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An Integrated Approach for Predicting Nitrogen Status in Early Cotton and Corn

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An integrated approach for predicting nitrogen status

in early cotton and corn

By

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Cotton (*Gossypium hirsutum* L.) and corn (*Zea mays* L.) spectral reflectance holds promise for deriving variable rate N (VRN) treatments calibrated with red-edge inflection (REI) type vegetation indices (VIs). The objectives of this study were to define the relationships between two commercially available sensors and the suitable VIs used to predict N status. Field trials were conducted during the 2012-2013 growing seasons using fixed and variable N rates in cotton ranging from 33.6-134.4 kg N ha^{-1} and fixed N rates in corn ranging from 0.0 to 268.8 kg N ha^{-1}. Leaf N concentration, SPAD chlorophyll and crop yield were analyzed for their relation to fertilizer N treatment. Sensor effects were significant and red-edge VIs most strongly correlated to N status. A theoretical ENDVI index was derived from the research dataset as an improvement and alternative to the Guyot’s Red Edge Inflection and Simplified Canopy Chlorophyll Content Index (SCCCI).

DEDICATION

For Charlie, Mike, Howard, and Jac.

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CHAPTER I

INTRODUCTION

Background

United States cotton (*Gossypium hirsutum* L.) and corn (*Zea mays* L.) producers face increasing challenges to remain competitive in the global textile and food markets. Because of competition with producing grain crops and variation in global demand, declining cotton acreage necessitates increased productivity, profitability, and sustainability (Perez, 2012; USDA-NASS, 2012). Furthermore, competitive dynamics between feed and bioenergy corn markets routinely push corn profit margins lower during bumper crop years (Harrison, 2009). Nitrogen, in various fertilizer forms, is vital to agriculture production systems. Cropping schemes require managed fertilization systems that avoid under and over application, both of which reduce production and profit (Mengel and Kirkby, 1978; Havlin et al., 1990). Nitrogen is required in the greatest quantity of all fertilizer nutrients, and constitutes the largest input expense for many crops (USDA-NASS, 2012). United States producers consumed approximately 11% of the world's manufactured N fertilizer supply in 2010 (14 million of a total 126 million tonne) (International Fertilizer Industry, 2013). If world population reaches 9 billion in 2050 as predicted by the United Nations, N consumption is predicted to reach at least 265-320 million tonne (Food and Agriculture Organization of the United Nations, 2012).

Inadequate N limits crop production and reduces yield while excess soil N can be lost through leaching, ammonia volatilization, and denitrification (Havlin et al., 2005; Andraski et al., 2000). Fertilizer N costs are closely tied to energy prices, and U.S. crop producers may face future challenges to remain competitive in global food, feed, and fiber markets as fuel prices trend higher and consumption increases (Socolow, 1999). Real-time optical sensing systems attuned to early crop development may help define appropriate fertilizer N application strategies and reduce N inputs. Site-specific nutrient management (SSNM) tools for visual assessment of N status are proposed and employed, but are not fully developed (Ferguson et al., 2002; Oldham, 2012). Identifying relationships between plant spectral properties and biophysical parameters such as chlorophyll content, canopy structure, and leaf and biomass N concentration may provide farmers with the information needed to improve N use efficiency (Baret et al., 2007; Cammarano et al., 2011).

Crop N status greatly affects yield and producers need tools to assess N status in young plants. Optically sensed N status can be integrated with variable-rate N (VRN) fertilizer technologies to help producers reduce fertilizer N inputs. However, small producers often find optical sensors and related operational software cost prohibitive. There is a need to develop and test relatively inexpensive tools to predict early N status in crops in order to reach a broader producer base for which economic limitations preclude sensor adoption.

Purpose of Study

The purpose of this study was to define the spectral attributes in young cotton and corn crops that predict N status. In order to provide practical N assessment tools to cotton and corn producers, this study combined previously developed theoretical models with readily available technologies and novel innovations. Furthermore, this study developed robust cotton and corn parameters and spectral data sets for calibrating existing and potential N status tools. Cotton and corn fertilizer N applications in Mississippi are typically applied in split fashion with a portion applied near planting and emergence, and the remainder as a side dressing during early vegetative growth (Feinerman et al., 1990; Mississippi State Extension, 2013). Side dress fertilization is typically applied to cotton as early as pinhead square appearance and to corn during early V6 to V8 growth stages. This research tested and calibrated two different radiometric sensors (leaf-level and canopy-level) for early detection of N status in cotton and corn prior to side dress fertilization.

The results of this research may help producers apply N inputs at more economically and ecologically adjusted rates. By way of this research, we aimed to assist producers in optimizing fertilizer N inputs through spectral assessment of young cotton and corn plant and leaf tissue N testing. Once calibrated through in-situ field measurements, fertilizer N rate recommendations can be made during early-detected stages of N stress in a cost-effective manner.

Study Hypotheses

Background soil albedo, or the lack thereof, causes scale-related differences between the two sensors studied. A 3 nm Spectral Evolution PSP-1100 (Lawrence, MA) (SE) sensor configuration will likely not be significantly different from a scaled-up SE 10 nm configuration. Leaf-level SE scaling effects should provide better prediction of leaf N status due to a lack of background interference noted in canopy-level sensing with the

YARA N-Sensor (tec5Helma Inc., Plainview, NY) (YARA) spectroradiometer (SR). Combined vegetation indices may correct for biomass variations relative to leaf plant tissue N concentration in canopy-level sensing. Finally, site-specific, sensor based variable rate N (VRN) recommendations could address and help correct for field level variations in available N, while improving fertilizer N use efficiency through either a reduction in overall fertilizer N use or an increase in yield, or both.

Study Objectives

The objectives of this research were:

1. To describe the effects of varying N supply on cotton and corn leaf N concentration, SPAD chlorophyll, and yield.
2. To compare cotton and corn leaf N status detection between leaf and canopy scale reflectance across widely varying N availability.
3. To determine leaf and canopy spectral properties in the detection of cotton and corn leaf N, leaf chlorophyll, and yield across widely varying N availability.
4. To evaluate sensor based VRN technology in producers fields using a combined VI calibrated against an N response database for cotton.

Study Significance and Limitations

This study is significant because the research was conducted in research plots and on-farm. Furthermore, this study reviewed multiple sensing tools in order to develop datasets for spectral and statistical analysis. Tools selected for this research are practical and cost-effective for many producers. This study assumed the current state of technology is appropriate for producers engaging in small to large-scale production scenarios with optimum return on investment for adoption will be a relatively brief time span (less than 2-3 years).

Limitations of this study include:

1. Procedures were limited to two specific crops, cotton and corn, and the varieties planted at each location. Results reveal a need for further testing of varietal and species performance differences not mentioned in this study.

CHAPTER II

LITERATURE REVIEW

Corn and Cotton Morphology and Physiology

Cotton Morphology and Physiology

Although no fossil records exist to substantiate the origin of cotton (*Gossypium hirsutum Pup* L.), the Malvacean family pollen records suggest that the cotton family evolved in arid, southern hemisphere climates over 30 million years before our present day (mybp) (Wendel et al., 2010). Approximately 12.5 mybp the *Gossypium* genus spread throughout pantropical climates in Australia, central Africa, and central and southern Mexico. The entire cotton genome, which includes at least 40 species, is widely diverse, and several species are cultivated for fiber and seed oil (Fryxell, 1986). Although wild cottons are typically found in subtropical and tropical environments, commercially bred cottons are cultivated into the 38th parallel latitude in the United States with limited production found as far north as northern California, Kansas, and Virginia (USDA, 2012).

The significant abiotic environmental factors promoting cotton production include climate (temperature, moisture, and solar irradiance), soils, and terrain, while other biotic factors promote resistance to disease and pestilence (Fryxell, 1986). Because of its indeterminate nature, cotton can take advantage of long growing seasons assuming nutrients, water, heat units, and solar irradiance are not limiting. Cotton requires warm soil temperatures (23-29°C) in order to establish early in the growing season. A minimum average soil temperature at 5 cm depth should be at least 16 °C for ten days prior to planting in moderately moist soils (Hopper et al., 1984; Purcell, 1992). Cotton's potential lengthy nutrient accumulation period requires well-managed N schemes to optimize yield (Sabbe and Hodges, 2010). Annual N recommendations for cotton crops range from 56-168 kg N ha^{-1} depending on soil type, management, application method, and irrigation.

Once cotton seedlings emerge, they develop deep and extensive root systems to support plant systems during the sometimes-arid growing season. Within 50 days of germination, aboveground plant tissue is typically less than 40% in height of the established rooting depth (Purcell, 1992). However, above-ground cotton plant tissues branch monopodially (vegetative) and sympodially (fruiting) early in the growing season, thus producing a canopy density, or leaf-area index (LAI), that closes between the rows in mid-season (Mauney, 1986a). A common trait of full-sun tolerant plants like cotton is leaf morphology that allows primary photoreceptors to be at other than right angles to the path of irradiance in order to prevent over saturation of the photosynthetic systems by direct interception (Srivastava, 2002).

Corn Morphology and Physiology

Maize is commonly referred to as "corn" in U.S. and is believed to have originated with other grass grains (families Poaceae and Gramineae) within the last 50-70 million years in Central America and Mexico (Buckler and Stevens, 1983). The *Zea mays* L. taxonomic class contains both cultivated maize and the wild teosinte cultures, which are highly polymorphic, diploid annual species. The crop's domestication is widely believed to have originated in multiple cultural centers throughout the central latitudes

(Galinat, 1988). Popular modern-day traits found in Dent varieties arise from historic breeding selections that produced an enclosed seed spike with tightly held fruit cases and are ideal for harvesting and long-term storage. Many hypotheses abound regarding adapting mid-latitude corn to higher latitudes and it is believed corn moved into the northern Americas within the last 2000 years. The minimum soil temperature required for corn germination is 10^{o}C at 5 cm depth with adequate moisture to soften the corn bran. Corn vegetative production typically occurs within the first 30-45 days after germination when temperatures meet or exceed optimal conditions (20-23^{o}C) (Poethig, 1994).

Corn is a C_4 metabolic pathway species that probably evolved during a period on earth when elevated temperatures were coupled with lower CO_2 levels and drought (Brown, 1997). Higher photosynthetic C_4 leaves are attributed with greater water- and nitrogen-use efficiencies, partly because of reduced competition for oxygen at CO_2 reaction sites. Corn drought-tolerant traits promote lower respiration rates during times of above average temperatures. In corn, a C_4 grass species, a direct, near-linear relationship exists between CO_2 fixation and increases in leaf N content. The inherent nature of C_4 nitrogen-use efficiency fixes CO_2 at higher rates per unit of N fertilization (Brown, 1997). Corn is ideally adapted for prairie soils found throughout the central U.S. stretching from Minnesota to Mississippi.

In the five-year period between 2008 and 2012, U.S. corn growers produced slightly more than 370 million Mt (12 billion bushels) corn annually (USDA-NASS, 2012). Corn Belt Dents and derived Southern Dent races, farmed predominantly in the Midwestern states for animal feed, produce slightly tapered or cylindrical ears with 14-22 rows of kernels aligned straight with the polar ends (Galinat, 1988). The dent germplasm most likely arose during the 1800s from genetic variability found in Northern Flint races. The amount of horny, embryonic starch varies between dent and flint races, where the flint horny layer extends over the kernel and prevents denting caused by shrinkage (Kiesselbach, 1999). Tillers, or lateral branches arising from the lowest auxiliary buds, are selectively bred out of dent varieties, which normally produce two or less ears of corn per stalk (Poethig, 1994). Variation in the number of leaves (typically 10-20) per shoot may be directly correlated to the induction of reproductive growth, or tassel initiation, along with appropriate temperature and photoperiod signals. Dent vegetative phyllotaxy is distichous and radial, non-branching with one leaf per phytomer, and some higher leaves develop a direct solar incidental arrangement (Galinat, 1994; Coe et al., 1988).

Nitrogen Sensing in Agriculture

The 2008 U.S. Farm Bill appropriated federal funds for the Conservation Stewardship Program (CSP) to help farmers and foresters address resource concerns (Natural Resources Conservation Service, 2010). The competitive CSP incentives include management practices that affect soil quality and erosion, water quality and quantity, air quality, and plant and animal resources. The 2014 Farm Bill proposed cutting conservation funding in hopes of claiming five billion dollars in savings over the next decade (Ellis, 2013). A reduction of conservation incentives may decrease the likelihood that producers will adopt innovative technology systems that are still under development and not fully proven to be effective in a broad set of circumstances.

Farmers want proven technologies and they require assurances that innovations will produce expected results. Farming operations require simple, ready-to-use tools with predictive capabilities that advance their crop production systems. Most modern farmers possess the capacity to decrease inputs and reduce N losses by integrating previous yield history into current cropping plans. However, farmers are risk averse and tend to use optimal N fertilization schemes to assure maximum output (Fox et al., 1989; Scharf et al., 2005a). Crop N recovery from soils and fertilizer exhibits a high degree of spatial variability (Breitenbeck, 1990; Raper et al., 2013; Varco et al., 2013). Fertilizer timing, rate, and application method are cropping decisions that, when inadequately addressed, produce high crop variability (Plant, 2001; Zhang et al., 2002). Ideally, a crop N status indicator should detect and allow correction for N excesses and deficiencies quickly during a growing season (Herrman and Taube, 2004).

Soil Nitrogen Variability

Soil testing for N availability is a time consuming and costly enterprise (Raper, 2011). Spring soil tests for N concentration is a compromise between obtaining results early enough to make management decisions and collecting the data late enough to avoid wet weather conditions (Blackmer et al., 1989). At soil depths up to 0.3 m, Buscalgia (2000) found available soil N was positively correlated to cotton plant height. Furthermore, soils with greater clay content tested for greater total soil N and carbon (C), although high clay content tended to bind the availability of the soil N. The mineralization of soil N in cotton was faster in coarse soils than in fine soils. In corn, a high degree of spatial dependency was found in soil physical and chemical properties, which included available soil N (Hubbard, 2012). In a two-year corn study, extractable NO_3^--N and NH_4^+-N soil levels appeared to moderate each other’s soil concentration by reversing the degree of each spatial dependency. Whole plant N uptake was slightly less spatially dependent than whole plant N concentration in corn that received N treatments ranging from deficient (0 kg N ha^{-1}) to excessive (269 kg N ha^{-1}). These results imply that spatially variable soils may be candidates for variable-rate N management that is facilitated by remote sensing crop status assessment.

Most soils contain varying levels of organic and inorganic forms of N (Gardner and Tucker, 1967). The inorganic nitrate form (NO_3^-) is used by cotton to the greatest extent and is directly relatable to cotton yield. In corn, evidence suggests that different N sources produce few variations in corn yield (Ekert, 1995). Soil N assessment is confounded by the nutrient's high solubility and is subject to loss mechanisms of either leaching or denitrification, which negatively affects grain yield. Too little available soil N will impede proper growth at critical stages, while excessive N becomes vulnerable to transport and transformational losses. To date, no single definitive remote sensing method has been developed to ascertain residual soil N concentrations. Crop reflectance measures are an indirect approach to estimating soil N reserves (Raper, 2011). Ground-based sensors connected to on-the-fly variable rate N fertilizer applicators may be employed to assess early crop leaf N status and to recommend appropriate supplemental N fertilization. By limiting the amount of vulnerable N placed in production fields, N-use efficiency (NUE) can be gained.

Plant (2001) proposed site-specific management (SSM) of agricultural crops in order to address field variability and reduce input costs. Rather than addressing crop fields on a whole-field basis, it was proposed that measures of field variability be incorporated into management decisions. Combine harvested crops georeferenced through global satellite systems (GPS) provide actionable datasets that can be used to make N treatment recommendations. The findings of this research suggest estimating nutrient requirements based solely on previous cropping history and does not adequately address multiple other mitigating factors such as excesses and deficiencies in moisture availability, pest competition, and soil physical and chemical properties. Plant proposed integrating continuous yield data with site-specific (point) data in order to achieve a stronger estimation of field variability.

Soil electrical conductivity (EC) maps may be incorporated into variable rate prescription in order to predict spatial N distribution and to improve N use efficiency (NUE) more accurately. Sudduth et al. (2001) proposed using soil EC as a surrogate for estimating soil attributes such as clay content. Whole-field soil EC maps may vary when taken on different measurement dates due to varying temperature and soil moisture content. Zhang and Wienhold (2002) found soil mineral N concentration was correlated with soil EC when measured *in situ* with a portable soil EC meter ($r^2 = 0.85$). However, large amounts of soil salts and free carbonates tend to confound soil EC measures.

Crop Nitrogen Use Efficiency

Crop NUE is modulated by many factors, and increasing fertilizer rates tends to decrease NUE and leave residual N susceptible to losses in the environment (Parr, 1973). The greatest return on N fertilizer investment and least loss of N to the environment occurs below the rate to produce maximum crop yield. In order to increase NUE, producers must accurately predict optimal N fertilizer rates, and account for residual and mineralized soil N resources. Nutrients removed from 15 Mg ha^{-1} (225 bu ac^{-1}) corn are 224, 40, 152 kg ha^{-1} of N, P, and K respectively (Abendroth et al., 2011). Gauer et al. (1992) found corn grain NUE to decrease with increasing N fertilization rates, and this was especially true if moisture was a limiting factor. Crops fertilized in-season have greater NUE than those grown on fields with winter-applied and incorporated fertilizer N (Olson and Swallow, 1984). Spring weather conditions may confound early in-season applications, and late-season N applications tend to subsidize increases in corn grain N content (Raun and Johnson, 1999).

Aber and Melillo (2003) defined NUE as "the mass of nutrient required to produce a given quantity of biomass." Although this can be the inverse of concentration at senescence, or when a tissue is shed by the plant in annuals, perennial NUE is based on litterfall, root turnover, and vegetative organic matter (Vitousek, 1981). Nutrient use efficiency (NutUE) can be expressed with different indices that include partial factor recovery, agronomic efficiency, apparent recovery efficiency, and physiological efficiency (Roberts, 2008; Lemus et al., 2008). Nutrient use efficiency is dependent upon genetics and environmental factors. Fertilizer use efficiency (FUE) is defined at the extent of fertilizer nutrient recovery in an agricultural crop typically measured as yield per unit fertilizer nutrient input (IPNI, 2006; FAO, 1984). Agronomic and best management practices can alter FUE that place fertilizer nutrients (right source) at the right rate at the right time in the right place (4Rs) (IPNI, 2006). This is especially true of nitrogen use efficiency (NUE) where cropping schemes require managed fertilization systems that avoid under- and over- application, both of which reduce production and NUE (Mengel and Kirkby, 1978; Havlin et al., 1990). However, NUE varies greatly by crop species, whereby some crops, like legumes, grow efficiently with limited or no supplemental N fertilizer. Other environmental factors, such as water availability, soil pH and microbiota, affect soil N availability and ultimately, NUE.

Corn fertilizer N savings and increased partial factor productivity are possible using sensor-based applications of N fertilizer applied in soil management zones (Roberts, 2009; Roberts et al., 2010). This was especially true where soil spatial variability existed. Fine silt-loam soils on eroded slopes produced higher fertilizer N savings under management zones than did coarse, sandy soils. The increased savings may be related to higher crop response on eroded soils with lower organic matter.

Partial factor productivity (PFP) of applied nutrients is used to measure nutrient-use efficiency (Cassman et al., 1996). The applied N PFP is calculated as the ratio of grain yield to N applied:

$$PFP = Y/N_r \tag{2.1}$$

where Y is grain yield and N_r is the amount of fertilizer N applied.

Corn was grown in central Nebraska during 2007-2008 in producer fields under irrigated conditions and varying soil types. Multiple variables, including fertilizer N rate, soil texture, topography and elevation, and soil EC were related to optical sensing results. The study found that in order to increase PFP, a producer must increase N uptake and indigenous N use or improve grain yield relative to N taken up by the crop. Sensor-based treatments were shown to improve PFP as much as ~13-75 kg grain (kg N applied^{-1}) (Roberts, 2009).

Crop Reflectance Relative to N Fertilization

In order to increase NUE and savings from appropriately distributed fertilizer N applications, management of fertilizer treatments must be made on a field-scale basis (Solie et al., 1996; Raun et al., 2002). Varying corn N treatments result in leaf canopy changes that subsequently affect reflectance measures (Walburg et al., 1982). Sensor-based N fertilization is limited by the inability to detect and discriminate between early N effects on young crops (Varco et al., 2013). Predicting early corn N status using canopy parameters may be particularly difficult due to the under developed architecture prior to the eighth leaf. In early corn, less than 30% of soil is covered by canopy vegetation and reflectance measures are compromised in the red and near-infrared regions (Walburg et al., 1982). Furthermore, few inferences between early crop parameters can be made as leaf N is most likely to be less than 3.3% and varies little with LAI. Finally, field soils exhibit spatial N variability across narrow and broad landscapes. Selecting a single vegetation index that will most closely approximate early crop N status introduces inherent limiting factors (Raper, 2011).

Strachcan et al. (2002) found no single vegetation index accurately described individual corn crop characteristics, such as leaf chlorophyll content, LAI, and yield, throughout the entire season. In order to assess the relationships between normal physical crop function and environmental factors, or "crop ecophysiology evolution", they employed multiple bandwidth selections and indices through canonical discriminatory analysis at three select points in a growing season. In the absence of environmental stresses where N stress was imposed by design, leaf expansion, LAI, and yield over a growing season were the most favored separable outcomes as a result of varying by N availability.

Reflectance of light measured in the green region (550 nm) will differentiate N among varying N treatments in corn leaves (Blackmer et al., 1994; Schepers et al., 1996; Gitelson et al., 2001). However, chlorophyll measured as a light transmittance ratio between 650 nm and 940 nm wavelengths produced by a SPAD-502 meter (Konica Minolta, Japan) was directly related to leaf N concentrations (Blackmer et al., 1994; Blackmer et al., 1995; Schepers et al., 1996; Bullock and Anderson, 1998). Nitrogen deficiency in corn canopies produces marked increases in red reflection (> 650 nm) and indirect decreases in the ratio between red and near-infrared wavelengths (Colwell, 1974; Walburg et al., 1982).

Optimized crop growth results from combined environmental and cultural factors including the spatial distribution of plants, temperature, sunlight and water resources, available N, soil constituency, variety selection, and management practices (Aldrich, 1980). Fluctuating crop conditions and variation in plant canopies between species obfuscates the development of N status assessment tools. Evidence supports modeling biophysical parameters such as chlorophyll content and leaf N concentration against spectral reflectance to predict N status, biomass accumulation, and yield (Baret and Guyot, 1991; Blackmer et al., 1994; Blackmer et al., 1995; Schepers et al., 1996; Bullock and Anderson, 1998; Cassanova et al., 1998; Aparicio et al., 2000; Gitelson et al., 2003a; Gitelson, 2005). The strength of the relationship between cotton leaf chlorophyll content and reflectance is weaker than that of corn leaf chlorophyll content and reflectance at similar bandwidths (cotton $r^2 = 0.61$; corn $r^2 = 0.92$) (Thomas and Gausman, 1977).

Indigenous soil N creates challenges in agronomic research (Cassman et al., 2002). Fertilizer N applications provide a large relative effect on corn growth and grain yield, while indigenous sources of soil N can be highly variable across a landscape. Cassman believed the amount of stover N had a small effect on crop physiological N efficiency (PEN) unless factors other than N were limiting growth and grain yield.

Cassman defined PEN as the change in grain yield per unit change in above ground biomass N accumulation. Predicting the effect of soil N on crop productivity was achieved by measuring the residual effect of N uptake in corn grain absent of stover measurements (Maskina et al., 1993). Maskina found stover uptake followed similar patterns in corn grain N uptake over varying N treatment applications. However, Maskina noted that, in a primarily climate stressed environment, the translocation of N from vegetative tissues to corn grain may preclude corn grain filling at an optimum level. High N supply typically results in less efficient N use, and variations in NUE may differ between N supply and crop genotypes (Moll et al., 1982). Total corn grain N content may vary with management practices (tillage intensity, N fertilization, and use of winter cover crops and manures) that increase mineral soil N reserves (Maskina et al., 1993).

Consideration for row spacing and plant density is not compulsory for estimating corn N rate, and the optimal corn fertilizer N range (including starter fertilizer) is between 84 and 252 kg ha^{-1} (Mamo et al., 2003; Shapiro and Wortmann, 2006). However, plant density and row spacing considerations are necessary for determining optimal cotton N rates because average rates, between 84 and 140 kg N ha^{-1}, may not be suitable for plants in narrow row-width and/or high population arrangements (Yasseen et al., 1990; Sadras, 1996; Boquet and Breitenbeck, 2006; Sabbe and Hodges, 2010). Differences between cotton and corn N uptake relative to plant density may be related to differing canopy architecture, leaf structure, and light interception (Sadras, 1996; Heitholt and Sassenrath-Cole, 2010).

Nitrogen Implications in Cotton Leaf Physiology

Cotton is an indeterminate plant that produces vegetative and fruiting branches (dimorphism) in response to environmental conditions (Eaton, 1955). Fruiting branches typically occur above the fourth main-stalk node. Cotton plant photosynthetic capacity, and related plant productivity, is affected by variations in lobe leaf morphology, phyllotaxy, and physiological condition (Wells et al., 1986). Mature leaf chlorosis, premature senescence, and lower plant biomass production are evidence of N deficiency in cotton (Gerik et al., 1998). Total leaf N analysis can predict leaf N % at $\pm$95% accuracy (Carlos Erba, Milan Italy), and typical cotton leaf N found in dry, combined mid-rib and lamina tissue ranges from 2 to 5%; similar to most vegetative tissues (Mengel and Kirkby, 1978). Total leaf N assay provides an indication of N accumulation by the leaf prior to sampling rather than petiole sampling which is more indicative of N transport (Gerik et al., 1998). Cotton leaf N-status levels have been estimated at the following levels: deficient $\leq$ 2.5% N, low = 2.5-3.0% N, sufficient = 3.0-4.5% N, and high >4.5% N (Sabbe et al., 1972; Sabbe and MacKenzie, 1973). Bell et al. (2003) recommended critical leaf N values of 5.4, 4.3, and 4.1% at early square, early bloom, and mid bloom, respectively. Plant N uptake and metabolism is species and environmentally dependent where arable crops grow under conditions of greater NO_3^- supply than NH_4^+ due to the rapid conversion by soil microbes to the oxidized form of the latter (Mengel and Kirkby, 1978). Although cotton is a drought-tolerant species, water stress limits N metabolism (Radin and Parker, 1979). Cotton N uptake progresses linearly from 1.5 – 2.0 kg ha^{-1}per day between 60 to 120 days after seeding (DAS) ($y = 0.6107x - 25.78$; $r^2 = 0.97$) then decreases to a plateau uptake rate averaging approximately 1.37 kg

ha^{-1} per day between 135 to 165 DAS (Bassett et al., 1970). Between June 15 and August 15, regardless of planting date, cotton plants uptake approximately 67 % of all seasonal N and P resources.

Nitrogen deficiency in water-stressed cotton produces a decrease in stomatal conductance and sensitivity (Radin and Ackerson, 1987) and the osmotic potential in leaves is slightly lower if N and water are limiting factors (Radin and Parker, 1979). Subsequently, high-N plants produce more leaves with greater leaf area than those plants with limited or low N. Reddy and Reddy (1998) found cotton leaf development to be directly related to temperature and is moderated by other factors such as N availability. Low-N plant structural leaf cells are reduced in size and this is especially evident in mesophyll cells that are noted for their chloroplast pigment abundance. In order to manage the tandem effects of limited N and water, xeromorphic leaf-cell differentiation tends to favor architectural changes in cell wall properties in lieu of other photosynthetic activities (Radin and Parker, 1979). Nitrogen and water stress interactions are thought to regulate abscisic acid (ABA) production and accumulation (Radin and Ackerson, 1987). Abscisic acid is believed to increase stomatal sensitivity under elevated carbon dioxide (CO_2) conditions, and the long-range climate-change predictions related to drought and rising CO_2 environments may have a deleterious effect on cotton crops that become both N and water limited.

Although vegetative-to-fruiting growth ratio and the cotton-boll flowering initiation do not appear totally N dependent, it is suggested that N status influences flowering termination (Yasseen 1990; Mauney, 1986b). Nitrogen deficiency is considered a limiting factor relative to extended flowering capacity because cotton is an indeterminate plant. A shortened flowering season coupled with lower boll production ultimately reduces cotton lint production.

Drought stress, as indicated topically as leaf wilting under high solar radiation and heat conditions, notably increases visible reflectance and lowers near-infrared reflectance ($\lambda > 700$ nm) in most species (Zygielbaum et al., 2009). Visual clues (400 nm $< \lambda >$ 700 nm) denoting N, P, K, and S deficiencies in cotton are noted in leaf hue intensity (Andrews, 1950). Where N is not a limiting factor, changes in leaf color did not provide a strong enough indicator for other elemental limitations. Soil N is highly mobile (Mengel and Kirkby, 1978) while other macronutrients may remain resident in soils depending on cultivation and irrigation practices (Andrews, 1950). Cotton spectral characteristics visible to the naked eye are not broadly equated to nutrient status (Fridgen and Varco, 2004). Nitrogen fertilizer recommendations do not meet actively growing cotton demands, vegetation and flowering activities are curtailed (Hodges and Constable, 2010).

Zhao et al. (2005) found hyperspectral leaf reflectance to be an indicator of cotton leaf N status. Leaf N concentrations were greatest between 40 and 70 DAS (first square to first flower stages) and increased with increasing N fertilizer rate. Changes in leaf N concentration were most notable in the uppermost, fully expanded mainstem leaves, and the results were positively correlated with leaf chlorophyll levels as measured with a SPAD Chlorophyll meter. Furthermore, leaf reflectance at 556 and 710 nm increased with decreasing N fertilizer rate. Cotton leaf N concentrations differ significantly when produced under varying levels of N fertilizer and CO_2 enrichment (Reddy et al., 2004). Leaf N concentrations were observed to decrease with increasing CO_2 treatments (180, 360, and 720 μmol mol^{-1}) under two N treatment regimens (continuous N and N withheld from flowering to harvest).

Although carotenoid pigments interact with, and are linearly related to, chlorophyll content, under varying N supply chlorophyll content in cotton is considered the most important independent factor affecting leaf reflectance (Thomas and Gausman, 1977). However, the strength of the relationship between cotton leaf chlorophyll and reflectance is markedly weaker than corn leaf chlorophyll and reflectance at similar bandwidths (cotton $r^2 = 0.61$; corn $r^2 = 0.92$).

Nitrogen Implications in Corn Plant Physiology

Corn leaves possess a strong mid-rib that is low in nutritional elements while the outer lamina has a greater concentration of minerals supporting photosynthetic activities (Jones, 1970). Nitrogen deficiencies lead to a decrease in chlorophyll concentration and alter the leaf color, absorbance, transmittance, and reflectance (Al-Abbass et al., 1974). With N stress in corn, canopy reflectance of red light rises, while near-infrared reflectance declines, although background spectral response mechanisms (soil cover and canopy density) interplay with resultant spectra (Walburg et al., 1982). The leaf-level spectral response to N stress is primarily related to low chlorophyll production in active leaf tissues. The average N content found in the ear leaf at silk stages is 2.7 to 3.5 %, but N nutrient sufficiency is possibly in the 4 to 5 % range (Walsh and Benton, 1973). In some cases, leaf N may be adequate, while leaf chlorophyll is impaired and vice-versa.

Plant essential elements are absorbed differentially by corn sub-species, and corn leaf analysis is complicated by macro- and micronutrient requirements that include N, P, K, Ca, Mg, Al, B, Cu, Fe, Mn, Mo, Cl, and Zn (Walsh and Benton, 1973; Jones et al., 1990; Taiz and Zeiger, 2010). Nitrogen and P interactions are relative to the concentration of each element, and K deficiency acts as a limiting factor to both primary nutrients (Voss et al., 1970). Nitrogen deficiency noted in isolated analysis suggests that visual chlorosis discrimination begins in older, lower leaves then progresses upward in the growing plant (Voss, 1993). Phosphorus deficient corn exhibits leaf tip and margins reddening, and an overall plant stunting during the early growth stages; however, some discoloration may improve as plants enlarge. Plant height and biomass will inevitably be limited by P deficiency despite positive leaf color. Chlorotic corn leaves may also be a function of K deficiency, and like N, K is mobilized upward in the plant during growth. Sulfur deficiency also produces chlorosis, but the mineral is not mobilized upwards in developing tissues. Magnesium deficiency exhibits yellow to white interveinal stripes, and the damaged tissues can give way to dead tissues within the leaf margins. Nitrogen and Mg deficiencies are common in sandy soils with low pH and high leaching potential. Chlorine deficiency in corn also promotes visual chlorosis, especially in younger leaves.

The chlorophyll-sensitive reflectance bandwidths (550 nm, 650 nm, and 710-840 nm) in canopy-level corn tend to increase, decrease, and increase respectively, until tasseling with little variance (Gausman et al. 1973; Thompson and Gausman 1977; Gitelson et al., 2005). Although a chlorophyll meter (e.g. SPAD) provides a unit-less means to measure plant greenness, the entire visual effect is not totally accounted for by chlorophyll content alone (Blackmer et al. 1994; Blackmer, et al. 1995; Schepers et al. 1996). Chlorophyll meters (SPAD) are related to canopy- and sensor-level datasets without undue influence from background soil information. However, the related canopy-level spectroradiometric samples, taken coincidently with SPAD readings, may possess soil albedo reflectance containing altered red and near-infrared bandwidth regions. Soil noise may negate correlating SPAD readings.

Corn leaf net photosynthetic capacity (P_n) is closely related to early leaf N concentration, and the production capacity declines with leaf N in most cases (Zhao et al., 2003). Measured differences in biomass are related to a reduction in plant size or leaf area rather than in chlorophyll content alone. Furthermore, N deficiency in corn may decrease the chlorophyll *a*:*b* ratio because chlorophyll-a appears to fall in content relative to chlorophyll-b and carotenoid concentrations in plants undergoing stress. Relative corn chlorophyll meter values (average SPAD/average SPAD sufficiency reference) have been calculated to produce a dark green color index useful in making N recommendations mid-growing season (Rorie et al., 2011; Sawyer et al., 2011).

Biophysical Parameters for Crop Sensing

Canopy Estimations

Leaf area index (LAI) as defined by Watson 1947 (In: Baker et al., 1978) is the area of leaf material divided by the ground surface area that it shades. Supported by a deep taproot, the cotton canopy produces greatest leaf weight when daytime/nighttime temperatures are above 20/12°C (Reddy et al., 1997). Greater leaf area supports photosynthetic activities critical for maximizing boll production (Purcell, 1992; Landivar et al., 2010) and for reducing soil evaporation losses through soil shading (Mauney, 1986).

LAI has been successfully correlated to biomass production in multiple crops, but its employment in remote sensing analysis is often dependent upon phenological sampling over the crop growth cycle prior to senescence (Baret and Guyot, 1991;

Cassanova et al., 1998; Madakadze et al., 1998; Aparicio et al., 2000; Gitelson et al., 2003; Gitelson, 2004). Cotton and corn canopy studies have correlated LAI to NDVI over a wide-range of values (Carlson and Ripley, 1997; Li et al., 2001). Early canopy leaf area is more highly correlated to NDVI than at later stages. Leaf area index modeled from emergence to senescence is not always correlative to N status modeling in crops, and LAI measures may or may not be useful in scaling up leaf-level to canopy-level spectroradiometer measures (Sellers, 1989; Ciganda et al., 2008; Hatfield et al., 2008). As a canopy develops, significantly more resources are added to structural components (stems, branches) that support leaves (Lemaire and Gastal, 1997). The estimation of the decrease in leaf area fraction associated with plant mass increase is coined leaf area ratio (LAR) and is calculated by dividing the specific leaf area by the shoot biomass. Lemaire and Gastal (1997) found LAR to be more strongly related to leaf N status than LAI.

Yoder and Pettigrew-Crosby (1995) found visible bandwidths (blue, green, red) best predict chlorophyll, and near infrared (NIR) bands best predict N, yet NIR at leaf-scale was a poor predictor of N status at the canopy-level in young maple seedlings. Stark et al. (2000) proposed a combined spectro- and photo-metric approach (vegetation fraction) in the visible spectral range to decouple leaf-scale and canopy-scale parameters for monitoring phenological changes in wheat (*Triticum aestivum* L.). The band combinations 700 nm, 550 nm, and 670 nm, were equally efficient for predicting vegetation percent against the background soil line in early and mature crops.

Nitrogen Estimations

Evaluating young cotton crops for N stress via remote sensing technology may not be possible through LAI measures owing to high background soil reflectance in underdeveloped canopies (Wullschleger and Oosterhuis, 1990). Nitrogen deficient cotton plants express a reduced LAI within 76 days after planting compared to plants receiving adequate N (Wullschleger and Oosterhuis, 1990). Baker et al. (1978) proposed measuring light interception in early crops by defining ground cover as a ratio between the canopy distance between rows and the plant height. Although photosynthesis is controlled at the leaf-level, scaling up single-point leaf-level data to canopy-level processes may not be possible without leaf environment parameters (Landivar et al., 2010). Reflection of radiation striking a heliotropic cotton plant with terete symmetry is diffusely scattered, and spectral measurements are complicated by plant conditions such as turgidity and nutrient status (Wilkinson, 1912, Schutt and Kimes, 1985; Landivar et al., 2010).

Photosynthesis is not always curtailed in early cotton when N deficiency threatens to stunt plant growth by reducing stem elongation and leaf expansion (Wullschleger and Oosterhuis, 1990; Hodges and Constable, 2010). The juvenile cotton leaf is deeply lobed and typically possesses lower chlorophyll concentrations than at the peak growth stage, when stark leaf margins and lobed features diminish (Constable and Oosterhuis, 2010). The carotenoid-to-chlorophyll pigment concentration in cotton leaves is approximately 1:12 where, in a vigorous growing state, the blue, green, and red wavelengths (450 nm, 550 nm, and 670 nm) are directly relatable to chlorophyll pigmentation (Thomas and Gausman, 1977).

Zhao et al. (2007) found linear relationships between reflective indices, such as NDVI, EVI, WDRVI and RVI (see Table 3.4) and log (LAI) and log above ground biomass (ABM). Both LAI and ABM saturate, or become unresponsive to indices, when values peak just after first flower or approximately 60 d after seeding. When expressed on a leaf area basis rather than a leaf area index, whole-canopy photosynthesis actually increases due to better light penetration relatable to lower LAI. Cotton stress related to N deficiency can be expressed by changes in canopy-level variables such as LAI (Wullschleger and Oosterhuis, 1990; Baret et al., 2007) and chlorophyll content (Gerik et al. 1998; Baret et al., 2007). Related to LAI, plant height alone is not a direct predictor of canopy photosynthesis (Kharche, 1984).

Spectral measures differentiating cotton N status have been successfully demonstrated in several studies (Read et al., 2002; Buscaglia and Varco, 2002; Bronson et al., 2003; Fridgen and Varco, 2004). Buscaglia and Varco (2000) found NDVI to be positively correlated with available soil N, plant height, and yield. Explaining how to best capture early cotton crop N status, at the canopy or leaf-level remains to be determined. It may be possible to scale-up leaf-level spectroradiometric sampling to the canopy level by developing a canopy coefficient from plant height-row distance measures suggested in Landivar et al. (2010). Haboudane et al. (2004) demonstrated radiative transfer models to tune vegetation indices to chlorophyll content by minimizing LAI effects against background soil data. Leaf chlorophyll concentration is correlated to N concentration at both leaf- and canopy-levels (Hansen and Schojoerring 2003; Baret et al., 2007). Partial least squares regression modeling has been demonstrated in calibrating normalized difference vegetation type indices to canopy biomass and N status and canopy surface-area variables were better fit to bandwidths using exponential curves to explain relationships (Hansen and Schojoerring, 2003). Hansen and Schojoerring's study did not examine the effect of variable on-the-fly N rate applications and related spectral responses. Most N rate studies reviewed for this work examine the effect of N rates applied at varying levels and then regressed against biophysical measurements.

Raper (2011) used a YARA N-Sensor (YARA (Hydro Agri), tec5Hellma) to determine that crop N content correlated with leaf N concentration multiplied by cotton plant height, which suggested it could be used as a proxy for whole plant N content. Although taller plants were associated with greater N fertilization rates, the fertilizer effect on plant height was not significant ($p \leq 0.05$). Furthermore, the findings infer that N application over an optimum rate does not increase plant height as it could be limited by other factors such as available water. The 600-680 nm region was most sensitive to plant height and the Simplified Canopy Chlorophyll Content index (SCCCI) (Barnes et al., 2000; El-Shihka et al., 2008; Raper and Varco, 2014) was least sensitive to this parameter. Varco (2006) proposed the plant height times leaf N concentration parameter for fitting crop N content to biomass related VIs [Green Normalized Difference Vegetation Index (GNDVI) (Gitelson et al., 1996) and (NDVI) (Rouse et al., 1979)]. Freeman et al. (2007) found NDVI multiplied by corn plant height might estimate forage N uptake prior to or at V10, although the relationship was weak for early growth stages when NDVI ≤ 0.4.

Houles et al. (2007) established the relationship between wheat chlorophyll content and absorbed N more reliably predicted the N nutrient deficit (ΔNU) at canopy-level than at the leaf-level. The results demonstrated N dilution curve that depicts the natural decline in tissue N concentration in aerial plant components as a crop matures. Leaf: stem weight ratio and leaf self-shading were indirectly related throughout plant development. Jia et al. (2004) proposed integration of soil N data prior to fertilizer recommendations for winter wheat production in order to compensate for errors made in predicting N requirements uncoupled from other biotic and abiotic factors. Jia et al (2004) found no direct correlation between absolute color value, leaf N concentration, and SPAD® Chlorophyll Meter (Konica-Minolta, Japan) readings taken at the boot stage. However, the study did note a significant negative linear relationship between normalized red, green, blue (RGB) values ($\lambda_1/\lambda_1+\lambda_2+\lambda_3$) and N and SPAD chlorophyll readings taken 28 days prior to and at the boot stage.

Chlorophyll Estimations

Cotton and corn leaf N concentration and chlorophyll status under varying fertilizer N rates have been successfully assessed in-season using proximal remote sensing technologies (Blackmer et al., 1996; Bullock and Anderson, 1998; Buscaglia and Varco, 2002; Read et al., 2002; Bronson et al., 2003; Gitelson et al., 2003b; Fridgen and Varco, 2004; Gitelson et al., 2005; Zhao et al., 2005; Hubbard, 2012). Sellers (1989) found leaf-scale spectral reflectance predicts N status and chlorophyll status but canopy-scale reflectance best estimates LAI and absorbed photosynthetically active radiation (aPAR). The red-edge position and maximum reflectance bands (green and NIR) are strongly correlated to chlorophyll and leaf N status, while the ratio between red and NIR bands strongly correlates to LAI (Gitelson et al., 1996; Gitelson and Merzlyak, 1996; Gitelson and Merzlyak, 1997; Lichtenthaler et al., 1996; Boegh et al., 2002; Gitelson et al., 2005). Baret et al., (2007) found the multiplicative effect of LAI times chlorophyll *a* and *b* (C_{ab}) created a parameter that was suitable for predicting N content in wheat at the canopy level. Because chlorophyll content and LAI affect green and red-edge bandwidth regions, it is necessary to decouple this effect and minimize the confounding canopy influence (Gitelson et al., 2003a).

Photoreception and Photo-pigment Development in Plant Leaves

Multiple plant tissue photoreceptors work independently of one another to register seasonal light variations, and are responsible for the production of biochemical products used in growth and development (Kendrick and Kronenberg, 1993; Srivastava, 2002). Phytochromes regulate many plant photoreceptor activities including chlorophyll production during leaf expansion, which differentiates etioplasts into chloroplasts through red light mediation. Spectroradiometric techniques are not able to distinguish phytochromes in plant tissues; therefore, chlorophyll content (SPAD units or mg m^{-2} leaf area) approximates phytochrome abundance in many ecological studies. Chlorophylls, which absorb maximally in the red (650 nm+) and blue (450 nm) regions, are of particular interest in remote sensing research because strong bandwidth correlations to pigments are relatable to multiple proxies including percent leaf N, vegetation fraction, and biomass accumulation (Mengel and Kirby, 1978; Lichtenthaler, 1987; Gitelson et al, 2001). The 450 and 650 nm bandwidth regions are considered antagonists in seed germination, and are inversely proportional in early crop leaf N status at the leaf- and canopy-levels (Buscaglia and Varco, 2002; Zhao et al., 2003).

The quality, quantity, direction, and duration of light received by developing corn and cotton plants profoundly influences organogenesis and photosynthesis (Coe et al., 1986; Kiesselbach, 1999; Wells and Stewart, 2010). Plant genetics regulate leaf shape, size, and most importantly leaf arrangement or phyllotaxy. Phyllotaxy describes the helical and predictable patterns of leaf organogenesis around a productive stem or sheath

(Steeves and Sussex, 1989). A generative spiral is produced in order of decreasing plant age and creates recognizable vertical leaf ranks each termed an orthostichy. Defining the phyllotatic pattern is the fraction of orthostiches to the number of gyres of the helix between successive leaves. Maize plants initiate leaves from the shoot apical meristem in a single, alternating pattern opposite each side of the corn stalk (Jackson and Hake, 1999) while the emerging direction of cotton orthostiches appear related to direction of fruiting branches in leaf axils as well as the directions of petal range (Wang, 1994).

Photoreceptors in plant leaf cells have evolved to aid in the reduction of stem elongation in high light conditions where maturing leaves receive blue and ultraviolet rays that mediate tissue differentiation (Srivastava, 2002). Young dicot and monocot leaves arise in a similar manner from apical meristematic tissues, but the leaf primordia from the two-angiosperm classes proceed in diverse manners in order to produce highly differentiated phyllotaxy. Corn and cotton full-sun stem and leaf characteristics are more compact with shorter internode spaces and higher ratios of internal to external leaf surface area. Full sun leaves possess lower chlorophyll content and accumulate higher carotenoid pigments that may promote discoloration of leaves trending toward chlorosis when photosynthetic nutrients are limited or sun levels are too extreme (Srivastava, 2002).

The primary photosynthetic pigments chlorophylls and carotenoids belong to a group of plant lipids knows as prenyl lipids (Lichtenthaler, 1987). Prokaryotic organisms, plants, ferns, mosses, and blue-green algae have chlorophyll-a as a major pigment and chlorophyll-*b* as an accessory pigment. The chlorophyll *a:b* ratio in high-light plant chloroplasts ranges between 3.2 to 4. Although carotenoids act as light absorbing pigments, the main function of the dominant senescent pigment is to protect chlorophyll-a from photooxidation (Gitelson and Merzlyak, 1994a and b; Zur et al., 2000). Green chlorophyll and yellow carotenoids are separable by plant pigment extract and the average, discriminatory peak-wavelengths are noted within the following ranges:

- total carotenoids (including β-carotene, lutein, violaxanthin, and neoxanthin) ~ 450 nm,
- chlorophyll-*a* ~ 428 and 660 nm, and
- chlorophyll-*b* ~ 452.2 and 641.8 nm (Lichtenthaler, 1987).

Because photosynthetic pigment's spectral characteristics are separately discernible, remote sensing technologies can be calibrated to delineate plant nutrient status throughout the growing season (Gitelson and Merzlyak, 1994a & b; Gitelson et al., 2005). In this study, attention will be given only to green chlorophyll pigments averaged as a single photosynthetic component (at ~440 nm & ~650 nm), and the lower bandwidth consideration will be avoided because the correspondence to carotenoids is marginally implicated in young crops. Healthy green leaves exhibit strong reflectance at approximately 550 nm and again at 700-710 nm and chlorophyll sensitivity in the visual red region (+/- 650 nm) decreases as leaf chlorophyll content increases.

Both stress and seasonal shifts to shorter daylight-hours initiate senescent-like characteristics in annuals and perennial deciduous plants such that carotenoids dominate leaf colors that shift from green to yellow (Gitelson and Merzlyak, 1994a; Srivastava, 2002). Under stress, plant nutrient resources are mobilized and redirected (or cannibalized) to support root storage and continued progeny development. Chlorophylls are degraded quickly, while carotenoids continue to photosynthesize in the blue bandwidth regions. This is particularly pronounced as daylight hours shorten in the northern hemisphere and deciduous trees turn autumn-like (Gitelson and Merzlyak, 1994b). At chloroplast metabolic breakdown, leaf cells in the epidermis and phloem cease to function and tissues are naturally abcissed (Srivastava, 2002). During senescence, the primary plant fertilizer, ammonia nitrogen, is converted to the proteins amides, glutamine, and asparagine by glutamine synthases (GS1 in cytosol and GS2 in plastids) for transport in phloem tissue. During stress, GS1 activity increases while GS2 activity decreases. Magnesium is implicated in chlorophyll breakdown as it is removed from the pigment porphyrin ring and the chlorophyll-binding proteins are degraded. Chlorophyll is further degraded in cell vacuoles when their catabolites are exported from the chloroplasts.

Nutrient Deficiency and Chloroplast Development

Multiple nutritional deficiencies and potential toxicities in field-grown conditions may complicate plant nutritional status assessment via visual diagnosis. Additive plant stresses, such as pests, soil, and climate conditions, further exacerbate meaningful correlation of *in situ* plant status to quantifiable plant resource needs (Thompson and Weier, 1962). Broadley et al., (1986) suggested a step-wise, visual, diagnostic technique for mineral-nutrient deficient young leaf blades and apical tissues. Uniform chlorosis is related to Fe and S deficiency, while interveinal or blotched chlorosis is most likely produced by reduced Zn and Mn. Necrotizing chlorosis may be related to Ca, B, and Cu deficiencies, while deformation anomalies in leaves are thought to be related to inadequate Mo, Zn, and B. Reduced N availability in crops affects maturing leaf blades, noting that although some soil N in early crops suffices to establish photosynthetic capabilities, N-depleted soil occurs rapidly as plants become well established.

Iron, in particular, is implicated in protein synthesis and chloroplast development (Broadley et al., 1986). Iron deficiency inhibits leaf-cell protein synthesis and is attributed to a protein-synthesizing ribosome decline. The structural proteins in grana, a membranous unit in the chloroplast thylakoid, as well as other chromoproteid components, also decline with reduced Fe availability. Chloroplast volume and protein per chloroplast levels decline with Fe deficiency, although the relative protein rates by content per leaf area, leaf cell volume, and chloroplast numbers appear to remain unaffected.

Phaseolus vulgarsis N, P, and K deficiencies typically reveal themselves visually in the younger basal leaves and in those nearest the shoot apex (Wallace, 1951 as quoted in Thomson and Weier, 1962). Older, well-developed leaves exhibit reduced relative macronutrient levels including N, P, K, and Mg as redistribution patterns in leaves prepare for senescence. Lower leaf plastids, the small plant organelle occurring in the chloroplast, may provide a source for N, P, K, and Mg while a plant is under deficient growing conditions.

Plastids undergo changes in ultrastructure relatable to nutrient stress conditions. Phosphorus and K availability is thought to be partitioned and translocated from the older leaves to newer in order to maintain plastid viability in the most rapidly expanding photosynthetic surfaces. Nitrogen and Mg deficient conditions produce chloroplasts in upper leaves that are morphologically unsound and appear immature in nature. Nitrogen is partitioned from older leaves and redistributed to younger, more rapidly expanding leaves. Zinc is also implicated in properly formed chlorophyll grana (stacks of thylakoid where light-dependent photosynthesis begins) that are found in both older to newer leaf distributions (Thompson and Weier, 1962).

Field Spectroscopy in Cotton and Corn

Theories on Scale-related Differences in Spectroscopy

Remote sensing N assessment in crop canopies aims to predict foliar chemical contents (Curran, 1989). Foliar reflectance in the 400-700 nm wavelength range is regulated by chlorophyll pigments (Card et al., 1988; Curran, 1989) while the internal structure and thickness of a plant leaf regulates near-infrared reflectance (Gausman and Allen, 1973). Although the crop N profile varies within the canopy, the leaf N content of most-recently matured leaves of many crops approximates plant N status (Lemaire et al., 1997).

Ideally, field sensors should have a spectral resolution of 10 nm or less in order to increase the signal to noise ratio at target bandwidths (Guyot et al., 1992). High spectral resolution also allows characterization of plant canopy red-edge. The goal of field sensing is to determine what combinations of broad spectral bands best characterize leaf chemical constituents in environments containing extraneous data such as soil diffuse reflectance. Ratioed index combinations of red and near-infrared bands are frequently employed because soil and vegetation contrasts are maximized at these wavelengths (Baret and Fourty, 1997).

Curran et al. (1990) found vegetation reflectance between 690-740 nm was linearly correlated to tree branch chlorophyll, but not whole canopy chlorophyll unless canopy cover was significant ($r^2 = 0.91$). Sensors scanning sparsely dense canopies register higher variation effects in irradiance, background properties, and reflectance. The "red edge" (690-740 nm) located between red and near infrared reflectance (650 and 840 nm, respectively) may be less sensitive to these variations. While above-canopy sensors may register reflection from extraneous sources, leaf-level sensors may be sensitive to variations in chlorophyll *a*:*b* ratios near the red edge (Guyot et al., 1992). However, the precise bandwidth definition (narrow versus broad) may also affect shift discrimination near the red-edge. The spectral position of the red-edge, or the red-edge inflection point, is calculated with first- and second-order derivatives, inverted Gaussian models, or Guyot's Red-Edge Inflection (Curran, 1990; Miller, 1990; Guyot et al., 1992; Raper, 2011).

The inverted Gaussian model proposed by Bonham-Carter (1988) may model the red-edge inflection point (REIP). Wavelength parameters define the position and shape of the REIP model, and the resultant points suggest where shifts in the red edge occur. This is especially important in modeling N stress and is applicable to multiple sensor types. The results of REIP modeling are highly dependent on inherent spectral noise and modeling methodology (Broge and Leblanc, 2000). It is possible to employ a limited number of bands to determine at what wavelength the shift in the red edge inflection point occurs (Guyot and Baret, 1988). Raper (2011) employed an inverted Gaussian model to detect red-edge shift in spectral samples captured using a YARA N-Sensor on cotton under varying N rates that ranged from deficient to excessive (0, 45, 90, and 135 kg N ha^{-1}).

Broadband indices tend to be less sensitive to the combined effects of canopy architecture and illumination geometry, yet, as mentioned previously, may contain less detailed information regarding biochemical and photochemical plant properties (Broge and Leblanc, 2000). Clevers et al. (1999) found the red edge region to elucidate plant reflectance information not found in the combination of NIR and visible space-based, broad-spectrum bands. Canopy and leaf sensing should negate any atmospheric effects noted in sensing from space-based or airborne platforms (Broge and Leblanc, 2000). However, little information exists to compare REIP between the ground-based units at different radiometric and spectral resolutions.

Precision mapping of spatially distributed N data is accomplished at varying scale definitions. All maps and geospatial models are abstractions of reality and produced through generalization of data (Emerson et al., 1999). The generalization process may involve scale issues including spatial and temporal elements (Meentemeyer and Box, 1987). At different scales, a landscape may appear heterogeneous or homogeneous (Cao and Lam, 1997) and scale related issues may affect spatial autocorrelation (Meentemeyer and Box, 1987). Spatial scale usually involves some degree of reduction of detail (Goodchild and Quattrochi, 1997). A reductionist science benefits from collecting data at a fine scale, but physical limitations often require data collection at coarser scales. A small study area permits a great level of discernible details and higher potential for experimental manipulation. Conversely, fewer emergent properties may be evident on a small study area where the variable value ranges are often reduced. A small study area may identify significant factors, but these tend to be related to chemical and biotic factors rather than physical and abiotic factors noted in larger study areas (Cao and Lam, 1997). The equilibria observed in larger area studies may be a result of the sum of spatial, temporal, cartographic, operational, and measurement dynamics observed in smaller area studies, yet apparent details are often lost with increased study area size.

Spatial resolution creates a limit to the scale of detectable spatial variability (Atkinson and Foody, 2002). Scaling up from a small to larger study area may introduce non-linear transforms of variables, and ultimately may affect the final prediction. Model stationarity, or autocorrelation, assumes we can fit a single model to all data and apply it over an entire geographic area. A non-stationary model allows parameters to vary with space and has the potential for greater prediction precision. Goodchild and Quattrochi (1997) proposed all observations have both small and large linear dimensions. Increasing distance away from an observable object introduces a decay function where other parameters may be introduced. The small linear dimension of a spatial data scale is well defined and limited in information, while a large linear dimension is coarse and often confounded by extraneous information. A manipulation of scale must rigorously address if transformations will aggregate or disaggregate the data. Furthermore, any impacts that a scale measure introduces must account for loss or gain of data.

The characteristics of plant canopies assayed with different sensors can be reduced to vegetation index values (Walsh et al., 1997). Geographic data is often scale dependent whereby observation patterns vary with spatial resolution (Walsh et al., 1997; Cao and Lam, 1997). Spatial autocorrelation tends to vary with scale if a pattern is concentrated at one scale but scatters at another. Modeling crop biophysical parameters at different sensor ranges may produce scaling errors (Friedl, 1997). This is due to the heterogeneous nature of input parameters. Soil nutrients and moisture tend to exhibit, over a short distance, high frequency variation, while temperature and irradiance, over the same short distance have low frequency variation. Early season soil tests to determine nitrate (NO_3^-) are the best predictor of N fertilizer response in corn (Fox et al., 1989). Experimental data obtained at leaf-level is primarily dependent upon pigment constituents. Experimental data obtained at above-canopy level is dependent upon three primary factors: leaf chlorophyll content, leaf area index, and leaf inclination angle (Guyot et al., 1992). Fox et al. (1989) found corn stalk (NO_3^-) concentration did not accurately predict soil N availability even though the tested fields had a history of legume cropping and manuring.

Vegetation Indices

A vegetation index (VI) is a mathematical algorithm used quantify green-leaf concentrations in remote sensing measurements. Vegetation indices enhance spectral signature functionality and minimize the background noise of soil and atmospheric reflectance, solar irradiance and sun angle, and senesced vegetation (Huete, 1989; Bella et al., 2004). There are two basic types of VIs: 1) ratio indices and 2) orthogonal indices (Huete, 1989). Ratio indices are sensitive to changes in soil characteristics like moisture and chemical composition, which ultimately affect color. Orthogonal indices produce biomass and greenness estimations by holding soil influences constant and maximally computing the green-vegetation signals. All utile VIs should be non-site specific and have global applications under highly varying environments (Huete, 1989; Sellers, 1989).

Birth and McVey (1968) documented the Ratio Vegetation Index (RVI) in order to quantify green features in spectroradiometric products. Ratio Vegetation Index is an older and well-known vegetation index in which a simple ratio of red to NIR reflectance is employed to calibrate green vegetation in an index range between 0-30. On average, green vegetation indexes between 2-8, and the RVI tends to saturate when leaf area progresses into the higher density ranges (above 3.5 LAI units) (Sellers 1985, Tucker 1979; Rouse et al., 1973; Pearson and Miller 1972). Pearson et al. (1976) employed two narrow bandwidths in a hand-held, above-canopy spectroradiometer to estimate gramineous biomass. The selected red and NIR bands (650-700 nm and 775-825 nm, respectively) revealed a strong inverse relationship between red reflectance and healthy green vegetation, and a strong direct relationship between NIR reflectance and the amount of vegetation present.

Rouse et al. (1973) proposed the Normalized Difference Vegetation Index (NDVI) as a robust algorithm that quantifies green features related to visual biomass viewed against varying background information. The NDVI is frequently employed to classify vegetation. Tucker (1980) compared three non-destructive, visual assessment techniques for quantifying biomass in grasses. Capacitance meter measures are limited by water present, either on or near the herbage under consideration. Calibration of capacitance meters is species composition specific. Raper et al. (2013) found fertilizer N rate affects cotton NDVI results at all growth stages but the index may not be a strong indicator of leaf N status.

Penuelas et al. (1994) found older leaves have greater reflectance at all canopy wavelengths, and leaf chlorophyll and N content were correlated with the first order derivative maxima of red edge and green regions. Roujean and Breon (1995) noted differences in NIR and red reflectances were less sensitive to plant canopy geometrical and optical properties. Carter (1994) found ratios of narrow NIR waveband leaf reflectances were an indicator of plant stress.

The Nitrogen Reflectance Index (NRI) (Schleicher et al., 2003) is employed to improve spectral reflectance complicated by background soil information in the early season through filtering of noise by subtracting the red (650 nm) from the green (550 nm) bandwidth and correlating the effects to improving canopy density estimation (LAI). NRI is also strongly correlated to the Nitrogen Sufficiency Index (NSI) (Varvel, 2007) and is based on SPAD chlorophyll assessment relative to N treatments (Samborski et al., 2009). Employment of the NSI requires *a priori* knowledge of leaf SPAD chlorophyll status, while the NRI requires N sufficiency test strips for calibration. The *a priori* knowledge makes both indices difficult to employ in production agriculture.

Varying dry matter percentage in field conditions tends to alter the biomass compression rates and is a limiting factor in the weighted disc method in that the measurements are not relative in heterogeneous pastures. Spectral measures employing the red and NIR bandwidths (~650 nm and ~840 nm respectively) are limited by variables associated with above canopy measures. Species composition, projected green leaf area, shadows, environmental conditions, and incoming irradiance required alternate calibration approaches to mitigate signal interference. Tucker (1979) proposed avoidance of the atmospheric water absorption bands, 760-780 nm and 920-980 nm, to reduce interference during calibration and sampling. Tucker (1979) also supported the employment of the 840 nm/650 nm ratio for detecting green leaf density and relating spectral changes to chlorophyll to green leaf interactions. Finally, Tucker (1979) reported the difference between NIR and red reflectance was sensitive to plant canopy photosynthetically active vegetation.

At-canopy, or on-the-leaf measures, may reduce above-canopy variables, although the estimate of leaf area will be compromised by sampling at a leaf site that is less than 4 mm (Gitelson et al., 2003a). The relatable scales of reflectance measures (leaf versus canopy) are not clearly defined for all crops. The “Red Edge” region of plant reflectance (690-740 nm) may indicate N status (Curran, 1989). Barnes et al. (2000) found the SCCCI (R790 and R700) clearly distinguished between cotton plants having low to high N content. The SCCCI appears sensitive to changes in background soil wetness and able to minimize the effects of canopy density. This is especially true if N is limiting. El Shihka et al. (2008) found the SCCCI was confounded by water stress. Furthermore, a cotton canopy greater than 30% developed (midseason near summer solstice or DOY 173) produced SCCCI values in the optimal N treatment ranges which were significantly greater than noted in the low N treatment plots. This finding suggests the SCCCI index is particularly suited for reducing background soil reflectance noise in early plants being assessed for N status in optimally water supplied conditions. This study proposes the employment of SCCCI in partial canopy sensing of cotton may improve the actual characterization of the undeveloped canopy cover over other legacy indices (e.g. NDVI, RVI).

Raper (2011) found mixed results in the coefficients of determination for SCCCI and leaf N concentration at early cotton squaring. Weather related factors such as temperature and post-N-application rainfall may have confounded early canopy assessment of cotton N status. Moreover, Raper (2011) noted both the SCCCI and Guyot’s Red Edge Inflection (REI) to be sensitive to N status early in the season when N fertilization decisions could have a positive impact on yield results. Varco et al. (2013)

utilized the SCCCI index to assess early cotton and corn N status with a canopy-level, tractor-mounted spectroradiometer. The SCCCI was the strongest indicator of leaf N concentration at the canopy scale among a total of four indices (NDVI, GNDVI, and NDRE). The study did not evaluate Guyot's REI for predicting early leaf N status.

A root-mean-square-error (RMSE) statistic was employed by Gitelson et al., (2003b) to estimate chlorophyll concentration in higher plant leaves. An inverse model transfers the biophysical parameters to VIs and calculates the difference between measured and predicted biophysical values. This estimation may be employed to study the suitability of different VIs used to predict plant status. The RMSE formulas is as follows:

$$RMSErrors = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}} \tag{2.2}$$

where yhat$_i$ is the predicted value, y_i is the observed value, and n is the number of samples. Spectroradiometric errors in reflectance tend to negatively influence r-square and RMSE regression modeling of NDVI and GNDVI algorithms when the spectral signature is raised or lowered in any order of magnitude. These same errors have less effect on r-square regression modeling of algorithms featuring red-edge bandwidths that measure a lateral, direct shift in reflectance.

Raper and Varco (2014) compared the Pearson's correlation coefficient of different spectral bands and calculated a sensitivity equivalent (*SEq*) of different VI's to early cotton leaf N status. Based on the interpretation of Vina and Gitelson's (2005) estimation of VI sensitivity to a biophysical parameter, Solari et al. (2008) calculated the *SEq* as the slope of a parameter to VI linear relationship divided by the RMSE. The higher Pearson's r correlation and *SEq* calculated values suggest stronger VI sensitivity to a biophysical parameter.

Commercially Produced Sensors

Several commercially available, ground-based sensors are available for on-the-fly plant status sensing. Two sensors priced less than $40,000 U.S. may aid producers in making N fertilization management decisions in a cost-effective manner. The sensors employed in this study possess moderately different sampling scales yet these may not preclude the development of efficient N status prediction algorithms.

SE PSP-1100

The Spectral Evolution PSP-1100 hand-held SR (Spectral Evolution, Lawrence MA) (SE) actively measures leaf-level reflectance by producing a signature of 520 bands, from 320-1131 nm, at a spectral resolution of 3.2 nm and sampling intervals of 1.5 nm. The SE instantaneous field of view (IFOV) is approximately 4 mm. The SE internal light source is a built-in two-watt tungsten-halogen lamp with SMA-905 connectors. The sensor employs a fiber optic input with diffraction grating and is calibrated using a Spectralon® (Labsphere, North Sutton, NH) diffusion reflectance target panel. The entire unit weighs less than three pounds and, when fitted with a leaf clip, shoulder strap, and spare batteries, it is an ideal field-scouting tool. Reflectance graphs can be generated with the proprietary *DARWin*® software or an MS Excel file can be generated from raw data outputs. The unit features an automatic exposure control and auto-shutter in order to simplify data collection. Battery life is typically 3 hours.

YARA N-Sensor

The YARA N-Sensor SR (tec5Helma Inc., Plainview, NY) is a two-diode array multispectral scanner operating in passive mode. The device contains a Zeiss MMS1 silicon diode array with the capacity to detect in a spectral range from 400 to 900 nm. Four quadrilateral fiber optics register upwelling reflectance and are calibrated by a single 180o hemispherical irradiance optic. The four-in-one light fibers receive reflectance, which is averaged to produce a single sampling result. For research purposes, the sensor is tractor-mounted and scans crops at approximately a height of 1.8 m capturing twenty (20) +/- 5 nm wide bands between 450-900 nm. The reflectance field of view for each optic is 12o and the four input optics are directed an average 64o oblique from nadir. For each pair of optics, one is centered at 45o and 135o from the direction of travel. Spectral data is collected in one-second acquisition intervals, and the approximate area scanned with this instrument is between 50-100 m^2 s^{-1} at an operating speed of 3.5 mph positioned geographically with a Trimble Pro XR global positioning satellite (GPS) unit. (Figure 2.1).

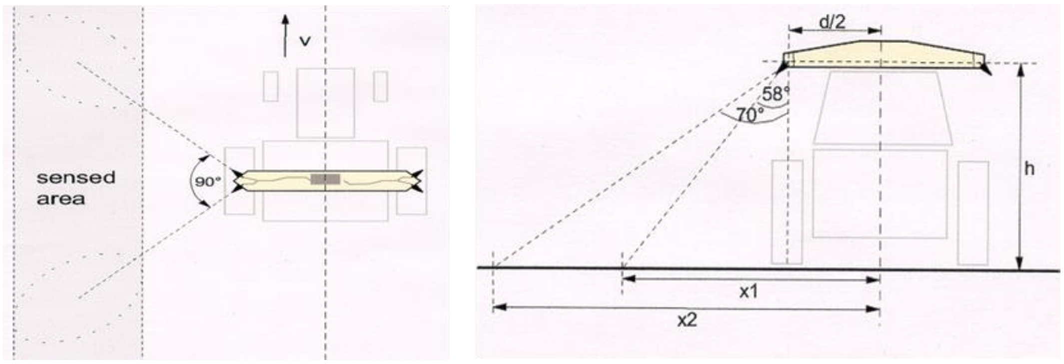


Figure 2.1 YARA sensor positioning of optical inputs as viewed from overhead and from behind.

(Source: YARA (formerly Hydro Agri), tec5Hellma adapted with permission)

The oblique quadrilateral viewing geometry of the YARA allows viewing of the shaded and sun-exposed plants and thereby negating the effects of the plant canopy non-Lambertian surface reflectance (Mistele and Schmidhalter, 2010). Although the YARA SR views the plant canopy in whole, individual leaf reflectances elucidating N status is relatable to YARA SR spectral signatures (Varco et al. 2013).

CHAPTER III

METHODS AND MATERIALS

Site Description

2012 Cotton

The 2012 rain-fed cotton crop was located in a production field (31°20’45.3”N, 91°22’41.5”W) south of Natchez, Miss., USA. The soils are mapped as Convent silt loam (coarse-silty, mixed, superactive, nonacid, thermic, fluvaquentic Endoaquepts) and Morganfield silt loam (coarse-silty, mixed, active, nonacid, thermic, typic, Udifluvents). Following the 2011 corn crop, the field was disked and hipped. Variable rate P, K, and lime were applied according to soil test recommendations. Spring tillage included in-row sub-soiling and for bed conditioning with a spiketooth harrow, rolling chopping blades and board leveler (a do-all). Weeds were controlled according to Mississippi State University Extension recommendations (Chesser et al., 2013). A Stoneville early to mid-maturing variety ST5288-B2F was planted at a rate of 10.5 seed/m^2 and grown under rainfed conditions. One-hundred twenty-five (125) sampling sites were predetermined with GPS locating. (Figure 3.1).

Figure 3.1 Mapped transects for 2012 research site south of Natchez, Miss.

White circles represent 5-m buffered points for data extraction centered on each soil and plant sampling site. Soil series are delineated.

The 2012 experimental design was a randomized complete block with three replicates. Four fixed fertilizer N rates (33.6, 67.2, 100.7, and 134.4 kg N ha^{-1}) and three variable fertilizer N rates (producer variable rate based on soil CEC, sensor driven MSU variable rate #1 (MSU-VR-1), and sensor driven plus adjustment for previous year yield map MSU variable rate #2 (MSU-VR-1)) were applied on 18-May 2012 at pinhead square to plots 12 rows wide and a 0.96 m spacing between rows with an average row length of 475 m (Figure 3.2).

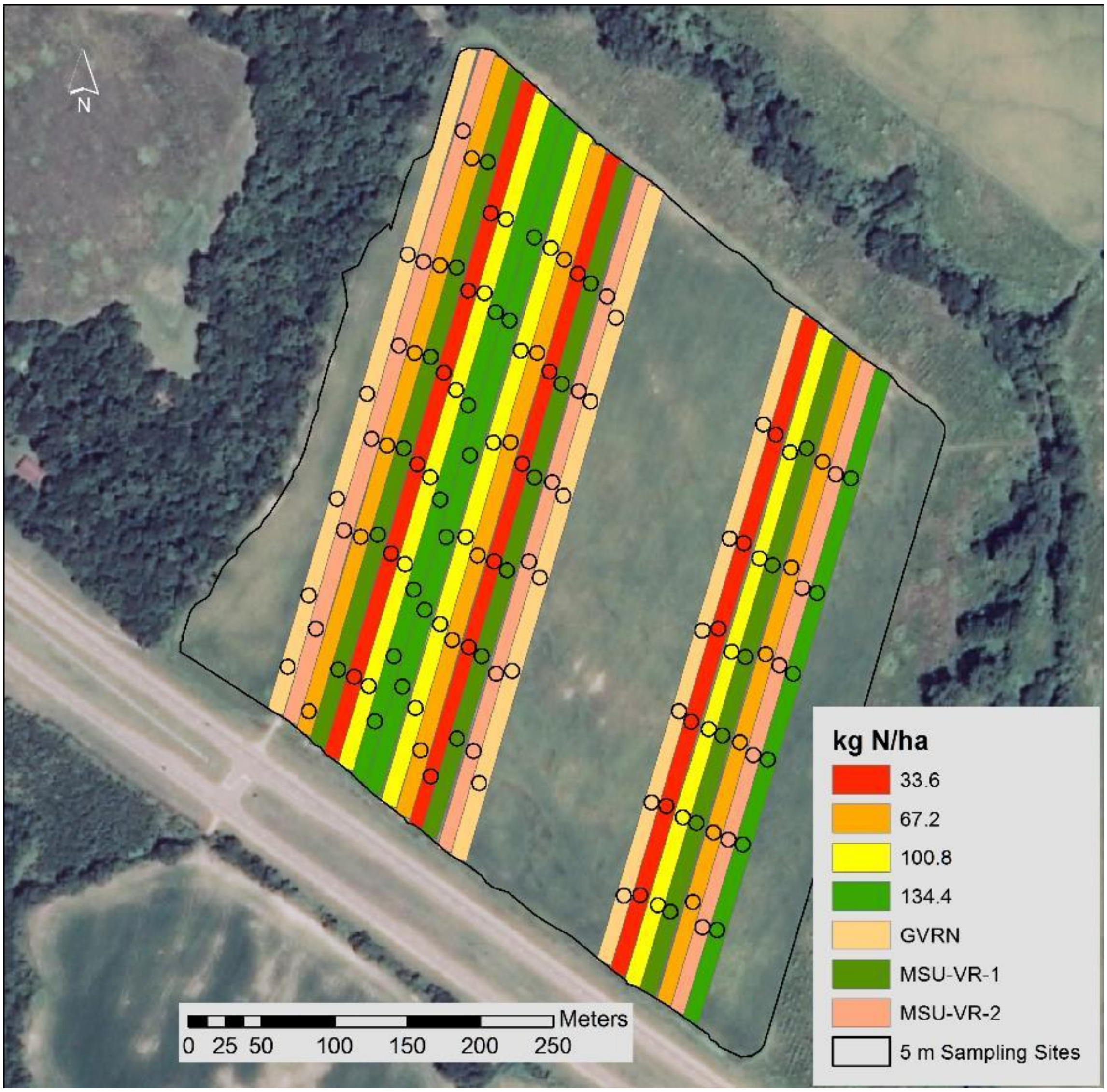


Figure 3.2 Map showing N treatments and three replications along with buffered sampling points south of Natchez, Miss. in 2012.

2013 Cotton

The 2013 cotton crop was located northwest of Money, Miss., USA (33º41’52.4”N, 90º20’35.9”W). Mapped soils include a Dubbs-Dundee complex (fine-silty, mixed, active, thermic, typic, Hapludalfs and Endoaqualfs) and a Tensas silty clay loam (fine, smectitic, thermic, chromic, vertic, Epiaqualfs). The 12.3 ha research site was located in the northern portion of a 49.8 ha field. In the fall of 2012 following corn harvest, 224 kg ha^{-1} of 0-0-60 fertilizer was broadcast applied. Following fertilization, rough beds were built with hipping disks with rows oriented from west to east. A furrow irrigation system was established mid-field with water running to the west for replicates 1 and 4 and to the east for replicates 2 and 3. The downward grade from the center to the west and east was approximately 1.5 %. Weeds were controlled according to Mississippi State University Extension recommendations. A mid-maturity cotton variety Deltapine DP1321-B2RF was planted at a rate of 10.5 seed/m^2. One-hundred twenty (120) sampling sites were predetermined with GPS locating. (Figure 3.3 and Table 3.1)

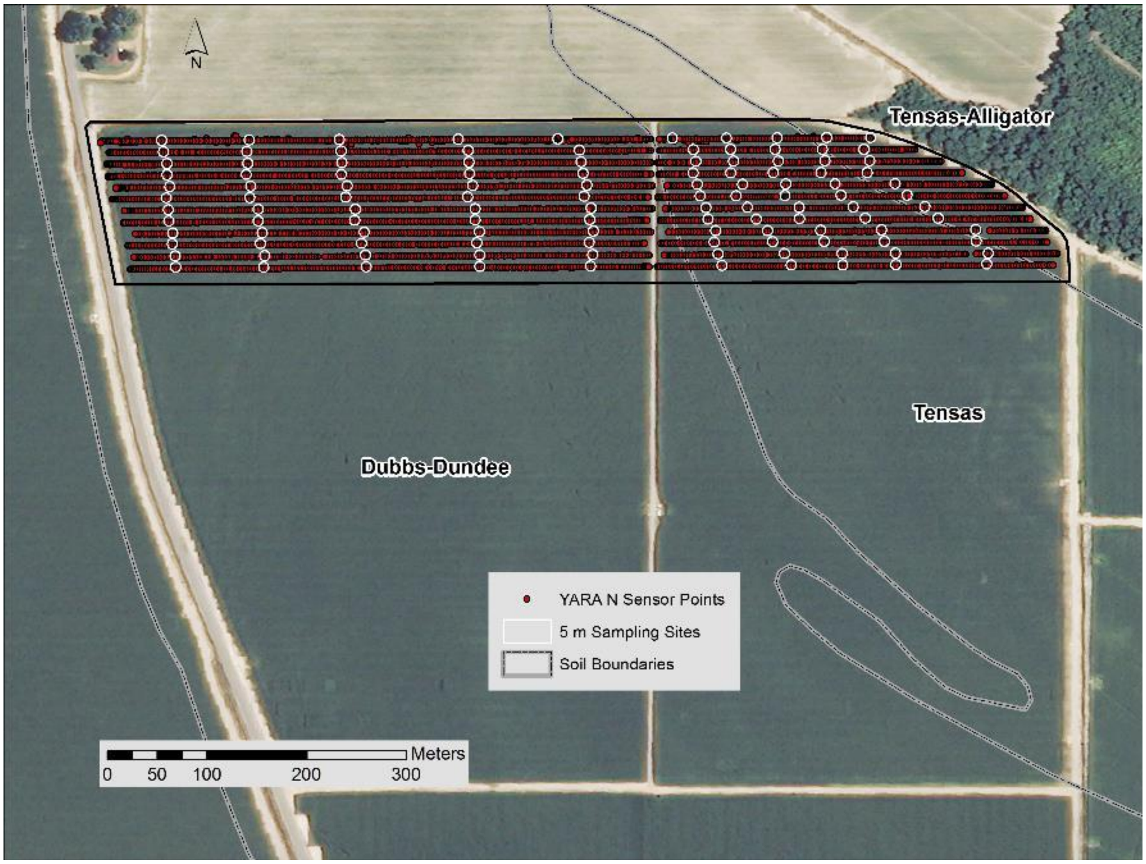


Figure 3.3 Mapped transects for 2013 research site northwest of Money, Miss. White circles represent 5 m buffered points for data extraction centered on each soil and plant sampling site. Soil series are delineated.

The experimental design was randomized complete block with four replications. The 2013 cotton plots were 12 rows wide with 0.96 m spacing between rows and an average row length of 370 m. On 15-June (25 DAP), four fixed fertilizer N rates (33.6, 67.2, 100.7, 134.4 kg N ha^{-1}) and a base rate of 33.6 kg N ha^{-1} on the two variable fertilizer N rates (MSU-VR1; MSU-VR2) were applied (Figure 3.4 and Table 3.1). The 2013 MSU-VR-1 fertilizer N rate was sensor based only and the MSU-VR-2 was sensor based with an adjustment for soil electrical conductivity (EC) (see section Cotton N

Treatments). On 1-July, the remainder sensor-based fertilizer N rate was calculated for MSU-VR1 and MSU-VR2 treatments and applied.

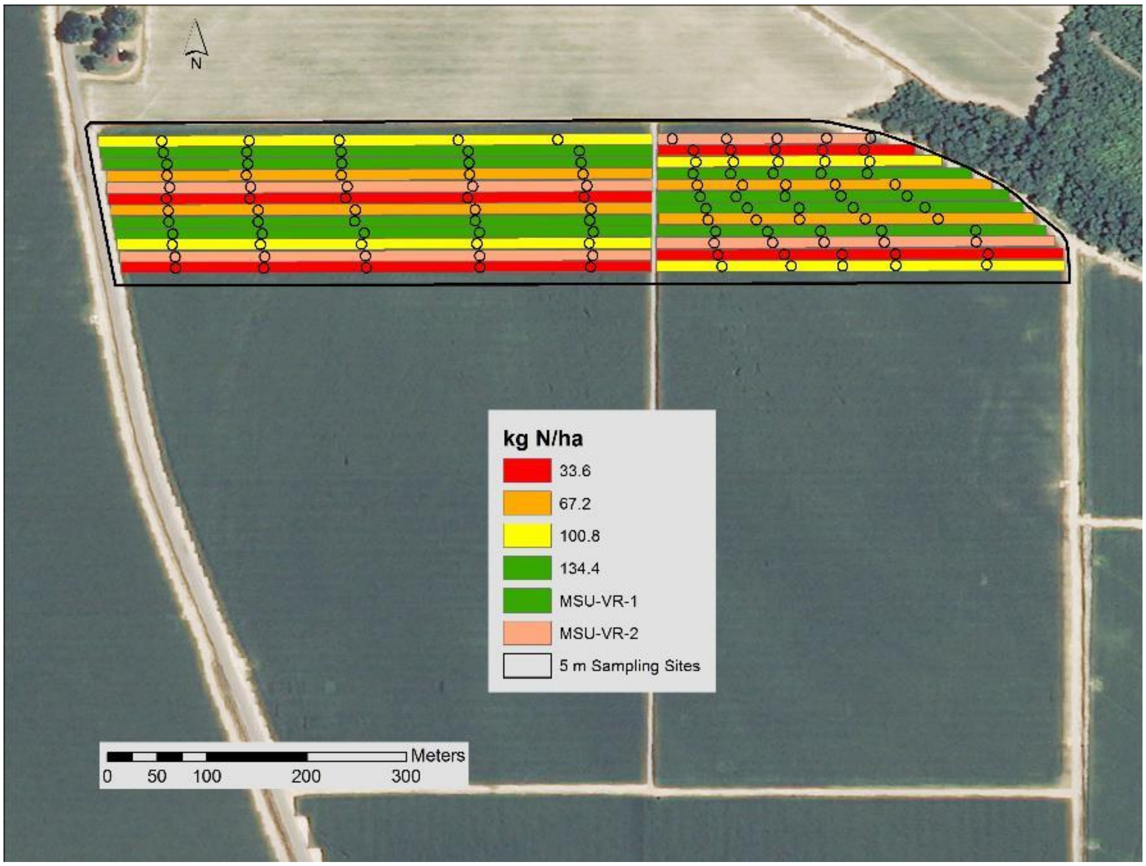


Figure 3.4 Map showing N treatments and four replications along with buffered sampling points northwest of Money, Miss. in 2013.

Variable rate treatments were applied as a sidedress following leaf sampling at first flower bud initiation. A urea ammonium nitrate (UAN) solution (28-0-0-5) was banded using a liquid applicator equipped with no-till coulters and attached liquid knives set at 22.9 cm from the row and 7.6 cm deep.

2012-2013 Corn

The 2012 and 2013 corn crops were located at the W.B. Andrews Agriculture Systems Research Farm (33º28'13.5"N, 88º45'48.0"W) Mississippi State, Miss., USA (Figure 3.5). The soil at the research site was a Marietta fine sandy loam (fine-loamy, mixed, thermic, siliceous, Aquic Fluventic Eutrochept). A high-yielding, Pioneer Hybrid 33N58 corn was planted at a rate of 6.9 kernels m^2. The site was pre-treated with 225 kg ha^{-1} 0-23-30 fertilizer broadcast prior to planting. Pests were managed according to Mississippi Cooperative Extension Service recommendations. Annual grasses and broadleaf weeds were managed according to Mississippi State University Extension recommendations. Each fall, cereal rye (*Secale cereal* L.) was planted as cover crop by broadcasting 67 kg ha^{-1} to provide benefits such as winter weed suppression, soil protection, organic matter, and recovery of residual soil N. The rye cover crop residual N was not taken into consideration when establishing N treatment rates (Figure 3.5).

Figure 3.5 Corn plot layout 2012-2013 at the W.B. Andrews Agriculture Systems Research Farm, Mississippi State, Miss.

Individual red dots represent YARA sensor data points. Soil types are delineated.

The experimental design was a randomized complete block with four replicates. Four fertilizer N rates of 0, 89.6, 179.2, and 268.8 kg N ha^{-1} were applied on plots 12 rows wide at 0.96 m spacing between the rows with a length of 37.5 m. Half the fertilizer was applied following crop emergence and the remainder was applied at V6-V7 following plant and leaf sampling. A urea ammonium nitrate solution (32 % N) was banded using a liquid applicator equipped with no-till coulters and attached liquid knives set at 22.9 cm from the row and 7.6 cm deep (Figure 3.6).

Figure 3.6 Fertilizer N treatment and replicates for corn study in 2012-2013 at the W.B. Andrews Agriculture Systems Research Farm, Mississippi State, Miss.

Crop Culture

Climate

Rainfall at the three research sites was measured with a HOBO Onset Model No RG2 Data Logging Rain Gauge (Onset Computer Corporation, Cape Cod, MA). Gauges were located adjacent to the plot area. Temperature averages for each site and differences from normal (DFN) were derived the U.S. Department of Agriculture National Agriculture Statistics Service in Mississippi (USDA-NASS-MS).

The USDA-NASS-MS collects temperature and rainfall data, which is subsequently compiled in a weekly Crop Progress and Condition Report (CPCR). When possible, rain data acquired at each site is also noted. The Mississippi State University weather station used to report data reported to USDA-NASS-MS was located within 1.6 km from the study site. The data from this site supplied the current temperatures and rainfall data was used when the plot rain gauge failed.

Nitrogen Treatments

Cotton N Treatments

Variable rate N prescription maps were constructed within three days following canopy sensing at early cotton. Cotton in 2012 and 2013 received fixed rate N treatments (33.6, 67.2, 100.7, 134.4 kg N ha^{-1}). Variable rate treatment sites selected for this study received a base rate of 33.6 kg N ha^{-1} at emergence. The sidedress variable rate prescription was calculated in the following manner, and the total N applied includes both the base rate and the variable sidedress rate.

The 2012 cotton variable rate N treatments were developed using two separate methods. The producer, who incorporated soil cation exchange capacity (CEC) data from soil test results, applied the grower's variable rate N (GVRN) intuitively. Two other variable rates were calibrated with the SCCCI vegetation index. The MSU-VR-1 was developed from sensor readings only. Three prior years of cotton sensing research (2009-2011) was used to define the SCCCI index linear response. The 2012 data was regressed, in Microsoft Excel (Microsoft Inc., Redmond, Wash) against fixed N treatments and averaged. The MSU-VR-2 was developed identically to the MSU-VR-1 treatment and then adjusted for prior-year corn productivity. Natural breaks (Jenks) groupings in

ArcGIS 10.1® software (Esri, Redlands CA) were applied to class the data. Where 2011 corn productivity was high (>8 Mg ha^{-1}), an additional 33.6 kg N ha^{-1} was added to the sensor-based rate. Where 2011 corn productivity was low (< 4 Mg ha^{-1}), 33.6 kg N ha^{-1} was subtracted from the sensor-based rate.

The 2013 cotton variable rate N treatments were developed using a single method with adjustments for soil electrical conductivity (EC). Two variable rates treatments were calibrated using the SCCCI vegetation index. The first variable rate (MSU-VR-1) was developed from sensor readings only. Using the same method as in 2012, early cotton N-Sensor readings were regressed against three year's prior cotton sensing research in Microsoft Excel. The second variable rate (MSU-VR-2) was developed identically to the MSUVR-1 treatment and then adjusted for soil EC. The shallow EC readings over 3.1 mS $m^{-1}s^{-1}$ were classed manually similar to the Natural breaks (Jenks) groupings derived in ArcGIS software. Where soil EC was high (>120 mS $m^{-1}s^{-1}$), an additional 33.6 kg N ha^{-1} was added to the sensor-based rate. Where soil EC was low (<60 mS $m^{-1}s^{-1}$), 33.6 kg N ha^{-1} was subtracted from the sensor-based rate.

Cotton N prescription maps were post-processed in ArcGIS software using Inverse Distance Weighting (IDW) interpolation. Prescription maps were exported using the WGS 84 Geographic Projection System and uploaded to the fertilizer applicator. Application of N fertilizer side-dress treatments occurred within four days of canopy sensing.

Corn N Treatments

Only fixed rate N treatments were applied to corn grown in 2012 and 2013. The intent of this research was to observe relationships over a two-year weather-variable period, and incorporate the research results into a sensor-calibration file similar to that used for cotton. The chosen fixed fertilizer N rates were 0.0, 89.6, 179.2, and 268.8 kg ha^{-1}. These rates provided a wide range of fertilizer N variability from deficient to high.

Sampling

Leaf and whole plant tissue sampling was conducted to determine N concentration of cotton and corn at three phenostages. Harvesting was performed using 6-row cotton pickers with bale making technology and corn was harvested with a 2-row combine. Soil samples were taken prior to cotton cropping in order estimate residual soil N and relate yield to total available N resources.

Nitrogen Status Sampling

Cotton Leaf N Concentration

Plant growth stages in cotton were defined as dates when 50 % of plants expressed the bud or flowering stage surveyed. Early square (a first-visible floral bud) was noted when >50 % of plants possessed a floral bud at least 3-mm in size. Early bloom was noted when >50 % of plants possessed first white flowers. Peak bloom was noted within three weeks after first bloom stage.

Cotton leaf sampling was conducted at first flower bud in 2012-13 (35 and 36 DAP respectively). Three most recently matured leaves (fully expanded leaves capable of maximum photosynthesis potential on main stem at fourth or fifth node from terminal) were gathered from rows 2-3 and 10-11 at each designated sub-plot sampling site (Figure 3.2). In 2012, leaves were placed in paper bags and delivered to a field site where SE spectral sampling occurred. In 2013, collected leaves were placed in a paper bag and placed on ice until delivered to the spectral sampling field station. After spectral sampling, leaves were again placed on ice for the duration of the sampling day. A forced-air oven set at 65 ^{o}C was employed to dry leaves thoroughly. After 4 d drying, leaves were ground through a 40-mesh sieve (0.425 mm) in a Wiley mill. Samples were again dried for 16 h at 60^{o}C and placed in airtight vials. Duplicates of cotton leaf samples were processed for total N concentration on a Carlo Erba N/C 1500 automated dry combustion analyzer (Carlo Erba, Milan, Italy). An atropine standard was used.

For 2012 and 2013, cotton leaves were also collected in the manner previously described at first bloom and peak bloom. Spectral samples were taken with two instruments coincident to the leaf sampling protocol (Table 3.1).

Table 3.1 Cultural and sampling/sensing dates of cotton over the experimental period, 2012 to 2013.

	Dates	
Cultural	2012	2013
Soil Sampling	10,11-May	16-May
Planting	21-April	21-May
First N Application	23-May	13-Jun
Second N Application	--	1-Jul
Sensing and Sampling		
Pin Head Square	22-May	--
Early Square	6,7-Jun	27,28-Jun
Early Flower	20,21-Jun	15-Jul
Peak Flower	17-Jul	29-Jul
Harvest	10-Oct	21-Oct

The 2013 cotton crop was furrow irrigated on 12-July, 19-July, and 20-August. The 2012 cotton crop did not receive supplemental irrigation.

Corn Leaf N Concentration

Corn leaf and whole plant sampling was conducted at the V-4 stage in 2012-13 (38 and 40 DAP respectively). Five most recently matured fully collared leaves were sampled from rows 2-3 and 10-11 of the 12 row plots. In 2012, leaves were placed in paper bags and delivered to a field site where SE spectral sampling occurred. In 2013, collected leaves were placed in a paper bag and placed on ice until delivered to the spectral sampling field station. After spectral sampling, leaf samples were deposited in paper bags and placed on ice. A forced-air oven set at 65°C was employed to dry leaves thoroughly. After 4 d drying, leaves were ground through a 40-mesh sieve (0.425 mm) in a Wiley mill. Samples were again dried for 16 h at 60°C and placed in airtight vials. Duplicates of corn leaf samples were processed for total N concentration on an automated dry combustion analyzer. An atropine standard was used.

For 2012 and 2013, corn leaves were also collected in the manner previously described at stage V8 in 2013 and at VT in 2012 and 2013. Spectral samples were taken with two instruments coincident to the leaf sampling protocol (Table 3.2).

Table 3.2 Cultural and sampling/sensing dates of corn over the experimental period, 2012 to 2013.

	Dates	
Cultural	2012	2013
Planting	10-Apr	18-Apr
First N Application	23-Apr	9-May
Second N Application	17-May	21-May
Sensing and Sampling		
V4-V5	15,18-May	21-May
Whole Plant & Stand Count	15-May	21-May
V8	--	14-Jun
VT	15,18-Jun	24, 26-Jun
Grain Harvest	9-Sep	10-Sep

A rice standard was employed to estimate the whole plant total N by dry combustion.

Corn Grain N

Corn grain subsamples were taken from whole plot harvested grain for each treatment and processed for total N analysis. Grain samples were dried at 65°C for 7 d and ground through a Wiley mill using a 40-mesh sieve (0.425 mm). Samples were again dried for 16 h at 60°C and placed in airtight vials. Duplicates of corn grain samples were processed for percent N concentration on an automated dry combustion analyzer calibrated with a rice standard.

Crop Yields

Cotton Lint Yield

To estimate cotton yield, seedcotton samples were collected randomly hand picking 25 bolls larger than 2.5 cm from the sensed rows in each sub-plot. Seedcotton samples were ginned to determine percent lint. Cotton seed was then acid delinted, dried at 65°C, and then ground in a coffee bean grinder. Cotton seed total N was determined on a dry combustion analyzer. For bulk yield, plots were harvested using a six row automated spindle-type picker. One round bale per plot was weighed, ginned, and actual lint yields were calculated on a per acre basis. The percent lint as a percentage of total seedcotton weight was employed to determine final lint yield.

Corn Grain Yield

Corn grain was harvested with a two-row plot combine and grain yield was calculated on an Mg ha^{-1} basis. Grain moisture was determined on harvested grain by subtracting the dry weight of 50 g samples from wet grain samples, which were dried at 65°C until no moisture loss was noted (typically 6 days). The remainder weight was divided by the weight difference and multiplied by 100 to achieve the moisture percentage. Grain yield was adjusted to a moisture content of 15.5 %.

Soil Sampling

Soil samples were taken prior to planting to determine extractable NH_4^+-N and NO_3^--N prior to planting both years (Table 3.1). Six soil cores were centered at each sub-plot location where three cores were taken from each side of the row from the side of the bed to furrow and three were taken on the bed near the row center. Sampling depths were 0- to 15-, 15- to 30-, and 30- to 60-cm. All cores from each sub-location were composited by sampling depth to produce a single soil sample per sub-plot location. Samples were immediately placed on ice and then frozen at -4°C within 12 hours of acquiring. Prior to extraction, soil samples were thawed at room temperature, crushed, and homogenized. For each sample, 20 g of soil was extracted with 200 mL 1*N* KCl as described in Keeney and Nelson (1982). A Flow Solution III Auto Analyzer (O.I Analytical, College Station, TX) was employed to determine NH_4^+ and NO_3^- concentrations. Additionally, 20 g of soil was oven-dried at 105°C and reweighed in order to determine soil moisture content. After determination of NO_3^- concentration, resultant values were multiplied by 200 mL and divided by the oven-dried soil weight to correct samples for moisture content.

Prior to extraction and during freezer storage in 2012 to 2013, cotton soil sample labels at various depths were damaged. The damaged samples were unidentifiable and none of the missing data was included in the soil analysis.

Reflectance Data Acquisition

Crop canopy reflectance was measured with the YARA N-Sensor, which was configured to capture 20 bandwidths from 450-850 nm with a spectral resolution of ±5 nm (Table 3.3). Leaf reflectance was captured with the SE sensor, which captures 512 bandwidths from 312.1-1113.4 nm with a spectral resolution of 3.2 nm. Sampling locations or sub-plots were marked using GPS using a Trimble Pro XR Receiver (Trimble Navigation Limited, Sunnyvale, CA). Spectral reflectance comparisons were made using the most similar and corresponding bandwidths.

Table 3.3 Bandwidth comparisons for two selected sensors (nanometers).

Bandwidth Region	YARA	SE
Green	450	450.6
	500	500.0
	550	550.0
	570	569.9
Red	600	600.6
	620	620.7
	640	639.3
	650	650.2
	660	659.5
	670	670.4
	680	679.8
	700	700.2
Red Edge	710	709.6
	720	720.6
	740	739.6
	760	760.2
	780	779.2
NIR	800	800.0
	840	840.0
	850	849.7

Because the spectral resolution of the two sensors is not identical, the nearest matching, single bandwidth definition of the SE was related to the YARA sensor. Two SE bands prior to and following the target YARA sensor bands were averaged in order to develop a broadband equivalency of SE to YARA sensor.

The SE sensor was calibrated in a slightly different manner in the 2012 sampling season than in the 2013 season. In 2012, the initial reference sample was read on a Spectralon® panel but no sample was recorded. In 2013, the reference sample was read and recorded.

The YARA sensor was mounted at approximately 1.8 m height on a 3-point tractor hitch and reflectance data were collected from rows 2-4 and 9-11 of 12 row plots. The tractor was driven at 5.6 km ha^{-1} above rows 6 and 7 facilitating the sensing of the targeted rows. The YARA sensor contains two diode array spectrometers that simultaneously captures and corrects upwelling reflectance with down-welling irradiance (Varco et al., 2013).

ArcGIS Desktop® 10.1 software was employed to reduce the multipoint dataset to individual sampling sites in cotton. Point data was selected by overlaying 5 m buffers at each predetermined site (Select by Location). Field Calculator was employed to assign site numbers to the captured YARA sensor data points. Site data were exported to Microsoft Excel® in .dbf format, and YARA sensor data points at each site were averaged to in order to calculate average reflectance and vegetation indices.

The SE sensor was employed to capture leaf reflectance from samples collected at sites within each plot. Three most-recently matured cotton leaves on the main stem (5^{th} node from terminal) were collected from predetermined sampling sites on rows 2-4 and

9-11 of the 12 row plots. The five most-mature, collared corn leaves were collected randomly from rows 2-3 and 10-11 of the 12 row plots. Leaf samples were deposited in paper bags and placed on ice. Cotton leaf reflectance was measured with a single staple at the terminal lobe away from the mid-rib and averaged per sampling site. Corn leaf reflectance was measured with a single staple mid-leaf between the mid-rib and leaf margin and averaged per sampling site. Site data were exported to Microsoft Excel® in .dbf format, and SE data points at each site were averaged to in order to calculate average reflectance and vegetation indices.

All cotton and corn leaf samples were sampled with a single SPAD 502Plus Chlorophyll Meter at the same leaf position that leaf-level reflectance was measured. One SPAD chlorophyll staple was taken per leaf sample and averaged per treatment plot or sub-plot.

Vegetation Indices

For the purpose of this study, 27 known vegetation indices (VIs) were employed to fit spectral measures to leaf N concentration, SPAD chlorophyll, and whole plant N concentration (corn only). Statistical experimentation fitting the biophysical parameters to reflectance measures revealed a new, novel VI that may be appropriate for predicting early leaf N status in corn. For the purpose of this study, an experimental vegetation index is proposed. Named the Early Nitrogen Detection Vegetation Index (ENDVI), this index is calculated by dividing the SCCCI index as proposed by Varco et al. (2013) into a transformed green bandwidth (R_{550}) (Table 3.4). The theoretical premise for the ENDVI algorithm is based on inclusion of green spectral data that may indicate N status. The relationship between N status and the 550 nm green spectral peak is inverse due to minimal chlorophyll absorption at this bandwidth (Fridgen and Varco, 2004). The SCCCI was previously shown to be sensitive to red-edge shift and biomass accumulation (Varco et al., 2013). The ENDVI algorithm was developed through experimentation in hopes of adding yet another elucidating segment of spectral samples for N detection. The ENDVI will be applied to both corn and cotton crops in the Results section of this paper. Table 3.4 details the VIs used in this study.

Table 3.4 Vegetation indices table.

Acronym	Name	Algorithm	Reference
RVI	Ratio Vegetation Index	R_{840}/R_{650}	Pearson and Miller (1972)
GRVI	Green RVI	R_{840}/R_{550}	Tucker (1979)
NDVI	Normalized Difference VI	$(R_{840}-R_{650})/(R_{840}+R_{650})$	Rouse et al. (1973)
GNDVI	Green NDVI	$(R_{840}-R_{550})/(R_{840}+R_{550})$	Gitelson et al. (1996)
DVI	Difference VI	$R_{840}-R_{650}$	Tucker (1979)
RDVI	Renormalized Difference VI	$(R_{850}-R_{670})/(SQRT(R_{850}+R_{670}))$	Roujean and Breon (1995)
NDRE	Normalized Difference Red Edge VI	$R_{780}-R_{720}/R_{780}+R_{720}$	Barnes et al. (2000); Varco et al. (2013)
SCCCI	Canopy Chlorophyll Content Index	NDRE/NDVI	Barnes et al. (2000); Varco et al. (2013); Raper and Varco, 2014)
R695/R760	R695/R760	$R_{695}{}^{\dagger\dagger}/R_{760}$	Carter (1994)
R750/R700	R750/R700	$R_{750}{}^{\dagger\dagger\dagger\dagger}/R_{700}$	Gitelson and Merzlyak (1997)
R750/R550	R750/R550	$R_{750}{}^{\dagger\dagger\dagger\dagger}/R_{550}$	Gitelson and Merzlyak (1997)
R780/R670	R780/R670	R_{780}/R_{670}	Pearson and Miller (1972)
R780/R700	R780/R700	R_{780}/R_{700}	Mistele and Schmidhalter (2010)
R780/R740	R780/R740	R_{780}/R_{740}	Mistele and Schmidhalter (2010)
MCARI (670,700)	Modified CARI	$[(R_{700}-R_{670})-0.2*(R_{700}-R_{550})]*(R_{700}/R_{670})$	Daugherty et al. (2000)
MCARI-1 (670,800)	Modified CARI-1	$1.2*[2.5(R_{800}-R_{670})-1.3*(R_{800}-R_{550})]$	Haboudane et al. (2004)
TCARI (670,700)	Transformed CARI	$3*[(R_{700}-R_{670})-0.2*(R_{700}-R_{550})]*(R_{700}/R_{670})$	Haboudane et al. (2004)
OSAVI1 (670,800)	Optimized Soil-Adjusted VI	$(1+0.16)*(R_{800}-R_{670})/(R_{800}+R_{670}+0.16)$	Rondeaux et al. (1996)
OSAVI2 (705,750)	OSAVI2	$(1+0.16)*(R_{750}{}^{\dagger\dagger\dagger\dagger}-R_{705}{}^{\dagger\dagger\dagger})/(R_{750}{}^{\dagger\dagger\dagger\dagger}+R_{705}{}^{\dagger\dagger\dagger}+0.16)$	Wu et al. (2008)
MSR (670,800)	Modified Simple Ratio	$(R_{800}/R_{670})-1/(SQRT(R_{800}/R_{670}+1))$	Chen (1996)
MSR-1 (705,750)	Revised MSR	$(R_{750}{}^{\dagger\dagger\dagger\dagger}/R_{705}{}^{\dagger\dagger\dagger})-1/(SQRT(R_{750}{}^{\dagger\dagger\dagger\dagger}/R_{705}{}^{\dagger\dagger\dagger}+1))$	Wu et al. (2008)
TCARI/ OSAVI-1	Revised TCARI/OSAVI	TCARI(670,700)/ OSAVI(670,800)	Wu et al. (2008)
MCARI-1/ OSAVI-1	MCARI1/OSAVI-1	MCARI(670,700)/ OSAVI(670,800)	Wu et al. (2008)
TCARI/ OSAVI-2	TCARI/OSAVI-2	TCARI(670,700)/ OSAVI(705,750)	Wu et al. (2008)
Guyot's REI	Guyot's Red Edge Inflection	$700+40*(((R_{670}+R_{780})/2)-R_{700})/(R_{740}-R_{700})$	Guyot et al. (1992)
WDRVI	Wide Dynamic Range VI	$(0.18*(R_{840}-R_{650}))/(0.18*(R_{840}+R_{650})$	Sakamoto et al. (2011)
EVI	Enhanced VI	$2.5*((R_{840}-R_{680})/(R_{840}+6*R_{680}-7.5*R_{480}{}^{\dagger}+1))$	Huete et al. (2002)
ENDVI	Early N Detection VI	$R_{550}{}^{\wedge.003}/SCCCI$	This paper.

† R_{480} replaced with R_{450} †† R_{695} replaced with R_{700} ††† R_{705} replaced with R_{710}
†††† R_{750} replaced with R_{760}

The VIs reviewed in this study were programmed in Microsoft Excel using VBA scripting, and the biophysical parameters were fitted to the indices using the r-squared coefficient of determination statistic as described in the Statistical Analysis section in this chapter.

Experimental Differences

As noted previously in these methods, experimental differences occured between the 2012 and 2013 sampling season. Cotton was not irrigated in 2012, which could have reduced the response to applied N. It is believed that water was the most limiting factor in 2012 and that the N response was negated by the lack of adequate moisture. More importantly, YARA sampling occured at early square in 2012 cotton and since residual herbicides were not applied at planting, weeds in some parts of the field had emerged, but were then sprayed with glyphosate. Concerns about extraneous green reflectance from weedy biomass were noted. The 2013 furrow irrigated cotton crop did receive adequate supplemental irrigation and water was not considered a limiting factor in the second year. Finally, the SE calibration procedure, as noted in these methods, may or may not have affected the total spectral sampling results between 2012 and 2013.

Statistical Analysis

Statistical analysis was conducted in SAS 10.1 (SAS Institute, Cary, NC). The PROC REG procedure was employed to determine what, if any, data outliers existed. The studentized residuals were calculated and the sample datasets were reviewed for their fitness. Statistical DFFITS and DFBETAS tests were applied on all points to measure the influence individual outliers have on the entire dataset. A DFFITS test measures how much a single observation affects its regression model fitted value while a DFBETAS test measures how a single observation affects the estimate of a regression coefficient (Kutner et al., 2004). Absolute DFFITS and DFBETAS values are considered highly influential when found to be greater than $2*\sqrt{(k+1)/n}$ and $2/\sqrt{n}$, respectively, where k is the minimum variance unbiased estimator and n is the sample size.

With the exception of two data points across all cotton and corn datasets from 2012 and 2013, all data points were within the acceptable ranges of DFFITS and DFBETAS. Site numbers 85 and 116 in 2013 cotton at early bloom and peak bloom, respectively failed to pass either fitness test. Therefore, all data points for both crops and both years at all stages were used and none were discarded for general modeling. However, site 116 was removed from spectral signature modeling due to the lateral shift created by the spectroradiometric error. Furthermore, Sites 85 and 116 points were removed when performing the inverse biophysical transfer model described later in this chapter. The removal of these points aided in removing a bias against the NDVI and GNDVI algorithms.

The PROC GLM procedure was used for ANOVA analysis. Fertilizer N rate was tested for its effects at all sampling and sensing dates. The ANOVA analysis was also employed to calculate the sensitivity equivalent (*SEq*) of VIs to biophysical parameters. The slope of a linear relationship was divided by the root-mean-square error. Pearson's product-moment correlation coefficients (r) were calculated in SigmaPlot 12.0 (Systat Software, Inc., San Jose, CA) and presented in tabular form. Whole plant N content provides an indication of N biomass and is calculated by multiplying the whole plant N concentration times the times the whole plant yield weight. Corn grain N content represents the amount of N removed and is calculated by multiplying the corn grain N concentration times the dried yield.

To study the scale-related behaviors of two different sensor types in early cotton and corn (early square and V5 respectively), the SE narrow band sensor was scaled up to match the YARA sensor bandwidths. Spectral Evolution bandwidths were averaged with two bands before and two bands after the target bandwidth. Sensor number one was the SE narrow band sensor. Sensor number two was the SE wide band dataset, and sensor number three was the YARA wide band dataset. A PROC GLM procedure was employed to determine what, if any effect, year, sensor type, and N treatment had on VI results at varying bandwidth definitions.

To study the predictive strength of VIs in cotton and corn at different growth stages, multiple biophysical parameters were fitted linearly to twenty-seven different VIs (see Table 3.4) using MS® Excel "RSQ" function (simple coefficient of determination). Cotton was tested at early square, early bloom, and peak bloom in 2012 and 2013. Corn was tested at V5 and VT in 2012 and V5, V8, and VT in 2013. The YARA sensor was employed to collect spectral samples at cotton and corn in early square and V5 stages only. The SE sensor was employed to collect spectral samples at all stages. A PROC GLM procedure was employed to rank the R-squared values for each of 28 VI responses.

Six VIs (NDVI, GNDVI, NDRE, SCCCI, ENDVI, and Guyot's REI) for each sensor at each growth stage were modeled for leaf N and whole plant N (corn only) concentration using an inverse biophysical transfer model to produce r-squared and root-mean-square-error (RMSE) statistics. The combined statistics were employed to rank VI suitability, and the highest R-squared result was noted for each dataset.

Graphs were constructed in SigmaPlot 12.0 and were used to examine linear and quadratic relationships for all models. Quadratic models were described if the quadratic term was significant at the 0.05 level of significance. An inverse biophysical transfer of selected VIs were modeled in Microsoft Excel software for predicting early leaf N status. The root-mean-square-error (RMSE) defined the best fitting VIs by measured versus predicted results. Cotton soil variability was described in raster surfaces using ordinary Kriging in ArcGIS 10.2 software.

Geographic data acquired at sampling sites was converted from native WGS 1984 geographic projection system to the appropriate UTM projected coordinate system. Soil N variability is displayed in raster format created with ArcGIS Desktop 10.1 Geostatistical Analyst extension. A log transformation and first order trend removal was applied and the resultant raster was classified using Jenks (Natural Breaks) format with five classes.

CHAPTER IV

RESULTS AND DISSCUSION

Climatic Conditions

Cotton Trials

The 2012 weekly temperature and rainfall data for the field site located south of Natchez, Miss. was obtained for the USDA-NASS Natchez, Miss. reporting site. When the Natchez reporting site was unavailable, weather data was collected from the Woodville, Miss. site. The Natchez, Miss. early weekly average temperature and rainfall was slightly below normal, which could have slowed or limited vegetative growth. Somewhat droughty conditions persisted later in the 2012 growing season and, at times, crop development was impeded by low soil moisture conditions (Table 4.1).

Table 4.1 Weekly average temperature and rainfall for the 2012 cotton growing period near Natchez, Miss.

	Temperature, °C		Precipitation, mm	
Period	Weekly Average	DFN	Weekly Average	DFN
2nd half Apr.	18.3	-1.7	4	-32
1st half May	21.7	-0.6	42	9
2nd half May	22.5	-0.8	4	-27
1st half June	25.0	-0.4	26	-3
2nd half June	26.7	-0.3	0	-26
1st half July	26.7	-0.6	63	39
2nd half July	27.5	-0.3	56	34
1st half Aug.	28.1	0.3	39	17
2nd half Aug.	26.1	-0.9	62	39
1st half Sep.	25.3	-0.3	1	-21
2nd half Sep.	22.2	-1.1	59	38
1st half Oct.	18.1	-2.8	14	-7
2nd half Oct.	17.5	-0.8	0	-23

Source: USDA-NASS-MS Crop Progress and Condition Report.
DFN=Departure from normal.

General area weather conditions for the 2013 site located northwest of Money, Miss. were obtained from the USDA-NASS Moorhead, Miss. reporting site. When the Moorhead site was unavailable, weather data was collected from either the Cleveland or Belzoni, Mississippi sites. Site-specific rain data was collected on the western edge of the research site. Rain gauge data was not available after July 18, 2013

The 2013 weather conditions were cooler and wetter than normal early in the season, but generally warmer conditions began in August and lasted until harvest. The crop was furrow irrigated three times between July and August. Available water was not considered a limiting factor in this study (Table 4.2).

Table 4.2 Weekly average temperature and rainfall for the 2013 cotton growing period near Money, Miss.

	Temperature oC		Precipitation, mm		
Period	Weekly Average	DFN	Weekly Average	DFN	Rain Gauge
1st half May	17.5	-3.3	57	25	n/a
2nd half May	23.9	0.6	27	-2	57
1st half Jun	25.3	-0.6	6	-19	4
2nd half Jun	27.5	0.6	22	-4	n/a
1st half Jul	25.8	-1.9	6	-23	25
2nd half Jul	26.9	-1.1	22	-5	n/a
1st half Aug.	27.6	-0.2	3	-13	n/a
2nd half Aug.	27.2	0.3	1	-13	n/a
1st half Sep.	28.3	3.3	0	-20	n/a
2nd half Sep.	26.4	3.1	32	11	n/a
1st half Oct.	n/a	n/a	n/a	n/a	n/a
2nd half Oct.	20.0	1.7	4	-14	n/a

Source: USDA-NASS-MS Crop Progress and Condition Report
DFN=Departure from normal.

Corn Trials

Climatic conditions for 2012 and 2013 at the W.B. Andrews Agriculture Systems Research Farm were obtained from the USDA-NASS Crop Progress and Condition Reports. Site-specific rain data was collected on the western edge of the research plot.

In 2012, average temperatures were warmer than normal, while rainfall was lower than normal. During dry periods, the corn showed some signs of stress such as leaf rolling in the afternoon, but timely rainfall during pollination limited any lasting effects. Gauged rainfall data collected on the western edge of the cornfield revealed critical rainfall received during early July (Table 4.3).

Table 4.3 Weekly average temperature and rainfall for the 2012 corn growing period near Starkville, Miss.

	Temperature, °C		Precipitation, mm		
Period	Weekly Average	DFN	Weekly Average	DFN	Rain Gauge
1st half Apr	18.3	2.8	3	-31	6
2nd half Apr	18.9	1.1	47	15	37
1st half May	23.3	3.3	36	6	16
2nd half May	23.3	1.4	4	-23	21
1st half Jun	24.7	0.8	12	-12	21
2nd half Jun	27	1.1	17	-7	5
1st half Jul	27.5	0.3	104	78	52
2nd half Jul	28.3	1.1	15	-9	13
1st half Aug	27.8	0.6	36	15	6
2nd half Aug	25	-1.4	51	33	47
1st half Sep	26.7	1.4	41	21	10

Source: USDA-NASS-MS Crop Progress and Condition Report
DFN=Departure from normal

The 2013 corn-growing season was characterized as having temperatures near the long-term average, and rainfall was reasonably distributed with near normal amounts received. The gauged rain data revealed early wet spring conditions followed by timely precipitation each month (Table 4.4).

Table 4.4 Weekly average temperature and rainfall for the 2013 corn growing period near Starkville, Miss.

	Temperature, °C		Precipitation, mm		
Period	Weekly Average	DFN	Weekly Average	DFN	Rain Gauge
1st half Apr	15.6	0.0	26	-8	22
2nd half Apr	17.2	0.0	41	9	33
1st half May	17.8	-1.7	43	13	39
2nd half May	23.1	0.9	34	7	6
1st half Jun	25.3	0.6	19	-5	23
2nd half Jun	27.2	1.1	9	-15	5
1st half Jul	25.6	-1.7	24	-2	32
2nd half Jul	26.7	-0.6	22	-2	8
1st half Aug	26.7	-0.4	16	-4	32
2nd half Aug	26.1	0.3	1	-17	1
1st half Sep	25.6	1.7	0	-21	0

Source: USDA-NASS-MS Crop Progress and Condition Report
DFN=Departure from normal

Objective I - Effects of Varying N Supply on Cotton and Corn Crops

The objective was to describe the effects of varying N supply on cotton and corn leaf N concentration, SPAD chlorophyll, and yield.

Cotton Response to N Supply

Leaf N Response

Leaf N concentration across fertilizer N rates of 33.6, 67.2, 100.8, and 134.4 kg ha^{-1} was monitored to evaluate its response at critical stages of cotton growth. The general trend in cotton leaf N concentration across the growing seasons differed by year and experimental site. Bell et al (2003) recommends a leaf N critical value of 5.4% at early square, 4.3% leaf N at early bloom, and 4.1% leaf N at peak bloom. In 2012 near Natchez, Miss., leaf N concentrations increased from the early square sampling to early bloom sampling, then declined as the crop progressed to early bloom indicating re-mobilization and demand by developing bolls. The 100.8 kg N ha^{-1} fertilizer rate achieved critical leaf N values during early bloom only and the relationship across the three sampling times indicates leaf N concentration peaked at approximately 110 kg ha^{-1} N, similar to the grower applied treatment (Figure 4.1)

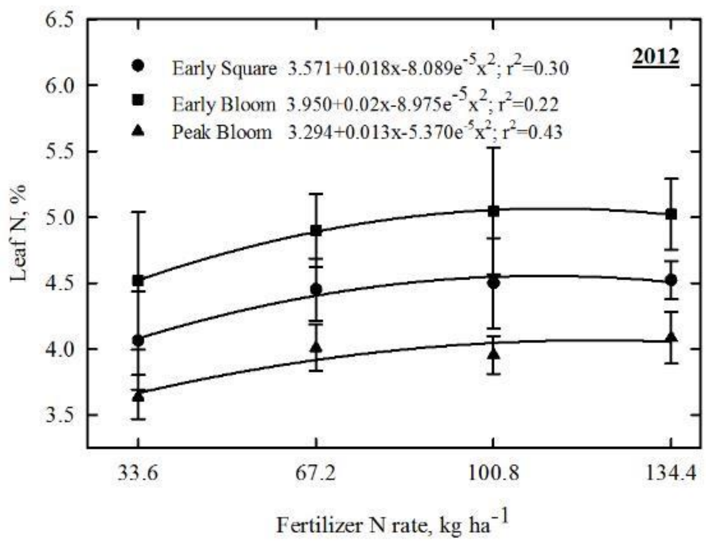


Figure 4.1 Cotton leaf N concentration response to fertilizer N rates in 2012 near Natchez, Miss.

Error bars represent a 95% confidence interval (n=72).

In 2013 at the site near Money, Miss., the response in leaf N concentration showed a more general increase with increasing fertilizer N rates for all sampling dates. Early square cotton was near or achieved critical leaf N values. During early bloom, all treatments fell below critical leaf N status. The fertilizer N rates ranging from 67.2-134.4 kg N ha^{-1} achieved critical leaf N values by peak bloom while the lowest treatment rate remained below the recommended critical value (Figure 4.2)

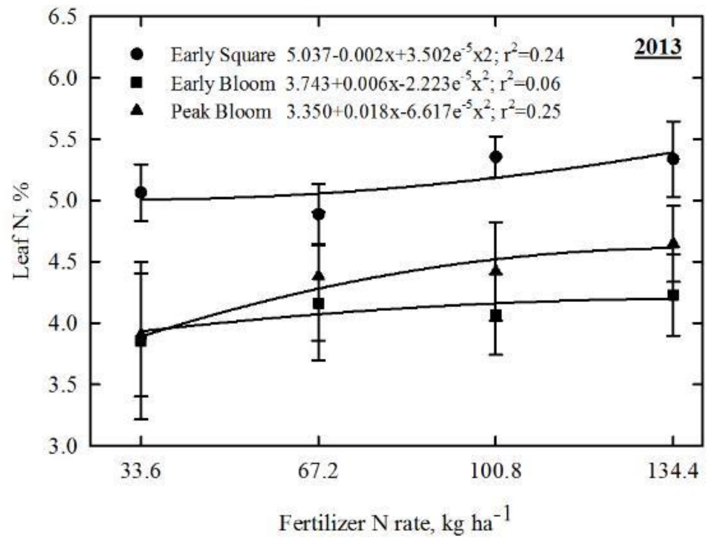


Figure 4.2 Cotton leaf N concentration response to fertilizer N rates in 2013 near Money, Miss.

Error bars represent a 95% confidence interval (n=80).

Raper (2011) attributed a decrease in early bloom leaf N concentrations to leaf (photosynthetic source) and boll (photosynthetic sink) physiological relationships whereby N resources are partitioned to the immediate demand. Bell et al. (2003) found low soil moisture and drought conditions reduced petiole N concentrations in a matter of hours. Although petiole analysis is not indicative of leaf N status, it is representative of daily supply acting as a water and nutrient conduit to leaves. In 2012, water was likely the most limiting factor and N resources were adequate to meet plant-growth demands. In 2013, plants flourished under well-watered conditions and N partitioning and leaf N concentrations exhibited patterns similar to those noted in Raper (2011) and Bell et al. (2003).

Leaf SPAD/Chlorophyll Response

In 2012, the trend in cotton SPAD chlorophyll response to fertilizer N rate increased at each sampled growth stage. Little difference between SPAD chlorophyll readings is noted across all fertilizer N treatments during the early bloom stage. The range of SPAD chlorophyll readings at both early and peak bloom was widest in plots treated with 67.2 and 100.8 kg fertilizer N ha^{-1}. However, the highest fertilizer N rate at peak bloom produced the greatest SPAD chlorophyll readings for the season (Figure 4.3).

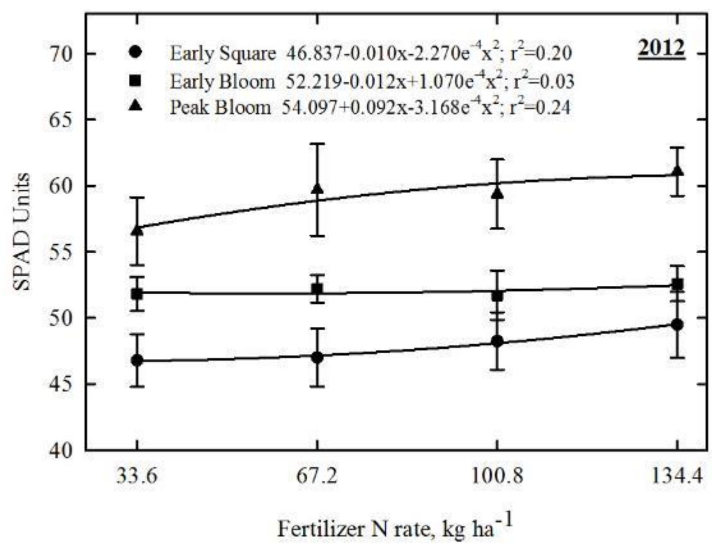


Figure 4.3 Cotton Leaf/SPAD chlorophyll response to fertilizer N rates in 2012 near Natchez, Miss.

Error bars represent a 95% confidence interval (n=72).

In 2013, SPAD chlorophyll response to fertilizer N rates varied less between growth stage sampling periods than in 2012. In different field locations, 2013 cotton plants were slightly smaller and less mature. A large variation within sampled fertilizer N rate locations and replications in 2013 is indicated by error bars (Figure 4.4).

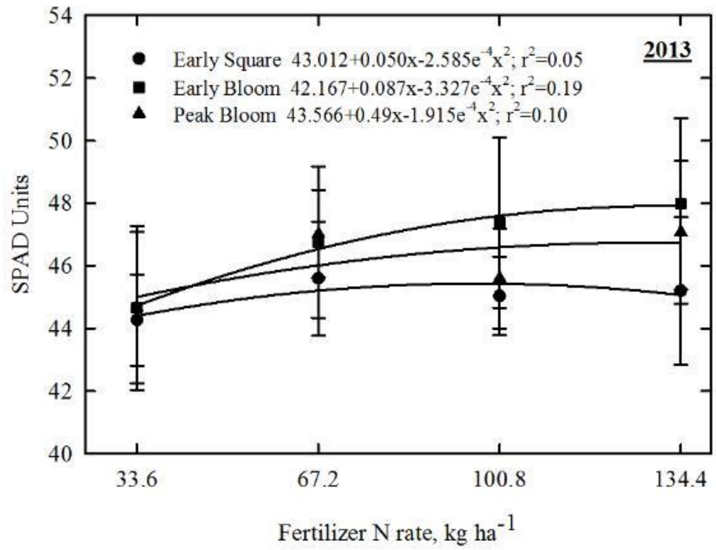


Figure 4.4 Cotton leaf SPAD chlorophyll response to fertilizer N rates in 2013 near Money, Miss.

Error bars represent a 95% confidence interval (n=80).

Overall, SPAD chlorophyll responded across both growing seasons and sites with a progression from lower to higher values. In general, measured values in 2013were lower than the lowest values observed in 2012. This anomaly may be related to non-irrigated production in 2012 as well as a prolonged period of minimal rainfall that likely constrained vegetative growth relative to N supply and thus, resulted in greater leaf N concentrations as well as SPAD chlorophyll readings. The Money Miss. site in 2013 was furrow irrigated, which can result in greater N losses through leaching and denitrification, while enhancing vegetative growth and a resultant dilution effect on tissue nutrient levels (Hake and Grimes, 2010).

Lint Yield Response to Fertilizer N Rates

Lint yield near Natchez, Miss. in 2012 was markedly lower than that achieved near Money, Miss.in 2013. Lower yields may be a result of several contributing factors including differences in soils at these two sites, yearly rainfall patterns and amounts, and irrigated versus non-irrigated conditions. A first-order derivative analysis (y=0) of cotton yield by fertilizer N rate revealed the 2012 lint yield rate increased up to the 100.8 kg N ha^{-1} rate, while the 2013 lint yield continued to increase with increasing fertilizer at a decreasing rate (Figure 4.5).

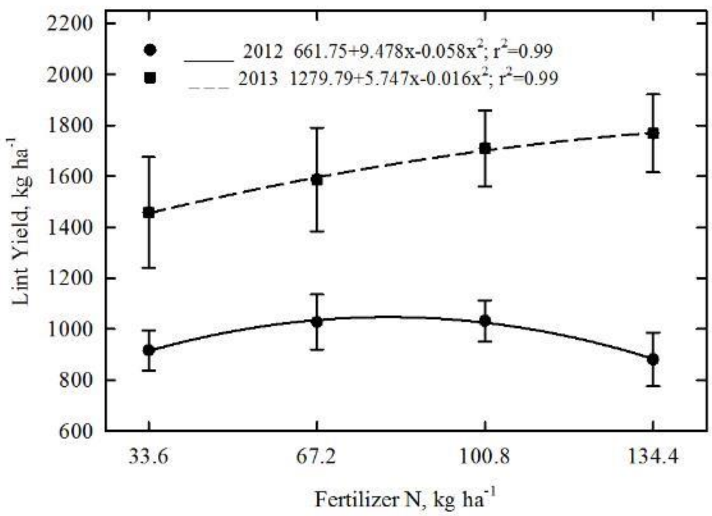


Figure 4.5 Cotton lint yield response to varying fertilizer N rates across two differing field site-years.

Error bars represent a 95% confidence interval (n=72 in 2012 and n=80 in 2013).

Discussion

Relationships between cotton leaf N samples and N rates for both seasons are weak ($r^2 < 0.50$). As both of these research sites were first year on farm studies, a contributing factor to a lack of fertilizer N response is likely due to spatial variability in residual N levels. Fertilizer N rate decisions and recommendations for side dress fertilization need to be made at or near early square sampling, a time when adequate vegetative growth has not yet occurred to adequately define spatial variability in soil N supply.

The relationships between all cotton SPAD chlorophyll results and fertilizer N rate for both seasons are weak ($r^2 < 0.50$), similar to the results for leaf N concentration. Weak response in leaf N concentration and SPAD chlorophyll readings to fertilizer N rates for these two site-years of cotton research may be related to inherent and anthropogenic spatial variability in residual soil N as indicated by extractable NH_4^+ and NO_3^- levels found shortly after crop emergence. Varying soil N resources can mask first year N response when working in producer's fields. Evaluating plant N needs via remote sensing could be confounded by the presence of varying soil N resources.

Water, as a limiting factor, contributed to lower 2012 yields and the lowest fixed rate N treatment produced higher yield than the maximum fixed rate. The 2013 furrow irrigated field produced increasing yields with increasing fixed rate treatments. Cotton variable rate fertilizer N research, including yield response rates, is expanded upon later in this chapter.

Corn Response to N Supply

Leaf N Response

Corn leaf N concentration response to fertilizer N rates was determined in 2012 at V5 and VT, and in 2013 at V5, V8, and VT growth stages. Jones (1990) suggests corn leaf tissue N sufficiency concentrations of 3.0 to 3.5% at V5 and 2.70 to 4.0% at VT. The general trends in 2012 corn leaf N concentration at V5 and VT stages indicated an increasing response to applied rates, albeit at a diminishing rate as N rate increased (Figure 4.6). A first-order derivative analysis (y = 0) of corn tissue leaf N by fertilizer N rate revealed in 2012 that maximum leaf N occurred at 179.2 kg ha^{-1} N. Although the quadratic response function suggests a decline in leaf N concentration at V5 with an increase in fertilizer N from 179.2 to 268.8 kg ha^{-1}, the actual mean increased from 3.60 to 3.73%. Leaf tissue N sufficiency at V5 was achieved at the maximum rate and 179.2 kg N ha^{-1} rate in 2012, and leaf tissue N sufficiency at VT was achieved at 179.2 and 268.8 kg N ha^{-1}.

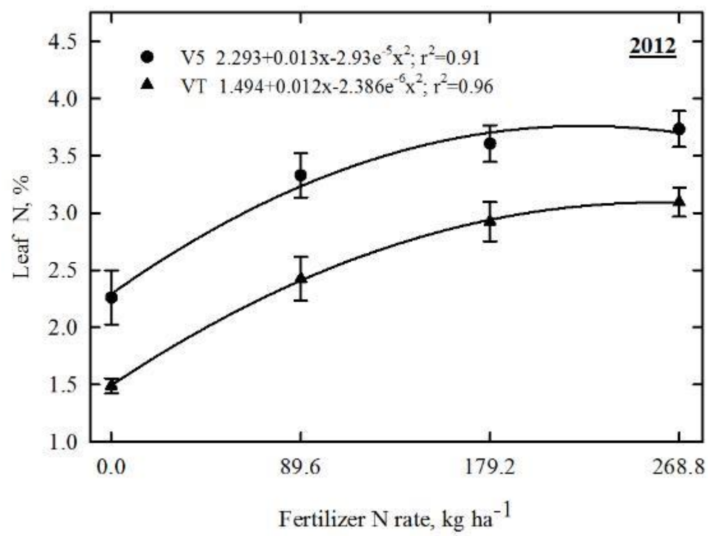


Figure 4.6 Corn leaf N concentration response to fertilizer N rates in 2012 at Mississippi State, Miss.

Error bars represent a 95% confidence interval (n=16).

The diminishing effect of increasing fertilizer N rate on leaf tissue N concentration is related to physiological processes of which water availability or degree of water stress are certainly factors to be considered. Soil variability including available water holding capacity due to slight variations in soil texture across the field and replications expressed itself with visual signs of moisture stress during periods of rainfall deficits.

In 2013, relationships between leaf N concentration and fertilizer N rates at V5 and VT produced a similar trend as was observed in 2012 (Figure 4.7). Leaf tissue N sufficiency was achieved at V5 under the maximum rate, and the VT leaf tissue sufficiency was achieved at both maximum and 179.2 kg ha^{-1} rates. At V5 and VT, maximum leaf N concentration was predicted at N rate of 268.8 kg ha^{-1}. The additional sampling at V8 indicated a similar trend, although a decline in leaf tissue N concentration from 179.2 to 268.8 kg ha^{-1} fertilizer N rates was observed and could be related to low rainfall received during this period.

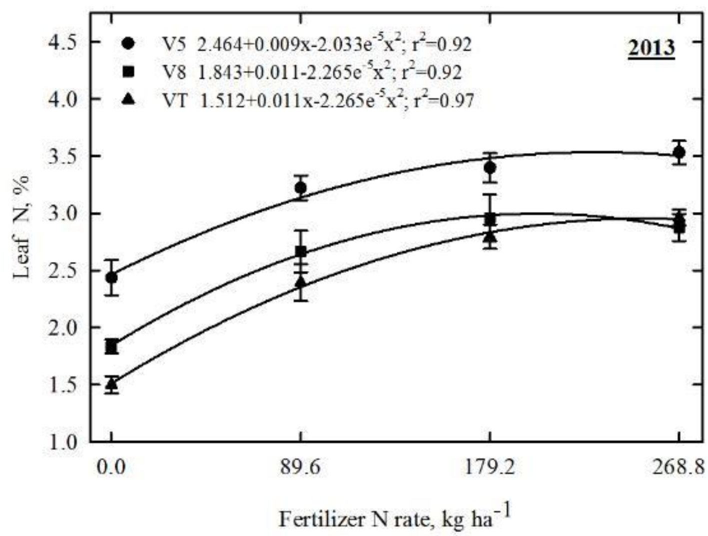


Figure 4.7 Corn leaf tissue N concentration response to fertilizer N rates in 2013 at Mississippi State, Miss.

Error bars represent a 95% confidence interval (n=16).

The 2013 growing season was cooler and wetter before and after planting than in 2012. The strength in relationships between all corn leaf tissue N concentrations and fertilizer N rates for both seasons at all growth stages appears to be related to the wide variability in N treatments.

Leaf SPAD/Chlorophyll Response

In 2012, SPAD leaf chlorophyll responded to increasing fertilizer N rates, albeit at a decreasing rate at both V5 and VT growth stages. Wide variability between replications in SPAD response was observed at V5, but diminished by the VT stage. At VT, SPAD chlorophyll response was markedly stronger than at V5 (Figure 4.8).

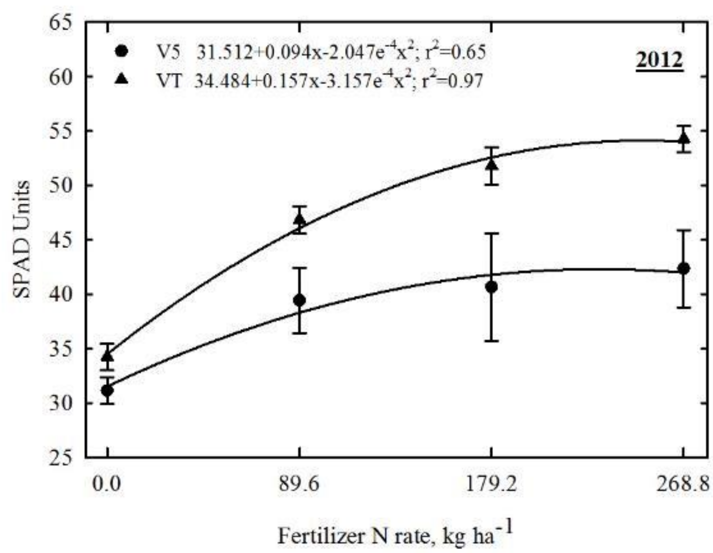


Figure 4.8 Corn leaf SPAD chlorophyll response to fertilizer N rates in 2012 at Mississippi State, Miss.

Error bars represent a 95% confidence interval (n=16).

The strength in leaf SPAD chlorophyll response to fertilizer N rates increased from V5 to VT stages for both years (Figure 4.8 and Figure 4.9). At VT, corn is not yet partitioning N resources to corn grain and so it is expected that leaf SPAD chlorophyll values would rise or maximize just prior to pollination and grain filling. The 2013 increase in SPAD chlorophyll response is particularly notable at the VT stage, although corn had experienced low soil moisture from V8 up to this stage. (Figure 4.9). With no N applied, SPAD chlorophyll readings declined from V8 to VT. This may be due to the extreme depletion of available soil N with no fertilizer N applied. In general, SPAD chlorophyll readings at V5 stage were lower in 2013 than in 2012. The 2013 climatic conditions were cooler and wetter, and delayed growth compared to 2012.

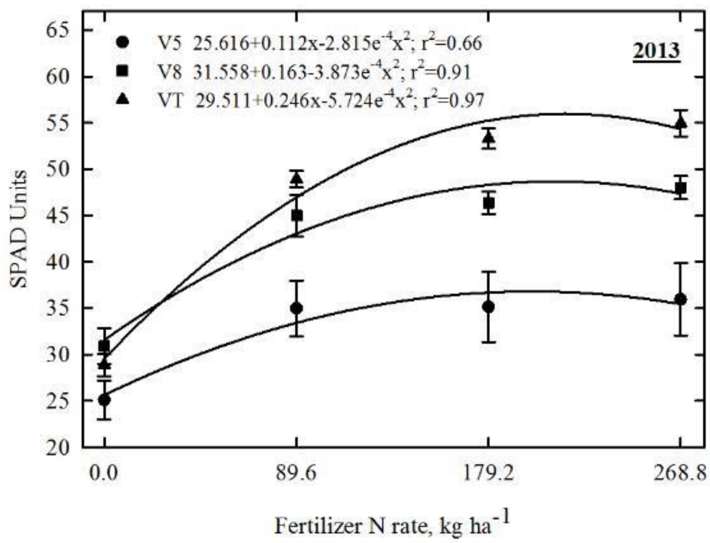


Figure 4.9 Corn leaf SPAD chlorophyll response to fertilizer N rates in 2013 at Mississippi State, Miss.

Error bars represent a 95% confidence interval (n=16).

For both years, early corn (V5 stage) did not produce strong relationships between SPAD chlorophyll response and fertilizer N rate. Similar to corn leaf N concentration in later growth stages, the relationships between all corn SPAD chlorophyll response and fertilizer N rates both seasons was significant ($r^2 > 0.90$).

Early Season Whole Plant N Response

Whole plants were randomly sampled at V5 to determine early season response to fertilizer N rates. Dry matter yield, N concentration, and N content were determined both years. The range in whole plant N (WPN) concentration was similar both years, but were lower than that for leaf N concentration. Overall, whole plant N concentration was greater in 2012 except at 0.0 kg N ha^{-1} where values were near equal (Figure 4.10).

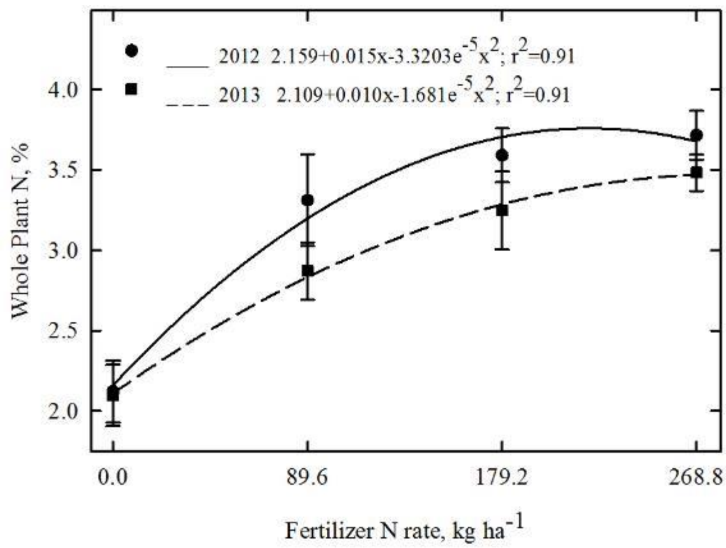


Figure 4.10 Fertilizer N rate effects on whole plant N concentration in 2012 and 2013 at V5.

Error bars represent a 95% confidence interval (n=16).

Although 2013 temperatures were near normal, the period preceding V5 sampling was wetter than normal. Above-canopy sensors detect multiple factors such as greenness (WPN concentration), biomass (dry matter yield), and background effects of leaf to soil ratios, while leaf-level sensors outputs are largely affected by greenness factors. For this purpose, total plant N (TPN) content was derived by multiplying WPN concentration times the dry matter weight of sampled plants and the number of plants per hectare.

A quadratic trend in TPN content at V5 in response to fertilizer N rates was observed both growing seasons (Figure 4.11).

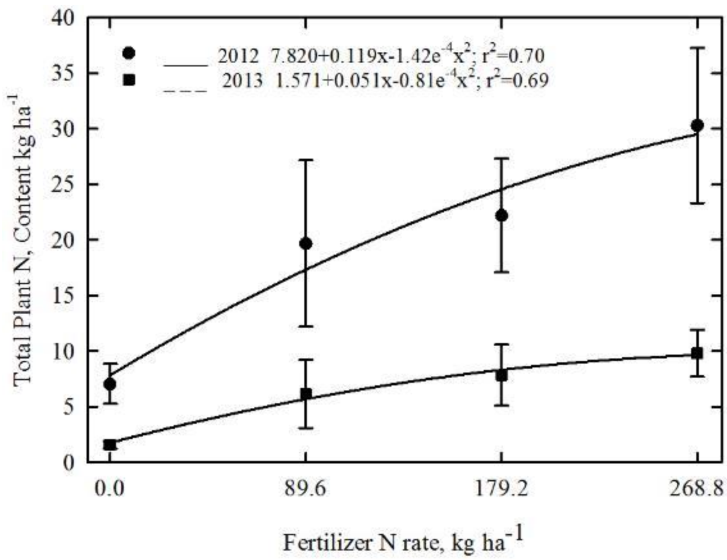


Figure 4.11 Fertilizer N rate effects on total plant N concentration in 2012 and 2013 at V5.

Error bars represent a 95% confidence interval (n=16).

Total plant N content in 2013 was lower across all fertilizer N rates. Sampled plants in the 2013 0.0 kg N ha-1 rate were 80% lower in dry matter yield than in 2012, while plants receiving fertilizer N treatment were, on average, 68% lower in dry matter yield than in 2012 (Table 4.5).

Table 4.5 Corn V5 dry matter yield by treatment average.

	g plant^{-1}	
N rate	2012	2013
0.0	26.9	5.7
89.6	47.6	17.0
179.2	50.3	18.9
268.8	66.0	21.8
LSD$_{(0.05)}$	53.69	53.0

Significant at $\alpha = 0.05$;

Although whole plant N concentration may be a more accurate proxy of N status when sampling reflectance at above-canopy levels, single leaf N concentration analysis may suffice for leaf-level sensing.

Grain N and Yield Response to Fertilizer N Rates

Corn grain N concentration (CGN) response to fertilizer N rates was studied in an effort to better understand what, if any, effect N rate had on grain characteristics. Increases in corn grain N concentration elucidates the adequacy of fertilizer N supply across a wide range of treatments. In 2013, CGN concentration was slightly more variable than in 2012, while the strength of the relationship both years was moderate (Figure 4.12). A slight decrease in CGN concentration at 89.6 kg ha^{-1} fertilizer N rate is reflective of the depleted N situation with the no N applied treatment and the first incrementally applied rate causing a large yield increase and a dilution of N within the plant. Corn grain N concentration alone may not be the strongest predictor of N uptake.

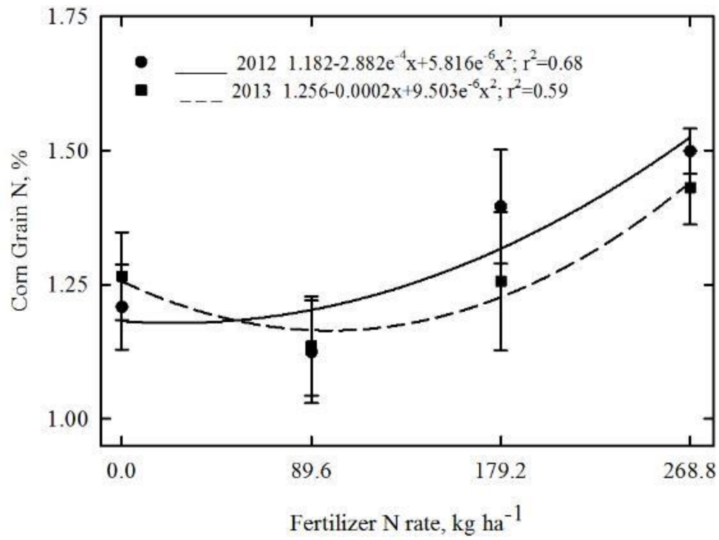


Figure 4.12 Fertilizer N rate effects on corn grain N concentration in 2012 and 2013 at Mississippi State, Miss.

Error bars represent a 95% confidence interval (n=16).

Corn grain N content was derived by multiplying CGN concentration by corn grain yield. The trend in corn grain content for both growing seasons was nearly linear and increased with increasing fertilizer N rates. The response in 2013 was greater than that of 2012 with the exception of the maximum fertilizer rate where the response was nearly equal (Figure 4.13)

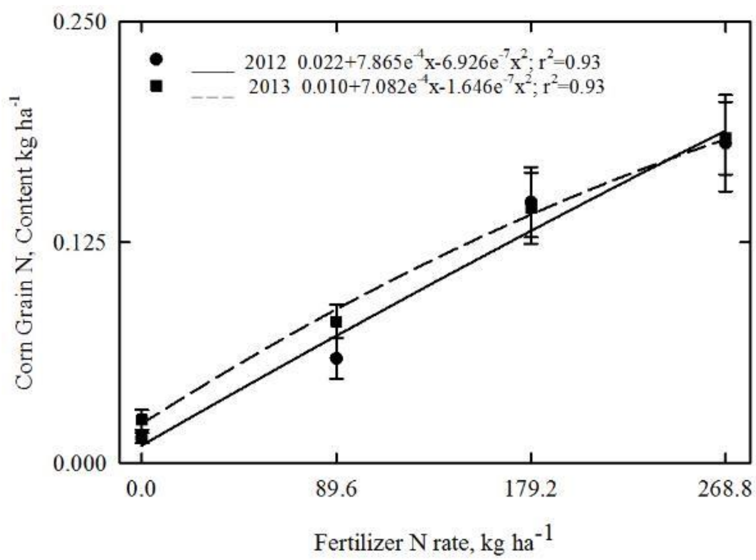


Figure 4.13 Fertilizer N rate effects on corn grain N content in 2012 and 2013 at Mississippi State, Miss.

Error bars represent a 95% confidence interval (n=16).

A cereal rye cover crop was grown each year in order to provide vegetative cover and recover any residual soil N each fall following corn harvest. Corn grain yield response to fertilizer N rates both years followed a quadratic trend. In 2012, yield output per unit of input decreased at a slightly faster rate than in 2013 (Figure 4.14). In 2013, grain yield at 0.0 and 89.6 kg N ha^{-1} rates were lower than the previous year while both of the higher N rates produced similar grain yields both years. A first order derivative analysis of yield indicated the corn grain yield in 2012 increased up to the 179.2 kg N ha^{-1} rate, while the 2013 yield continued to increase near the maximum N rate. A reduction in grain yield in 2012 at the 268.8 kg ha^{-1} N rate is mostly attributed to a single replicate of this treatment, which is located on an area having greater sand content and is more prone to drought stress. This plot yielded less than the other replicates both years.

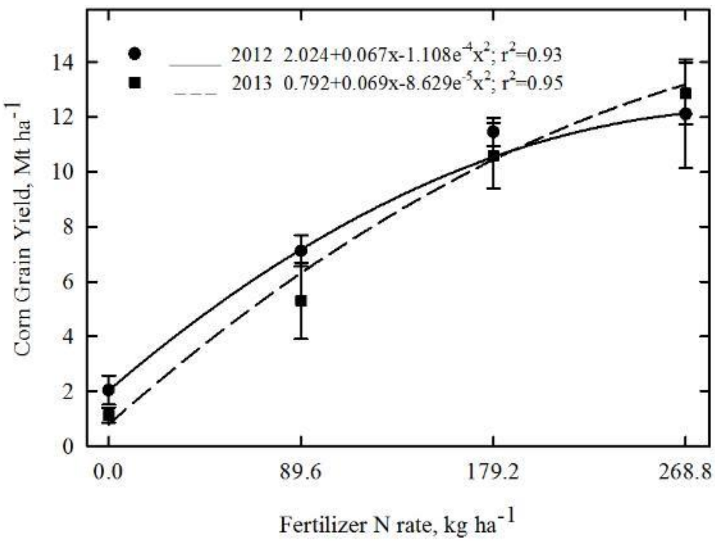


Figure 4.14 Fertilizer N rate effects on corn grain yield in 2012 and 2013 at Mississippi State, Miss.

Error bars represent a 95% confidence interval (n=16).

Discussion

In this study, it is inferred that the 268.8 kg N ha^{-1} fertilizer rate has higher levels of residual soil N resources than all other N treatment plots. The corn grown in this study was located on plots established at fixed rates that ranged from deficient to excess fertilizer N for two years and cotton for eight. Therefore, the strength in the relationships between fertilizer N and biophysical parameters is not surprising. Further corn research needs to be conducted using the 2012-2013 SCCCI range data to model and predict variable rate N treatments on fields where residual soil N is high but lacking systematic. Although high variability in soil and fertilizer N rates existed at pre-plant corn in both years of this study, the SPAD chlorophyll response at V5 stage was markedly weaker than would be expected or might be useful in making fertilizer N recommendations.

Objective II– Scale-Related Differences of Two Sensors

The second objective of this study was to compare cotton and corn leaf N status detection between leaf and canopy scale reflectance across widely varying N availability.

The SE and YARA sensors operate at uniquely different scales (leaf- and canopy-levels, respectively) and possess slightly different bandwidths (3 nm and 10 nm, respectively). Spectral signatures were acquired across fertilizer N rates at the early growth stages. Bandwidth configurations were compared, and wavelength correlations were calculated. Bandwidth comparisons across five different vegetation indices were made in order to ascertain differences between sensors related to sampling scale and spectral resolution. Vegetation index sensitivities were calculated and tabulated.

Bandwidth Comparisons

Cotton and corn sensing for this study included spectral samples taken at canopy- and leaf-levels. The canopy-level samples captured background environmental data, while leaf-level samples captured leaf tissue only. In order to ascertain whether the magnified leaf-level samples were affected by bandwidth, the SE data was scaled up to 10 nm bandwidths and compared to YARA N-Sensor data. Cotton fixed rate N sampling sites are averaged by plot (n=12 and n=16 in 2012 and 2013, respectively).

Cotton Bandwidths

For cotton, factors of year (2012 and 2013), fertilizer N treatment (33.6, 67.2, 100.8, and 134.4 kg fertilizer N ha^{-1}), and sensor type (SE narrow band, SE wideband, and YARA N-sensor wideband) were analyzed in a three-way cross classification analysis of variance (ANOVA) for main effects and interaction effects relative to mean

VI as determined by 5 methods (NDVI, GNDVI, NDRE, SCCCI, and Guyot's REI). All ANOVA's were obtained from PROC GLM in SAS (APPENDIX D). For each of the five methods for obtaining VI, the ANOVA indicates the three-factor interaction between year, N treatment, and sensor type is not significant, and the two factor interaction between year and sensor type, and the main effect of N treatment are significant ($P \leq 0.05$) with respect to mean VI as determined by each method (Table 4.6).

Table 4.6 Analysis of variance significance summarization examining response of early square cotton vegetation indices to sensor type (SE Narrow, SE Wide, and YARA Wide), fertilizer N rate, and years.

			P > F				
Source	NPARM	DF	NDVI	GNDVI	NDRE	SCCCI	Guyot's
Year	1	1	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Fertilizer N Rate	3	3	0.0366	0.0013	0.0020	0.0012	0.0002
Sensor	2	2	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Year x N rate	3	3	0.3058	0.4320	0.2279	0.3999	0.6165
Year x sensor	2	2	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
N rate x sensor	6	6	0.2439	0.5605	0.6715	0.9632	0.8888
Year x N rate x sensor	6	6	0.2813	0.6034	0.8130	0.9153	0.9537

The calculated means for each VI and model parameters are given in Table 4.7. Calculated means for each VI tested did not differ between SE narrow and SE wide band sensors. However, both SE sensor calculated mean VIs were different from the mean YARA N-Sensor VIs. The mean NDVI for both SE narrow and wide sensors was greater than the mean YARA derived NDVI both years, while the YARA GNDVI and NDRE were greater in 2012 and less than in 2013 than either SE configuration. The mean YARA SCCCI and Guyot's REI were greater than both the SE narrow and wide band sensors with regard to year.

Table 4.7 Calculated significant means (year by sensor) and estimated model parameters of sensor (SE Narrow, SE Wide, and YARA N-Sensor) vegetation index response to early square cotton leaf N concentration for 2012 and 2013 growing seasons.

	2012			2013		
Model	Sensors			Sensors		
Parameter	SE Narrow	SE Wide	YARA	SE Narrow	SE Wide	YARA
		NDVI			NDVI	
VI Mean	0.7860	0.7858	0.6251	0.7900	0.7899	0.3149
r^2	0.16	0.17	0.15	0.46	0.45	0.01
Intercept	0.2659	0.2617	1.3559	0.6091	0.6366	-0.0805
Linear	0.2441	0.2459	-0.2957	0.0569	0.0463	0.1507
Quadratic	-0.0285	-0.0287	0.0293	-0.0042	-0.0032	-0.0143
		GNDVI			GNDVI	
VI Mean	0.5873	0.5880	0.6140	0.5860	0.5869	0.3973
r^2	0.20	0.20	0.13	0.41	0.39	0.02
Intercept	0.5831	0.5694	1.1758	0.6186	0.6299	0.3032
Linear	-0.0065	0.0003	0.2379	-0.0294	-0.0332	0.0311
Quadratic	0.0017	0.0009	0.0249	0.0045	0.0048	-0.0025
		NDRE			NDRE	
VI Mean	0.2038	0.2045	0.2429	0.1986	0.1994	0.1096
r^2	0.46	0.45	0.09	0.23	0.23	0.04
Intercept	0.4968	0.4671	0.3785	1.0580	1.0705	0.3756
Linear	-0.1507	-0.1362	-0.0454	-0.3423	-0.3470	0.1850
Quadratic	0.0190	0.0173	0.0033	0.0340	0.0344	-0.0176
		SCCCI			SCCCI	
VI Mean	0.2593	0.2603	0.3883	0.2513	0.2524	0.3479
r^2	0.41	0.40	0.02	0.17	0.17	0.37
Intercept	0.8039	0.7682	0.1838	1.3935	1.4009	-0.7074
Linear	-0.2724	-0.2549	0.0961	-0.4502	-0.4527	0.4022
Quadratic	0.0337	0.0316	-0.0112	0.0442	0.0445	-0.0382
		Guyot's			Guyot's	
VI Mean	718.295	718.263	720.782	718.278	718.241	719.883
r^2	0.25	0.27	0.01	0.26	0.27	0.36
Intercept	726.3300	726.0200	722.2500	755.3200	756.4200	706.1000
Linear	-4.2052	-0.4086	0.5802	-14.7890	-15.2390	4.8514
Quadratic	0.5388	0.5261	0.0556	1.4713	1.5156	-0.4217

Corn Bandwidths

For corn, factors of year (2012 and 2013), fertilizer N treatment (0.0, 89.6, 179.2, and 268.8 kg fertilizer N ha^{-1}), and sensor type (SE narrow band, SE wideband, and YARA N-sensor wideband) were analyzed in a three-way cross classification analysis of variance (ANOVA) for main effects and interaction effects relative to mean VI as determined by 5 methods (NDVI, GNDVI, NDRE, SCCCI, and Guyot's REI). All ANOVA's were obtained from PROC GLM in SAS and are given in APPENDIX D.

For each of the five methods for obtaining VI, the ANOVA Table indicates that the three factor interaction between year, N treatment, and sensor type was not significant at V5. The NDVI and Guyot's REI two factor interaction between year and sensor type, and the NDVI two factor interaction between N rate and sensor were significant. The main effects were significant with respect to mean VI as determined by each method ($P \leq 0.0001$) (Table 4.8).

Table 4.8 Analysis of variance significance summarization examining response of V5 corn vegetation indices to sensor type (SE Narrow, SE Wide, and YARA Wide), fertilizer N rate, and years.

			P > F				
Source	NPARM	DF	NDVI	GNDVI	NDRE	SCCCI	Guyot's
Year	1	1	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Fertilizer N Rate	3	3	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Sensor	2	2	<0.0001	<0.0001	0.0300	<0.0001	<0.0001
Year x N rate	3	3	0.9041	0.1330	0.0566	0.0155	0.5563
Year x sensor	2	2	0.6991	0.0002	0.2699	0.0050	<0.0001
N rate x sensor	6	6	<0.0001	0.8454	0.6840	0.3892	0.5640
Year x N rate x sensor	6	6	0.9830	0.6292	0.7748	0.6249	0.9749

The mean NDVI, GDNVI, NDRE, SCCCI, and Guyot's REI VIs between SE narrow and SE wide band sensors were not different. However, both SE sensor mean VIs were different from the mean YARA N-Sensor mean VIs, and the mean YARA GNDVI, SCCCI, and Guyot's REI VIs were different by year as well (Table 4.9)

Table 4.9 Calculated significant VI means (year by sensor) Estimated model parameters of sensor (SE Narrow, SE Wide, and YARA N-Sensor) vegetation index response to V5 corn leaf N concentration for 2012 and 2013 growing seasons.

Model Parameter	2012 Sensors SE Narrow	SE Wide	YARA	2013 Sensors SE Narrow	SE Wide	YARA
		NDVI			NDVI	
VI Mean	*	*	*	*	*	*
r^2	0.89	0.89	0.63	0.71	0.71	0.80
Intercept	0.5267	0.5229	0.4714	0.5095	0.5081	1.3485
Linear	0.1068	0.1091	0.0260	0.0574	0.0583	-0.7957
Quadratic	-0.0102	-0.0105	0.0240	1.0e-5	-0.0001	0.1700
		GNDVI			GNDVI	
VI Mean	0.5302	0.5308	0.5787	0.4294	0.4307	0.5352
r^2	0.90	0.90	0.73	0.86	0.86	0.83
Intercept	0.0084	0.0073	0.4228	0.0976	0.0971	0.9798
Linear	0.2243	0.2256	0.0028	0.0997	0.1012	-0.4695
Quadratic	-0.0188	-0.0190	0.0136	0.0018	0.0015	0.1023
		NDRE			NDRE	
VI Mean	*	*	*	*	*	*
r^2	0.87	0.87	0.70	0.84	0.84	0.80
Intercept	-0.0863	-0.0839	0.0709	0.0311	0.0313	0.6886
Linear	0.1218	0.1209	0.0240	0.0151	0.0158	-0.4774
Quadratic	-0.0059	-0.0058	0.0094	0.0100	0.0098	0.1009
		SCCCI			SCCCI	
VI Mean	0.3173	0.3176	0.3814	0.2579	0.2589	0.3578
r^2	0.86	0.86	0.80	0.85	0.85	0.84
Intercept	-0.0662	-0.0613	0.1578	0.0600	0.0616	0.4815
Linear	0.1450	0.1429	0.0816	0.0325	0.0329	-0.1866
Quadratic	-0.0079	-0.0077	-0.0037	0.0095	0.0093	0.0459
		Guyot's			Guyot's	
VI Mean	718.780	718.794	719.998	715.883	715.918	719.334
r^2	0.90	0.90	0.83	0.87	0.87	0.87
Intercept	701.3900	701.3700	709.5900	698.3300	698.5900	719.6600
Linear	7.8175	7.8386	4.0935	7.1682	7.0531	-4.6898
Quadratic	-0.7291	-0.7322	-0.2615	-0.4965	-0.4825	1.4295

* Non-significant by year and sensor at $P \leq 0.05$.

Discussion on Bandwidth Comparisons

The mean vegetation index values between SE narrow and wide band configurations did not differ from each other by year, but the YARA N-Sensor wide band mean VIs did differ from the SE mean VIs for both cotton and corn. Cotton canopy-level samples taken with the YARA sensor tended to result in greater mean SCCCI and Guyot's REI readings, while producing typically lower mean NDVI. For corn, canopy-level mean GNDVI, SCCCI, and Guyot's REI values were highest when taken with the YARA sensor. Baret et al., (1987) found a spectral resolution of 5 nm allowed observation of the red-edge inflection point in wheat. Red-edge shifts with relationship to chlorophyll content and leaf structure (Guyot et al., 1992) and above-canopy detection of chlorophyll status is improved when incorporating red-edge shifts into a VI (Baret et al., 1992).

Scale related issues must be considered in any sampling design (Emerson et al., 1999). The spectroradiometric scale of this study is small in comparison to landscape sensing (1-10 nm), and the differences between SE narrow and SE wide band configurations is most likely too small to create variation in VI results. However, the observational scale (leaf- versus canopy-level sensing) is large enough to affect VI shifts in the red band regions. Since the mean SE sensor in narrow and wide VIs did not vary from one another, the SE narrow band configuration will be compared to the YARA wide band configuration for the remainder of this study.

Wavelength Correlations

The leaf-level SE and canopy-level YARA N-Sensor spectral wavelengths were correlated to biophysical parameters using Pearson's product-moment correlation coefficient (r) in 2012 and 2013 cotton and corn crops. Because cotton was grown at separate sites in 2012 and 2013, the correlations are presented separately. Corn was grown on the same site both years and the results are presented for the two-year period. For the V8 corn stage, samples were only collected in the 2013 growing season. Multiplying the whole plant N concentration by the number of plants per acre produces the V5 whole plant N content. Corn grain N content is calculated by multiplying corn grain concentration by yield.

Cotton Wavelengths

The 2012 leaf-level SE sensor bands were more highly correlated to SPAD readings than either leaf N concentration (Leaf N, %) or relative yield (Table 4.10). Unexpectedly, bandwidths between 450-720 nm were positively correlated to leaf tissue N concentration for both sensors.

Table 4.10 Correlation (Pearson's r) of cotton leaf (SE) and canopy (N Sensor) reflectance at early square in 2012 for each wavelength to biophysical measurements.

SE Sensor - Early Square				YARA N-Sensor - Early Square			
nm	SPAD	Leaf N, %	Relative Yield	nm	SPAD	Leaf N, %	Relative Yield
450.6	0.46	0.40	-0.05	450	-0.02	0.00	0.14
500.0	0.55	0.26	-0.21	500	-0.03	0.03	0.17
550.0	0.04	0.13	0.02	550	-0.05	-0.03	0.13
569.9	0.08	0.15	0.01	570	-0.07	0.01	0.17
600.6	0.26	0.12	-0.13	600	-0.08	0.05	0.22
620.7	0.37	0.12	-0.19	630	-0.08	0.07	0.23
639.3	0.42	0.14	-0.21	640	-0.08	0.08	0.24
650.2	0.50	0.17	-0.24	650	-0.08	0.09	0.25
659.5	0.53	0.17	-0.27	660	-0.08	0.09	0.25
670.4	0.56	0.17	-0.30	670	-0.08	0.10	0.26
679.8	0.58	0.18	-0.30	680	-0.08	0.10	0.26
700.2	0.05	0.01	-0.08	700	-0.09	0.02	0.20
709.6	-0.08	0.00	-0.01	710	-0.07	-0.08	0.09
720.6	0.06	0.10	-0.03	720	-0.01	-0.25	-0.09
739.6	0.34	0.27	-0.05	740	0.16	-0.44	-0.42
760.2	0.41	0.30	-0.08	760	0.20	-0.43	-0.46
779.2	0.42	0.29	-0.09	780	0.21	-0.43	-0.48
800.0	0.42	0.30	-0.09	800	0.20	-0.43	-0.47
840.0	0.43	0.29	-0.10	840	0.19	-0.42	-0.45

In 2013, leaf tissue N concentration negatively correlated with reflectance between 450-720 nm for both sensors (Table 4.11). The 2013 SE sensor, leaf-level, bands were more highly correlated to leaf tissue N concentration than either SPAD readings or relative yield. The 2013 N-Sensor, at canopy level, was more highly correlated to leaf tissue N concentration and SPAD readings than the SE at the leaf scale. Relative yield was weakly correlated to bands sensed at both leaf and canopy levels at this growth stage. Although this study does not propose to predict yield at early square, the yield correlations are included as a reference to later sampling stages.

Table 4.11 Correlation (Pearson's r) of cotton leaf (SE) and canopy (N Sensor) reflectance at early square in 2013 for each wavelength to biophysical measurements.

SE Sensor - Early Square				YARA N-Sensor - Early Square			
nm	SPAD	Leaf N, %	Relative Yield	nm	SPAD	Leaf N, %	Relative Yield
450.6	0.08	-0.06	0.03	450	-0.44	-0.33	0.12
500.0	0.04	-0.10	-0.11	500	-0.42	-0.32	0.08
550.0	-0.24	-0.26	-0.11	550	-0.35	-0.29	0.04
569.9	-0.23	-0.27	-0.11	570	-0.37	-0.28	0.03
600.6	-0.17	-0.27	-0.13	600	-0.39	-0.29	0.02
620.7	-0.10	-0.26	-0.10	630	-0.40	-0.29	0.03
639.3	-0.07	-0.25	-0.11	640	-0.41	-0.28	0.03
650.2	-0.01	-0.21	-0.11	650	-0.41	-0.28	0.04
659.5	0.02	-0.17	-0.11	660	-0.42	-0.28	0.04
670.4	0.06	-0.14	-0.13	670	-0.41	-0.28	0.04
679.8	0.06	-0.16	-0.17	680	-0.42	-0.28	0.04
700.2	-0.26	-0.27	-0.20	700	-0.41	-0.29	0.07
709.6	-0.26	-0.19	-0.18	710	-0.35	-0.28	0.09
720.6	-0.11	-0.04	-0.15	720	-0.23	-0.24	0.09
739.6	0.19	0.18	-0.06	740	-0.01	-0.12	0.10
760.2	0.28	0.23	-0.03	760	0.04	-0.10	0.12
779.2	0.28	0.24	-0.04	780	0.02	-0.10	0.14
800.0	0.27	0.24	-0.06	800	-0.01	-0.11	0.17
840.0	0.27	0.25	-0.08	840	-0.07	-0.12	0.23

By early bloom in 2012, at leaf scale from 450 to 720 nm, relationships with leaf tissue N concentration and relative yield strengthened and became more negative than those measured at early square (Table 4.12). By peak bloom in 2012, relative yield and SPAD reading correlations increased from the early bloom sampling stage, and leaf tissue N concentration correlations weakened.

Table 4.12 Correlation (Pearson's r) of cotton leaf (SE) reflectance at early and peak bloom in 2012 for each wavelength to biophysical measurements.

SE Sensor - Early Bloom				SE Sensor - Peak Bloom			
nm	SPAD	Leaf N, %	Relative Yield	nm	SPAD	Leaf N. %	Relative Yield
450.6	0.00	-0.22	-0.36	450.6	0.47	0.11	-0.55
500.0	0.00	-0.25	-0.38	500.0	0.44	0.03	-0.54
550.0	-0.16	-0.39	-0.41	550.0	-0.39	-0.44	-0.28
569.9	-0.14	-0.45	-0.46	569.9	-0.28	-0.35	-0.36
600.6	-0.08	-0.40	-0.43	600.6	0.07	-0.12	-0.49
620.7	-0.05	-0.40	-0.45	620.7	0.26	0.01	-0.55
639.3	-0.04	-0.38	-0.44	639.3	0.31	0.05	-0.54
650.2	-0.02	-0.37	-0.43	650.2	0.36	0.11	-0.54
659.5	-0.02	-0.35	-0.44	659.5	0.38	0.13	-0.54
670.4	-0.01	-0.31	-0.45	670.4	0.41	0.15	-0.55
679.8	0.00	-0.28	-0.46	679.8	0.43	0.12	-0.55
700.2	-0.17	-0.29	-0.35	700.2	-0.17	-0.27	-0.44
709.6	-0.27	-0.27	-0.31	709.6	-0.51	-0.42	-0.30
720.6	-0.25	-0.20	-0.27	720.6	-0.56	-0.43	-0.26
739.6	-0.10	-0.12	-0.26	739.6	-0.33	-0.26	-0.25
760.2	-0.04	-0.13	-0.29	760.2	-0.14	-0.11	-0.23
779.2	-0.05	-0.14	-0.30	779.2	-0.14	-0.08	-0.20
800.0	-0.05	-0.14	-0.29	800.0	-0.15	-0.08	-0.17
840.0	-0.05	-0.14	-0.29	840.0	-0.14	-0.06	-0.20

For both early and peak bloom in 2013, SE sensor leaf-level readings resulted in increased negative correlations with SPAD readings and reflectance across wavelengths was only weakly correlated to leaf tissue N concentration and relative yield (Table 4.13). At early bloom, correlations to biophysical measurements increased near the 700 nm bandwidth. The peak bloom leaf scale readings did not relate well to leaf tissue N and relative yield.

Table 4.13 Correlation (Pearson's r) of cotton leaf (SE) reflectance at early and peak bloom in 2013 for each wavelength to biophysical measurements

SE Sensor - Early Bloom				SE Sensor - Peak Bloom			
nm	SPAD	Leaf N, %	Relative Yield	nm	SPAD	Leaf N, %	Relative Yield
450.6	-0.06	0.17	0.02	450.6	-0.14	-0.01	0.04
500.0	-0.08	0.16	0.01	500.0	-0.14	-0.01	0.04
550.0	-0.47	0.16	-0.33	550.0	-0.14	0.00	0.03
569.9	-0.43	0.14	-0.30	569.9	-0.15	-0.01	0.03
600.6	-0.31	0.13	-0.18	600.6	-0.15	0.00	0.04
620.7	-0.21	0.13	-0.09	620.7	-0.15	-0.01	0.04
639.3	-0.18	0.14	-0.07	639.3	-0.14	-0.01	0.04
650.2	-0.14	0.14	-0.04	650.2	-0.14	-0.01	0.04
659.5	-0.10	0.16	0.00	659.5	-0.14	-0.01	0.04
670.4	-0.06	0.18	0.04	670.4	-0.14	0.00	0.04
679.8	-0.04	0.19	0.06	679.8	-0.14	0.00	0.04
700.2	-0.41	0.15	-0.26	700.2	-0.15	0.00	0.03
709.6	-0.58	0.20	-0.44	709.6	-0.14	0.02	0.03
720.6	-0.57	0.28	-0.48	720.6	-0.11	0.04	0.03
739.6	-0.48	0.37	-0.45	739.6	-0.08	0.08	0.04
760.2	-0.45	0.39	-0.45	760.2	-0.07	0.09	0.04
779.2	-0.46	0.39	-0.45	779.2	-0.07	0.09	0.04
800.0	-0.47	0.38	-0.46	800.0	-0.07	0.09	0.04
840.0	-0.47	0.38	-0.46	840.0	-0.07	0.09	0.04

Corn Wavelengths

Corn sensing samples both years at V5 revealed moderate to strong negative SPAD, leaf N concentration (Leaf N, %) and whole plant N concentration (WPN, %) correlations between the 450-720 nm bandwidth regions and moderate to strong positive correlations in the 720-840 nm regions for the same parameters (Table 4.14). These results indicate sensitivity to the wide variation in N availability due to the fertilizer regime imposed on the study site as well as the more controlled conditions and more limited field variability as compared to producer's fields.

Table 4.14 Correlation (Pearson's r) of corn leaf (SE) and canopy (N Sensor) reflectance at V5 from 2012 through 2013 for each wavelength to biophysical measurements.

SE Sensor - V5						YARA N-Sensor - V5					
nm	SPAD	Leaf N, %	WPN, %	TPNC, kg ha^{-1}	Relative Yield	nm	SPAD	Leaf N, %	WPN, %	TPNC, kg ha^{-1}	Relative Yield
450.6	-0.04	-0.15	-0.11	-0.07	-0.08	450	-0.88	-0.63	-0.67	-0.84	-0.64
500.0	-0.19	-0.34	-0.28	-0.20	-0.24	500	-0.89	-0.65	-0.69	-0.84	-0.66
550.0	-0.53	-0.73	-0.64	-0.42	-0.59	550	-0.90	-0.67	-0.72	-0.86	-0.62
569.9	-0.57	-0.77	-0.68	-0.46	-0.62	570	-0.91	-0.69	-0.73	-0.87	-0.65
600.6	-0.58	-0.79	-0.71	-0.51	-0.64	600	-0.91	-0.69	-0.73	-0.86	-0.68
620.7	-0.57	-0.74	-0.66	-0.48	-0.59	630	-0.91	-0.69	-0.73	-0.86	-0.68
639.3	-0.55	-0.71	-0.64	-0.46	-0.57	640	-0.91	-0.69	-0.72	-0.85	-0.68
650.2	-0.47	-0.64	-0.57	-0.40	-0.51	650	-0.90	-0.69	-0.72	-0.85	-0.69
659.5	-0.35	-0.54	-0.46	-0.30	-0.41	660	-0.90	-0.68	-0.72	-0.85	-0.69
670.4	-0.13	-0.34	-0.27	-0.12	-0.24	670	-0.90	-0.68	-0.71	-0.84	-0.69
679.8	-0.08	-0.28	-0.21	-0.09	-0.18	680	-0.90	-0.68	-0.71	-0.84	-0.69
700.2	-0.59	-0.76	-0.67	-0.49	-0.61	700	-0.92	-0.70	-0.73	-0.87	-0.68
709.6	-0.46	-0.69	-0.59	-0.35	-0.55	710	-0.90	-0.65	-0.69	-0.88	-0.59
720.6	-0.16	-0.46	-0.34	-0.06	-0.35	720	-0.70	-0.39	-0.46	-0.75	-0.28
739.6	0.26	-0.07	0.04	0.34	-0.02	740	0.47	0.59	0.52	0.33	0.66
760.2	0.36	0.04	0.14	0.44	0.06	760	0.58	0.66	0.60	0.44	0.72
779.2	0.37	0.05	0.15	0.44	0.07	780	0.59	0.67	0.61	0.45	0.72
800.0	0.37	0.05	0.16	0.45	0.08	800	0.56	0.66	0.59	0.42	0.71
840.0	0.38	0.05	0.16	0.45	0.08	840	0.52	0.64	0.58	0.37	0.70

Canopy-level YARA N-Sensor produced stronger correlative results as compared to the leaf-level SE sensor suggesting greater information is acquired at the canopy scale compared to the leaf scale. Correlations between YARA N-Sensor collected bands and WPN and total plant N content (TPNC) (measured in kg ha^{-1}) are particularly notable. The SE sensor correlations to WPN are notably weaker.

Leaf scale correlations strengthened from the V5 to the V8 and VT growth stages with the VT stage producing notably strong correlations of SPAD readings and leaf N concentration with leaf reflectance across sampled wavelengths (Table 4.15). Corn grain N concentration (CGN, %) correlations at VT were weak, but corn grain N content

(CGNC) (measured in Mt ha^{-1}) produced strong negative correlations for all sampled bandwidths. Relative yield had a strong negative correlation with VT leaf reflectance at all sampled wavelengths. In most cases, maximal reflectance of green and absorption of red occurred near 550 and 700 nm, respectively.

Table 4.15 Correlation (Pearson's r) of corn leaf (SE) reflectance at V8 and VT from 2012 through 2013 for each wavelength to biophysical measurements.

SE Sensor - V8				SE Sensor - VT				
nm	SPAD	Leaf N, %	Relative Yield	SPAD	Leaf N, %	CGN, %	CGNC, Mt ha^{-1}	Relative Yield
450.6	-0.57	-0.51	-0.41	-0.90	-0.86	-0.15	-0.71	-0.78
500.0	-0.69	-0.64	-0.51	-0.92	-0.87	-0.17	-0.73	-0.81
550.0	-0.83	-0.82	-0.67	-0.97	-0.92	-0.25	-0.80	-0.86
569.9	-0.84	-0.82	-0.67	-0.97	-0.92	-0.24	-0.79	-0.85
600.6	-0.83	-0.81	-0.66	-0.96	-0.90	-0.21	-0.78	-0.84
620.7	-0.82	-0.80	-0.65	-0.95	-0.90	-0.20	-0.77	-0.84
639.3	-0.82	-0.79	-0.64	-0.95	-0.89	-0.19	-0.76	-0.83
650.2	-0.79	-0.76	-0.62	-0.95	-0.89	-0.18	-0.75	-0.83
659.5	-0.77	-0.73	-0.59	-0.94	-0.88	-0.17	-0.75	-0.82
670.4	-0.72	-0.67	-0.54	-0.91	-0.85	-0.16	-0.72	-0.79
679.8	-0.69	-0.65	-0.50	-0.88	-0.81	-0.15	-0.69	-0.76
700.2	-0.83	-0.81	-0.66	-0.96	-0.90	-0.23	-0.78	-0.85
709.6	-0.83	-0.82	-0.67	-0.97	-0.92	-0.27	-0.81	-0.86
720.6	-0.81	-0.80	-0.65	-0.97	-0.92	-0.29	-0.81	-0.87
739.6	-0.52	-0.50	-0.33	-0.89	-0.84	-0.20	-0.72	-0.78
760.2	0.22	0.25	0.38	-0.73	-0.67	-0.05	-0.54	-0.61
779.2	0.32	0.36	0.47	-0.68	-0.62	-0.01	-0.49	-0.56
800.0	0.34	0.37	0.47	-0.66	-0.60	0.00	-0.47	-0.54
840.0	0.35	0.38	0.48	-0.65	-0.59	0.01	-0.46	-0.53

Discussion on Bandwidth Correlations

Previous studies noted strong correlations between cotton N status and leaf reflectance at or near the red edge region (Raper and Varco, 2014; Fridgen and Varco, 2004; Buscaglia and Varco, 2002). Employing the green bandwidths and red edge regions of spectral samples may increase N status predictions for the SE sensor. Blackmer et al.

(1994) found a separation by N rate near the 550 nm wavelength, whereby the lowest N rate produced the highest green reflectance due to the decreased amount of chlorophyll present in N deficient leaves. The study also noted the decrease in sensitivity of the 450 and 650 nm wavelength to N deficiency.

There is also evidence that supports integrating both green and red edge regions in VIs fitted to the YARA N-Sensor, but the green relationship in above-canopy sensing was weaker than that of the leaf-level SE sensing. Moreover, this study found a shift from indirect to direct bandwidth correlations in early crop sampling most likely to occur at or near the 720-740 nm spectral resolution. This is notable for corn at V5 where N varied systematically. Smaller but significant shifts in the red-edge region were also noted at early square in cotton, and shifts became less pronounced as growth progressed. Previous studies have found the 600-680 nm region most sensitive to plant height (Barnes et al., 2000; El-Shihka et al., 2008).

Chlorophyll-sensitive reflectance bandwidths (550, 650, and 710-840 nm) in canopy-level corn tend to increase, decrease, and increase respectively, until tasseling with little variance (Gausman et al. 1973; Thompson and Gausman 1977; Gitelson et al., 2005). The unitless SPAD meter is a means to measure plant greenness and yet the entire visual effect is not totally accounted for by chlorophyll content alone (Blackmer et al. 1994; Blackmer, et al. 1995; Schepers et al. 1996). Although canopy-level spectroradiometric samples related to SPAD chlorophyll possess soil albedo reflectance, which alter red and near-infrared bandwidth regions, leaf-level sampling did not provide stronger VI relationships with SPAD chlorophyll in all cases of this study. Most notably, SE leaf-level VIs did not consistently correlate to SPAD readings, as would be expected.

This study did not attempt to ascertain factors such as leaf type, thickness, chlorophyll density, and water content, which may affect SPAD chlorophyll correlations to spectral reflectance.

Vegetation Index Correlations

Cotton Indices

The theoretical model of the Early Nitrogen Detection Vegetation Index (ENDVI) (this paper) was compared to NDVI, GNDVI, NDRE, SCCCI, and Guyot's REI correlations to biophysical parameters. The ENDVI integrates red-edge and green bandwidth spectral characteristics (720-780 and 550 nm, respectively). Potentially, the phenological increase in biomass during a growing season will decrease the effectiveness of the ENDVI index. This may be due to relatively greater chlorophyll concentration in proportion to leaf thickness early in the season. The ENDVI algorithm is inversely correlated to parameters due to the incorporation of the green bandwidth.

In 2012, SPAD readings produced the strongest correlative results to both the leaf-level SE and canopy-level YARA N-Sensor data (Table 4.16). Leaf N concentration results may have been confounded by the presence of varying residual soil N. The SE sensor VI correlations to relative yield were almost half that of the YARA N-Sensor for data collected at early bloom, and most correlations were negative.

Table 4.16 Correlation (Pearson's r) of cotton leaf (SE) and canopy (N Sensor) reflectance at early square in 2012 for each vegetation index to biophysical measurements.

	SE Sensor - Early Square			YARA N-Sensor - Early Square		
VI	SPAD	Leaf N, %	Relative Yield	SPAD	Leaf N, %	Relative Yield
NDVI	-0.39	-0.05	0.25	0.15	-0.21	-0.39
GNDVI	0.32	0.09	-0.12	0.17	-0.19	-0.37
NDRE	0.63	0.32	-0.12	0.23	-0.18	-0.40
SCCCI	0.74	0.33	-0.19	0.39	-0.07	-0.34
ENDVI	-0.74	-0.32	0.20	-0.39	0.07	0.35
Guyot's	0.67	0.26	-0.23	0.40	-0.11	-0.39

In 2013, cotton at early bloom displayed moderate correlative relationships for SPAD readings and leaf N concentration for both sensors (Table 4.17). Furthermore, most correlations were positive, with the exception of the ENDVI index, which was negatively correlated to SPAD chlorophyll and leaf N concentration. The SCCCI and ENDVI indices produced very similar results. At early bloom, relative yield resulted in the weakest correlations to all VIs.

Table 4.17 Correlation (Pearson's r) of cotton leaf (SE) and canopy (N Sensor) reflectance at early square in 2013 for each vegetation index to biophysical measurements.

	SE Sensor - Early Square			YARA N-Sensor - Early Square		
VI	SPAD	Leaf N, %	Relative Yield	SPAD	Leaf N, %	Relative Yield
NDVI	0.13	0.36	0.09	0.46	0.25	0.11
GNDVI	0.43	0.45	0.07	0.43	0.28	0.15
NDRE	0.54	0.40	0.18	0.50	0.28	0.07
SCCCI	0.56	0.33	0.17	0.58	0.36	-0.11
ENDVI	-0.58	-0.32	-0.16	-0.58	-0.35	0.13
Guyot's	0.53	0.40	0.16	0.38	0.33	-0.05

The 2012 sampling occurred under conditions of some water stress. At early bloom, SE readings produced moderate correlations with SPAD chlorophyll and weak correlations with leaf N concentration and relative yield (Table 4.18). By the peak bloom sampling stage, the SE sensor produced stronger, more definitive results at the 2012 peak bloom sampling, whereby the SCCCI and ENDVI indices again were most strongly correlated to all parameters. The NDVI was most strongly correlated to yield at both early bloom and peak bloom sampling stages.

Table 4.18 Correlation (Pearson's r) of cotton leaf (SE) reflectance at early and peak bloom in 2012 for each vegetation index to biophysical measurements.

	SE Sensor - Early Bloom			SE Sensor - Peak Bloom		
VI	SPAD	Leaf N, %	Relative Yield	SPAD	Leaf N, %	Relative Yield
NDVI	0.00	0.38	0.41	-0.43	-0.13	0.51
GNDVI	0.19	0.44	0.39	0.40	0.48	0.23
NDRE	0.44	0.18	0.09	0.64	0.50	0.21
SCCCI	0.46	0.00	-0.11	0.76	0.54	0.08
ENDVI	-0.46	0.00	0.11	-0.76	-0.56	-0.09
Guyot's	0.36	0.07	-0.02	0.64	0.56	0.18

In 2013 at early and peak bloom, SE leaf-scale reflectance resulted in strong correlations to SPAD readings, while strong relationships to leaf N concentration only resulted at peak bloom (Table 4.19). At peak bloom, Guyot's REI was most strongly correlated to SPAD chlorophyll, leaf N concentration, and yield.

Table 4.19 Correlation (Pearson's r) of cotton leaf (SE) reflectance at early and peak bloom in 2013 for each vegetation index to biophysical measurements.

	SE Sensor - Early Bloom			SE Sensor - Peak Bloom		
VI	SPAD	Leaf N, %	Relative Yield	SPAD	Leaf N, %.	Relative Yield
NDVI	-0.03	0.03	-0.09	0.17	0.06	-0.02
GNDVI	0.33	0.17	0.14	0.32	0.28	0.17
NDRE	0.64	0.31	0.31	0.54	0.40	0.24
SCCCI	0.72	0.34	0.45	0.52	0.53	0.40
ENDVI	-0.74	-0.36	-0.46	-0.62	-0.61	-0.45
Guyot's	0.51	0.50	0.24	0.71	0.76	0.55

Corn Indices

For this analysis, the 2012 and 2013 corn sampling data was combined as the results represent replication, in time, as data was collected from the same location. The site with the current plot arrangement had been cropped to cotton from 2004-2011 and corn from 2012-2013. Fertilizer N rates for cotton were 0, 45, 90, and 135 kg ha^{-1} and for corn, they were 0, 89.8, 179.6, and 269.5 kg ha^{-1}. Fertilizer N rates have produced crops ranging from highly deficient to excessive in cotton and highly deficient to near optimum for corn. Samples taken at V8 were only collected for the 2013 growing season. The resulting VI correlation results were moderate to stronger across all sampling stages in corn when compared to cotton.

Leaf-level SE reflectance and canopy-level YARA N-Sensor data produced similar VI correlations to SPAD readings and leaf tissue N concentration at V5 where SCCCI, ENDVI, and Guyot's REI ranked the highest (Table 4.20). For both sensors, whole plant N (WPN) concentration and total plant N (TPN) content (measured in kg ha^{-1}) were more highly correlated to GNDVI and NDRE VIs, while relative yield was most strongly correlated to SCCCI, ENDVI, and Guyot's REI.

Table 4.20 Correlation (Pearson's r) of corn leaf (SE) and canopy (N Sensor) reflectance at V5 from 2012 through 2013 for each vegetation index to biophysical measurements.

SE Sensor - V5						YARA N-Sensor - V5				
VI	SPAD	Leaf N, %	WPN, %	TPNC, kg ha^{-1}	Relative Yield	SPAD	Leaf N, %	WPN, %	TPNC, kg ha^{-1}	Relative Yield
NDVI	0.84	0.63	0.68	0.86	0.54	0.90	0.77	0.78	0.83	0.77
GNDVI	0.93	0.78	0.81	0.90	0.67	0.91	0.82	0.82	0.81	0.81
NDRE	0.94	0.81	0.82	0.90	0.69	0.91	0.81	0.80	0.84	0.78
SCCCI	0.95	0.85	0.84	0.88	0.73	0.92	0.87	0.84	0.79	0.80
ENDVI	-0.95	-0.89	-0.87	-0.80	-0.78	-0.92	-0.89	-0.87	-0.77	-0.82
Guyot's	0.95	0.82	0.82	0.86	0.71	0.89	0.90	0.87	0.74	0.83

At V8 in 2013, GNDVI, NDRE, SCCCI, ENDVI, and Guyot's REI were similarly correlated to SPAD chlorophyll, leaf tissue N concentration, and relative yield (Table 4.21). These select five VIs produced the strongest correlative results at the VT stage as well. The VT stage sampling produced very weak VI correlations to grain N concentration, but very strong correlations to CGN.

Table 4.21 Correlation (Pearson's r) of corn leaf (SE) reflectance at V8 and VT from 2012 through 2013 for each vegetation index to biophysical measurements.

SE Sensor - V8				SE Sensor - VT				
VI	SPAD	Leaf N, %	Relative Yield	SPAD	Leaf N, %	CGN, %	CGNC, Mt ha^{-1}	Relative Yield
NDVI	0.83	0.80	0.67	0.96	0.91	0.20	0.78	0.85
GNDVI	0.85	0.84	0.72	0.99	0.95	0.30	0.84	0.89
NDRE	0.85	0.85	0.73	0.99	0.97	0.38	0.88	0.92
SCCCI	0.85	0.85	0.73	0.99	0.97	0.41	0.89	0.92
ENDVI	-0.84	-0.84	-0.72	-0.97	-0.91	-0.30	-0.81	-0.86
Guyot's	0.85	0.85	0.72	0.99	0.93	0.32	0.84	0.89

Discussion on Vegetation Index Correlations

In general, the red-edge indices more highly correlated to SPAD chlorophyll and leaf N concentration for both crops, sensors, and growing seasons. A notable exception is the high correlation of SE GNDVI to biophysical parameters in 2013 early square cotton, and this anomaly may be related to SE sensor calibration differences mentioned in the Methods and Materials section. At V8 and VT corn, all VIs produced strong correlations to biophysical parameters.

Vegetation Index Sensitivities

Sensitivity equivalents (*SEq*) were calculated for VIs linearly related to biophysical parameters by dividing the slope of an equation by the corresponding root-mean-square-error (Raper and Varco, 2014; Solari et al., 2008; Vina and Gitelson, 2005). Greater *SEq* values suggest greater VI sensitivity to the parameter in question. For this analysis, VIs evaluated included NDVI, GNDVI, NDRE, SCCCI, ENDVI, and Guyot's REI.

Cotton Sensitives

For 2012 at early square, the SCCCI was most sensitive to variations in SPAD readings and leaf tissue N concentrations when derived at the SE sensor leaf scale, while Guyot's REI and NDRE indices were most sensitive to SPAD chlorophyll and leaf tissue N concentrations, respectively, when derived from canopy-level YARA N-Sensor (Table 4.22).

Table 4.22 Root mean square errors, slopes, and sensitivity equivalents of selected indices at early square stage in 2012 cotton.

SE Sensor - Early Square				YARA N-Sensor - Early Square			
RMSE	SPAD	Leaf N, %	Relative Yield	*RMSE*	SPAD	Leaf N, %	Relative Yield
NDVI	0.0112	0.0121	0.0118	NDVI	0.0599	0.0592	0.0559
GNDVI	0.0135	0.0142	0.0141	GNDVI	0.0374	0.0372	0.0352
NDRE	0.0080	0.0098	0.0103	NDRE	0.0290	0.0293	0.0273
SCCCI	0.0089	0.0126	0.0131	SCCCI	0.0131	0.0141	0.0134
ENDVI	0.1301	0.1831	0.1894	ENDVI	0.0860	0.0931	0.0876
Guyot's	0.3093	0.4009	0.4042	Guyot's	0.5013	0.5426	0.5026
SLOPE				*SLOPE*			
NDVI	-0.0019	-0.0017	0.0305	NDVI	0.0038	-0.0376	-0.2427
GNDVI	0.0019	0.0038	-0.0179	GNDVI	0.0026	-0.0213	-0.1459
NDRE	0.0027	0.0098	-0.0128	NDRE	0.0028	-0.0157	-0.1225
SCCCI	0.0041	0.0130	-0.0262	SCCCI	0.0022	-0.0029	-0.0488
ENDVI	-0.0584	-0.1791	0.3883	ENDVI	-0.0149	0.0204	0.3344
Guyot's	0.1137	0.3208	-1.0039	Guyot's	0.0883	-0.1691	-2.1883
SEq				*SEq*			
NDVI	-0.1738	-0.1363	2.5949	NDVI	0.0629	-0.6352	-4.3449
GNDVI	0.1380	0.2675	-1.2684	GNDVI	0.0685	-0.5718	-4.1490
NDRE	0.3350	1.0000	-1.2415	NDRE	0.0960	-0.5354	-4.4886
SCCCI	0.4541	1.0342	-1.9992	SCCCI	0.1713	-0.2023	-3.6534
ENDVI	-0.4491	-0.9779	2.0499	ENDVI	-0.1737	0.2191	3.8196
Guyot's	0.3674	0.8001	-2.4838	Guyot's	0.1761	-0.3116	-4.3536

In 2013 at early square, leaf-level SE derived ENDVI and Guyot's REI indices were most sensitive to SPAD readings and leaf tissue N concentration, respectively (Table 4.23). For canopy-level YARA N-Sensor derived indices, ENDVI and NDRE and SCCCI were most sensitive to SPAD readings and leaf tissue N concentration, respectively. The 2012 and 2013 results suggests that red edge indices in general behave similarly to SPAD chlorophyll readings and leaf N status than do either NDVI or GNDVI.

Table 4.23 Root mean square errors, slopes, and sensitivity equivalents of selected indices at early square stage in 2013 cotton.

SE Sensor - Early Square				YARA N-Sensor - Early Square			
RMSE	SPAD	Leaf N, %	Relative Yield	*RMSE*	SPAD	Leaf N, %	Relative Yield
NDVI	0.0109	0.0103	0.0109	NDVI	0.0402	0.0439	0.0450
GNDVI	0.0133	0.0132	0.0147	GNDVI	0.0299	0.0318	0.0328
NDRE	0.0082	0.0089	0.0096	NDRE	0.0167	0.0185	0.0192
SCCCI	0.0091	0.0104	0.0108	SCCCI	0.0121	0.0138	0.0147
ENDVI	0.1413	0.1637	0.1709	ENDVI	0.1064	0.1219	0.1294
Guyot's	0.3481	0.3745	0.4036	Guyot's	0.6156	0.6271	0.6635
SLOPE				*SLOPE*			
NDVI	0.0008	0.0126	0.0088	NDVI	0.0114	0.0360	0.0469
GNDVI	0.0035	0.0213	0.0102	GNDVI	0.0079	0.0301	0.0451
NDRE	0.0029	0.0125	0.0155	NDRE	0.0053	0.0174	0.0135
SCCCI	0.0034	0.0118	0.0167	SCCCI	0.0047	0.0170	-0.0142
ENDVI	-0.0549	-0.1807	-0.2417	ENDVI	-0.0415	-0.1492	0.1446
Guyot's	0.1186	0.5321	0.6107	Guyot's	0.1372	0.7045	-0.2686
SEq				*SEq*			
NDVI	0.0726	1.2271	0.8024	NDVI	0.2840	0.8191	1.0431
GNDVI	0.2626	1.6135	0.6914	GNDVI	0.2625	0.9447	1.3742
NDRE	0.3521	1.4011	1.6251	NDRE	0.3178	0.9379	0.7006
SCCCI	0.3756	1.1390	1.5448	SCCCI	0.3886	1.2290	-0.9646
ENDVI	-0.3886	-1.1037	-1.4142	ENDVI	-0.3902	-1.2240	1.1178
Guyot's	0.3406	1.4208	1.5132	Guyot's	0.2228	1.1235	-0.4048

There appears to be little difference in 2012 leaf-level sensitivity in NDRE, SCCCI, and ENDVI with regards to SPAD readings at early bloom, while Guyot's REI and GNDVI were less sensitive and NDVI the least (Table 4.24). For leaf tissue N concentration, GNDVI was the most sensitive with NDVI slightly less. All other indices showed dramatically lower sensitivities to leaf N concentration.

Table 4.24 Root mean square errors, slopes, and sensitivity equivalents of selected indices at early and peak bloom stages in 2012 cotton.

SE Sensor - Early Bloom				SE Sensor - Peak Bloom			
RMSE	SPAD	Leaf N, %	Relative Yield	*RMSE*	SPAD	Leaf N, %	Relative Yield
NDVI	0.0146	0.0135	0.0133	NDVI	0.0133	0.0146	0.0127
GNDVI	0.0155	0.0142	0.0145	GNDVI	0.0154	0.0147	0.0163
NDRE	0.0082	0.0090	0.0091	NDRE	0.0150	0.0170	0.0191
SCCCI	0.0095	0.0106	0.0106	SCCCI	0.0152	0.0197	0.0234
ENDVI	0.0995	0.1122	0.1116	ENDVI	0.1340	0.1723	0.2072
Guyot’s	0.2744	0.2935	0.2942	Guyot’s	0.4190	0.4501	0.5346
SLOPE				*SLOPE*			
NDVI	0.0000	0.0122	0.0614	NDVI	-0.0020	-0.0082	0.0759
GNDVI	0.0021	0.0153	0.0637	GNDVI	0.0022	0.0330	0.0398
NDRE	0.0028	0.0036	0.0089	NDRE	0.0040	0.0399	0.0420
SCCCI	0.0034	0.0000	-0.0120	SCCCI	0.0057	0.0524	0.0204
ENDVI	-0.0362	-0.0035	0.1197	ENDVI	-0.0509	-0.4812	-0.1886
Guyot’s	0.0742	0.0469	-0.0529	Guyot’s	0.1109	1.2602	1.0258
SEq				*SEq*			
NDVI	0.0013	0.9051	4.6180	NDVI	-0.1511	-0.5594	5.9678
GNDVI	0.1355	1.0782	4.3843	GNDVI	0.1401	2.2432	2.4399
NDRE	0.3418	0.4044	0.9715	NDRE	0.2689	2.3550	2.1975
SCCCI	0.3605	-0.0035	-1.1342	SCCCI	0.3771	2.6601	0.8708
ENDVI	-0.3635	-0.0313	1.0729	ENDVI	-0.3799	-2.7922	-0.9099
Guyot’s	0.2705	0.1596	-0.1798	Guyot’s	0.2646	2.8000	1.9187

At peak bloom in 2012, SCCCI and ENDVI behaved similarly and had the greatest sensitivity to leaf SPAD chlorophyll readings, while NDRE and Guyot’s REI were similar with lower sensitivity. Although NDVI and GNDVI behaved similarly, they expressed the least sensitivity to measured parameters. Results were similar for leaf tissue N concentration except Guyot’s REI was most sensitive and GNDVI was similar to NDRE while NDVI had the least sensitivity. These results suggest that red edge indices are most sensitive to crop N status, which varied highly in this field. Interestingly, NDVI, which is a strong indicator of biomass, had the greatest sensitivity to lint yield at both early and peak bloom samplings.

In 2013, results differed somewhat than for 2012. At early bloom, the SCCCI and ENDVI were most sensitive to SPAD chlorophyll readings, while Guyot's REI had the greatest sensitivity to leaf tissue N concentration (Table 4.25). By peak bloom, Guyot's REI was the most sensitive to SPAD chlorophyll, leaf N concentration, and relative yield. At peak bloom, NDRE, SCCCI, and ENDVI also revealed marginally strong sensitivities to the measured parameters.

Table 4.25 Root mean square errors, slopes, and sensitivity equivalents of selected indices at early and peak bloom stages in 2013 cotton.

SE Sensor - Early Bloom				SE Sensor - Peak Bloom			
RMSE	SPAD	Leaf N, %	Relative Yield	*RMSE*	SPAD	Leaf N, %	Relative Yield
NDVI	0.0425	0.0425	0.0423	NDVI	0.0809	0.0819	0.0820
GNDVI	0.0306	0.0320	0.0321	GNDVI	0.0594	0.0602	0.0618
NDRE	0.0105	0.0130	0.0130	NDRE	0.0195	0.0212	0.0225
SCCCI	0.0105	0.0143	0.0135	SCCCI	0.0158	0.0158	0.0170
ENDVI	0.1598	0.2209	0.2105	ENDVI	0.2195	0.2233	0.2504
Guyot's	0.4547	0.4605	0.5149	Guyot's	0.4133	0.3836	0.4953
SLOPE				*SLOPE*			
NDVI	-0.0004	0.0025	-0.0359	NDVI	0.0062	0.0084	-0.0085
GNDVI	0.0037	0.0125	0.0381	GNDVI	0.0092	0.0314	0.0958
NDRE	0.0030	0.0099	0.0378	NDRE	0.0057	0.0164	0.0491
SCCCI	0.0038	0.0122	0.0611	SCCCI	0.0044	0.0173	0.0662
ENDVI	-0.0605	-0.1986	-0.9649	ENDVI	-0.0793	-0.3019	-1.1269
Guyot's	0.0945	0.6132	1.1290	Guyot's	0.1917	0.7989	2.8683
SEq				*SEq*			
NDVI	-0.0087	0.0591	-0.8502	NDVI	0.0772	0.1031	-0.1032
GNDVI	0.1202	0.3917	1.1852	GNDVI	0.1545	0.5213	1.5501
NDRE	0.2856	0.7621	2.9076	NDRE	0.2929	0.7731	2.1814
SCCCI	0.3622	0.8568	4.5140	SCCCI	0.2792	1.0968	3.8861
ENDVI	-0.3785	-0.8992	-4.5842	ENDVI	-0.3614	-1.3516	-4.5006
Guyot's	0.2078	1.3316	2.1926	Guyot's	0.4640	2.0826	5.7914

Corn Sensitivities

For both years, leaf-level Guyot's REI and SCCCI indices produced the strongest sensitivity to SPAD chlorophyll readings at V5, while canopy-level SCCCI was most sensitive to SPAD chlorophyll readings (Table 4.26). The ENDVI was most sensitive to leaf tissue N concentration and whole plant N concentration at leaf scale, and leaf-level SCCCI was most sensitive to total plant N content. At the canopy scale, Guyot's REI was most sensitive to leaf N concentration and whole plant N concentration, but canopy scale NDRE was most sensitive to total plant N content.

Table 4.26 SE and YARA N-Sensor root mean square errors, slopes, and sensitivity equivalents of selected indices calculated for 2012 through 2013 V5 corn

SE Sensor - V5						YARA N-Sensor V5					
RMSE	SPAD	Leaf N, %	WPN, %.	TPNC, kg ha^{-1}	Relative Yield	*RMSE*	SPAD	Leaf N, %	WPN, %.	TPNC, kg ha^{-1}	Relative Yield
NDVI	0.0260	0.0376	0.0353	0.0249	0.0407	NDVI	0.0483	0.0705	0.0693	0.0618	0.0693
GNDVI	0.0302	0.0518	0.0494	0.0365	0.0616	GNDVI	0.2891	0.0390	0.0393	0.0403	0.0406
NDRE	0.0198	0.0350	0.0337	0.0254	0.0424	NDRE	0.0266	0.0386	0.0390	0.0357	0.0406
SCCCI	0.0196	0.0338	0.0342	0.0308	0.0433	SCCCI	0.0174	0.0218	0.0235	0.0267	0.0262
ENDVI	0.2859	0.3948	0.4321	0.5244	0.5454	ENDVI	0.1359	0.1573	0.1702	0.2173	0.1927
Guyot's	0.8094	1.5352	1.5226	1.3351	1.8629	Guyot's	0.8226	0.7998	0.8986	1.2287	1.0073
Slope						*Slope*					
NDVI	0.0066	0.0556	0.0516	0.0040	0.0802	NDVI	0.0160	0.1533	0.1325	0.0088	0.2598
GNDVI	0.0126	0.1192	0.1046	0.0073	0.1714	GNDVI	0.0101	0.1034	0.0880	0.0054	0.1697
NDRE	0.0090	0.0868	0.0752	0.0051	0.1247	NDRE	0.0096	0.0957	0.0817	0.0053	0.1553
SCCCI	0.0098	0.0988	0.0839	0.0054	0.1432	SCCCI	0.0065	0.0696	0.0578	0.0034	0.1077
ENDVI	-0.1340	-1.4198	-1.1801	-0.0675	-2.0791	ENDVI	-0.0506	-0.5517	-0.4597	-0.0254	-0.8586
Guyot's	0.4104	3.9616	3.3943	0.2227	5.7915	Guyot's	0.2638	2.9944	2.4738	0.1305	4.6495
SEq						*SEq*					
NDVI	0.2545	1.4795	1.4591	0.1622	1.9737	NDVI	0.3302	2.1740	1.9125	0.1420	3.7474
GNDVI	0.4176	2.3022	2.1182	0.1989	2.7813	GNDVI	0.0350	2.6503	2.2384	0.1340	4.1754
NDRE	0.4526	2.4800	2.2286	0.2020	2.9401	NDRE	0.3626	2.4822	2.0955	0.1475	3.8211
SCCCI	0.5020	2.9205	2.4517	0.1755	3.3064	SCCCI	0.3762	3.1952	2.4635	0.1268	4.1178
ENDVI	-0.4687	-3.5962	-2.7309	-0.1287	-3.8123	ENDVI	-0.3726	-3.5081	-2.7018	-0.1168	-4.4568
Guyot's	0.5071	2.5806	2.2293	0.1668	3.1088	Guyot's	0.3207	3.7439	2.7530	0.1062	4.6157

Corn at V8, showed little difference in sensitivity between leaf-scale derived GNDVI, NDRE, SCCCI, ENDVI, and Guyot's REI to leaf SPAD chlorophyll readings, leaf N concentration, and relative yield (Table 4.27). However, at VT leaf scale NDRE was most sensitive to SPAD chlorophyll readings, leaf N concentration, and relative yield, while SCCCI was most sensitive to grain N concentration and grain N content.

Table 4.27 SE sensor root mean square errors, slopes, and sensitivity equivalents of selected indices calculated for 2012 through 2013 V8 and VT corn.

SE Sensor - V8				SE Sensor - VT					
RMSE	SPAD	Leaf N, %	Relative Yield	*RMSE*	SPAD	Leaf N, %	CGN N, %	CGNC, Mt ha^{-1}	Relative Yield
NDVI	0.0193	0.0206	0.0253	NDVI	0.0176	0.0254	0.0598	0.0386	0.0324
GNDVI	0.0365	0.0377	0.0489	GNDVI	0.0187	0.0340	0.1026	0.0593	0.0484
NDRE	0.0272	0.0275	0.0353	NDRE	0.0087	0.0193	0.0704	0.0368	0.0297
SCCCI	0.0312	0.0310	0.0397	SCCCI	0.0108	0.0217	0.0761	0.0398	0.0328
ENDVI	0.3926	0.3966	0.5019	ENDVI	0.2452	0.4386	1.0170	0.6383	0.5485
Guyot’s	1.1282	1.1313	1.4940	Guyot’s	0.5560	1.1646	3.0845	1.8030	1.5074
Slope				*Slope*					
NDVI	0.0038	0.0552	0.0640	NDVI	0.0061	0.0885	0.0791	0.7059	0.1588
GNDVI	0.0080	0.1187	0.1384	GNDVI	0.0111	0.1624	0.2055	1.3361	0.2941
NDRE	0.0059	0.0880	0.1042	NDRE	0.0079	0.1172	0.1853	0.9929	0.2147
SCCCI	0.0066	0.0995	0.1181	SCCCI	0.0087	0.1284	0.2190	1.0943	0.2352
ENDVI	-0.0809	-1.2081	-1.4240	ENDVI	-0.1086	-1.5449	-2.0133	-12.7066	-2.7959
Guyot’s	0.2436	3.6496	4.2227	Guyot’s	0.3361	4.8394	6.6360	40.4026	8.8407
SEq				*SEq*					
NDVI	0.1972	2.6734	2.5241	NDVI	0.3477	3.4776	1.3217	18.2673	4.8967
GNDVI	0.2198	3.1458	2.8277	GNDVI	0.5946	4.7781	2.0042	22.5157	6.0733
NDRE	0.2173	3.1974	2.9535	NDRE	0.9103	6.0767	2.6340	26.9511	7.2327
SCCCI	0.2122	3.2093	2.9718	SCCCI	0.8028	5.9229	2.8772	27.5231	7.1667
ENDVI	-0.2060	-3.0462	-2.8372	ENDVI	-0.4428	-3.5223	-1.9796	-19.9059	-5.0972
Guyot’s	0.2159	3.2261	2.8265	Guyot’s	0.6044	4.1555	2.1514	22.4085	5.8650

Discussion on Vegetation Index Sensitivities

As was noted in a previous analysis, red edge indices appear most sensitive to cotton and corn N status even when sensed at different scales. The SE leaf-level sensor is devoid of soil background information and results are dependent upon leaf color and architecture. Canopy-level YARA N-Sensor results possess a large degree of soil background information and yet the spectral samples are best calibrated to N status using red edge indices.

Strachcan et al. (2002) found no single vegetation index accurately described individual corn crop characteristics such as leaf chlorophyll content, LAI, and yield, throughout the entire season. It may be necessary to employ multiple bandwidth selections and indices through canonical discriminatory analysis at three select points in a growing season. Drought lowers near-infrared reflectance ($\lambda > 700$ nm) in most species (Gitelson and Merzlyak, 1994a). Corn canopy reflectance of red light rises with N stress, while near-infrared reflectance declines. Background factors such as soil color and canopy density interact with canopy-level sensing results (Walburg et al., 1980). A reduction in chlorophyll production is thought to lower spectral response during leaf N stress, but leaf N may be adequate during periods of impaired chlorophyll production (Walsh and Benton, 1973).

This study found no single selected red-edge index is superior over another for predicting leaf N and chlorophyll status. However, the SCCCI and ENDVI indices require fewer bands to calculate than the Guyot's REI, and both SCCCI and ENDVI predict early leaf N concentration better than NDRE. In multispectral sensing where unique bands may not be available, the SCCCI and ENDVI algorithms may provide adequate, if not superior, N status predictions over that of the more complex Guyot's REI. Moreover, the effect of unsystematic variation in cotton pre-plant field N resources and systematic, controlled variation in corn field N appears to produce weaker correlative results for cotton and stronger correlative results for corn.

There is a need to develop cost-effective sensing N tools for early leaf N status detection and for making fertilizer N recommendations in a timely manner. The SE sensor could be employed in a sensor-based field trial after extensive testing and calibration to a crop dataset. Red-edge and GNDVI indices warrant testing in leaf-level sensing. The YARA sensor shows promise in sensor-based fertilizer N recommendations, as discussed in the last objective of this Chapter.

Objective III - Leaf and Canopy Spectral Properties

The purpose of this objective is to determine leaf and canopy spectral properties in the detection of cotton and corn leaf N, leaf chlorophyll, and yield across widely varying N availability. Multiple vegetation indices (VIs) were considered for this study in order to best fit biophysical parameters to leaf- and canopy-level reflectance outputs. A comprehensive list of VIs initially considered for this study is found in APPENDIX B.

Linear r^2 values were calculated to predict the response of VIs to leaf N concentration (Leaf N, %) and SPAD chlorophyll. For corn, V5 whole plant N concentration (WPN, %) and VT corn grain concentration (Grain N., %) was also related to VIs. This study examined the potential of twenty-seven documented VIs and one novel VI theoretically derived from the sampling dataset. A complete list of VIs implemented in this study is found in (Table 3.4).

Linear relationships with $r^2 < 0.10$ are weak and most likely unrelated (NR). The strength of relationships between X and Y variables at three growth stages are described in the following discussion using the scale presented in (Table 4.28).

Table 4.28 Descriptive phrases identifying strength of r^2 values.

Relationship Description	r^2
NR	Not Related
Weak	<0.50
Moderate	> 0.51 but ≤ 0.70
Moderately Strong	> 0.71 but ≤ 0.80
Strong	> 0.81 but ≤ 0.90
Very Strong	>0.91

Vegetation Index Comparisons

Cotton Comparisons

2012 Early Square

The three highest-ranking VIs for 2012 early square cotton parameters, based on the r^2 for leaf N concentration derived with SE and YARA sensors employed centered around or near the red-edge inflection point (Table 4.29). These indices were ranked based on the strength of their relationship to leaf N concentration (Leaf N. %).

Table 4.29 Top-ranking sensor VIs to plant measurements based on leaf reflectance for 2012 cotton at early square.

SE r^2			YARA r^2		
VI Name	Leaf N, %	SPAD	VI Name	Leaf N, %	SPAD
R750/R700	0.44	0.11	TCARI/OSAVI2	0.74	NR
R695/R760	0.44	NR	TCARI/OSAVI1	0.75	NR
MSR (705,750)	0.44	0.50	MCARI1/OSAVI1	0.65	NR

The Modified Simple Ratio (MSR) (Wu et al., 2008) is similar to the NDVI index, but employs gain factors in both the VI numerator and denominator. The OSAVI1 is similar in configuration to the NDVI index but has added gain factors in both the numerator and denominator. The TCARI-type indices (TCARI, TCARI/OSAVI1, and

TCARI/OSAVI2) possess spectral data that includes 550, 670, and 700 nm bandwidth regions. The OSAVI2 configuration divided into TCARI mimics spectral data near the red-edge region.

The top ranking VIs for both the SE and YARA sensors were not strongly related to SPAD chlorophyll at early squaring. This may indicate the need for an alternative configuration to target SPAD chlorophyll or chlorophyll more directly.

2013 Early Square

The three highest-ranking VIs for the 2013 early square cotton parameters, based on r^2 values developed between leaf N concentration and leaf reflectance (SE sensor), were indices containing the 650 and 840 nm bandwidth spectral characteristics (Table 4.30). The three highest-ranking VIs for the 2013 early square cotton parameters, based on canopy reflectance (YARA N-Sensor), were compound indices with bands centered near the red-edge region.

Table 4.30 Top-ranking sensor VIs to plant measurements based on leaf reflectance for 2013 cotton at early square.

SE r^2			YARA r^2		
VI Name	Leaf N, %	SPAD	VI Name	Leaf N, %	SPAD
RVI	0.47	NR	Guyot’s	0.34	NR
WDRVI	0.47	NR	SCCCI	0.18	0.19
NDVI	0.46	NR	ENDVI	0.17	0.20

Practical factors may have influenced these results. The SE sensor was calibrated differently in 2013 than in 2012, as described in the Methods chapter. No single VI for leaf N status sampling at early square can be recommended. However, a case may be made for employing red-edge type VIs for predicting leaf N concentration based on the repeated high-ranking of this type of algorithm.

Similar to 2012, the top ranking VIs for both the SE and YARA sensors were not strong predictors of SPAD ($r^2 \leq 0.50$). This again may indicate the need for alternative configurations to target SPAD chlorophyll.

2012 and 2013 Early Bloom

The SE sensor was employed for spectral sampling of early bloom and peak bloom stages of cotton. The three highest-ranking VIs for the 2012 early bloom cotton parameters, ranked on strength of relationships to leaf N concentration for the SE sensor, were algorithms that employed the 550 nm bandwidth (Table 4.31). The three highest-ranking VIs for the 2013 early bloom cotton parameters were red-edge type indices

Table 4.31 Top-ranking SE sensor VIs to plant measurements based on leaf reflectance for 2012 and 2013 cotton at early bloom.

2012 SE r^2			2013 SE r^2		
VI Name	Leaf N, %	SPAD	VI Name	Leaf N, %	SPAD
R750/R550	0.49	NR	Guyot's	0.46	0.36
GRVI	0.48	NR	ENDVI	0.39	0.83
GNDVI	0.48	NR	SCCCI	0.37	0.80

The previously described differences in sampling protocols may account for the reversal of suitability for predicting leaf N. Moreover, the residual soil N variability was greater in 2013 than in 2012. The considerable increase in 2013 predictions of SPAD chlorophyll and yield over that of the 2012 predictions may suggest that the 2013 sampling procedures (e.g. leaf samples held on ice from the moment of collection) and environmental factors (climatic and soil differences) may be implicated in producing higher r^2 correlated results.

2012 & 2013 Peak Bloom

The three highest-ranking VIs for the 2012 peak-bloom cotton parameters for leaf N concentration with leaf based reflectance (SE sensor), were algorithms that employ the red-edge region (Table 4.32). The three top ranking VIs revealed weak to moderately strong (0.36 to 0.76) relationships to SPAD chlorophyll. The three highest-ranking VIs for 2013 peak bloom cotton parameters for leaf N concentration for leaf based reflectance (SE sensor) did not consistently employ a single region of the spectral bandwidth. Guyot's emphasizes the red-edge region, while the TCARI and MCARI integrate the 550, 670, and 700 nm bandwidth regions of spectral samples.

Table 4.32 Top-ranking SE sensor VIs to plant measurements based on leaf reflectance for 2012 cotton at peak bloom.

	2012 SE r^2			2013 SE r^2	
VI Name	Leaf N, %	SPAD	VI Name	Leaf N, %	SPAD
Guyot's	0.84	0.36	Guyot's	0.8	0.55
ENDVI	0.78	0.66	TCARI(670,700)	0.73	0.22
TCARI/OSAVI2	0.77	0.76	MCARI	0.73	0.22

Emphasis was placed, in this study, on comparisons between the NDVI, GNDVI, NDRE, SCCCI, ENDVI, and Guyot's REI indices and their comparative ranking among the 28 different VIs studied. Based on the strength of relationships, the selected VIs ranked as shown in Table 4.33 and Table 4.34:

Table 4.33 Ranking of selected VIs by sensor for 2012 and 2013 early square cotton leaf N concentration.

	SE		YARA	
	2012	2013	2012	2013
NDVI	28	3	11	18
GNDVI	13	5	16	10
NDRE	6	20	23	9
SCCCI	7	24	28	2
ENDVI	8	25	27	3
Guyot's	11	16	26	1

Lower number indicates higher ranking.

Table 4.34 Ranking of selected SE sensor VIs for 2012 and 2013 early and peak bloom cotton.

	Early Bloom		Peak Bloom	
	2012	2013	2012	2013
NDVI	6	14	27	24
GNDVI	3	22	13	15
NDRE	17	5	7	11
SCCCI	21	3	5	6
ENDVI	24	2	2	4
Guyot's	28	1	1	1

Lower number indicates higher ranking.

Selected red-edge indices improved in ranking as the cotton crop progressed and, at canopy-level, in 2013 early square. Green wavelengths appear to be implicated in the elevated leaf-level rankings. However, a countervailing ranking between GNDVI and ENDVI occurs in both seasons and both sensors.

Corn Comparisons

2012 Corn

The three highest-ranking VIs derived from SE leaf and YARA canopy-level scans for 2012 V5 corn in relationship to leaf N concentration possessed red-edge components, and the vegetation index relationships to leaf N %, SPAD chlorophyll, and WPN % were moderately strong or greater (Table 4.35).

Table 4.35 Top-ranking SE and YARA sensor VIs to plant measurements based on leaf reflectance for 2012 corn at V5.

	SE r^2				YARA r^2		
VI Name	Leaf N, %	SPAD	WPN, %	VI Name	Leaf N, %	SPAD	WPN, %
TCARI/OSAVI2	0.92	0.78	0.94	TCARI/OSAVI2	0.85	0.74	0.87
R695/R760	0.91	0.82	0.93	ENDVI	0.83	0.84	0.84
ENDVI	0.91	0.82	0.92	Guyot's	0.83	0.84	0.84

2013 Corn

Two of the three highest-ranking VIs derived from SE leaf scans for 2013 V5 corn in relationship to leaf N concentration were red-edge type indices (Table 4.36) Guyot's REI and OSAVI2 do not contain green bandwidth information. At the canopy scale, the three highest-ranking VIs based on their relationship to leaf N concentration in 2013 at V5 were compound indices with bands located around or near the red-edge region. The YARA N-Sensor results best predicted leaf N status with more complex indices containing more bandwidths and, in particular, bandwidths with red-edge spectral information. The ENDVI, Guyot's REI, and SCCCI were more strongly related to SPAD chlorophyll than was TCARI/OSAVI2. The ENDVI and Guyot's REI VIs for canopy scale V5 corn in 2013 strongly predicted SPAD chlorophyll (>0.80) and moderately predicted whole plant N concentration.

Table 4.36 Top-ranking SE and YARA sensor VIs to plant measurements based on canopy reflectance for 2013 corn at V5.

	SE r^2				SE r^2		
VI Name	Leaf N, %	SPAD	WPN, %	VI Name	Leaf N, %	SPAD	WPN, %
ENDVI	0.89	0.93	0.59	ENDVI	0.87	0.89	0.67
Guyot's	0.87	0.93	0.56	Guyot's	0.86	0.88	0.67
OSAVI2(705,750)	0.86	0.93	0.58	TCARI/OSAVI2	0.83	0.86	0.61

V8 Relationships

The SE sensor was employed for spectral sampling at V8 only in 2013 and VT corn in 2012 and 2013. The three highest-ranking VIs at V8 for relationships with corn leaf N concentration were algorithms with red-edge spectral components (Table 4.37). The OSAVI2 and Guyot's RED VIs revealed moderately strong relationships to SPAD chlorophyll.

Table 4.37 Top-ranking SE sensor VIs to plant measurements based on leaf reflectance for 2013 corn at V8.

	SE r^2 Values	
VI Name	Leaf N, %	SPAD
OSAVI2(705,750)	0.73	0.742
Guyot's	0.72	0.72
SCCCI	0.73	0.71

VT Relationships

At VT in 2012, the highest-ranking VIs, relative to the strength in relationship to leaf N concentration and SE sensor acquired leaf reflectance, were red-edge type algorithms (Table 4.38). Highest-ranking VI relationships to leaf N concentration in 2013 VT corn were not limited to employment of a single region of the spectral signature.

Table 4.38 Top-ranking SE sensor VIs to plant measurements based on leaf reflectance for 2012 and 2013 corn at VT.

	2012 SE r^2				2013 SE r^2		
VI Name	Leaf N, %	SPAD	Grain N, %	VI Name	Leaf N, %	SPAD	Grain N, %
SCCCI	0.98	0.99	0.37	GRVI	0.96	0.97	NS
R780/R740	0.97	0.99	0.40	R780/R740	0.96	0.99	NS
NDRE	0.97	0.98	0.34	MSR(705,750)	0.96	0.99	NS

The GRVI is a simple index that ratios the NIR spectral region to the green bandwidth region (840 and 550 nm, respectively). The R780/R740 and MSR indices ratio red-edge regions of the spectral signature. The three top ranking VIs for both years produced significant relationships with SPAD chlorophyll, and weak or no relationships with grain N concentration.

Based on the strength of relationships, the VIs selected for emphasis in this study ranked as shown in Table 4.39 and 0.

Table 4.39 Ranking of selected VIs by sensor for 2012 and 2013 early square cotton.

	SE		YARA	
	2012	2013	2012	2013
NDVI	7	18	14	7
GNDVI	4	4	6	6
NDRE	13	6	8	8
SCCCI	18	5	4	4
ENDVI	3	1	2	1
Guyot's	6	2	3	2

Lower number indicates higher ranking.

Table 4.40 Ranking of selected SE sensor VIs for 2012 and 2013 V8 and VT corn.

	V8		VT	
	2012	2013	2012	2013
NDVI	n/a	19	19	20
GNDVI		9	10	10
NDRE		4	3	5
SCCCI		3	1	16
ENDVI		16	9	11
Guyot's		2	7	11

Lower number indicates higher ranking.

Discussion on Cotton and Corn Vegetation Indices Rankings

The ranking results indicate, in general, red-edge indices best relate to leaf N status and SPAD chlorophyll readings in both corn and cotton. Previous research supports this outcome (Schlemmer et al., 2013; Hubbard, 2012; Raper, 2011). The red-edge spectral band employed in detecting leaf N status is approximately 20 nm wide (720-740 nm) while chlorophyll absorption peaks are relatively narrow (*chl a* and *b* ~ 465 and 665nm, 460 and 647 nm, respectively). Baret et al. (2007) found canopy chlorophyll content quantifies, and is related to, canopy-level N status. However, there are multiple limiting factors in production sensing. Abiotic stresses may affect plant hydration and osmotic potential, which change throughout the day even in normal circumstances (Larcher, 2003; Taiz and Zeiger, 2010). As leaves wilt under temperature and water stress, canopy absorbance declines, and greater areas of soil are exposed (Earl and Davis, 2003). Plant developmental stage and soil color are also capable of confounding sensing results.

With the exception to 2012 early square cotton, red-edge type indices responded moderately strong or greater to leaf N concentration, and VIs employing 600-700 nm bandwidths related well to SPAD readings. Overall, the Guyot's REI appears reasonably suited to predict leaf N concentrations at most sampling stages in cotton. Furthermore, Guyot's REI appears related to SPAD chlorophyll at peak bloom, but weakly related at early bloom and early square. Increasing the number of bands employed to calculate a VI does not appear to increase the relationship between VI and either leaf N concentration or SPAD chlorophyll. More importantly, the choice of bands, especially those that integrate red-edge, biomass, and greenness characteristics, appear to strengthen N status relationships to VIs.

Corn red-edge type indices rank consistently in the top ten of all 28 considered VIs for both sensor types (leaf and canopy level). The resultant ranking between the two sensors in 2012 suggests that measurement scale (leaf vs. canopy) in corn had less of an effect on spectral characteristics denoting leaf N status compared to cotton. In 2012, both the SE and YARA sensors produced moderately strong or higher VI relationships of corn leaf N status and SPAD readings with red-edge VI configurations. Furthermore, 2012 whole plant N concentration was strongly related with the top three ranking VIs at V5. Corn grain N concentration was weakly related to VIs in 2012.

In 2013, both sensors, with data acquired at differing scales, performed similarly when calibrated with like indices at V5. Furthermore, the ENDVI and Guyot's REI indices were most suited to predict early leaf N concentration in corn despite the technical differences in wavelengths and methods of calculation. A case may be made for employing red-edge type VIs for predicting corn leaf N status based on the repeated high-ranking of algorithms containing spectral bandwidths within the 720 to 780 nm region.

The top ranking 2013 VIs for both sensors were moderately strong or stronger in predicting corn SPAD chlorophyll at all growth stages. The ENDVI and Guyot's REI ranked highest at predicting SPAD parameters with both sensors in 2013 and were statistically similar to the SPAD highest-ranking VIs in 2012. Whole plant N concentration was moderately predicted by both sensors in 2013, but corn grain N concentration relationships were not significant.

As was noted in the previous objective, the Guyot's REI is complicated to calculate and requires bandwidths in spectral resolutions not commonly found on aerial or suborbital spectroradiometric platforms suitable for wide area analysis. The ENDVI relationship to corn leaf N concentration diminishes as the crop progresses. At the peak of corn growth, N resources are preferentially partitioned to developing corn grain, while leaf N is used with resulting lower concentrations than at earlier stages of growth. The reduction in leaf N concentration and widening of the range in leaf N concentration across N rates in later stages of corn may be responsible for the decreased effectiveness of the ENDVI and NDVI indices in predicting leaf N status. However, structural changes in leaves (e.g. thickness) at VT stage may also account for the similar suitability of the Guyot's REI, ENDVI, SCCCI, NDRE, GNDVI, and NDVI VIs. Corn leaf structure factors were not considered in this study.

Overall, the ENDVI index appears reasonably suited to predict leaf N concentrations at the earliest sampling stage in corn. In later stages of corn growth, the SCCCI and Guyot's REI were more effective at relating spectral sensing data to leaf N status. At all stages of corn growth, the VIs that best related sensed data to leaf N status also related the same data to SPAD chlorophyll.

Inverse Biophysical Transfer Model Results

Inverse biophysical transfer modelling (IBTM) was applied to all cotton and corn datasets for both sensors in 2012-2013 growing seasons. Leaf N and whole plant N concentration (corn only) were the dependent variables (Y) and six VIs (NDVI, GNDVI, NDRE, SCCCI, ENDVI, and Guyot's REI) were the independent variables (X). The regression formula derived using one-half of a randomized dataset of Y=X (modeling dataset) was inverted and tested for its ability to predict the remainder of the randomized dataset (prediction dataset). Models were ranked from highest to lowest (1-6 scale) based on r^2 values. Root-mean-square-error values derived from the prediction dataset were ranked from lowest to highest (1-6 scale). The ranks were totaled and the lowest total is given the highest ranked suitability. A tie in ranking score was broken by ranking the VI with the greater r^2 above its paired match.

Cotton Leaf N Models

For cotton, the r^2 values from the IBTM prediction dataset were similar to values obtained in the original, non-randomized dataset. The exception to this pattern was in 2013 for early and peak bloom data where a single outlier existed, noted in the Methods. This data point was not removed from the IBRM to prevent large resampling data errors.

At early square, the RMSE tended to be greater with the SE derived dataset than for the YARA N-Sensor dataset (Table 4.41). The RMSE statistic was always greatest at the peak bloom stage. The GNDVI was most often ranked highest across all growth stages with the SE sensor. In 2012, NDVI and GNDVI ranked high for relationships to leaf N status developed with data acquired with the YARA N-Sensor at early square and bloom. The IBTM relationships of leaf N concentration to VIs were slightly higher, but statistically similar to those created through linear regression.

Table 4.41 Cotton leaf N concentration r^2 and root-mean-square-error (RMSE) statistics for SE and YARA sensor VIs at three growth stages.

			Sensor			
			SE	YARA	SE	SE
VIs	Year	Stage	Early Square		Early Bloom	Peak Bloom
NDVI	2012	r^2	0.02	0.07	0.16	0.02
		RMSE	0.2406	0.2629	0.2616	0.2414
	2013	r^2	0.14	0.06	0.10	0.16
		RMSE	0.2234	0.1755	0.2428	0.3091
GNDVI	2012	r^2	0.02	0.07	0.22	0.28
		p value	0.7147	0.2560	1.4353	0.9015
	2013	r^2	0.20	0.10	0.18	0.65
		RMSE	1.3895	0.4496	1.2734	2.1448
NDRE	2012	r^2	0.13	0.06	0.04	0.23
		p value	2.3635	0.8000	1.9885	1.8134
	2013	r^2	0.14	0.09	0.19	0.53
		RMSE	2.7863	0.9608	2.9673	4.2551
SCCCI	2012	r^2	0.09	0.03	0.02	0.30
		p value	2.2277	0.7661	1.4496	1.6028
	2013	r^2	0.14	0.13	0.13	0.49
		RMSE	2.0871	0.4560	2.1178	3.7949
ENDVI	2012	r^2	0.11	0.02	0.04	0.27
		p value	1.2407	0.8413	1.1753	1.2098
	2013	r^2	0.11	0.14	0.15	0.47
		RMSE	1.4011	1.3911	1.2772	2.2082
Guyot's	2012	r^2	0.09	0.02	0.03	0.34
		p value	11.9308	7.7387	10.7735	12.8946
	2013	r^2	0.14	0.14	0.28	0.60
		RMSE	15.3494	9.3698	15.7494	22.9861

Level of significance $\alpha = 0.05$

Linear regression of cotton leaf N concentration at all growth stages indicated red-edge indices were best related to early square YARA VIs in 2013. The 2012 early square YARA VI relationships were not significant. The SE sensor leaf N relationships to VIs decreased at early bloom when high leaf N concentrations may be partitioned to new and expansive growth (Bell et al., 2003). The GNDVI was sensitive to the single outlying sample in the 2013 data set, whereby the errant data point reduced the peak bloom r^2 value from 0.64 to 0.08. The reduction in r^2 at early bloom 2013 is not considered due to an outlying data sample. Overall, the NDVI and GNDVI algorithms performed poorly when relating early and peak bloom leaf N using the SE sensor. By peak bloom, SE leaf N concentration relationships to red-edge indices increased both growing seasons (Table 4.42 and Table 4.43). Figure 4.15 through Figure 4.22 depict the linear VI responses to cotton biophysical parameters.

Table 4.42 Cotton leaf N concentration linear coefficients of determination and p values for regression model effects of six VIs calculated from YARA and SE sensor reflectance during the 2012-2013 growing season.

			Sensor			
			SE	YARA	SE	SE
			Early Square		Early Bloom	Peak Bloom
NDVI	2012	r^2	0.00	0.05	0.14	0.02
		P>F	0.6937	0.0733	0.0010	0.2600
	2013	r^2	0.13	0.06	0.00	0.00
		P>F	0.0012	0.0283	0.8205	0.6091
GNDVI	2012	r^2	0.01	0.04	0.19	0.23
		P>F	0.4461	0.1065	0.0001	<0.0001
	2013	r^2	0.20	0.08	0.03	0.08
		P>F	<0.0001	0.0119	0.1416	0.0114
NDRE	2012	r^2	0.11	0.03	0.03	0.25
		P>F	0.0055	0.1304	0.1319	<0.0001
	2013	r^2	0.16	0.08	0.10	0.16
		P>F	0.0003	0.0124	0.0050	0.0002
SCCCI	2012	r^2	0.11	0.01	0.00	0.29
		P>F	0.0041	0.5683	0.9826	<0.0001
	2013	r^2	0.11	0.13	0.12	0.28
		P>F	0.0027	0.0012	0.0018	<0.0001
ENDVI	2012	r^2	0.10	0.01	0.00	0.31
		P>F	0.0065	0.5358	0.9129	<0.0001
	2013	r^2	0.10	0.13	0.13	0.37
		P>F	0.0035	0.0013	0.0011	<0.0001
Guyot's	2012	r^2	0.07	0.01	0.01	0.32
		P>F	0.0253	0.3788	0.5477	<0.0001
	2013	r^2	0.16	0.11	0.25	0.58
		P>F	0.0002	0.0030	<0.0001	<0.0001

Level of significance $\alpha = 0.05$

Table 4.43 Cotton linear regression models of leaf N relationships with VIs from sensor reflectance data at all growth stages during the 2012-2013 growing seasons.

		Sensor			
		SE	YARA	SE	SE
		Early Square		Early Bloom	Peak Bloom
VI	Year	y=			
NDVI	2012	0.793 - 0.002x	0.791 - 0.038x	0.759 + 0.012x	0.847 - 0.008x
	2013	0.725 + 0.013x	0.132 + 0.036x	0.800 + 0.003x	0.772 + 0.008x
GNDVI	2012	0.571 + 0.004x	0.707 - 0.021x	0.581 + 0.015x	0.554 + 0.033x
	2013	0.477 + 0.021x	0.244 + 0.030x	0.559 + 0.013x	0.461 + 0.031x
NDRE	2012	0.161 + 0.010x	0.312 - 0.016x	0.234 + 0.004x	0.121 + 0.040x
	2013	0.135 + 0.012x	0.021 + 0.017x	0.164 + 0.010x	0.131 + 0.016x
SCCCI	2012	0.202 + 0.013x	0.400 - 0.003x	0.308 - $6.164e^{-5}x$	0.135 + 0.052x
	2013	0.191 + 0.012x	0.258 + 0.017x	0.202 + 0.012x	0.176 + 0.017x
ENDVI	2012	4.628 - 0.179x	2.481 + 0.202x	3.246 - 0.003x	4.820 - 0.481x
	2013	4.890 - 0.180x	3.655 - 0.149x	4.767 - 0.199x	5.288 - 0.302x
Guyot's	2012	716.891 + 0.320x	721.489 - 0.168x	719.666 + 0.047x	715.625 + 1.260x
	2013	715.543 + 0.529x	716.187 + 0.702x	715.669 + 0.614x	715.037 + 0.798x

Level of significance α = 0.05

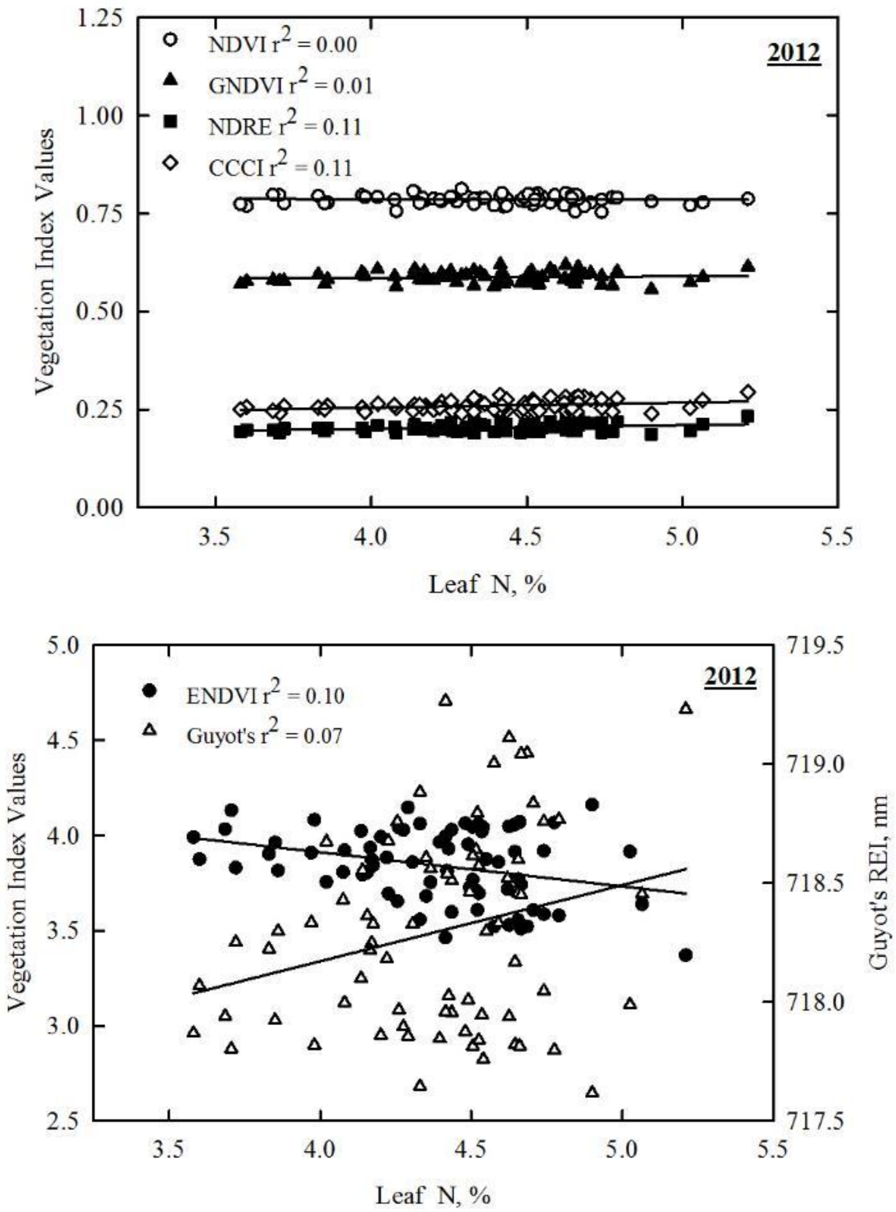


Figure 4.15 Relationship between cotton leaf N concentration and SE sensor VIs for 2012 at early square stage.

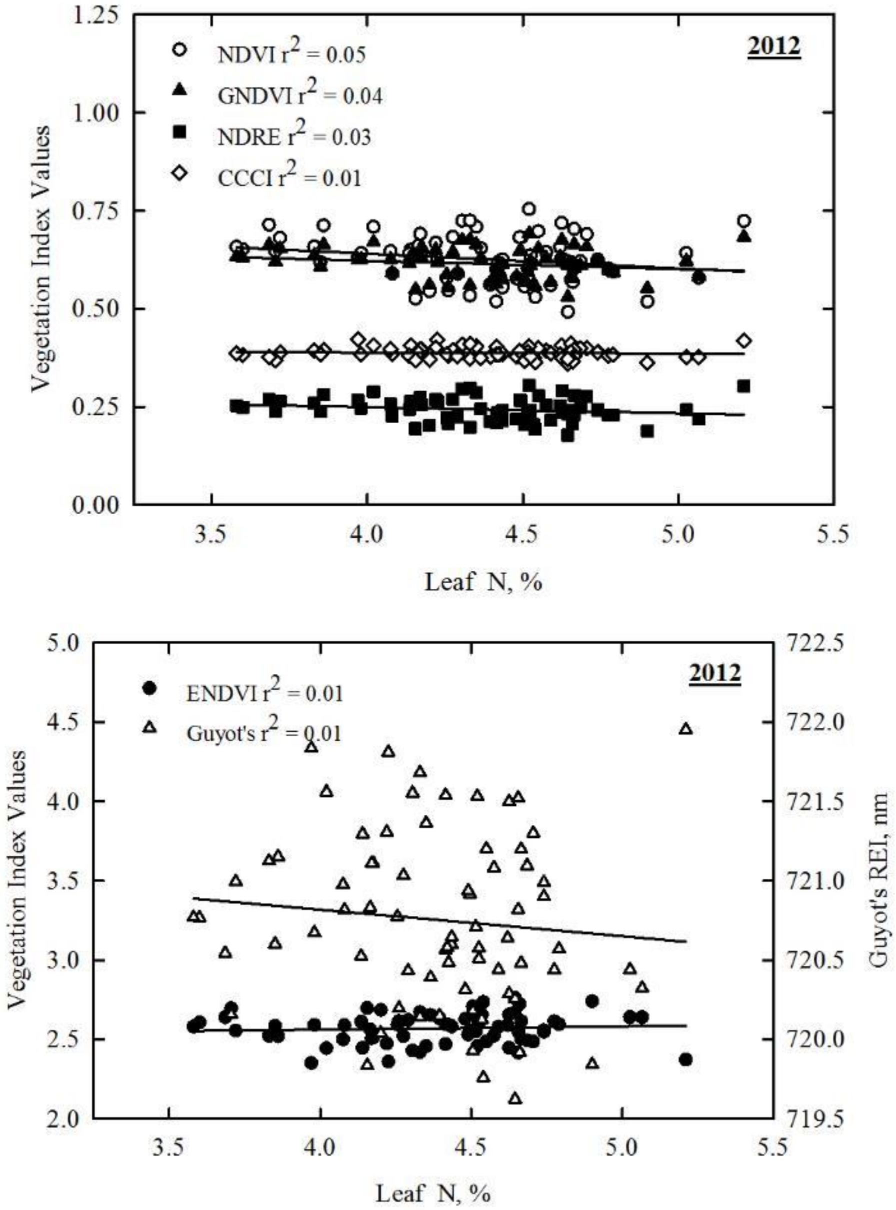


Figure 4.16 Relationship between cotton leaf N concentration and YARA N-Sensor VIs for 2012 at early square stage.

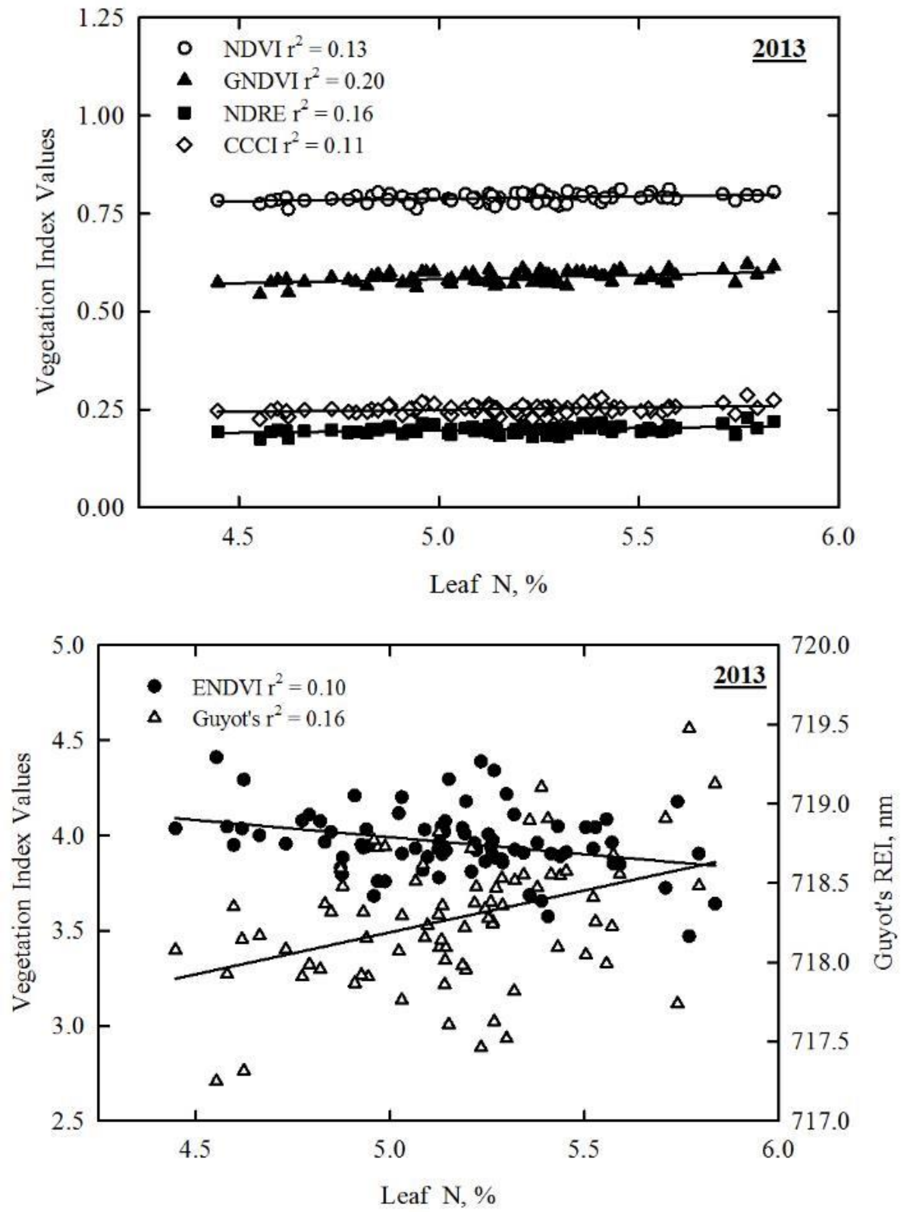


Figure 4.17 Relationship between cotton leaf N concentration and SE sensor VIs for 2013 at early square stage.

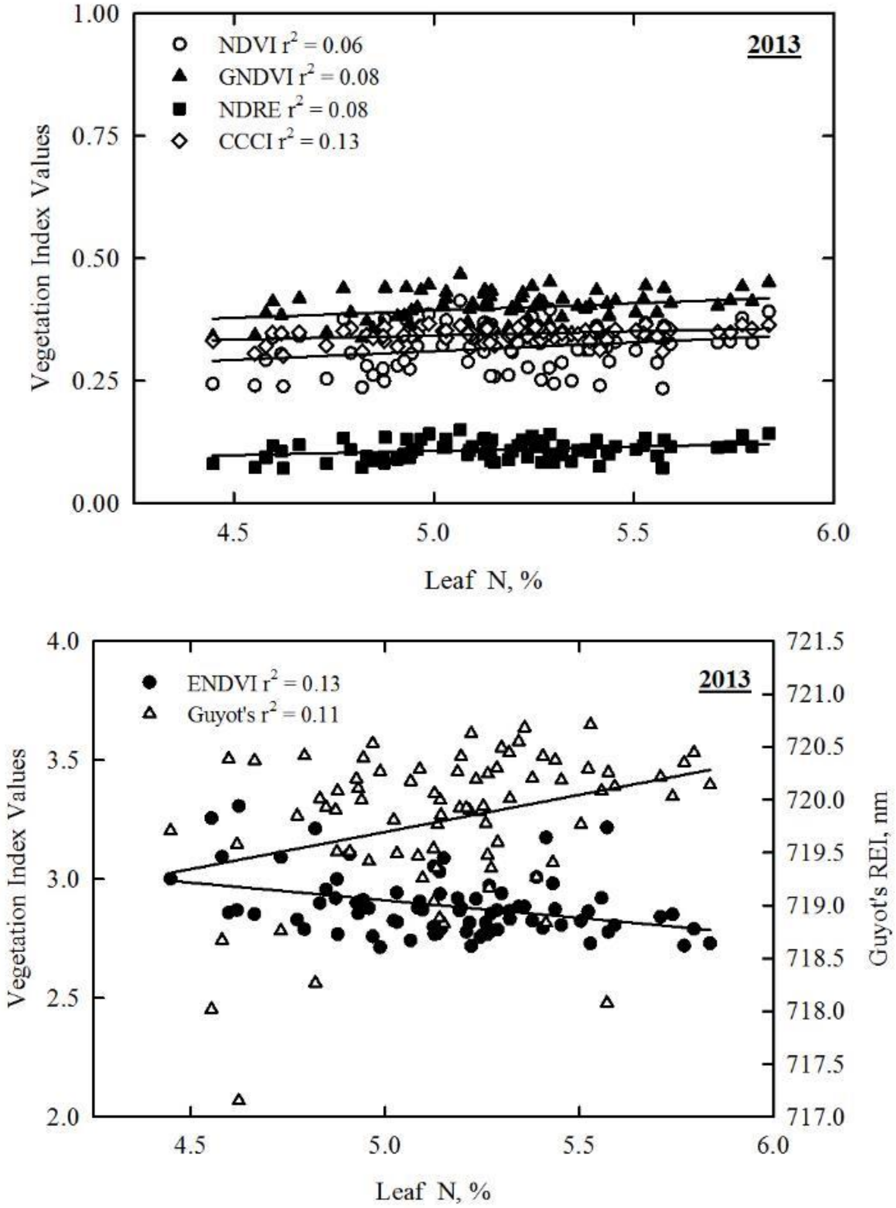


Figure 4.18 Relationship between cotton leaf N concentration and YARA sensor VIs for 2013 at early square stage.

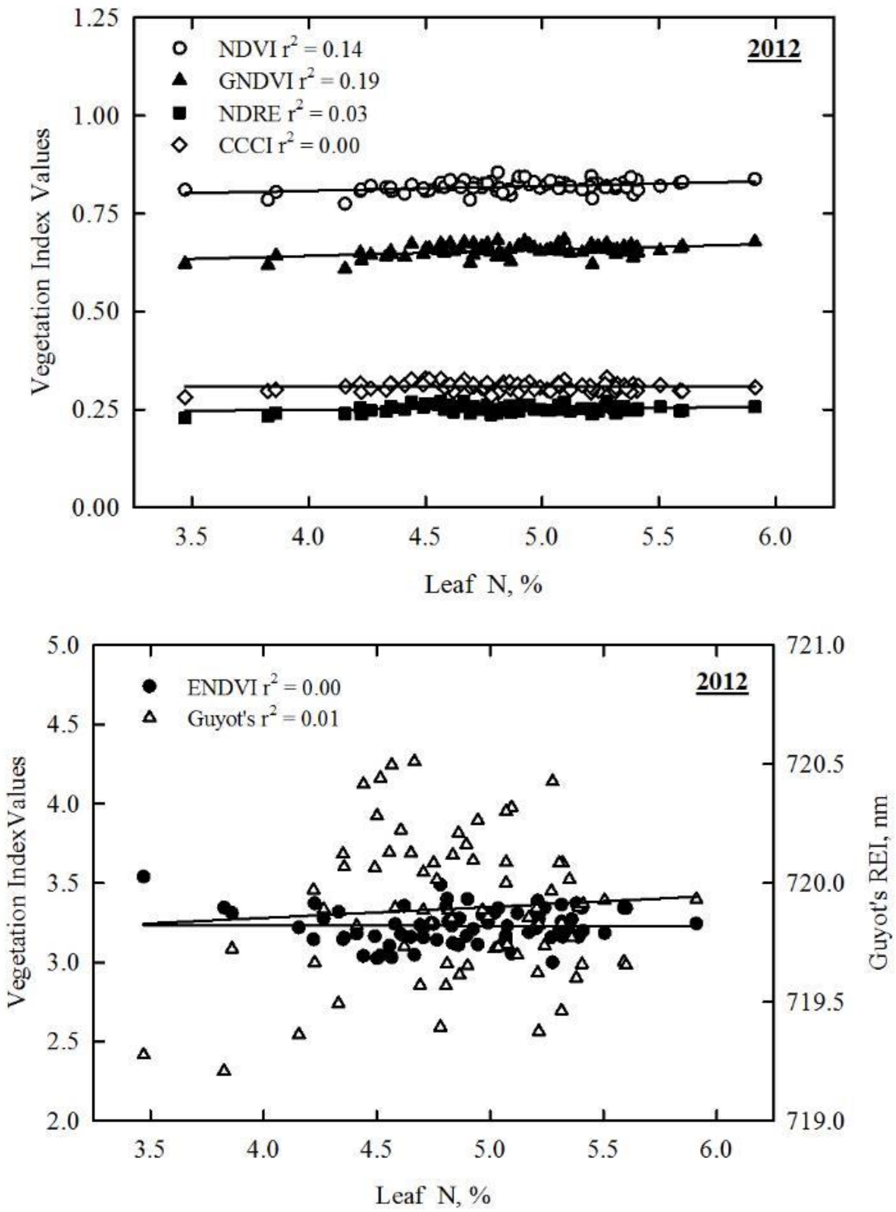


Figure 4.19 Relationship between cotton leaf N concentration and SE sensor VIs for 2012 at early bloom stage.

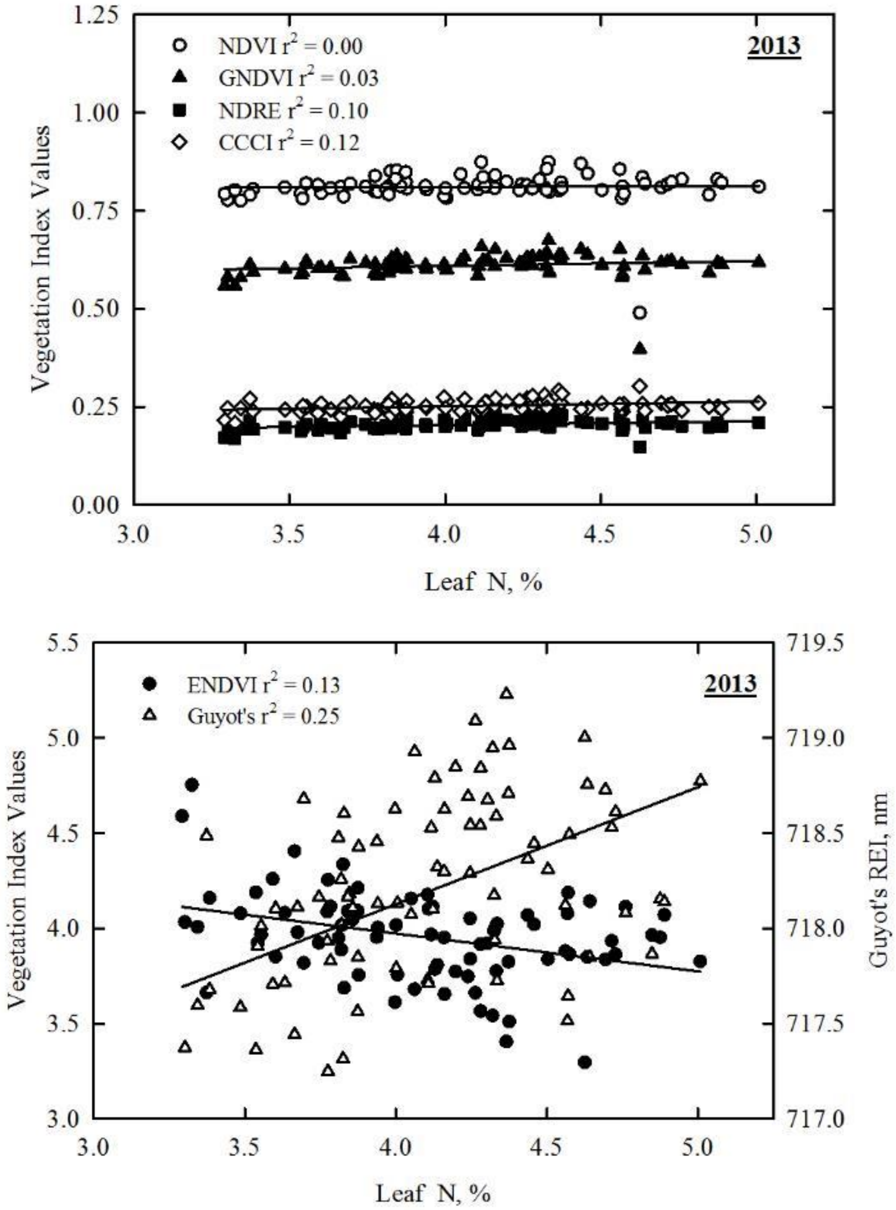
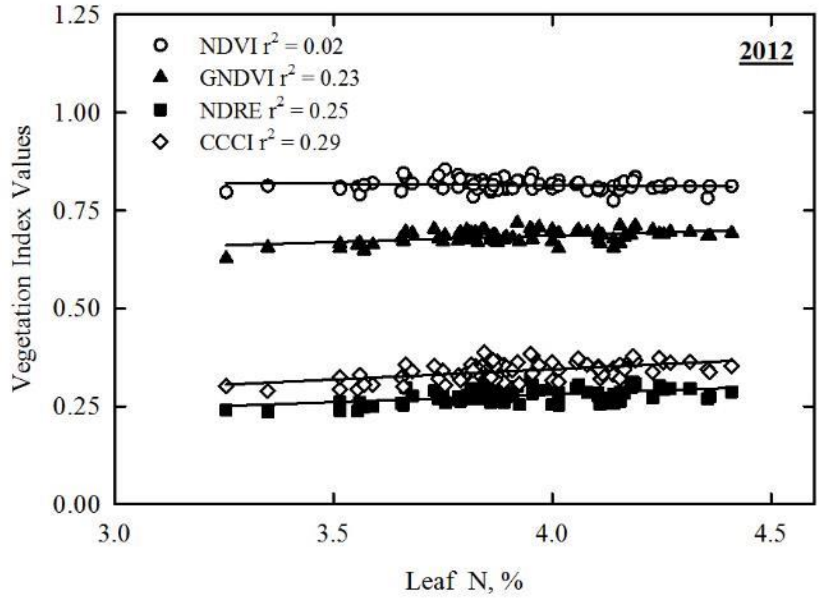


Figure 4.20 Relationship between cotton leaf N concentration and SE sensor VIs for 2013 at early bloom stage.



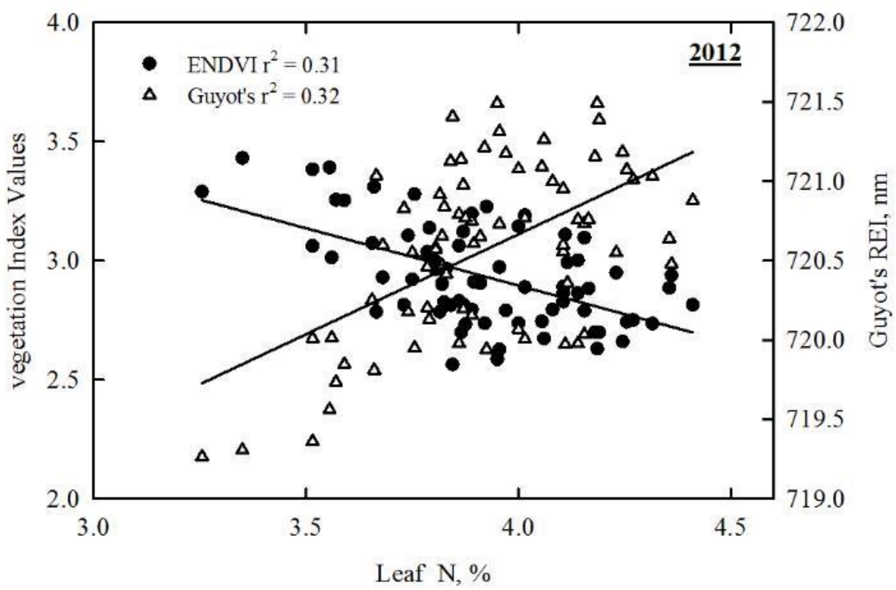


Figure 4.21 Relationship between cotton leaf N concentration and SE sensor VIs for 2012 at peak bloom stage.

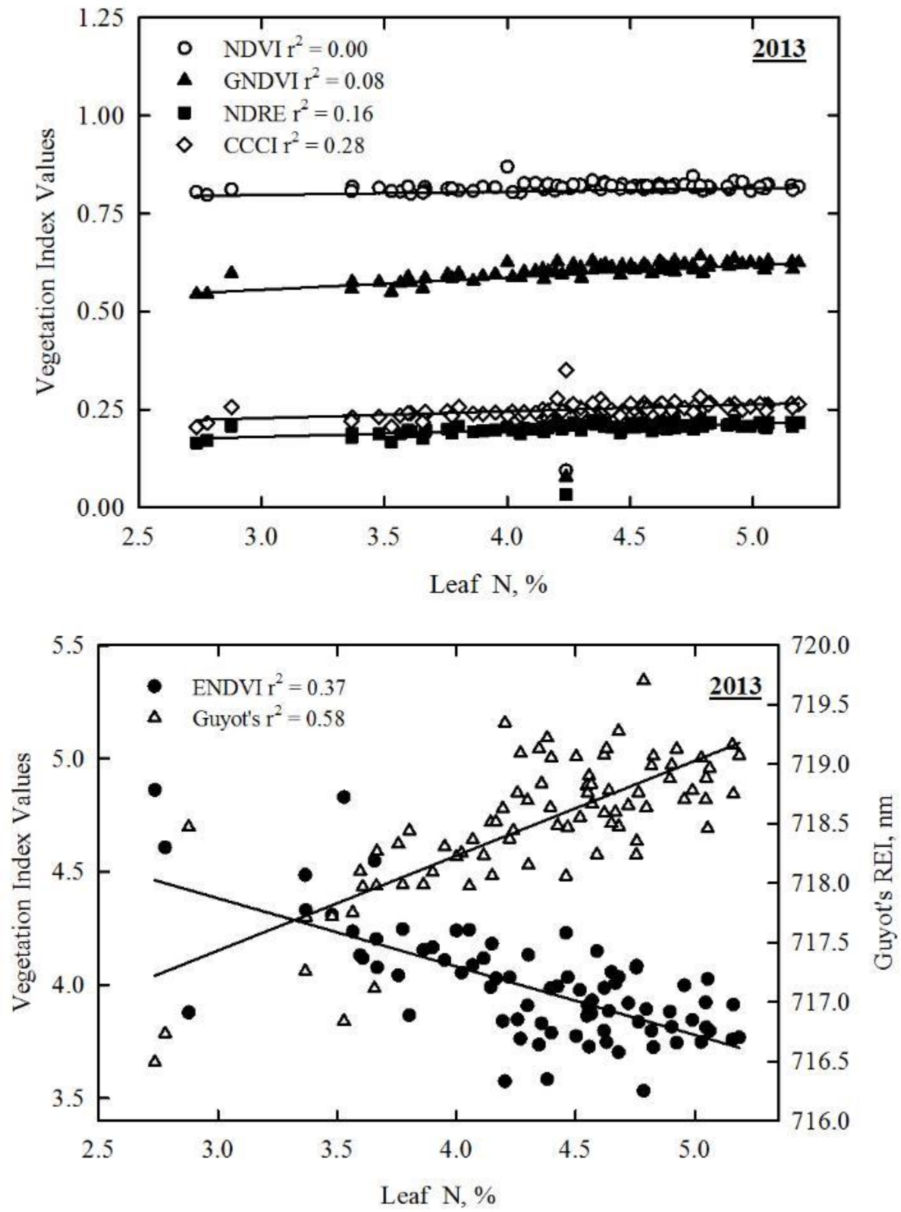


Figure 4.22 Relationship between cotton leaf N concentration and SE sensor VIs for 2013 at peak bloom stage.

Corn Leaf N Models

The corn IBTM contained 16 samples, which were divided into half and randomized. Corn leaf N concentration at V5, V8, and VT growth stages was modeled to the NDVI, GNDVI, NDRE, SCCCI, ENDVI, and Guyot's REI algorithms.

The six VIs chosen for this test tend to produce moderately strong relationships to leaf N concentration at V5 and VT stages. However, all IBTM r^2 values declined at V8 stage similar to cotton. In general, red-edge indices appear to predict leaf N concentration at all growth stages in a moderately strong manner (Table 4.44)

Table 4.44 Corn leaf N concentration r^2 and root-mean-square-error (RMSE) statistics for SE and YARA sensor VIs at three growth stages.

			Sensor			
			SE	YARA	SE	SE
VIs	Year	Stage	V5		V8	VT
NDVI	2012	r^2	0.86	0.54	n/a	0.84
		RMSE	0.2865	0.4375	n/a	0.2864
	2013	r^2	0.74	0.73	0.63	0.87
		RMSE	0.2661	0.2781	0.3889	0.2573
GNDVI	2012	r^2	0.87	0.71	n/a	0.94
		RMSE	1.3356	0.7898	n/a	1.2422
	2013	r^2	0.86	0.79	0.64	0.94
		RMSE	1.4079	0.4122	1.1433	1.0092
NDRE	2012	r^2	0.86	0.67	n/a	0.97
		RMSE	2.2887	1.8211	n/a	2.1524
	2013	r^2	0.80	0.79	0.73	0.95
		RMSE	2.4611	1.5152	1.9925	1.8236
SCCCI	2012	r^2	0.85	0.83	n/a	0.98
		RMSE	1.9354	1.8409	n/a	1.8557
	2013	r^2	0.83	0.83	0.76	0.94
		RMSE	2.0525	1.4400	1.7721	1.6176
ENDVI	2012	r^2	0.83	0.84	n/a	0.94
		RMSE	1.3296	1.9370	n/a	1.3778
	2013	r^2	0.84	0.84	0.72	0.90
		RMSE	1.3566	1.5892	1.2652	1.0477
Guyot's	2012	r^2	0.88	0.76	n/a	0.95
		RMSE	12.9751	15.3100	n/a	13.5803
	2013	r^2	0.88	0.86	0.74	0.91
		RMSE	12.1798	12.9249	11.5648	10.6540

Level of significance $\alpha = 0.05$

A linear regression of leaf N concentration to VIs produced similar r^2 values at all growth stages to those produced in the IBTM model. This suggests low variation in the corn dataset. Again, red-edge indices appear to predict leaf N concentration at all growth stages in a moderately strong manner. However, the SE sensor appears to calibrate leaf N concentration to GNDVI in a manner fitting of a leaf-scale sampling device (Table 4.45 and Table 4.46). Figure 4.23 through Figure 4.29 depict the linear relationships between VIs and corn biophysical parameters.

Table 4.45 Corn leaf N concentration linear coefficients of determination and p values for regression model effects of six VIs calculated from YARA and SE sensor reflectance during the 2012-2013 growing season.

			Sensor			
			SE	YARA	SE	SE
VIs	Year	Stage	V5		V8	VT
NDVI	2012	r^2	0.88	0.63	n/a	0.91
		P>F	<0.0001	0.0003	n/a	<0.0001
	2013	r^2	0.71	0.75	0.68	0.90
		P>F	<0.0001	<0.0001	<0.0001	<0.0001
GNDVI	2012	r^2	0.90	0.73	n/a	0.94
		P>F	<0.0001	<0.0001	n/a	<0.0001
	2013	r^2	0.86	0.78	0.71	0.92
		P>F	<0.0001	<0.0001	<0.0001	<0.0001
NDRE	2012	r^2	0.87	0.70	n/a	0.93
		P>F	<0.0001	<0.0001	n/a	<0.0001
	2013	r^2	0.84	0.74	0.71	0.93
		P>F	<0.0001	<0.0001	<0.0001	<0.0001
SCCCI	2012	r^2	0.86	0.80	n/a	0.91
		P>F	<0.0001	<0.0001	n/a	<0.0001
	2013	r^2	0.85	0.81	0.69	0.92
		P>F	<0.0001	<0.0001	<0.0001	<0.0001
ENDVI	2012	r^2	0.91	0.83	n/a	0.91
		P>F	<0.0001	<0.0001	n/a	<0.0001
	2013	r^2	0.88	0.87	0.67	0.90
		P>F	<0.0001	<0.0001	<0.0001	<0.0001
Guyot's	2012	r^2	0.89	0.83	n/a	0.92
		P>F	<0.0001	<0.0001	n/a	<0.0001
	2013	r^2	0.87	0.86	0.69	0.91
		P>F	<0.0001	<0.0001	<0.0001	<0.0001

Level of significance α = 0.05

Table 4.46 Corn regression models of leaf N relationships with VIs from sensor reflectance data at all growth stages during the 2012-2013 growing seasons.

		Sensor			
		SE	YARA	SE	SE
		V5		V8	VT
VIs	Year	y=			
NDVI	2012	0.611 + 0.047x	0.273 + 0.116x	n/a	0.472 + 0.080x
	2013	0.510 + 0.057x	-0.093 + 0.208x	0.547 + 0.060x	0.283 + 0.144x
GNDVI	2012	0.164 + 0.113x	0.310 + 0.083x	n/a	0.055 + 0.144x
	2013	0.083 + 0.110x	0.164 + 0.113x	0.119 + 0.126x	-0.283 + 0.255x
NDRE	2012	-0.037 + 0.087x	-0.007 + 0.079	n/a	-0.077 + 0.104x
	2013	-0.053 + 0.074x	-0.167 + 0.118x	-0.049 + 0.093x	-0.309 + 0.178x
SCCCI	2012	-7.4999e-4 + 0.098x	0.189 + 0.060x	n/a	-0.010 + 0.112x
	2013	-0.020 + 0.088x	0.092 + 0.084x	3.8113 + 0.104x	-0.279 + 0.195x
ENDVI	2012	7.400 - 1.269x	4.096 - 0.52x	n/a	6.777 - 1.173x
	2013	8.946 - 1.579x	5.052 - 0.711x	7.111 - 1.256x	11.719 - 2.672x
Guyot's	2012	707.431 + 3.511x	711.758 + 2.549x	n/a	706.548 + 3.840x
	2013	702.545 + 4.237x	707.536 + 3.748x	706.636 + 3.784x	692.861 + 8.113x

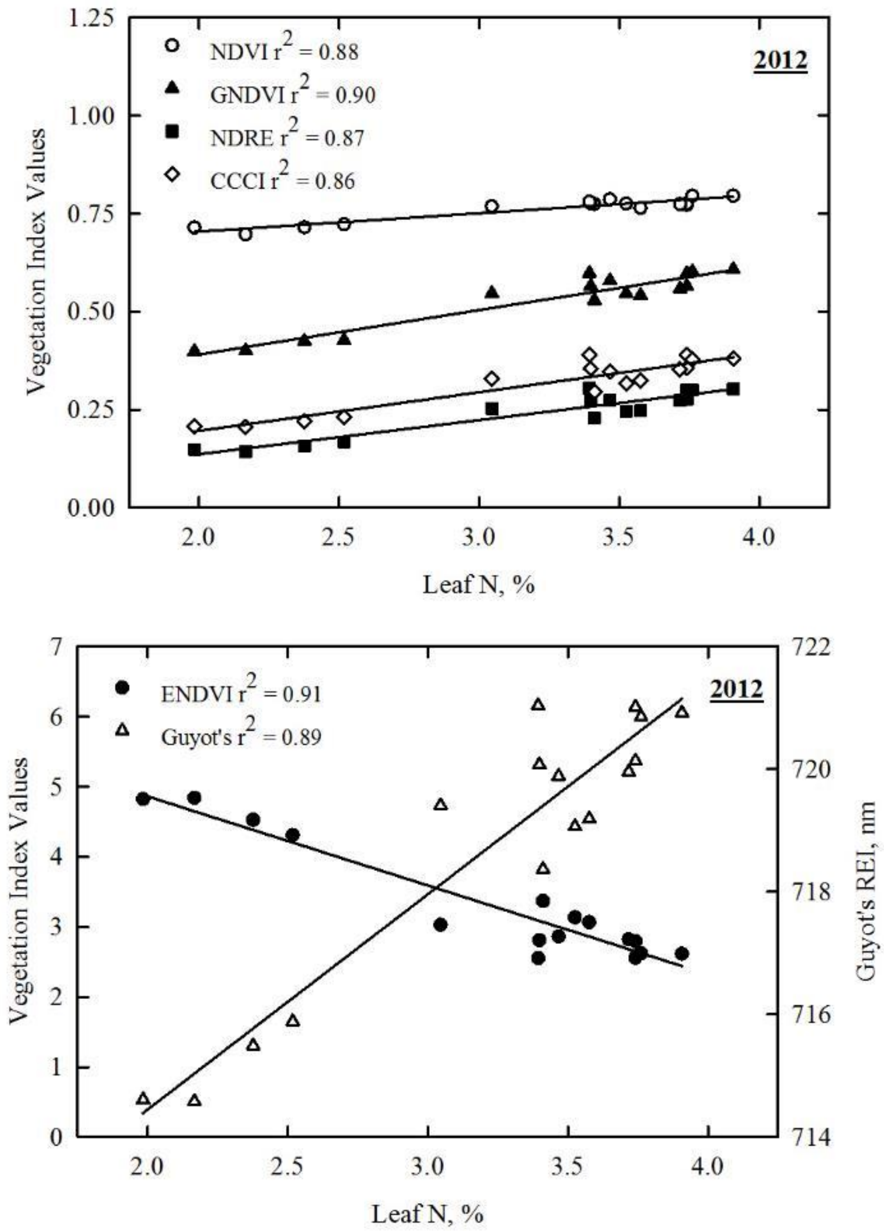


Figure 4.23 Relationship between corn leaf N concentration and SE sensor VIs for 2012 at V4 stage.

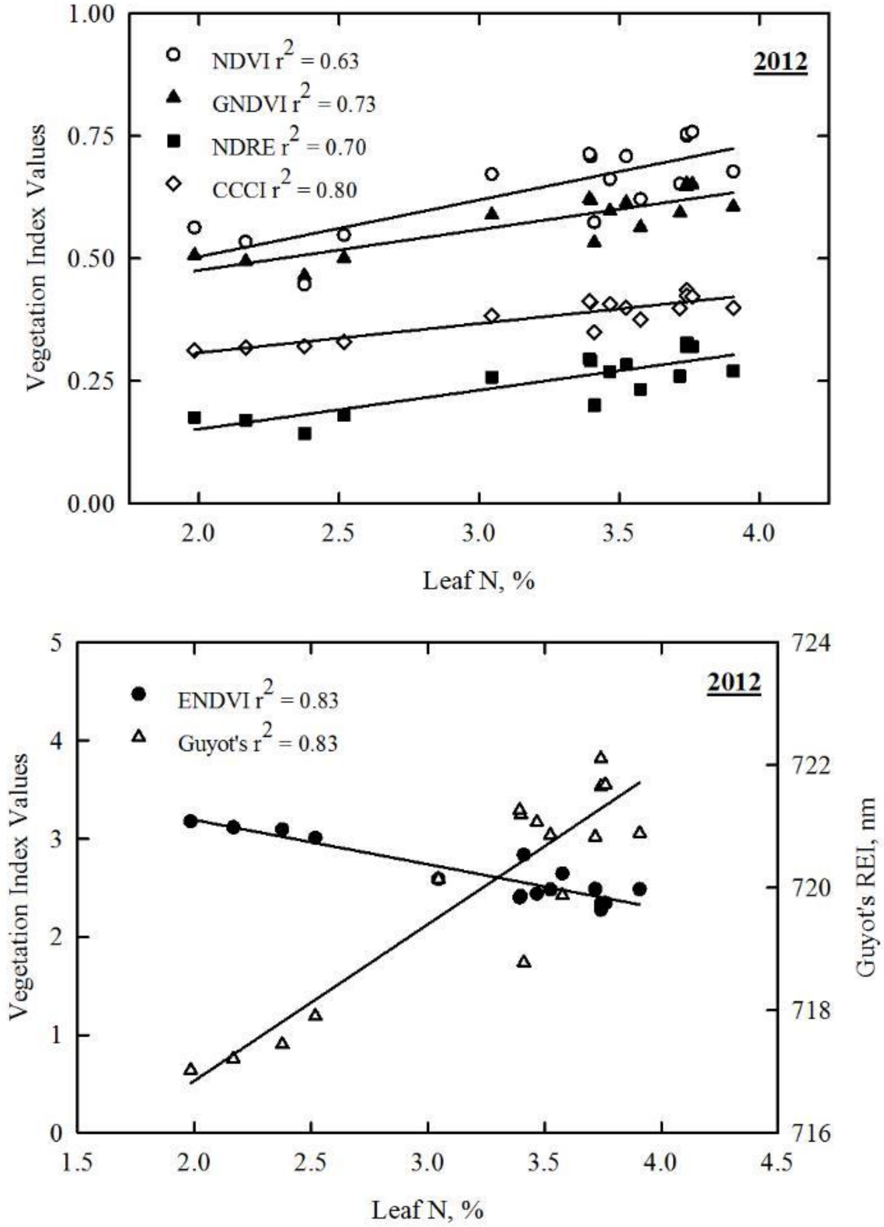


Figure 4.24 Relationship between corn leaf N concentration and YARA sensor VIs for 2012 at V4 stage.

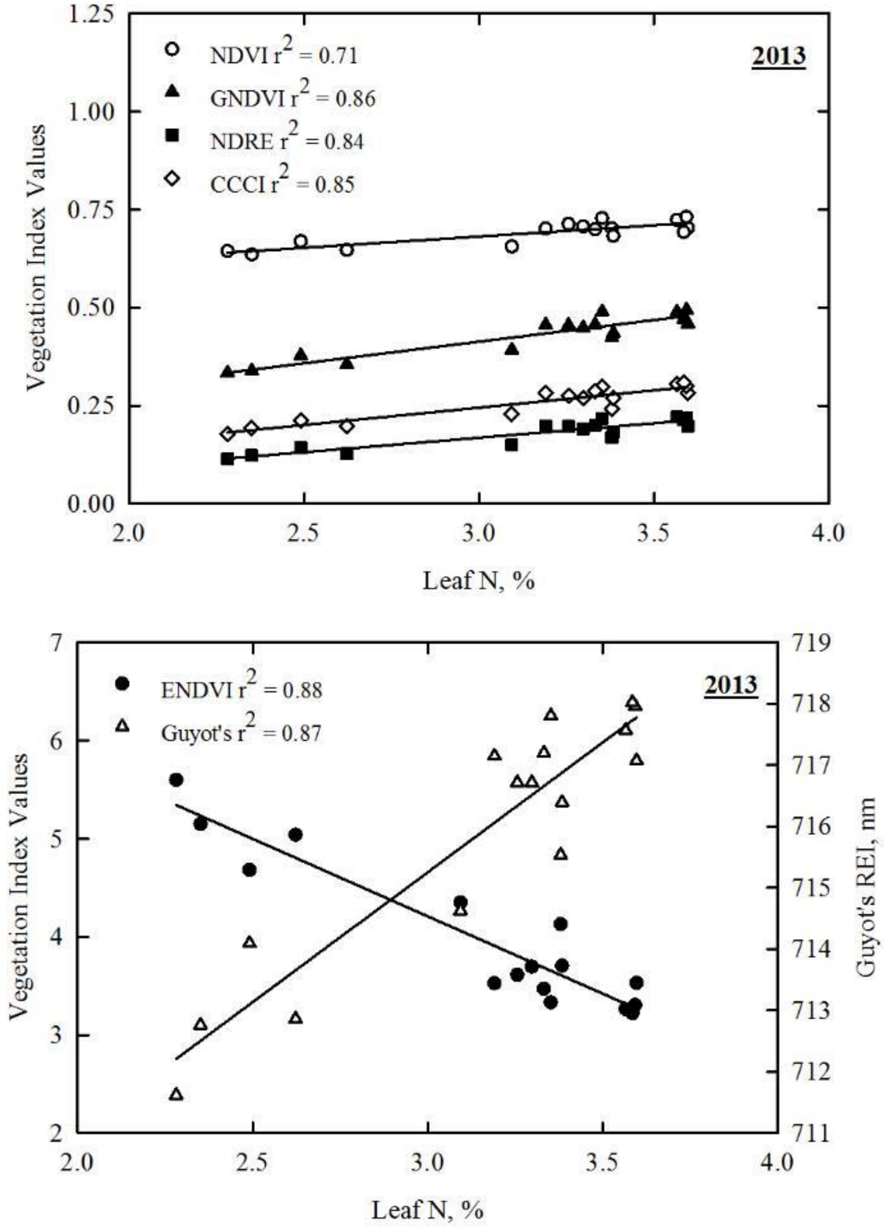
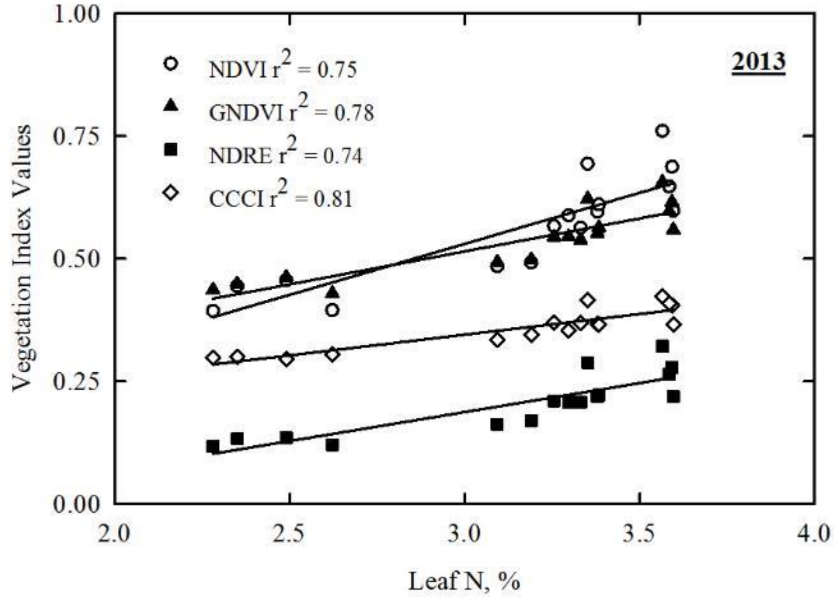


Figure 4.25 Relationship between corn leaf N concentration and SE sensor VIs for 2013 at V4 stage.



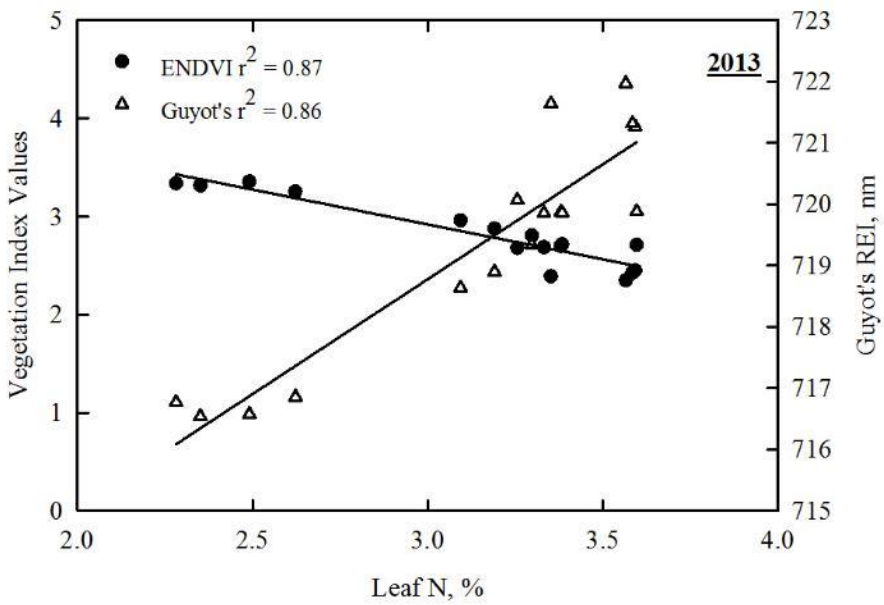


Figure 4.26 Relationship between corn leaf N concentration and YARA sensor VIs for 2013 at V4 stage.

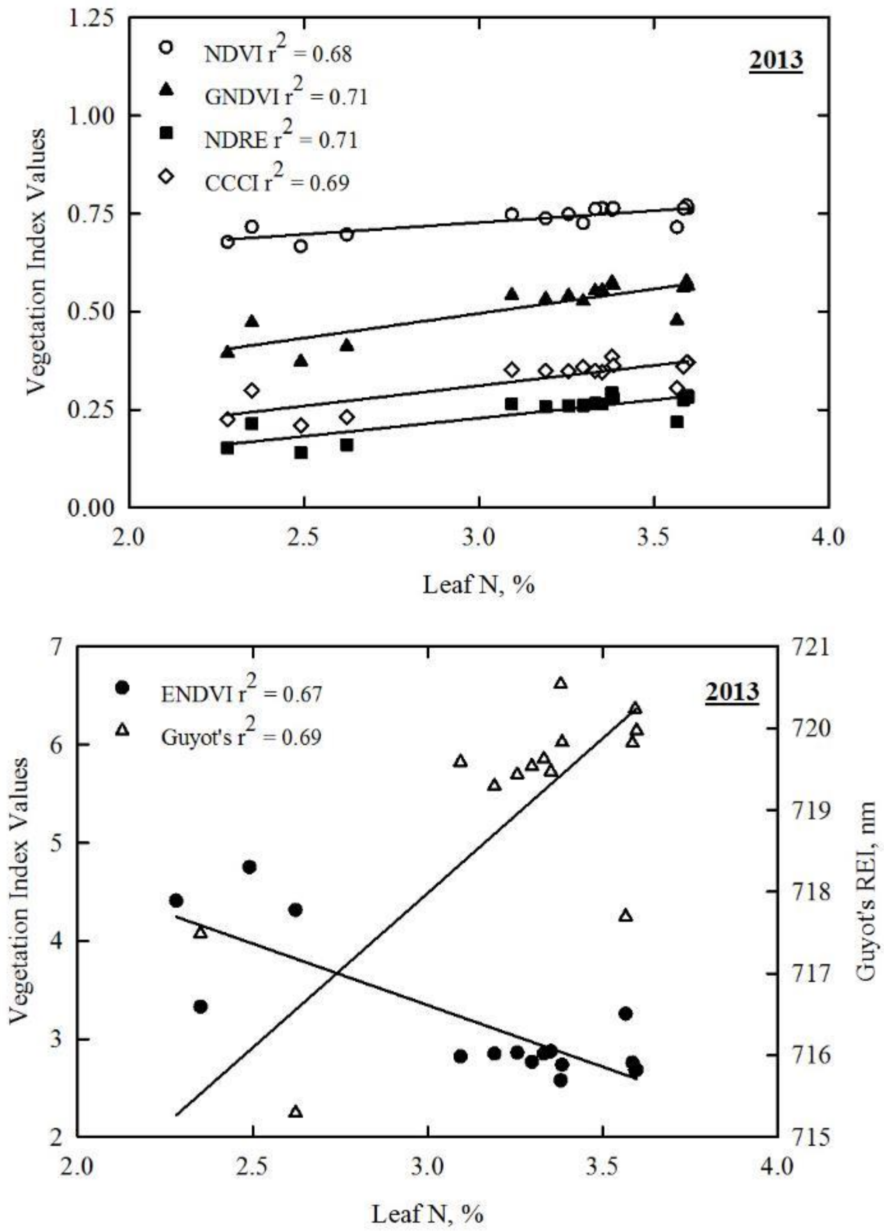
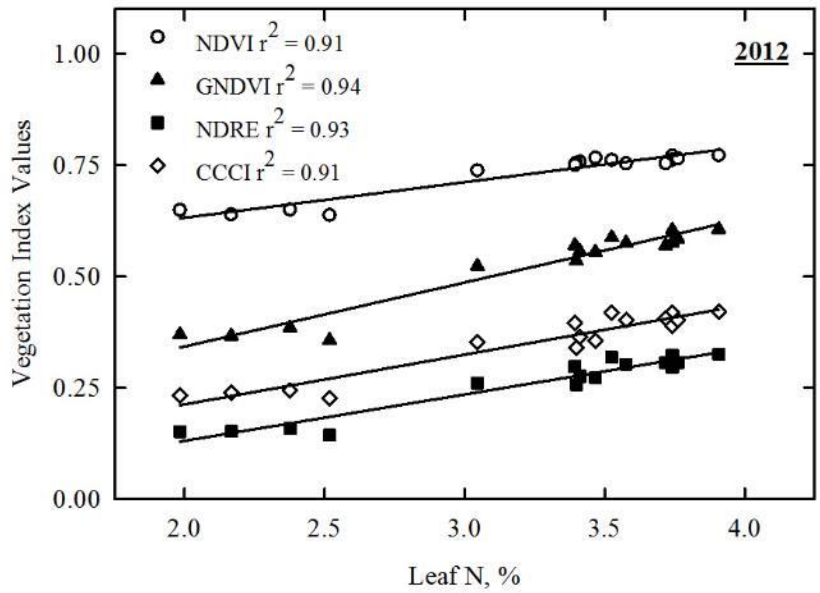


Figure 4.27 Relationship between corn leaf N concentration and SE sensor VIs for 2013 at V8 stage.



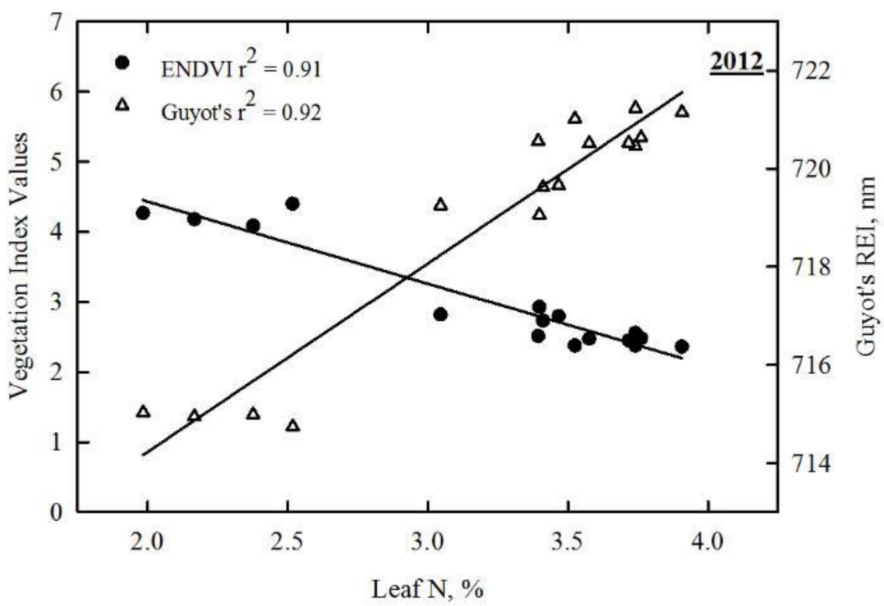


Figure 4.28 Relationship between corn leaf N concentration and SE sensor VIs for 2012 at VT stage.

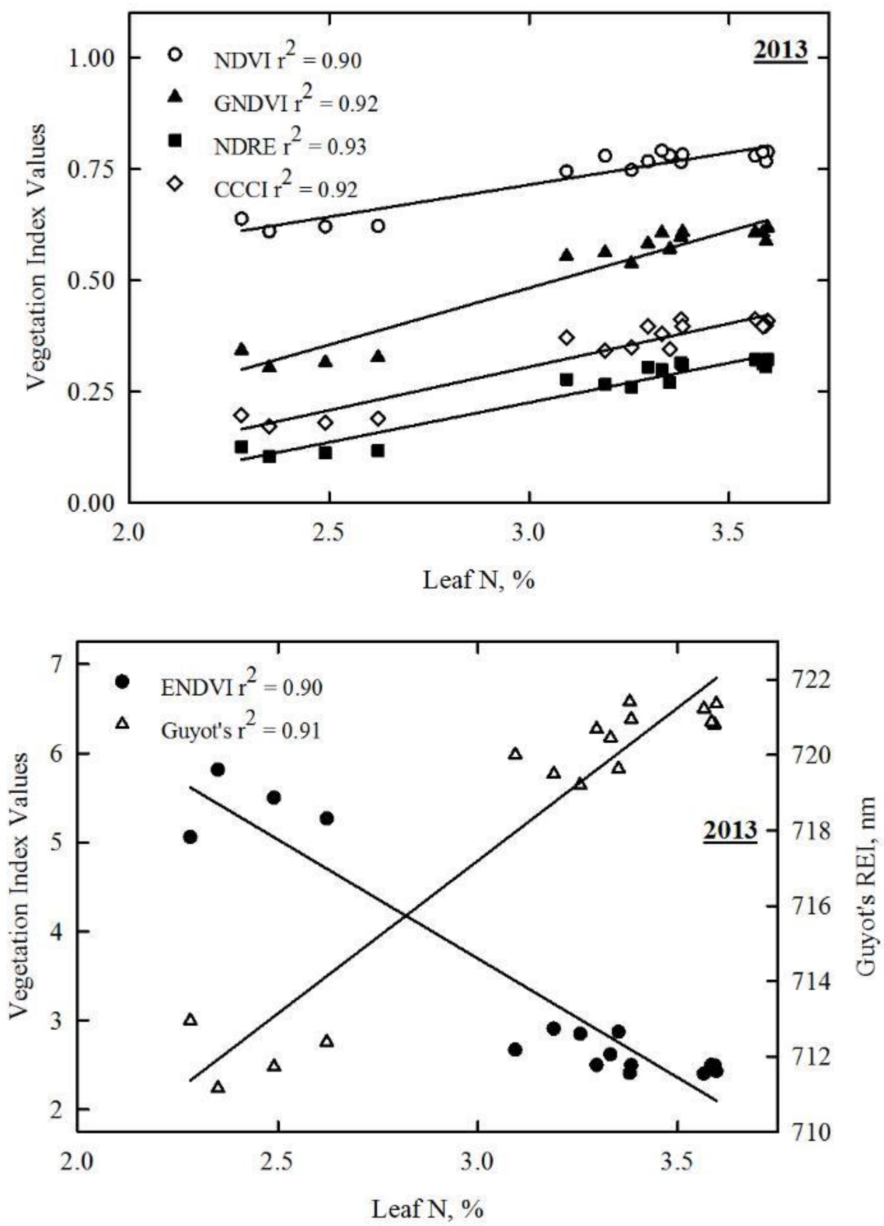


Figure 4.29 Relationship between corn leaf N concentration and SE sensor VIs for 2013 at VT stage.

Discussion on IBTM

At the leaf scale and SE sensor, the GNDVI index was appropriate for estimating leaf N status at most stages for cotton and corn. The GNDVI algorithm exploits the difference between NIR and green reflectance, and appears to strengthen as red absorption increases. However, the red-edge indices also produced strong relationships to leaf N in early corn and 2012 cotton and are suitable for leaf-level monitoring of N status.

Differences between the linear regression and IBTM results reveal the effect an outlying data sample has on GNDVI values. The NDVI and GNDVI relationship to leaf N concentration was reduced by a single data outlier, whereas biomass indices primarily accentuate ratioed, vertical shifts in NIR and red or green reflectance. Red-edge indices in cotton were not sensitive to the single outlying value due to the integration of lateral shifts in bandwidths located at or near the 720-740 nm spectral range. Compounded indices such as SCCCI and ENDVI, which include NDVI, appear unaffected by the data outlier.

Across cotton and corn samples, the ENDVI RMSE was not proportionally higher, and sometimes markedly lower, than the NDVI, GNDVI, NDRE, and SCCCI RMSE statistics, even though ENDVI values were 2-5 times greater in scale of magnitude than the NDVI, GNDVI, NDRE, and SCCCI. This appears to suggest that ENDVI IBTM error is similar to the other established indices evaluated in this study.

As stated earlier, there is a need to test the SE sensor in field trials for predicting early crop leaf N status and making fertilizer N recommendations. Furthermore, there is a need to research the ENDVI in variable rate, sensor-based, field trials to determine whether the VI improves canopy-level, early N status detection and improves yield. Applying the ENDVI to a crop database where early leaf N status was sensed in fields with systematic, high N soil variability could produce a calibration for variable rate applications. Notable comparisons to ENDVI include SCCCI and Guyot’s REI.

Objective IV - Sensor-based Variable Rate Nitrogen Demonstration

The objective was to evaluate sensor based VRN technology in producers fields using a combined VI calibrated against an N response database for cotton. In 2012, a laboratory and field demonstration of sensor based precision N fertilization was conducted at a site located near Natchez, Miss. in Adams County (31°20'45.3"N, 91°22'41.5"W). Due to the grower's decision not to grow cotton in 2013, a new site for 2013 was located 180 miles to the northeast in the Mississippi Delta. The 2013 project was conducted in Leflore County northwest of Money, Miss. and west of Hwy 49E USA (33°41'52.4'N, 90°20'35.9"W).

2012 Cotton, Natchez, Miss.

Agronomic Results

The study was conducted on a 21 hectare demonstration site. Approximately 50% of the field was Convent silt-loam (coarse-silty, mixed, superactive, nonacid, thermic, fluvaquentic Endoaquepts) soil and the remainder Morganfield silt loam (coarse-silty, mixed, active, nonacid, thermic, typic, Udifluvents). The 2012 extractable soil N concentrations (NO_3^- and NH_4^+) are noted by N treatment in APPENDIX F. The greater quantity of soil NO_3^- was likely related to rapid nitrification under warm conditions prior to sampling and any residual fertilizer sources from the previous growing season. The 2012 NO_3^- quantities were approximately 4.5 times more than the quantity of NH_4^+ (Table 4.47).

Table 4.47 Pre-fertilization soil extractable quantities of NH_4^+ and NO_3^- averaged across sub-sampling locations within N treatment designated plots.

N Treatment kg ha^{-1}	Soil Depth (cm) 0-15	15-30	30-60	Sum NH_4^+	Soil Depth (cm) 0-15	15-30	30-60	Sum NO_3^-	Total Soil N kg ha^{-1}
	kg NH_4^+ ha^{-1}				kg NO_3^- ha^{-1}				
33.6	5.94	2.90	5.91	14.75	46.20	8.72	9.23	64.15	78.90
67.2†	6.56	3.32	5.59	15.47	51.10	14.23	12.41	77.74	93.21
100.8†	5.61	2.87	5.58	14.06	47.37	7.40	10.13	64.90	78.96
134.4†	7.41	2.99	5.33	15.73	47.32	7.65	12.92	67.89	83.62
110.0 VR	5.85	3.00	5.97	14.82	51.95	8.71	11.82	72.48	87.30
86.0† VR	4.93	2.68	5.14	12.75	43.94	7.79	8.83	60.59	73.31
75.0† VR	6.24	2.69	5.68	14.61	52.31	9.44	12.12	73.87	88.48

†Missing samples are noted in Methods chapter.
VR=Variable rate N application

Using an as applied N fertilization map and ARCGIS Desktop 10.1 software, the average fertilizer N rate was derived for each treatment. Canopy reflectance was acquired using a tractor mounted YARA N-Sensor at pinhead square approximately 25 DAP. Data post-processing included removal of points outside and within 3-m of the interior of each end of the defined plot areas. Data points for fixed N rates were discarded. The SCCCI values were calculated and sorted in ascending and descending order. Maximum and minimum SCCCI values were noted and employed to set the variable rate fertilizer N treatment range (Table 4.48). Data points for variable rate treatment plots were calibrated in Microsoft Excel to a 3-year average early square cotton dataset acquired between 2009 and 2011 at the W.B. Andrews Agriculture Systems Research Farm, Mississippi State, Miss.

Table 4.48 Regression models used to calibrate cotton variable rate fertilizer N prescription.

Year	Regression Formula
2009	(-4195.2*[SCCCI]) + 1470.8
2010	(-1910.1*[SCCCI]) + 787.22
2011	(-1968.7*[SCCCI]) + 697.94
Average	(-2384.4*[SCCCI]) + 890.78

Fertilizer N rates of 33.7, 67.4, 101.1, 134.8 kg N ha^{-1} were applied 23 May 2012 at a field south of Natchez, Miss. along with variable rate treatments. The farmer applied variable rate treatment (Grower) based on soil test CEC values averaged 110 kg N ha^{-1}, SCCCI sensor based rate (MSUVR1) was 86 kg N ha^{-1}, and SCCCI sensor based adjusted for productivity zones rate (MSUVR2) was 75 kg N ha^{-1} (Table 4.49). Leaf N concentration was monitored at early square, early bloom, and peak bloom to gauge the effectiveness of the constant rate and variable rate treatments. For early square, the MSUVR1 leaf N concentration was near the 100.8 and 134.4 fixed N rate. However, the producer and Grower variable rates produced greater leaf N concentrations at early square. Leaf N critical values at early and peak bloom exceeded recommended levels (Bell et al., 2003).

Table 4.49 Treatment effects on cotton leaf N concentration throughout the growing season.

Fertilizer N treatment kg ha^{-1}	Sampling Time/Date Early Squaring 6/6/12	Early Flowering 6/20/12	Peak Flowering 7/17/12
	Leaf N, %		
33.6	4.08	4.52	3.64
67.2	4.45	4.90	4.01
100.8	4.50	5.05	3.95
134.4	4.52	5.02	4.08
Grower - 110	4.71	5.14	4.14
MSUVR1 - 86	4.49	4.99	4.02
MSUVR2 - 75	4.60	4.98	4.06
$LSD_{(0.05)}$	0.48	0.34	0.17

This indicates reduced sensor-based variable rates provided adequate available N for the cotton crop by early bloom. The lower yield with sensor based adjusted for productivity zones may lie in the fact that areas actually needing more fertilizer N (low historical yield zone) received less and areas needing less fertilizer N (high historical yield zone) received more. The hypothesis of applying greater fertilizer N rates in zones, which historically are highly productive and reducing rates when zones are classified as low productivity may be invalid for cotton. Given that early and peak bloom leaf N values of all fertilizer rates exceeded critical leaf N values even at reduced fertilizer N rates with the sensor-derived treatment, suggests the average MSUVR1 rate could have been reduced even further.

Soil N and Lint Yield

ArcGIS Desktop 10.1 Geostatistical Analyst Ordinary Kriging was employed to map the production field total soil N variability. Individual sites, located in the eastern field, with missing soil data were removed from the Krig. The range of residual soil N was 43 to 125 kg ha^{-1} in the westernmost area of the field and 72 to 179 kg ha^{-1} in the easternmost portion of the field. A sharp decline, noted in red, in residual soil N occurred in the northwestern field where elevation was highest (Figure 4.30).

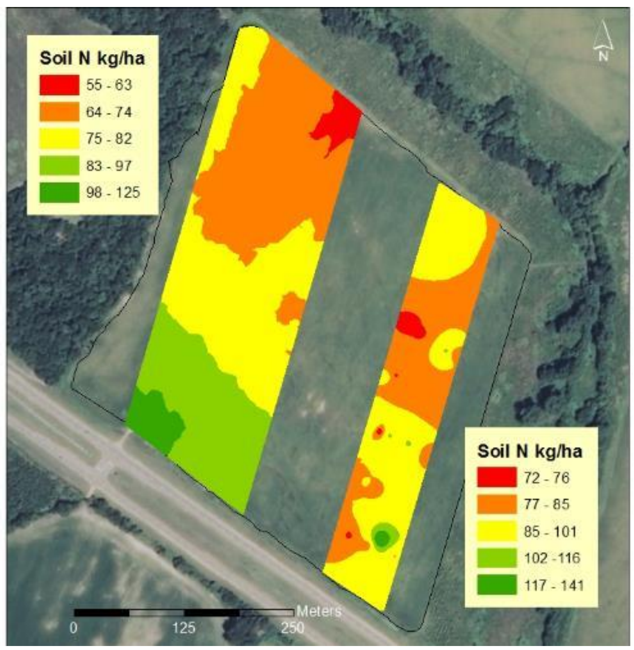


Figure 4.30 Soil N variability in 2012 near Natchez, Miss.

The average total available N (residual soil N plus fertilizer N rate) was derived for each treatment by summing the soil N at three depths and the applied fertilizer N at each sampling site, and averaging the results by N treatment. The MSUVR1 averaged 146 kg N ha^{-1} and MSUVR2 averaged 154 kg N ha^{-1}.

Factoring in the residual soil N tested prior to planting and the applied N against yield revealed that the MSUVR1 rate produced greater lint yield per unit of total N resources than did the Grower CEC adjusted VR and MSUVR2 productivity adjusted rates (Table 4.50). The MSUVR2 treatment resulted in a slightly higher lint per unit of fertilizer N applied, but produced 11% less lint yield. These results demonstrate sensor driven variable rate N fertilization using a VI with known sensitivity to chlorophyll and tissue N levels could improve N use efficiency for spatially variable alluvial soils.

Table 4.50 Fertilizer N treatment effects on lint yield south of Natchez, Miss. in 2012.

Fertilizer N treatment kg ha^{-1}	kg lint kg N^{-1}	kg lint kg^{-1} available N
33.6	27.29	8.12
67.2	15.30	6.76
100.8	10.25	5.87
134.4	6.55	4.06
Grower - 110	9.27	6.99
MSUVR1 - 86	12.65	7.45
MSUVR2 - 75	12.96	6.31
LSD$_{(0.05)}$	5.71	7.19

Not accounting for residual soil N, the lint output per kg fertilizer N applied decreased with increasing rates. The MSUVR1 treatment at resulted in the greatest yield and outperformed the Grower treatment. The MSUVR2 treatment resulted in a lower average N rate applied, but yields were reduced below that the MSUVR1 rate (Figure 4.31).

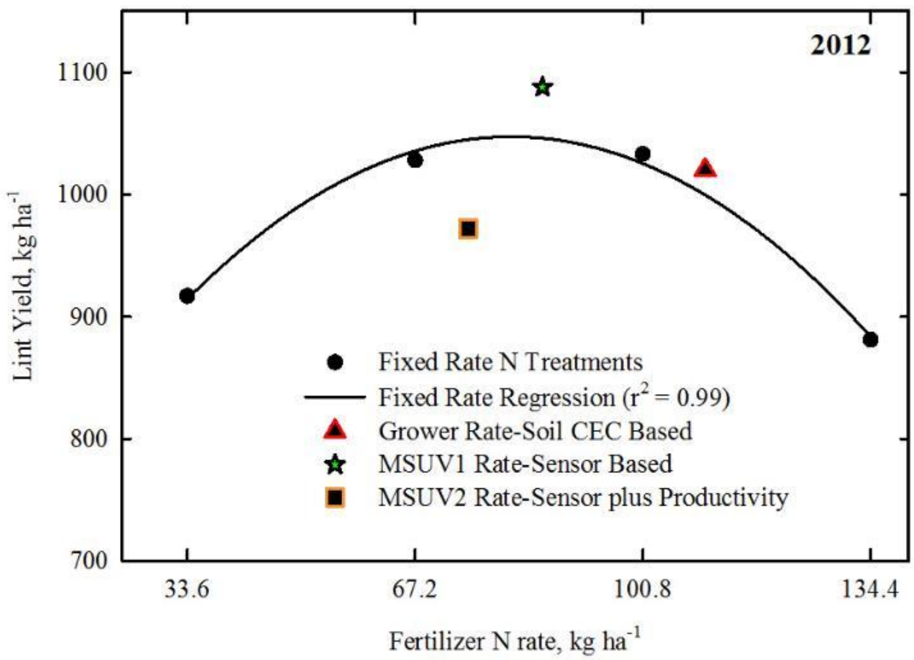


Figure 4.31 Lint yield response to fixed and variable rate fertilizer N treatments in 2012 south of Natchez, Miss [$LSD_{(0.05)}$ = 65.6].

2013 Cotton, Money, Mississippi

Agronomic Results

A study was conducted on a 49 ha demonstration site on soils classified as Dubbs-Dundee (fine-silty, mixed, active, thermic, typic, Hapludalfs and Endoaqualfs complex) (43 ha), Tensas silt clay loam (fine, smectitic, thermic, chromic, vertic, Epiaqualfs) (13 ha), and Tensas-Alligator complex (very-fine, smectitic, thermic Chromic Dystraquerts) (1 ha). The field had received a 2012 fall application of 134.4 kg K_2O ha^{-1} from muriate of potash and in the spring of 2013. Fertilizer UAN 28-0-0-5S served as the N source for all treatments. Similar to the 2012 study, soil NO_3^- concentrations near Money, Miss., were greater than soil NH_4^+ concentrations. Residual NO_3^- was greater than NH_4^+ by a factor of two across all treatments. The 2013 extractable soil N (NO_3^- and NH_4^+) across all treatment plots prior to any N fertilization are shown in Table 4.51, and detailed by individual sites in APPENDIX F.

Table 4.51 Pre-fertilization soil extractable quantities of NH_4^+ and NO_3^- averaged across sub-sampling locations within N treatment designated plots.

N Treatment kg ha^{-1}	Soil Depth (cm) 0-15	15-30	30-60	Sum NH_4^+	Soil Depth (cm) 0-15	15-30	30-60	Sum NO_3^-	Total Soil N kg ha^{-1}
	kg NH_4^+ ha^{-1}				kg NO_3^- ha^{-1}				
33.6	3.09	2.84	4.18	10.11	6.48	5.22	11.52	23.22	33.33
67.2	5.72	3.35	5.20	14.27	9.09	6.61	13.54	29.24	43.51
100.8	4.69	2.91	4.21	11.81	7.39	4.54	9.46	21.39	33.20
134.4	5.11	2.57	4.46	12.14	7.94	5.75	11.29	24.98	37.12
103.0 VR	6.21	2.91	5.07	14.19	8.75	6.20	13.46	28.41	42.60
119.0 VR	5.67	3.60	5.51	14.78	8.07	6.55	13.50	28.12	42.90

VR=Variable rate N application

The experimental site was located on the north end of the grower's field. Fertilizer N rates of 33.6, 67.2, 100.8, and 134.4 kg N ha^{-1} and two variable base rates of 33.6 kg N ha-1 were applied at 25 DAP. The remainder variable rate fertilizer N treatments calibrated with sensor and sensor plus CEC, was applied at 40 DAP. At pinhead to first week of squaring (38 DAP), canopy reflectance was measured with a tractor mounted YARA sensor. The sensor-based only rate (MSUVR1) used canopy reflectance calibrated to the SCCCI. The second sensor-based management strategy (MSUVR2) used the SCCCI and was adjusted for soil EC differences. Leaf samples were taken at five sub-plot locations within each treatment plot at early squaring, early flowering, and peak flowering to monitor treatment effects on leaf tissue N.

The MSUVR1 side dress fertilization resulted in 41 to 100 kg N ha^{-1} applied spatially for a total (including pre-application of 33.6 kg N ha^{-1}) rate applied of 75 to 133 kg N ha^{-1}. When soil EC management zones were included with the MSUVR2 treatment, adjustments to the sensor based rate were an additional 33.6 kg N ha^{-1} added when soil EC was rated high, none when rated medium, and 33.6 kg N ha^{-1} was subtracted when rated as low. The calculated MSUVR2 rate range was 36 to 121 kg N ha^{-1} for a total rate applied of 69 to 155 kg N ha^{-1}. The average fertilizer N rate was derived for each variable rate N treatment using ArcGIS software. The MSUVR1 treatment averaged 103.0 kg N ha^{-1}, while MSUVR2 averaged 119.8 kg N ha^{-1}.The cooperator's fertilizer N rate on this field was 134.4 kg N ha^{-1} and this rate was used as the maximum of the four fixed N rates.

Leaf N concentration tended to increase from early bloom to peak bloom, possibly due to an irrigation event on 12 July (Table 4.52). The Grower applied N rate resulted in greater leaf tissue N at early squaring and flowering than for MSUVR1 and MSUVR2, but at peak flowering both variable rate treatments maintained greater leaf tissue N than the Grower VR treatment. Nitrogen rate effects were most evident at peak bloom, as VR treatments maintained greater leaf N than the greatest constant rate applied at each site. Critical leaf N values were not reached at any treatment rate at early squaring and early bloom, according to Bell et al. (2003). However, at peak flowering critical N recommendations were met or exceeded on all treatments except the 33.6 kg N ha^{-1} rate.

Table 4.52 Treatment effects on leaf N concentration throughout the growing season.

Fertilizer N Treatment kg ha^{-1}	Sampling Time/Date Early Squaring 6/27/13	Early Flowering 7/15/13	Peak Flowering 7/29/13
	Leaf N, %		
33.6	5.06	3.90	3.86
67.2	4.89	4.16	4.38
100.8	5.35	4.07	4.42
134.4	5.34	4.23	4.65
MSUVR1 - 103	5.11	4.06	4.90
MSUVR2 - 119	5.13	4.12	4.93
$LSD_{(0.05)}$	0.18	0.29	0.22

Soil N and Lint Yield

Soil samples taken following cotton emergence, but prior to any N fertilization indicated a range in available N ($NH_4^+ + NO_3^-$) from 13.4 to 187.0 kg ha^{-1} for the surface 60-cm depth sampled. As previously described, Ordinary Kriging was employed to map the production field total soil N variability. Residual soil N was greatest across the northwestern tier and there was a sharp decline towards the eastern and southwestern portions of the field where elevation was approximately 1.5% lower than at the north-south irrigation road located centerfield. Poorly drained soils in the eastern portion of the field contain greater clay content than soils in the west and northwest field locations (Figure 4.32).

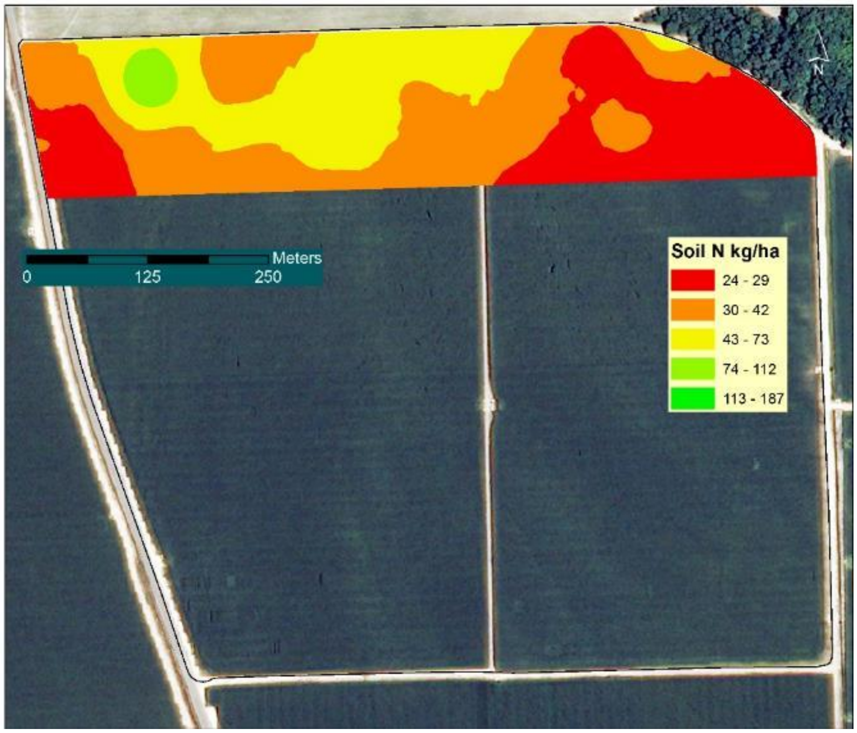


Figure 4.32 Soil N variability in 2012 near, Money, Miss.

Yield estimates based on total N rate reveal a lint yield gain for MSUVR1 and MSUVR2 treatments, although fertilizer plus soil available N differed by 17 kg ha^{-1}. Lint yields were, on average, 300 kg ha^{-1} higher in the western portion of the field than in the eastern portion (replications 1 and 4 vs. 2 and 3) when averaged over all directional plots. Both sensor-derived rates produced more lint yield than did the greatest fertilizer plus available soil N treatment. The MSUVR1 total N treatment averaged 146 kg N ha^{-1} while the MSUVR2 averaged 163 kg N ha^{-1}. Factoring the residual soil N prior to planting and the applied fertilizer N against yield revealed that the MSUVR1 treatment resulted in greater lint yield per unit of total N resources than did the grower or MSUVR2 treatments (Table 4.53). The MSUVR1 treatment produced greater lint yield with less fertilizer N inputs than the MSUVR2 treatment. This suggests that although 16 kg N ha^{-1} less fertilizer N was applied with the MSUVR1 treatment, the spatial distribution of fertilizer N may have been more accurate providing a more efficient use of the fertilizer N input. Furthermore, the MSUVR1 treatment produced 21 kg lint ha^{-1} less than the farmer rate of 134.4 kg N ha^{-1}, but with 31.4 kg ha^{-1} less fertilizer N. Thus, fertilizer N use efficiency equated to 15.13 kg lint per kg N ha^{-1} with the sensor based application, while the commonly employed 134.4 kg N ha^{-1} fixed rate resulted in 11.75 kg lint per kg N ha^{-1}.

Table 4.53 Effects of fertilizer N treatments on plot scale lint yields.

Fertilizer N treatment kg ha^{-1}	kg lint kg N^{-1}	kg lint kg available N
33.6	43.39	21.76
67.2	23.62	14.30
100.8	16.95	12.75
134.4	13.15	10.28
MSUVR1 - 103	16.94	11.95
MSUVR2 - 119	14.40	10.51
$LSD_{(0.05)}$	6.79	7.77

As found in 2012, these results demonstrate that sensor-driven variable rate fertilizer application using a vegetative index with known sensitivity to chlorophyll and tissue N levels could improve N use efficiency for spatially variable alluvial soils (Figure 4.33).

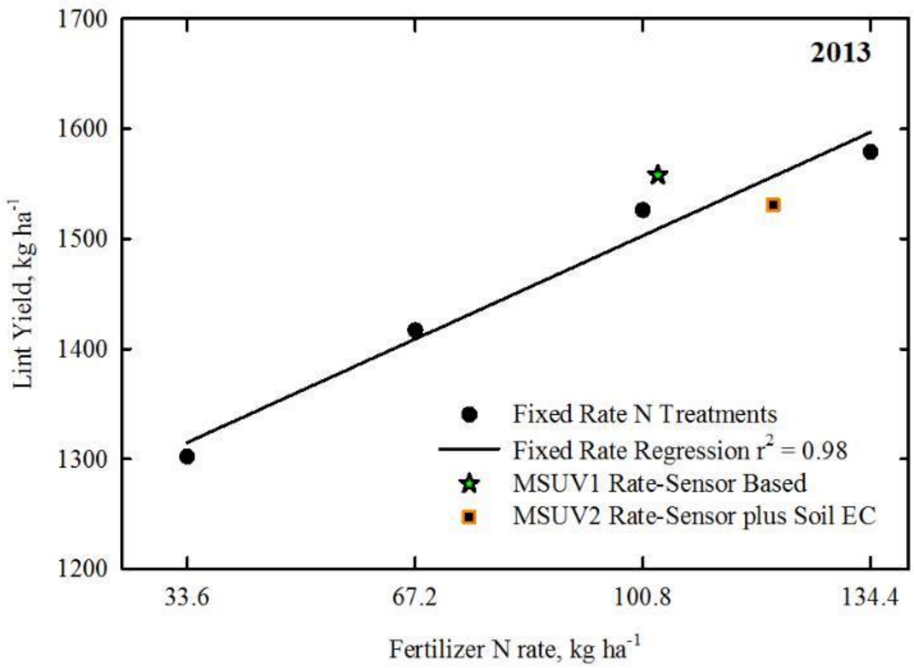


Figure 4.33 Lint yield response to fixed and variable rate fertilizer N treatments in 2013 north of Money, Miss. [$LSD_{(0.05)}$ = 113.0].

Discussion on Variable Rate Nitrogen Demonstration

Results from the 2012 and 2013 field studies suggests that sensor based VRN prescriptions can reduce fertilizer N inputs, while maintaining or increasing the potential for greater lint yield. This is especially noteworthy when extractable soil N is included as part of the analysis of N response. Early cotton showed very little leaf N and spectral variation both years with both sensors. However, at the end of both seasons, the results confirmed successful implementation of VRN when calibrated with the SCCCI algorithm.

CHAPTER V

CONCLUSIONS AND RECOMMENDATIONS

General Observations

Well-established paradigms are challenged, and often broken, when the gradual buildup of conflicting anomalies precipitates a crisis large enough to compel change (Kuhn, 1962). Sulloway (1996) found a positive correlation between crisis events and the adoption of technological solutions precipitating such events. Established theories must be broken down in order to supply a motivation for change. Sulloway proffered:

> "In the most technical sciences, the esoteric nature of the issues being considered often forestalls a successful paradigm shift long after the signs of theoretical breakdown have begun to emerge. It is one matter for scientists to recognize a growing problem. It is another matter entirely for them to come up with a successful solution."

Such may be the case with variable rate sensing (VRS) in that no emergent crisis has impelled universal, early adoption of tools showing promise of reducing fertilizer N inputs. Although cotton and corn spectral reflectance holds promise for deriving variable rate N prescriptions, established theories about VRS and an apparent lack of crisis may be reducing the number of individuals willing to risk VRS investment and implementation. The American Society of Agronomy (ASA) formed a Sensor-Based Nutrient Management Community in 2012 to promote N-status prediction-algorithm research for precision agriculture (Vetsche et al., 2014). The widespread adoption of VRS technology is problematic. Increased occurrence of harmful algal blooms and expansion of oceanic dead zones may precipitate a crisis but, to date, few changes have necessitated VRS adoption.

Producer access to reasonably priced fertilizer inputs may be a key factor suppressing early adoption (Weber and McCann, 2015). Fertilizer N prices remain closely related to energy prices, and current U.S. prices remain stable despite wider investment costs experienced by other nations. Although soil N testing impacts N treatment rate decisions, the costs of mechanization, computer technology, and re-fitting of equipment also tend to suppress interest in novel technologies aimed, ultimately, at reducing the producer's burden (Ribaudo et al, 2011). Biophysical factors may also suppress early adoption. Weather-related and soil moisture issues have been shown to confound sensing results, and high levels of residual soil N that produce low field N variability depress early N status detection results in some crops. Finally, social factors play a key role in early adoption (Weber and McCann, 2015). Corn producers receiving N strategy recommendations from a third-party consultant, instead of a fertilizer dealer, are more likely to adopt N reduction strategies especially if incentivized by federal or state programs (Weber and McCann, 2015; Ribaudo et al., 2011). However, producer age is negatively correlated with adoption strategies.

This study has identified several factors affecting the utility of VRS technology and found on-farm, early cotton N sensing problematic for several reasons. In both years, the participating producers required a minimum 33.6 kg ha^{-1} N rate in order to assure some yield in every treatment. This decision inhibited evaluation of the proposed methodology based on underlying spatial variability in available soil N alone without the confounding effects of N fertilization. The 2012 cotton crop was limited by lack of soil moisture, which reduced yield potential despite adequate N resources and high levels of residual soil N. Furthermore, in 2012 the presence of spotty flushes of seedling weeds could have influenced the crop canopy reflectance although the N Sensor utilizes off-nadir reflectance allowing greater viewing of upright plants. The 2013 cotton and corn crop plantings were delayed due to inclement weather that produced smaller plants at critical sensing periods.

Objective I

This objective determined the effects of varying N supply on cotton and corn leaf N concentration, SPAD chlorophyll, and yield. As stated previously, producers tend to apply fertilizer N at rates greater than recommended to account for N losses and ensure maximized production. This practice tends to increase residual soil N concentrations over time as shown in the on-farm cotton studies reported herein.

Relationships between fertilizer N treatments and early square cotton leaf N concentration were weak when water was a limiting factor. Similarly, weak relationships between cotton SPAD chlorophyll and N treatment occurred. Corn leaf N concentrations were highly related to fertilizer N rate and the strength is attributed to the high N spatial variability of the plot design. Corn SPAD chlorophyll response at V5 stage was markedly weaker than would be expected or might be considered useful in making fertilizer N recommendations. In cotton, SPAD chlorophyll response at early square stage was highly variable. In both cases, the use of SPAD chlorophyll data to estimate N status has limitations. Utilizing SPAD chlorophyll readings as a biophysical parameter predicting N status is likely referential but not definitive. Larger variation in soil N resources (from deficient to excess N) appears to increase the potential for SPAD to predict early N status, as was noted in corn.

Research is needed to test corn in real-world cropping where residual soil N varies non-systematically. Further research is needed to develop cost-effective sensing N tools for early leaf N status detection and for making fertilizer N recommendations in a timely manner. Bi-directional reflectance distribution function modeling should be employed to study canopy effects in N status monitoring.

Objective II

The purpose of this was to compare scale-related differences in cotton and corn using two radiometric assessment techniques employed in leaf- and canopy-level sensing. This study found no difference between the 1.5 nm and scaled 10 nm SE sensors in predicting leaf N concentration and SPAD chlorophyll. However, prediction differences were noted between the SE, leaf-level and the YARA canopy-level sensors. As is noted in previous research, red-edge shifts provide an adequate, if not superior, means of detecting leaf N status at the canopy level. Furthermore, red-edge detection at the leaf-level appears to increase N status detection in some cases. However, sensitivity equivalents reveal benefits from incorporating green wavelengths at both scales. The proposed theoretical ENDVI produced weaker relationships to biophysical parameters than the Guyot's REI, in most cases, but the novel VI was an improvement on the SCCCI in corn, where N variation was systematic.

The SE sensor should be tested in a sensor-based field trial after extensive testing and calibration to a crop dataset. Red-edge and GNDVI indices warrant testing in leaf-level sensing. This research might include a study to determine what effects leaf type, thickness, and water content have on N status assessment at two different scales.

Objective III

The purpose of this objective was to determine leaf and canopy spectral properties in the detection of cotton and corn leaf N, chlorophyll index, and yield across widely varying N availability. Cotton and corn VIs were analyzed for detecting leaf N and whole plant N (corn only) status at various growth stages at canopy and leaf levels.

The findings in Objective III support those noted in Objective II. No single VI unequivocally predicted cotton or corn N status at all growth stages although VIs possessing red-edge reflectance were significantly relevant throughout the observed sampling periods. Red-edge indices included, but were not limited to SCCCI, ENDVI, and Guyot's REI. Several red-edge type indices containing portions of reflectance near the 720-740 nm bandwidths performed adequately and ranked high in predicting leaf N status. The SE sensor VIs responded strongly to cotton leaf N status when calibrated with the GNDVI index in most cases, and this result is to be expected due to the lack of soil albedo confounding reflectance measures. Corn N status detection was best estimated by red-edge indices at all stages for both sensors, although the GNDVI algorithm also ranked well in predicting leaf N status with the SE sensor; again, as expected.

Test results from an inverse biophysical transfer modeling of leaf N to VIs suggest that VI leaf N status prediction improved through employment of red-edge bandwidths. Furthermore, red-edge indices are less sensitive to data errors between the NIR and red or green ratioed indices. The ENDVI theoretical index incorporates green wavelengths into the compound, red-edge SCCCI index, and shows promise as an alternative early N status prediction algorithm to the Guyot's REI in situations where the 670 and 700 nm bandwidths are not available. More research is required to ascertain what, if any, utility the ENDVI algorithm has in on-farm conditions where variability of multiple production factors tends to increase.

Objective IV

The purpose of this objective was to evaluate sensor based VRN technology in producer's fields using a combined VI calibrated against an N response database for cotton. Geographic Information Systems, r^2 statistics, and ANOVAs were conducted to determine what, if any, sensor-based fertilizer N recommendations can be made in early cotton that concomitantly reduce fertilizer N inputs, while maintaining or increasing lint yields to suggest spatial adjustments.

Results of these experiments suggests that VRN fertilization derived from SCCCI sensor-based calibration reduce fertilizer N inputs and can maintain or increase lint production. This relationship held true when residual soil N resources were factored in post-analysis and fertilization. This finding warrants further early N-status prediction research, which should include a variety of planophile and erectophile crops. What effect, if any, leaf architecture and position has on reflectance measures should also be considered when researching to improve early N status assessments. Furthermore, the ENDVI early leaf N prediction algorithm should be tested in cotton to ascertain what, if any, benefit can be gained by this configuration. Finally, in-field testing on corn for utility of sensor based driven scripts for VRN fertilization based on VIs such as SCCCI and ENDVI algorithms is warranted.

Further research needs to be conducted to determine if corn grown in fields where high residual soil N lacking systematic variability would still present significant relationships between dependent and independent variables. In this study, the general quadratic trend in leaf N status and SPAD readings to fertilizer N treatment persisted in cotton and corn crops, but cotton cropped in fields with high and unsystematic residual N produced weaker relationships between VIs and the biophysical parameters. However, yield response in the cotton demonstration was significant.

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APPENDIX A

WEATHER DATA FOR RESEARCH SITES

Table A.1 Weekly average temperature and rainfall for the 2012 cotton growing period near Natches, Miss.

	Temperature, °C					Rain, mm	
End Week	TMAX	TMIN	TAVE	TNORM	TDFN	1 WEEK	RDFN
18-Mar-12	28.3	13.9	21.7	15.6	6.1	0	-39
25-Mar-12	28.9	8.9	18.9	16.1	2.8	46	5
1-Apr-12	28.3	12.2	21.7	16.7	5.0	0	-40
8-Apr-12	29.4	8.9	20.0	17.2	2.8	32	-6
15-Apr-12	28.3	10.6	19.4	18.3	1.1	1	-36
22-Apr-12	n/a	n/a	n/a	18.9	n/a	7	-28
29-Apr-12	28.9	6.1	18.3	20.0	-1.7	0	-35
6-May-12	n/a	n/a	n/a	21.1	n/a	26	-8
13-May-12	31.7	11.1	21.7	22.2	-0.6	58	26
20-May-12	31.1	12.8	21.1	22.8	-1.7	0	-31
27-May-12	32.8	15.0	23.9	23.9	0.0	8	-23
4-Jun-12	32.8	13.3	24.4	24.4	0.0	25	-5
10-Jun-12	33.3	19.4	25.6	25.6	0.0	4	-25
17-Jun-12	33.3	17.2	25.0	26.1	-1.1	48	20
24-Jun-12	33.9	17.8	25.6	26.7	-1.1	01	-26
1-Jul-12	36.1	17.8	27.8	27.2	0.6	0	-26
8-Jul-12	35.6	18.9	27.8	27.2	0.6	6	-18
15-Jul-12	32.8	18.9	25.6	27.2	-1.7	120	97
22-Jul-12	33.9	21.1	27.2	27.8	-0.6	39	16
29-Jul-12	33.3	21.7	27.8	27.8	0.0	73	51
5-Aug-12	35.6	22.2	28.9	27.8	1.1	0	-21
12-Aug-12	33.9	20.0	27.2	27.8	-0.6	77	56
19-Aug-12	33.3	21.1	27.8	27.2	0.6	34	12
26-Aug-12	31.7	16.1	24.4	27.2	-2.8	24	1
2-Sep-12	32.2	21.1	26.1	26.7	-0.6	129	106
9-Sep-12	34.4	13.3	27.2	26.1	1.1	3	-21
16-Sep-12	31.1	12.2	23.3	25.0	-1.7	0	-22
23-Sep-12	30.6	9.4	21.1	23.9	-2.8	38	16
30-Sep-12	31.1	16.1	23.3	22.8	0.6	81	60
7-Oct-12	28.9	9.4	18.9	21.7	-2.8	28	7
14-Oct-12	28.9	4.4	17.2	20.0	-2.8	0	-21
21-Oct-12	27.8	5.0	17.2	18.9	-1.7	0	-22
28-Oct-12	28.9	2.8	17.8	17.8	0.0	0	-24

Source: USDA-NASS-MS Crop Progress and Condition Report

Table A.2 Weekly average temperature and rainfall for the 2012 corn growing period near Mississippi State University, Miss.

	Temperature, °C					Rain, mm	
Week Ending	TMAX	TMIN	TAVE	TNORM	TDFN	1 WEEK	RDFN
1-Apr-12	28.9	12.8	21.1	14.4	6.7	16	-20
8-Apr-12	30.0	8.9	20.0	15.0	5.0	5	-30
15-Apr-12	28.3	3.9	16.7	16.1	0.6	2	-32
22-Apr-12	29.4	7.2	17.8	17.2	0.6	88	56
29-Apr-12	29.4	7.8	20.0	18.3	1.7	6	-26
6-May-12	32.8	18.3	25.0	19.4	5.6	5	-26
13-May-12	32.8	12.8	21.7	20.6	1.1	67	38
20-May-12	31.1	15.6	22.8	21.7	1.1	8	-20
27-May-12	33.9	12.8	23.9	22.2	1.7	1	-26
4-Jun-12	35.0	15.0	24.4	23.3	1.1	18	-7
10-Jun-12	32.8	16.7	25.0	24.4	0.6	6	-18
17-Jun-12	32.2	17.2	25.0	25.0	0.0	51	28
24-Jun-12	36.1	17.8	26.7	26.1	0.6	0	-23
1-Jul-12	39.4	16.1	29.4	26.7	2.8	0	-25
8-Jul-12	37.8	21.1	29.4	27.2	2.2	76	51
15-Jul-12	33.3	20.0	25.6	27.2	-1.7	131	104
22-Jul-12	35.0	21.1	27.8	27.2	0.6	0	5
29-Jul-12	35.6	21.7	28.9	27.2	1.7	0	-24
5-Aug-12	37.8	21.7	28.9	27.2	1.7	2	-20
12-Aug-12	35.6	17.8	26.7	27.2	-0.6	70	50
19-Aug-12	33.9	18.9	25.6	26.7	-1.1	99	81
26-Aug-12	32.8	15.6	24.4	26.1	-1.7	3	-15
2-Sep-12	33.3	18.3	26.7	25.6	1.1	36	17
9-Sep-12	34.4	13.3	26.7	25.0	1.7	45	24

Source: USDA-NASS-MS Crop Progress and Condition Report

Table A.3 Gauged weekly rainfall for the 2012 corn crop grown at Ramsey Bottom near MSU, Miss.

Period	mm
4/2-4/8	5
4/9-4/15	6
4/16-4/22	75
4/23-4/29	0
4/30-5/6	4
5/7-5/13	28
5/14-5/20	44
5/21-5/27	0
5/28-6/3	19
6/4-6/10	39
6/11-6/17	3
6/18-6/24	0
6/25-7/1	10
7/2-7/8	20
7/9-7/15	84
7/16-7/22	25
7/23-7/29	0
7/30-8/5	1
8/6-8/12	12
8/13-8/29	117
8/20-8/26	3
8/27-9/2	23
9/3-9/9	20
9/10-9/16	0
9/17-9/23	88
9/24-9/30	7

Table A.4 Weekly average temperature and rainfall for the 2013 cotton growing period near Money, Miss.

	Temperature, °C					Rain, mm	
End Week	TMAX	TMIN	TAVE	TNORM	TDFN	1 WEEK	RDFN
31-Mar-13	18.9	-1.1	8.3	15.0	-6.7	21	-14
7-Apr-13	23.3	5.6	12.2	16.1	-3.9	28	-6
14-Apr-13	29.4	6.1	18.9	17.2	1.7	83	49
21-Apr-13	29.4	6.1	18.3	18.3	0.0	65	31
28-Apr-13	25.6	5.0	15.6	18.9	-3.3	20	-12
5-May-13	27.8	4.4	16.1	20.6	-4.4	89	57
12-May-13	27.2	10.0	18.9	21.1	-2.2	24	-8
19-May-13	29.4	9.4	21.1	22.2	-1.1	10	-20
26-May-13	31.1	17.8	24.4	23.3	1.1	14	-15
2-Jun-13	31.7	19.4	26.1	24.4	1.7	57	30
9-Jun-13	31.1	17.8	23.3	25.6	-2.2	11	-14
16-Jun-13	33.3	20.6	27.2	26.1	1.1	1	-24
23-Jun-13	32.8	20.6	26.1	26.7	-0.6	43	18
30-Jun-13	35.0	22.8	28.9	27.2	1.7	1	-26
7-Jul-13	32.2	16.1	25.0	27.8	-2.8	9	-20
14-Jul-13	33.3	19.4	26.7	27.8	-1.1	4	-26
21-Jul-13	34.4	21.7	27.8	27.8	0.0	0	-28
28-Jul-13	32.8	18.3	26.1	28.3	-2.2	43	18
4-Aug-13	33.9	20.6	27.8	27.8	0.0	0	-20
11-Aug-13	36.7	23.9	30.0	27.8	2.2	2	-13
18-Aug-13	35.0	17.2	25.0	27.8	-2.8	7	-5
25-Aug-13	33.3	18.9	25.6	27.2	-1.7	1	-11
1-Sep-13	36.1	21.7	28.9	26.7	2.2	0	-15
8-Sep-13	n/a	n/a	n/a	n/a	n/a	n/a	n/a
15-Sep-13	36.7	14.4	28.3	25.0	3.3	0	-20
22-Sep-13	35.6	19.4	28.3	23.9	4.4	0	-21
29-Sep-13	31.1	15.0	24.4	22.8	1.7	65	44
6-Oct-13	n/a	n/a	n/a	n/a	n/a	n/a	n/a
13-Oct-13	n/a	n/a	n/a	n/a	n/a	n/a	n/a
20-Oct-13	30.6	5.0	20.0	18.3	1.7	4	-14

Source: USDA-NASS-MS Crop Progress and Condition Report

Table A.5 Weekly average temperature and rainfall for the 2013 corn growing period near Mississippi State University, Miss.

	Temperature, °C					Rain, mm	
End Week	TMAX	TMIN	TAVE	TNORM	TDFN	1 WEEK	RDFN
31-Mar-13	23.3	-2.8	8.9	13.9	-5.0	16	-19
7-Apr-13	24.4	5.6	12.8	15.0	-2.2	26	-9
14-Apr-13	30.6	5.0	18.3	16.1	2.2	26	-8
21-Apr-13	30.0	3.9	17.8	16.7	1.1	61	28
28-Apr-13	28.3	5.0	16.7	17.8	-1.1	22	-10
5-May-13	27.8	3.9	17.2	18.9	-1.7	64	34
12-May-13	29.4	9.4	18.3	20.0	-1.7	23	-7
19-May-13	30.0	6.7	21.1	21.1	0.0	59	31
26-May-13	32.2	13.3	23.3	22.2	1.1	17	-10
2-Jun-13	32.2	16.7	25.0	23.3	1.7	25	0
9-Jun-13	32.8	16.1	23.9	24.4	-0.6	21	-4
16-Jun-13	35.0	18.9	26.7	25.0	1.7	17	-6
23-Jun-13	33.3	18.9	26.1	25.6	0.6	7	-16
30-Jun-13	35.6	18.9	28.3	26.7	1.7	10	-14
7-Jul-13	31.7	16.1	23.9	27.2	-3.3	44	19
14-Jul-13	35.0	20.0	27.2	27.2	0.0	4	-23
21-Jul-13	35.0	20.6	27.2	27.2	0.0	3	-22
28-Jul-13	34.4	20.0	26.1	27.2	-1.1	41	17
4-Aug-13	34.4	18.3	26.7	27.2	-0.6	1	-21
11-Aug-13	35.0	20.6	28.3	27.2	1.1	22	2
18-Aug-13	34.4	15.6	25.0	26.7	-1.7	24	5
25-Aug-13	33.9	20.0	26.1	26.1	0.0	3	-15
1-Sep-13	36.1	16.7	26.1	25.6	0.6	0	-19
8-Sep-13	n/a	n/a	n/a	n/a	n/a	n/a	n/a
15-Sep-13	36.1	13.3	25.6	23.9	1.7	0	-21
22-Sep-13	34.4	12.2	23.9	22.8	1.1	97	75
29-Sep-13	29.4	11.1	21.1	21.7	-0.6	19	-1
6-Oct-13	n/a	n/a	n/a	n/a	n/a	n/a	n/a
13-Oct-13	n/a	n/a	n/a	n/a	n/a	n/a	n/a
20-Oct-13	29.4	4.4	18.3	16.7	1.7	8	-11
27-Oct-13	23.3	1.1	12.2	15.6	-3.3	0	-20

Source: USDA-NASS-MS Crop Progress and Condition Report

Table A.6 Gauged weekly rainfall for the 2013 corn crop grown at Ramsey Bottom near MSU, Miss.

Period	Rain, mm
4/8 - 4/13	22
4/14 - 4/20	50
4/21 - 4/27	16
4/28 - 5/4	43
5/5 - 5/11	21
5/12 - 5/18	52
5/19 - 5/25	12
5/26 - 6/1	0
6/2 - 6/8	33
6/9 - 6/15	12
6/16 - 6/22	8
6/23 - 6/29	3
6/30 - 7/6	49
7/7 - 7/13	15
7/14 - 7/20	1
7/21 - 7/27	23
7/28 - 8/3	2
8/4 - 8/10	46
8/11 - 8/17	18
8/18 - 8/24	1
8/25 - 8/31	0
9/1 - 9/7	0

Table A.7 Weekly average temperature and rainfall for the 2013 cotton growing period near Money, Miss.

	Temperature, °C					Rain, mm	
End Week	TMAX	TMIN	TAVE	TNORM	TDFN	1 WEEK	RDFN
31-Mar-13	18.9	-1.1	8.3	15.0	-6.7	21	-14
7-Apr-13	23.3	5.6	12.2	16.1	-3.9	28	-6
14-Apr-13	29.4	6.1	18.9	17.2	1.7	83	49
21-Apr-13	29.4	6.1	18.3	18.3	0.0	65	31
28-Apr-13	25.6	5.0	15.6	18.9	-3.3	20	-12
5-May-13	27.8	4.4	16.1	20.6	-4.4	89	57
12-May-13	27.2	10.0	18.9	21.1	-2.2	24	-8
19-May-13	29.4	9.4	21.1	22.2	-1.1	10	-20
26-May-13	31.1	17.8	24.4	23.3	1.1	14	-15
2-Jun-13	31.7	19.4	26.1	24.4	1.7	57	30
9-Jun-13	31.1	17.8	23.3	25.6	-2.2	11	-14
16-Jun-13	33.3	20.6	27.2	26.1	1.1	1	-24
23-Jun-13	32.8	20.6	26.1	26.7	-0.6	43	18
30-Jun-13	35.0	22.8	28.9	27.2	1.7	1	-26
7-Jul-13	32.2	16.1	25.0	27.8	-2.8	9	-20
14-Jul-13	33.3	19.4	26.7	27.8	-1.1	4	-26
21-Jul-13	34.4	21.7	27.8	27.8	0.0	0	-28
28-Jul-13	32.8	18.3	26.1	28.3	-2.2	43	18
4-Aug-13	33.9	20.6	27.8	27.8	0.0	0	-20
11-Aug-13	36.7	23.9	30.0	27.8	2.2	2	-13
18-Aug-13	35.0	17.2	25.0	27.8	-2.8	7	-5
25-Aug-13	33.3	18.9	25.6	27.2	-1.7	1	-11
1-Sep-13	36.1	21.7	28.9	26.7	2.2	0	-15
8-Sep-13	n/a	n/a	n/a	n/a	n/a	n/a	n/a
15-Sep-13	36.7	14.4	28.3	25.0	3.3	0	-20
22-Sep-13	35.6	19.4	28.3	23.9	4.4	0	-21
29-Sep-13	31.1	15.0	24.4	22.8	1.7	65	44
6-Oct-13	n/a	n/a	n/a	n/a	n/a	n/a	n/a
13-Oct-13	n/a	n/a	n/a	n/a	n/a	n/a	n/a
20-Oct-13	30.6	5.0	20.0	18.3	1.7	4	-14

Source: USDA-NASS-MS Crop Progress and Condition Report, Moorhead, Miss.

APPENDIX B

VEGETATION INDICES REVIEWED FOR THIS STUDY

Table B.1 Vegetation indices considered for this research.

Acronym	Name	Algorithm	Reference
RVI	Ratio Vegetation Index	R_{840}/R_{650}	Pearson and Miller (1972)
GRVI	Green RVI	R_{840}/R_{550}	Tucker (1979)
NDVI	Normalized Difference VI	$(R_{840}-R_{650})/(R_{840}+R_{650})$	Rouse et al. (1973)
GNDVI	Green NDVI	$(R_{840}-R_{550})/(R_{840}+R_{550})$	Gitelson et al. (1996)
DVI	Difference VI	$R_{840}-R_{650}$	Tucker (1979)
RDVI	Renormalized Difference VI	$(R_{850}-R_{670})/(SQRT(R_{850}+R_{670}))$	Roujean and Breon (1995)
NDRE	Normalized Difference Red Edge VI	$R_{780}-R_{720}/R_{780}+R_{720}$	Barnes et al. (2000); Varco et al. (2013)
SCCCI	Canopy Chlorophyll Content Index	NDRE/NDVI	Barnes et al. (2000); Varco et al. (2013)
R695/R760	R695/R760	R_{695}/R_{760}	Carter (1994)
R695/420	R695/420	R_{695}/R_{420}	Carter (1994)
R750/R700	R750/R700	R_{750}/R_{700}	Gitelson and Merzlyak (1997)
R750/R550	R750/R550	R_{750}/R_{550}	Gitelson and Merzlyak (1997)
R780/R670	R780/R670	R_{780}/R_{670}	Pearson and Miller (1972)
R780/R700	R780/R700	R_{780}/R_{700}	Mistele and Schmidhalter (2010)
R780/R740	R780/R740	R_{780}/R_{740}	Mistele and Schmidhalter (2010)
TVI	Triangular VI	60*(R840-R550)-100*(R650-R550)	Broge and Leblanc (2000)
MTVI1	Modified TVI	1.2*[1.2*(R800-R550)-2.5*(R670-R550)]	Haboudane et al. (2004)
MTVI2	Modified TVI-2	1.2*[1.5*(R800-R550)-2.5*(R670-550)]/((2*R800+1)^2-(6*R800-*(R670)^.5)-.5)^.5	Haboudane et al. (2004)
CARI	Chlorophyll Absorption Ratio Index	$\{(\vert 670[(R_{700}-R_{550})/150]+R_{670}+R_{550}-550[(R_{700}-R_{550})/150]\}\vert)/[(a^2+1)1/2]\}*(R_{700}/R_{670})$	Kim et al. (1994)
MCARI(670,700)	Modified CARI	$[(R_{700}-R_{670})-0.2*(R_{700}-R_{550})]*(R_{700}/R_{670})$	Daugherty et al. (2000)
MCARI1(670,800)	Modified CARI-1	$1.2*[2.5(R8_{00}-R_{670})-1.3*(R8_{00}-R_{550})]$	Haboudane et al. (2004)
MCARI2(670,800)	Modified CARI-2	$\{1.2*[2.5(R8_{00}-R_{670})-1.3*(R8_{00}-R_{550})]\}/\{[(2R_{800}+1)^2-(6R_{800}-5(R_{670})^{0.5})-0.5]^{0.5}\}$	Haboudane et al. (2004);
TCARI(670,700)	Transformed CARI	$3*[(R_{700}-R_{670})-0.2*(R_{700}-R_{550})]*(R_{700}/R_{670})$	Haboudane et al. (2004)
OSAVI1(670,800)	Optimized Soil-Adjusted VI	$(1+0.16)*(R_{800}-R_{670})/(R_{800}+R_{670}+0.16)$	Rondeaux et al. (1996)
OSAVI2(705,750)	OSAVI2	$(1+0.16)*(R_{750}-R_{705})/(R_{750}+R_{705}+0.16)$	Wu et al. (2008)
MSR(670,800)	Modified Simple Ratio	$(R_{800}/R_{670})-1/(SQRT(R_{800}/R_{670}+1))$	Chen (1996)
MSR1(705,750)	Revised MSR	$(R_{750}/R_{705})-1/(SQRT(R_{750}/R_{705}+1))$	Wu et al. (2008)
TCARI/OSAVI1	Revised TCAR/OSAVI	TCARI(670,700)/OSAVI(670,800)	Wu et al. 2008
MCARI-/OSAVI1	MCARI1/OSAVI-1	MCARI(670,700)/OSAVI(670,800)	Wu et al. 2008
TCARI/OSAVI2	TCARI/OSAVI-2	TCARI(670,700)/OSAVI(705,750)	Wu et al. 2008
MCARI2/OSAVI2	MCARI-2/OSAVI-2	MCARI(705,750)/OSAVI(705,750)	Wu et al. 2008

Table B.1 (continued)

Guyot's S REI	Guyot's Red Edge Index	$700+40*(((R_{670}+R_{780})/2)-R_{700})/(R_{740}-R_{700})$	Guyot et al. (1992); Cleavers (1994)
WDRVI	Wide Dynamic Range VI	$(.18*(R_{840}-R_{680}))/(.18*(R_{840}+R_{680})$	Sakamoto et al. (2011)
NRI	Nitrogen Reflectance Index	R_{840}/R_{550}	Schleicher et al. (2003)
EVI	Enhanced VI	$2.5*((R_{840}-R_{679.8})/(R_{840}+6*R_{679.8}-7.5*R_{480.5}+1))$	Huete et al. (1997)

APPENDIX C

COTTON AND CORN SPECTRAL SIGNATURES

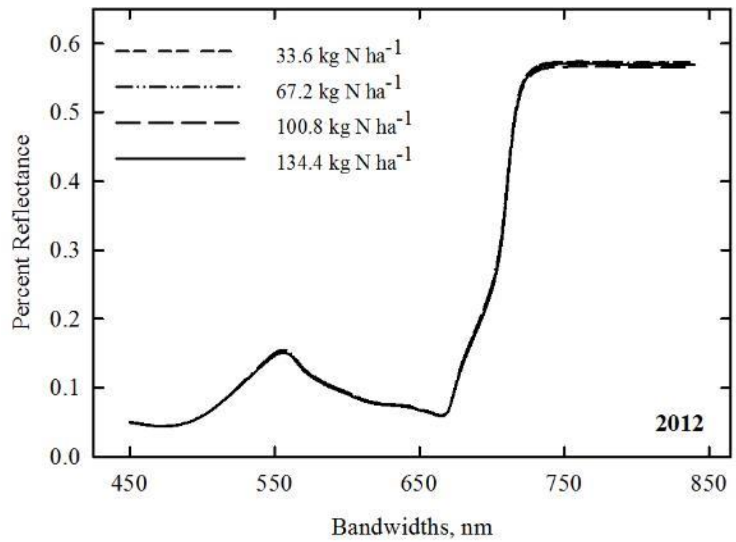

Figure C.1 SE sensor spectral signatures for 2012 early square cotton. Signatures represent average N rate.

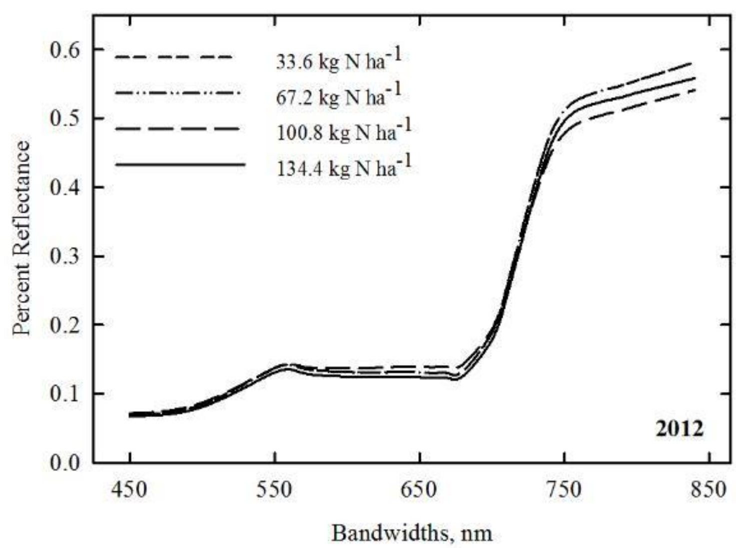

Figure C.2 YARA sensor spectral signatures at for 2012 early square cotton. Signatures represent average N rate.

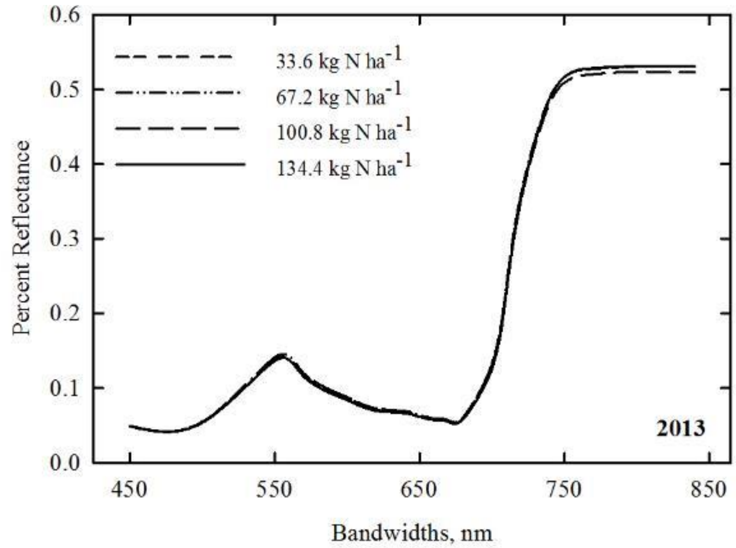

Figure C.3 SE sensor spectral signatures for 2013 early square cotton. Signatures represent average N rate.

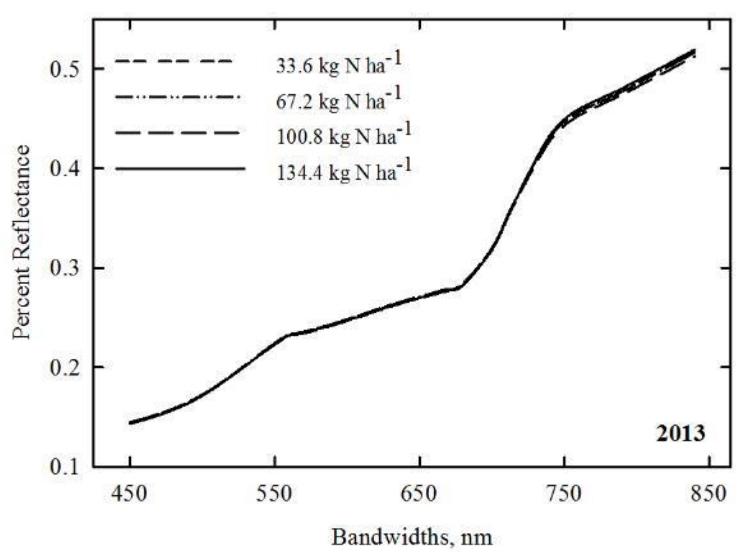

Figure C.4 YARA sensor spectral signatures for 2013 early square cotton. Signatures represent average N rate.

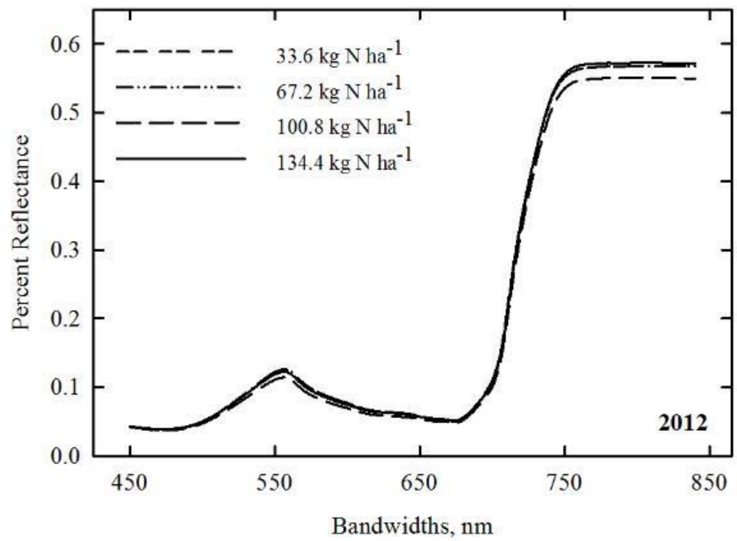

Figure C.5 SE sensor spectral signatures for 2012 early bloom cotton. Signatures represent average N rate.

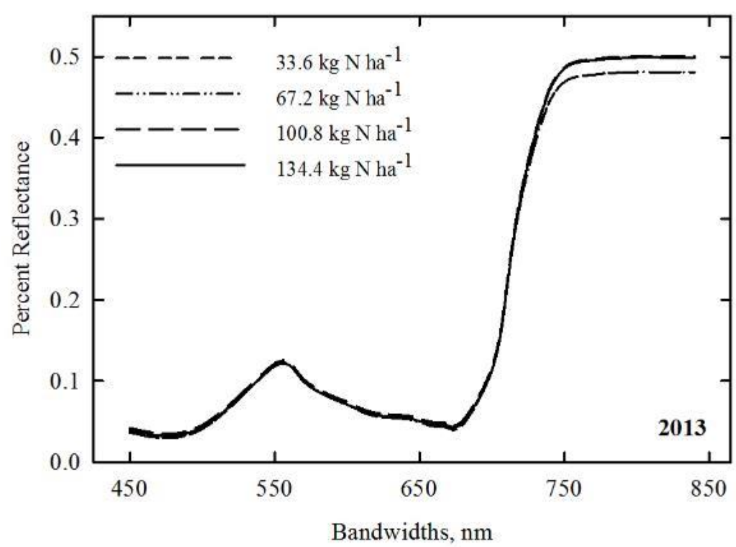

Figure C.6 SE sensor spectral signatures for 2013 early bloom cotton. Signatures represent average N rate.

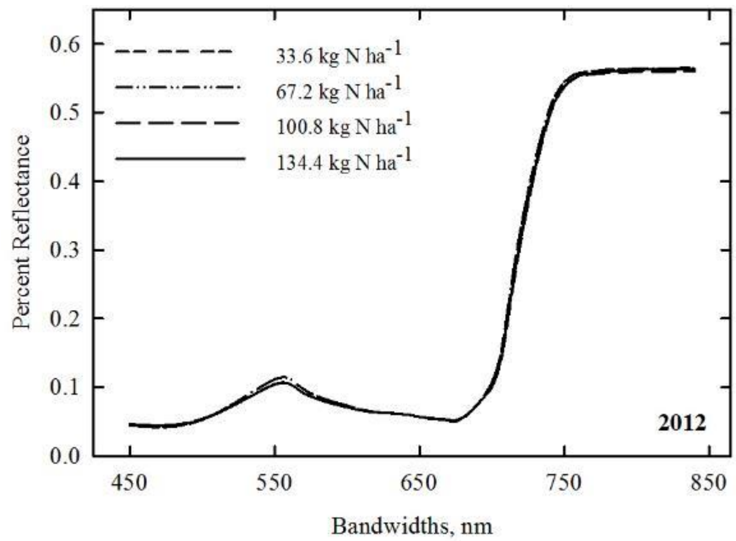

Figure C.7 SE sensor spectral signatures for 2012 peak bloom cotton. Signatures represent average N rate.

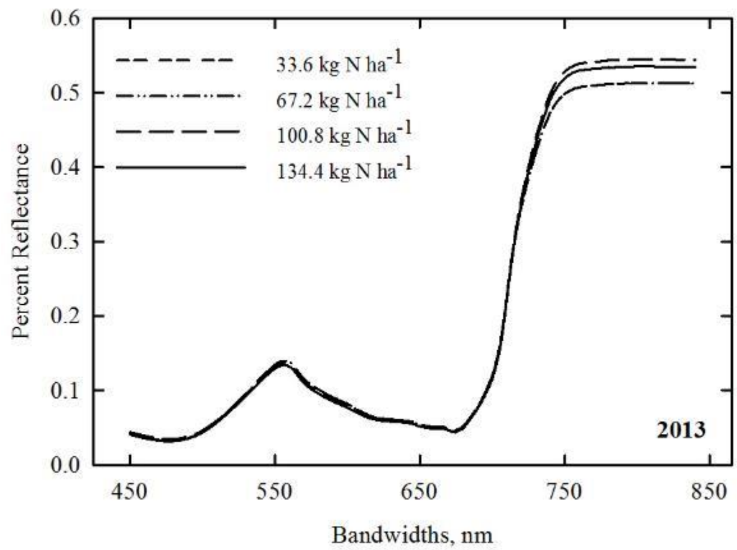

Figure C.8 SE sensor spectral signatures for 2013 peak bloom cotton. Signatures represent average N rate.

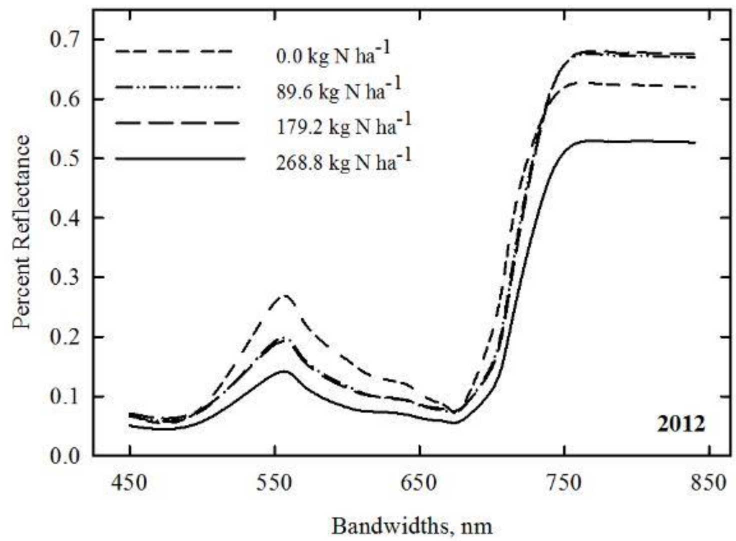

Figure C.9 SE sensor spectral signatures for 2012 V5 stage corn. Signatures represent average N rate.

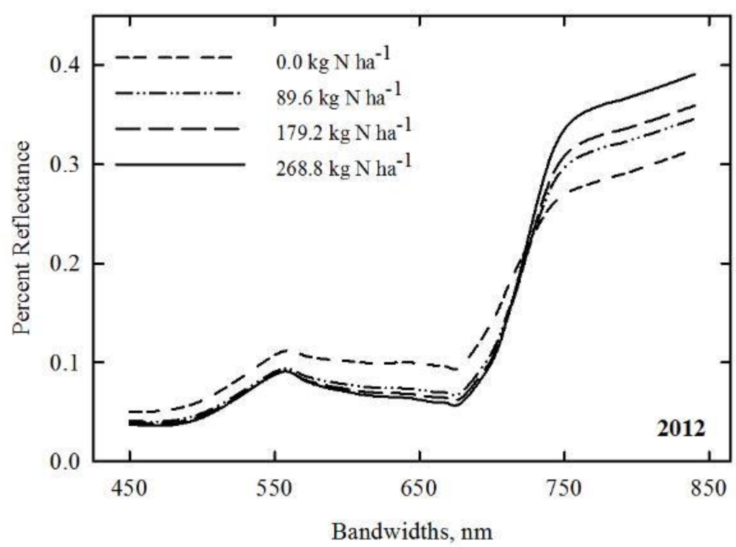

Figure C.10 YARA sensor spectral signatures for 2012 V5 stage corn. Signatures represent average N rate.

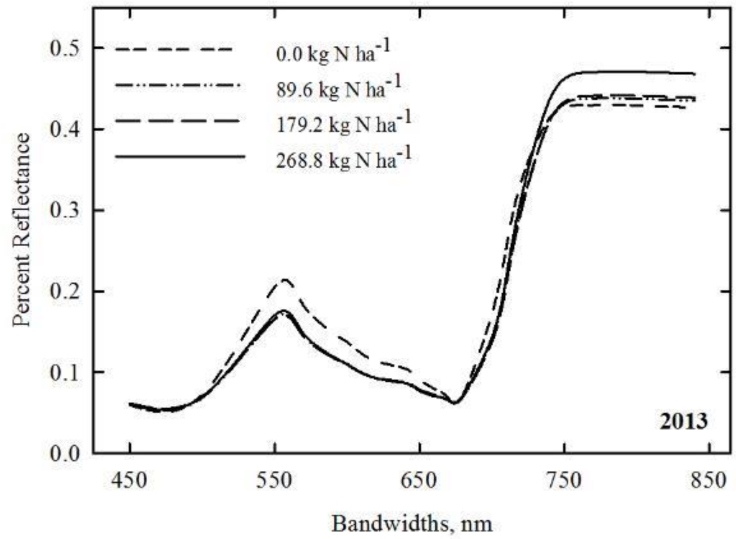

Figure C.11 SE sensor spectral signatures for 2013 V5 stage corn. Signatures represent average N rate.

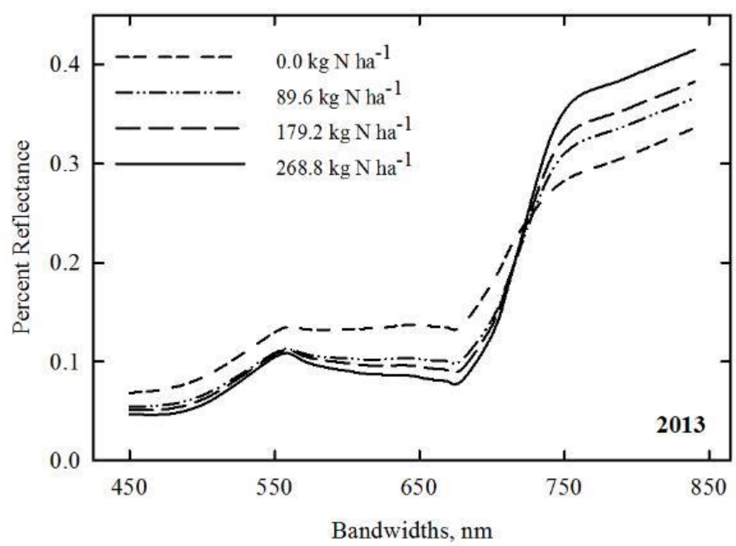

Figure C.12 YARA sensor spectral signatures for 2013 V5 stage. Signatures represent average N rate.

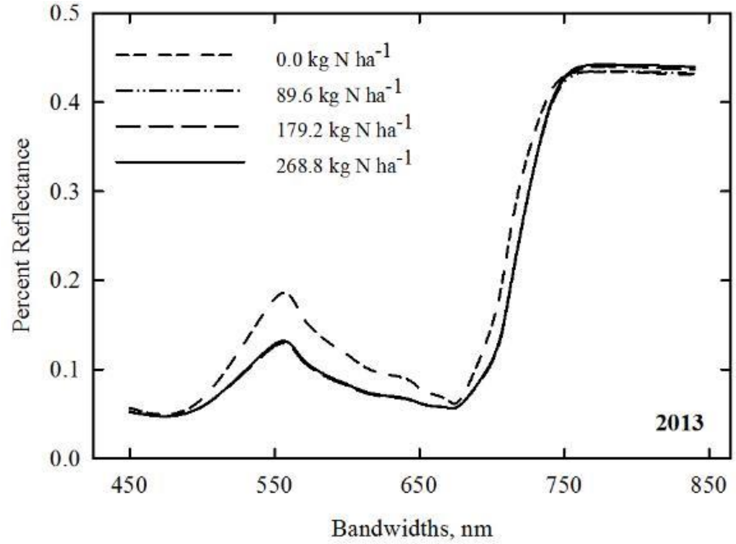

Figure C.13 SE sensor spectral signatures for 2013 V8 stage corn.

Signatures represent average N rate.

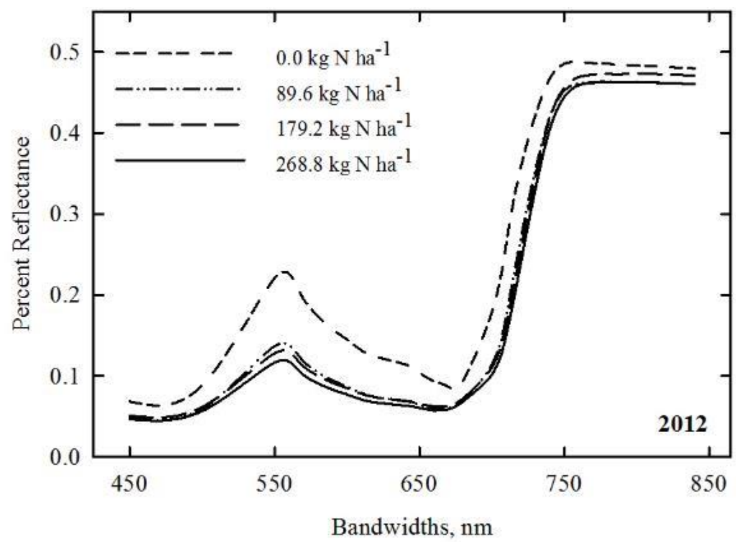

Figure C.14 SE sensor spectral signatures for 2012 VT stage corn.

Signatures represent average N rate.

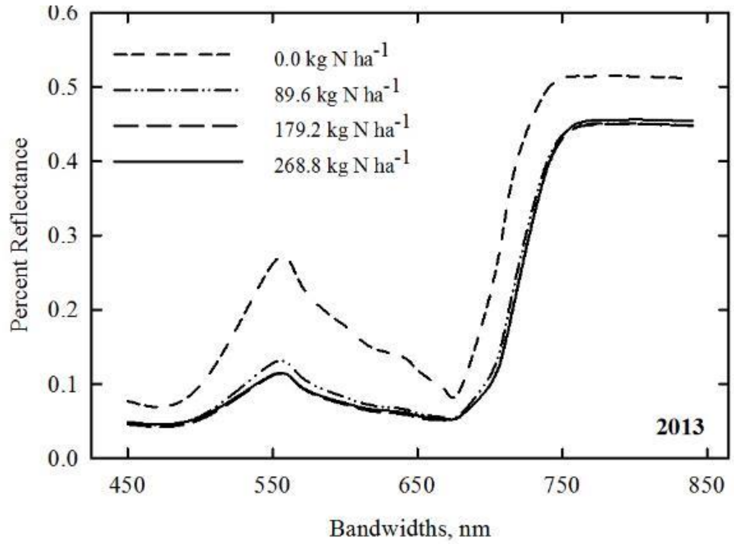

Figure C.15 SE sensor spectral signatures for 2013 VT stage corn.

Signatures represent average N rate.

APPENDIX D

COTTON AND CORN BANDWIDTH TEST ANOVAS

Table D.1 Cotton bandwidth ANOVA table for method = NDVI.

The GLM Procedure

Dependent Variable: VI

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	23	2.82846691	0.12297682	545.59	<.0001
Error	60	0.01352415	0.00022540		
Corrected Total	83	2.84199106			

R-Square	Coeff Var	Root MSE	VI Mean
0.995241	2.225032	0.015013	0.674750

Source	DF	Type III SS	Mean Square	F Value	Pr > F
YEAR	1	0.20871504	0.20871504	925.97	<.0001
NTREAT	3	0.00204177	0.00068059	3.02	0.0366
YEAR*NTREAT	3	0.00083340	0.00027780	1.23	0.3058
SENSOR	2	1.84829073	0.92414536	4099.98	<.0001
YEAR*SENSOR	2	0.45136223	0.22568111	1001.24	<.0001
NTREAT*SENSOR	6	0.00184469	0.00030745	1.36	0.2439
YEAR*NTREAT*SENSOR	6	0.00172786	0.00028798	1.28	0.2813

Table D.2 Cotton LSD multiple comparisons of nitrogen NDVI means.

T Comparison Lines for Least Squares Means of NTREAT

LS-means with the same letter are not significantly different.

		VI LSMEAN	NTREAT	LSMEAN Number
	A	0.68632042	4	4
	A			
	A	0.68589093	3	3
	A			
B	A	0.68165246	1	1
B				
B		0.67391678	2	2

NOTE: To ensure overall protection level, only probabilities associated with pre-planned comparisons should be used.

Table D.3 Cotton LSD multiple comparison results for year X sensor type NDVI means.

T Comparison Lines for Least Squares Means of YEAR*SENSOR

LS-means with the same letter are not significantly different.

	VI LSMEAN	YEAR	SENSOR	LSMEAN Number
A	0.78998931	2	1	4
A				
A	0.78986712	2	2	5
A				
A	0.78600392	1	1	1
A				
A	0.78582458	1	2	2
B	0.62509700	1	3	3
C	0.31488894	2	3	6

Table D.4 Cotton bandwidth ANOVA table for method = GNDVI.

The GLM Procedure

Dependent Variable: VI

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	23	0.49960467	0.02172194	221.88	<.0001
Error	60	0.00587400	0.00009790		
Corrected Total	83	0.50547866			

R-Square	Coeff Var	Root MSE	VI Mean
0.988379	1.783720	0.009894	0.554708

Source	DF	Type III SS	Mean Square	F Value	Pr > F
YEAR	1	0.10972954	0.10972954	1120.83	<.0001
NTREAT	3	0.00174649	0.00058216	5.95	0.0013
YEAR*NTREAT	3	0.00027306	0.00009102	0.93	0.4320
SENSOR	2	0.12103564	0.06051782	618.16	<.0001
YEAR*SENSOR	2	0.21234956	0.10617478	1084.52	<.0001
NTREAT*SENSOR	6	0.00048034	0.00008006	0.82	0.5605
YEAR*NTREAT*SENSOR	6	0.00044695	0.00007449	0.76	0.6034

Table D.5 Cotton LSD multiple comparisons of nitrogen GNDVI means.

T Comparison Lines for Least Squares Means of NTREAT

LS-means with the same letter are not significantly different.

	VI LSMEAN	NTREAT	LSMEAN Number
A	0.56503106	4	4
A			
A	0.56379468	3	3
B	0.55677149	1	1
B			
B	0.55410194	2	2

NOTE: To ensure overall protection level, only probabilities associated with pre-planned comparisons should be used.

Table D.6 Cotton LSD multiple comparison results for year X sensor type GNDVI means.

T Comparison Lines for Least Squares Means of YEAR*SENSOR

LS-means with the same letter are not significantly different.

	VI LSMEAN	YEAR	SENSOR	LSMEAN Number
A	0.61404725	1	3	3
B	0.58799558	1	2	2
B				
B	0.58728367	1	1	1
B				
B	0.58685631	2	2	5
B				
B	0.58603744	2	1	4
C	0.39732850	2	3	6

Table D.7 Cotton bandwidth ANOVA table for method = NDRE.

The GLM Procedure

Dependent Variable: VI

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	23	0.14624377	0.00635842	90.47	<.0001
Error	60	0.00421680	0.00007028		
Corrected Total	83	0.15046058			

R-Square	Coeff Var	Root MSE	VI Mean
0.971974	4.419263	0.008383	0.189700

Source	DF	Type III SS	Mean Square	F Value	Pr > F
YEAR	1	0.04717253	0.04717253	671.21	<.0001
NTREAT	3	0.00117233	0.00039078	5.56	0.0020
YEAR*NTREAT	3	0.00031297	0.00010432	1.48	0.2279
SENSOR	2	0.01173054	0.00586527	83.46	<.0001
YEAR*SENSOR	2	0.07506336	0.03753168	534.03	<.0001
NTREAT*SENSOR	6	0.00028397	0.00004733	0.67	0.6715
YEAR*NTREAT*SENSOR	6	0.00020681	0.00003447	0.49	0.8130

Table D.8 Cotton LSD multiple comparisons of nitrogen NDRE means.

T Comparison Lines for Least Squares Means of NTREAT

LS-means with the same letter are not significantly different.

	VI LSMEAN	NTREAT	LSMEAN Number
A	0.19766189	4	4
A			
A	0.19603833	3	3
B	0.18947344	1	1
B			
B	0.18930617	2	2

NOTE: To ensure overall protection level, only probabilities associated with pre-planned comparisons should be used.

Table D.9 Cotton LSD multiple comparison results for year X sensor type NDRE means.

T Comparison Lines for Least Squares Means of YEAR*SENSOR

LS-means with the same letter are not significantly different.

	VI LSMEAN	YEAR	SENSOR	LSMEAN Number
A	0.24289767	1	3	3
B	0.20452767	1	2	2
B				
B	0.20376417	1	1	1
B				
B	0.19938756	2	2	5
B				
B	0.19855875	2	1	4
C	0.10958394	2	3	6

Table D.10 Cotton bandwidth ANOVA table for method = SCCCI.

The GLM Procedure

Dependent Variable: VI

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	23	0.23889990	0.01038695	179.30	<.0001
Error	60	0.00347576	0.00005793		
Corrected Total	83	0.24237566			

R-Square	Coeff Var	Root MSE	VI Mean
0.985660	2.607291	0.007611	0.291917

Source	DF	Type III SS	Mean Square	F Value	Pr > F
YEAR	1	0.00723637	0.00723637	124.92	<.0001
NTREAT	3	0.00103723	0.00034574	5.97	0.0012
YEAR*NTREAT	3	0.00017349	0.00005783	1.00	0.3999
SENSOR	2	0.23033595	0.11516798	1988.08	<.0001
YEAR*SENSOR	2	0.00483089	0.00241544	41.70	<.0001
NTREAT*SENSOR	6	0.00008190	0.00001365	0.24	0.9632
YEAR*NTREAT*SENSOR	6	0.00011672	0.00001945	0.34	0.9153

Table D.11 Cotton LSD multiple comparisons of nitrogen SCCCI means.

T Comparison Lines for Least Squares Means of NTREAT

LS-means with the same letter are not significantly different.

		VI LSMEAN	NTREAT	LSMEAN Number
	A	0.29728861	4	4
	A			
B	A	0.29578210	3	3
B				
B	C	0.29175338	2	2
	C			
	C	0.28820429	1	1

NOTE: To ensure overall protection level, only probabilities associated with pre-planned comparisons should be used.

Table D.12 Cotton LSD multiple comparison results for year X sensor type SCCCI means.

T Comparison Lines for Least Squares Means of YEAR*SENSOR

LS-means with the same letter are not significantly different.

	VI LSMEAN	YEAR	SENSOR	LSMEAN Number
A	0.38829100	1	3	3
B	0.34786369	2	3	6
C	0.26032125	1	2	2
C				
C	0.25929225	1	1	1
D	0.25243113	2	2	5
D				
D	0.25134325	2	1	4

Table D.13 Cotton bandwidth ANOVA table for method = Guyot REI.

The GLM Procedure

Dependent Variable: VI

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	23	81.99151481	3.56484847	56.85	<.0001
Error	60	3.76214724	0.06270245		
Corrected Total	83	85.75366205			

R-Square	Coeff Var	Root MSE	VI Mean
0.956128	0.034830	0.250405	718.9346

Source	DF	Type III SS	Mean Square	F Value	Pr > F
YEAR	1	2.01603306	2.01603306	32.15	<.0001
NTREAT	3	1.40842649	0.46947550	7.49	0.0002
YEAR*NTREAT	3	0.11315268	0.03771756	0.60	0.6165
SENSOR	2	77.85278571	38.92639286	620.81	<.0001
YEAR*SENSOR	2	3.53300594	1.76650297	28.17	<.0001
NTREAT*SENSOR	6	0.14305087	0.02384181	0.38	0.8888
YEAR*NTREAT*SENSOR	6	0.09745412	0.01624235	0.26	0.9537

Table D.14 Cotton LSD multiple comparisons of nitrogen Guyot REI means.

T Comparison Lines for Least Squares Means of NTREAT

LS-means with the same letter are not significantly different.

	VI LSMEAN	NTREAT	LSMEAN Number
A	719.113	4	4
A			
A	719.050	3	3
B	718.879	2	2
B			
B	718.786	1	1

NOTE: To ensure overall protection level, only probabilities associated with pre-planned comparisons should be used.

Table D.15 Cotton LSD multiple comparison results for year X sensor type Guyot's REI means.

T Comparison Lines for Least Squares Means of YEAR*SENSOR

LS-means with the same letter are not significantly different.

	VI LSMEAN	YEAR	SENSOR	LSMEAN Number
A	720.782	1	3	3
B	719.883	2	3	6
C	718.295	1	1	1
C				
C	718.278	2	1	4
C				
C	718.263	1	2	2
C				
C	718.241	2	2	5

Table D.16 Corn bandwidth ANOVA table for method = NDVI.

The GLM Procedure

Dependent Variable: VI

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	23	0.71867139	0.03124658	22.94	<.0001
Error	72	0.09808937	0.00136235		
Corrected Total	95	0.81676076			

R-Square	Coeff Var	Root MSE	VI Mean
0.879904	5.385513	0.036910	0.685358

Source	DF	Type III SS	Mean Square	F Value	Pr > F
YEAR	1	0.13997781	0.13997781	102.75	<.0001
NTREAT	3	0.19133368	0.06377789	46.81	<.0001
YEAR*NTREAT	3	0.00076909	0.00025636	0.19	0.9041
SENSOR	2	0.31698503	0.15849252	116.34	<.0001
YEAR*SENSOR	2	0.00098010	0.00049005	0.36	0.6991
NTREAT*SENSOR	6	0.06720177	0.01120030	8.22	<.0001
YEAR*NTREAT*SENSOR	6	0.00142390	0.00023732	0.17	0.9830

Table D.17 Corn NDVI means for year.

The GLM Procedure
Least Squares Means

YEAR	VI LSMEAN	Standard Error	Pr > |t|
1	0.72354333	0.00532751	<.0001
2	0.64717313	0.00532751	<.0001

Table D.18 Corn LSD multiple comparison results for N treatment X sensor type NDVI means.

T Comparison Lines for Least Squares Means of NTREAT*SENSOR

LS-means with the same letter are not significantly different.

		VI LSMEAN	NTREAT	SENSOR	LSMEAN Number
	A	0.75012163	3	1	10
	A				
	A	0.75003325	3	2	11
	A				
	A	0.73838213	1	1	4
	A				
	A	0.73837950	1	2	5
	A				
	A	0.73473587	2	1	7
	A				
	A	0.73459713	2	2	8
	B	0.69244675	3	3	12
	B				
	B	0.68097425	0	1	1
	B				
C	B	0.68069838	0	2	2
C					
C		0.64403900	2	3	9
	D	0.60698750	1	3	6
	E	0.47290338	0	3	3

Table D.19 Corn bandwidth ANOVA table for method = GNDVI.

The GLM Procedure

Dependent Variable: VI

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	23	0.61701392	0.02682669	30.24	<.0001
Error	72	0.06387045	0.00088709		
Corrected Total	95	0.68088437			

R-Square	Coeff Var	Root MSE	VI Mean
0.906195	5.887984	0.029784	0.505845

Source	DF	Type III SS	Mean Square	F Value	Pr > F
YEAR	1	0.15933707	0.15933707	179.62	<.0001
NTREAT	3	0.30378145	0.10126048	114.15	<.0001
YEAR*NTREAT	3	0.00512558	0.00170853	1.93	0.1330
SENSOR	2	0.12524336	0.06262168	70.59	<.0001
YEAR*SENSOR	2	0.01728179	0.00864089	9.74	0.0002
NTREAT*SENSOR	6	0.00237475	0.00039579	0.45	0.8454
YEAR*NTREAT*SENSOR	6	0.00386992	0.00064499	0.73	0.6292

Table D.20 Corn LSD multiple comparisons of nitrogen GNDVI means.

T Comparison Lines for Least Squares Means of NTREAT

LS-means with the same letter are not significantly different.

	VI LSMEAN	NTREAT	LSMEAN Number
A	0.55628588	3	4
B	0.53436546	2	3
B			
B	0.52196154	1	2
C	0.41076546	0	1

NOTE: To ensure overall protection level, only probabilities associated with pre-planned comparisons should be used.

Table D.21 Corn LSD multiple comparison results for year X sensor type GNDVI means.

T Comparison Lines for Least Squares Means of YEAR*SENSOR

LS-means with the same letter are not significantly different.

	VI LSMEAN	YEAR	SENSOR	LSMEAN Number
A	0.57868913	1	3	3
B	0.53515588	2	3	6
B				
B	0.53081594	1	2	2
B				
B	0.53024919	1	1	1
C	0.43071675	2	2	5
C				
C	0.42944063	2	1	4

Table D.22 Corn bandwidth ANOVA table for method = NDRE.

The GLM Procedure

Dependent Variable: VI

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	23	0.28455181	0.01237182	16.75	<.0001
Error	72	0.05317393	0.00073853		
Corrected Total	95	0.33772574			

R-Square	Coeff Var	Root MSE	VI Mean
0.842553	12.53139	0.027176	0.216862

Source	DF	Type III SS	Mean Square	F Value	Pr > F
YEAR	1	0.08022675	0.08022675	108.63	<.0001
NTREAT	3	0.18577287	0.06192429	83.85	<.0001
YEAR*NTREAT	3	0.00582682	0.00194227	2.63	0.0566
SENSOR	2	0.00544132	0.00272066	3.68	0.0300
YEAR*SENSOR	2	0.00197032	0.00098516	1.33	0.2699
NTREAT*SENSOR	6	0.00291370	0.00048562	0.66	0.6840
YEAR*NTREAT*SENSOR	6	0.00240003	0.00040000	0.54	0.7748

Table D.23 Corn NDRE means for year.

The GLM Procedure
Least Squares Means

YEAR	VI LSMEAN	Standard Error	Pr > |t|
1	0.24577063	0.00392250	<.0001
2	0.18795383	0.00392250	<.0001

Table D.24 Corn LSD multiple comparison results for sensor type NDRE means.

T Comparison Lines for Least Squares Means of SENSOR

LS-means with the same letter are not significantly different.

	VI LSMEAN	SENSOR	LSMEAN Number
A	0.22750634	3	3
B	0.21175881	2	2
B			
B	0.21132153	1	1

Table D.25 Corn LSD multiple comparisons of nitrogen NDRE means.

T Comparison Lines for Least Squares Means of NTREAT

LS-means with the same letter are not significantly different.

		VI LSMEAN	NTREAT	LSMEAN Number
	A	0.25659371	3	4
	A			
B	A	0.24139138	2	3
B				
B		0.22653833	1	2
	C	0.14292550	0	1

Table D.26 Corn bandwidth ANOVA table for method = SCCCI.

The GLM Procedure

Dependent Variable: VI

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	23	0.39882892	0.01734039	29.52	<.0001
Error	72	0.04229570	0.00058744		
Corrected Total	95	0.44112462			

R-Square	Coeff Var	Root MSE	VI Mean
0.904118	7.691086	0.024237	0.315133

Source	DF	Type III SS	Mean Square	F Value	Pr > F
YEAR	1	0.05353705	0.05353705	91.14	<.0001
NTREAT	3	0.18350392	0.06116797	104.13	<.0001
YEAR*NTREAT	3	0.00651677	0.00217226	3.70	0.0155
SENSOR	2	0.14222364	0.07111182	121.05	<.0001
YEAR*SENSOR	2	0.00669745	0.00334872	5.70	0.0050
NTREAT*SENSOR	6	0.00376767	0.00062794	1.07	0.3892
YEAR*NTREAT*SENSOR	6	0.00258242	0.00043040	0.73	0.6249

Table D.27 Corn LSD multiple comparison results for year X sensor type SCCCI means.

T Comparison Lines for Least Squares Means of YEAR*SENSOR

LS-means with the same letter are not significantly different.

	VI LSMEAN	YEAR	SENSOR	LSMEAN Number
A	0.38136950	1	3	3
B	0.35776087	2	3	6
C	0.31762194	1	2	2
C				
C	0.31725388	1	1	1
D	0.25889581	2	2	5
D				
D	0.25789744	2	1	4

Table D.28 Corn bandwidth ANOVA table for method = Guyot's REI.

The GLM Procedure

Dependent Variable: VI

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	23	575.1473284	25.0064056	29.89	<.0001
Error	72	60.2401496	0.8366687		
Corrected Total	95	635.3874780			

R-Square	Coeff Var	Root MSE	VI Mean
0.905191	0.127374	0.914696	718.1179

Source	DF	Type III SS	Mean Square	F Value	Pr > F
YEAR	1	110.4737710	110.4737710	132.04	<.0001
NTREAT	3	316.3979148	105.4659716	126.05	<.0001
YEAR*NTREAT	3	1.7521476	0.5840492	0.70	0.5563
SENSOR	2	115.0760701	57.5380350	68.77	<.0001
YEAR*SENSOR	2	26.3537126	13.1768563	15.75	<.0001
NTREAT*SENSOR	6	4.0765745	0.6794291	0.81	0.5640
YEAR*NTREAT*SENSOR	6	1.0171379	0.1695230	0.20	0.9749

Table D.29 Corn LSD multiple comparisons of nitrogen treatment REI means.

T Comparison Lines for Least Squares Means of NTREAT

LS-means with the same letter are not significantly different.

	VI LSMEAN	NTREAT	LSMEAN Number
A	719.529	3	4
A			
A	719.231	2	3
B	718.695	1	2
C	715.016	0	1

NOTE: To ensure overall protection level, only probabilities associated with pre-planned comparisons should be used.

Table D.30 Corn LSD multiple comparison results for year X N treatment SCCCI means.

T Comparison Lines for Least Squares Means of YEAR*NTREAT

LS-means with the same letter are not significantly different.

	VI LSMEAN	YEAR	NTREAT	LSMEAN Number
A	0.38216975	1	3	4
A				
A	0.37141017	1	2	3
B	0.35024392	1	1	2
C	0.31843292	2	3	8
C				
C	0.31385617	2	2	7
C				
C	0.30325350	2	1	6
D	0.25116992	1	0	1
E	0.23052958	2	0	5

APPENDIX E

VEGETATION INDICES FITNESS BY R-SQUARED RANKING

Table E.1 Early square cotton VI R-squared ranking for 2012 SE sensor.

VI Name	Crop Stage	Number Bands	r^2 Leaf N	r^2 SPAD	r^2 Yield
R750/R700	1	2	**0.4442**	0.1089	0.0028
R695/R760	1	2	**0.4425**	0.0924	0.0056
MSR(705,750)	1	2	**0.4373**	0.4983	0.0236
OSAVI2(705,750)	1	2	0.4324	0.5510	0.0252
R780/R700	1	2	0.4266	0.1167	0.0013
NDRE	1	2	0.3734	0.5995	0.0385
SCCCI	1	4	0.2823	**0.7128**	0.0763
ENDVI	1	5	0.2650	**0.6992**	0.0798
R750/R550	1	2	0.2419	0.3662	0.1009
EVI	1	3	0.2285	0.0016	0.0916
Guyot's REI	1	4	0.2222	**0.6349**	0.1362
GRVI	1	2	0.2158	0.3637	0.1152
GNDVI	1	2	0.2137	0.3437	0.1038
RDVI	1	2	0.1467	0.0391	0.0208
TCARI/OSAVI2	1	5	0.1390	0.6199	0.1491
DVI	1	2	0.1381	0.2466	0.0041
TCARI/OSAVI1	1	4	0.1137	0.5957	0.1671
MCARI1(670,700)	1	3	0.1061	0.0705	0.0116
R780/R740	1	2	0.1016	0.5607	**0.2149**
TCARI(670,700)	1	3	0.0822	0.5825	0.1811
MCARI	1	3	0.0822	0.5825	0.1811
MCARI1/OSAVI1	1	3	0.0799	0.2328	0.0034
OSAVI1(670,800)	1	2	0.0592	0.1769	0.2033
R780/R670	1	2	0.0005	0.5628	**0.2479**
MSR(670,800)	1	2	0.0005	0.5650	**0.2500**
RVI	1	2	0.0003	0.5251	0.1792
WDRVI	1	2	0.0002	0.5226	0.1874
NDVI	1	2	0.0002	0.5213	0.1917

Highest R-squared value noted in bold.

Table E.2 Early square cotton VI R-squared ranking for 2012 YARA sensor.

VI Name	Crop Stage	Number Bands	r^2 Leaf N	r^2 SPAD	r^2 Yield
TCARI/OSAVI2	1	5	**0.7380**	0.0157	0.1191
TCARI/OSAVI1	1	4	**0.7373**	0.0009	0.2498
MCARI1/OSAVI1	1	3	**0.6380**	0.0577	0.3483
MCARI	1	3	0.4959	0.0714	0.4574
TCARI(670,700)	1	3	0.4959	0.0714	0.4574
DVI	1	2	0.4582	0.1104	0.4744
MCARI1(670,700)	1	3	0.3996	0.1349	0.4934
RDVI	1	2	0.3298	0.1476	**0.5071**
EVI	1	3	0.3004	0.1555	**0.5018**
OSAVI1(670,800)	1	2	0.2156	0.1794	0.5005
NDVI	1	2	0.1596	0.1863	0.4906
WDRVI	1	2	0.1502	0.1810	0.4803
OSAVI2(705,750)	1	2	0.1451	0.2142	0.4780
MSR(670,800)	1	2	0.1331	0.1851	0.4707
R695/R760	1	2	0.1326	0.2090	0.4694
GNDVI	1	2	0.1309	0.1908	0.4871
RVI	1	2	0.1239	0.1829	0.4661
R780/R670	1	2	0.1186	0.1848	0.4599
GRVI	1	2	0.1121	0.1887	0.4664
R780/R700	1	2	0.1020	0.2057	0.4530
R750/R700	1	2	0.1001	0.2023	0.4432
R750/R550	1	2	0.0977	0.1978	0.4500
NDRE	1	2	0.0974	0.2477	0.4991
MSR(705,750)	1	2	0.0951	0.2185	0.4487
R780/R740	1	2	0.0741	0.3016	**0.5654**
Guyot's REI	1	4	0.0172	**0.3813**	0.4965
ENDVI	1	5	0.0027	**0.3456**	0.3759
SCCCI	1	4	0.0019	**0.3413**	0.3599

Highest R-squared value noted in bold.

Table E.3 Early square cotton VI R-squared ranking for 2013 SE sensor.

VI Name	Crop Stage	Number Bands	r^2 Leaf N	r^2 SPAD	r^2 Yield
RVI	1	2	**0.4706**	0.0001	0.0373
WDRVI	1	2	**0.4664**	0.0001	0.0354
NDVI	1	2	**0.4637**	0.0000	0.0342
GRVI	1	2	0.4219	0.0654	0.0343
GNDVI	1	2	0.4174	0.0745	0.0267
MSR(670,800)	1	2	0.4155	0.0033	0.0782
R780/R670	1	2	0.3996	0.0025	0.0907
OSAVI1(670,800)	1	2	0.3440	0.0032	0.0168
R750/R550	1	2	0.3388	0.0738	0.0559
R780/R700	1	2	0.2813	0.0346	**0.1385**
R750/R700	1	2	0.2637	0.0363	**0.1416**
R695/R760	1	2	0.2533	0.0482	**0.1298**
RDVI	1	2	0.2346	0.0102	0.0004
EVI	1	3	0.1826	0.0054	0.0184
DVI	1	2	0.1713	0.0197	0.0076
Guyot's REI	1	4	0.1464	**0.0825**	0.0677
OSAVI2(705,750)	1	2	0.1442	0.0750	0.0837
MSR(705,750)	1	2	0.1390	0.0629	0.0975
R780/R740	1	2	0.1312	**0.0823**	0.0197
NDRE	1	2	0.1209	0.0747	0.0826
MCARI1(670,700)	1	3	0.0536	0.0026	0.0084
TCARI/OSAVI1	1	4	0.0504	0.0695	0.0623
TCARI/OSAVI2	1	5	0.0445	0.0810	0.0603
SCCCI	1	4	0.0430	0.0808	0.0634
ENDVI	1	5	0.0355	**0.0943**	0.0550
MCARI	1	3	0.0282	0.0650	0.0569
TCARI(670,700)	1	3	0.0282	0.0650	0.0569
MCARI1/OSAVI1	1	3	0.0001	0.0015	0.0377

Highest R-squared value noted in bold.

Table E.4 Early square cotton VI R-squared ranking for 2013 YARA sensor.

VI Name	Crop Stage	Number Bands	r^2 Leaf N	r^2 SPAD	r^2 Yield
Guyot's REI	1	4	**0.3441**	0.0155	0.0142
SCCCI	1	4	**0.1745**	**0.1913**	0.0708
ENDVI	1	5	**0.1714**	**0.2010**	0.0929
TCARI/OSAVI2	1	5	0.1464	**0.1715**	**0.3199**
TCARI/OSAVI1	1	4	0.1145	0.0576	0.2178
MCARI	1	3	0.0432	0.0013	0.1103
TCARI(670,700)	1	3	0.0432	0.0013	0.1103
R780/R740	1	2	0.0265	0.1348	**0.5972**
NDRE	1	2	0.0215	0.0380	0.0453
GNDVI	1	2	0.0188	0.0002	0.2183
GRVI	1	2	0.0141	0.0005	**0.2258**
R750/R550	1	2	0.0106	0.0497	0.0306
MSR(705,750)	1	2	0.0055	0.0977	0.0011
OSAVI2(705,750)	1	2	0.0051	0.0901	0.0018
R695/R760	1	2	0.0046	0.0991	0.0002
MCARI1/OSAVI1	1	3	0.0035	0.0145	0.0313
EVI	1	3	0.0034	0.0000	0.1434
NDVI	1	2	0.0019	0.0094	0.0969
R780/R700	1	2	0.0018	0.0730	0.0059
MCARI1(670,700)	1	3	0.0017	0.0178	0.0374
R750/R700	1	2	0.0013	0.0909	0.0008
DVI	1	2	0.0013	0.0036	0.1568
RDVI	1	2	0.0004	0.0006	0.1278
RVI	1	2	0.0003	0.0080	0.0982
R780/R670	1	2	0.0001	0.0497	0.0163
MSR(670,800)	1	2	0.0000	0.0380	0.0308
WDRVI	1	2	0.0000	0.0145	0.0727
OSAVI1(670,800)	1	2	0.0000	0.0303	0.0402

Highest R-squared value noted in bold.

Table E.5 Early bloom cotton VI R-squared ranking for 2012 SE sensor.

VI Name	Crop Stage	Number Bands	r^2 Leaf N	r^2 SPAD	r^2 Yield
R750/R550	2	2	**0.4862**	0.0005	**0.3001**
GRVI	2	2	**0.4810**	0.0032	**0.3022**
GNDVI	2	2	**0.4792**	0.0024	**0.2902**
WDRVI	2	2	0.3439	0.0350	0.2760
RVI	2	2	0.3436	0.0432	0.2873
NDVI	2	2	0.3424	0.0320	0.2702
MSR(670,800)	2	2	0.2730	0.0551	0.2891
R780/R670	2	2	0.2701	0.0561	0.2893
OSAVI1(670,800)	2	2	0.2647	0.1362	0.1983
OSAVI2(705,750)	2	2	0.2293	0.0720	0.0959
R695/R760	2	2	0.2184	0.0003	0.1877
R750/R700	2	2	0.2161	0.0001	0.2030
MSR(705,750)	2	2	0.2119	0.0735	0.1249
R780/R700	2	2	0.2046	0.0000	0.2002
MCARI1/OSAVI1	2	3	0.1635	0.0176	0.1975
R780/R740	2	2	0.0971	0.0009	0.0710
NDRE	2	2	0.0790	0.1264	0.0271
MCARI1(670,700)	2	3	0.0593	0.0741	0.0977
RDVI	2	2	0.0395	**0.1964**	0.0013
TCARI/OSAVI2	2	5	0.0170	0.1237	0.0038
SCCCI	2	4	0.0117	**0.2124**	0.0329
TCARI/OSAVI1	2	4	0.0103	0.1050	0.0028
EVI	2	3	0.0096	0.1806	0.0007
ENDVI	2	5	0.0079	**0.2181**	0.0288
MCARI	2	3	0.0019	0.1239	0.0000
TCARI(670,700)	2	3	0.0019	0.1239	0.0000
DVI	2	2	0.0017	0.0993	0.0547
Guyot's REI	2	4	0.0000	0.0251	0.0008

Highest R-squared value noted in bold.

Table E.6 Early bloom cotton VI R-squared ranking for 2013 SE sensor.

VI Name	Crop Stage	Number Bands	r^2 Leaf N	r^2 SPAD	r^2 Yield
Guyot's REI	2	4	**0.4558**	0.3596	0.2372
ENDVI	2	5	**0.3854**	0.8289	**0.6033**
SCCCI	2	4	**0.3651**	0.7996	0.5703
TCARI/OSAVI2	2	5	0.3157	**0.9159**	**0.6734**
NDRE	2	2	0.2866	0.5984	0.5798
TCARI/OSAVI1	2	4	0.2847	**0.8839**	**0.6193**
TCARI(670,700)	2	3	0.2491	**0.8522**	0.5991
MCARI	2	3	0.2491	0.8522	0.5991
MSR(705,750)	2	2	0.2154	0.4836	0.5757
OSAVI2(705,750)	2	2	0.1632	0.0843	0.0884
OSAVI1(670,800)	2	2	0.0904	0.5554	0.4335
MSR(670,800)	2	2	0.0852	0.2999	0.0597
R750/R550	2	2	0.0806	0.2467	0.4353
NDVI	2	2	0.0725	0.2051	0.0514
GRVI	2	2	0.0691	0.1353	0.2976
R780/R670	2	2	0.0665	0.2355	0.0284
R750/R700	2	2	0.0475	0.0104	0.0977
RDVI	2	2	0.0449	0.5260	0.5131
WDRVI	2	2	0.0393	0.1665	0.0161
R780/R700	2	2	0.0385	0.0010	0.0576
MCARI1(670,700)	2	3	0.0340	0.5128	0.5682
GNDVI	2	2	0.0223	0.0570	0.1580
EVI	2	3	0.0166	0.4689	0.5294
DVI	2	2	0.0134	0.4241	0.4929
R780/R740	2	2	0.0124	0.1167	0.1608
RVI	2	2	0.0105	0.0777	0.0014
MCARI1/OSAVI1	2	3	0.0052	0.3784	0.5125
R695/R760	2	2	0.0012	0.0055	0.0082

Highest R-squared value noted in bold.

Table E.7 Peak bloom cotton VI R-squared ranking for 2012 SE sensor.

VI Name	Crop Stage	Number Bands	r^2 Leaf N	r^2 SPAD	r^2 Yield
Guyot's REI	3	4	**0.8288**	0.3566	0.0924
ENDVI	3	5	**0.7746**	0.6538	0.0189
TCARI/OSAVI2	3	5	**0.7671**	0.7599	0.0017
TCARI/OSAVI1	3	4	0.7558	**0.7693**	0.0003
SCCCI	3	4	0.7541	0.6570	0.0176
R780/R740	3	2	0.7327	0.2484	0.1383
NDRE	3	2	0.6952	0.3678	0.1232
TCARI(670,700)	3	3	0.6930	**0.8440**	0.0024
MCARI	3	3	0.6930	**0.8440**	0.0024
OSAVI2(705,750)	3	2	0.6579	0.1867	0.1868
R750/R550	3	2	0.6243	0.0693	0.1358
GRVI	3	2	0.6042	0.0460	0.1390
GNDVI	3	2	0.5983	0.0458	0.1415
MSR(705,750)	3	2	0.5953	0.2188	0.2020
MCARI1(670,700)	3	3	0.1930	0.7691	0.0040
MCARI1/OSAVI1	3	3	0.1910	0.3436	0.1052
R695/R760	3	2	0.1715	0.0234	**0.4680**
R780/R700	3	2	0.1674	0.0288	**0.4695**
R750/R700	3	2	0.1674	0.0249	**0.4682**
OSAVI1(670,800)	3	2	0.0551	0.6957	0.2835
R780/R670	3	2	0.0496	0.5464	0.3591
MSR(670,800)	3	2	0.0488	0.5482	0.3754
RDVI	3	2	0.0420	0.7078	0.0767
EVI	3	3	0.0349	0.6125	0.0338
RVI	3	2	0.0295	0.5189	0.3979
WDRVI	3	2	0.0281	0.5030	0.4285
NDVI	3	2	0.0278	0.4965	0.4409
DVI	3	2	0.0157	0.4488	0.0010

Highest R-squared value noted in bold.

Table E.8 Peak bloom cotton VI R-squared ranking for 2013 SE sensor.

VI Name	Crop Stage	Number Bands	r^2 Leaf N	r^2 SPAD	r^2 Yield
Guyot's REI	3	4	**0.8040**	**0.5450**	**0.6457**
TCARI(670,700)	3	3	**0.7309**	0.2187	**0.6647**
MCARI	3	3	**0.7309**	0.2187	**0.6647**
ENDVI	3	5	0.6828	0.4434	0.5954
TCARI/OSAVI2	3	5	0.6349	0.4991	0.4015
SCCCI	3	4	0.5921	0.3419	0.5604
GRVI	3	2	0.5353	0.3758	0.3552
R750/R550	3	2	0.5069	0.3943	0.3266
R780/R740	3	2	0.5055	0.4542	0.3180
TCARI/OSAVI1	3	4	0.4260	0.4023	0.2257
NDRE	3	2	0.3617	**0.5198**	0.1842
MSR(705,750)	3	2	0.3306	**0.5210**	0.1628
R780/R700	3	2	0.2766	0.5098	0.1361
R750/R700	3	2	0.2535	0.5130	0.1181
GNDVI	3	2	0.2482	0.2914	0.1121
R780/R670	3	2	0.0798	0.0317	0.1249
OSAVI2(705,750)	3	2	0.0788	0.4226	0.0102
R695/R760	3	2	0.0643	0.2423	0.0064
RVI	3	2	0.0543	0.1865	0.0174
DVI	3	2	0.0530	0.0348	0.0454
OSAVI1(670,800)	3	2	0.0426	0.0902	0.1251
MSR(670,800)	3	2	0.0425	0.0497	0.0965
WDRVI	3	2	0.0288	0.1596	0.0006
NDVI	3	2	0.0148	0.1287	0.0012
EVI	3	3	0.0080	0.0933	0.0053
MCARI1/OSAVI1	3	3	0.0052	0.0952	0.0080
RDVI	3	2	0.0042	0.1040	0.0404
MCARI1(670,700)	3	3	0.0005	0.0022	0.0008

Highest R-squared value noted in bold.

Table E.9 Corn V5 stage VI R-squared ranking for 2012 SE sensor.

VI Name	Crop Stage	Number Bands	r^2 Leaf N	r^2 SPAD	r^2 Whole Plant N	r^2 Yield
TCARI/OSAVI2	1	5	**0.9154**	0.7747	**0.9420**	0.7720
R695/R760	1	2	**0.9128**	0.8149	**0.9309**	0.7814
ENDVI	1	5	**0.9059**	0.8236	0.9214	0.7825
GNDVI	1	2	0.8985	0.8481	0.9249	**0.7939**
TCARI/OSAVI1	1	4	0.8955	0.8050	**0.9325**	0.7764
Guyot's REI	1	4	0.8925	0.8572	0.9122	**0.7891**
NDVI	1	2	0.8819	0.7177	0.8969	0.7124
R780/R700	1	2	0.8787	0.8652	0.9075	0.7812
R750/R700	1	2	0.8779	0.8616	0.9110	0.7665
WDRVI	1	2	0.8778	0.7211	0.8950	0.7107
MCARI	1	3	0.8760	0.7973	0.9193	0.7638
TCARI(670,700)	1	3	0.8760	0.7973	0.9193	0.7638
NDRE	1	2	0.8717	0.8842	0.9008	0.7868
MSR(705,750)	1	2	0.8674	**0.8870**	0.9022	0.7732
RVI	1	2	0.8635	0.7220	0.8843	0.7011
R750/R550	1	2	0.8627	0.8845	0.8974	**0.7887**
GRVI	1	2	0.8606	0.8866	0.8943	0.7880
SCCCI	1	4	0.8602	**0.8910**	0.8890	0.7868
OSAVI2(705,750)	1	2	0.8404	0.8129	0.8648	0.7615
R780/R740	1	2	0.8312	**0.9048**	0.8650	0.7722
MSR(670,800)	1	2	0.7040	0.4899	0.7223	0.5236
R780/R670	1	2	0.6919	0.4778	0.7103	0.5107
MCARI1/OSAVI1	1	3	0.2787	0.2406	0.3159	0.2195
MCARI1(670,700)	1	3	0.1569	0.1416	0.1857	0.1207
OSAVI1(670,800)	1	2	0.0806	0.0402	0.0704	0.0930
RDVI	1	2	0.0006	0.0001	0.0000	0.0035
DVI	1	2	0.0001	0.0005	0.0002	0.0019
EVI	1	3	0.0000	0.0001	0.0007	0.0016

Highest R-squared value noted in bold.

Table E.10 Corn V5 stage VI R-squared ranking for 2012 YARA sensor.

VI Name	Crop Stage	Number Bands	r^2 Leaf N	r^2 SPAD	r^2 Whole Plant N	r^2 Yield
TCARI/OSAVI2	1	5	**0.8471**	0.7423	**0.8737**	0.7206
ENDVI	1	5	**0.8312**	**0.8347**	**0.8413**	**0.7554**
Guyot's REI	1	4	**0.8293**	**0.8360**	**0.8393**	**0.7586**
SCCCI	1	4	0.7950	**0.8439**	0.8028	**0.7338**
R780/R740	1	2	0.7677	0.8246	0.7661	0.7244
GNDVI	1	2	0.7257	0.8266	0.7187	0.7110
TCARI/OSAVI1	1	4	0.7246	0.5517	0.7748	0.5783
NDRE	1	2	0.7016	0.8290	0.6907	0.6867
GRVI	1	2	0.6804	0.8118	0.6624	0.6669
R750/R550	1	2	0.6544	0.8097	0.6339	0.6470
OSAVI2(705,750)	1	2	0.6539	0.8209	0.6394	0.6558
R695/R760	1	2	0.6515	0.7964	0.6380	0.6585
MSR(705,750)	1	2	0.6437	0.8111	0.6242	0.6415
NDVI	1	2	0.6280	0.7794	0.6102	0.6427
RDVI	1	2	0.5921	0.7816	0.5744	0.6168
R780/R700	1	2	0.5911	0.7725	0.5612	0.5927
OSAVI1(670,800)	1	2	0.5900	0.7743	0.5709	0.6148
R750/R700	1	2	0.5860	0.7720	0.5560	0.5893
EVI	1	3	0.5857	0.7773	0.5679	0.6090
DVI	1	2	0.5812	0.7855	0.5661	0.6044
WDRVI	1	2	0.5790	0.7547	0.5522	0.5952
RVI	1	2	0.5584	0.7359	0.5213	0.5608
MSR(670,800)	1	2	0.5560	0.7387	0.5222	0.5672
MCARI1(670,700)	1	3	0.5268	0.7520	0.5066	0.5639
R780/R670	1	2	0.5250	0.7106	0.4845	0.5298
MCARI1/OSAVI1	1	3	0.3127	0.5858	0.2944	0.3767
MCARI	1	3	0.0470	0.1840	0.0310	0.0942
TCARI(670,700)	1	3	0.0470	0.1840	0.0310	0.0942

Highest R-squared value noted in bold.

Table E.11 Corn V5 stage VI R-squared ranking for 2013 SE sensor.

VI Name	Crop Stage	Number Bands	r^2 Leaf N	r^2 SPAD	r^2 Whole Plant N	r^2 Yield
ENDVI	1	5	**0.8836**	0.9335	**0.5889**	**0.6207**
Guyot's REI	1	4	**0.8668**	0.9321	0.5639	0.6092
OSAVI2(705,750)	1	2	**0.8601**	0.9384	**0.5763**	**0.6318**
GNDVI	1	2	0.8596	0.9272	**0.5767**	**0.6150**
SCCCI	1	4	0.8531	**0.9582**	0.5527	0.6089
NDRE	1	2	0.8421	**0.9438**	0.5480	0.6080
R780/R740	1	2	0.8292	**0.9425**	0.5458	0.6094
GRVI	1	2	0.8288	0.9265	0.5417	0.5937
R695/R760	1	2	0.8274	0.8882	0.5380	0.5937
MSR(705,750)	1	2	0.8246	0.9317	0.5230	0.5871
R750/R550	1	2	0.8242	0.9241	0.5350	0.5875
TCARI/OSAVI2	1	5	0.8175	0.8694	0.5042	0.5464
R780/R700	1	2	0.7960	0.8909	0.4978	0.5661
R750/R700	1	2	0.7941	0.8899	0.4956	0.5639
TCARI/OSAVI1	1	4	0.7785	0.8642	0.4504	0.5065
MCARI	1	3	0.7219	0.8207	0.3930	0.4512
TCARI(670,700)	1	3	0.7219	0.8207	0.3930	0.4512
NDVI	1	2	0.7098	0.7392	0.4969	0.5397
WDRVI	1	2	0.6951	0.7328	0.4806	0.5264
RVI	1	2	0.6713	0.7212	0.4560	0.5046
OSAVI1(670,800)	1	2	0.4717	0.4175	0.4635	0.4694
EVI	1	3	0.3723	0.2443	0.4207	0.3836
DVI	1	2	0.3498	0.2936	0.3891	0.3587
RDVI	1	2	0.3497	0.2876	0.3984	0.3759
MSR(670,800)	1	2	0.3485	0.3542	0.2638	0.3038
R780/R670	1	2	0.3437	0.3501	0.2600	0.2982
MCARI1/OSAVI1	1	3	0.1530	0.2248	0.0349	0.0630
MCARI1(670,700)	1	3	0.0066	0.0295	0.0104	0.0024

Highest R-squared value noted in bold.

Table E.12 Corn V5 stage VI R-squared ranking for 2013 YARA sensor.

VI Name	Crop Stage	Number Bands	r^2 Leaf N	r^2 SPAD	r^2 Whole Plant N	r^2 Yield
ENDVI	1	5	**0.8737**	**0.8906**	**0.6656**	0.6745
Guyot's REI	1	4	**0.8586**	**0.8816**	**0.6700**	0.6634
TCARI/OSAVI2	1	5	**0.8342**	0.8536	0.6088	0.5164
SCCCI	1	4	0.8102	**0.8806**	0.6034	0.6283
R695/R760	1	2	0.7927	0.8017	0.6341	**0.7172**
GNDVI	1	2	0.7808	0.8117	**0.6344**	0.6872
NDVI	1	2	0.7521	0.7689	0.6168	**0.7019**
NDRE	1	2	0.7408	0.8040	0.5822	0.6502
OSAVI2(705,750)	1	2	0.7272	0.7760	0.5792	0.6610
OSAVI1(670,800)	1	2	0.7226	0.7375	0.5950	**0.6957**
R780/R740	1	2	0.7123	0.8031	0.5606	0.6024
RDVI	1	2	0.6987	0.7120	0.5833	0.6839
MSR(705,750)	1	2	0.6840	0.7621	0.5403	0.6193
GRVI	1	2	0.6753	0.7569	0.5439	0.6072
EVI	1	3	0.6746	0.6982	0.5644	0.6657
R750/R550	1	2	0.6700	0.7536	0.5353	0.6071
MCARI1(670,700)	1	3	0.6593	0.6720	0.5527	0.6695
DVI	1	2	0.6551	0.6711	0.5551	0.6555
WDRVI	1	2	0.6548	0.7078	0.5430	0.6377
MSR(670,800)	1	2	0.6026	0.6748	0.5028	0.5956
R750/R700	1	2	0.5967	0.6923	0.4813	0.5654
R780/R700	1	2	0.5965	0.6931	0.4812	0.5641
RVI	1	2	0.5479	0.6407	0.4588	0.5414
MCARI1/OSAVI1	1	3	0.5455	0.5014	0.4654	0.6337
R780/R670	1	2	0.5210	0.6147	0.4406	0.5280
TCARI/OSAVI1	1	4	0.4906	0.5720	0.3008	0.1767
MCARI	1	3	0.4104	0.3656	0.4113	0.5841
TCARI(670,700)	1	3	0.4104	0.3656	0.4113	0.5841

Highest R-squared value noted in bold.

Table E.13 Corn V8 stage VI R-squared ranking for 2013 SE sensor.

VI Name	Crop Stage	Number Bands	r^2 Leaf N	r^2 SPAD	r^2 Yield
OSAVI2(705,750)	2	2	**0.7268**	**0.7392**	0.5268
Guyot's REI	2	4	**0.7201**	0.7214	0.5108
SCCCI	2	4	**0.7183**	0.7143	0.5357
NDRE	2	2	0.7168	0.7237	0.5324
MSR(705,750)	2	2	0.7154	**0.7300**	0.5171
TCARI/OSAVI1	2	4	0.7136	0.7181	0.4795
TCARI(670,700)	2	3	0.7113	0.7127	0.4733
MCARI	2	3	0.7113	0.7127	0.4733
GNDVI	2	2	0.7099	**0.7285**	0.5107
R780/R740	2	2	0.7084	0.6996	**0.5433**
R695/R760	2	2	0.7076	0.7276	0.4885
TCARI/OSAVI2	2	5	0.7029	0.7126	0.4825
GRVI	2	2	0.6999	0.7195	0.5149
R750/R550	2	2	0.6993	0.7209	0.5130
R780/R700	2	2	0.6981	0.7188	0.4912
ENDVI	2	5	0.6968	0.7021	0.5129
R750/R700	2	2	0.6967	0.7192	0.4887
NDVI	2	2	0.6387	0.6830	0.4537
WDRVI	2	2	0.6317	0.6789	0.4526
RVI	2	2	0.6162	0.6684	0.4495
OSAVI1(670,800)	2	2	0.6086	0.6525	0.4932
DVI	2	2	0.5962	0.5933	**0.5517**
RDVI	2	2	0.5953	0.6177	**0.5357**
MCARI1/OSAVI1	2	3	0.5941	0.6213	0.3698
EVI	2	3	0.5911	0.5727	0.5140
MSR(670,800)	2	2	0.5454	0.6094	0.4074
R780/R670	2	2	0.5401	0.6069	0.4080
MCARI1(670,700)	2	3	0.4324	0.4458	0.2207

Highest R-squared value noted in bold.

Table E.14 Corn VT stage VI R-squared ranking for 2012 SE sensor.

VI Name	Crop Stage	Number Bands	r^2 Leaf N	r^2 SPAD	r^2 Grain N	r^2 Yield
SCCCI	3	4	**0.9757**	**0.9890**	**0.3681**	**0.9201**
R780/R740	3	2	**0.9698**	**0.9892**	**0.3968**	**0.9309**
NDRE	3	2	**0.9679**	**0.9839**	**0.3391**	**0.9092**
MSR(705,750)	3	2	0.9604	0.9719	0.3190	0.9039
GRVI	3	2	0.9603	0.9626	0.3299	0.9039
R750/R550	3	2	0.9584	0.9591	0.3257	0.8992
Guyot's REI	3	4	0.9497	0.9686	0.2928	0.8938
OSAVI2(705,750)	3	2	0.9443	0.9668	0.2798	0.8817
ENDVI	3	5	0.9407	0.9675	0.2723	0.8650
GNDVI	3	2	0.9380	0.9553	0.2665	0.8647
R780/R700	3	2	0.9284	0.9448	0.2689	0.8796
TCARI/OSAVI1	3	4	0.9136	0.9214	0.2437	0.8506
MCARI	3	3	0.9126	0.9118	0.2588	0.8548
TCARI(670,700)	3	3	0.9126	0.9118	0.2588	0.8548
TCARI/OSAVI2	3	5	0.9012	0.9201	0.2182	0.8300
R695/R760	3	2	0.9006	0.9273	0.2167	0.8333
RVI	3	2	0.8615	0.8906	0.1946	0.7907
WDRVI	3	2	0.8585	0.8915	0.1819	0.7811
NDVI	3	2	0.8552	0.8902	0.1746	0.7740
MCARI1/OSAVI1	3	3	0.8277	0.8211	0.2330	0.7484
MSR(670,800)	3	2	0.8168	0.8746	0.1689	0.7464
R780/R670	3	2	0.8132	0.8710	0.1702	0.7448
OSAVI1(670,800)	3	2	0.7650	0.8412	0.1413	0.7056
MCARI1(670,700)	3	3	0.6454	0.6011	0.2309	0.5798
RDVI	3	2	0.5090	0.5912	0.0797	0.4825
DVI	3	2	0.2420	0.2953	0.0288	0.2378
EVI	3	3	0.0709	0.1153	0.0052	0.0961
R750/R700	3	2	0.0108	0.0209	0.1930	0.0090

Highest R-squared value noted in bold.

Table E.15 Corn VT stage VI R-squared ranking for 2013 SE sensor.

VI Name	Crop Stage	Number Bands	r^2 Leaf N	r^2 SPAD	r^2 Grain N	r^2 Yield
GRVI	3	2	**0.9588**	0.9707	0.0244	**0.8265**
R780/R740	3	2	**0.9579**	**0.9891**	0.0674	**0.8298**
MSR(705,750)	3	2	**0.9572**	0.9855	0.0316	0.8147
R750/R550	3	2	0.9564	0.9675	0.0215	**0.8217**
NDRE	3	2	0.9525	**0.9928**	0.0392	0.8068
R780/R700	3	2	0.9520	0.9729	0.0241	0.8131
R750/R700	3	2	0.9499	0.9702	0.0214	0.8088
SCCCI	3	4	0.9464	**0.9923**	0.0536	0.8001
OSAVI2(705,750)	3	2	0.9375	0.9879	0.0264	0.7776
GNDVI	3	2	0.9310	0.9790	0.0140	0.7613
Guyot's REI	3	4	0.9238	0.9865	0.0268	0.7500
TCARI(670,700)	3	3	0.9138	0.9776	0.0119	0.7170
MCARI	3	3	0.9138	0.9776	0.0119	0.7170
R695/R760	3	2	0.9122	0.9728	0.0113	0.7324
TCARI/OSAVI1	3	4	0.9073	0.9761	0.0115	0.7107
ENDVI	3	5	0.8960	0.9788	0.0210	0.7107
MCARI1/OSAVI1	3	3	0.8907	0.9425	0.0007	0.6819
MCARI1(670,700)	3	3	0.8811	0.9187	0.0001	0.6583
WDRVI	3	2	0.8808	0.9286	0.0005	0.7108
NDVI	3	2	0.8788	0.9376	0.0009	0.6999
TCARI/OSAVI2	3	5	0.8783	0.9653	0.0080	0.6743
RVI	3	2	0.8757	0.9040	0.0001	0.7226
MSR(670,800)	3	2	0.8581	0.9034	0.0007	0.7026
OSAVI1(670,800)	3	2	0.8552	0.9329	0.0190	0.7258
R780/R670	3	2	0.8529	0.8924	0.0004	0.7031
RDVI	3	2	0.5413	0.6398	**0.1821**	0.5724
EVI	3	3	0.0915	0.0726	**0.4368**	0.0228
DVI	3	2	0.0018	0.0110	**0.3387**	0.0296

Highest R-squared value noted in bold.

APPENDIX F

COTTON SOIL N BY KCL EXTRACTION

Table F.1 Pre-planting extractable soil N – 2012, Natchez, Miss.

N Treat.	Site	Plot	Rep	NH4+ kg/ha	NO3- kg/ha	TOTAL N kg/ha	NH4+ kg/ha	NO3- kg/ha	TOTAL N kg/ha	NH4+ kg/ha	NO3- kg/ha	TOTAL N kg/ha	Soil N Total
				0-15 depth			15-30 depth			30-60 depth			All Depths
33.6 kg ha-1	24	5	1	11.16	56.94	68.10	5.31	12.53	17.84	5.05	6.90	11.95	97.89
	25	5	1	11.16	34.28	45.45	3.62	13.63	17.25	4.93	9.15	14.08	76.78
	26	5	1	6.83	32.86	39.69	3.22	7.67	10.89	7.53	6.75	14.28	64.85
	27	5	1	7.38	39.59	46.96	2.08	5.55	7.63	4.83	3.99	8.82	63.41
	28	5	1	6.09	45.35	51.44	2.24	5.55	7.79	6.30	6.73	13.04	72.26
	29	5	1	7.55	34.01	41.56	3.55	7.87	11.42	7.52	8.36	15.88	68.86
	60	11	2	2.24	60.29	62.52	3.17	9.88	13.06	5.54	12.14	17.68	93.26
	61	11	2	3.28	51.38	54.66	2.54	8.60	11.14	5.60	7.02	12.61	78.41
	62	11	2	4.46	43.32	47.78	1.94	6.61	8.56	6.52	7.45	13.97	70.30
	63	11	2	1.00	52.77	53.77	2.15	10.79	12.94	5.56	10.62	16.18	82.89
	64	11	2	10.73	49.80	60.53	1.54	8.55	10.09	5.85	8.30	14.15	84.77
	65	11	2	2.50	44.35	46.85	1.68	12.54	14.22	5.16	13.36	18.52	79.59
	90	16	3	8.35	52.64	61.00	4.42	11.02	15.43	7.04	10.61	17.65	94.08
	91	16	3	3.64	44.70	48.33	2.38	9.24	11.62	5.09	10.02	15.11	75.06
	92	16	3	3.64	46.70	50.34	1.92	6.61	8.53	6.61	11.78	18.39	77.27
	93	16	3	3.82	43.34	47.16	3.10	6.07	9.17	5.12	10.37	15.49	71.83
	94	16	3	7.63	57.25	64.88	3.51	7.89	11.40	5.76	12.04	17.80	94.07
	95	16	3	5.55	42.09	47.65	3.80	6.36	10.16	6.34	10.59	16.93	74.74
			Average	5.94	46.20	52.15	2.90	8.72	11.62	5.91	9.23	15.14	78.91
67.2 kg ha-1	12	3	1	9.42	42.07	51.49	2.97	8.79	11.76	3.96	10.72	14.68	77.93
	13	3	1	6.68	43.15	49.83	4.35	14.75	19.10	6.58	9.99	16.57	85.50
	14	3	1	6.46	42.66	49.12	2.65	7.05	9.70	7.49	10.15	17.64	76.46
	15	3	1	7.10	38.71	45.81	1.82	5.75	7.57	7.09	11.61	18.70	72.08
	16	3	1	10.59	46.29	56.88	3.34	7.82	11.16	4.80	14.32	19.12	87.16
	17	3	1	6.62	57.74	64.36	4.02	8.47	12.49	7.91	11.13	19.04	95.89
	54	10	2	2.44	37.16	39.60	1.67	7.80	9.46	3.46	8.21	11.67	60.74
	55	10	2	4.31	52.77	57.08	1.87	6.95	8.81	5.36	10.35	15.71	81.61
	56	10	2	3.33	30.30	33.62	2.04	15.56	17.59	5.32	34.34	39.66	90.88
	57	10	2	4.32	62.67	66.99	2.13	9.95	12.08	6.37	9.60	15.97	95.03
	58	10	2	2.23	71.41	73.64	2.62	8.19	10.81	4.95	17.51	22.46	106.91
	59	10	2	4.09	67.32	71.41	2.91	9.12	12.04	6.50	13.06	19.56	103.01
	108	19	3	8.50	54.67	63.17	10.82	88.58	99.39	5.09	11.08	16.17	178.73
	109	19	3				2.87	8.60	11.47	4.99	8.83	13.82	25.29
	110	19	3	10.99	74.65	85.64	3.78	13.07	16.85	6.40	10.59	16.99	119.47
	111	19	3				3.21	7.25	10.46	4.03	9.72	13.75	24.21
	112	19	3	10.34	53.53	63.86				4.80	12.15	16.95	80.81
	113	19	3	7.50	42.54	50.03				5.60	10.00	15.60	65.64
			Average	6.56	51.10	57.66	3.32	14.23	17.55	5.59	12.41	18.00	93.21

Table F.1 (Continued)

100.8 kg ha-1	30	6	1	5.99	45.00	50.99	1.89	7.23	9.13	4.47	8.75	13.22	73.34
	31	6	1	4.37	42.06	46.44	3.10	4.79	7.89	4.46	6.64	11.10	65.42
	32	6	1	6.43	43.19	49.62	3.27	10.12	13.39	5.32	12.71	18.02	81.03
	33	6	1	11.58	54.78	66.36	3.51	5.58	9.09	4.28	3.85	8.13	83.57
	34	6	1	7.65	53.65	61.31	3.66	7.44	11.11	4.65	6.01	10.67	83.08
	35	6	1	6.27	54.13	60.39	3.95	12.08	16.03	5.36	7.60	12.96	89.39
	48	9	2	4.98	50.37	55.34	3.03	10.71	13.74	7.19	14.30	21.48	90.57
	49	9	2	3.84	30.72	34.56	2.21	5.29	7.50	4.70	5.92	10.61	52.67
	50	9	2	2.26	52.97	55.23	3.75	7.73	11.48	9.13	9.77	18.90	85.62
	51	9	2	2.09	43.10	45.19	1.50	5.92	7.41	6.67	8.47	15.15	67.75
	52	9	2	1.65	39.99	41.64	2.65	6.02	8.67	4.28	6.33	10.61	60.92
	53	9	2	1.27	37.09	38.36	1.91	5.61	7.51	4.90	5.45	10.34	56.22
	96	17	3	8.60	47.22	55.82	2.53	6.66	9.19	7.31	17.53	24.84	89.85
	97	17	3	8.10	45.41	53.51	3.58	7.68	11.26	5.66	17.95	23.61	88.38
	98	17	3	10.16	59.68	69.84	3.01	10.81	13.82	5.53	29.40	34.93	118.59
	99	17	3	4.09	54.46	58.54	2.40	6.83	9.24	6.83	10.07	16.89	84.67
	100	17	3	6.10	51.49	57.59	2.76	5.33	8.08	3.76	6.81	10.56	76.24
	101	17	3							5.98	4.80	10.78	10.78
			Average	5.61	47.37	52.99	2.87	7.40	10.27	5.58	10.13	15.71	78.96
134.4 kg ha-1	36	7	1	8.64	55.28	63.92	3.89	11.53	15.42	5.62	21.79	27.41	106.75
	37	7	1	14.90	50.06	64.97	2.99	8.67	11.66	4.24	9.69	13.92	90.55
	38	7	1	10.38	35.53	45.91	3.31	7.91	11.22	3.42	10.77	14.19	71.32
	39	7	1	6.36	46.53	52.89	2.45	8.42	10.87	5.35	16.06	21.41	85.16
	40	7	1	5.68	44.34	50.02	4.15	7.14	11.30	4.43	9.27	13.70	75.02
	41	7	1	5.17	37.12	42.29	1.71	4.05	5.76	4.26	7.00	11.26	59.31
	42	8	2	4.20	37.05	41.25	2.42	6.91	9.33	4.05	6.21	10.26	60.83
	43	8	2	4.43	41.87	46.30	3.86	8.01	11.87	4.32	6.00	10.32	68.49
	44	8	2	4.69	42.66	47.35	2.87	8.07	10.94	7.20	17.77	24.97	83.25
	45	8	2	4.04	40.01	44.05	2.13	4.10	6.23	4.91	10.07	14.98	65.26
	46	8	2	7.99	63.61	71.60	1.77	5.12	6.90	5.97	7.91	13.88	92.37
	47	8	2	6.67	64.44	71.11	1.73	8.19	9.92	4.75	13.17	17.92	98.95
	120	21	3	10.83	52.20	63.04	3.69	7.59	11.28	6.83	10.49	17.32	91.64
	121	21	3	6.82	52.38	59.20	3.39	11.07	14.47	6.87	16.93	23.80	97.46
	122	21	3	6.24	40.41	46.65	3.76	9.64	13.41	6.13	15.47	21.60	81.65
	123	21	3	7.20	46.03	53.23	2.90	6.22	9.11	6.23	10.23	16.45	78.79
	124	21	3	8.61	47.93	56.55	3.72	7.36	11.09	5.85	10.49	16.34	83.98
	125	21	3	10.62	54.26	64.88				5.46	33.19	38.66	103.53
			Average	7.41	47.32	54.73	2.99	7.65	10.63	5.33	12.92	18.24	83.61

Table F.1 (Continued)

110.0 kg ha-1	1	1	1	19.21	58.97	78.18	6.14	12.31	18.45	8.51	19.84	28.35	124.99
	2	1	1	10.72	40.88	51.60	1.70	9.38	11.08	4.59	12.17	16.76	79.44
	3	1	1	6.45	44.92	51.38	3.93	9.61	13.54	7.42	23.00	30.41	95.33
	4	1	1	10.04	58.96	69.00	1.94	5.73	7.68	4.74	9.21	13.95	90.62
	5	1	1	6.43	57.21	63.64	1.41	9.81	11.22	4.31	10.70	15.01	89.87
	78	14	2	2.63	34.58	37.21	1.76	6.49	8.24	4.53	5.50	10.03	55.49
	79	14	2	2.28	45.09	47.37	1.91	7.72	9.63	3.86	7.82	11.69	68.69
	80	14	2	3.01	41.28	44.29	4.61	5.85	10.46	3.44	6.40	9.84	64.60
	81	14	2	3.08	41.17	44.25	2.27	4.22	6.49	5.24	16.05	21.29	72.02
	82	14	2	5.64	78.30	83.94	1.58	6.15	7.72	10.81	8.03	18.84	110.50
	83	14	2	3.60	49.81	53.41	3.08	8.62	11.70	4.94	7.20	12.14	77.24
	84	15	3	3.34	49.22	52.55	3.78	9.72	13.50	7.64	12.74	20.38	86.43
	85	15	3	4.74	48.36	53.10	3.01	5.11	8.12	7.34	11.24	18.59	79.80
	86	15	3	5.73	72.63	78.37	3.31	12.48	15.79	5.21	13.43	18.64	112.80
	87	15	3	1.79	40.38	42.17	4.35	21.04	25.40	8.06	21.82	29.89	97.45
	88	15	3	3.86	51.05	54.90	2.04	6.31	8.34	6.60	7.00	13.61	76.85
	89	15	3	6.93	70.27	77.20	4.17	7.56	11.72	4.25	8.78	13.03	101.95
			Average	5.85	51.95	57.80	3.00	8.71	11.71	5.97	11.82	17.79	87.30
86.0 kg ha-1	18	4	1	5.05	25.71	30.77	2.09	10.03	12.12	5.59	10.39	15.97	58.86
	19	4	1	6.44	28.85	35.28	1.82	5.79	7.61	3.48	5.21	8.69	51.59
	20	4	1	3.83	25.58	29.41	2.01	4.64	6.66	2.59	4.03	6.63	42.70
	21	4	1	4.74	56.72	61.46	3.48	6.81	10.30	5.93	3.82	9.76	81.51
	22	4	1	6.53	43.02	49.56	3.93	9.92	13.85	5.00	11.23	16.23	79.63
	23	4	1	8.86	72.98	81.84	2.90	12.14	15.04	3.54	11.43	14.97	111.85
	66	12	2	1.43	32.00	33.43	2.59	10.19	12.78	5.25	6.84	12.09	58.31
	67	12	2	3.94	62.63	66.57	1.70	6.42	8.12	3.19	7.30	10.48	85.18
	68	12	2	1.64	44.09	45.72	2.16	5.03	7.18	3.97	5.87	9.85	62.75
	69	12	2	5.03	41.37	46.40	1.70	8.51	10.20	4.08	7.55	11.63	68.23
	70	12	2	1.63	46.17	47.80	1.34	4.39	5.73	4.46	5.13	9.60	63.12
	71	12	2	2.42	38.89	41.31	2.62	5.02	7.64	4.73	6.42	11.15	60.10
	102	18	3							6.49	6.95	13.44	13.44
	103	18	3				4.11	8.31	12.42	7.97	10.67	18.64	31.06
	104	18	3										0.00
	105	18	3				3.63	10.61	14.24				14.24
	106	18	3	9.59	58.12	67.71				7.78	20.69	28.47	96.18
	107	18	3	7.83	39.00	46.83	4.15	9.00	13.15	8.16	17.70	25.86	85.84
			Average	4.93	43.94	48.86	2.68	7.79	10.47	5.14	8.83	13.97	73.30

Table F.1 (continued)

75.0 kg ha-1	6	2	1	6.52	46.25	52.76	2.45	13.70	16.16	7.72	21.50	29.22	98.14
	7	2	1	6.48	41.69	48.16	1.99	6.27	8.26	6.54	12.38	18.92	75.35
	8	2	1	6.15	33.71	39.86	3.47	15.86	19.33	7.67	19.27	26.94	86.13
	9	2	1	4.49	37.46	41.95	2.58	11.07	13.65	8.08	5.80	13.88	69.48
	10	2	1	8.07	41.69	49.76	2.20	5.63	7.83	3.94	5.38	9.33	66.92
	11	2	1	12.07	61.81	73.88	3.35	10.12	13.48	3.06	16.01	19.07	106.42
	72	13	2	2.42	62.82	65.25	1.53	14.95	16.48	5.46	13.94	19.40	101.13
	73	13	2	2.42	49.63	52.05	2.87	9.78	12.65	6.15	7.63	13.78	78.48
	74	13	2	9.95	47.69	57.64	0.99	4.47	5.46	5.95	7.20	13.15	76.25
	75	13	2	1.79	53.93	55.72	1.87	6.24	8.11	4.55	7.36	11.91	75.74
	76	13	2	3.76	72.84	76.60	1.67	9.65	11.32	5.95	14.93	20.88	108.80
	77	13	2	4.18	54.29	58.47	1.74	9.61	11.35	2.32	5.68	7.99	77.82
	114	20	3				4.62	7.87	12.49	4.72	6.20	10.92	23.41
	115	20	3	9.30	73.33	82.63	3.68	10.60	14.28	6.00	15.78	21.78	118.69
	116	20	3	7.93	49.32	57.26	3.01	7.43	10.44	5.14	5.97	11.11	78.81
	117	20	3	8.02	58.21	66.23	3.44	8.47	11.91	7.01	11.05	18.06	96.21
	118	20	3				3.44	11.27	14.71	5.52	16.81	22.32	37.04
	119	20	3				3.42	6.91	10.33	6.54	25.34	31.88	42.21
			Average	6.24	52.31	58.55	2.69	9.44	12.12	5.68	12.12	17.81	88.48

Empty cells indicate missing samples

Table F.2 Pre-planting extractable soil N – 2013, Money, Miss.

				NH4+ kg/ha	NO3- kg/ha	Total N kg/ha	NH4+ kg/ha	NO3- kg/ha	Total N kg/ha	NH4+ kg/ha	NO3- kg/ha	Total N kg/ha	Total Soil N
N Treat.	Site	Plot	Rep	0-15 depth			15-30 depth			30-60 depth			All Depths
33.6 kg ha-1	56	12	1	3.22	6.33	9.55	2.61	10.11	12.72	3.70	12.57	16.27	38.54
	57	12	1	3.05	10.04	13.09	3.59	7.28	10.87	4.70	14.63	19.33	43.30
	58	12	1	2.85	10.19	13.04	2.89	9.60	12.49	4.25	17.93	22.18	47.71
	59	12	1	2.90	9.38	12.28	3.28	13.18	16.46	7.11	36.35	43.46	72.20
	60	12	1	3.58	3.14	6.72	3.53	3.49	7.02	5.17	7.98	13.15	26.89
	11	3	2	2.64	6.60	9.24	2.08	4.59	6.67	3.28	7.45	10.73	26.64
	12	3	2	2.74	3.36	6.10	2.40	1.65	4.05	4.45	3.08	7.54	17.69
	13	3	2	9.45	7.58	17.03	1.72	5.32	7.04	2.47	8.93	11.41	35.48
	14	3	2	3.39	10.31	13.70	2.58	5.92	8.50	3.02	7.51	10.52	32.72
	15	3	2	3.60	10.98	14.58	2.52	5.24	7.77	5.00	12.21	17.21	39.56
	106	22	3	2.99	3.21	6.20	4.48	0.81	5.29	4.72	5.50	10.22	21.71
	107	22	3	2.45	7.60	10.05	2.98	0.51	3.50	4.03	14.75	18.78	32.32
	108	22	3	2.36	2.74	5.10	2.56	2.12	4.68	3.79	5.15	8.95	18.73
	109	22	3	2.42	2.88	5.30	2.72	2.96	5.68	3.82	4.81	8.63	19.60
	110	22	3	1.95	2.97	4.92	2.50	4.00	6.50	4.39	5.48	9.88	21.30
	116	24	4	2.27	5.39	7.66	3.47	4.44	7.91	5.36	11.83	17.19	32.75
	117	24	4	3.15	7.18	10.32	2.72	7.51	10.22	4.25	13.69	17.94	38.48
	118	24	4	3.23	5.12	8.35	3.25	7.81	11.06	4.92	9.64	14.56	33.97
	119	24	4	3.19	11.75	14.93	4.35	4.42	8.77	4.79	24.98	29.78	53.48
	120	24	4	0.38	2.93	3.31	0.48	3.46	3.94	0.46	5.84	6.30	13.55
			Average	3.09	6.48	9.57	2.84	5.22	8.06	4.18	11.52	15.70	33.33
67.2 kg ha-1	36	8	1	7.26	2.40	9.66	2.52	6.38	8.90	3.26	7.17	10.43	28.99
	37	8	1	11.19	13.45	24.64	1.90	8.74	10.64	3.74	12.25	16.00	51.27
	38	8	1	12.35	5.08	17.43	2.61	6.61	9.23	2.72	8.10	10.83	37.48
	39	8	1	16.51	39.24	55.75	2.05	36.29	38.34	3.67	89.66	93.33	187.42
	40	8	1	13.14	5.95	19.10	2.16	3.82	5.99	2.67	6.29	8.96	34.04
	46	10	2	3.36	11.58	14.94	5.63	4.48	10.11	4.69	13.01	17.70	42.75
	47	10	2	4.11	11.57	15.68	4.64	1.77	6.41	6.17	4.45	10.62	32.72
	48	10	2	4.85	4.48	9.33	3.47	4.55	8.02	7.97	8.08	16.04	33.39
	49	10	2	3.12	4.26	7.38	2.05	3.61	5.66	3.06	4.95	8.01	21.05
	50	10	2	2.77	5.69	8.47	1.86	5.65	7.51	3.24	12.52	15.76	31.73
	71	15	3	3.03	5.02	8.05	3.13	5.84	8.97	4.91	6.98	11.89	28.91
	72	15	3	2.20	4.09	6.29	3.12	3.35	6.47	7.01	7.89	14.90	27.66
	73	15	3	3.94	5.61	9.55	7.78	2.11	9.89	9.29	10.63	19.92	39.36
	74	15	3	4.06	11.86	15.93	6.23	1.37	7.60	8.28	3.75	12.03	35.56
	75	15	3	4.21	5.44	9.65	2.22	2.45	4.67	5.74	11.44	17.18	31.51
	61	13	4	2.95	4.36	7.31	2.63	4.28	6.91	5.20	7.90	13.09	27.31
	62	13	4	3.54	5.83	9.36	2.97	5.30	8.27	3.68	8.83	12.51	30.14
	63	13	4	3.84	11.87	15.71	3.79	6.95	10.74	4.04	13.49	17.54	43.99
	64	13	4	4.28	11.43	15.71	2.72	9.06	11.77	10.29	21.00	31.28	58.77
	65	13	4	3.59	12.61	16.20	3.59	9.69	13.28	4.45	12.41	16.87	46.34
			Average	5.72	9.09	14.81	3.35	6.61	9.97	5.20	13.54	18.74	43.52

Table F.2 (continued)

100.8 kg ha-1	1	1	1	9.62	7.37	16.99	2.13	4.51	6.64	3.95	6.60	10.55	34.18
	2	1	1	10.01	16.42	26.43	3.05	10.06	13.11	5.64	43.44	49.09	88.63
	3	1	1	3.43	6.68	10.11	3.30	4.40	7.70	3.19	6.28	9.47	27.28
	4	1	1	3.89	9.99	13.88	1.95	5.32	7.26	2.25	9.74	11.98	33.13
	5	1	1	4.09	14.52	18.61	2.28	5.84	8.12	4.46	7.91	12.37	39.10
	26	6	2	14.36	11.13	25.50	7.14	2.07	9.21	4.10	4.09	8.19	42.89
	27	6	2	3.66	9.04	12.70	3.17	2.92	6.09	4.30	4.05	8.35	27.14
	28	6	2	3.49	3.93	7.41	1.33	3.03	4.36	3.56	5.36	8.92	20.69
	29	6	2	4.34	3.26	7.60	2.64	2.41	5.05	3.92	5.44	9.37	22.02
	30	6	2	12.20	3.40	15.60	1.90	4.03	5.93	3.73	6.70	10.43	31.97
	111	23	3	2.30	2.42	4.72	3.19	2.84	6.03	3.59	4.27	7.87	18.62
	112	23	3	2.00	2.70	4.70	2.38	2.16	4.54	5.31	5.12	10.43	19.67
	113	23	3	1.73	5.07	6.80	3.65	4.08	7.74	5.29	8.89	14.19	28.72
	114	23	3	2.18	1.72	3.90	4.69	2.40	7.08	3.78	3.46	7.24	18.22
	115	23	3	2.91	5.52	8.43	2.90	0.98	3.87	5.12	10.07	15.19	27.49
	96	20	4	2.77	4.22	6.99	2.38	6.14	8.52	5.49	10.38	15.87	31.38
	97	20	4	2.27	12.07	14.34	2.93	6.17	9.10	4.09	18.94	23.04	46.47
	98	20	4	2.67	10.21	12.87	2.83	6.37	9.20	4.97	10.48	15.45	37.52
	99	20	4	2.90	8.77	11.67	2.58	7.63	10.21	4.13	9.93	14.06	35.95
	100	20	4	2.90	9.41	12.31	1.85	7.46	9.31	3.34	8.04	11.38	32.99
			Average	4.69	7.39	12.08	2.91	4.54	7.45	4.21	9.46	13.67	33.20
134.4 kg ha-1	16	4	1	8.18	15.48	23.67	2.09	11.36	13.45	3.29	14.78	18.07	55.19
	17	4	1	9.25	8.77	18.03	1.84	14.95	16.79	4.98	27.03	32.01	66.82
	18	4	1	2.62	4.39	7.01	1.77	3.54	5.31	4.03	4.54	8.57	20.89
	19	4	1	2.93	16.79	19.72	2.21	9.39	11.60	4.71	34.45	39.16	70.48
	20	4	1	3.98	8.76	12.74	1.69	3.73	5.42	5.42	6.05	11.48	29.64
	31	7	2	7.83	4.88	12.71	1.67	3.96	5.63	3.02	6.36	9.38	27.72
	32	7	2	11.37	5.07	16.43	2.08	4.31	6.40	3.13	7.69	10.82	33.65
	33	7	2	6.80	4.39	11.19	2.48	2.78	5.26	3.11	7.46	10.57	27.02
	34	7	2	7.52	7.90	15.42	5.38	1.04	6.42	7.57	4.82	12.40	34.24
	35	7	2	7.60	9.61	17.21	3.53	3.15	6.69	3.10	8.03	11.13	35.03
	66	14	3	3.65	7.79	11.44	3.20	6.15	9.35	6.38	19.69	26.07	46.86
	67	14	3	5.54	4.07	9.61	4.48	2.61	7.09	3.99	4.42	8.41	25.10
	68	14	3	3.47	3.64	7.11	2.24	2.54	4.79	4.20	6.37	10.57	22.47
	69	14	3	3.25	5.40	8.65	2.27	5.20	7.46	3.68	9.10	12.78	28.89
	70	14	3	2.41	4.18	6.59	1.96	4.03	5.99	4.38	7.21	11.60	24.18
	81	17	4	2.77	2.10	4.87	1.81	4.49	6.29	4.18	4.82	9.00	20.16
	82	17	4	2.83	7.26	10.09	2.06	6.37	8.43	3.82	8.42	12.24	30.76
	83	17	4	3.51	11.67	15.17	3.31	9.33	12.65	4.82	13.34	18.16	45.98
	84	17	4	3.61	18.57	22.18	2.18	8.65	10.83	5.38	21.18	26.56	59.56
	85	17	4	3.12	8.17	11.29	3.11	7.40	10.51	5.99	10.13	16.12	37.92
			Average	5.11	7.94	13.06	2.57	5.75	8.32	4.46	11.29	15.75	37.13

Table F.2 (continued)

103.3 kg ha-1	21	5	1	16.97	9.33	26.31	8.26	6.75	15.01	3.64	7.72	11.37	52.69
	22	5	1	7.31	38.93	46.24	1.81	24.72	26.53	3.14	59.68	62.82	135.60
	23	5	1	15.61	5.28	20.89	1.50	3.73	5.23	3.07	6.96	10.03	36.15
	24	5	1	17.37	7.81	25.18	2.82	7.25	10.07	2.90	12.36	15.25	50.51
	25	5	1	18.39	9.36	27.75	2.39	9.39	11.78	4.15	14.73	18.88	58.41
	51	11	2	3.03	3.34	6.38	2.03	3.02	5.05	6.91	5.71	12.63	24.06
	52	11	2	4.69	5.59	10.27	2.60	3.95	6.55	9.17	6.31	15.48	32.31
	53	11	2	5.35	5.15	10.50	2.97	4.28	7.25	5.46	6.65	12.10	29.86
	54	11	2	2.87	7.37	10.23	4.20	3.58	7.77	5.46	15.23	20.69	38.69
	55	11	2	3.63	11.37	15.00	4.31	4.14	8.46	5.97	13.05	19.01	42.47
	86	18	3	2.59	8.46	11.05	3.74	5.05	8.79	5.66	16.06	21.72	41.56
	87	18	3	3.54	1.47	5.01	2.91	1.12	4.04	5.30	5.82	11.12	20.17
	88	18	3	2.58	2.56	5.14	2.04	3.83	5.86	4.71	8.92	13.63	24.63
	89	18	3	2.37	3.90	6.26	2.48	3.63	6.11	5.37	6.17	11.54	23.92
	90	18	3	2.55	2.78	5.33	2.16	2.42	4.58	4.15	5.01	9.16	19.06
	76	16	4	2.72	7.76	10.47	2.93	7.98	10.91	6.50	13.01	19.51	40.89
	77	16	4	3.37	12.83	16.20	2.59	8.07	10.67	5.80	16.90	22.70	49.56
	78	16	4	2.68	17.40	20.08	1.78	10.23	12.02	4.44	28.34	32.78	64.88
	79	16	4	2.93	8.04	10.97	2.41	7.28	9.69	5.26	14.08	19.34	39.99
	80	16	4	3.68	6.25	9.93	2.31	3.54	5.85	4.35	6.43	10.78	26.57
			Average	6.21	8.75	14.96	2.91	6.20	9.11	5.07	13.46	18.53	42.60
119.0 kg ha-1	41	9	1	3.21	0.99	4.20	2.99	2.19	5.18	7.30	3.21	10.51	19.89
	42	9	1	3.28	16.95	20.23	2.84	12.82	15.66	8.48	47.19	55.66	91.55
	43	9	1	3.07	6.43	9.50	2.83	5.68	8.51	5.90	8.73	14.63	32.65
	44	9	1	3.30	11.35	14.66	3.28	13.97	17.26	5.53	28.71	34.24	66.15
	45	9	1	3.26	4.38	7.64	2.79	6.32	9.10	6.21	13.34	19.55	36.29
	6	2	2	19.46	15.86	35.32	4.44	4.35	8.80	7.04	8.38	15.42	59.54
	7	2	2	11.91	8.89	20.80	2.49	4.78	7.28	2.60	9.48	12.08	40.16
	8	2	2	9.79	1.63	11.42	2.50	1.87	4.37	4.46	4.45	8.91	24.70
	9	2	2	5.38	4.16	9.54	2.80	3.19	5.99	5.39	5.10	10.49	26.02
	10	2	2	19.08	15.47	34.55	1.71	20.69	22.40	8.44	21.26	29.70	86.64
	91	19	3	2.80	2.25	5.05	17.06	3.15	20.21	5.11	6.03	11.14	36.39
	92	19	3	3.01	2.75	5.76	2.28	7.43	9.71	5.13	23.15	28.28	43.75
	93	19	3	3.72	23.53	27.25	4.02	11.27	15.29	4.89	14.36	19.25	61.80
	94	19	3	3.31	4.37	7.67	2.54	0.61	3.15	5.82	4.56	10.38	21.20
	95	19	3	4.31	10.44	14.75	1.84	1.66	3.50	6.66	11.70	18.36	36.62
	101	21	4	3.24	3.76	7.00	3.14	4.33	7.47	3.95	7.11	11.06	25.53
	102	21	4	2.33	7.13	9.46	3.31	9.17	12.48	3.98	13.02	17.00	38.94
	103	21	4	2.39	3.90	6.29	2.89	4.62	7.51	3.90	8.05	11.95	25.75
	104	21	4	3.52	10.81	14.34	2.61	5.98	8.59	4.18	19.75	23.94	46.86
	105	21	4	3.02	6.37	9.39	3.70	6.99	10.69	5.23	12.39	17.62	37.70
			Average	5.67	8.07	13.74	3.60	6.55	10.16	5.51	13.50	19.01	42.91