensor-based and PSNT N treatments represent a marginal category according to the ISU test, however, these N management strategies produced comparable corn grain yield to the at-planting N treatment. Care must be taken when considering these categorizations because there are many factors affecting N uptake. While the factors associated with time of application or irrigation affect N , generally, under dry conditions, corn will have higher levels of nitrate in the lower cornstalk than irrigated corn (Table 1.7).

A water stress sensing method needed for sensor-based irrigation control was not successfully developed in either season. Although we acquired infrared thermometer data (IRt) in the 2000 season, there were no data differences due to the wet season.

The difficulty with current irrigation scheduling programs, such as Jenson (1969), is that they require the estimation of daily evapotranspiration (Etr) from a reference crop and a defined crop coefficient (Kc). Wright's crop coefficient (Kcb) has the difficulty of needing to estimate the time interval from planting time to effective cover. The advantages of the reflectance-based crop coefficient (Kcr) over traditional crop coefficients is its lack of dependence on a time based variable such as planting date to effective cover (Bausch, 1993). In addition, the effective cover is reached when the NDVI reaches its maximum (Neale et al., 1989). The previously introduced reflectance-based crop coefficient (Kcr) for corn estimated from NDVI has been shown to overestimate the basal crop coefficient for corn by 24% (Bausch et al., 1993). We investigated GNDVI to develop a reflectance-based crop coefficient (Kcr) over two growing seasons. We used the same procedure developed by Neale et al. (1989) and substituted GNDVI for NDVI after calculating the multiplier and the offset from multi-spectral reflectance. Table 1.8 shows a comparison between the multiplier and the offset values (2000 growing season) for the three vegetation indices (GNDVI, NDVI, and SAVI). From this analysis we developed the following equation for Kcr from GNDVI for corn in the temperate region:

$$Kcr = 1.256 * GNDVI - 0.1699 \tag{1.6}$$

Figures 1.6a and 1.6b show the temporal progress of the crop coefficient estimated from planting date and effective cover for Kcb (Wright) and the Kcr calculated crop coefficient from canopy reflectance for NDVI, SAVI, and GNDVI for irrigated and non-irrigated N treatments for 1999. All three vegetation indices were similar in mimicking Kcb (Wright) for the full growing season. Reflectance-based crop coefficients (Kcr) for all vegetation indices, whether irrigated or non-irrigated, had not under- or overestimated evapotranspiration for the 1999 growing season compared to Kcb (Wright) as illustrated in Figure 1.6. Because irrigation was not significant in the analysis of variance in the 2000 growing season, Figure 1.7 only shows Kcr (2000) data from NDVI, SAVI, and GNDVI for N treatments without irrigation. Figure 1.7 also illustrates that NDVI overestimated the corn crop coefficient compared to Kcb (Wright), and therefore overestimated the amount of irrigation needed especially in times of higher demand for water by the crop. The soil adjusted vegetation index (SAVI) crop coefficient follows Kcb (Wright) and it does not overestimate irrigation water at the time of demand because there is no soil background effect. Green normalized difference vegetation index (GNDVI) crop coefficient, however, follows Kcb and SAVI curves because we used the green reflectance in calculating Kcr instead of the red reflectance. Green reflectance represents the amount of chlorophyll present in the crop canopy and hence the activity and transpiration of the whole leaf canopy. When regression analysis was performed between Kcb (Wright) and Kcr obtained from NDVI, SAVI, and GNDVI, there was a very high correlation between Kcb (Wright) and the Kcr from NDVI, SAVI, and GNDVI, as can be seen in Table 1.9. These correlations illustrate that all vegetation indices studied can be used to develop an instantaneous crop coefficient from crop growth and development independent of the planting date and effective cover.

CONCLUSION

Early season drought in 1999 resulted in lower leaf chlorophyll even after intervention N application until irrigation or rainfall occurred in early July at which time leaf chlorophyll recovered. Starter N application was necessary to avoid early season N stresses and subsequent yield losses. Interactive N management through PSNT and sensor-based strategies resulted in less N application than prescription at-planting N treatment based on yield goals while producing comparable corn grain yields. There was significant N x water interaction when irrigation water was applied, but these interactions were absent when irrigation was not needed in the wet season of 2000. Chlorophyll meter readings could be used to schedule N fertilizer by predicting N stress in corn. Nonetheless, there are still unanswered questions of how, when, and what rate of N fertilizer to apply for sensor-based N application. This study would have benefitted from an analysis of total soil N prior to planting to more accurately determine how much starter was needed for intervention N treatments at planting time to prevent N stress in the crop.

Vegetation indices can be used to develop an instantaneous crop coefficient from crop growth and development data independent of the planting date and effective cover. Each vegetation index has advantages and disadvantages. While NDVI is sensitive to soil backgrounds interference, SAVI is more susceptible to interference from sky illumination. Green normalized difference vegetation index (GNDVI) is sensitive to soil background but is not affected by sky illumination. Green normalized difference vegetation index (GNDVI) was transformed into a reflectance-based crop coefficient. The crop coefficient from GNDVI performed well when compared to Kcr from SAVI and Kcb (Wright) and did not under- or overestimate evapotranspiration of corn. An equation ($Kcr = 1.256 \times GNDVI - 0.1699$) was derived that represented all field environments for estimating a corn crop coefficient. Reflectance-based crop coefficients can be used to apply variable irrigation water based on water stress in corn rather than on the current basis of demand or weather-based water budgets which do not account for spatial variability within a field. In addition, it is possible to remotely monitor water stress in plants and apply irrigation water based on site-specific needs of corn within a field rather than to apply water uniformly over a field as is the current practice.

Figure 1.1. Monthly average precipitation and potential evapotranspiration for the years 1970 - 2000 at KBS

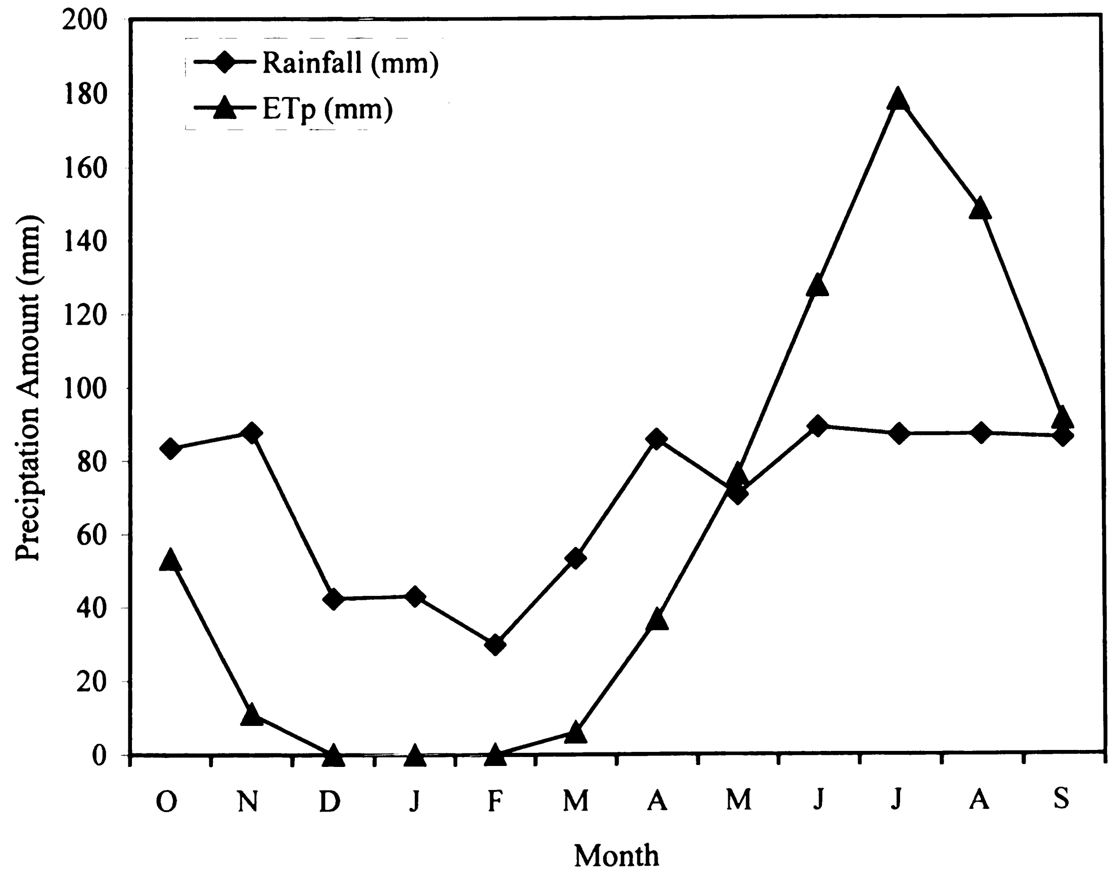
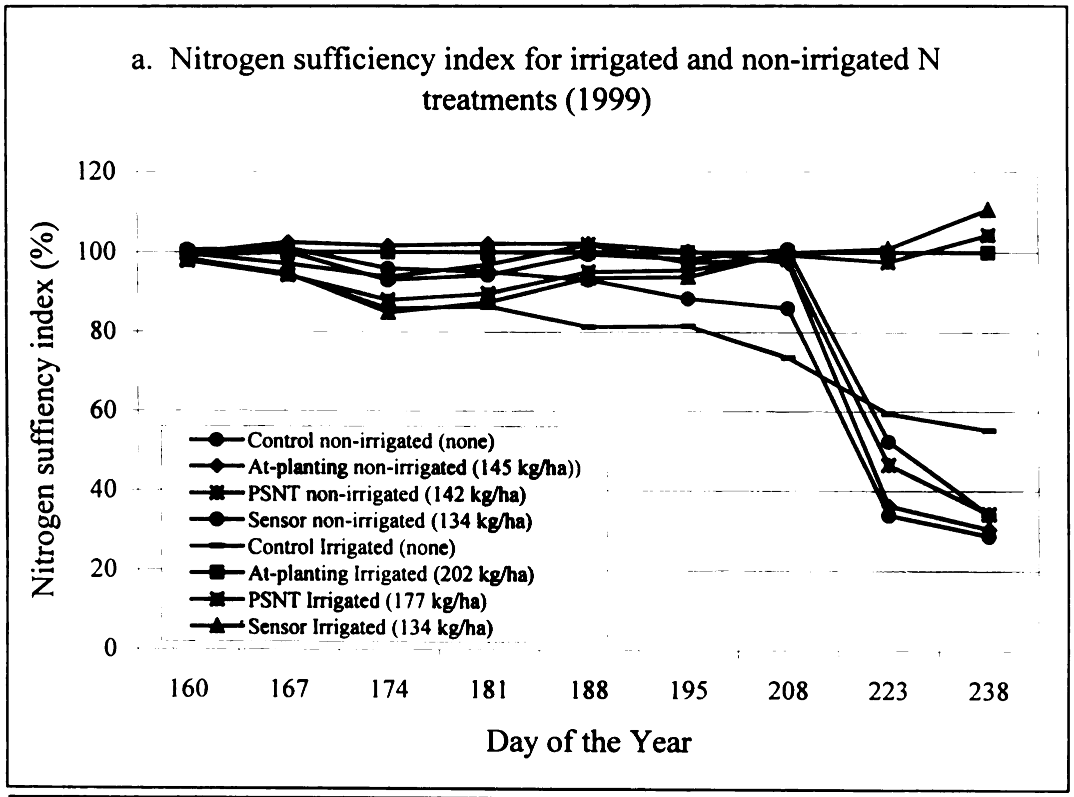


Figure 1.2. Nitrogen sufficiency index (NSI) for all N treatments.
a) an irrigated 1999 season, and b) a non-irrigated 2000 season



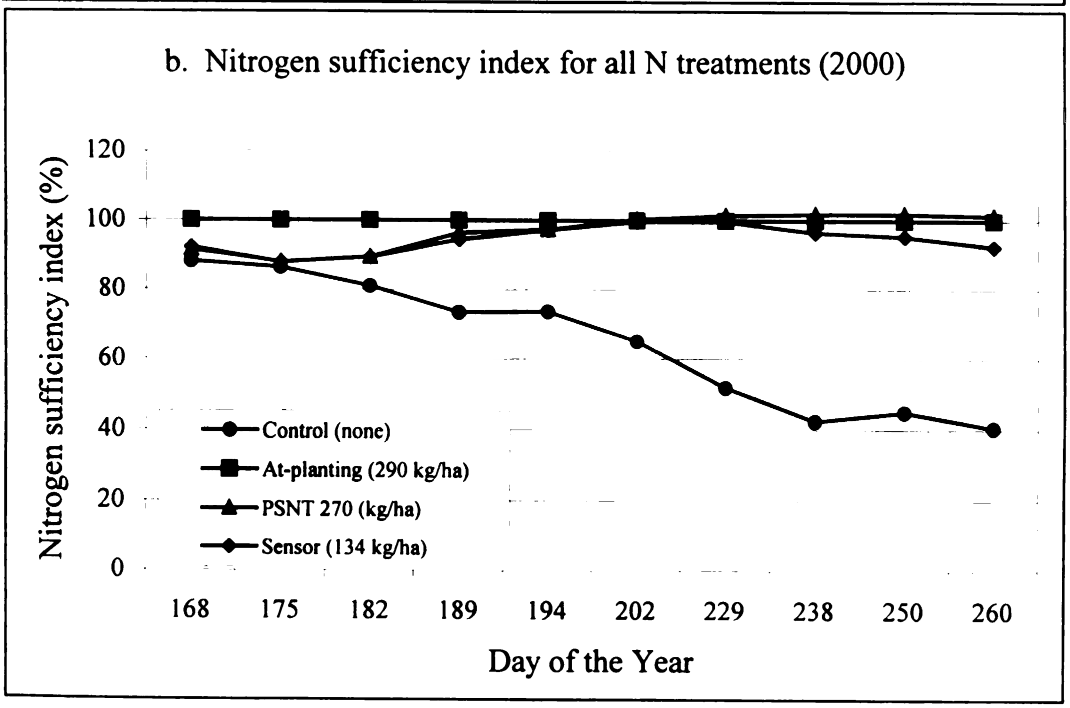


Figure 1.3. Effect of N treatments and irrigation on corn grain yield. a) effects of irrigation and N treatments on corn grain yield in the dry irrigated 1999 season, and b) effects of N treatment without irrigation on corn grain yield for the wet 2000 growing season

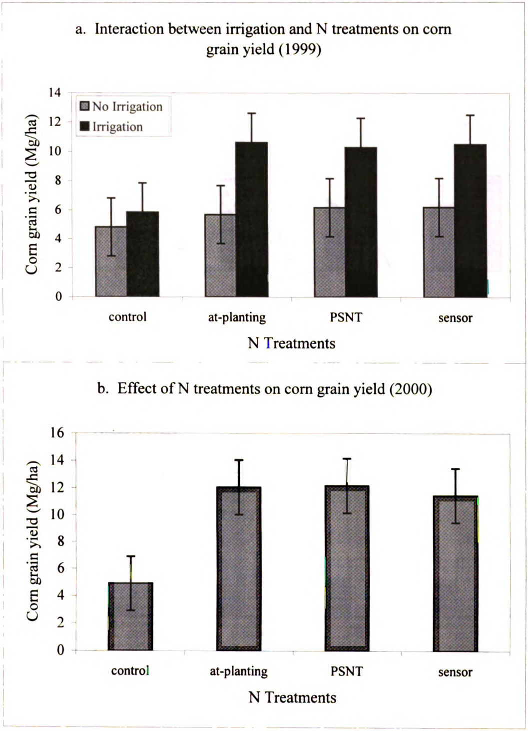


Figure 1.4. Soil pre-sidedress nitrate test (PSNT) for N treatments at V6, silking, and after harvesting for a) a dry irrigated 1999 season, and b) a wet 2000 growing season without irrigation

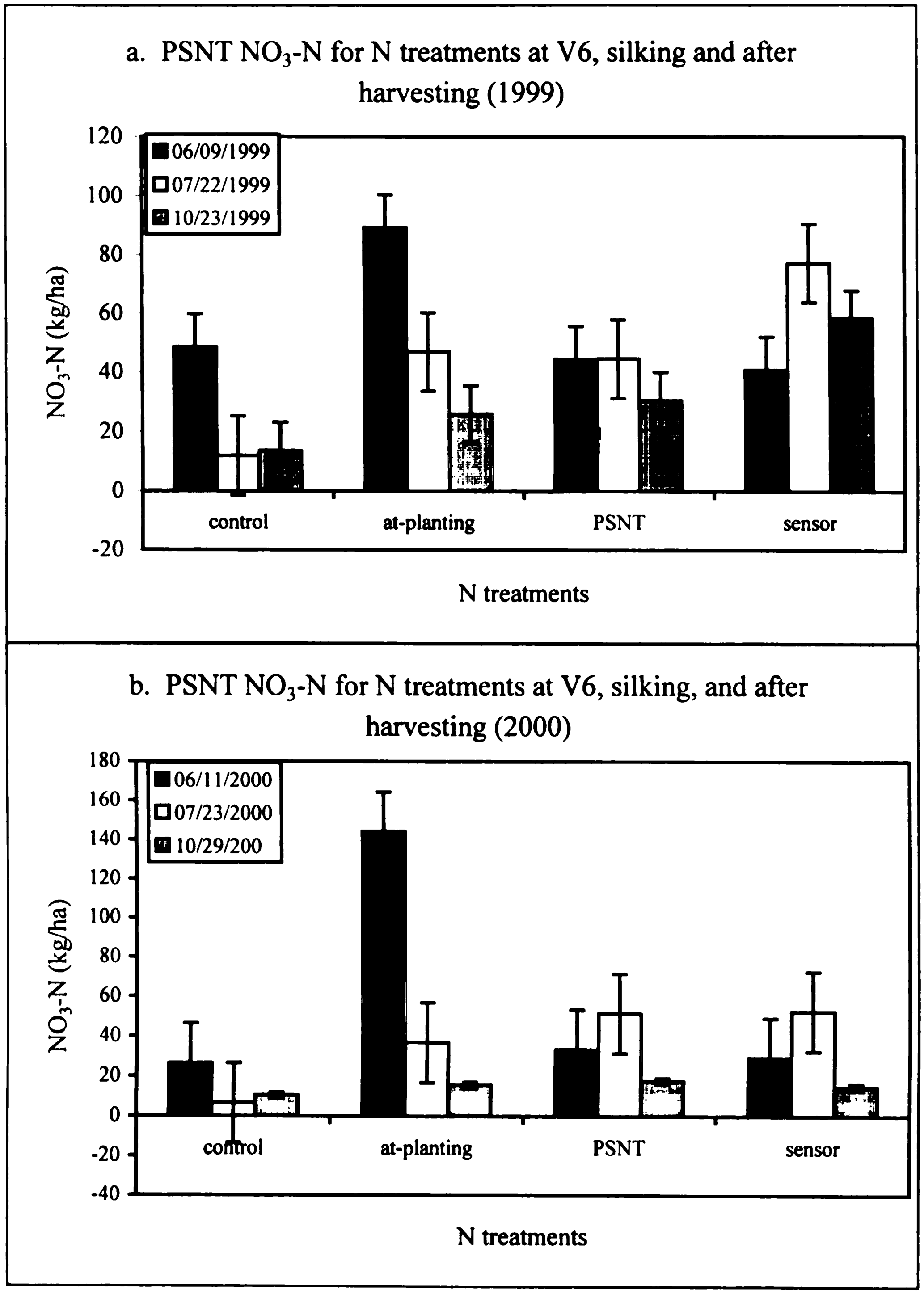


Figure 1.5. Effects of N treatments on soil profile NO_3-N distribution in the effective root zone after harvesting for a) a dry irrigated 1999 growing season with values ranging from 3 to 58 kg/ka and b) a wet 2000 growing season without irrigation with nitrate values ranging from 4 to 20 kg/ha

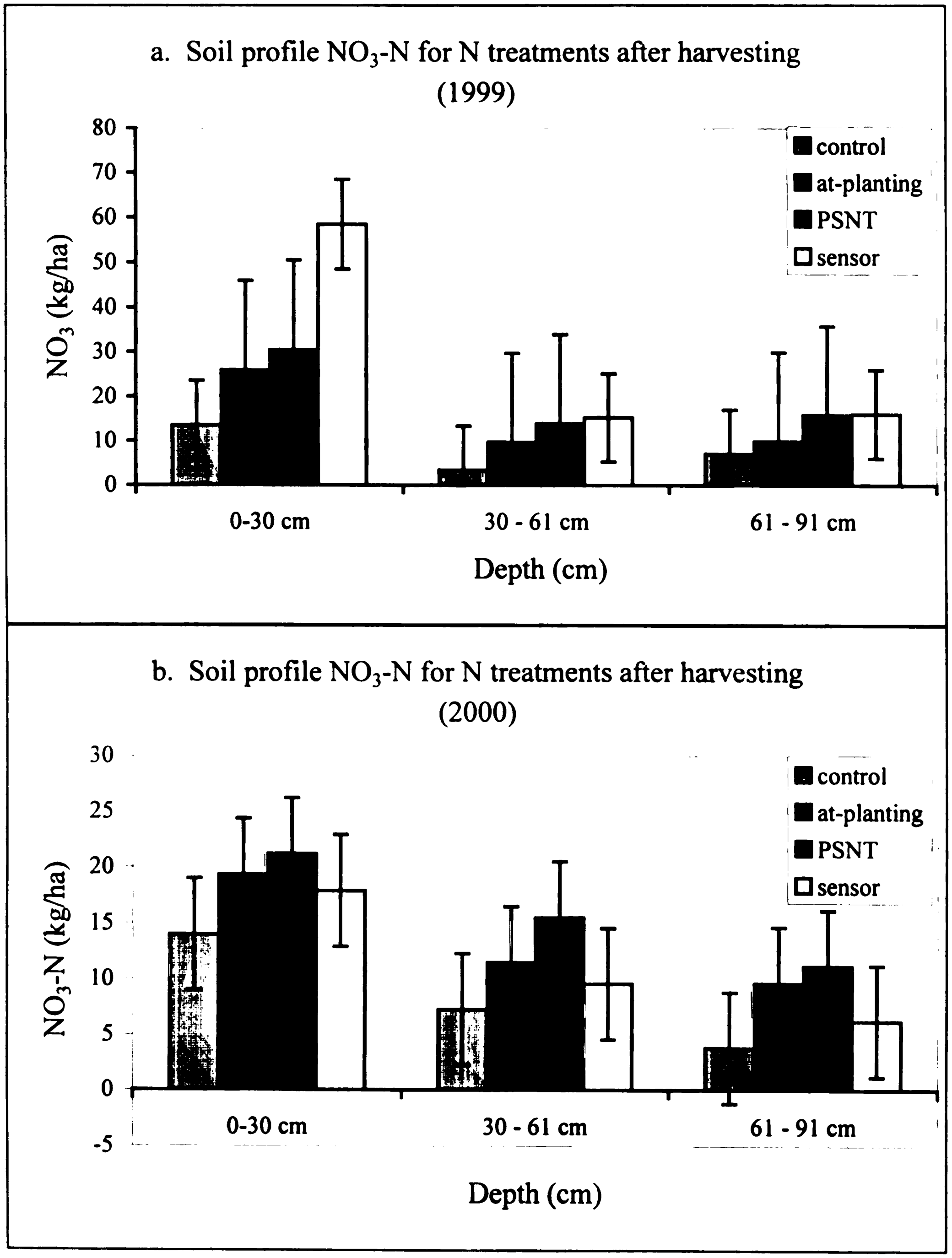


Figure 1.6. Basal crop coefficient (Kcb Wright) and crop coefficients (Kcr) from vegetation indices vs the day of the year for irrigated and non-irrigated N treatments (1999)

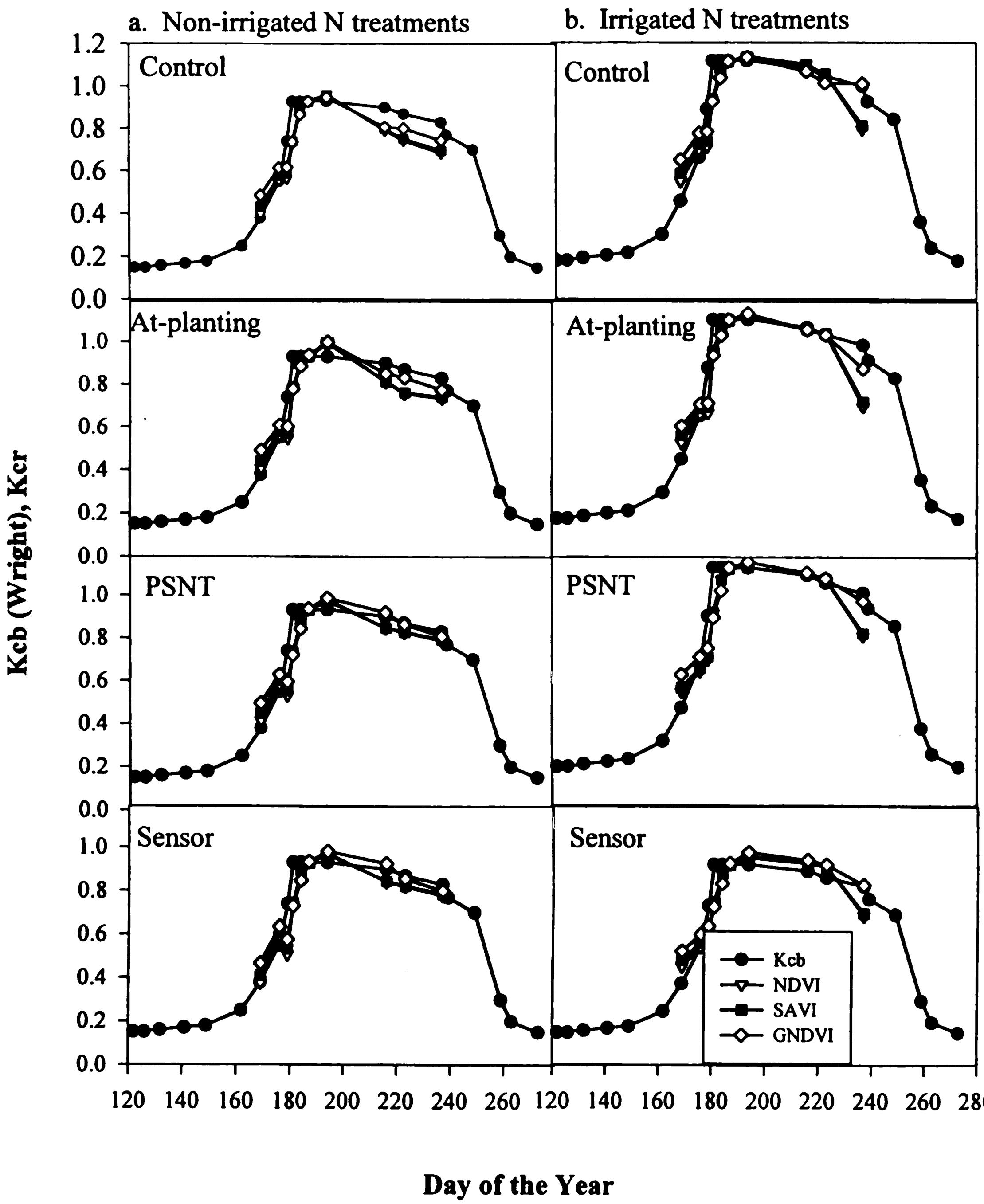


Figure 1.7. Temporal performance of Kcb (Wright) and Kcr from vegetation indices for all N treatments (2000) vs day of the year

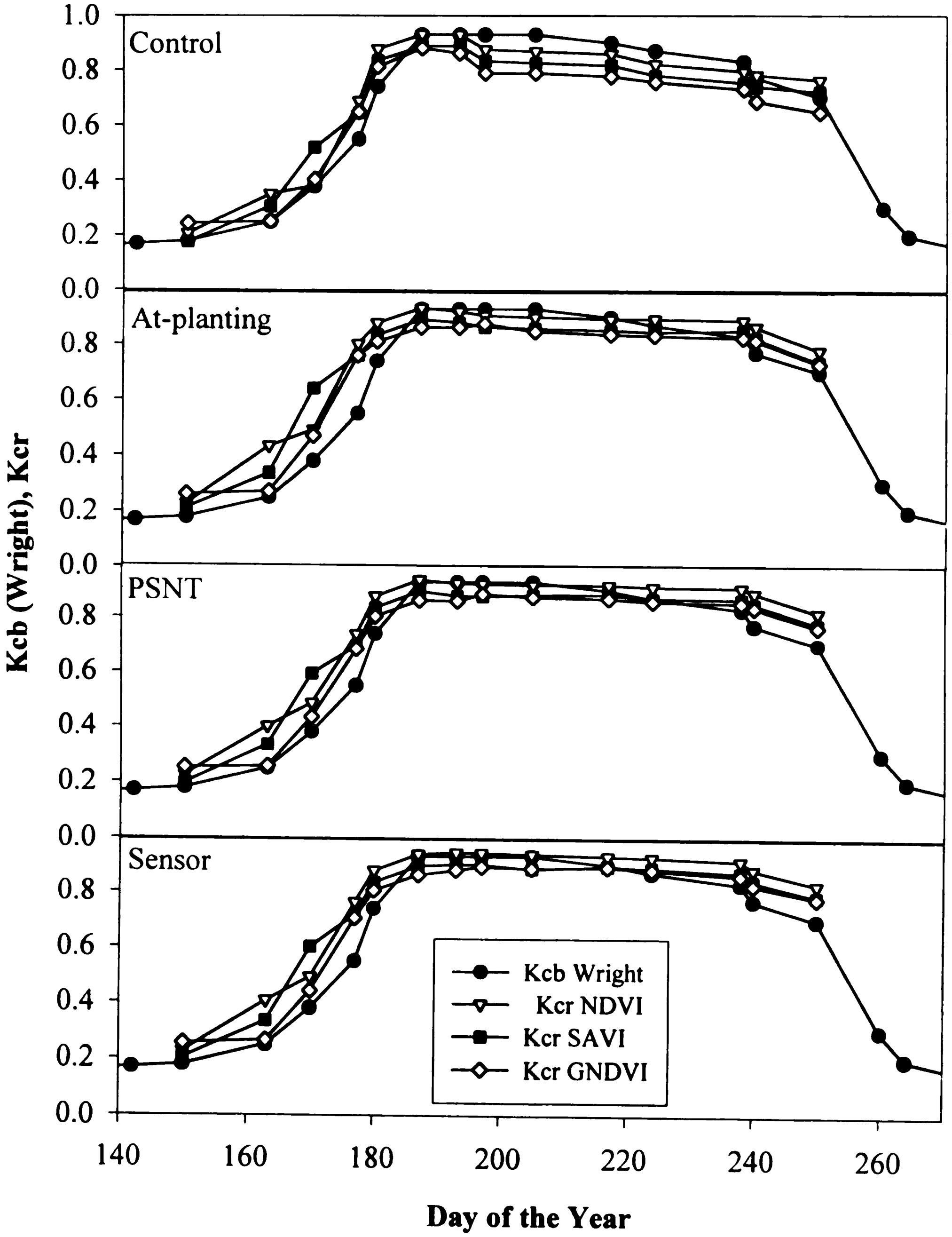


Table 1.1. Least square means for corn grain yield (Mg/ha) for two growing seasons

Treatment	Control	Pre-Plant	PSNT	Sensor
No Irrigation (1999)	4.8161 a	5.6867 b	6.1705 b	6.2041 b
Irrigated (1999)	5.8477 a	10.6141 b	10.2826 b	10.5010 b
N treatments (2000)	4.899a	12.037b	12.1551b	11.433b

Note: comparison and significance between N treatments at a given irrigation treatment.

Table 1.2. Nitrogen fertilizer applied and least square means of PSNT (NO_3-N) for different N treatments at V6 growth stage, silking and after harvesting for 2000 season

	2000			
	Total N Fertilizer Applied	PSNT (kg/ha) V6	PSNT (kg/ha) Silking	PSNT (kg/ha) After Harvest
N Treatment	kg/ha	6/19/2000	7/23/2000	10/29/2000
Control	None	26.34 a	5.15 a	10.59 a
At planting	291	144.37 b	36.76 b	15.56 b
PSNT (MSU)	270	33.16 a	51.39 c	17.63 b
Sensor N	134	29.06 a	52.46 c	14.53 ab

Note: comparison and significance between N treatments at a given date. 202 kg of 291 kg/ha N was applied at planting and 84 kg/ha was applied on 6/20/2000 . For PSNT treatment the 270 kg/ha N was applied as 70 kg/ha (as starter N fertilizer for 2000 season only) and then after the PSNT was conducted at V6 (6/19/2000) and applied on 6/20/2000 according to the MSU N fertilizer recommendation. Then N fertilizer was not applied for PSNT treatment at silking after PSNT was conducted on 7/23/2000. For Sensor-based N treatment the 134 kg/ha was applied in 70 kg/ha increments. The first dose was applied at planting then from V6 to silking according to the nitrogen sufficiency index (NSI). If NSI of the N treatment was <96% of the reference treatment then N was applied.

Table 1.3. Analysis of variance table of KCl extract as soil NO_3-N (kg/ha) for PSNT at V6 leaf stage and at silking for 1999 and 2000 growing seasons

Source of Variation	1999	2000
Replication	NS	NS
Irrigation	NS	NS
N Treatment	***	***
Irrigation X N Treatment	NS	NS
Date	**	***
Irrigation X Date	NS	NS
N Treatment X Date	***	***
Irrig. x N Treatment x Date	NS	**

, *, **** significant at 0.05, 0.01, and 0.001 probability levels respectively

Table 1.4. Analysis of variance table of KCl extract for soil profile NO_3-N after corn harvest for 1999 and 2000 growing seasons

	1999			2000		
Source of Variation	Depth 1	Depth 2	Depth 3	Depth 1	Depth 2	Depth 3
Replication	NS	***	NS	**	NS	**
Irrigation	NS	****	NS	NS	NS	NS
N Treatment	***	****	****	**	****	****
Irrigation x N treatments	NS	NS	NS	NS	NS	NS

, *, **** significant at 0.05, 0.01, and 0.001 probability levels respectively

Table 1.5. Least squares means for post-harvest soil profile NO_3-N (kg/ha) for 1999 and 2000 growing seasons

	0 - 30 cm		30 - 61 cm		61 - 91 cm	
1999						
	Non-irrig	Irrigated	Non-irrig	Irrigated	Non-irrig	Irrigated
control	20.26	8.95	6.42	1.68	8.51	3.66
At planting	26.34	21.41	10.61	6.90	10.67	5.69
PSNT	45.06	21.41	15.35	9.27	11.04	10.74
Sensor	44.67	56.39	14.85	10.82	10.10	11.38
2000						
control		13.97 a		7.26 a		3.80 a
At planting		19.32 ab		11.49 ab		9.62 b
PSNT		21.15 b		15.47 b		11.13 b
Sensor		17.86 ab		9.55 ab		6.18 ab

Note significance at 0.05 probability levels across treatment at each depth. Irrig = irrigated.

Table 1.6. Analysis of variance table for plant nitrogen for 1999 and 2000 growing seasons

Source of Variation	1999 Earleaf	1999 Grain	1999 Stalk	1999 Yield	2000 Earleaf	2000 Grain	2000 Stalk	2000 Yield
Replication	NS	NS	NS	NS	NS	NS	NS	NS
Irrigation	NS	**	**	****	NS	NS	NS	NS
N Treatment	****	****	**	****	NS	NS	****	****
Irrigation x N	NS	NS	NS	****	NS	NS	**	NS

, *, **** significant at 0.05, 0.01, and 0.001 probability levels respectively

Table 1.7. Least squares means for plant nitrogen for irrigated and non-irrigated N treatments for a dry irrigated 1999 and a relatively wet 2000 season

	1999					2000		
Source of	Ear-leaf	Grain %		Stalk (ppm NO_3-N)		Ear-leaf	Grain	Stalk
Variation	%	Non-Irrig	Irrig	Non-Irrig	Irrig	%	%	(ppm)
Control	2.06a	1.30 a	1.09a	44a	22a	2.96a	1.33a	23a
At-planting	3.01b	1.57 b	1.33b	1335b	839b	3.09a	1.35a	1849b
PSNT	2.94b	1.53 b	1.29b	647c	416c	3.30a	1.39a	1282b
Sensor	2.90b	1.56 b	1.32b	722c	498c	2.98a	1.30 a	360a

Note: significance at 0.05 probability levels across treatment at each plant N parameter. Irrig = irrigated. Nitrogen expressed as percentage for earleaf and grain and as ppm for stalk.

Table 1.8. Average and effective vegetation indices, multiplier (a) and offset (b) from GNDVI, NDVI, and SAVI (2000)

Source of			Multiplier (a)			Offset (b)		
Variation	Avg	Effective	Avg	Stdev	CV	Avg	Stdev	CV
NDVI	0.7055	0.82288	1.167	0.0094	0.008	-0.1563	0.0014	-0.009
SAVI	0.7675	0.81869	1.173	0.0095	0.008	-0.1995	0.0019	-0.009
GNDVI	0.6445	0.76540	1.275	0.0132	0.010	-0.188	0.0023	-0.012

Avg is average, stdev is the standard deviation and CV is the coefficient of variation.

Table 1.9. Coefficient of determination (R^2) and RMSE for Kcb and Kcr for NDVI, SAVI and GNDVI for N treatments (2000)

Source of	NDVI		SAVI		GNDVI	
Variation	RMSE	R^2	RMSE	R^2	RMSE	R^2
Control	0.068	0.94	0.075	0.93	0.073	0.93
At-planting	0.081	0.91	0.098	0.87	0.077	0.92
PSNT	0.064	0.95	0.077	0.92	0.059	0.95
Sensor	0.064	0.95	0.077	0.92	0.060	0.95

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CHAPTER II
REMOTE SENSING OF CORN CANOPY DYNAMICS AND BIOPHYSICAL VARIABLES ESTIMATION IN MICHIGAN

ABSTRACT

This study was initiated to evaluate sensor-based nitrogen and water application for corn (*Zea mays* L.) in Michigan. The specific objectives of this study were: 1) to identify wavelengths that are more sensitive to N deficiency in corn, 2) to determine when to predict corn grain yield from spectral remote sensing data, and 3) to estimate biophysical variables of corn such as leaf area index (LAI) and fractional cover (Fc) from spectral vegetation indices (SVI) obtained from radiometric measurements over corn canopy. Nitrogen treatments included control, at-planting, pre-sidedress nitrate test (PSNT), and sensor-based N treatment based upon chlorophyll meter readings. Corn was either irrigated or non-irrigated. Sensitivity to N status centered around 560 and 810 nm. These two wavelengths provided the best separation between different N treatments. Corn grain yield was correlated with the NDVI (normalized difference vegetation index), the GNDVI (green normalized difference vegetation index), and with chlorophyll meter readings. The highest correlation between SVI and corn grain yield was achieved at the R2, R3, R4, and R5 growth stages. There was a very high correlation between the GNDVI and chlorophyll meter readings. These results suggested that GNDVI could be used to substitute for chlorophyll meter readings in N scheduling. While NDVI and GNDVI reasonably estimated the corn LAI, SAVI overestimated the LAI for all N treatments. All spectral vegetation indices performed very well in estimating Fc over the growing season.

INTRODUCTION

Optical remote sensing provides a powerful tool for monitoring changes in the crop canopy over the growing season and can provide crop developmental information that is time-critical for site-specific crop management. Radiometric measurements in the solar spectral domain contain important information pertinent to the health of vegetation. Remote sensing has been used to characterize properties of vegetation, to estimate yield, to estimate total biomass, and to monitor plant health and plant stress (Jackson and Pinter, 1986).

From an energy balance viewpoint, all solar radiant flux incident upon an object is either reflected, transmitted, or absorbed. Vegetation is unique in its three-segment partitioning of solar irradiance. In the visible part of the spectrum (400 - 700 nm), reflectance is very low, transmittance is nearly zero, and absorption is high. The fundamental control of energy-matter interactions with vegetation in this part of the spectrum is plant pigmentation. In this spectral range light reflectance increases with N deficiency (Blackmer et al , 1994). In the longer wavelengths of the near-infrared portion of the spectrum (700 - 1350 nm), both reflectance and transmittance are high whereas absorption is very low. Sensor-based strategies rely on the fact that N deficiency in corn reduces chlorophyll content of leaves thereby increasing the amount of light transmitted through a leaf. Because chlorophyll content affects the amount of light absorbed or reflected (Al-Abbas et al., 1974), leaf chlorophyll has been positively correlated with N concentration. A typical reflectance curve shows a peak at around 550 nm corresponding to green color due to reflection of light by chlorophyll and a dip in the plant spectral signature around 690 nm corresponding to a red color due primarily to chlorophyll absorption.

Many spectral vegetation indices (SVI) have been presented in the literature. Jackson and Huete (1991) interpreted the utility of some of the vegetation indices. Spectral vegetation indices (SVI) have been used to measure the photosynthetic capacity of a plant canopy and to estimate yield (Wiegand et al., 1991). Spectral vegetation indices reduce multiband observations into a single numerical index. The most widely used indices are:

1) Ratio Vegetation Index (RVI) - reflectance in the near infrared (NIR) spectral region divided by the reflectance in the red spectral region (red);
2) Green Ratio Vegetation Index (GRVI) - reflectance in the near infrared (NIR) spectral region divided by the reflectance in the green spectral region (green);
3) NDVI - normalized difference vegetation index calculated as (NIR-red)/(NRI + red);
4) GNDVI - green normalized difference vegetation index calculated as (NIR-green)/(NRI + green); and
5) SAVI - soil adjusted vegetation index - a modified NDVI using a constant (L) value of approximately 0.5 to block interference from soil background reflectance.

Biophysical variables that are of great interest and can be estimated from remote sensing data are grain yield, the leaf area index (LAI), and fractional cover (Fc).

Remote sensing has been used for yield estimation where grain yield has been correlated to a single measurement of NDVI. Tucker et al. (1980) used NDVI as a time integral to estimate yield. Blackmer et al. (1996) correlated relative corn grain yield to a reflective radiation from a photometric cell centered around 550 nm. They concluded that this wavelength was also more sensitive than other wavelengths to N stress in corn. Blackmer et al. (1996) analyzed aerial photos for N stress and found that black and white photos centered around 536 nm also predicted corn grain yield at the R5 growth stage. Therefore, identification of spectral wavelengths sensitive to N stress can aid in site-specific management of corn.

The leaf area index (LAI) is an important parameter in light interception by plants and was used extensively as an input to predict crop response in many simulation models. Remote sensing has been used to estimate biophysical variables such as LAI and Fc. There are three approaches as reported by Qi et al. (2000a) to estimate LAI. These include a simple regression that uses multi-band regression, a modeling approach and a vegetation index approach. The vegetation index approach is associated with SVI such as NDVI. Here the LAI can be estimated using an empirical relationship.

The LAI-SVI relationship has the following forms:

$$LAI = aX^3 + bX^2 + cX + d \tag{2.1}$$

$$LAI = a + bX^n \tag{2.2}$$

$$LAI = 1/2a \ln(1 - X) \tag{2.3}$$

where X is either vegetation indices or reflectance derived from remote sensing data. Coefficients a, b, c and d vary with vegetation type. This equation can be applied to remote sensing data to map spatial and temporal dynamics of vegetation (Qi et al., 2000a). The approach is simple and easy to compute. However, this approach varies with the form of the equation used (polynomial, power, or exponential), and the coefficients which depend on the vegetation types. Radiative transfer modeling is an alternative to the empirical approach. Here LAI is an input parameter to the model and reflectance is the output of the model. There are many models in the remote sensing literature (Suita, 1972, and Strahlar, 1994). The major advantage of modeling is that it is independent of vegetation types. Carlson et al. (1997) used a simple transfer model to illustrate that NDVI, LAI, and Fc are dependent on each other. Qi et al. (2000a) used an empirical approach to estimate LAI and Fc from imagery acquired from Landsat TM, SPOT VEGETATION, and aircraft sensors. Recently Qi et al. (2000b) used the Neural fuzzy inference system to estimate LAI from remote sensed data. Fraction cover (Fc) is a very important property of vegetation. It can be used on a daily basis when considering variable rate application of agricultural inputs. Qi et al (2000a) used the object void vegetation technique to estimate Fc from NDVI as follows:

$$Fc = (NDVI - NDVI_{soil}) / (NDVI_{veg} - NDVI_{soil}) \qquad (2.4)$$

where NDVI is the NDVI at any time while $NDVI_{soil}$ is the NDVI value of bare soil, and $NDVI_{veg}$ is the NDVI maximum of a pure pixel of vegetation.

Measurements of canopy multispectral reflectance can provide a quick, in-expensive, and non-destructive real time assessment of the corn crop status on a whole field basis.

Objectives

The objectives of this study were:

1) to identify spectral wavelengths that are more sensitive to corn N deficiency detection and yield estimation, 2) to identify the optimum growth stage for corn grain yield estimation, and 3) to estimate biophysical variables of corn such as LAI and Fc from multi-spectral data acquired over a corn canopy during two growing seasons.

MATERIALS AND METHODS

Site Description

The study was conducted at the W. K. Kellogg Biological Station (KBS), which is located in Southwest Michigan (85^0 24' W longitude, 42^0 24' N latitude) in the northern portion of the Midwest corn belt. The W. K. Kellogg Biological Station is on the pitted outwash plain of the morianic system left by the last retreat of the Wisconsin glaciation, about 12000 years ago (Robertson et al., 1997). Soils in the area were developed on the glacial outwash; soils at the site are Typic Hapludalfs, either fine-loamy, mixed, mesic Kalamazoo series or coarse-loamy, mixed, mesic Oshtemo series (Mokma and Doolittle, 1993). Mean annual temperature at KBS is 9.4^0C; precipitation is approximately 920 mm annually and spread evenly all throughout the year, and potential evaporation exceeds precipitation (30 years mean) for three growing months per year (Crum et al., 1990). These soils respond to irrigation in most years and are vulnerable to leaching because of the coarse textured soil materials and shallow depth of the groundwater. The experimental area is gently sloping, decreasing in elevation from west to north and decreasing in elevation from east to west. It is well known from previous studies that the soils are variable over short distances making it possible to conduct spatial variability studies (Francis J. Pierce, Personal communication).

Experimental Design

The experiment evaluated two irrigations and four N treatments in a split-plot experimental design. Irrigation was the main plot and N treatments were subplots with four replications. The irrigation treatments evaluated were 1) none (control), and 2) irrigation scheduled according to the Michigan irrigation scheduling program (Shayya et al., 1990). The four N fertilizer treatments evaluated included none (control), N applied at planting, (202 and 145 kg/ha for irrigated and non-irrigated corn respectively), N application based on PSNT values plus yield at V6 leaf stage of corn, and 4) stress-based N applied in 70 kg/ha increments using remotely sensed chlorophyll measurements.

***Measurement*s**

Water was applied to N treatments using drip irrigation system. Since N management and soil parameters affect corn growth and development, each N plot within the irrigation treatment was irrigated independently using a drip irrigation system devised to apply water between each row. The irrigation scheme used in the 1999 season consisted of applying 12.7 mm (0.5 inch) of water every 3 to 4 days; allowances were made for rainfall. Irrigation was scheduled in 1999 with the MSU SCHED program when 50% of plant available water was depleted within the crop root zone. The crop was exposed to water stress early in 1999 before irrigation lines were installed. A weather station at KBS provided input for irrigation scheduling calculations. A rain gauge was maintained at the site to ensure a site-specific rainfall record. Soil profile water content was measured weekly from planting to maturity using Time Domain Reflectometry (TDR). Time Domain Reflectometry access tubes were inserted in the middle of each plot prior to planting to a depth of 90 cm. A tube access probe with a mobile moisture meter (Trime Moisture Measuring System)™ was used to measure volumetric soil water content at 18, 36, 53, 71, and 89 cm intervals on a weekly basis.

A multi-spectral ground based radiometer (CropScan, MSR87) was used to measure the green, red, and NIR spectral reflectance bands. The CropScan radiometer contains a set of eight narrow band filters, centered at:

460 nm, 510 nm , 560 nm, 610 nm, 660 nm, 710 nm, 760 nm, and 810 nm.

The CropScan radiometer has a 28 degree field of view for reflected irradiation. The sensor was mounted on 2.62 m pole above the canopy at nadir viewing and a cherry picker was used when the crop was very high. Two measurements per plot were taken in 1999 between 10:30 am and 1:30 pm local time for the following dates: (day of the year) 162, 167, 175, 177, 181, 188, 195, 217, 224, and 238. Three measurements per plot were taken in 2000 on day of the year 161, 168, 172, 179, 188, 202, 208, 217, 222, 229, 238, 245, and 250. The sensor was oriented parallel to the corn rows resulting in an oval ground area of about 1.53 m^2. Weekly multi-spectral measurements were taken using the CropScan radiometer from the V6 growth stage to the R5 (dent) growth stage. Leaf area was measured from V6 (2000 season only) to silking for each plot using the LAI-2000 plant canopy analyzer (Li Cor (R) leaf area meter).

All fertilizer N was applied as 28% solution using a precise liquid fertilizer applicator equipped with a capacity to apply N throughout the N uptake phase of corn growth and development. Fertilizer N recommendations for corn following corn was based on MSU fertilizer recommendations (N recommendation = -27 + 1.36* yield goal). Pre-sidedress nitrate test (PSNT) fertilizer N rates were reduced based on the PSNT values (6*ppm N in the surface 0-30 cm). Nitrogen applied at planting time was 145 kg/ha for a yield goal of 7,800 kg/ha for non-irrigated corn and 202 kg/ha was applied for a yield goal of 12,480 kg/ha for irrigated corn. Nitrogen was applied in 70 kg/ha increments from V6 to V14 for sensor-based N treatments based on leaf chlorophyll readings.

A Minolta SPAD-502 mobile chlorophyll meter (Spectrum Technologies Inc.) was used to measure red (690 nm) and NIR (940 nm) canopy absorbance and transmittance in all plots. Leaf chlorophyll contents of 30 plants per plot were measured using a SPAD chlorophyll meter from V6 to V14 stages of growth to evaluate sensor-based chlorophyll readings treatment. Nitrogen fertilizer application was triggered in the stress-based N treatment when reflectance of corn reached 96% of the reflectance of well-fertilized corn as this level has been shown to maintain corn yield (Scheppers et al., 1996).

The soil was chisel plowed in the fall of 1998 and was fit with a field cultivator prior to planting in 1999 and in 2000. The site was mapped in the spring prior to planting for elevation and soil conductivity using commercial mapping procedures. These data were used in conjunction with soil profile measurements to establish the variability of soils and landscape parameters on the experimental site. Pioneer 3730 corn variety was planted on April 26, 1999 and April 29, 2000. The seeding rates were 64,250 seeds/ha for non-irrigated corn and 86,500 seeds/ha for irrigated corn. Crop measurements recorded included plant emergence, crop phenology, plant count and spacing, earleaf N at silking, stalk N, grain N, grain moisture, and grain yield. Soil measurements included water content at weekly intervals over the growing season using TDR, soil mineral N at V6 and silking (0 - 30 cm), and soil profile N after harvesting (0 - 90 cm). Corn grain yields were determined by harvesting two rows from each plot 9.84 m (30 ft) by 1.64 m (5 ft) for a total area of 16.1 m^2 (150 ft^2). Corn grain moisture was adjusted to 155 g/kg.

Statistical Analysis

An analysis of variance (ANOVA) and covariance was performed using the SAS Mixed Procedure (SAS Institute, 2000). The Mixed Procedure in SAS uses a maximum restricted likelihood estimation of linear statistical models involving both fixed and random terms, such as the linear model underlying the split-plot analysis and therefore was well-suited to this task. Because there was a significant N effect and irrigation x N interaction, regression analysis was performed on grain yield for each plot for all N treatments at different wavelengths and against selected vegetation indices such as NDVI, SAVI, RVI, GNDVI, and GRVI using the SAS PROC REG procedure (SAS Institute, 2000). Coefficients of determination and RMSE were reported in these results to compare the results at different wavelengths and the performance of spectral vegetation indices (SVI).

RESULTS AND DISCUSSION

Chlorophyll meter readings were used to schedule sensor-based N treatment by calculating a N sufficiency index (NSI). Nitrogen sufficiency index is the ratio of chlorophyl meter readings from different N treatments to the chlorophyl meter reading from a reference N treatment that has sufficient N. In this study the reference N treatment consisted of N applied at planting (145 kg/ha was applied for a yield goal of 7,800 kg/ha for non-irrigated corn and 202 kg/ha applied for a yield goal of 12,480 kg/ha for irrigated corn). The at-planting N treatment was the reference N treatment and compared to different N treatments over the entire growing season. The nitrogen sufficiency index for both 1999 and 2000 growing seasons is illustrated in Figure 2.1a and Figure 2.1b. The control treatment showed a decline in leaf chlorophyll content as the season progressed. Early season drought in 1999 resulted in a lower leaf chlorophyll content even after N was applied until irrigation or rainfall occurred in early July when leaf chlorophyll recovered as shown in Figure 1.2a. Figure 1.2b showed that leaf chlorophyll for sensor-based and PSNT N treatments for the 2000 growing season recovered immediately once the intervention management N was applied.

Canopy reflectance values for two years (percentage reflectance) showed sensitivity to N treatments centered around 560 nm, 710 nm, and 810 nm (Figure 2.2). The greatest separation between different N treatments occurred at wavelengths of 560, 710 and 810nm. The sensitivity centered around 560 nm where N strongly reflects light. When linear regression was performed on a single wavelength reflectance, it was clear that 560, 610, 710, and 810 nm have a better correlation with grain yield (Table 2.1). The correlation between a single wavelength and corn grain yield started very weak early in the season and peaked on day of the year 224 (August 12, 1999) that coincided with the growth stage of R5 (dent). Wavelength 560 nm ($R^2 = 0.90$ and RMSE = 875) was superior to all other wavelengths followed by 710 nm ($R^2 = 0.88$ and RMSE = 957), then 810 nm ($R^2 = 0.78$ and RMSE = 1298).

The relative reflectance as defined by Blackmer et al. (1996) is the ratio of reflected radiation from different N treatments to reflected radiation from a reference canopy treatment. The purpose of the relative reflectance is to eliminate non N-based illumination differences between different N treatments. Relative reflectance showed important information about wavelength sensitivity to N treatments at 560, 660, 710, and 810 nm at silking. However, after N was applied to PSNT and sensor-based N treatments the difference was only apparent between the reference N treatment and the control treatment and between irrigated and non irrigated treatments in 1999 (Figure 2.3).

Vegetation indices were extensively used in the past for yield prediction. The most widely used indices were RVI and the NDVI. Both indices use NIR and red reflectance values. Because corn N sensitivity centers around 560 um (which is the line between the green and the yellow) GNDVI and GRVI were tested here for corn grain yield prediction. GNDVI and GRVI are defined as follows:

$$GNDVI = (\rho_{NIR} - \rho_{green}) / (\rho_{NIR} + \rho_{green}) \quad (2.5)$$

$$GRVI = \rho_{NIR} / \rho_{green} \quad (2.6)$$

where ρ is the reflectance

Table 2.2 shows that there is a trend of low correlation between grain yield and vegetation indices prior to tasseling and after grain dent time late in the season. A 50% correlation was observed at silking. This increased at R2, R3 and reaches its maxima at R5 (dent). After R5 there was no correlation between corn grain yield and SVI. There was a significant difference between different SVI for corn grain yield prediction in the 2000 growing season. All SVI were very efficient in predicting corn grain yield (Figure 2.4a). GNDVI and GRVI were more superior in corn yield prediction than NDVI or RVI for 1999 (Figure 2.4b). This is attributed to the sensitivity of the green reflectance at 560 nm due to chlorophyll. This study suggests that corn grain yield is best predicted at reproductive stages of growth from milk to dent time. In addition, vegetation indices that use green reflectance values such as GNDVI and GRVI are better suited for corn grain yield prediction than vegetation indices that use red reflectance values. Improved correlation in 2000 growing season was attributed to a very wet growing season that did not require irrigation. Figure 2.4a shows a very high correlation between corn grain yield and chlorophyll readings acquired using the SPAD meter. This high correlation was only apparent at reproductive stages of growth. In addition, Figures 2.4a and 2.4b also illustrate the high correlation between GNDVI and the chlorophyll meter readings. This suggests that GNDVI or GRVI values could be used to replace chlorophyll meter readings in N scheduling. Green normalized vegetation index (GNDVI) is relatively easy to calculate and quick to acquire compared to a chlorophyll meter readings that require the measurement of 30 plant leaves.

Remote sensing can be used to estimate biophysical variable such as LAI and Fc. To examine the temporal dynamics of corn vegetation, LAI was measured for the 2000 growing season using a Li Cor 2000 leaf area meter. The data acquisition was not possible in the 1999 growing season. Leaf area index (LAI) is a variable describing the density of green vegetation and is defined as the total single-area of green leaves per unit ground area. We modeled LAI from NDVI, SAVI, and GNDVI for different N treatments (Figure 2.5a) using the equation developed by Qi et al. (2000) as follows:

$$GLAI = 18.99X^3 - 15.24X^2 + 6.124X - 0.352 \qquad (2.7)$$

$$LAI = 18.99X^3 - 15.24X^2 + 6.124X - 0.7 \qquad (2.8)$$

The equation was previously developed using data from grassland in the Southwest US. To apply this equation for corn we changed the coefficient that is not associated with the vegetation index (0.352) in the original equation to 0.7. When validating the modeled LAI with the measured LAI the results show that GNDVI is more accurate in estimating LAI than and SAVI (Figure 2.5b). Both NDVI and GNDVI did not predict LAI very well early in the season. However, they are consistent with published corn LAI values (Westgate et al., 1997). Conversely, SAVI over-predicted LAI because of soil background blockage inherent in the index. Green normalized vegetation index (GNDVI) performed better than NDVI in modeling LAI as shown in Table 2.3. This is due to the use of green reflectance values instead of red reflectance in developing the GNDVI.

In order to assess the temporal dynamics of the corn canopy, Fc was modeled using the equation 2.4. All vegetation indices including NDVI, SAVI, and GNDVI are very useful in modeling Fc. There was no significant difference between these indices in modeling Fc as shown in Figure 1.6. All indices predict Fc very reasonably except SAVI which exceeds 100% estimation of fractional cover probably due to human or experimental error.

CONCLUSION

Nitrogen deficiency in corn was detected using a radiometer in the short wavelength radiation in the range of 460 to 810 nm. A spectral region centered around 560 nm provided the best separation between different N treatments. These results suggest that a future corn N sensor could be developed that uses a simple combination of limited spectral bands centered around 560 and 810 nm for variable N rate application. Spectral vegetation indices such as GNDVI and GRVI performed better for corn grain yield prediction than RVI and NDVI. This was due to sensitivity to N deficiency in the green region of the spectrum that centers around 560 nm. Spectral vegetation indices (SVI) such as NDVI and GNDVI performed very well in estimating biophysical variables such LAI and Fc. Extensive ground truth data were still needed to verify the validity of these results. Finally, because remote sensing measurements in the temperate region are hampered by a very high percentage of cloud cover, care must be taken when making these measurements.

Table 2.1. Coefficients of determination (R^2) and RMSE between corn grain yield and wavelengths (510, 560, 610, 660, 710, 760, and 810 nm) at different dates for 1999

Wavelength, nm	Day of the Year	188	195	217	224	238
510	R2	0.42	0.32	0.51	0.68	0.005
	RMSE	2089	2263	1923	1559	2730
560	R2	0.38	0.39	0.794	0.90	0.09
	RMSE	2163	2141	1242	875	2615
610	R2	0.47	0.38	0.67	0.82	0.10
	RMSE	1985	2153	1566	1164	2600
660	R2	0.45	0.34	0.56	0.68	0.16
	RMSE	2023	2217	1822	1549	2503
710	R2	0.43	0.37	0.75	0.88	0.15
	RMSE	2061	2167	1370	957	2527
760	R2	0.12	0.02	0.49	0.68	0.12
	RMSE	2562	2709	1963	1557	2568
810	R2	0.20	0.0	0.63	0.78	0.12
	RMSE	2445	2737	1670	1298	2561

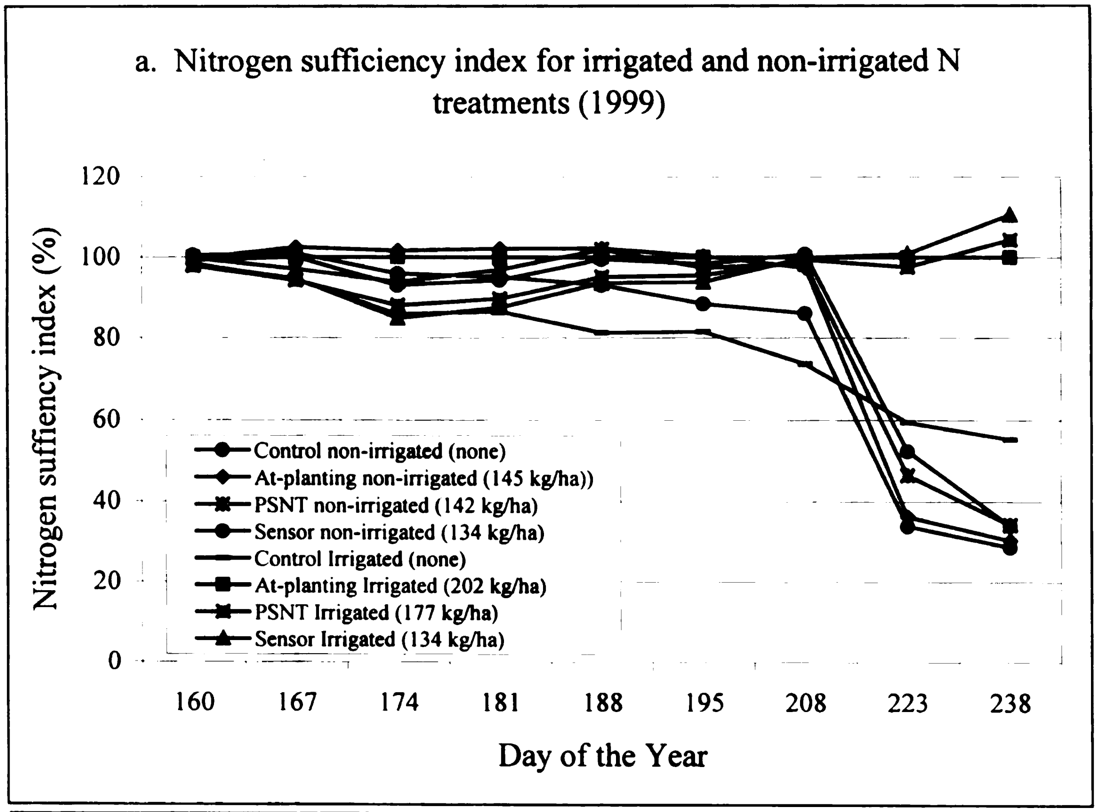
Table 2.2. Coefficient of determination (R^2) and RMSE between corn grain yield and vegetation indices at different dates and growth stages for 1999 and 2000.

DOY	NDVI		RVI		GNDVI		GRVI		Growth Stage
	R2	RMSE	R2	RMSE	R2	RMSE	R2	RMSE	
Coefficient of determination R^2 and RMSE (1999)									
162	0.10	2593	0.11	2589	0.07	2694	0.07	2709	V6 leaf
167	0.1	2601	0.1	2610	0.09	2613	0.09	2617	V7 leaf
175	0.49	1947	0.38	1956	0.34	2225	0.38	2236	V8 leaf
181	0.48	1934	0.48	1978	0.32	2258	0.48	2292	Tasseling
188	0.48	1966	0.49	1858	0.48	1973	0.50	1944	Tasseling
195	0.36	2195	0.40	2129	0.44	2046	0.45	2026	Silking
217	0.61	1719	0.74	1382	0.87	1002	0.90	853	R2 -R3
224	0.71	1487	0.82	1167	0.92	788	0.95	607	R5 -Dent
238	0.20	2456	0.18	2473	0.19	2468	0.16	2511	Maturity
Coefficient of determination R^2 and RMSE (2000)									
161	0.005	3258	0.002	3262	0.11	3074	0.11	3080	V6 leaf
168	0.12	3056	0.13	3055	0.12	3056	0.11	3088	V7-V8
172	0.27	2842	0.23	2878	0.29	2755	0.27	2783	V10
179	0.23	2861	0.23	2865	0.18	2960	0.18	2962	V12-V14
188	0.31	2601	0.27	2790	0.43	2357	0.37	2590	Tasseling
202	0.48	2345	0.48	2365	0.49	3232	0.49	2337	Tasseling
217	0.90	1002	0.86	1218	0.96	667	0.96	683	Silking
222	0.94	811	0.98	719	0.97	578	0.98	503	R2 -R3
229	0.91	992	0.96	760	0.96	561	0.97	554	R4
238	0.93	875	0.96	690	0.97	572	0.97	532	R5
245	0.70	1797	0.68	1840	0.74	1674	0.72	1743	R5
250	0.05	3182	0.04	3196	0.04	3203	0.03	3214	Maturity

Table 2.3. Coefficient of determination (R^2) and RMSE between measured and modeled LAI (from different vegetation indices) for different N treatments (2000).

Vegetation Indices	NDVI		SAVI		GNDVI	
N Treatment	R2	RMSE	R2	RMSE	R2	RMSE
Control	0.89	0.296	0.65	0.383	0.70	0.357
At-planting	0.94	0.244	0.90	0.316	0.95	0.211
PSNT	0.92	0.273	0.84	0.388	0.94	0.244
Sensor	0.92	0.286	0.88	0.363	0.94	0.246

Figure 2.1. Nitrogen sufficiency index (NSI) for all N treatments.
a) an irrigated 1999 season, and b) a non-irrigated 2000 season



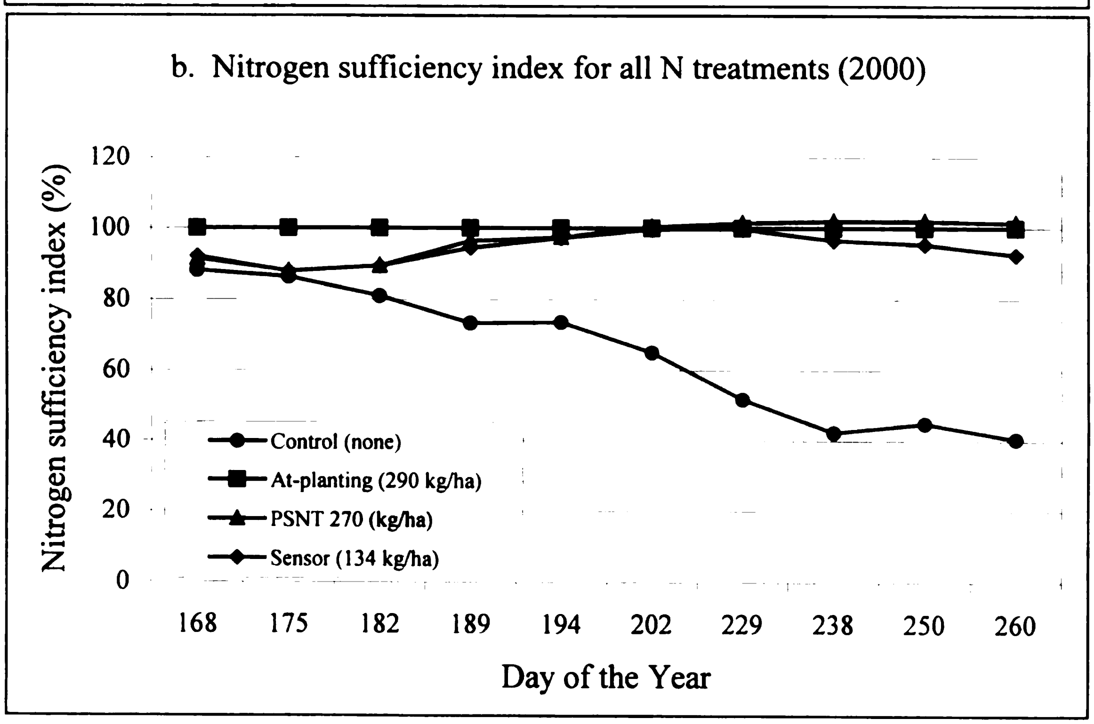


Figure 2.2. Percentage reflectance of N treatments at different wavelengths with a) irrigation in 1999 and b) without irrigation in 2000

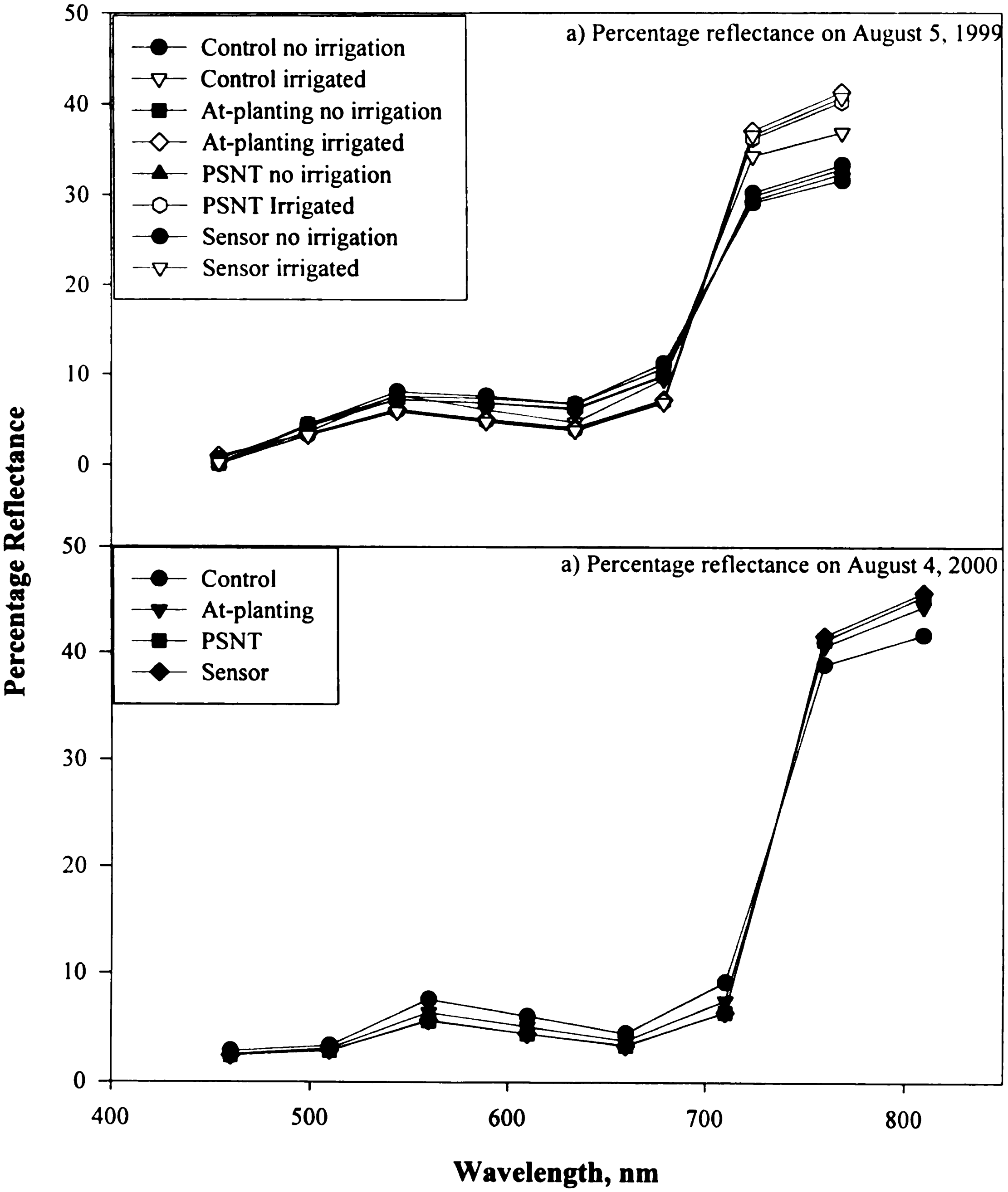


Figure 2.3. Relative reflectance for N treatments at all wavelengths with a) irrigation in 1999 and b) without irrigation in 2000

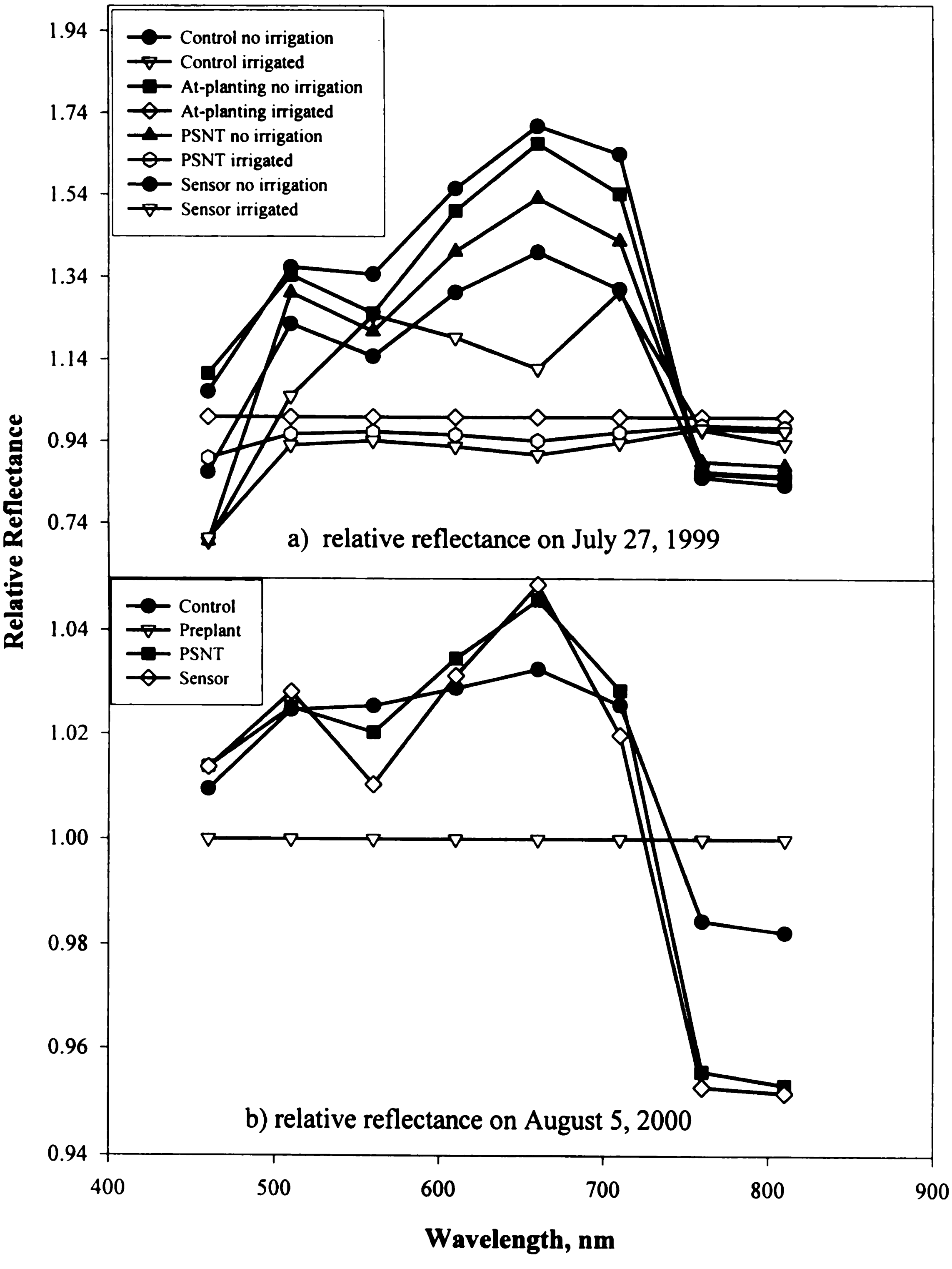


Figure 2.4a. Corn grain yield for all N treatments vs vegetation indices on August 12, 1999

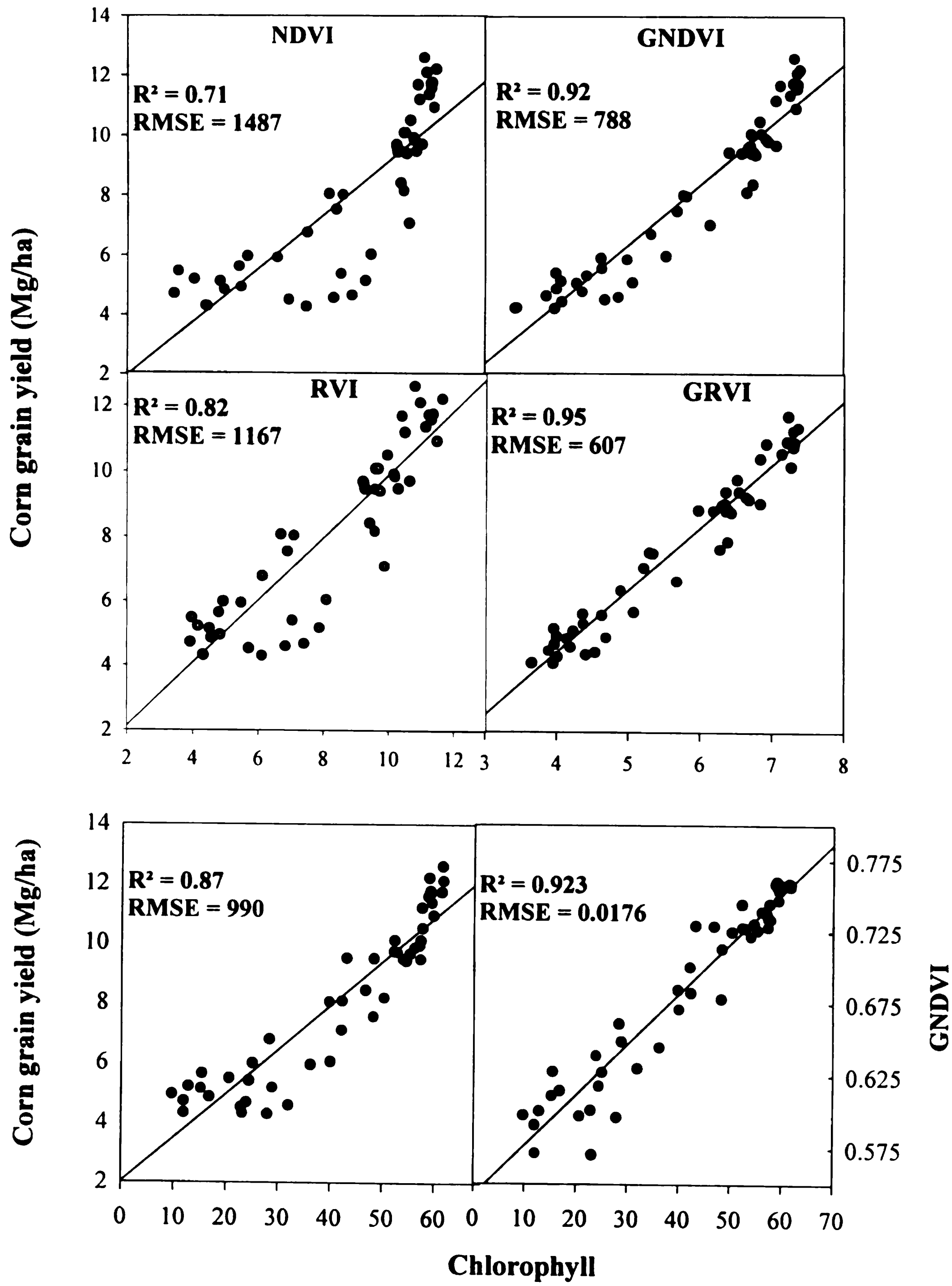


Figure 2.4b. Corn grain yield for all N treatments vs vegetation indices on August 9, 2000

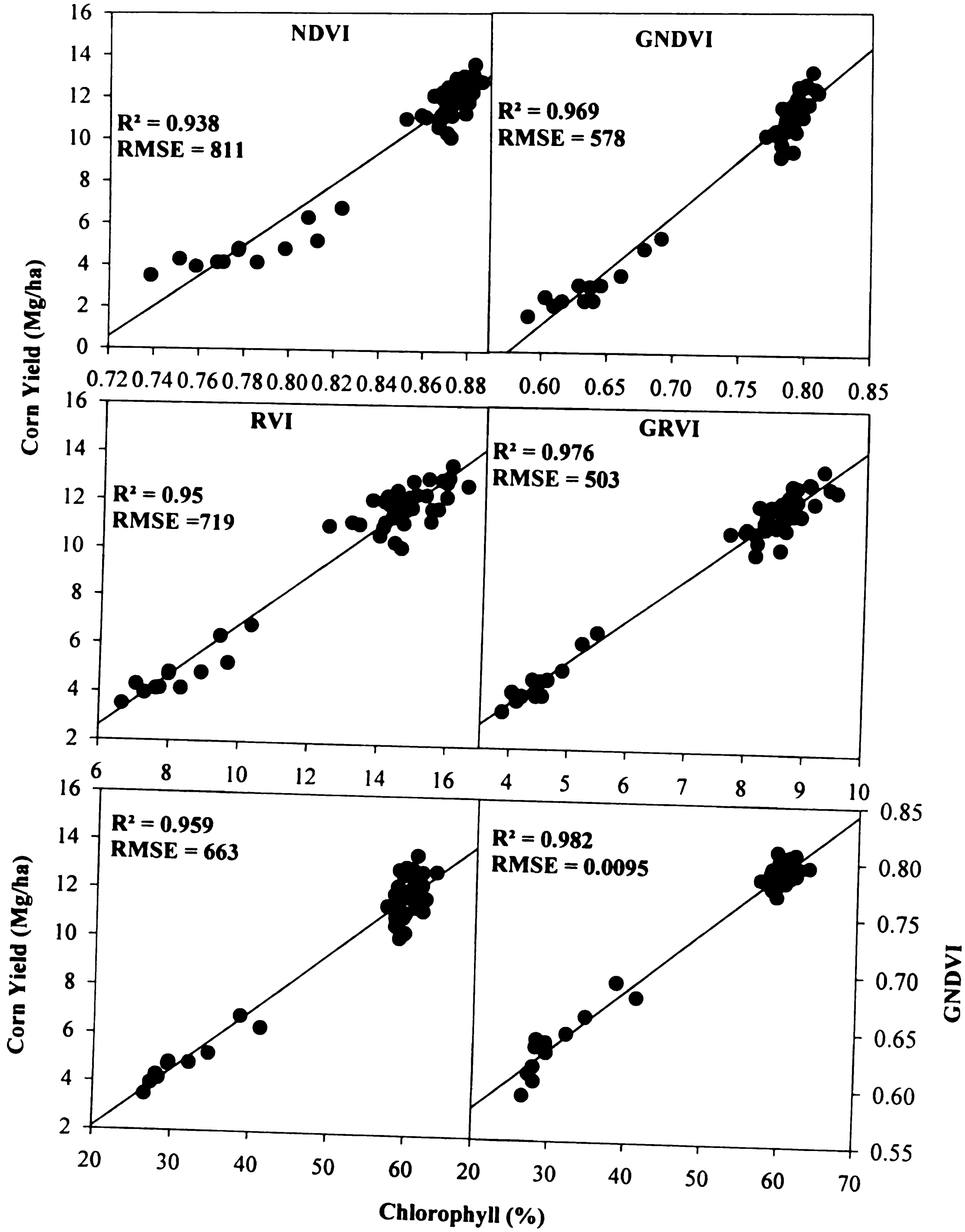


Figure 2.5a. Modeled leaf area index (LAI) from vegetation indices using empirical coefficients for N treatments (2000)

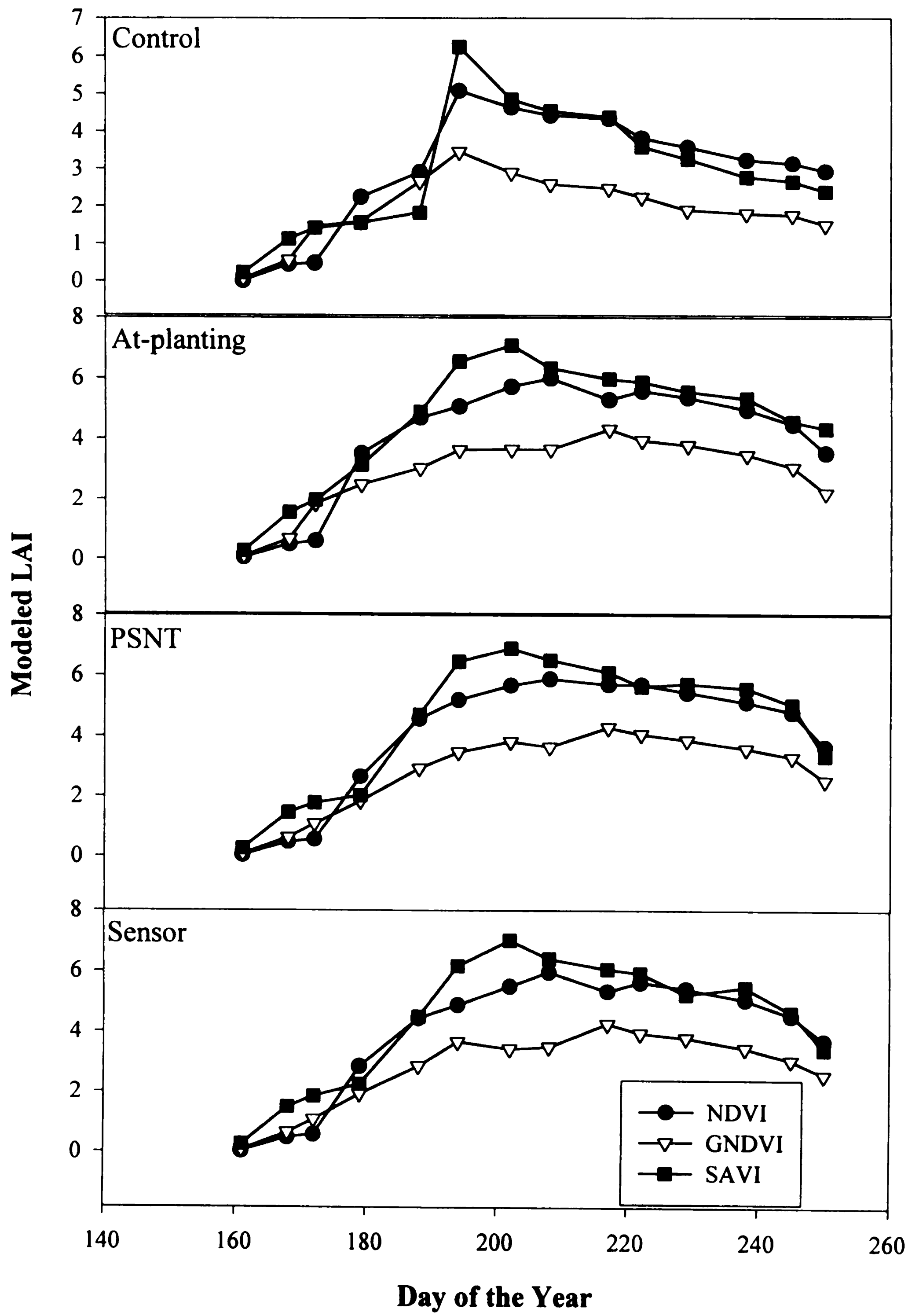


Figure 2.5b. Measured vs modeled LAI from vegetation indices for at-planting N treatment (2000)

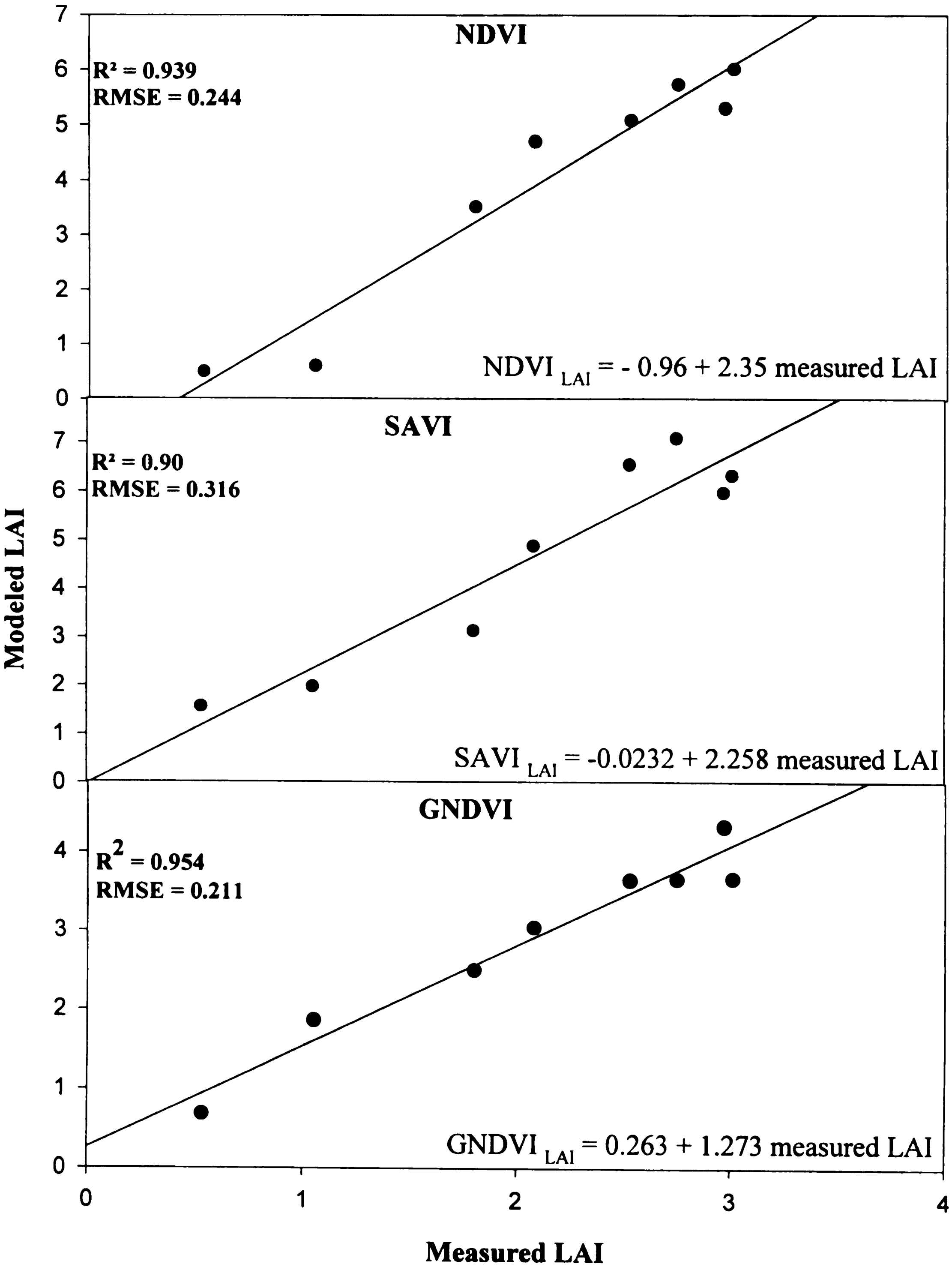
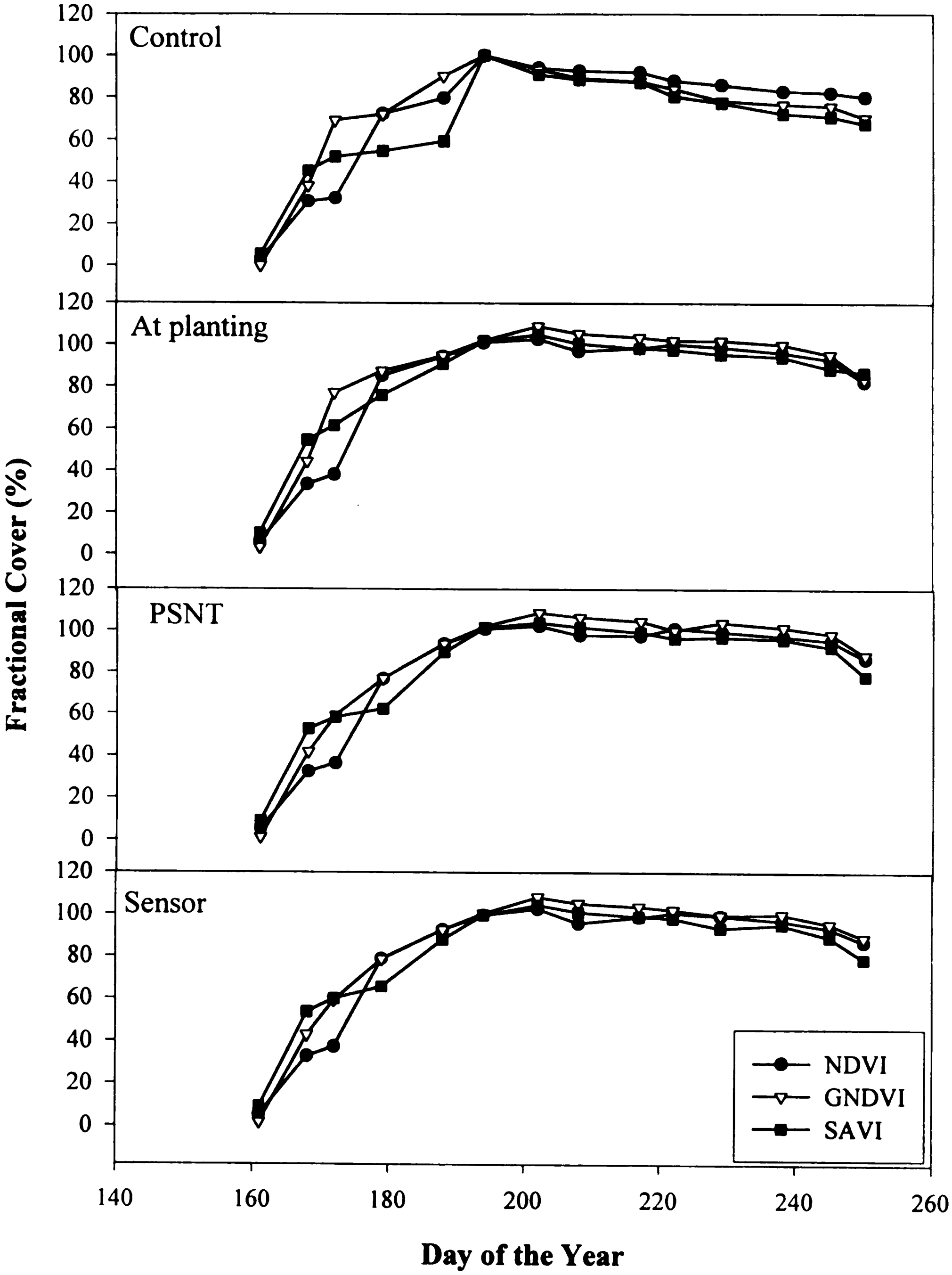


Figure 2.6. Modeled fractional cover from vegetation indices for N treatments (2000)



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CHAPTER III
ASSESSING THE SPATIAL VARIABILITY OF SELECTED SOIL RESOURCES AND THEIR RELATIONSHIP TO CORN GRAIN YIELD IN MICHIGAN

ABSTRACT

Understanding the structure of soil variability is imperative for the precise management of agricultural production systems. The objective of this study was to evaluate the spatial variability of selected physical soil properties and landscape attributes and their relationship to corn grain yield (*Zea mays L.*). Soil properties, such as horizon depth, bulk density, soil water content at - 10, - 33, and -1500 kPa, soil texture, as well as elevation and slope were collected from a 224 m long transect in a 48 plot field in Southwest Michigan. These properties exhibited a wide range of variability. Ap depth and Bt1 depth had coefficients of variation (CV) of 27.5% and 26.4% respectively. Soil texture in the Ap horizon was also highly variable. Variability of soil water content surprisingly was similar in the plowed layer and Bt1 horizon. Slope had the highest variation with a CV of 66%, while elevation exhibited the lowest variation with a CV of 0.3%. For all properties tested, variability exhibited strong spatial structure, and 50 to 100 percent of the sample variance was spatially dependent and autocorrelated over a range of 5 to 224 m. Stepwise multiple regression analysis showed that Ap depth, Ap silt, Bt1 bulk density, and Bt1 silt were significant in explaining corn yield variation. Corn grain yield and these soil properties exhibited a very strong spatial cross correlation and 50 -100% of the sample covariance was spatially dependent over a range of 26 to 212 m. Cumulative probability and Spearman rank correlation coefficient were used to evaluate the temporal stability of the spatial soil water storage over the growing season.

INTRODUCTION

Precision Agriculture (PA) or site-specific crop management (SSCM) involves the management of spatially variable factors according to localized conditions (Larson and Robert, 1991, and Pierce and Sadler, 1997). Pierce and Novak (1999) defined PA as the application of technologies to manage the spatial and temporal variability within all aspects of agricultural production for the purpose of improving crop performance and environmental quality. There is an increasing interest in whether this variability implies that there could be an advantage in managing field crops in a spatially variable way instead of treating them according to average conditions (Robert, 1993). Precision agriculture is concerned with variability in the two dimensions of space and time. Soil properties and processes that regulate corn production and environmental sensitivity vary in both space and time (Lake et al., 1997; Pierce and Nowak, 1999; Bell et al., 1995). Therefore, understanding the relationship between crop yield and environmental spatial variables is essential for SSCM.

Pierce and Nowak (1999) postulated that prospects for precision management increase as the degree of spatial dependence increases, but the degree of difficulty in achieving precision management increases with temporal variance. Without variability, the concept of precision agriculture has no meaning according to Mulla and Schepers (1997). They suggested that the most important factors in variability included spatial patterns in pest infestations, plant available water, soil drainage, crop rooting depth, nutrient availability, soil texture, organic matter content, and pH. Knowledge of soil variability within a field is a required first step in the development of PA strategies.

Variability of soil properties results in spatially varying crop yields. A preliminary report by Pierce and Warncke (1994) suggested that neither yield maps nor soil tests by themselves were sufficient to explain the crop yield variability. They also reported that there was little correlation between soil test levels and yield. Pierce et al. (1995) concluded that the grid sampling method had little effect on estimating accuracy of average field fertility. Corn yield was highly variable and generally not correlated to soil fertility. They added that plant population and soil physical properties, particularly their effect on water relations, were more important in explaining yield variability than fertility. One challenge for PA management is to determine which major factors are responsible for variations in crop yield. Beckett and Webster (1971) found that most within-field variability was within an area of one hectare.

Although the emphasis in PA had been on nutrient management, the correlation between soil nutrient levels and yield is not always strong (Pierce et al., 1995; Everett and Pierce, 1996). Plant available water, soil physical and morphological properties, and landscape attributes may be more important than soil fertility in explaining crop yield variability. Soil microbial activity (Robertson et al., 1988; Robertson et al., 1993; Robertson and Gross, 1994; and Robertson et al., 1997), soil moisture (Jaynes et al., 1995), and soil and landscape attributes (Khakural et al., 1996), have an evident effect on soil variability and hence on site-specific crop management.

Spatial data do not comply with the assumptions of classical statistics, in particular independence. Tobler's first law of geography (Tobler, 1970) states that "everything is related to everything else, but near things are more related than distant things". Soil properties frequently exhibit spatial dependence, i.e., samples collected close to one another are often more similar in value than widely spaced samples (Trangmar et al., 1985). Mallants et al. (1996) found spatial structure for water retention data in a multi-layered soil profile. There are many geostatistical methods available that have been adopted for detecting spatial dependence of soil properties. The most widespread is the semivariance analysis. Semivariance analysis provides a versatile and unbiased means for examining autocorrelation in environmental data (Robertson and Gross, 1994). This involves calculating the semivariance for all possible distance intervals within an area yielding a semivariogram or a variogram that describes the dependence among samples as a function of direction and separation distance, then fitting the appropriate model to the semivariogram (Issaks and Srivastava,1989). A variogram is basically a plot of dissimilarity (semi-variance) between samples against distance between samples (Issaks and Srivastava, 1989). The omnidirectional semivariance is defined as:

$$\gamma(h) = [1/2N(h)] \sum [z_i - z_{i+h}]^2 \tag{3.1}$$

where:

$\gamma(h)$ = semivariance for interval distance class h;
z_i = measured sample value at point i;
z_{i+h} = measured sample value at point i + h; and
N(h) = total number of samples for the lag interval h.

The semi-variance ideally increases with distance between sample locations, to a more or less constant value (the sill or total semi-variance or the population variance) at a given separation distance, called the range of spatial dependence (Trangmar et al., 1985).

Attributes separated by distances closer than the range are spatially related. Those separated by distances greater than the range are not spatially related. The semi-variance, when the distance of sample separation tends to zero, or y -intercept, is called the nugget variance or nugget effect (Webster, 1985). The nugget effect gives an indication of variability at scales less than the data spacing and/or due to analytical or random error. The difference between the sill and the nugget is the structural variance. The proportion of the total variance accounted for by the structural or spatially dependent variance (Structural/(Structural + nugget)) is a useful index of the spatially dependent predictability of the attribute. As an exploratory tool, the semivariogram documents any spatial component to the variability and the strength of the component. The semivariogram also reveals the spatial scale over which autocorrelation occurs. Using geostatistical procedures, Mallants et al. (1996) concluded that most hydraulic parameters, including water retention, at different profile layers fit semivariograms that could be described by means of spherical model functions with a spatial range from 4 to 7 m. Variograms for bulk density have ranges reported to vary from 18 to 56 m (Boyer et al., 1996; and Chung et al., 1995) and can differ between horizons of a given profile, e.g. 35 m for Ap horizon and 51 m for the A1 horizon, as documented by Poier and Richter (1992). Other soil physical characteristics reported to exhibit spatial dependence include saturated hydraulic conductivity (range varied from 10.2 and 13.8 m) as reported by Reinert (1990); sand content (range = 40 m), silt content (range = 78 m), clay content (range = 43 m) as documented by Boyer et al. (1996); and organic carbon content (range varied from 47 to 56 m) reported by Boyer et al. (1996). The semivariogram documents whether there are spatial components to the variability and how distinct the patterns may be. The semivariogram also reveals the spatial scale over which autocorrelation occurs.

Though variability may occur naturally as a result of complex geological and pedological or manmade processes, knowing the degree of spatial dependence and its extent is critical for evaluating its agricultural significance. Semivariance analysis can quantify the degree of spatial dependence for an attribute and explicitly define the scale over which the dependence is expressed. That makes the analysis more valuable for inferences about the attributes and possible effects on associated plants (Robertson and Gross, 1994). Application of geostatistical techniques may provide more power for analyzing spatial variability and semivariance analysis gives a robust means for quantifying autocorrelation in spatial and temporal dimensions.

Objectives

The objective of this study was to assess the spatial variability of selected soil physical properties and landscape attributes and their relationship to corn grain yield and additionally, evaluate the temporal stability of spatial soil water storage.

MATERIALS AND METHODS

The study was conducted at the W. K. Kellogg Biological Station (KBS), which is located in Southwest Michigan (85^0 24' W longitude, 42^0 24' N latitude) in the northern portion of the Midwest corn belt. The W. K. Kellogg Biological Station is on the pitted outwash plain of the morianic system left by the last retreat of the Wisconsin glaciation, about 12000 years ago (Robertson et al., 1997). Soils in the area were developed on the glacial outwash; soils at the site are Typic Hapludalfs, either fine-loamy, mixed, mesic Kalamazoo series or coarse-loamy, mixed, mesic Oshtemo series (Mokma and Doolittle, 1993). Mean annual temperature at KBS is 9.4^0C; precipitation is approximately 920 mm annually and spread evenly throughout the year, and potential evaporation exceeds precipitation (30 years mean) for three months per year (Crum et al., 1990). These soils respond to irrigation in most years and are vulnerable to leaching because of the coarse textured soil materials and shallow depth of the groundwater. The experimental area is gently sloping, decreasing in elevation from west to north and decreasing from east to west. It is well known from previous studies that the soils are variable over short distances making it possible to conduct spatial variability studies (Francis J. Pierce, Personal communication).

Measurements

The experiment evaluated two irrigation and four N treatments in a split-plot experimental design. Water was applied to N treatments using drip irrigation. Since N management and soil parameters affect corn growth and development, each N plot within the irrigation treatment was irrigated independently using a drip irrigation system devised to apply water between each row. The irrigation scheme used in the 1999 season consisted of applying 12.7 mm (0.5 inch) of water every 3 to 4 days; allowances were made for rainfall. Irrigation was scheduled in 1999 with the MSU SCHED program when 50% of plant available water was depleted from the crop root zone. The crop was exposed to water stress early in 1999 before irrigation lines were installed. A weather station at KBS provided input for irrigation scheduling calculations. A rain gauge was maintained at the site to ensure a site-specific rainfall record. Soil profile water content was measured weekly from planting to maturity using Time Domain Reflectometry (TDR). Time Domain Reflectometry (TDR) access tubes were inserted in the middle of each plot prior to planting to a depth of 90 cm. A tube access probe with a mobile moisture meter (Trime moisture measuring system)™ was used to measure volumetric soil water content at 18, 36, 53, 71 and 89 cm intervals on a weekly basis.

In 2000, intact soil profile cores were obtained from the center of each plot immediately after harvesting. Plastic sleeve tubes (4.127 cm internal diameter and 91 cm depth) were inserted into the hydraulic truck probe from the surface to a depth of 91 cm. The samples were taken away from the wheel track and 20 cm away from the corn row. The sampled tubes were capped at both ends, transported to the laboratory and stored at 4°C. The soil samples were classified according to different horizons and each horizon thickness was then recorded. Duplicates of undisturbed small sections (5 cm depth) were cut from each soil horizon and water retention was measured at -10, -33 and -1500 kPa (Klute, 1986). The horizons were identified as Ap, Bt1, Bt2, and 2bt2 (C). The section was then oven dried at 104 °C and used for bulk density determination (Blake and Hartge, 1986). The remainder of the samples were carefully ground and used to determine particle size by the standard hydrometer method (Gee and Bauder, 1986). Water retention for Ap and Bt1 horizons was determined at -10, -33 and -1500 kPa (Klute, 1986) on weight basis, then converted to volumetric water content by multiplying by the bulk density. Plant available water was computed as the difference between water content at field capacity (water content at - 10 or - 33 kPa) and water content at - 1500 kPa. Available water storage capacity (AWSC) for each horizon was computed by multiplying the depth of the horizon by plant available water. Soil properties for each horizon are recorded in the appendix, Tables 1- 4.

The experimental plots were chisel plowed in the fall of 1998 and fit with a field cultivator prior to planting in 1999 and in 2000. The site was mapped in the spring prior to planting for elevation using as global positioning system (GPS) and soil electrical conductivity using electromagnetic induction (EM38). These data were used in conjunction with soil profile measurements to establish the variability of soil and landscape parameters on the experimental site. Pioneer 3730 corn variety was planted on April 26, 1999 and April 29, 2000. Corn grain yields were determined by harvesting two rows from each plot 9.84 m (30 ft) by 1.64 m (5 ft) for a total area of 16.1 m^2 (150 ft^2). Corn grain moisture was adjusted to 155 g/kg moisture.

Statistical Analysis

Stepwise multiple linear regression was performed on corn grain yield for selected soil physical properties to determine what factors affect yield the most using the SAS Proc Reg Procedure (SAS Institute, 2000). Spatial statistics (S-Plus) software was used to develop the scatter plots for auto- and cross-correlation plots and calculate the slope for the spatial data. Geostatistical analysis (Robertson and Gross, 1994) was performed using GS + (Gamma Design 5.1, 2002). Gamma design software (GS +) was used to develop semivariogram and cross variograms for auto-and cross-correlation plots. The proportion of the sample variance (the variogram sill or $C_o + C$) explained by the structural variance C ($C/C_o + C$) was used as a measure of spatial dependence for all variables. If this proportion ($C/C_o + C$) approaches 1, spatial dependence is high: a large proportion of a sample variance, s^2, is spatially dependent (Robertson et al., 1997). When this proportion approaches zero, apparent spatial dependence is low indicating that measurement error is high or spatial dependence occurs primarily at scales smaller than the average distance of the first lag separation distance. The range is the separation distance over which sample locations are autocorrelated, i.e. over which there is spatial dependence among sample locations. For some models there is a difference between the range parameter A_o and the effective range. The range parameter is the value A_o that is used in the formula that defines the best-fit line. The effective range is the separation distance at which the spatial dependence is apparent. For spherical and linear-to-sill models the effective range is defined as A_o. For exponential models the effective range is defined as $3 * A_o$, or the distance at which the sill is within 5% of the asymptote. For gaussian models the effective range is $(3^{0.5}) * A_o$. Reduced sum of squares (RSS) were used here as a criterion to choose the model that best fit the data.

To characterize soil water content and soil water storage for precise variable rate irrigation application, the temporal stability of spatial soil water content variation has to be

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be determined. Vachaud et al. (1985) used cumulative probability function and the Spearman correlation coefficient with mean relative difference and the standard deviation of the time mean technique to evaluate the temporal stability of spatial soil water storage. Cassel et al. (2000) applied the Spearman correlation coefficient technique to evaluate the temporal stability of soil spatial water content. The method uses the Spearman rank correlation coefficient as a criteria to evaluate the temporal stability of spatial soil water content. The relative difference in soil water content is defined by:

$$\delta_{i\,j} = (\theta_{i\,j} - \theta_j) / \theta_j \qquad (3.2)$$

where:

j is time of the measurement
θ_{ij} is soil water content measurement at location i
θ_j is the average soil water content

RESULTS AND DISCUSSION

Figure 3.1a and 3.1b illustrate sample locations for the 48 plots overlain over the contour lines and the elevation of the study site. Table 3.1 summarized the statistics of corn grain yield and selected physical soil properties and landscape attributes for the 48 plots across the transect of the study area. Corn grain yield ranged from 3.504 to 13.565 Mg/ha due mainly to N treatments effects. Ap depth ranged from 20 to 54 cm with a coefficient of variation (CV) of 27.5 percent and a mean of 30.75 cm above the mean of Ap horizon depth (25 cm) for a typical sandy loam soil (Cassel et al., 2000). Water content ranged from 0.144 to 0.262, from 0.128 to 0.247, and from 0.027 to 0.081 m^3/m^3 for 10, - 33, and - 1500 kPa with CV of 14, 15, and 19.5% respectively. Plant available water for Ap horizon ranged from 0.117 to 0.231 m^3/m^3 for - 10 kPa and from 0.086 to 0.214 m^3/m^3 for - 33 kPa. Available water storage capacity (AWSC) ranged from 3.120 to 11.628 cm for - 10 kPa and from 2.559 to 10.514 cm for - 33 kPa with CV of 34 and 37 percent respectively. The Ap horizon bulk density ranged from 1.11 to 1.47 g/cm^3 with very little variation along the transect. The Bt1 bulk density ranged from 1.18 to 1.87 g/cm^3 with a CV of 14% as shown in Table 3.1. The Ap soil texture varied widely. Sand content ranged from 24.6% to 76.35% sand with a CV of 23.8%, and a mean of 46.37%, silt content ranged from 10.05 to 65.02% with a CV of 26.7% and a mean of 39%, and clay content ranged from 7.7 to 24.3% with a CV of 23.3% and a mean of 14.61%. Slope ranged from - 3.4% to 0 with a mean of 1.6% and exhibited the highest variation among all variables measured in this study with a CV of 66.1%. The elevation ranged from 283.45 to 285.44 m with an average of 284.4 m and exhibited the minium variation among all variables measured with a CV of 0.3%.

Variograms revealed that all studied soil properties showed spatial dependence although to different degrees. Ap thickness, sand, silt and clay contents, bulk density, elevation, and slope all exhibited strong auto-correlation within the range from 5 to 224 m with spatial structural variance accounting for more than 95% of the total model variance with the exception of clay content (53%) and bulk density (66%) as summarized in Table 3.2. Ap texture was well structured except for clay which had the lowest spatial structure as illustrated in Figure 3.2. Because N treatments had a significant effect on corn grain yield, corn grain yield residuals were used in the geostatistical analysis and showed a spatial dependence over a range of 31.5 m. The spatial dependence of the e

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elevation and slope exceeded the range of 224 m we examined (Table 3.2). Ap depth, soil texture, bulk density, and corn grain yield all had a spatial range of less than 75 m proving that these soil are highly variable and changed over short distances. Therefore, when making precision crop management decision one must take into account the size of the research plots or management zones.

Variograms of Ap soil water at different pressures showed that the auto-correlation of soil water content and available soil water storage capacity had a very narrow range (Figure3.3). A 50 m range was used for comparative reasons; however, when soil water was autocorrelated over the entire range the correlation was very weak (Table 3.3). Ap soil water content was autocorrelated over a range of 19 and 18 m for - 10 and - 33 kPa pressure respectively, and available soil water storage capacity autocorrelated over a range of 32 and 30 m for - 10 and - 33 kPa respectively. There was no significant difference between the range of autocorrelation of soil water content at different pressures whether we used 50 m range or the entire range. Nonetheless, the correlation coefficient indicated by the R^2 is very low for the entire range for soil water content at both pressures. When the entire range was used for available water storage capacity, it was autocorrelated over a range of 203 and 197.6 m for -10 and - 33 kPa respectively. In addition, the coefficient of determination was very high for both the entire range and the 50 m range. These results illustrate that soil water content in these soils were autocorrelated only over very short distances. Therefore, a management decision has to take into account this variability in managing these soils for research purposes and precision water management decisions.

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In order to study the spatial relationship between corn grain yield and soil properties, the factors that affect yield the most need to be identified. The stepwise multiple regression analysis was used to identify the most important soil properties affecting the variation observed on crop yield among the 48 studied plots. Stepwise model selection was applied to yields (after adjusting the effects of nitrogen treatment using a dummy variable). Among all available soil measurements, only those with a variance inflation factor below 10 were used as independent variables. This was carried out to minimize multi-colinearity among soil properties (Freund and Littell, 2000). For the Ap horizon, properties that satisfied this condition were thickness, bulk density, available water storage capacity at – 10 kPa (AWSC10), silt content, slope, and elevation. All of them were able to explain collectively only 29% of the variation observed on yield after adjusting for the effect of nitrogen treatments. The results for the stepwise model selection were presented in Table 3.4. The only two factors accounting for significant variation were Ap depth and Ap silt. Ap depth accounted for the most variation; however it explained only 20% of the total variation of corn grain yield.

For the Bt1 horizon, the soil properties used in the stepwise model selection were depth, bulk density, available water storage capacity at 10 kPa (AWSC10), sand content, silt content, slope, and elevation (after excluding properties with variance inflation factor greater than 10). These soil properties collectively explained 38% of the variation on corn grain yield. Two factors accounted for significant variation of 37%: Bt1 bulk density and Bt1 silt (Table 3.4). The bulk density accounted for the most variation at 24% and Bt1 silt explained the additional 13%.

The spatial relationship between these significant variables and corn grain yield over a 100 m range was illustrated in Figure 3.4. Although elevation was not significant in the stepwise regression analysis, it is shown here in Figure 3.4 to illustrate the spatial relationship between corn grain yield and elevation. All these properties expressed strong spatial relationship with corn grain yield (Table 3.5). The structural cross correlation variance explained more than 88% of the sample variance. One exception was Bt1 bulk density for which the cross correlation variance explained only 65% of the sample variance.

In these glaciated, rolling soils, elevation and slope are the major factors determining many soil properties such as soil water and soil texture (Robertson et al., 1997). Figure 3.5 shows the spatial relationship between elevation and Ap soil water at different pressures, Ap thickness, and Ap silt content. With the exception of Ap soil water content, all properties showed a nested periodic pattern and therefore, fit to a gaussian model as shown by the model parameters in Table 3.6. All the properties showed strong cross correlation with elevation, because the structural cross correlation variance explained more than 99% of the cross sample variance. The only difference was the range over which this cross correlation occurred. The smallest distance was water content that occurred over a range of 122 m and Ap silt that ranges over 150 m. Available water had the highest range of 711 and 570 for -10 and - 33 kPa respectively.

The spatial cross correlations between slope and Ap soil water, Ap thickness and Ap clay showed similar patterns of elevation for these properties (Figure 3.6) with the exception that these properties were negatively correlated to slope. There was a strong spatial cross correlation where the cross structural variance explained almost all the cross sample variance (Table 3.7). Again, with the exception of the Ap soil water content, all the properties showed a nested periodic pattern that was fitted to a Gaussian model.

In order to characterize spatial soil water content and storage, and reduce the number of measurements or samples for site-specific crop management, the temporal stability of spatial water content variation was evaluated as described by Vauchad (1985). Volumetric soil water content was measured on a weekly basis using TDR access tubes for five intervals segments to 90 cm depth. The five depth intervals were 18, 36, 53, 71, and 89 cm for 17 measuring dates throughout 2000 growing season. Figure 3.7 illustrates the dynamics at three measuring dates (at the beginning of the season, silking, and at physiological maturity) for the five depth intervals. It was clear the lowest measurements occurred on July 22nd because of the plant root actions and the high demand for water by the crop. To characterize the temporal stability of spatial water content and spatial water storage, cumulative probability function and Spearman rank correlation coefficient were used. Spearman rank correlation coefficient used in conjunction with measurements mean relative difference and the time standard deviation.

The data for soil water storage was ranked from smallest to largest and the cumulative probability function was identified as normal. The 50% probability was selected as field average storage. In addition, one standard deviation, σ ,and 2σ could be selected for extreme locations. This method depends on the probability of a certain location to maintain its rank in the cumulative probability function for different measuring dates as illustrated in Figure 3.8. The methods were defined by Vachuad et al.

(1985) as time stability and they suggested that the wet locations would remain wet and the dry locations would remain dry because of soil texture. Spearman rank correlation coefficient, the mean relative difference and the standard deviation were also used to characterize the temporal stability of spatial soil water storage (Vachuad et al., 1985). Spearman rank correlation coefficient, the mean relative difference and the standard deviation were computed for soil water content and soil water storage measurements using SAS software (SAS institute 2000). The criteria used for significance of the rank is that, "The smaller the standard deviation the more significant is the rank". The location that their respective rank was relatively stable could be used as a management zone for homogeneous water application and no more soil sampling would be needed. Locations with unstable rankings need to be sampled frequently and treated differently when using variable rate irrigation. Figure 3.9 presents the temporal stability of soil water storage using the Spearman correlation coefficient, the mean relative difference, and the standard deviation. Figure 3.10 shows a stable temporal stability in soil water content measured by the mean relative difference in the upper depths compared to the lower depths due to the actions of plant roots. Our results showed that the rank was different for the same plot at different depths because of soil textural differences. The mean relative difference increased with depth because of the stability of the parent material in deeper layers as reported by Cassel et al. (2000)

CONCLUSION

Soil properties such as depth of the horizon, bulk density, soil water content at - 10, - 33, and -1500 kPa, soil texture, elevation, and slope from a 224 m long transect exhibited a wide variability. For all properties tested, variability exhibited strong spatial structure, and 50 to 100 percent of the sample variance was spatially dependent and autocorrelated over a range of 5 to 224 m. Stepwise multiple regression analysis was applied on yields to identify the most important soil properties affecting the variation. Ap depth and Ap silt were significant in explaining yield variation in Ap horizon. Bt1 bulk density and Bt1 silt were significant in explaining corn yield variation on Bt1 horizon. Surprisingly, soil water content was not significant in the stepwise multiple regression to identify the most important variable that affected corn grain yield. That may be due to the fact that samples for this study were taken in a relatively wet year (2000) which did not require irrigation. Corn grain yield and those soil properties in the Ap and Bt1 horizon exhibited a very strong spatial cross correlation. Fifty-100% of the sample covariance was spatially dependent over a range of 26 to 212 m. Spearman rank correlation coefficient of the soil water content showed a relatively temporal stability in the upper depth of soil and a relative temporal instability in deeper depths. It is evident from these results that the soil resources tested were highly variable and very heterogeneous. In addition, these soil properties were spatially structured. The degree and scale of spatial dependence found in this study was similar to a previous experiment at KBS by Robertson et al. (1988). This structure should be considered when designing an experiment and making management decisions. Geostatistical analysis provided a substantial and a robust technique for determining the scale over which spatial dependence occurs.

Cumulative probability function, Spearman rank correlation coefficient, the mean relative difference, and the standard deviation values were used to characterize the temporal stability of the spatial water content and the spatial soil water storage. The smaller the standard deviation, the more significant the rank. The locations at which their respective ranks are relatively stable can be used as a management zone for homogeneous water application, and no more soil sampling would be needed except low, medium and high rank locations. There was a stable temporal stability in soil water content in the upper depths compared to the lower depths due to the actions of plant roots.

Table 3.1. Statistics for corn grain yield and selected physical soil properties and landscape attributes for 48 sample locations along the main transect. SD is the standard deviation and CV is the coefficient of variation

Variable	mean (SD)	Range		CV
Number of samples	48	48		48
		Min	Max	%
Corn grain yield (Mg/ha)	10.10 (3.23)	3.504	13.565	32
EM38	13.94 (0.62)	12.80	15.20	4.5
Slope %	0.016 (0.01)	-0.004	0.034	66.1
Elevation (m)	284.40 (0.78)	283.45	285.44	0.30
	Ap Horizon			
Depth (cm)	30.75 (8.46)	20.00	54.000	27.5
Water content - 10 kPa m^3/m^3	0.196 (0.028)	0.144	0.262	14.2
Water content - 33 kPa m^3/m^3	0.177 (0.028)	0.128	0.247	15.6
Water content - 1500 kPa m^3/m^3	0.062 (0.012)	0.027	0.081	19.4
Available water at - 10 kPa m^3/m^3	0.17 (0.027)	0.117	0.231	16.1
Available water at - 33 kPa m^3/m^3	0.146 (0.027)	0.086	0.214	18.5
Available water storage capacity at - 10 kPa	5.22 (1.8)	3.12	11.628	34.4
Available water storage capacity at - 33 kPa	4.52 (1.71)	2.560	10.514	37.80
Bulk density (g/cm^3)	1.27 (0.09)	1.109	1.465	7.3
Sand %	46.37(11.03)	24.60	76.350	23.8
Silt %	39.03 (10.41)	10.05	65.015	26.7
Clay %	14.61 (3.4)	1.100	24.30	23.3
	Bt1 Horizon			
Depth (cm)	24.73 (6.53)	12.00	40.00	26.4
Water content - 10 kPa m^3/m^3	0.195 (0.033)	0.150	0.281	16.8
Water content - 33 kPa m^3/m^3	0.176 (0.028)	0.131	0.236	15.7
Water content - 1500 kPa m^3/m^3	0.059 (0.012)	0.025	0.075	19.5
Available water at - 10 kPa m^3/m^3	0.19 (0.028)	0.142	0.256	14.9
Available water at - 33 kPa m^3/m^3	0.164 (0.022)	0.120	0.207	13.3
Available water storage capacity at - 10 kPa	4.72 (1.59)	2.180	8.621	33.7
Available water storage capacity at - 33 kPa	4.07 (1.338)	1.836	7.840	32.8
Bulk density (g/cm^3)	1.42 (0.205)	1.184	1.871	14.4
Sand %	51.417(14.33)	21.16	77.050	27.9
Silt %	28.354(10.70)	2.78	52.09	37.7
Clay %	20.228 (7.81)	5.20	24.30	38.6

Table 3.2. Variogram model parameters and sample variance (s^2) for selected variables that were investigated across the study site

Property	Model Parameters Range (m)	$C/(C+C_o)$	R^2	s^2
Ap thickness (cm)†	56.1	0.993	0.959	71.6
Ap sand %†	36.9	0.999	0.936	123.5
Ap silt %†	36	0.999	0.969	103
Ap clay %‡	43	0.534	0.452	11.5
Ap bulk density (g/cm^3)†	71.1	0.658	0.95	0.0088
Elevation (m)𝄞	265.87	1.00	0.99	0.613
Slope (%)𝄞	352.64	0.874	0.892	0.0041
Corn grain yield (Mg/ha)†	46.5	0.649	0.611	0.605

Notes †exponential model, ‡ spherical model, and 𝄞 Gaussian model

Table 3.3. Variogram model parameters and sample variance (s^2) for soil water content and available water storage capacity at - 10 and - 33 kPa for 70 m range and the entire range of 224 m across the study site

Property	Model Parameters 50 m Range (Entire Range) (m)	$C/(C+C_o)$	R^2	s^2
Ap soil WC at - 10 kPa	19.6 (21.0)	0.999 (1.00)	0.68 (0.069)	0.023
Ap soil WC at - 33 kPa	18.3 (22.8)	1.00 (1.00)	0.63 (0.077)	0.024
Ap soil AW at - 10 kPa	16.44 (19.7)	1.00 (1.00)	0.71 (0.072)	0.025
Ap soil AW at - 33 kPa	17.64 (18.9)	0.998 (1.00)	0.67 (0.017)	0.038
Ap AWSC at - 10 kPa	32.4(203.0)	0.88 (0.966)	0.88 (0.947)	0.097
Ap AWSC at - 10 kPa	30.3(197.6)	0.95 (0.99)	0.82 (0.969)	0.108

Note: The brackets indicate the values for entire range parameters. WC is water content, AW is the available water, and AWSC is available water storage capacity.

Table 3.4. Stepwise multiple regression analysis of soil properties that affect yield variation in the Ap and Bt1 horizons.

Predictors	Predicted yield	Cumulative r^2	P-value
	Ap		
Ap depth (cm)	Yield = 48.99 + 0.0525 Ap depth	0.2017	0.0014*
Ap silt (%)	Yield = 48.99 + 0.02475 Ap silt + 0.0525 Ap depth	0.2641	0.0569**
Ap AWSC - 10 kPa		0.2784	0.356
Elevation (m)		0.2796	0.791
Slope (%)		0.2849	0.578
	Bt1		
Bt1 bulk density (g/cm3)	Yield = - 4.99 + 2.43 Bt1 bulk density	0.2404	0.0004*
Bt1 silt (%)	Yield = - 4.99 + 0.035 Bt1 silt + 2.43 Bt1 bulk density	0.3716	0.0037*
Slope (%)		0.3767	0.553
Bt1 depth (cm)		0.3803	0.621
Bt1 sand (%)		0.3832	0.658

*, **, significant at 0.05 and 0.10 probability levels respectively, AWSC is available water storage.

Table 3.5. The spatial relationship between corn grain yield (Mg/ha) and selected soil properties that are significant in determining yield variation in stepwise regression analysis.

	Model Parameters			
Variable	Range (m)	(C/Co + C)	R^2	s^2
Corn grain yield and Ap depth †	176	0.875	0.609	0.0048
Corn grain yield and Ap silt†	31.5	0.999	0.109	0.0045
Corn grain yield and Bt1 bulk density‡	157.9	0.653	0.556	0.0038
Corn grain yield and Bt1 silt †	26.10	0.934	0.021	0.0045
Corn grain yield and elevation 𝄞	211.83	0.998	0.782	0.0051

Notes: † is an exponential model, ‡ is a spherical model while 𝄞 is a gaussian model

Table 3.6. The spatial relationship between elevation (m) and Ap soil water at different pressures, Ap thickness and Ap silt over the entire range of the study site

	Model Parameter			
Property	Range (m)	(C/Co + C)	R^2	s^2
Ap water content at - 10 kPa and elevation †	121.76	1.00	0.512	0.0197
Ap water content at - 33 kPa and elevation †	121.07	0.998	0.491	0.0241
Ap available water at - 10 kPa and elevation 𝄞	711.70	0.998	0.938	0.0281
Ap available water at - 33 kPa and elevation 𝄞	570.88	0.999	0.962	0.031
Ap water storage capacity at - 10 kPa and elevation 𝄞	231.92	0.998	0.968	0.091
Ap water storage capacity at - 10 kPa and elevation 𝄞	233.83	0.998	0.963	0.141
Ap thickness and elevation 𝄞	548.02	1.00	0.998	0.059
Ap silt and elevation 𝄞	149.65	0.999	0.833	0.052

Note: † is an exponential model and 𝄞 is a gaussian model

Table 3.7. The spatial relationship between slope (%) and Ap soil water at different pressures, Ap thickness and Ap clay over the entire range of the study site

	Model Parameter			
Property	Range (m)	(C/Co + C)	R^2	s^2
Ap water content at - 10 kPa and slope †	150.90	1.00	0.249	0.0004
Ap water content at - 33 kPa and slope †	132.60	1.00	0.223	0.0006
Ap available water at - 10 kPa and slope 𝄞	711.70	0.998	0.925	0.0003
Ap available water at - 33 kPa and slope 𝄞	668.18	0.974	0.961	0.0004
Ap water storage capacity at - 10 kPa and slope 𝄞	270.89	0.999	0.962	0.0022
Ap water storage capacity at - 10 kPa and slope 𝄞	264.31	0.998	0.957	0.0023
Ap thickness and slope 𝄞	260.00	0.999	0.973	0.063
Ap clay and slope 𝄞	325.8	1.00	0.941	0.0009

Note: † is an exponential model and 𝄞 is a gaussian model

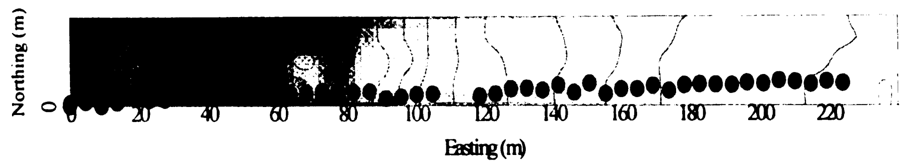


Figure 3.1a. Sample locations of the study site overlaid over the contour lines

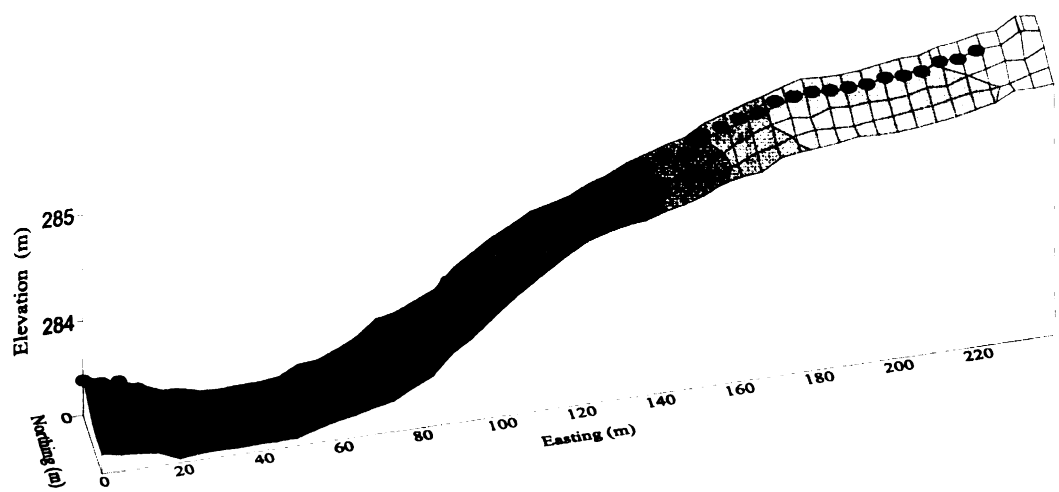


Figure 3.1b. Sample locations on the main transect overlaid over elevation

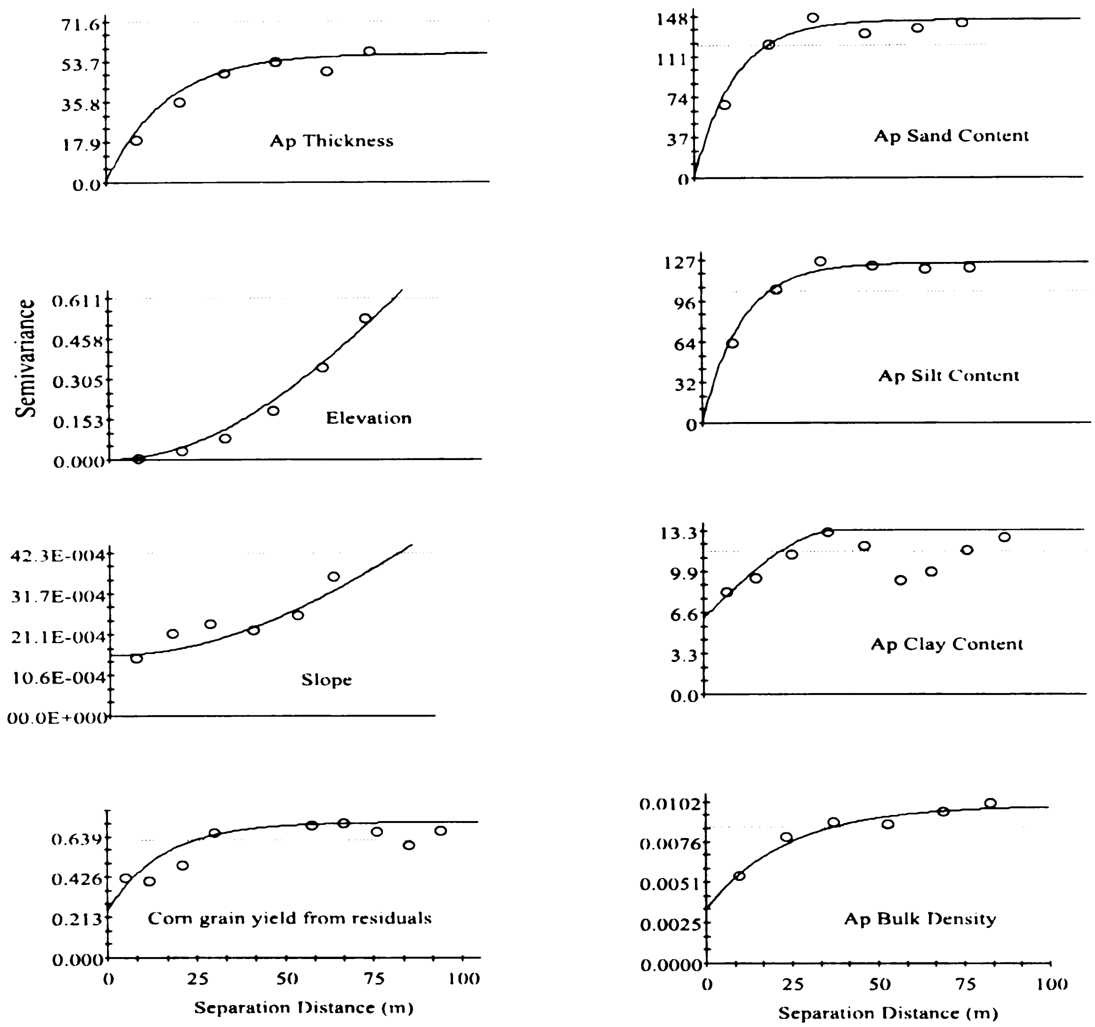


Figure 3.2. Variograms of soil properties for Ap horizon, Ap thickness, Ap texture bulk density, elevation, slope, and corn grain yield (from residuals)

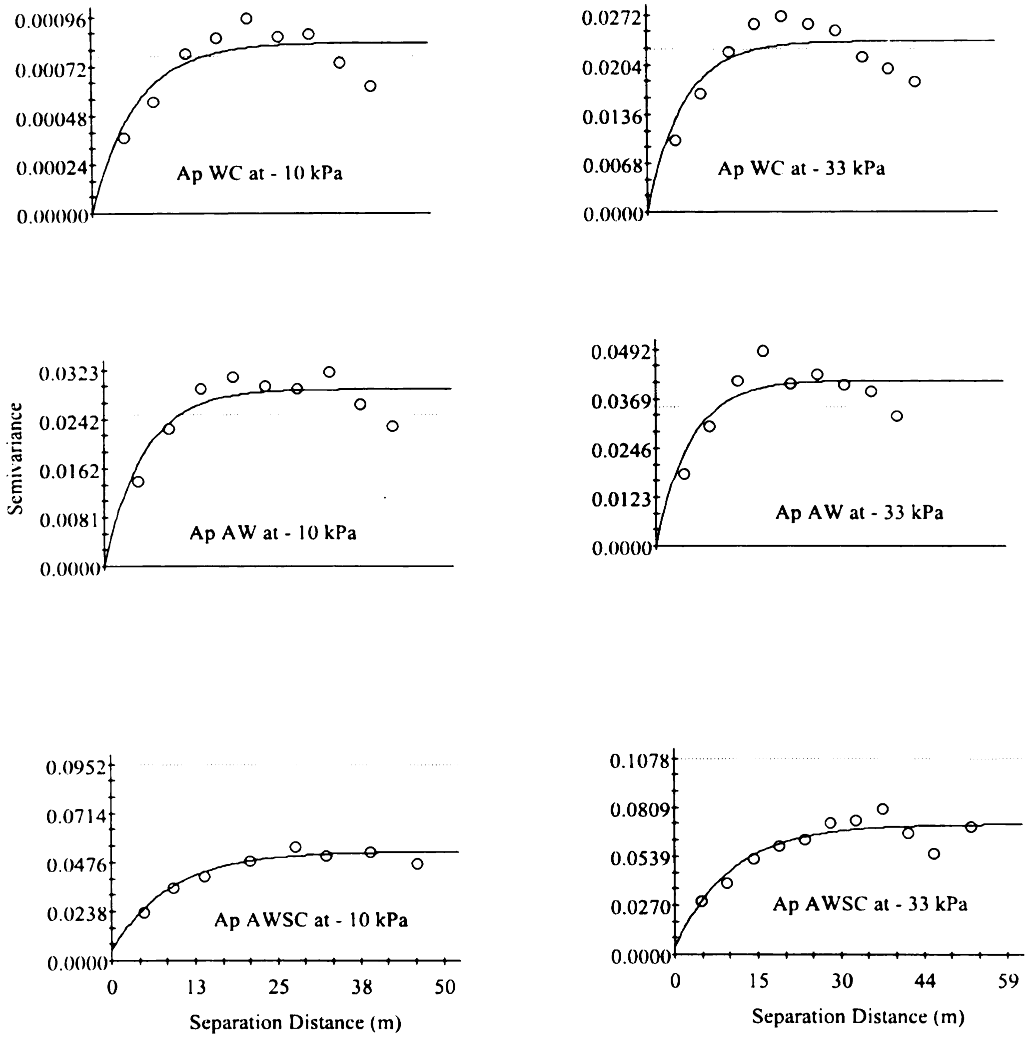


Figure 3.3. Variograms of soil water in Ap horizon. WC is water content, AW is available water, and AWSC is available water storage capacity.

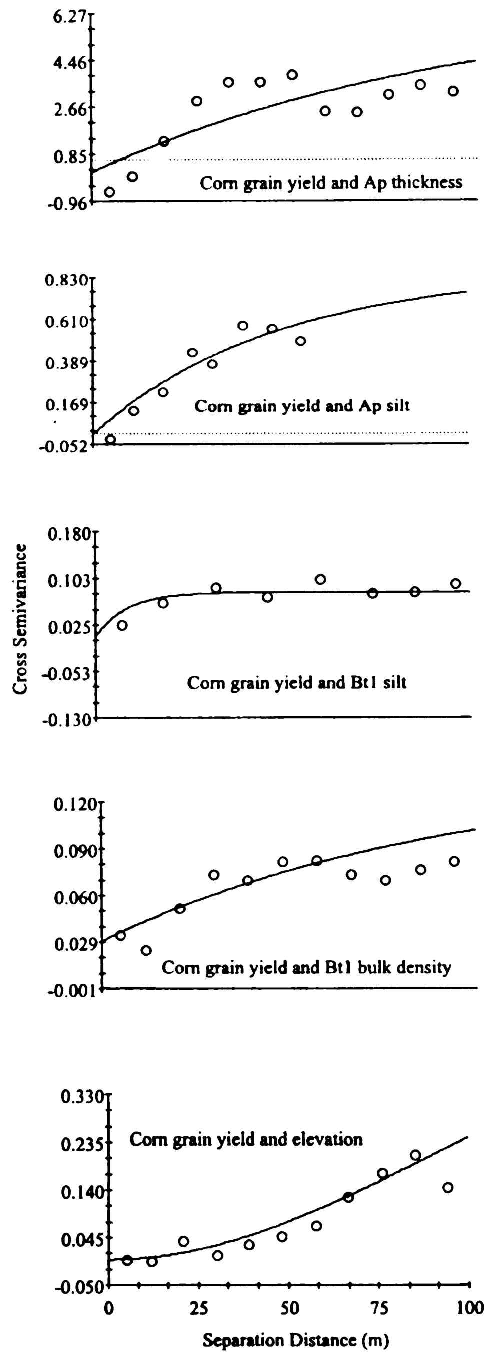


Figure 3.4. Cross variograms of residual corn grain yield (Mg/ha) and significant soil properties in the Ap and Bt1 horizons and elevation. Dotted lines indicate sample covariance.

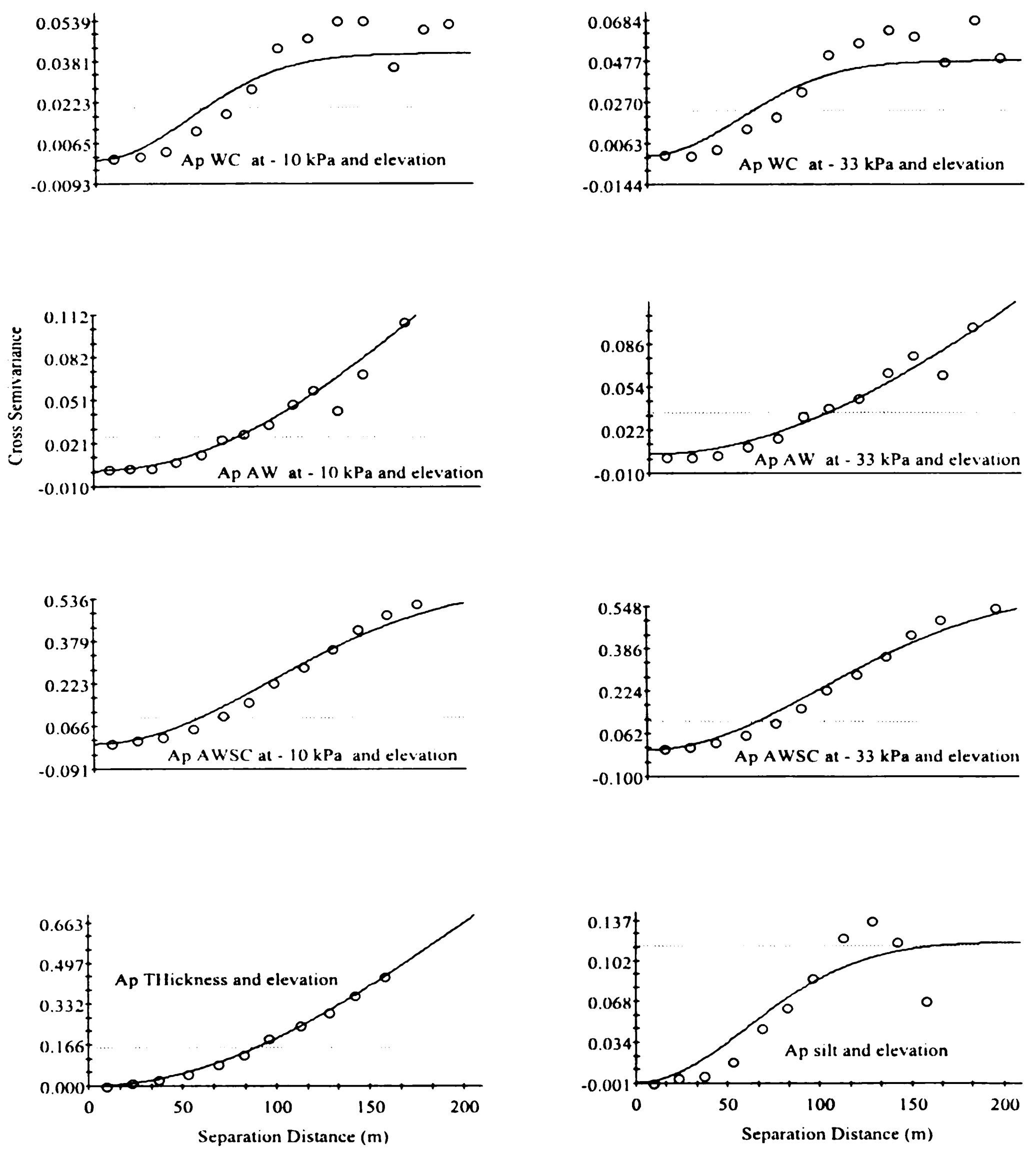


Figure 3.5. Cross variograms of elevation and soil water at different pressures, Ap thickness, and Ap silt. Dotted lines, if present, indicate sample covariance, and if not present, the sample covariance is out of range of y-axis. WC is water content, AW is available water, and AWSC is available water storage capacity.

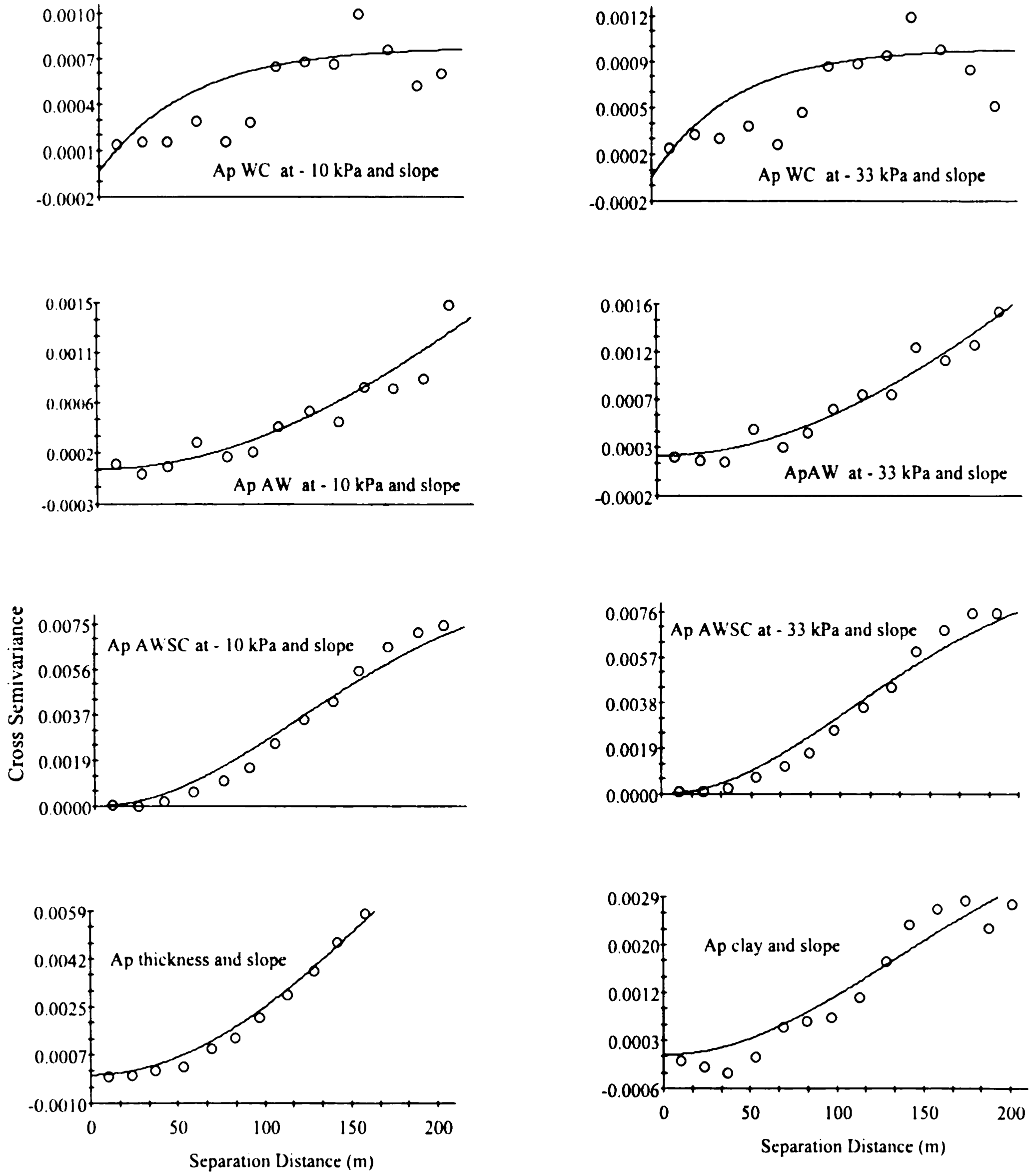


Figure 3.6. Cross variograms of slope and soil water at different pressures, Ap thickness and Ap clay. WC is water content, AW is available water, and AWSC is available water storage capacity.

Figure 3.7. Volumetric water content (TDR) for three different dates at five different depths in the effective rootzone

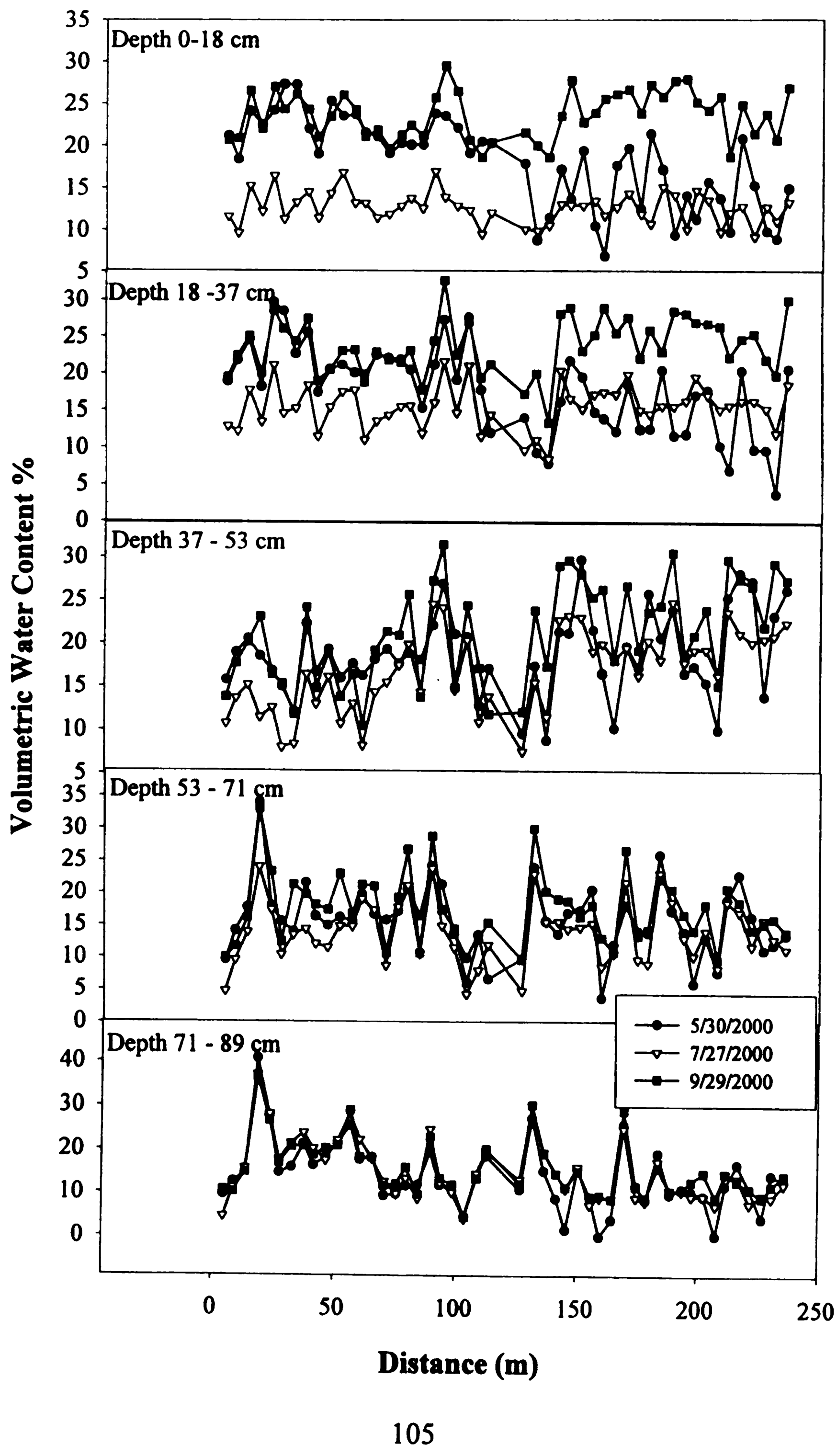


Figure 3.8. Cumulative probability of soil water storage(0 - 90) for two different dates: The most dry on June 2, 2000 and the most wet storage conditions on Agust 16, 2000.

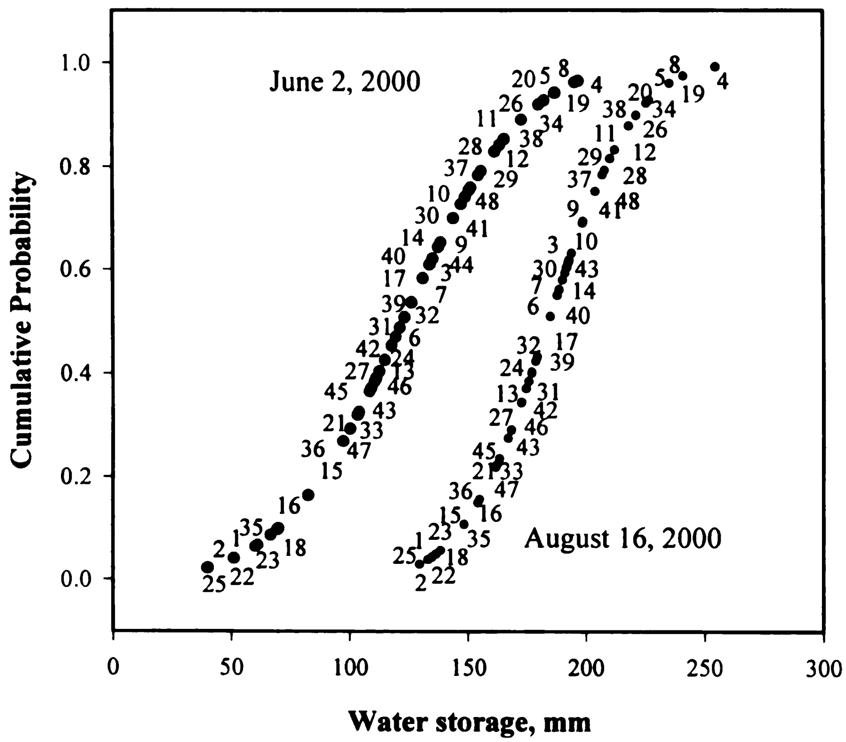


Figure 3.9. Rank of temporal relative deviation from the mean spatial water storage. Vertical bars are associated time standard deviations and numbers are measuring locations or plots.

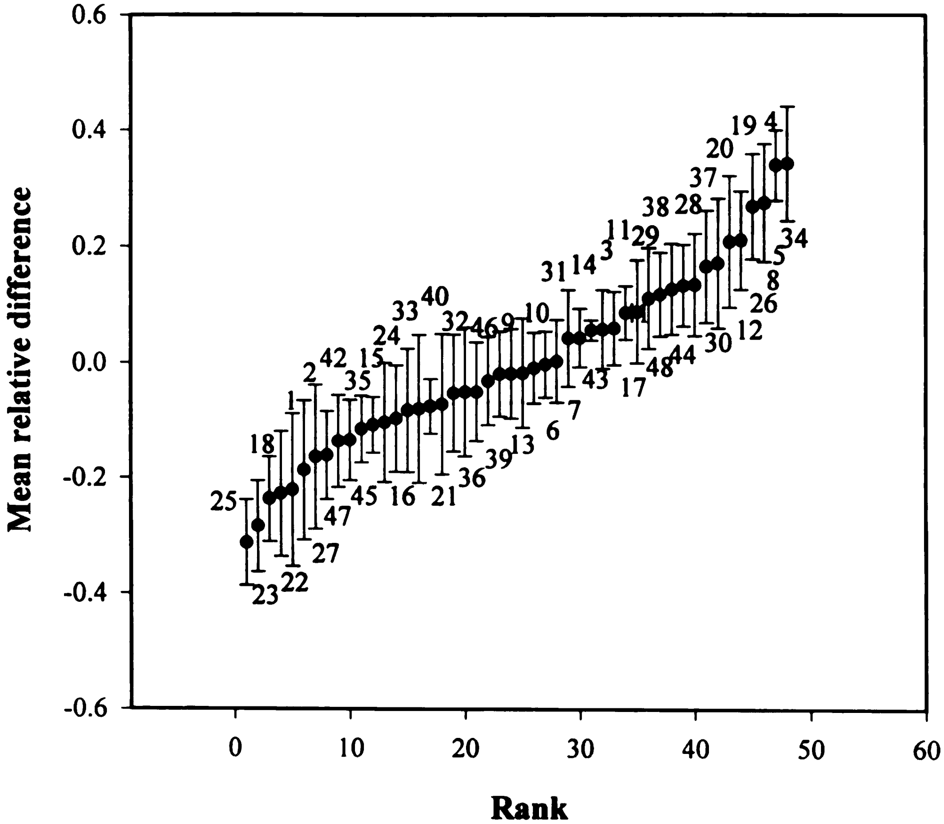
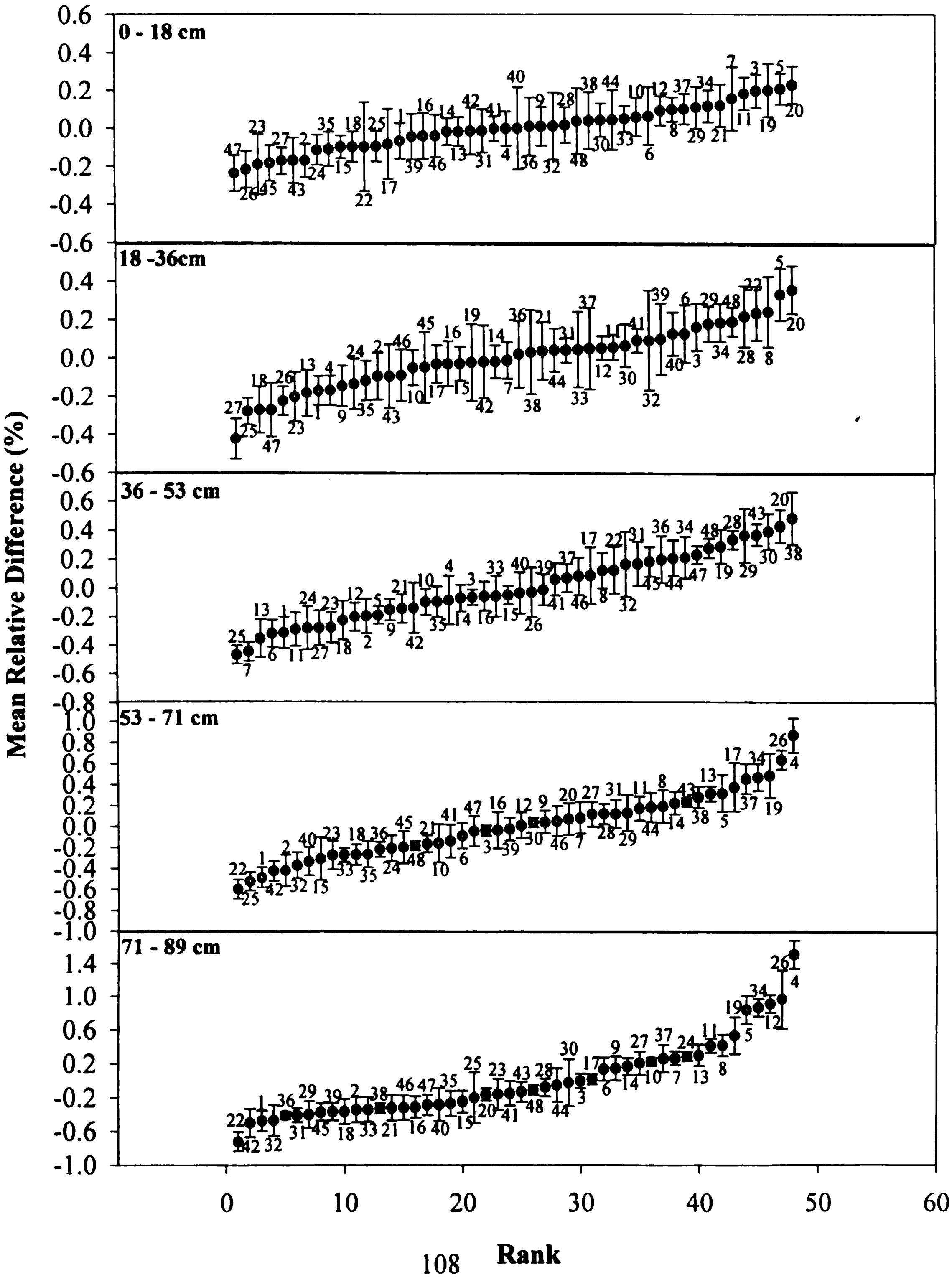


Figure 3.10. Rank of temporal relative deviation from the mean spatial water content. Vertical bars are associated time standard deviations and numbers are measuring locations or plots.



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SUMMARY

Early season drought in 1999 resulted in lower leaf chlorophyll even after intervention N application until irrigation or rainfall occurred in early July which resulted in increased leaf chlorophyll. Starter N application at planting time was necessary to avoid early season N stresses and subsequent yield losses. Interactive N management based upon PSNT or leaf chlorophyll readings resulted in less N applied and produced a comparable yield. There was a significant N x water interaction when irrigation water was applied in 1999, but the interaction was absent when irrigation was not needed in the wet 2000 growing season. Irrigation increased corn grain yield but not without N application. Nitrogen was the main factor determining corn grain yield in the relatively wet 2000 season. Soil NO_3-N measurements (though PSNT) revealed that most of the N applied at planting was lost even before the crop reached silking. Irrigation had no effect on earleaf N content. Nitrogen application increased leaf N in the dry 1999 season but had no effect in the wet 2000 growing season. Irrigation and N application had very significant effects on grain N content. While irrigation reduced grain N content on one hand, N addition to the crop increased grain N content on the other hand. There was no irrigation x N interaction in either seasons. End of the season assessment of nitrate concentrations in the lower portion of cornstalk showed that N fertilization had a significant impact on lower stalk NO_3-N build up. Irrigation reduced stalk NO_3-N accumulation in the lower stalk and there was an irrigation x N interaction. When cornstalk NO_3-N levels were compared to levels in an Iowa State University test, optimal

stalk NO_3-N levels were found only in the at-planting N treatment. Sensor-based and PSNT N treatments represented a marginal NO_3-N category based on the ISU data, however, the lower PSNT and sensor-based applications produced comparable yields to those of the at-planting N treatment. Care must be taken when considering these categorizations because there are many factors affecting N uptake. Generally under dry conditions, corn will have higher levels of nitrate accumulated in the lower cornstalk than will the lower stalks of irrigated corn.

Vegetation indices can be used to develop instantaneous crop coefficients from crop growth and development that are independent of the planting date and effective cover. While NDVI is sensitive to soil backgrounds, SAVI is more susceptible to sky illumination. Green normalized difference vegetation index (GNDVI) is sensitive to soil background but is not affected by sky illumination. The green normalized difference vegetation index (GNDVI) was transformed into a reflectance-based crop coefficient. Kcr GNDVI performed well when compared to Kcr from SAVI and Kcb (Wright) and did not under- or overestimate evapotranspiration of corn. An equation *(Kcr = 1.256 x GNDVI - 0.1699)* was derived that represented all field environments for estimating corn crop coefficient and did not require any more calibration. Reflectance-based crop coefficients can be used to apply variable irrigation rates based on water stress in corn rather than on the current basis of demand or weather-based water budgets which do not account for spatial variability within a field. In addition, it is possible to remotely monitor water stress in plants and apply irrigation water based on site-specific needs of corn within a field rather than to apply water uniformly over a field as is the current practice

Nitrogen deficiency in corn was detected using a radiometer in the short wavelength range of 460 to 810 nm. A spectral region centered around 560 nm provided the best separation between N treatments. These results suggest that a future corn N status sensor could be developed that uses a simple combination of limited spectral bands centered around 560 and 800 nm for variable N rate application. Spectral vegetation indices such as GNDVI and GRVI performed better for corn grain yield prediction than RVI and NDVI. This was due to the sensitivity to N deficiency in the green region of the spectrum that centers around 560 nm. Vegetation indices such as GNDVI could be used to replace chlorophyll meter readings to schedule N fertilizer and to predict N stress in corn. Nonetheless, there are questions to be addressed such as how, when, and what rate of N fertilizer to apply for sensor-based N application. Spectral vegetation indices (SVI) such as NDVI and GNDVI performed very well in estimating biophysical variables such LAI and Fc. Extensive data are still needed to verify the validity of these results. Finally, because remote sensing measurements in the temperate region are hampered by a very high percentage of cloud cover, suitable atmospheric conditions must be present to obtain high quality measurements.

Geostatistical analysis provides a substantial and a robust technique for determining the scale over which spatial dependence occurs. Soil properties such as length of the horizon, bulk density, soil water content at - 10, - 33, and - 1500 kPa, soil texture, elevation, and slope from a 224 m long transect in the experimental area exhibited a wide range of variability. For all properties tested, variability exhibited strong spatial structure, and 50 to 100 percent of the sample variance was spatially dependent and autocorrelated over a range of 5 to 224 m. Stepwise multiple regression analysis was applied on corn grain yields to identify the most important soil properties affecting yield variation in the Ap and Bt1 horizons. Ap depth and Ap silt were significant in explaining corn grain yield variation in Ap horizon. Bt1 bulk density and Bt1 silt were significant in explaining corn yield variation in Bt1 horizon. Surprisingly, soil water content was not significant in the stepwise multiple regression conducted to identify the variables that most affected corn grain yield. This may be due to the fact that the 2000 season was relatively wet and did not require irrigation. Corn grain yield and the soil properties in the Ap and Bt1 horizon exhibited a very strong spatial cross correlation. Fifty to 100% of the sample covariance was spatially dependent over a range of 26 to 212 m. It is evident from these results that the soil resources tested are highly variable and very heterogeneous. In addition, properties such as Ap texture, Ap bulk density, Ap depth, Ap water content at different pressures, Bt1 bulk density, and Bt1 silt are spatially structured. Landscape properties such as elevation and slope are spatially well-structured and nested or cyclic. The degree and scale of spatial dependence found in this study is similar to an experiment conducted at KBS by Robertson et al. (1988). This variable soil structure should be considered when designing experiments and making management decisions.

Cumulative probability function, Spearman rank correlation coefficient, the mean relative difference, and the standard deviation were used to characterize the temporal stability of spatial water storage and spatial water content. The smaller the standard deviation the more significant was the rank. The location whose respective rank is relatively stable can be used as the management zone for homogeneous water application, and no more soil sampling is needed except at low, medium and high rank locations. There is a temporal stability in soil water content in the upper soil depths compared to the lower depths due to the action of plant root.

APPENDIX

The following tables provide supplementary soil profile data collected from the study site after harvesting for Ap, Bt1, Bt2 and 2Bt2 (C) horizons.

1. Soil Properties in Ap Horizon

Plot #	Length of Horizon (cm)	Water Content 0.10 Bar	Water Content 0.33 Bar	Water Content 15 Bar	Bulk Density g/cm^3	Sand %	Silt %	Clay %
101	38	0.17	0.15	0.12	1.14	60.13	30.75	9.13
102	37	0.23	0.19	0.14	0.95	52.95	33.90	13.15
103	27	0.20	0.18	0.13	0.99	51.40	35.63	12.97
104	35	0.20	0.18	0.10	1.11	46.79	39.36	13.85
105	37	0.17	0.15	0.12	1.02	47.45	37.08	15.47
106	30	0.26	0.25	0.17	0.94	45.90	38.36	15.74
107	45	0.22	0.21	0.18	0.90	40.08	41.69	18.24
108	48	0.23	0.21	0.18	0.90	28.93	52.93	18.15
109	54	0.32	0.25	0.11	0.92	24.79	65.02	10.20
110	45	0.23	0.21	0.16	0.97	24.60	60.11	15.29
111	52	0.22	0.25	0.16	0.92	34.23	53.26	12.52
112	34	0.21	0.19	0.16	0.94	44.85	42.80	12.35
201	44	0.17	0.16	0.12	1.00	54.33	31.73	13.95
202	43	0.18	0.16	0.11	1.02	60.64	31.22	8.15
203	41	0.15	0.13	0.09	1.12	63.80	26.53	9.67
204	37	0.18	0.15	0.12	1.11	62.17	27.63	10.20
205	34	0.16	0.15	0.12	1.08	54.05	32.53	13.42
206	29	0.21	0.18	0.17	1.05	76.35	10.05	13.60
207	25	0.24	0.23	0.17	1.01	42.31	49.99	7.70
208	24	0.25	0.22	0.18	1.06	39.87	35.83	24.30
209	30	0.20	0.18	0.16	1.09	73.38	10.53	16.10
210	24	0.18	0.17	0.13	0.98	45.18	39.63	15.20
211	30	0.17	0.15	0.13	1.01	55.53	31.15	13.33
212	25	0.15	0.14	0.09	1.19	62.28	22.53	15.20
301	25	0.16	0.15	0.10	1.16	55.50	29.12	15.38
302	29	0.19	0.16	0.13	1.08	54.10	35.70	10.20
303	27	0.18	0.17	0.13	1.15	44.43	39.66	15.92
304	29	0.24	0.20	0.17	1.13	35.32	56.18	8.50
305	28	0.19	0.18	0.17	1.07	44.25	40.10	15.65
306	26	0.18	0.15	0.08	1.12	55.38	31.92	12.70
307	25	0.15	0.14	0.11	1.06	54.80	32.14	13.06
308	32	0.17	0.15	0.12	1.12	45.83	41.82	12.35
309	24	0.19	0.17	0.11	0.99	43.83	39.72	16.45
310	23	0.19	0.17	0.14	1.12	42.32	42.48	15.20
311	25	0.14	0.13	0.10	1.08	42.38	38.68	18.95
312	22	0.18	0.16	0.15	0.96	42.85	41.50	15.65
401	25	0.21	0.18	0.12	1.04	40.03	41.38	18.60
402	27	0.21	0.19	0.16	1.02	34.10	47.30	18.60
403	25	0.21	0.19	0.17	1.06	35.65	47.45	16.90
404	24	0.21	0.19	0.17	1.05	38.03	44.72	17.26
405	25	0.20	0.18	0.15	0.95	40.95	42.60	16.45
406	20	0.18	0.17	0.14	1.08	40.38	43.98	15.65
407	24	0.19	0.17	0.14	0.95	38.83	45.08	16.10
408	26	0.19	0.18	0.14	0.97	39.75	44.60	15.65
409	26	0.20	0.18	0.12	1.04	41.00	42.90	16.10
410	25	0.20	0.18	0.15	0.99	41.90	44.77	13.33
411	22	0.21	0.18	0.14	0.95	41.03	42.88	16.10
412	24	0.23	0.20	0.16	1.01	40.99	36.50	22.52

2. Soil Properties in Bt1 Horizon								
Plot #	Length of Horizon (cm)	Water Content 0.10 Bar	Water Content 0.33 Bar	Water Content 15 Bar	Bulk Density g/cm^3	Sand %	Silt %	Clay %
101	19	0.15	0.14	0.12	1.18	64.58	19.96	15.47
102	18	0.16	0.13	0.08	1.12	71.38	12.71	15.92
103	16	0.12	0.10	0.07	1.28	77.05	14.62	8.33
104	25	0.25	0.21	0.12	1.03	37.77	39.99	22.25
105	14	0.13	0.09	0.06	1.50	76.80	13.89	9.31
106	36	0.12	0.11	0.07	1.44	74.85	16.82	8.33
107	15	0.10	0.09	0.04	1.50	74.25	14.74	11.01
108	28	0.14	0.13	0.11	1.48	61.45	27.90	10.65
109	32	0.18	0.18	0.10	1.25	69.33	25.47	5.20
110	35	0.10	0.10	0.09	1.50	69.50	20.21	10.29
111	35	0.20	0.19	0.12	1.22	48.50	33.17	18.33
112	20	0.15	0.14	0.12	1.44	45.33	43.58	11.10
201	29	0.20	0.19	0.17	1.09	44.79	30.36	24.85
202	19	0.16	0.14	0.12	1.52	52.63	32.18	15.20
203	16	0.12	0.11	0.07	1.38	69.78	21.63	8.60
204	31	0.23	0.19	0.12	1.22	44.74	43.81	11.45
205	32	0.23	0.21	0.19	0.96	31.03	39.76	29.22
206	20	0.22	0.21	0.18	1.00	48.35	23.05	28.60
207	40	0.25	0.24	0.20	0.99	21.16	45.70	33.15
208	21	0.24	0.22	0.16	1.03	46.21	44.05	9.75
209	33	0.21	0.19	0.17	1.12	48.80	25.28	25.92
210	28	0.19	0.17	0.13	1.09	56.93	19.93	23.15
211	21	0.13	0.12	0.10	1.36	72.40	16.95	10.65
212	15	0.13	0.13	0.08	1.18	74.10	10.16	15.74
301	12	0.11	0.09	0.04	1.28	55.43	21.88	22.70
302	26	0.18	0.16	0.14	1.06	52.44	31.12	16.45
303	32	0.17	0.15	0.12	1.19	56.90	22.45	20.65
304	27	0.28	0.23	0.20	0.99	38.92	30.43	30.65
305	31	0.21	0.19	0.17	0.99	41.68	30.09	28.24
306	24	0.19	0.17	0.14	1.00	50.02	29.79	20.20
307	27	0.21	0.20	0.18	1.06	43.68	30.68	25.65
308	26	0.20	0.19	0.16	1.11	73.97	2.78	23.25
309	13	0.09	0.08	0.06	1.37	33.26	44.39	22.35
310	16	0.21	0.20	0.15	1.05	40.21	52.09	7.70
311	23	0.19	0.17	0.15	1.08	55.88	17.23	26.90
312	20	0.20	0.18	0.18	1.12	46.40	28.04	25.56
401	22	0.19	0.18	0.13	1.11	36.43	41.68	21.90
402	26	0.21	0.20	0.16	1.10	33.50	39.15	27.35
403	27	0.20	0.19	0.16	1.10	42.18	32.18	25.65
404	19	0.21	0.19	0.17	1.03	50.25	21.60	28.15
405	25	0.21	0.19	0.15	0.97	36.88	34.18	28.95
406	30	0.20	0.18	0.17	1.02	38.18	33.68	28.15
407	24	0.18	0.16	0.13	1.05	43.10	29.55	27.35
408	25	0.19	0.18	0.15	1.03	49.69	22.06	28.25
409	24	0.21	0.20	0.17	1.03	37.95	34.70	27.35
410	33	0.12	0.11	0.08	1.07	41.05	35.62	23.33
411	25	0.26	0.19	0.19	1.02	37.60	36.30	26.10
412	20	0.23	0.22	0.17	1.10	50.82	23.53	25.65

Plot #	Length of Horizon (cm)	Water Content 0.10 Bar	Water Content 0.33 Bar	Water Content 15 Bar	Bulk Density g/cm^3	Sand %	Silt %	Clay %
101								
102								
103								
104	28	0.20	0.18	0.15	1.15	37.19	36.46	26.35
105	13	0.12	0.11	0.07	1.59	78.23	12.29	9.49
106	19	0.15	0.14	0.12	1.48	66.98	17.47	15.56
107	12	0.11	0.10	0.06	1.33	80.48	6.11	13.42
108								
109	16	0.16	0.11	0.10	1.19	74.06	13.25	12.70
110								
111	4	0.18	0.17	0.13	1.31	55.65	23.43	20.92
112	12	0.14	0.14	0.12	1.54	55.75	28.33	15.92
201	16	0.17	0.16	0.14	1.14	67.27	7.89	24.85
202	11	0.11	0.10	0.06	1.43			
203	14	0.08	0.06	0.04	1.33	87.38	6.53	6.10
204	9	0.23	0.20	0.15	1.19	62.58	12.23	25.20
205	15	0.19	0.17	0.14	1.07	78.83	5.26	15.92
206	20	0.20	0.18	0.16	1.09	55.13	22.18	22.70
207	23	0.26	0.24	0.16	1.02	49.91	24.44	25.65
208	26	0.11	0.10	0.05	1.27	86.23	1.08	12.70
209	9	0.15	0.13	0.11	1.24	74.40	12.90	12.70
210	22	0.09	0.06	0.05	1.29	87.65	1.52	10.83
211	8	0.09	0.08	0.05	1.23	79.43	5.38	15.20
212	16	0.12	0.11	0.07	1.23	78.73	5.63	15.65
301	10	0.08	0.07	0.04	1.26	86.25	5.78	7.97
302	23	0.23	0.20	0.16	1.01	51.29	27.61	21.10
303	20	0.18	0.16	0.14	1.27	56.25	20.60	23.15
304	13	0.19	0.14	0.11	1.22	76.69	5.61	17.70
305	10	0.17	0.16	0.14	1.23	73.93	10.34	15.74
306	14	0.14	0.12	0.09	1.17	65.67	14.49	19.85
307	12	0.13	0.12	0.10	1.15	76.35	8.18	15.47
308	14	0.13	0.12	0.09	1.26	54.07	23.58	22.35
309	15	0.21	0.18	0.14	1.04	67.05	11.05	21.90
310	24	0.21	0.15	0.14	1.08	64.43	26.63	8.95
311	11	0.14	0.13	0.11	1.28	76.10	6.20	17.70
312	18	0.17	0.15	0.13	1.20	68.85	5.50	25.65
401	17	0.22	0.18	0.14	1.02	49.85	22.80	27.35
402	12	0.20	0.18	0.14	1.07	57.33	16.58	26.10
403	17	0.15	0.14	0.12	1.31	69.88	9.48	20.65
404	20	0.08	0.07	0.05	1.28	72.58	6.51	20.92
405	15	0.11	0.10	0.07	1.41	83.63	3.68	12.70
406	24	0.16	0.15	0.12	1.15	72.85	9.00	18.15
407	12	0.16	0.15	0.12	1.17	67.95	18.45	13.60
408	18	0.15	0.14	0.11	1.13	74.33	13.78	11.90
409	15	0.16	0.13	0.08	1.12	85.85	3.05	11.10
410	11	0.14	0.13	0.09	1.30	75.70	8.56	15.74
411	17	0.13	0.12	0.09	1.17	66.90	9.50	23.60
412	12	0.20	0.18	0.11	1.14	75.90	8.01	16.10

4. Soil Properties in 2Bt2 (C) Horizon								
Plot #	Length of Horizon (cm)	Water Content 0.10 Bar	Water Content 0.33 Bar	Water Content 15 Bar	Bulk Density g/cm³	Sand %	Silt %	Clay %
101	18	0.05	0.04	0.03	1.27	92.28	2.17	5.56
102	20	0.08	0.07	0.05	1.39	86.48	3.86	9.67
103	21	0.12	0.11	0.09	1.45	88.03	3.92	8.06
110								
111								
201								
202						81.01	7.89	11.10
203								
204	13	0.24	0.19	0.17	1.27	76.35	7.95	15.70
205	7	0.24	0.08	0.06	1.33	89.65	0.59	9.76
206	17	0.08	0.06	0.04	1.32	91.70	3.10	5.20
207								
208								
209	17	0.06	0.05	0.04	1.33	91.23	1.79	6.99
210								
211								
212	17	0.12	0.11	0.07	1.50	78.53	5.65	15.83
301	9	0.06	0.06	0.03	1.18	78.75	5.60	15.65
302	11	0.18	0.17	0.11	1.19	75.02	18.95	6.03
303	10	0.14	0.13	0.09	1.47	56.05	20.53	23.42
304	12	0.11	0.09	0.06	1.31	86.54	0.76	12.70
305	14	0.07	0.06	0.05	1.33	87.83	2.60	9.58
306	18	0.10	0.09	0.07	1.32	80.83	6.83	12.35
307	13	0.06	0.05	0.03	1.31	91.73	0.22	8.06
308	13	0.09	0.08	0.06	1.37	81.23	3.58	15.20
309	23	0.10	0.08	0.05	1.21	88.32	3.44	8.25
310	14	0.17	0.16	0.12	1.39	56.80	33.00	10.20
311	16	0.08	0.07	0.05	1.34	88.88	0.48	10.65
312	20	0.10	0.09	0.07	1.34	63.18	26.00	10.83
401	26	0.17	0.14	0.10	1.24	80.63	3.73	15.65
402	17	0.12	0.11	0.01	1.32	85.85	1.81	12.35
403	10	0.06	0.05	0.04	1.15	89.80	3.30	6.90
404	13	0.14	0.13	0.10	1.09	89.55	2.30	8.15
405	10	0.13	0.13	0.10	1.52	80.30	4.23	15.47
406	14	0.08	0.07	0.06	1.38	89.83	2.03	8.15
407	22	0.12	0.11	0.08	1.37	85.85	1.80	12.35
408	16	0.09	0.07	0.05	1.26	88.55	1.60	9.85
409	12	0.07	0.07	0.05	1.32	84.93	3.98	11.10
410	11	0.08	0.08	0.05	1.35	86.50	5.26	8.24
411	16	0.24	0.03	0.03	1.27	78.30	9.35	12.35
412	15	0.13	0.08	0.05	1.27	87.73	3.32	8.95

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