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NITROGEN AND WATER EFFECTS ON CANOPY SENSOR MEASUREMENTS FOR SITE-SPECIFIC MANAGEMENT OF CROPS

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Water and nitrogen (N) are undoubtedly the two largest agricultural inputs globally. Coupled with advances in site-specific management technology their integration into production agriculture will allow for the most efficient use these crop input resources. Active canopy sensors offer the ability to measure biophysical plant traits rapidly and make assessments about plant status. Specifically, optical sensor measurements of light reflectance assess plant N status allowing for in-season and on-the-go N recommendations and applications; while infrared thermometers (IRT) measurement of canopy temperature can be used a tool for irrigation management. To evaluate how these technologies work among different plant stress environments a series of experiments were formulated. The first experiment compared reference strategies for normalizing reflectance data across multiple vegetation indices (VI). We found the virtual reference concept helped reduce variation of the calculated reference and placed sufficiency index values in a range that corresponded to plant N status. Additionally, VI varied in their ability to show significant responses to applied N fertilizer. In the second experiment, we sought to understand the influence of VI on how an in-season N application algorithm performs as well as the confounding effects of irrigation might

have. We found N application rates would change based on algorithm and VI. Also, N rate can be affected by apparent water stress. In this case, reduced reflectance in the NIR spectrum reduced leaf area from leaf rolling. The final objective was to quantify the effect of N fertility on plant canopy temperature and determine if functions of canopy temperature could be useful for detecting apparent N stress. We concluded that plant canopy temperature can be affected by N stresses and that canopy temperature and canopy/air temperature difference provided equal sensitivity to plant stress. Therefore, these technologies will be vital to help conserve resources and maximize efficiency in production agriculture.

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General Introduction

Nitrogen (N) fertilizer management has continually evolved since the Harbor-Bausch process provided a high-grade source of anthropogenic N (Kissel, 2014). In 2010, the United States consumed 11.1 million Mg of N fertilizer with corn (*Zea mays* L.) production accounting for 46 % of total N fertilizer use (USDA-ERS, 2013). In Nebraska, corn grain production in 2009 was 40 million Mg; therefore proper N management has an economic and environmental impact for this state (USDA-NASS, 2010). Additionally, within the past two decades, rising N fertilizer prices coupled with a focus on environmental impact have spurred research on improving N management practices and to increase nitrogen use efficiency (NUE).

Principles of Nitrogen Use Efficiency (NUE)

Nitrogen is generally accepted as the most limiting nutrient in non-legume cropping systems (Havlin et al., 2005). Additionally, N may be present in the soil as inorganic and/or organic forms and is subject to loss at many points within the soil N cycle. This uniqueness has led to extensive research efforts to limit loss and maximize N use. In general, world NUE for cereal production is low, 33%, with many factors contributing to this number (Raun and Johnson, 1999). Raun and Johnson based this calculation on total N removed by grain less soil and natural deposition divided by fertilizer N applied. Moll et al. (1982) offer an alternate definition of NUE by expressing two primary components of NUE: (1) the efficiency of absorption (uptake) and (2) the efficiency with which the N absorbed is utilized to produce grain. Moll et al. therefore define NUE as grain production per unit of N available in the soil. A simplified calculation using the ratio of grain yield to unit N fertilizer applied known as partial factor productivity (PFPN) has shown an increase in NUE of 36% for corn production in the United States over the past 21 years (Cassman et al., 2002). With so many definitions, data required or sources of data, NUE can be as complex as N itself. For this paper, NUE will be defined as: grain yield above the check yield divided by N rate.

Historic management practices have emphasized pre-plant N fertilizer applications to reduce economic risk of not having enough plant available N to support crop growth. These applications, often made in the fall, are subject to many loss pathways. Losses may also be related to the type of fertilizer or application method as well as weather conditions between application and plant uptake. These N loses from the root zone may occur in many ways including: denitrification; surface runoff; volatilization; immobilization and leaching (Raun and Johnson, 1999). The practice of applying the majority of recommended fertilizer N prior to plant growth leads to poor synchronization between fertilizer N supply and plant N uptake effectively reducing efficiency.

From an agronomic view point, the best way to increase fertilizer uptake is to reduce the likelihood of fertilizer loss. Research has shown many ways to accomplish such a task. Fertilizer additives or enhancement products are designed to prevent N loss by retarding N transformations in the soil. Radel et al. (1988) suggested one means of reducing ammonia volatilization loss from surface applied urea and urea based fertilizers would be the incorporation of urease inhibitors. Many studies have focused on N-(n-butyl) thiophosphoric triamide (NBPT), a common formulation used to inhibit urease activity. Bronson et al. (1990) observed significant responses in tissue N concentration and grain yield when favorable volatilization conditions were present after fertilizer application. Hendrickson (1992) compiled a summary of 78 trials in which NBPT was used. He concluded that responses will only be obtained when the crop can respond to the N conserved by the inhibitor and inhibitors appeared to offer an environmentally safe alternative to excessive N fertilization.

Nitrification inhibitors reduce the rate at which ammonium is converted to nitrate; an N form that can easily be lost via leaching. Hauck (1980) summarized the mode of action of this inhibitor group and listed chemicals used and/or patented as nitrification inhibitors. Rodgers and Ashworth (1982) experimented with dicyandiamide (DCD); their work showed increased N uptake and grain yield with use of DCD. Shi and Norton (2000) demonstrated that nitrapyrin successfully blocked nitrification of fall applied anhydrous ammonia. These chemicals were in Hauck's original list of nitrification inhibitors and are still in use today; nitrapyrin (N-Serve) actively marketed by Dow AgroSciences (Indianapolis, Indiana) and dicyandiamide (Super-U) marketed by Koch Fertilizers (Wichita, Kansas).

Controlled release fertilizers offer another avenue to prevent N conversion and loss. Several coating concepts have been investigated over the past half century. Early experiments with sulfur-coated urea demonstrated slower, more uniform N uptake with higher total forage yields (Allen and Mays, 1971). More recently, new polymer coated products have been marketed to producers. Weber (2010) showed environmentally safe nitrogen (ESN) (Agrium Calgary, Canada) to be an effective product to increase grain yield and fertilizer recovery in corn.

Fertilizer N placement can significantly influence loss even when comparing the same fertilizer source. Placement options include, but are not limited to, surface and sub-surface; broadcast and band/striped. Mengel et al. (1982) examined how different placement methods affected yield and NUE and concluded that subsurface placement of urea-ammonium nitrate (UAN) increased both compared to surface broadcast applications.

As mentioned earlier, fertilizer application timing and its synchrony with plant N uptake plays a crucial role in efficiency. Having an adequate N supply available for early plant growth while ensuring sufficient N supply later in the season are both essential to obtain optimum yield. Multiple or split applications of fertilizer have been shown to increase NUE without negatively affecting grain yield (Gehl et al., 2005). The ultimate goal of a split application is to adjust recommended N fertilizer rate based on the N status or health of the plant, thus applying an appropriate rate during the time of rapid N uptake. Traditional N recommendation approaches have relied on predictive yield goals and accounting for N credits such as sub-soil nitrate, N mineralization from organic matter and nitrate in irrigation water. Using an approach that encompasses plant based information from the growing season would help adjust such a recommendation when split applying N fertilizer. There has been substantial work done on multiple methods of adjusting N fertilizer rate based on such measurements of plant N status.

Managing Nitrogen In-Season

Nitrogen status assessment in-season can be done qualitatively and quantitatively. Simple qualitative assessment of plant "greenness" has been done for millennia by farmers while tending to their crops. Even today, simple color panels are used as a simple diagnostic assessment of N fertility (Girma et al., 2005). Many quantitative methods of assessment in-season have been developed and put into practice within the last century. These methods range from destructive plant sampling requiring labor and chemical analysis in a laboratory to remote sensing methods which do not require a presence at the field.

Physical sampling of plant tissues produce varied results based on the time of sampling and the method of analysis used. Work on how to best use plant analysis to establish sufficiency and toxicity levels for a wide range of crops began in the 1930s (Fox and Walthall, 2008). Specifically for corn, total N concentration of ear-leaves at silking is a common approach for monitoring N fertility. This method is not without its problems, with several papers showing ear-leaf N concentration to be too variable for use in yield prediction (Blackmer and Schepers, 1994; Fox and Piekielek, 1983). Another common test for corn N sufficiency is corn stalk nitrate concentration at physiological maturity (Blackmer and Schepers, 1994; Brouder et al. 2000). A number of studies have measured corn grain N concentration to assess N sufficiency but this post-harvest analysis cannot impact in-season changes to N recommendations (Pierre et al. 1977; Steele et al. 1982; Brouder et al., 2000).

Non-destructive assessment of crop N status was shown to be possible by Al-Abbas et al. (1974) using hyper-spectral analysis. This work quantified the visual N assessment of greenness and was some of the first work in plant “sensing”. This approach also eliminated the need for laboratory analysis which can be time consuming and costly. In 1982, the Japanese Ministry of Fishery and Agriculture, in conjunction with the Minolta Corporation, developed what would become known as the SPAD

(Special Products Analysis Division) meter (Fox and Walthall, 2008). This small hand-held instrument has had a large impact on world-wide N research. The SPAD meter has used been successfully by many researchers to identify and quantify N deficiencies (Blackmer et al., 1994; Smeal and Zhang, 1994) and to recommend in-season N fertilizer rates (Varvel et al., 2007). However this system lacks the ability for on-the-go use and is difficult to be used on a spatial scale. This led teams of researchers in Oklahoma and Nebraska to develop on-the-go optical sensors that can detect and quantify N status from which N fertilizer recommendations can be calculated.

Optical Canopy Sensors and Vegetative Indices

Proximal plant sensing with active optical sensor (AOS) technology commercially introduced during the last decade offers a non-destructive on-the-go avenue in N research. Scientists and engineers have developed two systems in the United States; the GreenSeeker (Trimble, Sunnyvale, California) and Crop Circle (Holland Scientific, Lincoln, Nebraska). Active optical sensors irradiate a plant canopy with modulated light and measure the reflected radiation (light) from the canopy (Holland et al., 2012). These sensor platforms are termed 'active' due to the fact they use internally modulated light, thereby eliminating interference by sunlight. With a modulated light source, the reflected light is measured by the sensor's synchronized detectors offering a unique feature that allows the sensor to perform equally well under all lighting conditions (Holland et al., 2012). The AOS systems measure reflected light in specific areas or 'bands' of the electromagnetic spectrum. These 'bands' are subsequently used in the calculations of vegetation indices (VIs) that provide increased sensitivity to biophysical characteristics (Fox and Walthall, 2008). Vegetation indices also reduce multiple-wavelength measurements to a single numerical metric which has been the base of AOS technology development.

Numerous (Agapiou et al., 2012) VIs have been published in peer reviewed literature with specific target measurements in mind. Measurements are most frequently focused on detection of photosynthetic pigment content or biomass estimations. Undoubtedly the most recognizable VI is normalized difference vegetation index (NDVI). Rouse et al. (1974) developed this VI to assess vegetative cover. This normalized ratio [(NIR-Red) / (NIR+Red) involves two areas of the electromagnetic spectrum; red and near infrared (NIR). These two bands are used since there is a chlorophyll absorption peak in the red (600-700 nm) spectral region and a reflectance plateau in the NIR region (750-900 nm).

Indices have been developed with more specific measurements in mind. Work by Datt (1999) targeted wavelengths to measure chlorophyll content of eucalyptus leaves. In constructing their index, they cite a need for contrast between a reference band that is least sensitive to pigment absorptions and a band that shows maximum sensitivity to pigment absorptions. The index created [(NIR-Red Edge) / (NIR-Red)] is based on three distinct regions of the spectrum; chlorophyll absorption near 680 nm, the transitional zone from red to NIR, and maximum reflectance in NIR region around 850 nm. It is interesting to note that Datt chose 850 nm specifically because it is an area of the NIR region that is least affected by water absorptions.

Gitelson et al. (2005), in an attempt to estimate canopy chlorophyll content in field crops using available satellite capabilities, developed multiple models. These models had to estimate chlorophyll content of crops with different canopy architectures and leaf structures such as corn and soybean. The developed model [$(R_{NIR} / R_{720\text{-}730})$-1] was found to estimate chlorophyll of both species and thus should be useful for monitoring crops not included in the original study. This model is often referred to as the Chlorophyll Index Red Edge (CIRE). Like the VI mentioned here, most if not all, VIs were developed with something other than N management in mind, but they often can be easily adapted for this purpose. The indices mentioned in this introduction are just a few of countless publications in peer reviewed journals; but will be focused on later in the paper.

The marriage of AOS technology and VIs makes determining plant N status and creating an N fertilizer recommendation in real time possible. Developing N application algorithms first begins with selecting a VI that is responsive for the crop in question. Raun et al. (2005) used NDVI to develop an N application algorithm for winter wheat. The NDVI is well suited for winter wheat since it involves spectral regions sensitive to chlorophyll in the red region (N status) and biomass in the NIR region (tillering). Tucker (2009) used NDVI as a base for making N recommendations for grain sorghum (*Sorghum bicolor* L.). As with wheat, sorghum is a crop that tillers making NDVI well suited for the purpose of assessing N fertility. Both algorithms (wheat and sorghum) use additional factors like growth stage to predict yield when calculating fertilizer N to be applied (Raun et al., 2001). This approach coined “INSEY” for in-season prediction of yield, builds an N recommendation on predicted yield based on in-season growth and plant N status. Solari et al., (2010) tested two indices in the development of an algorithm for corn; concluding that the chlorophyll index (CI, Gitelson et al., 2003) worked best with the sensor used to collect plant canopy reflectance data.

The next step in turning index values into usable data involves calibrating the VIs to local conditions by normalizing the collected values. Peterson et al. (1993) used the ‘sufficiency index’ (SI) concept (SI=Average bulk reading/Average reference area reading) to normalize and interpret SPAD readings for fertigation. The values for ‘bulk area’ is the field area to be fertilized, with reference strip being an area where the amount of N applied is adequate to insure that plants do not exhibit an N deficiency. This concept was easily adapted for AOS collected data (Biggs et al., 2002). Scientists at Oklahoma State University used ‘response index’ when measuring crop response to added N fertilizer (Raun et al., 2002). Essentially SI and RI are reciprocals of each other and a point of contention among certain groups. Raun et al. (2008) proposed the ramped calibration strip as a method to replace the high N reference originally used by Peterson. Another method by Holland (2009) sought a statistical approach to simplify the way a reference value was determined. This method, termed the ‘virtual reference’, assigns the cumulative 95^{th} percentile value of a histogram of VI measurements collected over a representative area of a crop field that has received a modest preplant or planting time application of N fertilizer as the reference.

Construction of an N application model is possible once a VI is selected and the sensor data are normalized. When creating a model, the researcher needs to define what physiological characteristic upon which to base crop N need. For example, does one fertilize based on how to get all the corn plants to a non-stress level ‘happy corn’ (J. Schepers, USDA-ARS personal communication) or fertilize based on predicting grain yield (Raun et al., 2002). Other parameters that may go into models include previous N applications, growth stage, growing degree days (GDD) since planting, fertilizer N costs and grain prices along with other coefficients. Several of these factors are included in traditional preplant N recommendations but have to be predicted well before the crop is growing. The final model developed may range in complexity but needs to address the requirement for making a rapid assessment of crop N status and derive an in-season N recommendation based on that assessment.

The N application models, commonly referred to as N algorithms, range in complexity based on which previously mentioned factors are included. As previously mentioned, scientist at Oklahoma State University included crop growth stage (based on climatic data during the growing season) to predict in-season grain yield to make winter wheat and corn N applications. Work by Solari et al., (2008) developed an algorithm in Nebraska based on the relationship of AOS to SPAD data from previous studies. While simple and providing reasonable N recommendations, the algorithm lacked flexibility based on crop growth stage and crediting previous N applications during the same cropping season.

Canopy Temperature

The first part of this introduction has focused on assessing plant stress by means of monitoring plant health via interactions with light. There are other biophysical properties that can be measured to quantify plant stresses. When plants transpire, water evaporates at the leaf cell and atmosphere interface. This exothermic process releases energy into the atmosphere, thereby cooling the plant (Sadras and Calderini, 2009). Therefore the temperature of plants and leaves may be a useful indicator of plant health. Miller and Saunders (1923) used a thermocouple with a clamping devise to measure leaf temperature of alfalfa (*Medicago sativa* L.). This work was perhaps the first to show that leaf temperature could be lower than the air temperature; however the concept was highly criticized at the time as noted by Moran (2004). Later work by Ehrler, (1973) involved embedding thermocouples in cotton leaves to measure leaf temperature; results showed the difference between temperature before and after irrigation.

With the advent of inexpensive hand held infrared thermometers (IRTs) the concept of measuring canopy temperature was then transferable to farmers and irrigation managers. Idso et al. (1977) and Jackson et al. (1977) measured canopy and air temperatures to develop an index of crop water status. The difference of canopy and air temperature measured at the same time was termed as 'stress-degree-day'. Jackson et al. (1981) refined this approach by fixing the assumption that other environmental factors were manifested in the temperature difference. The inclusion of vapor pressure deficit (VPD), the driver of transpiration, resulted in what is known as "Crop Water Stress Index" (CWSI). Several authors have gone on to demonstrate CWSI as a useful measurement to manage irrigation timing (Irmak et al., 2000; Alderfusi and Nielson, 2001).

Not all work with plant temperature has focused on plant water. Seligman et al. (1983) examined how N deficiency in wheat advanced maturity. Their study noted that N deficient plants generally had higher canopy temperatures which enhanced crop maturity. A study of phenological characteristics of rice (*Oryza sativa* L.) examined how N fertilizer affected leaf temperature (Yan et al. 2010). This work showed that higher N fertilizer applications significantly lowered leaf temperatures. Hegde (1986) concluded that the additions of N fertilizer lead to decreased canopy temperatures in onion (*Allium cepa* L.). Yeun et al. (1994) showed that canopy temperature can be related to the favorability of bacterial infection of dry bean (*Phaseolus vulgaris* L.) in western Nebraska. In general, there is little work on canopy temperature as affected by factors other than plant/soil water and water stress.

Research Objectives

The objective of this research was to build upon previous studies with the goal of answering additional questions while exploring new methods to analyze data obtained by crop canopy sensors. The specific objectives by chapter were to:

Chapter 1.

1. Compare descriptive statistics of virtual and high-N plot reference strategies across a growing season.
2. Evaluate vegetative indices with both strategies and their response to N rate.

Chapter 2.

1. Compare the performance of vegetation indices for measuring N status in corn at three levels of irrigation.
2. Determine how these indices affect a calculated N rate.

Chapter 3.

1. Quantify the effect N fertility has on plant canopy temperature and the canopy/air temperature difference.
2. Determine if canopy temperature or the canopy/air temperature difference is more sensitive to N status

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Chapter 1. Comparison of Reference Approaches to Calculate Sufficiency Index of Corn (*Zea mays* L.) for Nitrogen Fertilization

Abstract

Active optical sensors (AOS) have demonstrated their ability to make nondestructive assessments of crop nitrogen (N) status. Since their introduction to production agriculture, fertilizer equipment and monitor capabilities have advanced making new algorithm approaches available. The objective of this study was to compare reference strategies for normalizing reflectance data across multiple vegetation indices. A study was conducted from 2011 to 2013 with corn (Zea mays L.) at two sites in Nebraska. Treatments consisted of irrigation (Full, 75% of Full, and rain fed) and N fertilizer rate (0, 84, 140, 196, and 252 kg N ha^{-1}). Crop canopy reflectance was measured at multiple growth stages by a three band (670, 720, and 760 nm) sensor. The virtual reference concept helped reduce variation of calculated reference and placed sufficiency index values in a range that corresponds to plant N status. Of the three vegetation indices used, the DATT and CIRE index most often showed significant responses to applied N fertilizer. The NDVI index was the least responsive of the indices tested and would cause the highest variability when calculating reference values.

Introduction

In-season nitrogen (N) recommendations start with an assessment of plant N status. Visual assessment of 'greenness' and plant health has been around as long as cultivated cereal production itself. Quantitative assessments of plant N status began in the 1930's with plant tissue testing (Fox and Walthall, 2008). Tissue testing has been used to predict grain yield and assess N fertility. It follows that tissue sampling can be a useful tool for agronomic management of crop production; however these methods can be labor intensive and time consuming, making rapid assessment difficult.

In 1982, the Japanese Ministry of Fishery and Agriculture in conjunction with the Minolta Corporation developed what would become known as the SPAD (Special Products Analysis Division) meter (Fox and Walthall 2008). This small hand-held instrument measures light absorption (660 nm) and transmission (940nm) through a leaf to estimate chlorophyll concentration based on the ratio of absorption to transmission. The output data are a unitless value, simply referred to as a SPAD reading. These values have been well correlated to N status of cereal grains (Schepers et al. 1992; Peng et al. 1995; and Vidal et al. 1999) and thus make an excellent inference to N fertility. This method of assessment has several drawbacks that limit its use. Data logging and export is limited to storing a finite number of readings (30 readings) and the device only displays the most recent reading or an average. Additionally, the SPAD meter requires a contact measurement so sampling cannot be done on-the-go. This limitation also creates problems when assessing a field that may exhibit spatial variability.

During the early 2000s, proximal sensors using their own light source were developed to measure light reflectance in specific bands as a means to assess N status.

The reflectance values measured by an active optical sensor (AOS) are often transformed by an equation known as vegetation index (VI). A VI offers increased sensitivity to specific biophysical characteristics, specifically plant N status (Fox and Walthall, 2000). The most recognizable VI, normalized difference vegetation index (NDVI) has been used by many researchers to detect N status of a variety of plant species (Raun et al., 2001; Raun et al., 2005; and Xiong et al., 2007). Other VI such as chlorophyll index (Solari et al. 2008) and chlorophyll index red edge (Holland and Schepers, 2013) have been used to describe the relationship of AOS reflectance to N status. Recently, Shiratsuchi et al. (2011) compared multiple VI and the affect drought stress can play in the ability to detect N status. Their work indicated the DATT index (Datt, 1999) had the best ability to separate N rates.

An additional benefit of AOS is their non-contact nature, making them conducive for use as an on-the-go sensor conducting N status assessments and making application decisions in real time. Since they can be integrated with GPS and application equipment monitors, they offer the ability to map field conditions that can be later processed with GIS software. Both technologies, SPAD and AOS, need a method to convert sensor reading into a scale or index that relates to crop vigor.

Peterson et al. (1993) used a simple equation (1-1) to normalize SPAD data collected in the field to recommend fertigation timing for corn.

$$Sufficency\ Index = \frac{Average\ Bulk\ Reading}{Average\ Reference\ area\ Reading}$$

Equation 1-1 Sufficiency Index

This method termed sufficiency index (SI) had been the foundation of many scientific works investigating both SPAD and AOS data. In the equation, *Reference Area VI* is the value for healthy non-N limited plants and *Bulk VI* is a representative sample of the area to be fertilized. The non-N limited or high-N fertility area is usually given extra N fertilizer prior to planting. A second method of normalization is known as response index (RI) (Raun et al., 2002). Essentially SI and RI are reciprocals of one another.

Since the original concept of SI was published, the ability to collect, record and process data has grown exponentially. The combination of AOS, global positioning systems (GPS) and computing have made it possible for scientists to revisit SI and integrate the concept into today's agricultural systems. In an attempt to improve upon a single high-N rate, Raun et al. (2008) proposed the ramped calibration strip. The method consists of applying stepped N rates in a strip and comparing with an adjacent high-N reference so that a growth plateau can be determined by an AOS or visually. Holland (2009) patented a statistical method to establish a reference value from representative field situations that include spatial variability. This method uses data values collected after making a pass across a representative area of the field under investigation – a virtual reference approach. These values are plotted in a histogram and a cumulative 95th percentile value is recorded (Figure 1.1). Both the N ramp and virtual reference approaches can be used in place of the high-N fertilized reference plot. The Holland method was demonstrated by Holland and Schepers (2013) in conjunction with a proposed universal N application algorithm.

There is little work comparing reference approaches for AOS use to control in-season N fertilization. Variations in reference values have the potential to greatly change calculated N rates since SI is how AOS data is converted to drive N applications. Additionally, how the reference value is derived is directly linked to how much user input is required to properly us AOS technology.

This study set out to test two main hypotheses: (i) the virtual reference approach reduces variation and improves the accuracy of economic optimum N rate prediction in comparison to a non-N limiting reference; (ii) the selection of VI does not impact the ability of either reference approach to predict economic optimum N rate.

Materials and Methods

Experimental Design and Site Description

Field experiments were established in 2012 at the West Central Water Lab (BWL; 41.0294 ° N, -101.958292 ° W) near Brule, Nebraska and at the South Central Agriculture Lab (SCAL; 40.58145 ° N, -98.14147 ° W) near Clay Center, Nebraska. The BWL has variable soils across the experiment location; dominant soil series were Satanta loam (fine-loamy, mixed, superactive, mesic Aridic Argiustolls) 3 to 6% slope, Bankard loamy sand (sandy, mixed, mesic Ustic Torifluvents) channeled and Bayard very fine sandy loam (coarse-loamy, mixed, superactive, mesic Torriorthentic Haplustolls) 1 to 3% slope. In 2012, treatment design consisted of a split-plot replicated Latin square (3 replications); in 2013 the design was simplified to a randomized complete block (6 replications). In 2012, irrigation (Full, 75% of Full, 40% of Full) served as the main plot and N rate (0, 84, and 252 kg N ha^{-1}) as the sub plot. In 2013, variable irrigation failed so N rate became the main plot with no subplots. For both years, plots were 6.1 meters wide (8 rows) and 37.5 to 53.6 meters in length depending on distance from the pivot point.

The dominant soil series at SCAL is Hastings silt loam (fine, smectitic, mesic Udic Argiustolls), 0 to 1% slope. Treatment design consisted of a split-plot randomized complete block with irrigation (Full, 75% of Full, and rain fed) as the main plot and N rate (0, 84, 140, 196, and 252 kg N ha^{-1}) as the sub plot; treatments were replicated 4 times at this site. Plot size was 6.1 meters wide (8 rows) by 53.3 meters long. For both sites, the study was no-till, continuous corn with the previous year's corn managed uniformly. Planting date and plant population were based on local best management practices (BMPs) for each respective site (Table 1.1). Fertilizer was applied after crop emergence as 28% urea ammonium nitrate solution (UAN) at all sites. The UAN for BWL was surface-banded by a high clearance applicator equipped with drop tubes placing UAN on 152-cm centers. The SCAL site used subsurface coulter application of UAN on 76-cm centers. Irrigation events at BWL site were triggered by the station manager when a visual inspection of the crop indicated stress was present. For SCAL, irrigations were started when soil matric potential became lower than a pre-determined value based on the soil texture at the experiment site. Weed and pest management followed BMPs for each site.

Canopy Sensing

Canopy reflectance data were collected with Holland Scientific (Lincoln, NE) Crop Circle model ACS 470 (in 2011) or ACS 430 (2012 & 2013) sensors. Two sensors were positioned 40 to 60-cm above the crop canopy directly over the row; data were logged by a Holland Scientific GeoSCOUT with DGPS receiver (model 16A, Garmin International, Olathe, KS) recoding at a rate of 5 Hz. Sensors were mounted on a high-clearance tractor traveling approximately 4 to 6 km $hour^{-1}$, resulting in an average of 180 data recordings per plot. Data were filtered using ArcGIS software (ESRI, Redlands, CA) to remove border effects from neighboring treatments. Sensors field of view is 45° by 10°; making the sensed footprint approximately 1500 cm^2. Sensors recorded reflectance in three wave bands: red (670 nm), red-edge (730 nm) and near-infrared (NIR, 760). These bands were used to calculate three vegetation indices: Normalized Difference Vegetation Index (NDVI), Chlorophyll Index Red-Edge (CIRE) and DATT (Table 1.2). Multiple sampling dates were selected within the growing season to monitor VI response at various crop growth stages (Table 1.3).

Sufficiency index calculations used two reference methods: traditional non-N limited crop and the virtual reference concept. The traditional non-N limited reference was the mean of all VI values within the 252 kg N ha^{-1} treatment. The virtual reference value calculation involved all points within a block across all N treatments, as determined by the 95th percentile value of a histogram. Once the two reference values were determined by block, SI was calculated (Equation 1) for every filtered data point within the study area. Finally, all values were averaged within a plot for statistical analysis.

Data Analysis and Statistics

Descriptive statistics for both reference approaches were calculated for VI using Microsoft Excel 2010 (Microsoft Corp., Redmond, WA). Reference approach and VI affects from N rates within the full irrigation main plot were analyzed using the PROC GLIMMIX procedure for SAS 9.2 (SAS Institute Inc., Cary, NC). Blocks were treated as a random effect with sensing dates being compared within a year. No cross-year analysis was performed due to the large weather variations across the duration of the experiment.

Results and Discussions

Growing season weather summaries for BWL (Figures 1.2 and 1.3) and SCAL (Figures 1.4 and 1.5) are presented for each year. Overall, temperatures were similar for sites within a year, with 2012 warmer than average May through August; and 2013 being cooler to normal early and warmer late. Rainfall was low for both sites in 2012, triggering early irrigations at BWL (10-May) and with SCAL receiving the first irrigation on 7-July. Higher rainfall was received in 2013 for BWL resulting in less frequent irrigation events; as in the previous year, SCAL was first irrigated on 7-July. At both sites, the study was located on land uniformly managed the previous year so no historical effects were expected.

Reference Method

Sensing dates and growth stages are presented in Table 1.3. Although some sensing occurred after ideal N side dress timing, later sensing could be useful for further N applications of a method to monitor plant health. Each site year had a minimum of three sensing dates. For two sampling dates at SCAL (27 July, 2012 and 21 June, 2013) only three of four replications of data were recorded due to equipment failing to properly log data. Reference values for each sampling date for each year are presented in Tables 1.4 through 1.16. For all but two sampling dates (BWL 23 August, 2012 and SCAL 3 July, 2013) the average reference value calculated with the virtual reference approach resulted in a lower coefficient of variation. It is also important to note that for every date the ‘High N’ reference value was lower than the ‘Virtual’ regardless of VI used. This lower reference value resulted in a narrow range of calculated SI values, thus making the sensed crop appear sufficient in N when that may not be the case.

The VI used had an effect on the variability of the calculated reference value. The CIRE and NDVI were more variable than DATT. The DATT index had very low variability for every sampling date with a maximum CV of 4.3 % (BWL 23 August, 2012). This observation of DATT's low variance would help explain and support the findings of Shiratsuchi et al. (2011) that displayed the low influence that irrigation and previous crop had. The DATT index's ability to produce reference values with low variation makes it appealing for use in algorithms for N applications. For all VIs and site years, variability tended to decrease as the growing season progressed.

Analysis of variance for each site year is presented in Table 1.17. The method for calculating reference values was highly significant (<0.001) for all site years. As previously mentioned, lower reference values from the high N treatment resulted in higher average SI values in contrast to the virtual reference. This difference ranged from 0.21 (BWL 2012) to 0.07 (SCAL 2012). The interaction of VI and reference approach is a result of the DATT index having a smaller difference between the two reference methods than CIRE and NDVI. This interaction occurred in every site year. Sensing date also interacted with reference approach. At all dates high N SI was greater than Virtual SI. For the two BWL years, 2012 exhibited as the season progressed, the difference between reference approaches increased by date. SI calculated from the high N approach significantly increased at each date during the season. In 2013, the largest difference between calculation methods was observed July 9, with subsequent dates becoming closer together. High N SI gradually decreased as the season progressed while virtual SI first increased then dropped. For SCAL in 2012, SI on the first two sensing dates were statistically the same within reference method with the final sensing date having an average SI lower than the first two sensing dates. In 2013, the virtual approach SI statistically (alpha=0.01) never changed throughout the growing season. As in 2012, the high N SI declined from the first sensing date forward but the second and third dates were not different from each other.

Vegetation Index

Vegetation indices performed differently from one another for each site year (Table 1.17). Additionally, VI responded differently to N rate and sensing date at three of four site years with BWL in 2012 being the unresponsive site in both cases. The ability of VI to respond to N rate across reference strategies is shown in Figures 1.6-1.8. The data for BWL 2013 (Figure 1.6, Table 1.18) shows that SI for CIRE was significantly lower than NDVI and DATT for all N rates. The NDVI was significantly lower than DATT at 0 kg N ha^{-1} but equal at 84 and 252 kg of N ha^{-1}. All three indices showed a significant response to every level of N applied. Data for the date by index interaction is not presented since there were no three-way interactions between index, N rate, and date.

In 2012 at SCAL (Figure 1.7, Table 1.19), all three indices were unable to distinguish between the top two N rates averaged across the season. Additionally, there was no difference in SI for NDVI from 140 kg N ha^{-1} to 252 kg N ha^{-1} treatments. The CIRE had the largest range in values of the three indices. There was a significant date by index interaction as well as a three way with date, index and N (Figure 1.9). Over the three sensing date in 2012, CIRE routinely had the largest range in response. The DATT developed a larger range of responsive with each sensing date. This increase in response for CIRE and DATT is most likely due to increased N demand by the plant as it progresses in development. The CIRE showed this increased responsiveness on the third sensing date, with the first two essentially the same. The NDVI did not change over the course of the growing season, with several N rates (0, 140 and 252 kg N ha^{-1}) being statistically the same at all three sensing dates.

The VI response for SCAL 2013 (Figure 1.8, Table 1.20) was similar to 2012 with CIRE and DATT not able to distinguish between 196 and 252 kg N ha^{-1} treatments. The response of NDVI to N rate was complex with NDVI not indicating a response from 96 to 140 kg N ha^{-1} while showing a significant decrease from 196 to 252 kg of N ha^{-1}. Again CIRE displayed the largest response range of SI values. The three-way date, index and N rate interaction is displayed in Figure 1.10. This interaction behaved very differently than in 2012 mainly due to the lack of moisture in June (Figure 1.5). The first sensing date for all indices was unresponsive across N rates; this may be a result of the growth stage at the time of sensing (V 6/8) which was earlier than in 2012 (V 10/11). The second sensing date resulted in better N responsiveness for the three indices, with CIRE and NDVI showing lower SI values for the highest N treatment. These lower SI values can be accredited to water stress at the time of sensing which was present in the highest N fertility treatments across the entire study (figure 1.5). It is interesting to point out that the DATT index does not show this characteristic; providing further evidence of the findings of Shiratsuchi et al. (2011) that DATT can provide N status assessment regardless of water stress. The final sensing pass on July-12 occurred after an irrigation event that eliminated the drop in SI at 252 kg N ha^{-1} due to reduced moisture stress conditions. At this time, all three indices displayed a higher degree of response as compared to earlier in the season.

Conclusions

This study compared virtual and high N plot reference strategies across a growing season and three vegetation indices and their response to N rate and sensing date. Results indicate that the virtual reference approach provides several advantages in calculating SI. First this method reduced variation in reference calculation in 10 of 12 sensing date/site/years. Second it placed calculated SI values in a range that better corresponds to plant N status. Moving to calculating reference values based on the virtual concept should be a goal of any AOS directed N applications. This practice will eliminate the need to apply an often excess N application to an area of the field while being able to provide the producer a view of the variability in their by examining the histogram of VI values. Computing power has evolved since the original SI concept was developed by Peterson et al. (1993) making this a fairly easy adjustment. The three vegetative index methods resulted in very different response functions and magnitudes. The DATT index provided a consistently significant measure of N response due in part to its low error. However it may lack the magnitude of response needed to work well in N application algorithms. Consequently, CIRE always had a large response but was more variable at times. The NDVI did not show the responsiveness of DATT or CIRE and also had the highest variability when calculating reference. Moving forward, producers should use caution when using AOS technology if the sensor is limited to calculating a select few vegetative indices.

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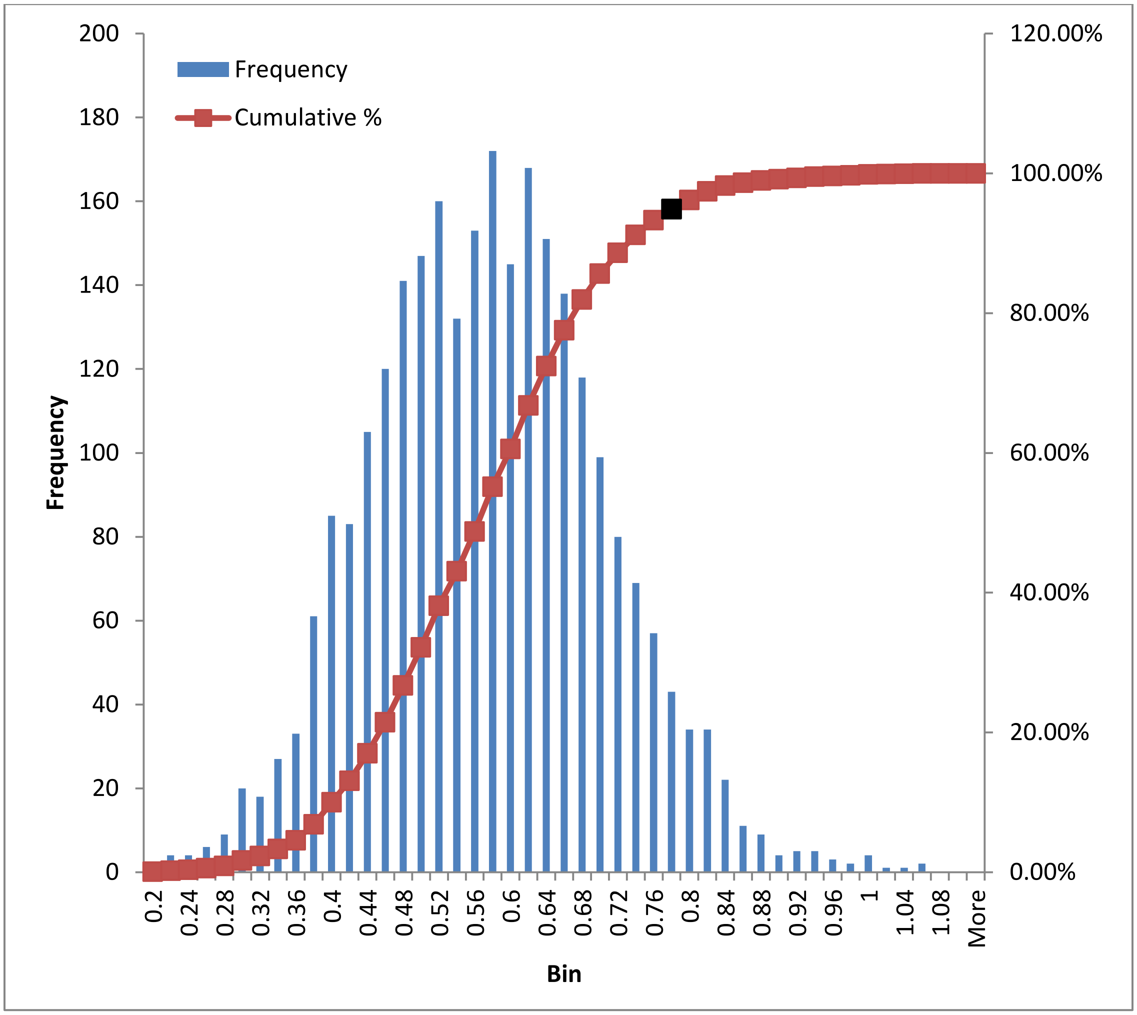

Figure 1-1 Sufficiency Index histogram and cumulative percentile calculated from Chlorophyll Index Red Edge of corn at South Central Ag Lab (V11 growth stage 2013). The black data point represents the cumulative 95th percentile value that is used for the 'Virtual Reference'.

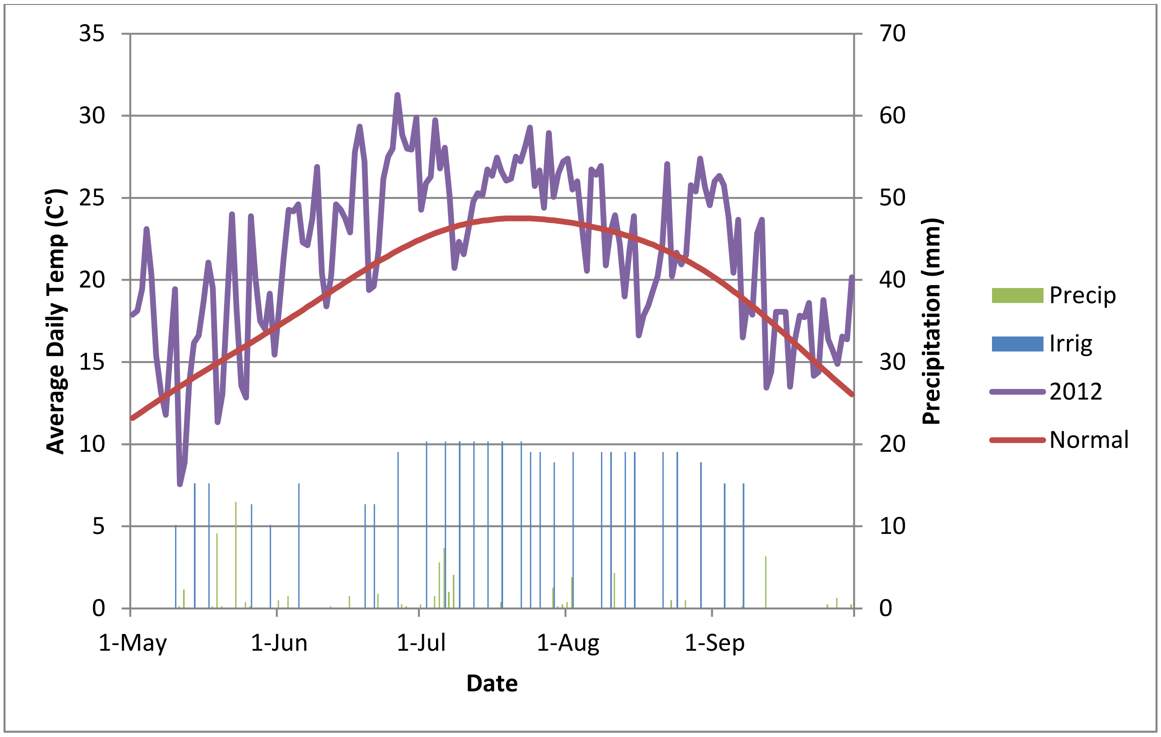

Figure 1-2 Growing season weather conditions for the 2012 BWL site. Temperatures were generally above normal for the season with frequent irrigations. Any precipitation event were small and infrequent.

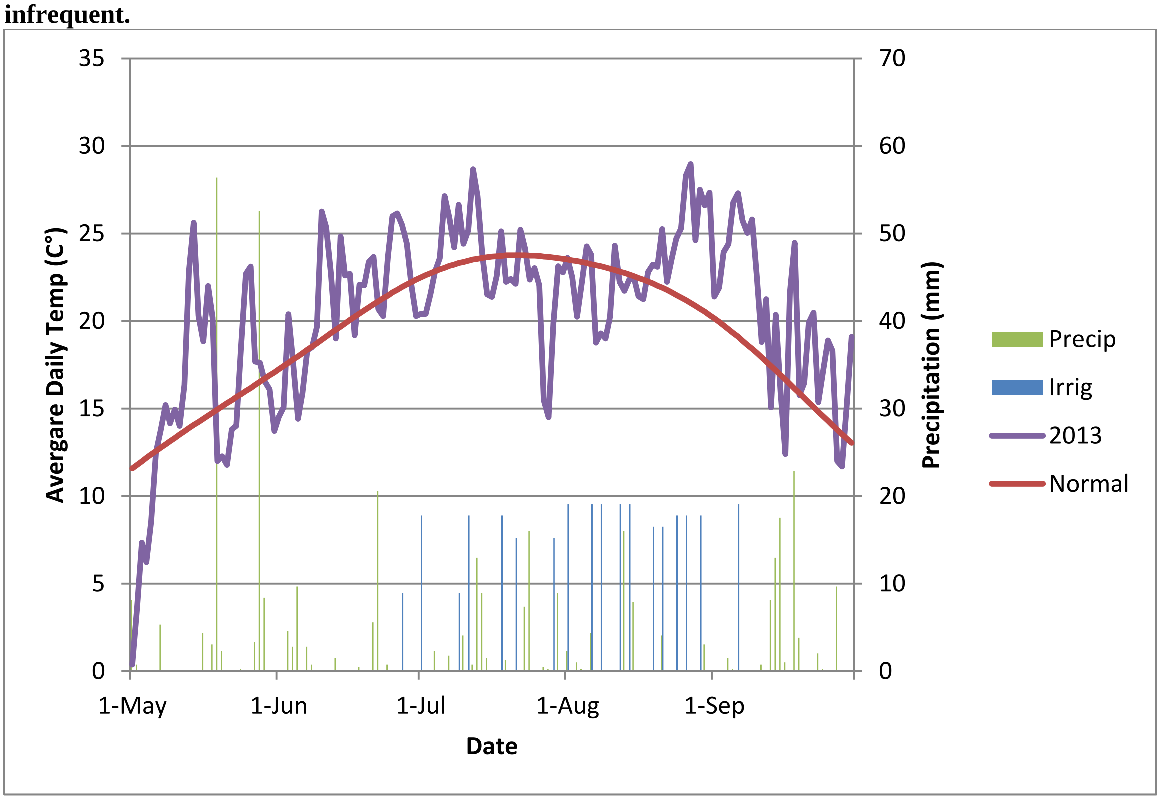

Figure 1-3 Growing season weather conditions for the 2013 BWL site. Early and mid-season temperatures were below average. There were more rainfall events and less frequent irrigations than in 2012.

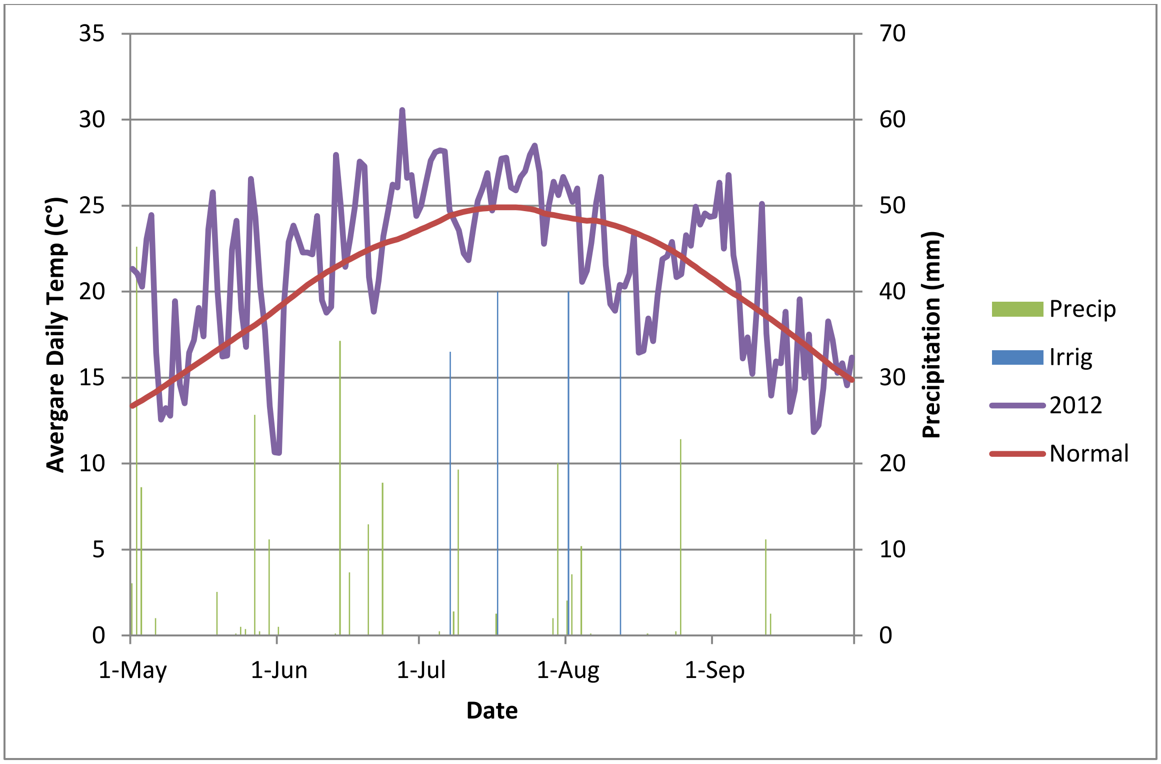

Figure 1-4 Growing season weather conditions for the 2012 SCAL site year. Temperatures were in general above average with regular but small rainfall events through the season.

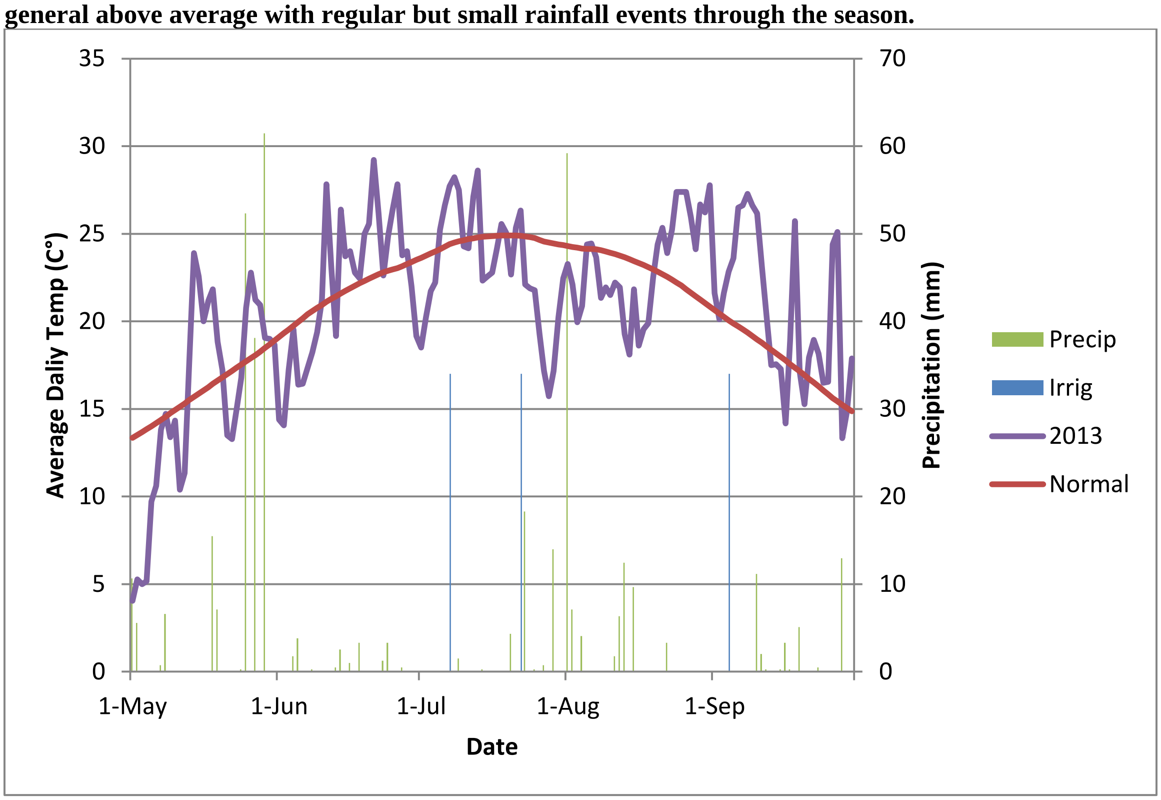

Figure 1-5 Growing season weather conditions for the 2013 SCAL site year. Temperatures were below normal early to halfway through the season. Rainfall was high for the first month followed by low and infrequent precipitation events.

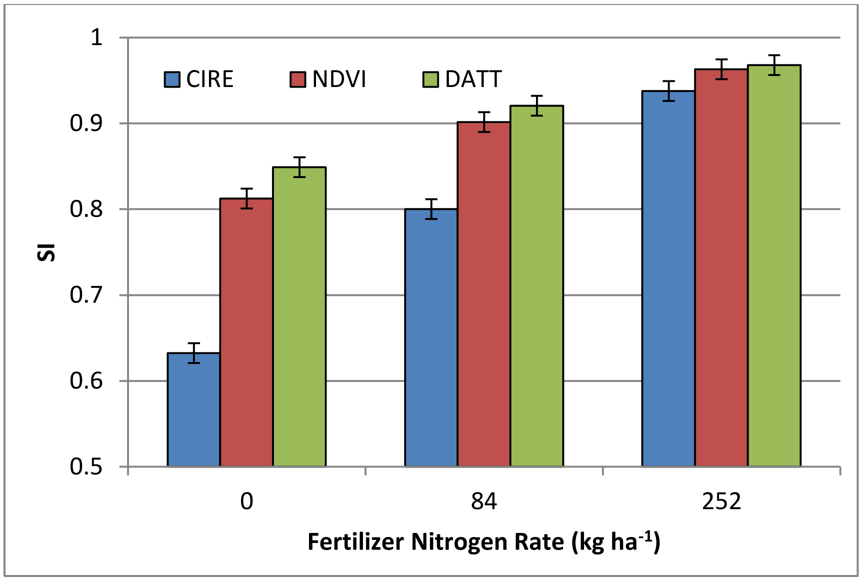

Figure 1-6 BWL 2013 VI by N rate interaction across reference methods and date. The CIRE was significantly lower than both NDVI and DATT at all N rates. The NDVI was significantly lower than DATT at 0 kg of N ha^{-1} but equal at the 84 and 252 kg N rate. All indices showed response between each rate of N fertilizer. Error bars indicate standard error.

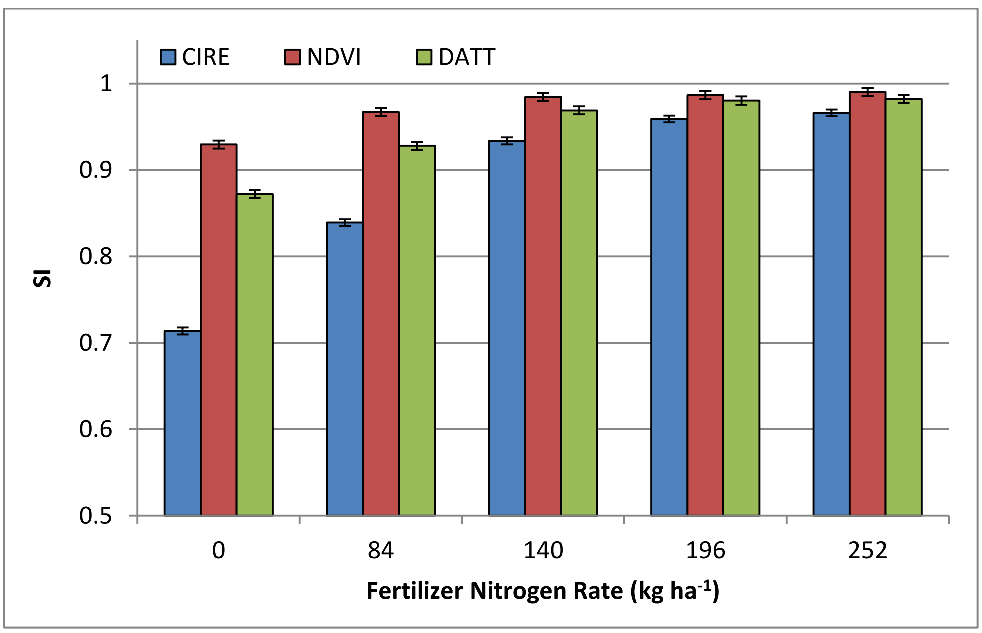

Figure 1-7 SCAL 2012 VI by N rate interaction across reference methods and date. All indices were unable to differentiate the two highest N rates. The NDVI was statistically the same from the 140 to 252 kg of N. Error bars indicate standard error.

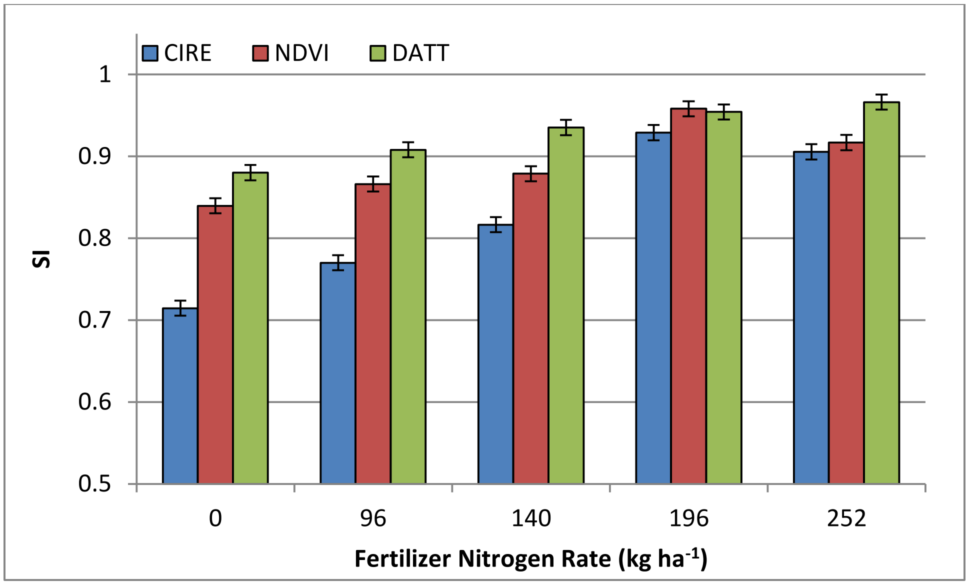

Figure 1-8 SCAL 2013 VI by N rate interaction across reference methods and date. The CIRE and DATT saw no response above 196 kg of N. The NDVI saw no response from 96 to 140 and a negative response from 196 to 252 kg N. Error bars indicate standard error.

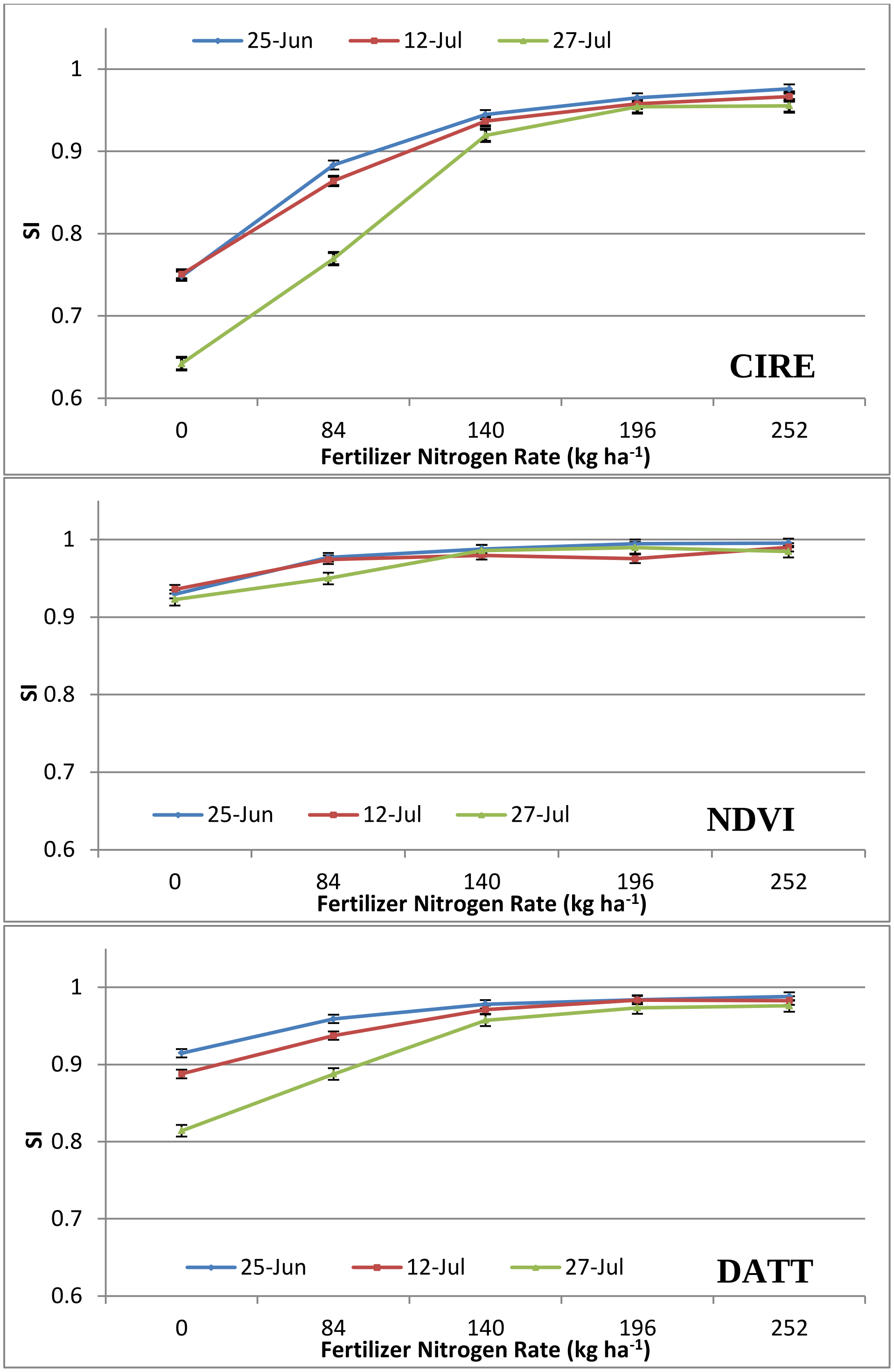

Figure 1-9 SCAL 2012 three way interaction of VI, sensing date and N rate across reference methods. The CIRE demonstrated a similar response to N for the first two sensing dates while exhibiting a larger response range for the third sensing date. The NDVI maintained a similar response to added fertilizer N across all sensing dates with three N rates (140, 196 and 252 kg N ha-1) having statistically the same SI across all three dates. The DATT progressively developed a larger response range as the season progressed. Error bars indicate standard error.

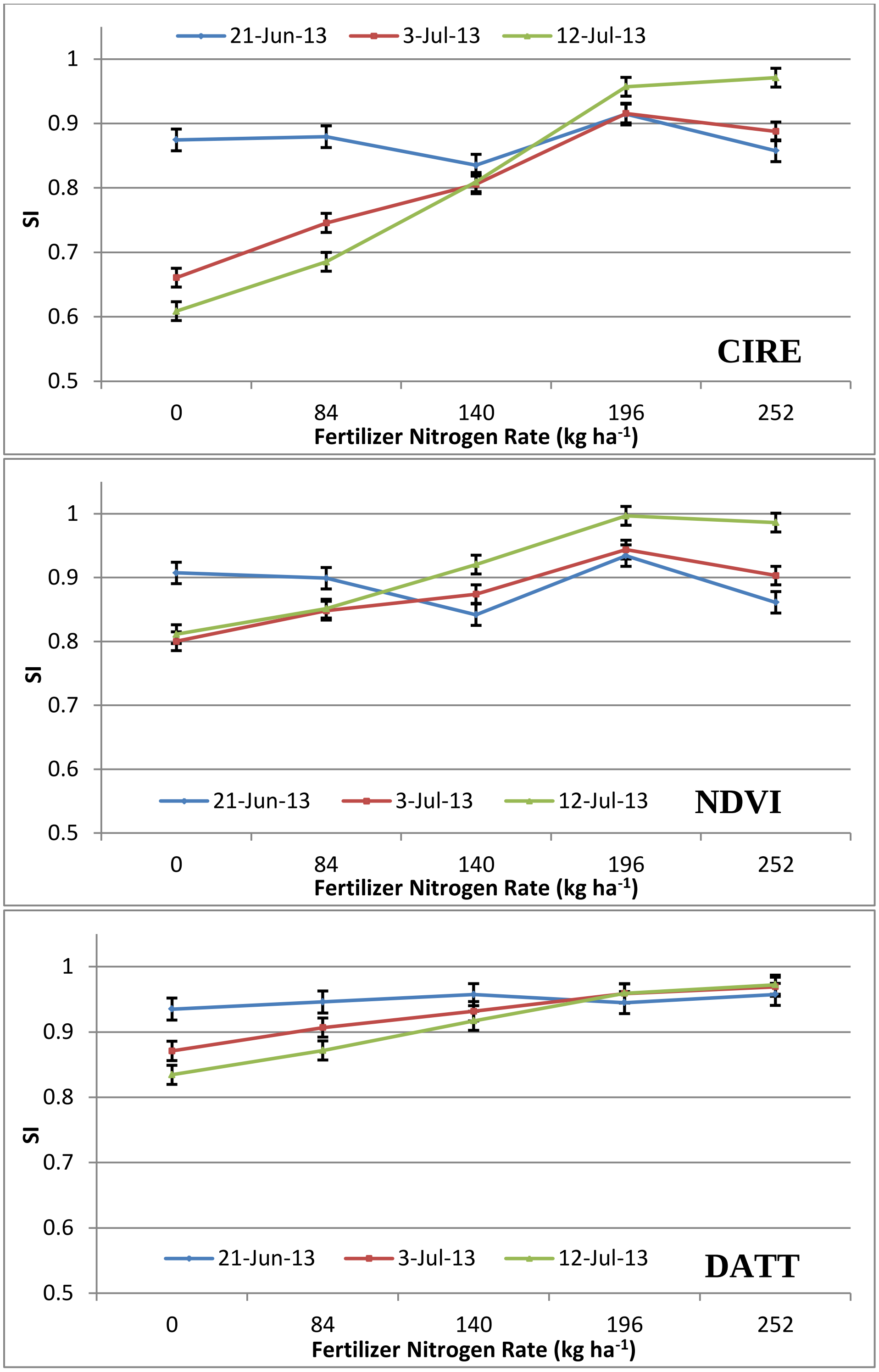

Figure 1-10 SCAL 2013 three way interaction of VI, date and N rate across reference methods. All indices were unresponsive to N rate for the first sensing date. For the second and third date, all indices responded to fertilizer N rates. As in 2012, CIRE demonstrated the largest range in SI for N responsive dates, with the third sensing date having the largest SI range. Error bars represent standard error.

Table 1-1 Planting characteristics

		BWL		SCAL	
		2012	2013	2012	2013
Planting Date		8-May	10-May	25-Apr	16-May
Hybrid		Pioneer 3544	Pioneer 1151	Pioneer 1498HR	Pioneer 876CHR
Plant Population (plants ha^{-1})	Irrigated	79200	79200	74100	74100
	Dryland	n/a	n/a	64300	64300

Table 1-2 Vegetative indices, wavebands used, formulas and references

Indices	Wavebands (mm)	Equation	Reference
NDVI	670, 760	$NDVI = \frac{NIR_{760} - Red_{670}}{NIR_{760} + Red_{670}}$	Tucker, 1979
CIRE	720, 760	$CIRE = \frac{NIR_{760}}{RedEdge_{720}} - 1$	Gitelson et al, 2005
DATT	670, 720, 760	$DATT = \frac{NIR_{760} - RedEdge_{720}}{NIR_{760} - Red_{670}}$	Datt et al, 1999

Table 1-3 Date and crop growth stage of crop sensing

2012			2013		
Location	Date	Growth Stage	Location	Date	Growth Stage
BWL	17-Jul	V12/V13	BWL	9-Jul	V10
BWL	31-Jul	VT/R1	BWL	18-Jul	V13/V14
BWL	23-Aug	R3	BWL	31-Jul	R1
SCAL	25-Jun	V12	BWL	14-Aug	Late R2
SCAL	12-Jul	R1	SCAL	21-Jun	V5/V6
SCAL	27-Jul	R3	SCAL	3-Jul	V8/V9
			SCAL	12-Jul	V11/V12

Table 1-4 Reference values for SI calculations at V12/V13 BWL 7-17-2012

Sampled reference values						
Rep	$CI_{red\ edge}$		NDVI		DATT	
	Virtual	High N	Virtual	High N	Virtual	High N
1	1.235	1.036	0.826	0.767	0.620	0.582
2	1.215	0.943	0.821	0.721	0.624	0.573
3	1.278	0.951	0.827	0.683	0.634	0.587
Mean	1.242	0.977	0.825	0.724	0.626	0.581
SD	0.032	0.052	0.003	0.042	0.007	0.007
CV (%)	2.6	5.3	0.4	5.8	1.2	1.3

Table 1-5 Reference values for SI calculations at VT/R1 BWL 7-31-2012

Sampled reference values						
Rep	$CI_{red\ edge}$		NDVI		DATT	
	Virtual	High N	Virtual	High N	Virtual	High N
1	1.083	0.817	0.796	0.680	0.599	0.542
2	1.075	0.748	0.781	0.633	0.611	0.540
3	1.133	0.733	0.782	0.575	0.625	0.555
Mean	1.097	0.766	0.786	0.629	0.612	0.546
SD	0.031	0.045	0.008	0.053	0.013	0.008
CV (%)	2.8	5.9	1.1	8.4	2.2	1.5

Table 1-6 Reference values for SI calculations at R3 BWL 8-23-2012

Sampled reference values						
Rep	$CI_{red\ edge}$		NDVI		DATT	
	Virtual	High N	Virtual	High N	Virtual	High N
1	0.826	0.569	0.642	0.502	0.617	0.521
2	0.833	0.547	0.628	0.483	0.641	0.525
3	0.925	0.574	0.669	0.473	0.650	0.485
Mean	0.861	0.563	0.646	0.486	0.636	0.510
SD	0.055	0.015	0.021	0.015	0.018	0.022
CV (%)	6.4	2.6	3.2	3.0	2.8	4.3

Table 1-7 Reference values for SI calculations at V10 BWL 7-9-2013

Sampled reference values						
Rep	$CI_{red\ edge}$		NDVI		DATT	
	Virtual	High N	Virtual	High N	Virtual	High N
1	1.104	0.856	0.728	0.594	0.649	0.615
2	1.098	0.860	0.728	0.593	0.649	0.617
3	0.981	0.729	0.653	0.519	0.653	0.609
4	0.822	0.488	0.601	0.374	0.672	0.589
5	1.086	0.771	0.715	0.543	0.651	0.610
6	1.186	0.978	0.763	0.666	0.645	0.615
Mean	1.046	0.780	0.698	0.548	0.653	0.609
SD	0.128	0.167	0.060	0.099	0.009	0.010
CV (%)	12.2	21.4	8.5	18.1	1.4	1.7

Table 1-8 Reference values for SI calculations at V13/V14 BWL 7-18-2013

Sampled reference values						
Rep	$CI_{red\ edge}$		NDVI		DATT	
	Virtual	High N	Virtual	High N	Virtual	High N
1	1.244	1.086	0.802	0.737	0.641	0.612
2	1.304	1.123	0.802	0.737	0.650	0.621
3	1.249	1.047	0.788	0.698	0.648	0.618
4	0.997	0.735	0.709	0.564	0.636	0.577
5	1.209	0.898	0.785	0.651	0.638	0.593
6	1.300	1.121	0.818	0.765	0.647	0.608
Mean	1.217	1.002	0.784	0.692	0.643	0.605
SD	0.114	0.155	0.039	0.074	0.006	0.017
CV (%)	9.3	15.5	4.9	10.7	0.9	2.8

Table 1-9 Reference values for SI calculations at R1 BWL 7-31-2013

Sampled reference values						
Rep	$CI_{red\ edge}$		NDVI		DATT	
	Virtual	High N	Virtual	High N	Virtual	High N
1	1.349	1.130	0.781	0.736	0.670	0.622
2	1.376	1.113	0.783	0.724	0.675	0.622
3	1.322	1.089	0.765	0.706	0.672	0.625
4	1.177	0.943	0.727	0.655	0.665	0.587
5	1.294	1.054	0.767	0.700	0.667	0.618
6	1.380	1.144	0.793	0.753	0.669	0.617
Mean	1.316	1.079	0.769	0.712	0.670	0.615
SD	0.076	0.074	0.023	0.034	0.004	0.014
CV (%)	5.7	6.8	3.0	4.8	0.5	2.3

Table 1-10 Reference values for SI calculations at Late R2 BWL 8-14-2013

Sampled reference values						
Rep	$CI_{red\ edge}$		NDVI		DATT	
	Virtual	High N	Virtual	High N	Virtual	High N
1	1.243	1.059	0.746	0.705	0.665	0.618
2	1.312	1.075	0.755	0.701	0.673	0.624
3	1.267	1.052	0.739	0.684	0.672	0.626
4	1.172	0.942	0.705	0.641	0.676	0.614
5	1.278	1.043	0.743	0.677	0.680	0.627
6	1.325	1.096	0.771	0.722	0.671	0.619
Mean	1.266	1.044	0.743	0.688	0.673	0.622
SD	0.055	0.054	0.022	0.028	0.005	0.005
CV (%)	4.3	5.1	2.9	4.1	0.8	0.8

Table 1-11 Reference values for SI calculations at V12 SCAL 6-25-2012

Sampled reference values						
Rep	$CI_{red\ edge}$		NDVI		DATT	
	Virtual	High N	Virtual	High N	Virtual	High N
1	1.832	1.598	0.840	0.803	0.714	0.688
2	1.819	1.620	0.843	0.804	0.714	0.690
3	1.878	1.662	0.847	0.814	0.719	0.693
4	1.862	1.651	0.848	0.813	0.716	0.691
Mean	1.848	1.633	0.845	0.808	0.716	0.690
SD	0.027	0.029	0.003	0.006	0.002	0.002
CV (%)	1.5	1.8	0.4	0.7	0.3	0.4

Table 1-12 Reference values for SI calculations at R1 SCAL 7-12-2012

Sampled reference values						
Rep	$CI_{red\ edge}$		NDVI		DATT	
	Virtual	High N	Virtual	High N	Virtual	High N
1	1.128	1.042	0.757	0.727	0.621	0.605
2	1.122	1.041	0.759	0.729	0.621	0.605
3	1.125	1.033	0.762	0.729	0.621	0.602
4	1.122	1.022	0.760	0.726	0.620	0.600
Mean	1.124	1.035	0.760	0.728	0.621	0.603
SD	0.003	0.009	0.002	0.001	0.000	0.002
CV (%)	0.2	0.9	0.3	0.2	0.1	0.4

Table 1-13 Reference values for SI calculations at R3 SCAL 7-27-2012

Sampled reference values

Rep	$CI_{red\ edge}$		NDVI		DATT	
	Virtual	High N	Virtual	High N	Virtual	High N
1	1.196	0.997	0.732	0.674	0.656	0.615
2	1.158	0.939	0.733	0.673	0.648	0.598
4	1.162	0.955	0.732	0.680	0.650	0.599
Mean	1.172	0.964	0.732	0.676	0.651	0.604
SD	0.021	0.030	0.001	0.003	0.004	0.010
CV (%)	1.8	3.1	0.1	0.5	0.6	1.6

Table 1-14 Reference values for SI calculations at V5/V6 SCAL 6-21-2013

Sampled reference values

Rep	$CI_{red\ edge}$		NDVI		DATT	
	Virtual	High N	Virtual	High N	Virtual	High N
1	0.472	0.366	0.426	0.337	0.578	0.533
2	0.459	0.372	0.438	0.352	0.569	0.521
3	0.507	0.407	0.466	0.375	0.575	0.529
Mean	0.479	0.382	0.443	0.355	0.574	0.528
SD	0.025	0.022	0.021	0.019	0.005	0.006
CV (%)	5.2	5.7	4.6	5.4	0.8	1.1

Table 1-15 Reference values for SI calculations at V8/V9 SCAL 7-3-2013

Sampled reference values

Rep	$CI_{red\ edge}$		NDVI		DATT	
	Virtual	High N	Virtual	High N	Virtual	High N
1	0.781	0.662	0.622	0.534	0.603	0.571
2	0.814	0.676	0.638	0.533	0.604	0.579
3	0.786	0.653	0.610	0.521	0.610	0.574
4	0.847	0.696	0.676	0.550	0.602	0.577
Mean	0.807	0.672	0.637	0.535	0.605	0.575
SD	0.030	0.019	0.029	0.012	0.004	0.003
CV (%)	3.8	2.8	4.5	2.2	0.6	0.6

Table 1-16 Reference values for SI calculations at V11/V12 SCAL 7-12-2013

Sampled reference values

Rep	$CI_{red\ edge}$		NDVI		DATT	
	Virtual	High N	Virtual	High N	Virtual	High N
1	1.010	0.835	0.740	0.643	0.617	0.577
2	1.037	0.848	0.734	0.631	0.628	0.589
3	1.052	0.912	0.745	0.669	0.627	0.592
4	1.059	0.915	0.744	0.680	0.618	0.588
Mean	1.040	0.877	0.741	0.656	0.623	0.587
SD	0.022	0.042	0.005	0.023	0.005	0.006
CV (%)	2.1	4.8	0.7	3.5	0.9	1.1

Table 1-17 Analysis of variance of four site years of AOS reflectance data with different reference calculation methods (Virtual and High N), vegetative indices (CIRE, NDVI, DATT), collection dates and N application rates.

	BWL 2012		BWL 2013			SCAL 2012	SCAL 2013
Effect	Num DF	Pr > F	Num DF	Pr > F	Num DF	Pr > F	Pr > F
Reference	1	<.0001	1	<.0001	1	<.0001	<.0001
Index	2	<.0001	2	<.0001	2	<.0001	<.0001
Index*Reference	2	<.0001	2	<.0001	2	<.0001	<.0001
Date	2	0.0777	3	0.0002	2	<.0001	<.0001
Date*Reference	2	<.0001	3	<.0001	2	<.0001	<.0001
N	2	<.0001	2	<.0001	4	<.0001	<.0001
N*Reference	2	0.8116	2	0.0829	4	0.0178	0.6228
Date*N	4	0.3747	6	0.4261	8	<.0001	<.0001
Date*Index	4	0.1039	6	<.0001	4	<.0001	<.0001
N*Index	4	0.1812	4	<.0001	8	<.0001	<.0001
Date*Index*Reference	4	0.6653	6	<.0001	4	<.0001	0.203
N*Index*Reference	4	0.9927	4	0.6243	8	0.2081	0.9935
Date*N*Reference	4	0.9945	6	0.9772	8	0.8487	0.9943
Date*N*Index	8	0.9986	12	0.1188	16	<.0001	<.0001
Date*N*Index*Reference	8	1	12	1	16	0.9998	1

Table 1-18 BWL 2013 SI mean estimates of N rate by vegetation index.

Vegetation Index	N (kg ha^{-1})	SI

CIRE	0	0.632
	84	0.800
	252	0.938
NDVI	0	0.812
	84	0.902
	252	0.963
DATT	0	0.849
	84	0.920
	252	0.968

Table 1-19 SCAL 2012 SI mean estimates of N rate by vegetation index.

Vegetation Index	N (kg ha^{-1})	SI
CIRE	0	0.714
	84	0.839
	140	0.934
	196	0.959
	252	0.966
NDVI	0	0.929
	84	0.967
	140	0.984
	196	0.987
	252	0.990
DATT	0	0.872
	84	0.928
	140	0.969
	196	0.980
	252	0.982

Table 1-20 SCAL 2013 SI mean estimates of N rate by vegetation index.

Vegetation Index	N (kg ha^{-1})	SI
CIRE	0	0.715

	84	0.770
	140	0.817
	196	0.929
	252	0.906
NDVI	0	0.840
	84	0.866
	140	0.879
	196	0.958
	252	0.917
DATT	0	0.880
	84	0.908
	140	0.935
	196	0.954
	252	0.966

Chapter 2 Comparison of Nitrogen Application Algorithms for Corn (*Zea mays* L.) Using Different Vegetation Indices under Varying Levels of Water Stress

Abstract

Active crop canopy sensors offer a viable method to recommend sidedress nitrogen (N) rates in-season by monitoring plant canopy color and biomass. Much debate has occurred about how to derive algorithms to predict plant N need based on canopy sensor information. Little work has looked at the influence of vegetation index (VI) on how the N application algorithm performs. Can algorithms developed with one VI be successfully used with another that may be less sensitive to non N-related stresses? A study was conducted with corn (*Zea mays* L.) at two sites in Nebraska from 2011 to 2013. Treatments were designed as split plots consisting of five N rates (0 to 252 kg ha^{-1}) within three rates of irrigation (full irrigation to rain fed). All plots were continuous corn cropping system with previous year's corn managed uniformly to reduce carry over effects. Three VIs were used to evaluate two different algorithms. Grain yield was affected by irrigation level in three site years, by N level in four site years with significant interaction between irrigation and N occurring in three site years. The same response was observed during crop sensing passes at time of ideal N sidedress. The three VI resulted in significantly different sufficiency index (SI) values while also showing different responses to irrigation and N rate. When calculating sidedress N rates, rate was affected by algorithm and index while showing response to N fertility and irrigation treatment. This study demonstrates how important selecting both VI and N algorithm can be when using AOS for determining side-dress N rates.

Introduction

Increasing nitrogen use efficiency (NUE) has long been a goal of producers and researchers alike. Producing more grain per unit of N fertilizer helps the economics of producers while aiding in the reduction of nitrate leaching to ground water, thus creating a healthier society. Side-dress or split applications have been cited by some as one method of reaching higher NUE (Cassman et al., 2002). The idea behind split application is to apply N to the crop closer to the period of highest N uptake likely reducing the opportunity for loss. However this approach does not necessarily address changing the overall N application rate. Prescribing N fertilizer rate in-season by assessing the N status of the crop has long been a focus of research aimed at increasing NUE.

Assessing the N status of a crop can be as simple as a visual check of crop greenness; this method cannot be quantified and repeated. During the mid-1900s, plant tissue testing for nitrate or total N concentration became a preferred method to determine crop N adequacy (Fox and Walthall, 2008). These laboratory analyses can be costly, time consuming and requires destruction of plant tissues. Fox and Walthall (2008) cite several studies that set critical N concentrations for corn plant tissues; however of these papers, few agree on what the critical values are. The range in critical values and need to select the right plant tissue has restricted adoption of tissue sampling.

The introduction of the SPAD meter in the early 1990s enabled a non-destructive, quantifiable estimate of chlorophyll concentration. Numerous researchers (e.g., Fox et al., 1994; Turner and Jund, 1991) used this estimate of chlorophyll concentration and its relationship to N fertility to infer crop N status. Varvel et al. (2007) developed an N application algorithm to recommend in-season fertilizer need using normalized SPAD readings. This system of in-situ analysis and in-season fertilizer N recommendations provided improvement from previous practices but still does not account for the spatial variability seen in producer's fields and the devise must be in contact with plant tissue preventing on-the-go use.

Current on-the-go active crop canopy sensor systems offer the ability to both non-destructively monitor plant N status and map field variability. These active optical sensors (AOS) were commercialized during the early to mid-2000s but still have challenges that need to be addressed. Reflectance data collected with an AOS is typically processed using a vegetation index (VI) and then normalized before being used to assess plant health or to direct N application algorithms. The VI transformation is an equation using light reflectance in specific wavebands to enable assessment of biophysical properties of vegetation. Vegetation indices have different response functions to leaf area index (Vina et al., 2011), crop water stress (Shiratsuchi et al., 2011) and N rate (Solari et al., 2010). Therefore sound decision making is required when selecting an index for an algorithm input. Normalization of VI data essentially generates a scale of crop vigor.

Finally, algorithms are often developed with a single vegetation index in mind. Ruan et al., (2005) used normalized difference vegetation index (NDVI) (Rouse et al. 1974) to develop an N application algorithm for winter wheat. Similarly, Tucker (2009) used NDVI as a base for fertilizer N recommendations for grain sorghum. Both algorithms used additional factors like days after planting or accumulated growing degree days as co-factors when calculating fertilizer N to be applied, but used the same VI (NDVI) to quantify the vigor of the growing vegetation. Solari et al., (2010) tested two indices in the development of an algorithm for corn; concluding that the chlorophyll index (CI) (Gitelson et al. 2003) worked best with the Crop Circle ACS 210 sensor that he used to collect plant reflectance data. His final algorithm did not include any cofactors or attempt to predict yield potential.

Limited active-sensor based algorithm research has been conducted with VIs other than NDVI and CI. Shiratuchi et al. (2011) evaluated five VIs in terms of how previous crop and water stress affected N responsiveness of corn. Their work indicated that water stress confounded how certain VI respond to N stress. Even though water stress caused variability in calculated SI values, it did not stop the VI from showing an N response.

This study set out to test the hypotheses: The use of different VI in published N application algorithms should result in the same predicted N application rate and (ii) water stress will cause changes in calculated N application.

Materials and Methods

Experimental Design and Site Description

Field experiments were established in 2012 at the West Central Water Laboratory (BWL; 41.0294 ° N, -101.958292 ° W) near Brule, Nebraska and at the South Central Agriculture Lab (SCAL; 40.58145 ° N, -98.14147 ° W) near Clay Center, Nebraska. The BWL has variable soils across the experiment location; dominant soil series were Satanta loam (fine-loamy, mixed, superactive, mesic Aridic Argiustolls) 3 to 6% slope, Bankard loamy sand (sandy, mixed, mesic Ustic Torifluvents) channeled and Bayard very fine sandy loam (coarse-loamy, mixed, superactive, mesic Torriorthentic Haplustolls) 1 to 3% slope. In 2012, the treatment design consisted of a split-plot replicated Latin square (3 replications); in 2013 the design was simplified to a randomized complete block (6 replications). In 2012, irrigation level (full, 75% of full, 40% of full) served as the main plot and N rate (0, 84, and 252 kg N ha^{-1}) as the sub plot. In 2013, variable irrigation failed so N rate became the main plot with no subplots. For both years, plots were 6.1 m wide (8 rows) and 37.5 to 53.6 m in length depending on distance from the pivot point. The dominant soil series at SCAL is Hastings silt loam (fine, smectitic, mesic Udic Argiustolls), 0 to 1% slope. Treatment design consisted of a split-plot randomized complete block with irrigation level (full, 75% of full, and rain fed) as the main plot and N rate (0, 84, 140, 196, and 252 kg N ha^{-1}) as the sub plot; treatments were replicated 4 times at this site. Plot size was 6.1 m wide (8 rows) by 53.3 m long. Both study sites were under no-till, continuous corn management with the previous year's corn managed uniformly. Planting date and plant population were based on local best management practices (BMPs) for each respective site (Table 2.1). Fertilizer was applied after crop emergence as 28% or 32% urea-ammonium nitrate solution (UAN) at all sites. The UAN for BWL was surface-banded by a high clearance applicator equipped with drop tubes placing UAN on 152-cm centers. The SCAL site used subsurface coulter application of UAN on 76-cm centers. Irrigation events at BWL site were triggered by the station manager when a visual inspection of the crop indicated stress was present. For SCAL, irrigations were started when soil matric potential became lower than a pre-determined value based on the soil texture at the experiment site. Weed and pest management followed BMPs for each site.

Canopy Sensing

Canopy reflectance data were collected with a Holland Scientific (Lincoln, NE USA) ACS-470 (in 2011) or ACS-430 (2012 & 2013). Two sensors were positioned 40 to 60 cm above the crop canopy directly over the row; data were logged by a Holland Scientific GeoSCOUT with DGPS receiver (model 16A, Garmin International, Olathe, KS USA) recoding at a rate of 5 Hz.. Sensors were mounted to a high-clearance tractor traveling approximately 4 to 6 km hr^{-1}, resulting in an average of 180 data recordings per plot. Points were extracted for each plot using ArcMap GIS software V 10.1 (Redlands, CA USA) and averaged per plot. Sensors provided reflectance at three wave bands: red (670 nm), red-edge (730 nm) and near infrared (NIR, 760 nm). These bands were used to calculate three vegetation indices: Normalized Difference Vegetation Index (NDVI) (Rouse et al. 1974), Chlorophyll Index Red-edge (CIRE) (Gitelson et al. 2005) and a VI proposed by DATT et al. (1999) (DATT). The indices used were chosen based on their previous use in studies that use sensors to derive N rate calculations or have been proposed for algorithm use. Calculations, wavebands and references for each index are presented in Table 2.2.

Vegetation indexes were normalized using the sufficiency index (SI) (Equation 2.1) concept that was first was proposed by Peterson et al. (1993). In this study, the virtual reference concept (Holland and Schepers, 2010) described in Chapter 1 was used in place of the high-N fertility reference.

$$SI = \frac{VI\ sensed}{VI\ reference}$$

Equation 2-1 Sufficiency Index

In order to evaluate how VI influenced N application rate, two application algorithms which were developed with crop response data from Nebraska were used to calculate theoretical side-dress N fertilizer rates for each treatment of the studies. The first algorithm published by Solari et al. (2010) is a very simple and straight forward calculation (Equation 2.2). The second equation used was published by Holland and Schepers (2010) as a general algorithm that would be applicable over a large geographic area (Equation 2.3).

$$Napp = 317 \cdot \sqrt{0.97 - SI}$$

Equation 2-2 Solari N application algorithm

$$Napp = (Nopt - Nprefert - Nom) \cdot \sqrt{\frac{(1-SI)}{\Delta SI \cdot \left(1 + 0.1 \cdot e^{m \cdot (SIthreshold - SI)}\right)}}$$

Equation 2-3 Holland and Schepers N application algorithm

For equation 2.2, SI is for the crop being fertilized with 317 being a constant factor. In equation 2.3, Nopt is the economic optimum N rate or the maximum N rate prescribed by producers; N prefert is the sum of fertilizer N applied prior to crop sensing; Nom is the N credit for the average organic matter content within the field; SI is the sufficiency index; ΔSI is the range of SI values seen in a field that can typically be brought back to full yield potential by timely application of N fertilizer; *m* is the back-off rate variable ($0 < m < 100$); and $SI_{threshold}$ is the back-off cut-on point. In the analysis performed for this study, N_{opt} is the University of Nebraska-Lincoln (UNL) soil test approach, $N_{prefert}$ was the N rate treatments applied following planting. For simplicity, the N_{om} and $SI_{threshold}$ back-off function were not used for final calculations.

A sensing date representing likely fertilizer N side-dress timing (Solari et al. 2008; Kitchen et al. 2010) from each site year was chosen for N application calculations (Table 2.3). Values for SI were calculated for each point within every plot. The reference value in SI equation was derived from the 95th percentile value in a histogram of VI values within a block. After SI calculations, each point was processed through both equations giving a calculated side-dress N rate for each recorded data point. These values were then averaged within individual plots and used for statistical analysis.

Statistical Analysis

To evaluate the treatment effect on corn grain yield, the PROC GLMMIX procedure was used in SAS 9.2 (SAS Institute Inc., Cary, NC). Site years were analyzed independently and replications were treated as random effects. No cross year analysis was performed due to large variations in weather year-to-year and site locations. Data collection dates used for calculated N rate applications were first analyzed using a similar method. Calculated N rates were then analyzed to examine algorithm by index interactions.

Results and Discussion

The 2011 data from BWL were not analyzed due to experimental design and irrigation system problems. Further, a system malfunction in 2013 resulted in only a full level of irrigation therefor any analysis of data from the BWL 2013 site year does not include an irrigation variable. Growing season weather for 2012 was warmer and drier than the historical average for this site. Hot conditions prior to planting resulted in early and frequent irrigations throughout the 2012 growing season (Figure2.1). Weather for the

BWL 2013 site year was quite different with warm temperatures until early July followed by a month of cooler than normal conditions (Figure 2.2). Rainfall events were large early and more frequent with the first irrigation occurring on 27-June. Weather conditions for SCAL were unique for each year of the study. In 2011, average daily temperatures were close to normal with small frequent rain events occurring though the growing season. The first irrigation was initiated on 27 July (Figure 2.3). For 2012, temperatures were above long-term averages for the first half of the growing season then turning cooler for August and September. Rainfall events in 2012 were less frequent than 2011 with the first irrigation occurring on 7 July (Figure 2.4). For 2013, temperatures started cooler than historical averages with several large rainfall events in May, then turning hot with little rainfall in June and July with the first irrigation occurring on 7 July (Figure 2.5). A severe storm occurred on 1 August resulting in heavy defoliation, reducing yields and preventing equipment from re-entering the field site for further data collection.

Grain Yield Response

The BWL 2012 site year experienced a significant response to irrigation, but did not respond to fertilizer N and had no irrigation by N rate interaction (Table 2.4). The full and 70 percent of full irrigation treatments averaged 7,500 and 8,500 kg ha^{-1}, respectively, significantly higher than the rain fed treatment at 4,900 kg ha^{-1} (Figure 2.5). There was no clear pattern of N fertilizer response at any level of irrigation. Lack of N response may be attributed to confounding factors such as high pre-plant N mineralization and large in-season N applications from irrigation water with high nitrate concentrations (Table 2.5).

For the 2013 BWL site year, yields were substantially higher than those obtained in 2012. A significant grain yield response to fertilizer N was observed (Table 2.4). Grain yield experienced a significant increase from the check (8854 kg ha^{-1}) for each fertilizer N treatment 10470 and 13470 kg ha^{-1} at 84 and 252 kg N ha^{-1} respectively (Figure 2.7).

The 2011 SCAL site year experienced a strong response to fertilizer N rate as well as a strong irrigation by N interaction (Table 2.4). As the amount of supplemental irrigation dropped, the magnitude of N response decreased at the highest two N rates (196 and 252 kg N ha^{-1}), but yields trended higher at the lowest N rate (84 kg ha^{-1}). A lack of grain yield response to irrigation was due in part to these N response relationships. For all SCAL site years, irrigation water was low in nitrate concentration ruling out in-season N additions (Table 2.5). For SCAL 2012 and 2013 site years, significant main effects of irrigation level and N rate as well as significant interactions were observed (Table 2.4, Figures 2.8, 2.9). In 2012, N responsiveness increased with increasing irrigation amount (Figure 2.8). The rain fed treatment did not experience an N response to a rate greater than 140 kg N ha^{-1}, while the full and 75 percent of full irrigation treatments did not demonstrate a significant grain response to an N rate over 196 kg ha^{-1}; the full irrigation treatment displayed a strong trend for response at 252 kg N ha^{-1}. As previously mentioned, the 2013 site year experienced greatly reduced grain yields due to a weather event on 1 August. The SCAL site showed a response to irrigation and continued to show the same grain yield responses to N rate treatment affect as in 2011 and 2012 with N responsiveness decreasing with decreasing supplemental irrigation (Figure 2.9).

Plant Response at N Side-dress Timing

Weather patterns from year-to-year caused variation in plant growth and development, resulting in different dates from year-to-year and site-to-site at which sensor driven side-dress applications would most appropriately occur. The sensing dates and VI data analysis for the corresponding dates are displayed in Table 2.5. The VI analysis of the 2012 BWL site responded much like corn grain yield results. Overall, there was a response to irrigation and differences in VI, but no significant response to fertilizer N. Additionally, there was an interaction between irrigation treatment and VI (Figure 2.11). The DATT index was not affected by irrigation level while both CIRE and NDVI had significantly different SI for each irrigation treatment. There were no other interactions of significance for the site year.

The analysis of AOS data for BWL in 2013 only examined N rate and differences among VI (Table 2.6). The three VI experienced different magnitudes of response to fertilizer N with CIRE and NDVI having significantly different levels of SI at all three N rates while DATT could only differentiate between the check and two higher rates of fertilizer N (Figure 2.12).

The SCAL 2011 site experienced significant treatment differences in canopy reflectance readings to irrigation, fertilizer N rate, and VI as well as an interaction between irrigation and VI (Table 2.6). The 196 and 252 kg ha^{-1} N rates had similar SI values but significantly higher than 84 and 140 kg ha^{-1} rates (Figure 2.13). As with the BWL 2012 site year, the DATT index showed no effect from one irrigation regime to the other, while CIRE was significantly different at each level of irrigation (Figure 2.14). For SCAL 2011, the NDVI was significantly higher at 75% of full irrigation compared to rain fed and full irrigation treatment. Unlike BWL 2012, at the time of sensing for the SCAL 2011 site year, an irrigation event had not yet occurred, therefore the only difference between irrigation treatments was the lower plant population of the rain fed treatment. It is intriguing that this difference was seen in only two of the three VI calculated.

In 2012, a three way interaction between VI, irrigation rate and N treatment was observed at SCAL. The CIRE displayed the largest SI range in response to N rate across all irrigation treatments (Figure 2.15). The NDVI and DATT experienced a lower SI response across N rates. All three indices showed a lack of N response for the rain fed treatment in which only the 0 kg N ha^{-1} rate was significantly different than all others. As was the case in 2011, at the time of sensing no irrigation event had occurred. For CIRE, SI for the higher N rates under rain fed conditions were significantly different than those of the two irrigated treatments.

In 2013, there was no significant three-way interaction between VI, irrigation and N treatment (Table 2.6). There were interactions between VI and irrigation, VI and N rate, and irrigation and N rate (Figures 2.16, 2.17 and 2.18). The VI irrigation treatment interaction was similar to what was observed in the first two years for the SCAL site with SI for CIRE and NDVI lower with reduced irrigation. The unique circumstance in 2013 is that the sensing pass occurred after an irrigation treatment. The VI by N rate effects also mirror those of previous site years in that CIRE had the largest response range followed by NDVI and DATT with the smallest. The CIRE was able to differentiate among all N treatments, while DATT and NDVI were able to separate the lowest four N treatments. Finally, the N by irrigation treatment interaction show the overall reduction in SI values with reduced irrigation while with full irrigation, SI values for the 196 and 252 kg N ha^{-1} rates were the highest overall and statistically the same.

Simulated N rates

Calculated side-dress N application rates generally followed the trends of VI analysis (Table 2.7). For the BWL 2012 site year, the calculated N side dress rates experienced significant main effects of irrigation and N rate as well as interactions with VI and algorithm approach. The response to N treatment was solely due to the Holland and Schepers (HS) algorithm taking into account previous N applications when calculating an N rate. The three VI had significantly different response to irrigation treatment (Figure 2.19) with CIRE reducing N rate as irrigation level increased, NDVI increasing N rate as irrigation level increased and DATT maintaining a similar N rate across all irrigation levels. In the interaction between VI and algorithm (Figure 2.20) the HS calculated the same N rate averaged across all irrigation and N treatments with no difference among VI; while the Solari algorithm calculated a much higher N rate with CIRE, NDVI and DATT were similar. This could be due to low SI values obtained with CIRE and the 0.97 factor used in the algorithm. The three-way interaction of irrigation, N rate and algorithm (Figure 2.21) displays how the previous N addition factor with the HS approach affects a calculated N application. Across all irrigation treatments, HS significantly decreased calculated N rate for each level of N treatment regardless of irrigation level. The Solari algorithm generated a significant decrease in N rate for only the 252 kg N ha^{-1} N treatment at 70% of full and full irrigation regimes. The BWL 2012 data indicates how significantly VI and application algorithm can affect a prescribed side-dress N rate.

The BWL 2013 site also experienced a significant main effect of N rate and a three-way interaction of N rate by VI by algorithm (Table 2.7). This interaction (Figure 2-22) mirrors what was seen in 2012 in that the HS algorithm tended for higher N rates at 0 kg N ha^{-1} and no N at 252 kg N ha^{-1} with Solari algorithm maintaining relatively constant N rates for all N treatments. Additionally in 2013, the Solari algorithm N rates were highest for CIRE, followed by NDVI and DATT. The HS algorithm had the highest N rates calculated by NDVI with CIRE and DATT being essentially the same.

The SCAL 2011 site calculated N rates followed what AOS measurements indicated (Table 2.7). The interaction of irrigation treatment and VI (Figure 2.23) shows how only DATT calculated the same N rate across irrigation treatments. This is troublesome since no variable rate irrigation had taken place at the time of AOS data collection. The interaction of irrigation level and algorithm (Figure 2.24) show the HS calculating a similar N rate across irrigation treatments while the Solari calculated a different N rate for each irrigation treatment. A three-way interaction between N treatment, VI and algorithm (Figure 2.25) illustrates the difference in algorithms with all VI calculating a 0 kg N ha^{-1} for the 252 kg N treatment when using HS. This effect may be a function of the HS' previous N credit cofactor when making side-dress N calculations. The CIRE produced the highest overall N rate followed by NDVI with DATT having much lower N rates over all N treatments.

For SCAL 2012, all three-way interactions were significant (Table 2.7). The CIRE had the highest calculated N rates across all irrigation and N treatments with the high N treatments resulting in calculated N rates of 67, 38 and 36 kg N ha^{-1} for rainfed, 75% of full and full irrigation respectively (Figure 2.26). The NDVI resulted in lower calculated N rates for the two irrigated treatments at all N treatments above 84 kg N ha^{-1} with calculated N rates for the rainfed treatment being between those of CIRE and DATT. The DATT resulted in the lowest calculated N rate at the 0 kg N ha^{-1} treatment across all irrigation treatments and the lowest calculated N rates for all N treatments for the rain fed irrigation treatment. In the interaction of irrigation level, N treatment and algorithm (Figure 2.27), the HS approach calculated the highest N rate for the 0 kg N ha^{-1} treatment while recommending 0 kg N ha^{-1} for the 196 and 252 kg ha^{-1} treatments across all irrigations. The high calculated N rates at 0 kg N ha^{-1} for the HS approach are likely due to not using the back-off function. The Solari approach resulted in higher calculated N rates for all N treatments above 0 kg N ha^{-1} with the rain fed irrigation treatment being significantly higher calculated N rates than those of the 75% and full irrigations. As in 2011, the SCAL site in 2012 had not received an irrigation before the collection of AOS data.

The HS approach calculated the same N rate across irrigation levels for each respective VI in the three-way interaction of irrigation, VI and algorithm (Figure 2.28). Further, the Solari approach calculated higher N rates for the CIRE and NDVI at the rain fed level of irrigation, while DATT resulted in the same calculated N rate across all irrigation treatments. For the interaction of VI, N treatment and algorithm (Figure 2.29), the CIRE resulted in the highest calculated N rates across all N treatments and both algorithm approaches. The NDVI and DATT resulted in similar calculated N rates for both algorithm approaches. With HS, calculated N came close to or reached 0 kg ha^{-1} for the highest N treatments when using any VI, this results is similar to the results for previous site years.

Finally in 2013, the SCAL site resulted in similar patterns of calculated N rates as previous years but with significant interaction of all four terms: irrigation, N treatment, VI and algorithm (Figure 2.30). The HS approach resulted in the highest calculated N rate across all irrigation rates and VI at the 0 kg ha^{-1} N treatment. Once again this is a function of not having used the 'back-off' function when calculating rates. The HS approach does reach a 0 kg ha^{-1} calculated rate at the highest N treatment (252 kg N ha^{-1}) across all irrigation and VI. The Solari approach reduced N rate with increase in N treatment but never resulted in a calculated rate of lower than 55 kg N ha^{-1} (Figure 2.30 I). This was the only year in which irrigation had taken place before data collection and this is manifested in the different VI. The calculated N rates remained virtually the same for both algorithm approaches when using DATT (Figure 2.30 C, F and I), while CIRE and NDVI decreased N rates as irrigation increased, although the magnitude of the decrease was much higher for NDVI (450 kg ha^{-1}, Figure 2.30 B to 350 kg ha^{-1} Figure 2-30 H).

With this analysis, clear patterns emerge across site years. The CIRE has a larger response (SI) range than other VI, leading to higher calculated N rates. The NDVI had inconsistent responses to irrigation level even when no irrigation had been applied (SCAL 2011 and 2012). Since there is a difference in plant population between the rain fed and two irrigation treatments any NDVI response is likely due to biomass amount. This certainly becomes a problem in water stressed environments in which plants respond by limiting exposed leaf area i.e. leaf rolling. The DATT index was stable across irrigation treatments at all four site years although it's low range of SI values lead to lower calculated N rates.

Conclusions

This study tested if different VI and published N application algorithms should result in the same predicted N application rate and effects water stresses would cause in calculated N application rates. Canopy reflectance data indicated significant responses to irrigation level and VI for all site years and N treatment response for all SCAL site years. When this data was used in separate algorithm approaches, it resulted in very different N rate calculations. Further, these calculations did show a difference due to irrigation level but only two of four site years (BWL 2012 and SCAL 2013) had irrigations events prior to data collection. Despite the presence of potential water stress, one VI (DATT) continually was unaffected in response (SI).

The application algorithms used for N rates, calculated highly different N rates, but was consistent within their respective algorithm. The Solari approach calculated N rates with little change across N treatments, while HS was able to make large adjustments across N treatment for each site year analyzed.

The results of this study would lead us to conclude that using a robust VI such as DATT with the HS approach would be ideal for producers using AOS technology to apply N to their crops.

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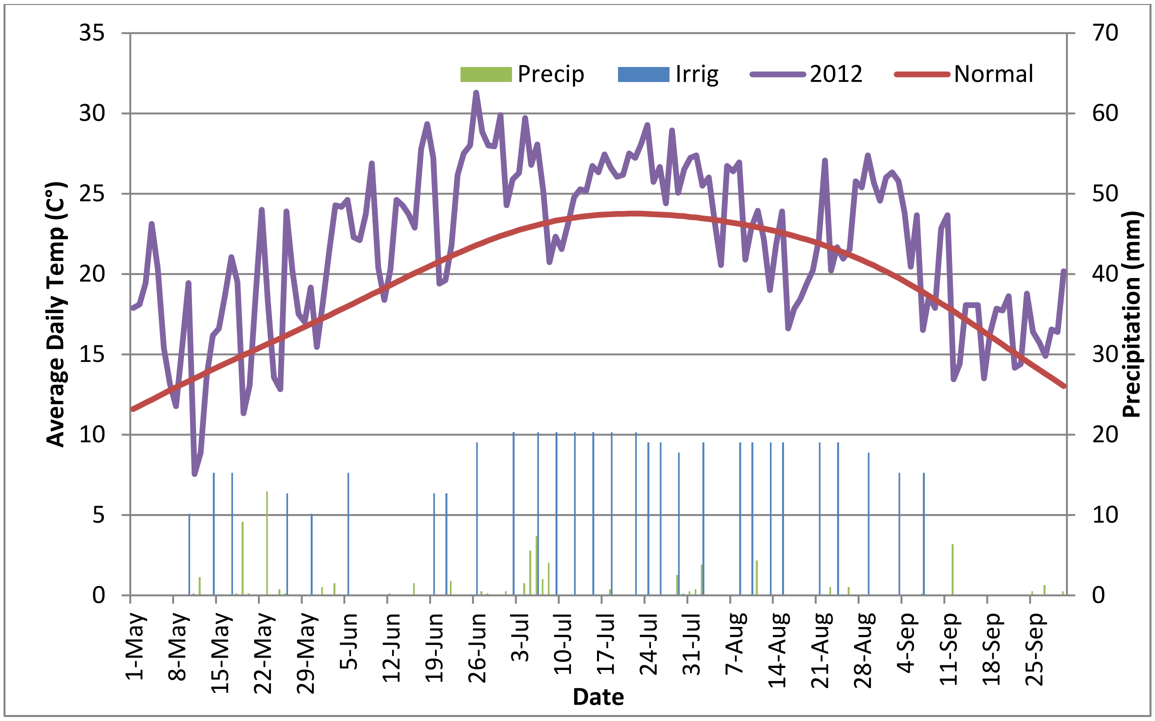

Figure 2-1 Growing season weather conditions for the 2012 BWL site year. Temperatures were generally above normal for the season with frequent irrigations. Any precipitation events were small and infrequent.

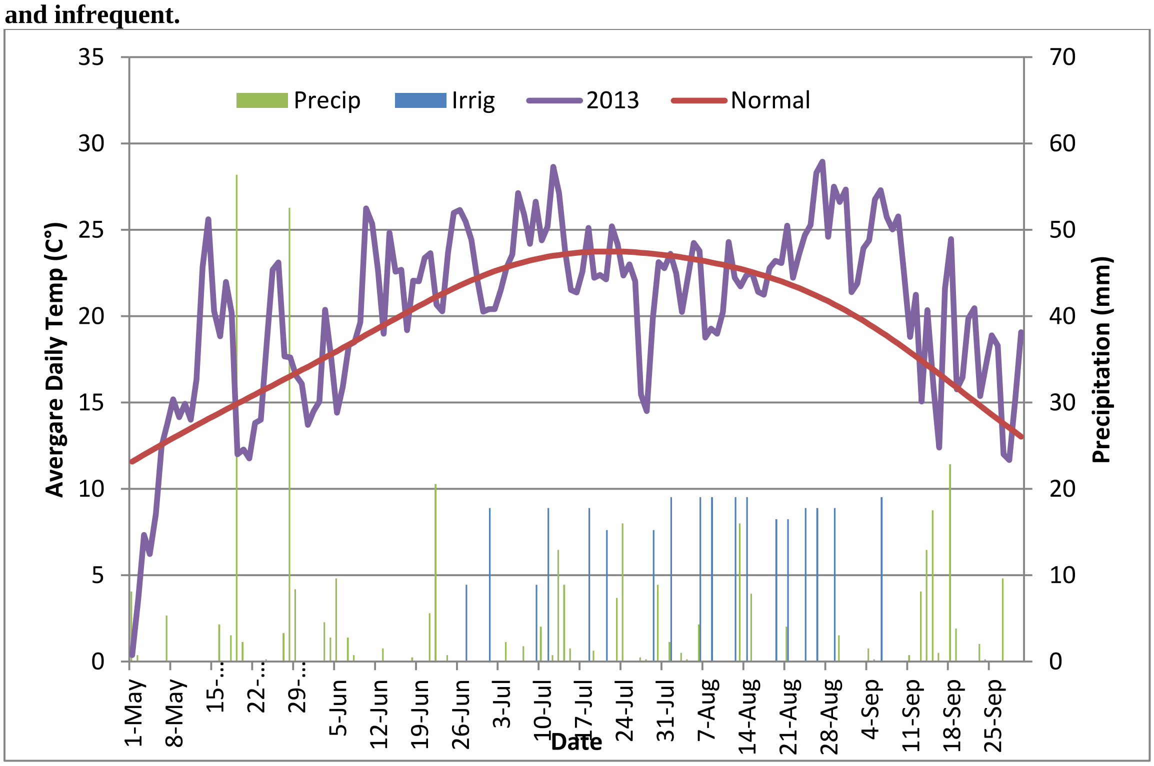

Figure 2-2 Grow Growing season weather conditions for the 2013 BWL site. Early and mid-season temperatures were below average. There were more rainfall events and less frequent irrigations than in 2012.

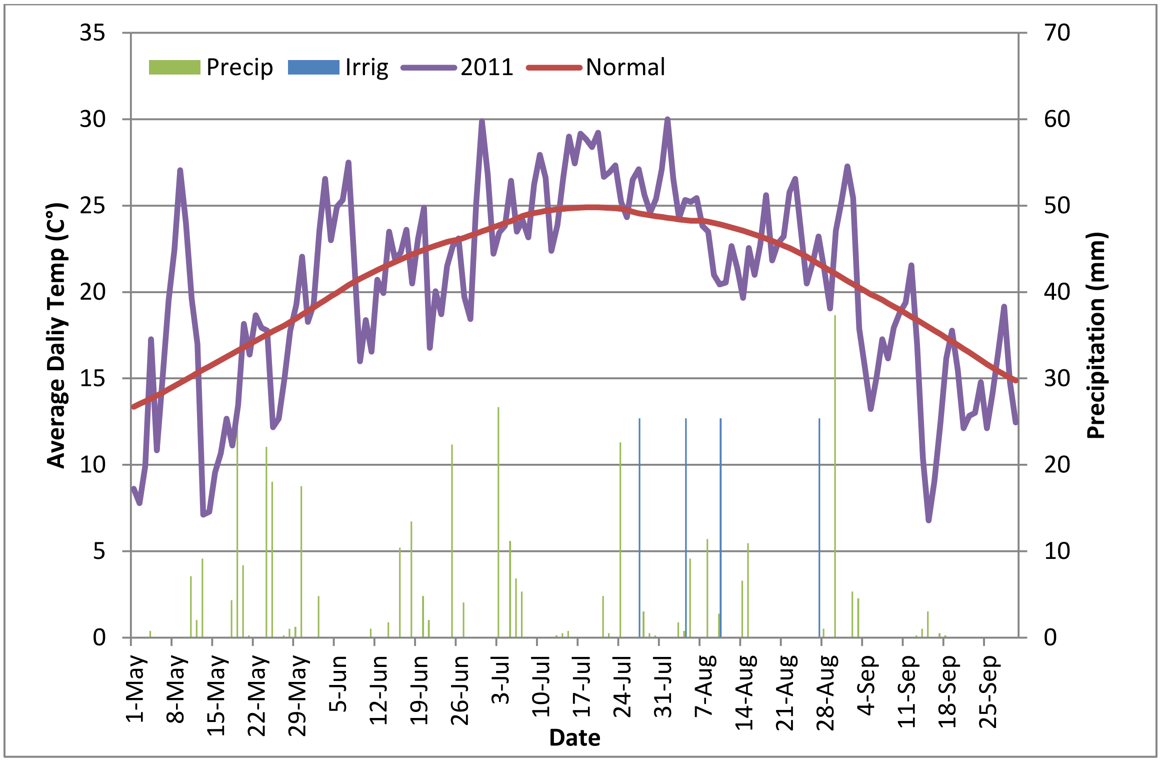

Figure 2-3 Growing season weather conditions for the 2011 SCAL site year. Temperatures mostly followed long term averages for length of the growing season with regular rainfall events during May and June. The first irrigation was initiated on 27 July with four irrigation events total.

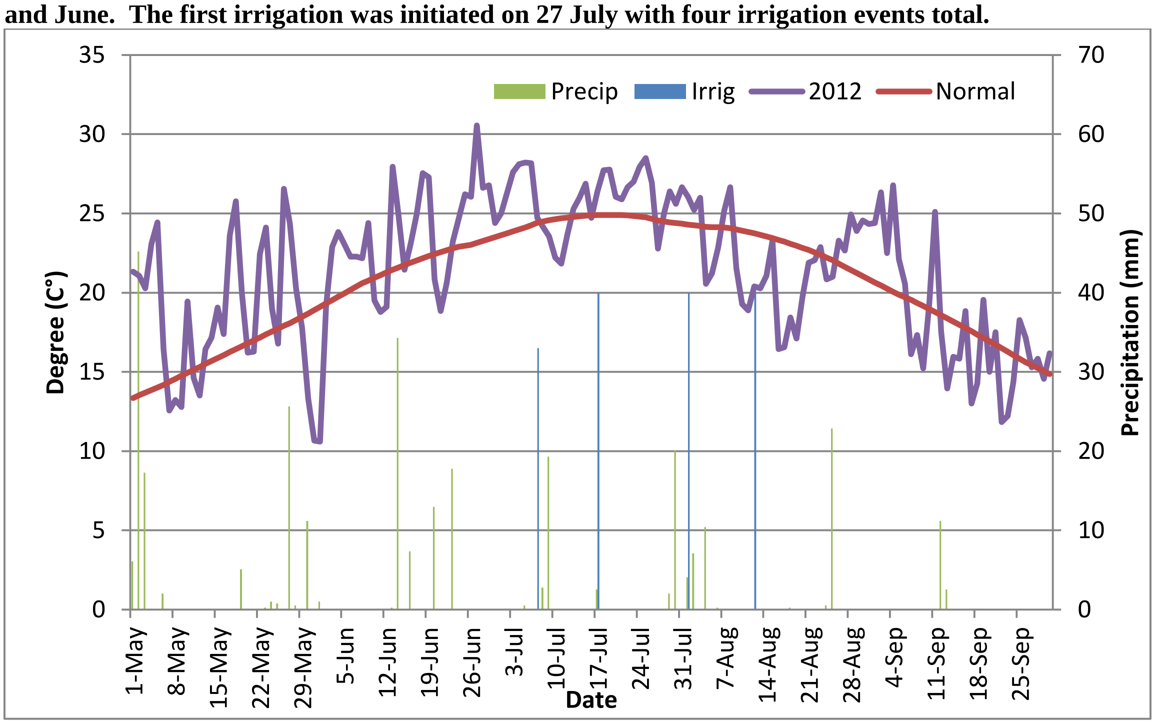

Figure 2-4 Growing season weather conditions for the 2012 SCAL site year. Temperatures were in general above average with regular but small rainfall events occurring though the growing season. The first irrigation was applied on 7 July, with a total of four irrigations occurring during 2012.

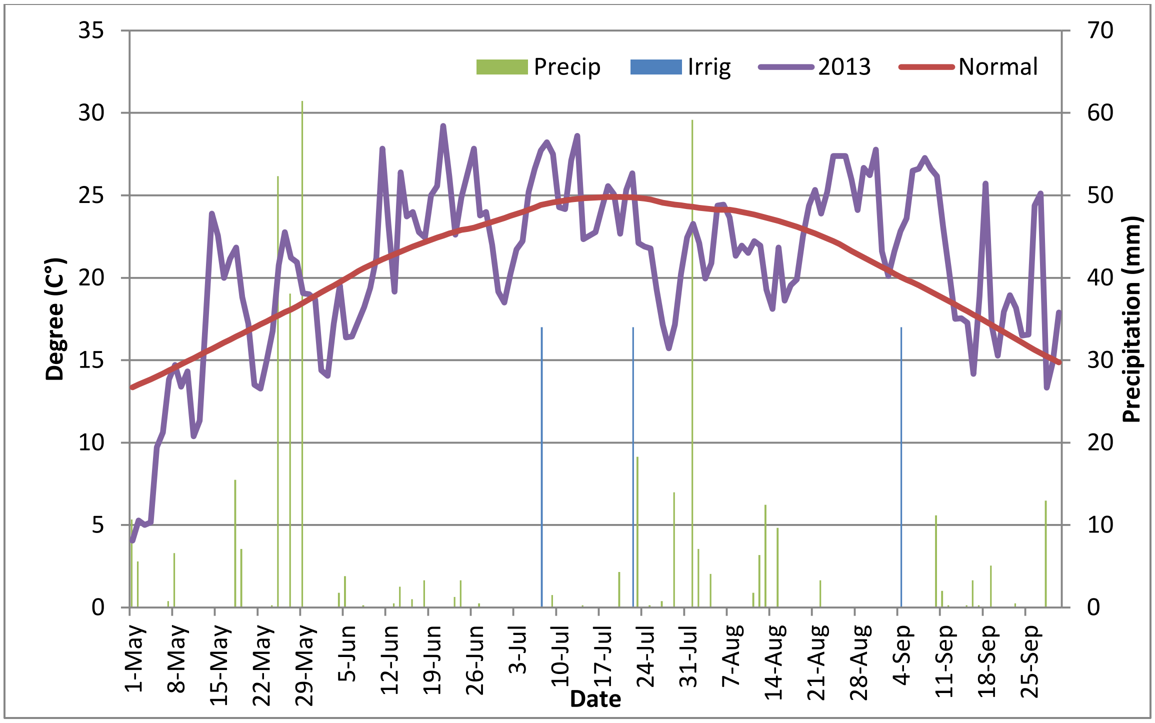

Figure 2-5 Growing season weather conditions for the 2013 SCAL site year. Temperatures were below normal early to halfway through the season. Rainfall was high for the first month followed by low and infrequent precipitation events. The first irrigation was applied on 7 July with three total irrigations for the season.

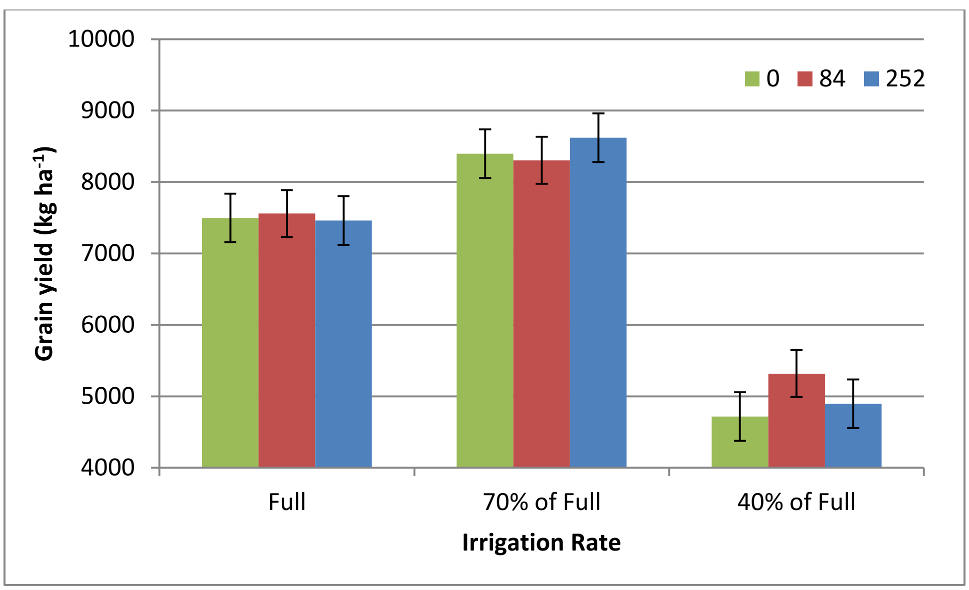

Figure 2-6 Corn grain yield for the BWL 2012 site year. A significant response to irrigation treatment was observed, with no effect of N treatment observed. Error bars represent standard error.

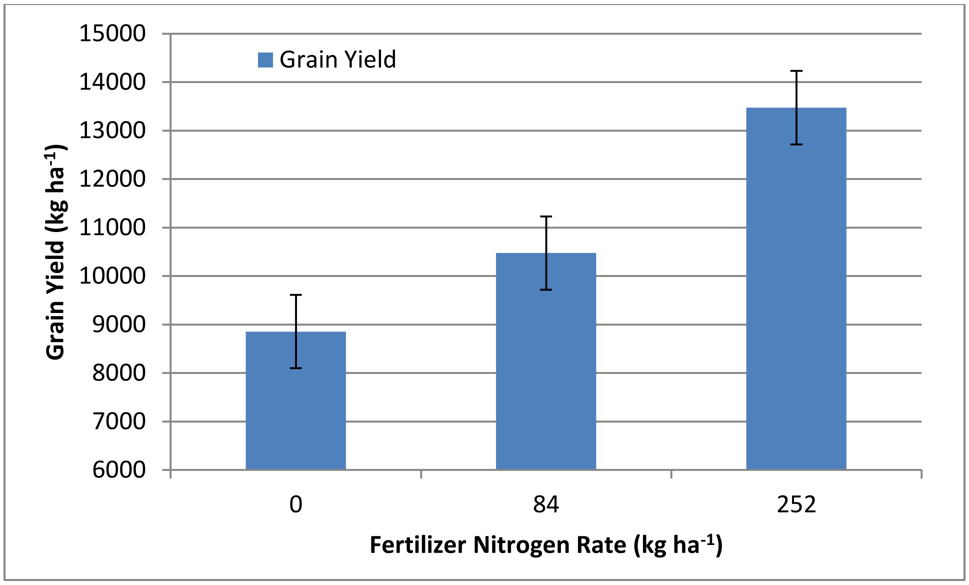

Figure 2-7 Corn grain yield for the BWL site in 2013, yields were substantially higher than the same site in 2012. A significant response to fertilizer N was observed from the 84 and 252 kg ha^{-1} rates. Error bars represent standard error.

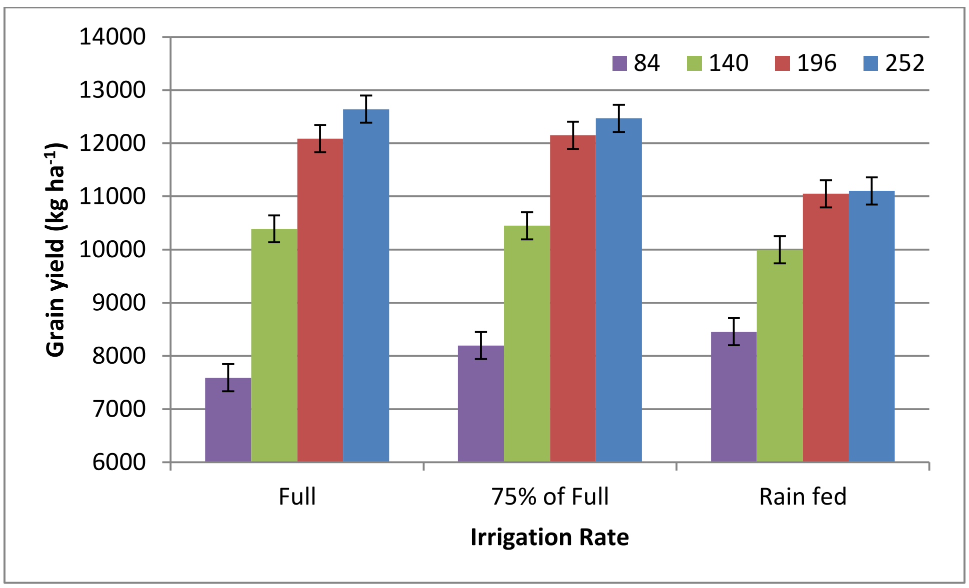

Figure 2-8 Corn grain yield for the SCAL 2011 site year. A Significant response to N treatment and an interaction between N and irrigation treatment were observed. Reduction in irrigation resulted in higher yield at low N rates with lower yields at high N rates. Error bars represent standard error.

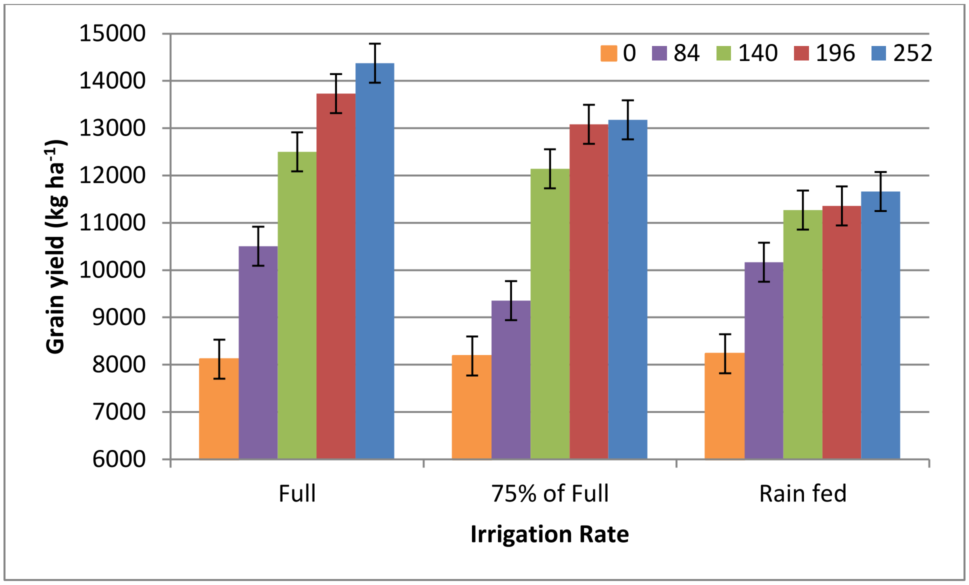

Figure 2-9 Corn grain yield for the SCAL 2012 site year. A significant response to irrigation and N treatment along with an interaction between the two was observed. Larger yield responses to N were seen with increased irrigation rate. Error bars represent standard error.

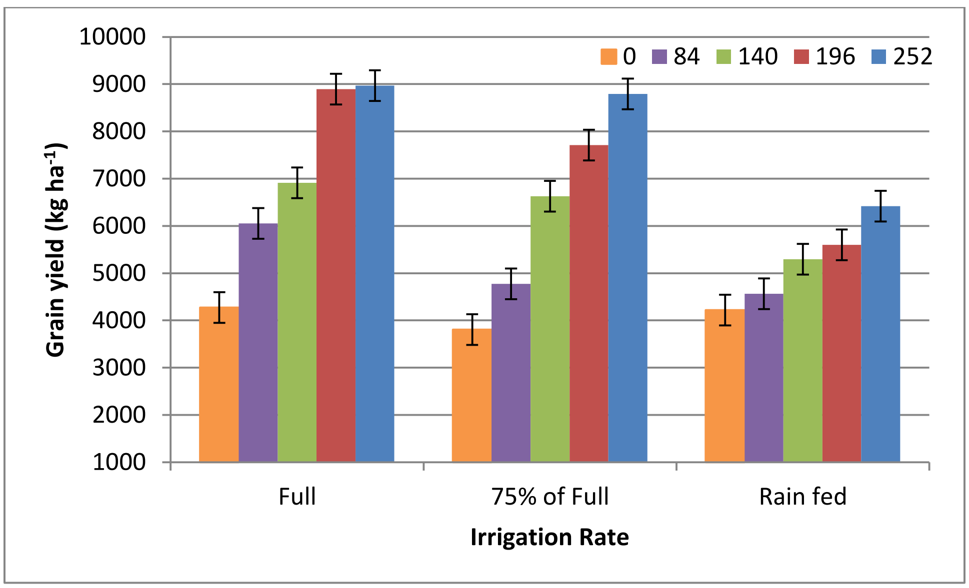

Figure 2-10 Corn grain yield for the SCAL 2013 site year. A significant response to irrigation and N treatment along with an interaction between the two was observed. Larger yield response to N were seen with increased irrigation rate, however at full irrigation there was no response over 196 kg N. Error bars represent standard error.

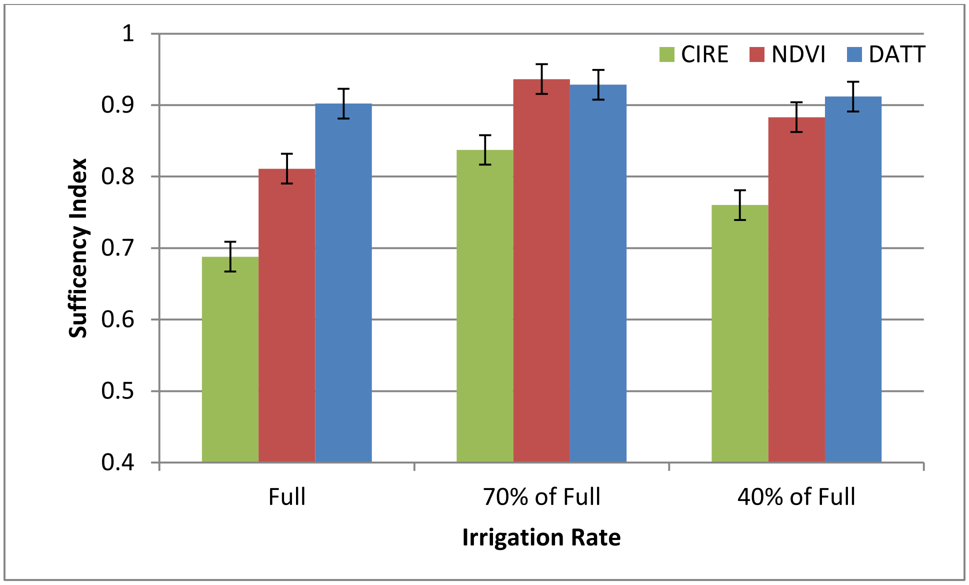

Figure 2-11 The BWL 2012 site year interaction of VI and irrigation treatment on SI at the V12/V13 growth stage. The DATT index showed no effect from irrigation regime while both CIRE and NDVI had a significantly different SI for each irrigation treatment. Error bars represent standard error.

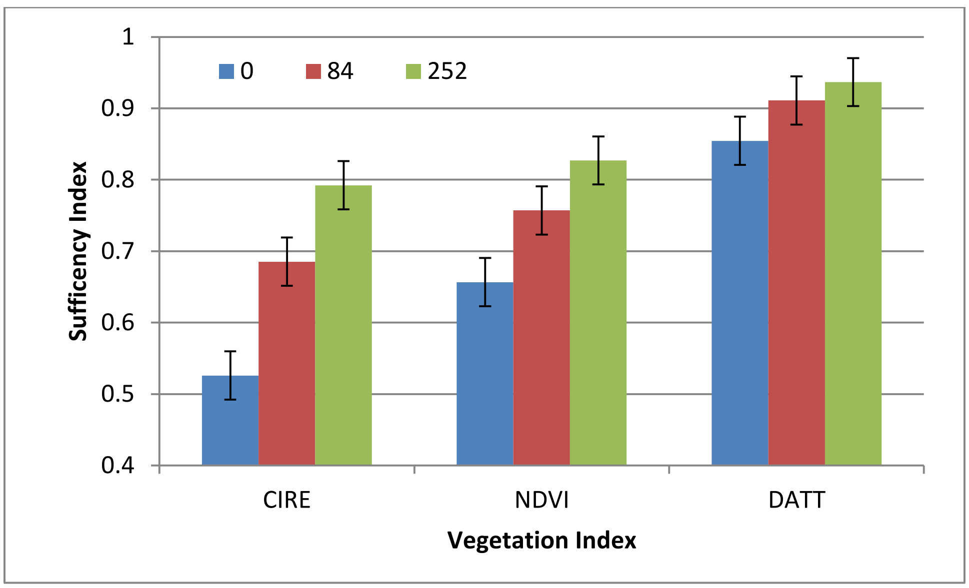

Figure 2-12 Interaction of N rate and VI on SI at the V 10 growth stage for the BWL 2013 site year. Both CIRE and NDVI had significant SI between all N rates while the 84 and 252 kg N rate for DATT were statistically similar. Error bars represent standard error.

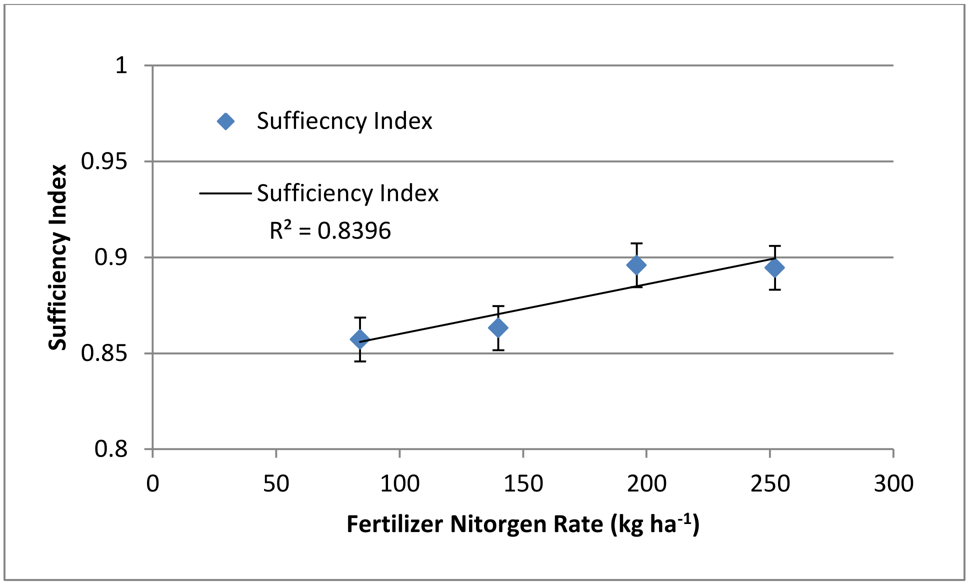

Figure 2-13 The response of VI to fertilizer N rate at the V8/V9 growth stage for SCAL 2011 site year. Error bars represent standard error.

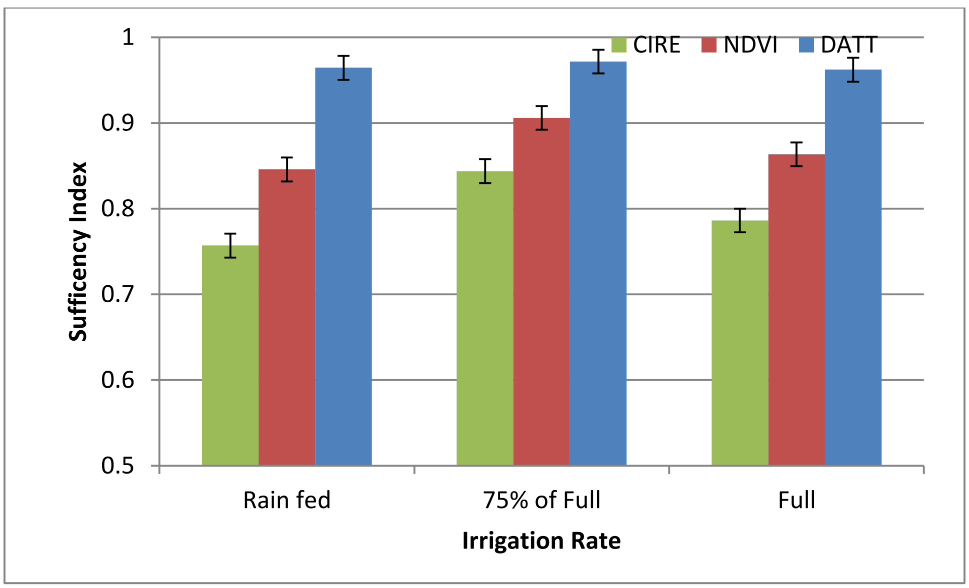

Figure 2-14 The SCAL 2011 site year interaction of VI and irrigation treatment on SI at the V8/V9 growth sta. The DATT index showed no effect from one irrigation regime to the other, while CIRE was significantly different at each level of irrigation. NDVI was significantly higher at 75% of full irrigation compared to rain fed and full irrigation treatment. Error bars represent standard error.

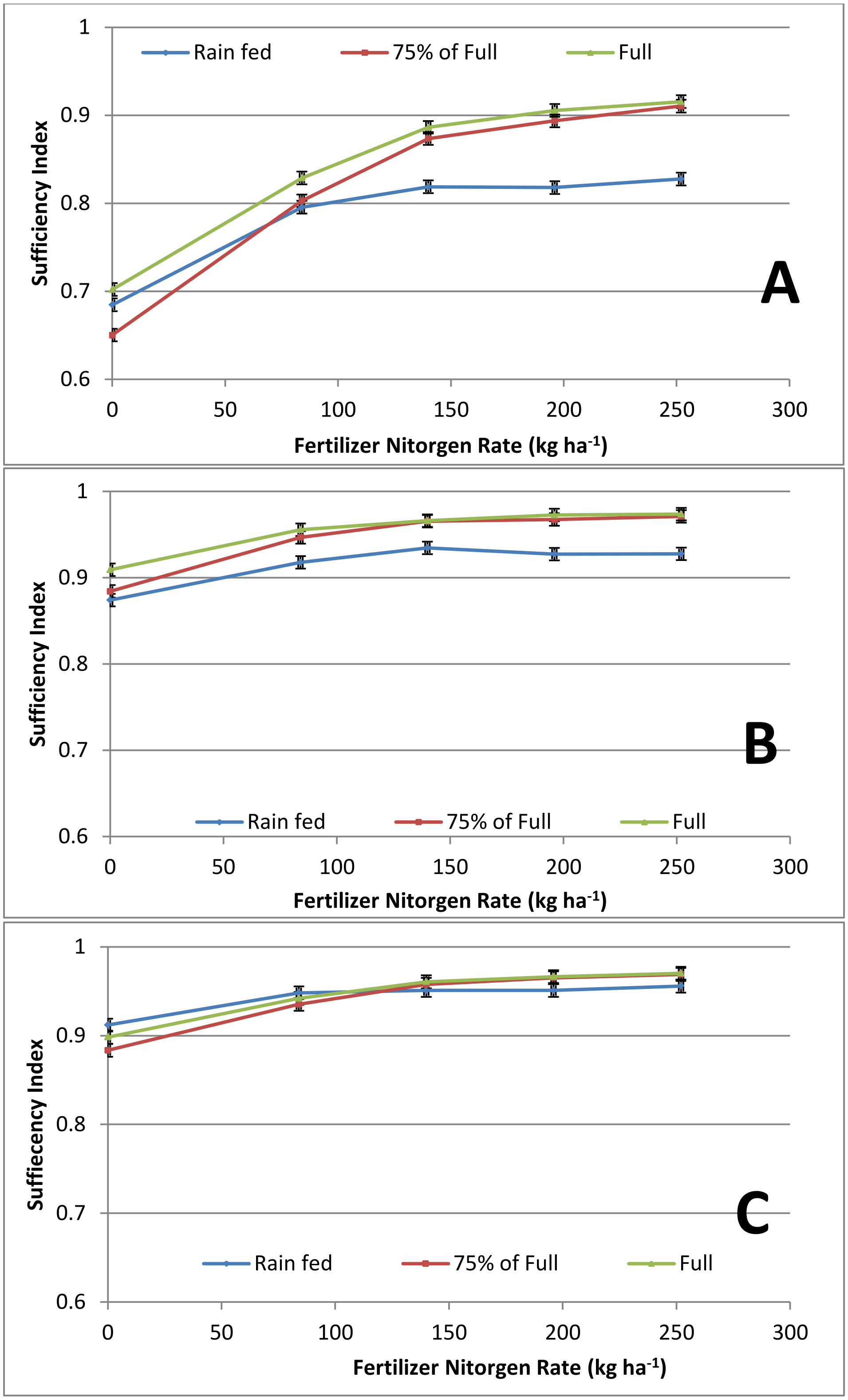

Figure 2-15 The VI by irrigation by N rate response of SI at the V12 growth stage for the SCAL 2012 site year. The CIRE (A) displayed the largest range of response to N across all irrigation rates while NDVI (B) and DATT (C) showed a lower response range. All three indices show the lack of N response for the rain fed treatment. Error bars represent standard error.

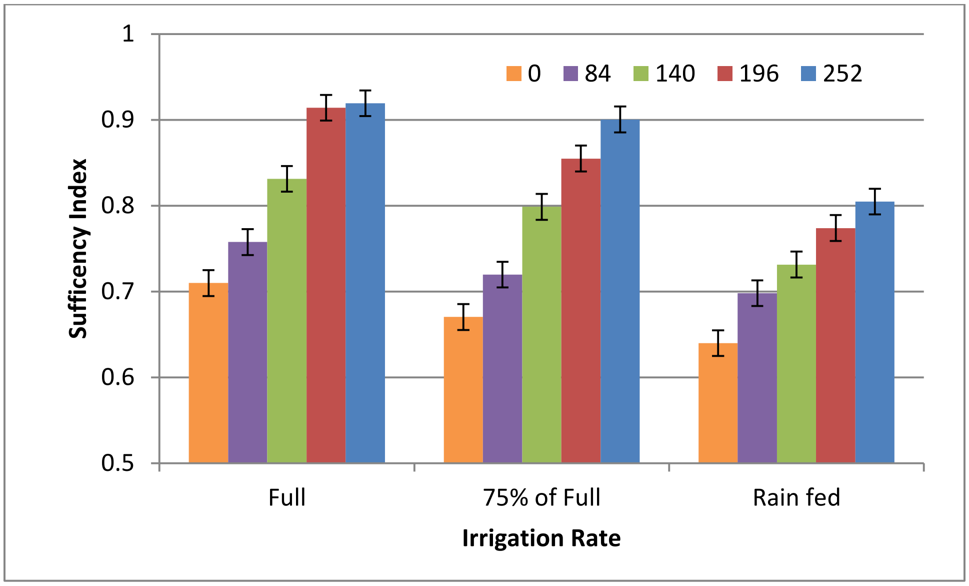

Figure 2-0-16 Interaction of irrigation and N rate on SI across all VI at V11/V12 growth stage for the SCAL 2013 site year. The calculated SI dropped as irrigation rate decreased. Error bars represent standard error.

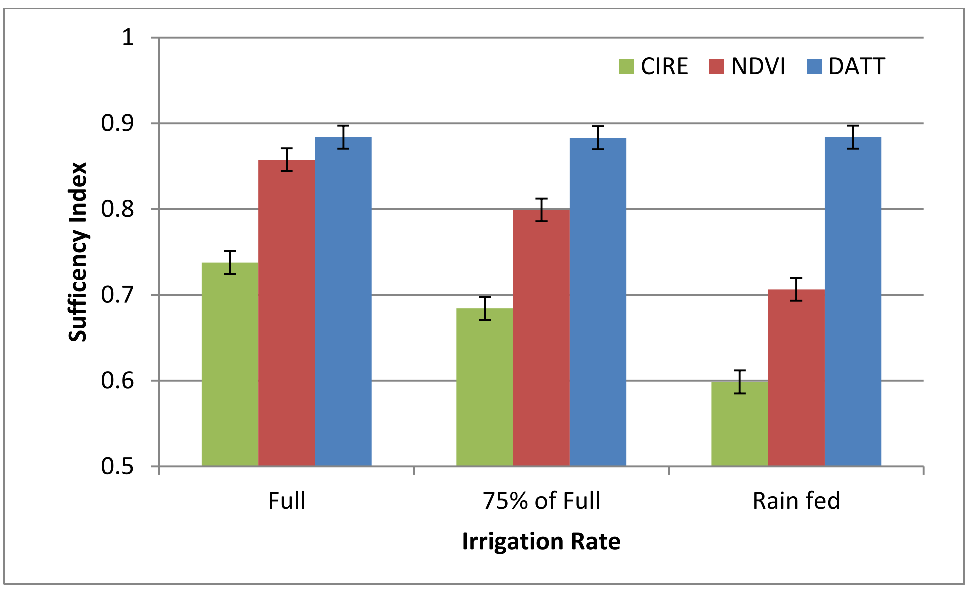

Figure 2-17. Interaction of irrigation rate and VI on SI across all N rates for the SCAL 2013 site year. For doth CIRE and NDVI SI decreased as irrigation decreased, while the DATT index remained constant across all irrigation treatments. Error bars represent standard error.

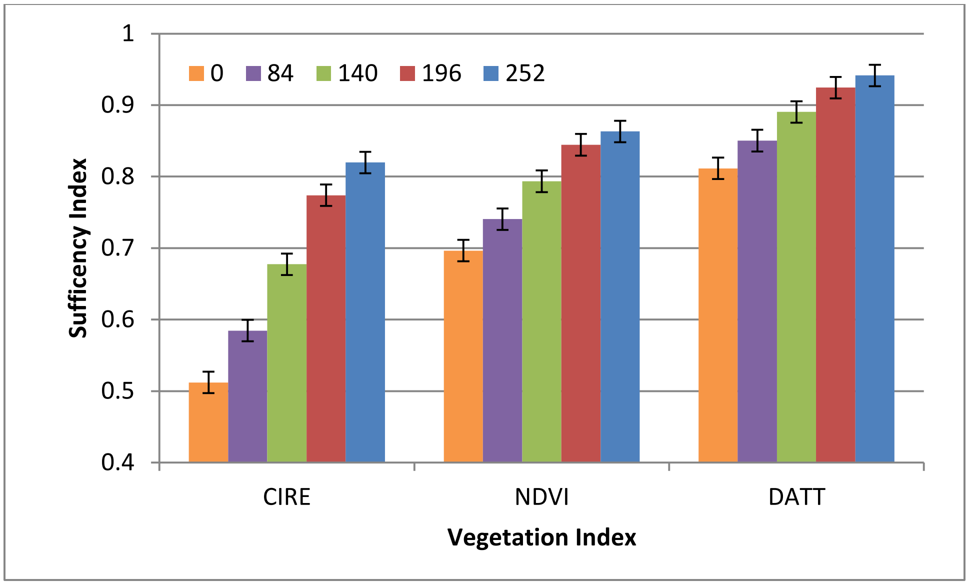

Figure 2-18. Interaction of N rate and VI on SI across all irrigation rates for the SCAL 2013 site year. The CIRE experienced significant response to all N rates while NDVI and DATT did not indicate better N fertility above 196 kg N ha^{-1}. Error bars represent standard error.

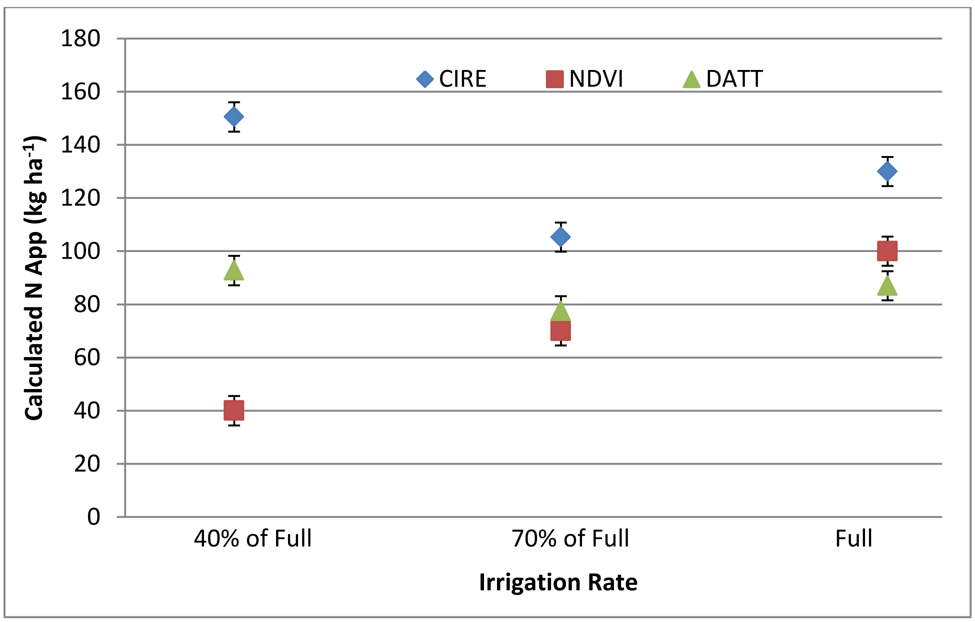

Figure 2-19. Interaction of irrigation rate with VI for calculated N application rate for the BWL 2012 site year. Error bars represent standard error.

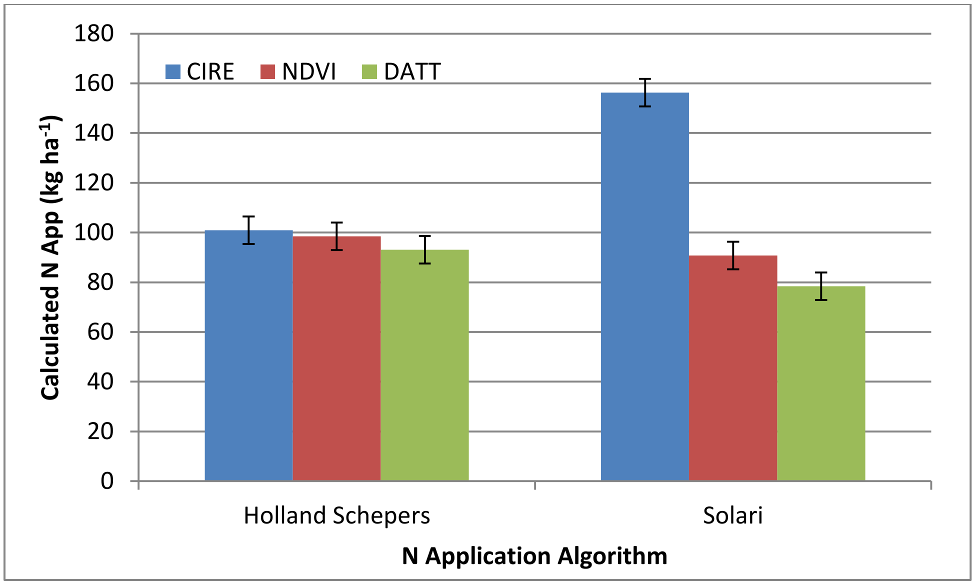

Figure 2-20 Interaction of VI and algorithm on calculated side dress N rates for the BWL 2012 Site year. There was no significant difference among VI for N rates calculated by the Holland & Schepers approach, while the CIRE was significantly higher than NDVI and DATT with the Solari equation. Error bars represent standard error.

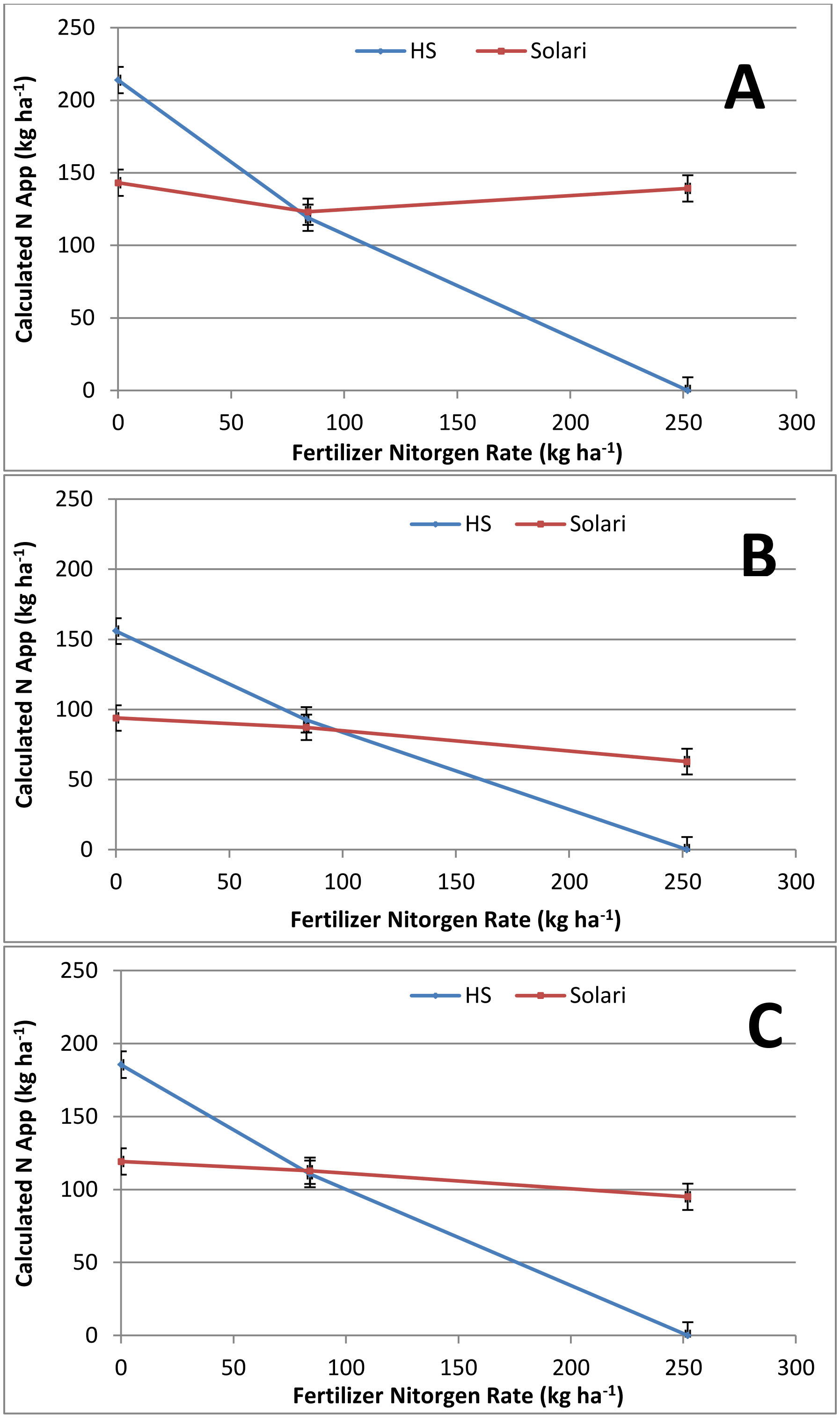

Figure 2-21. Three way interaction of irrigation rate (A: 40% of full, B: 70% of full and C: full), N treatment and algorithm on calculated N side dress rates for the BWL 2012 site year. The Holland-Shcepers approach significantly decreased calculated N rate for each level of N treatment regardless of irrigation treatment. The Solari approach experience a significant decrease in calculated N rate for only the 252 kg N ha^{-1} N treatment at 70% of full and full irrigation regimes. Error bars represent standard error.

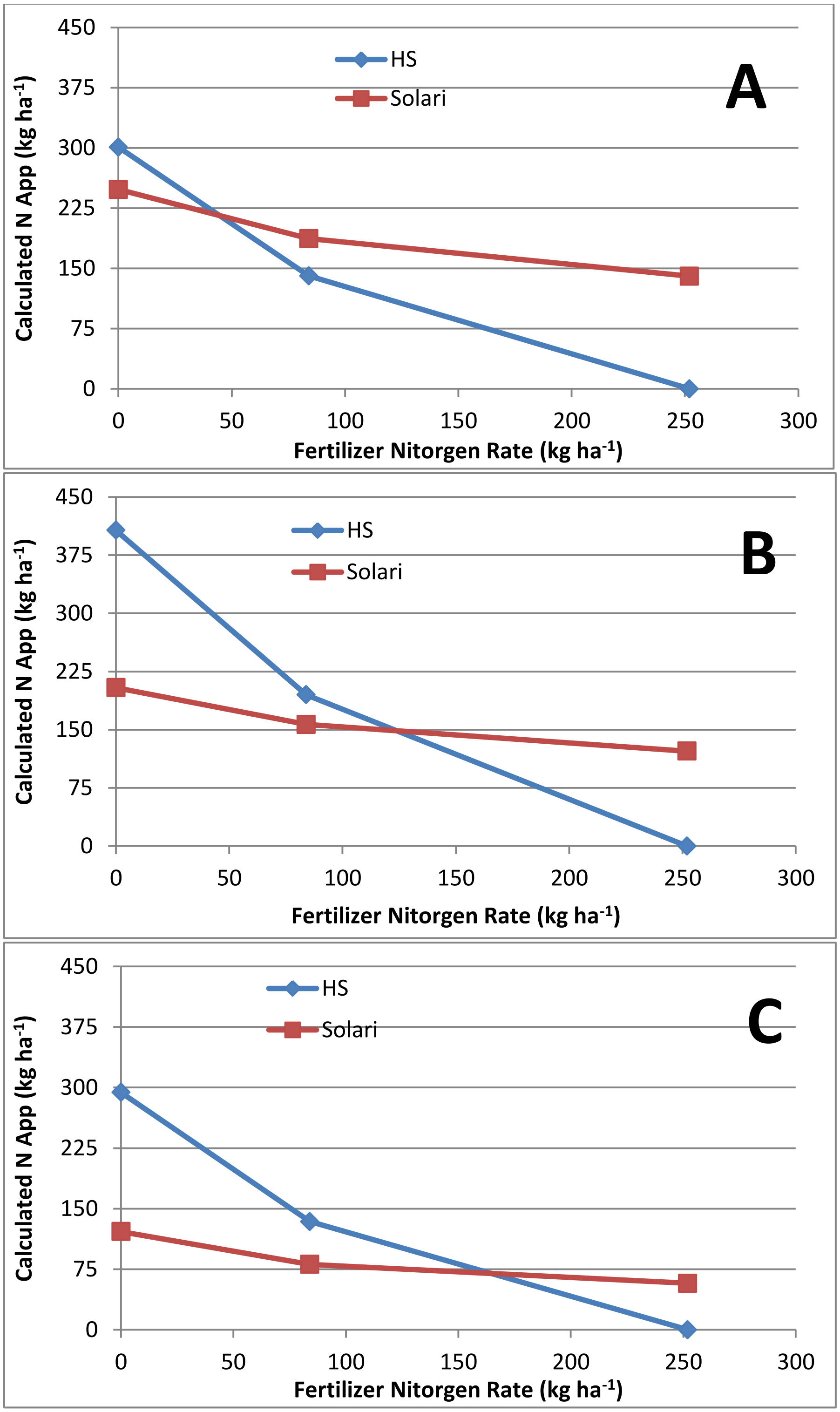

Figure 2-22 Three way interaction of vegetation index (A: CIRE, B: NDVI and C: DATT), N treatment and algorithm on calculated N side dress rates for the BWL 2013 site year. Error bars represent standard error.

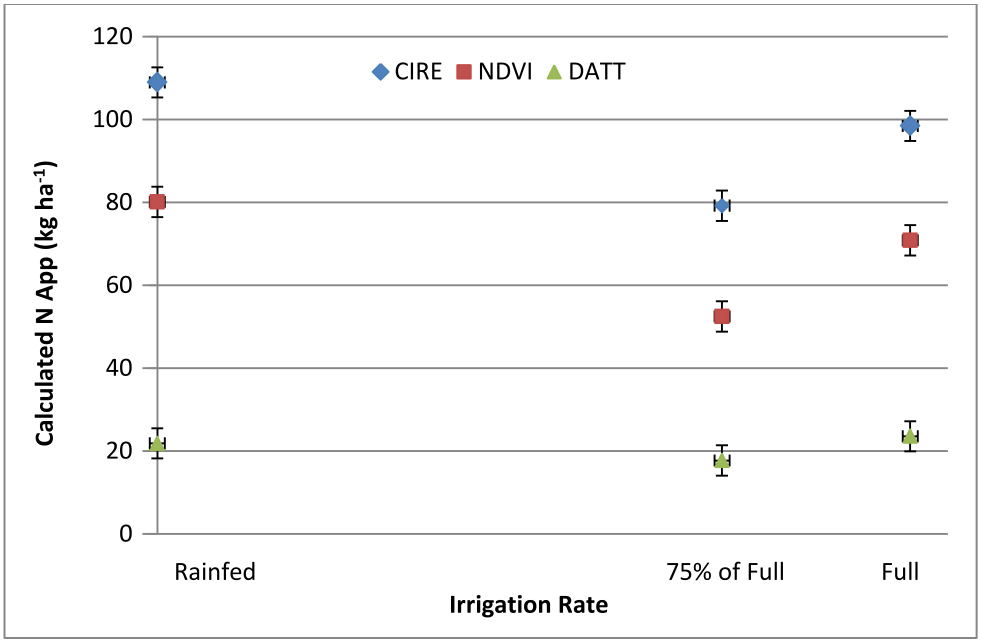

Figure 2-23 Interaction of irrigation rate and VI for calculated N side dress rates for the SCAL 2011 site year. Error bars represent standard error.

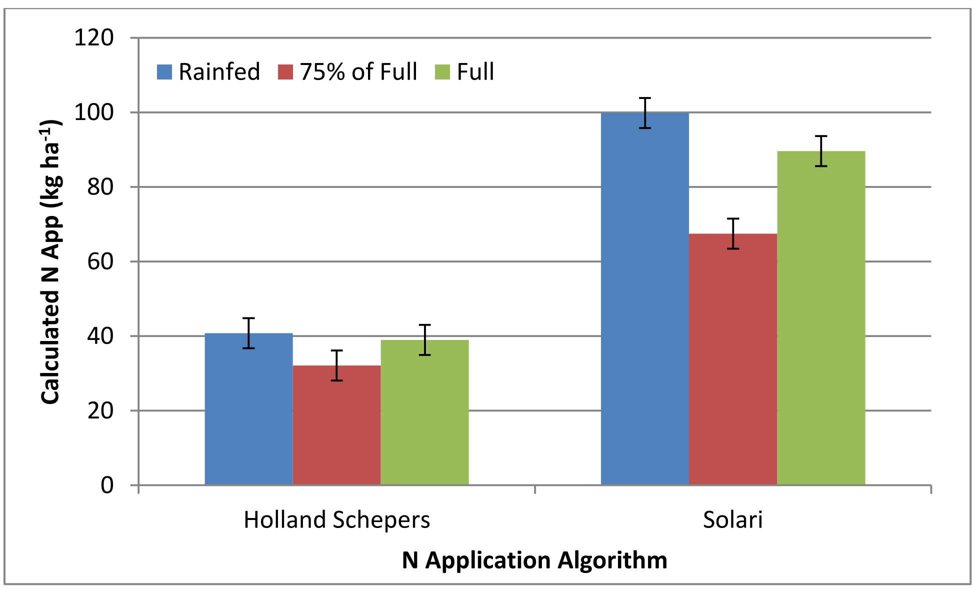

Figure 2-24 Interaction of irrigation rate and algorithm on calculated N side dress rates for the SCAL 2011 site year. Error bars represent standard error.

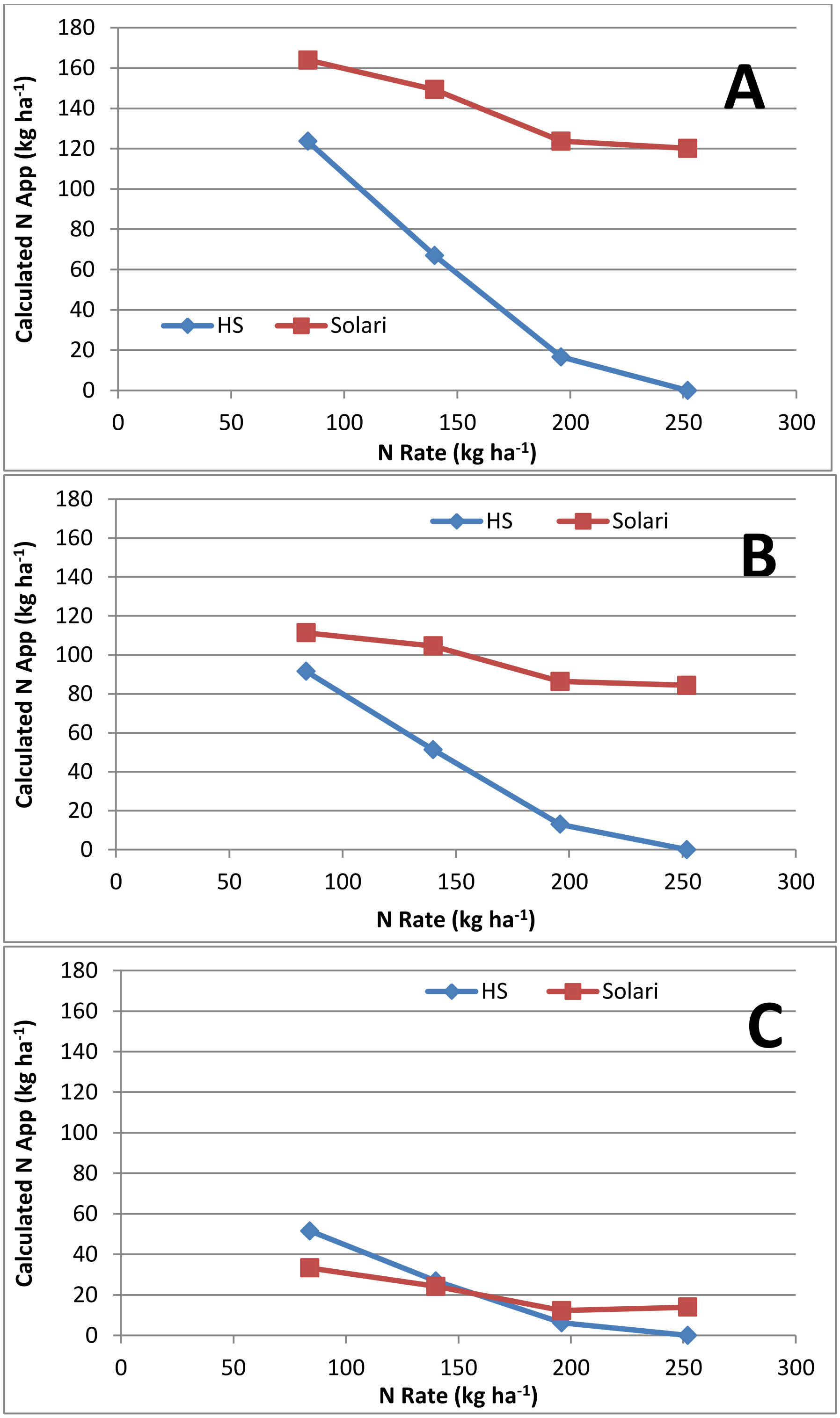

Figure 2-25 The three-way interaction of N treatment, VI and algorithm on calculated side dress N rates for the SCAL 11 site year. A-CIRE, B-NDVI and C-DATT.

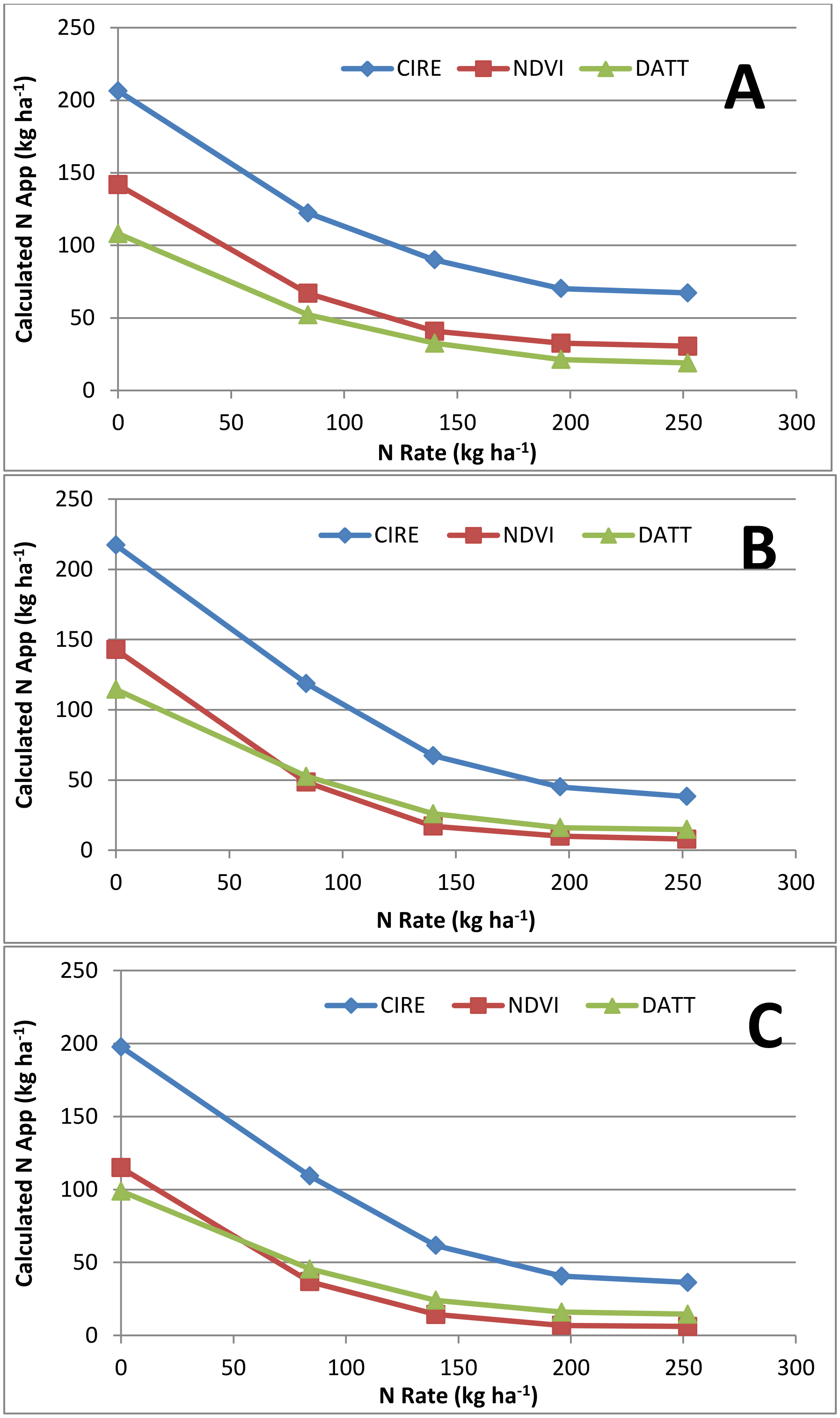

Figure 2-26 Three-way interaction of irrigation rate (A: Rain fed), B: 75% of Full and C: Full irrigation), N treatment and VI on calculated N side dress application rates for the SCAL 12 site year. The CIRE had the highest N rates across all irrigations and N treatments, while NDVI resulted in lower N rates for the two irrigated treatments at N treatments above 84 kg N ha-1. The DATT resulted in the lowest N rate at the 0 kg N ha-1 treatment across all irrigation treatments.

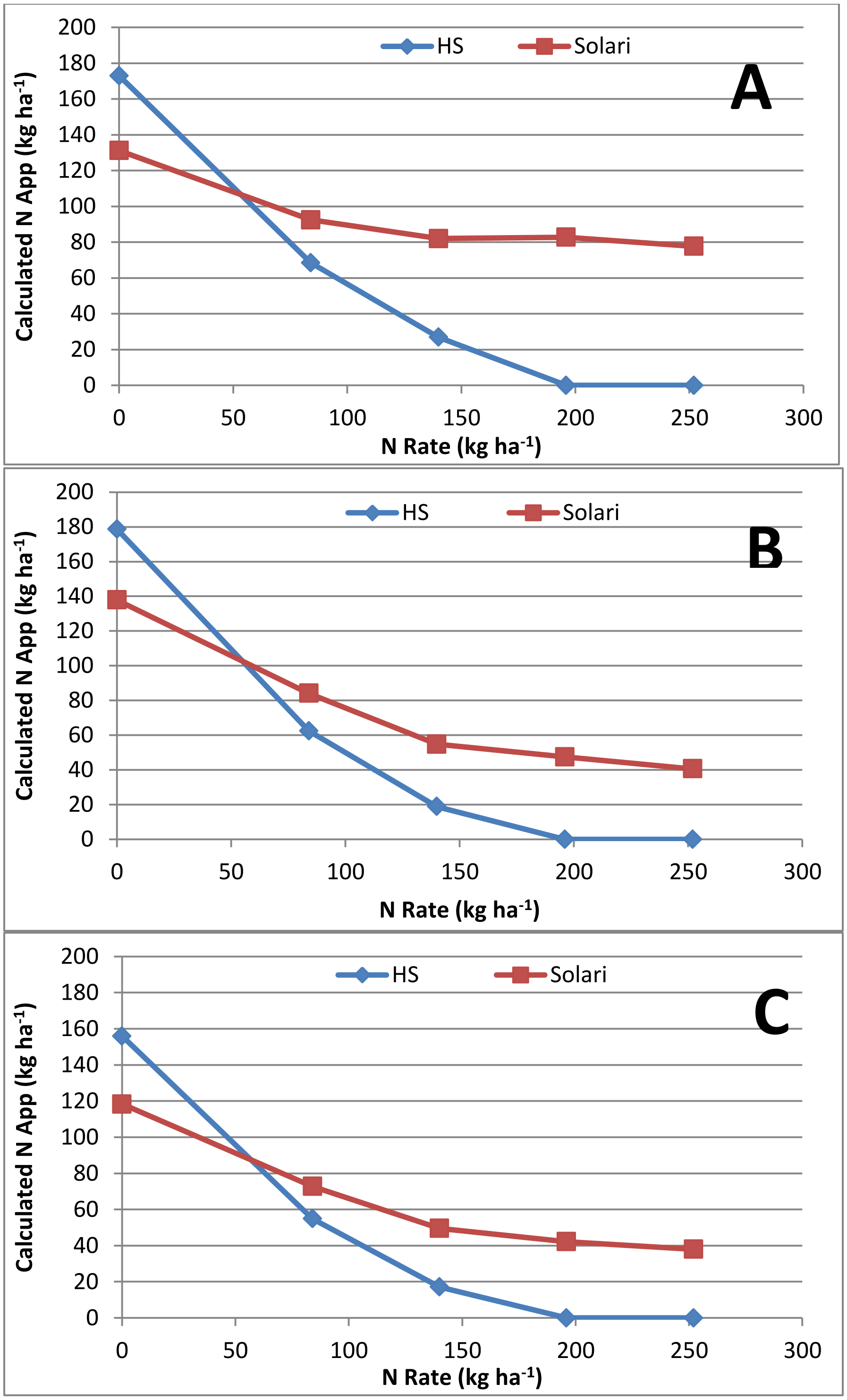

Figure 2-27 Three-way interaction of irrigation (A: rain fed, B: 75% of Full and C: Full), N treatment and algorithm on calculated N side dress rates for the SCAL 2012 site year. The HS approach calculated the highest N rate for the 0 kg N ha-1 treatment while recommending 0 kg N ha-1 for the 196 and 252 kg ha-1 treatments across all irrigations. The Solari approach resulted in higher calculated N rates for all N treatments above 0 kg N ha-1 with the rain fed irrigation treatment have significantly higher calculated N rates than those of the 75% and full irrigations.

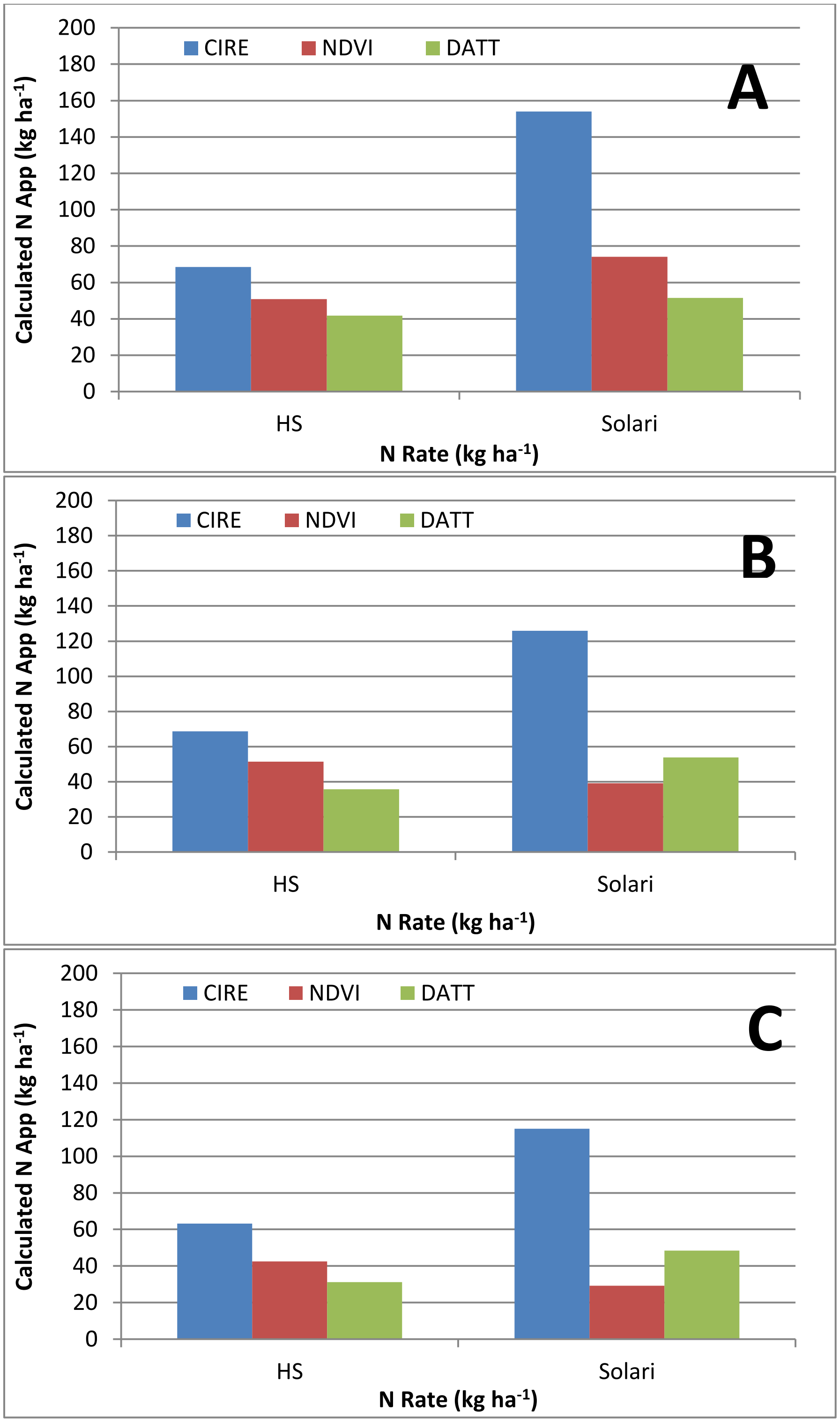

Figure 2-28 Three-way interaction of irrigation (A: rain fed, B: 75% of full and C: full), VI and algorithm on calculated N side dress application rates for the SCAL 2012 site year. The HS approach calculated the same N rate across irrigations for each respective VI. The Solari approach calculated higher N rates for the CIRE and NDVI at the rain fed treatment while DATT resulted in the same rate across irrigation treatments.

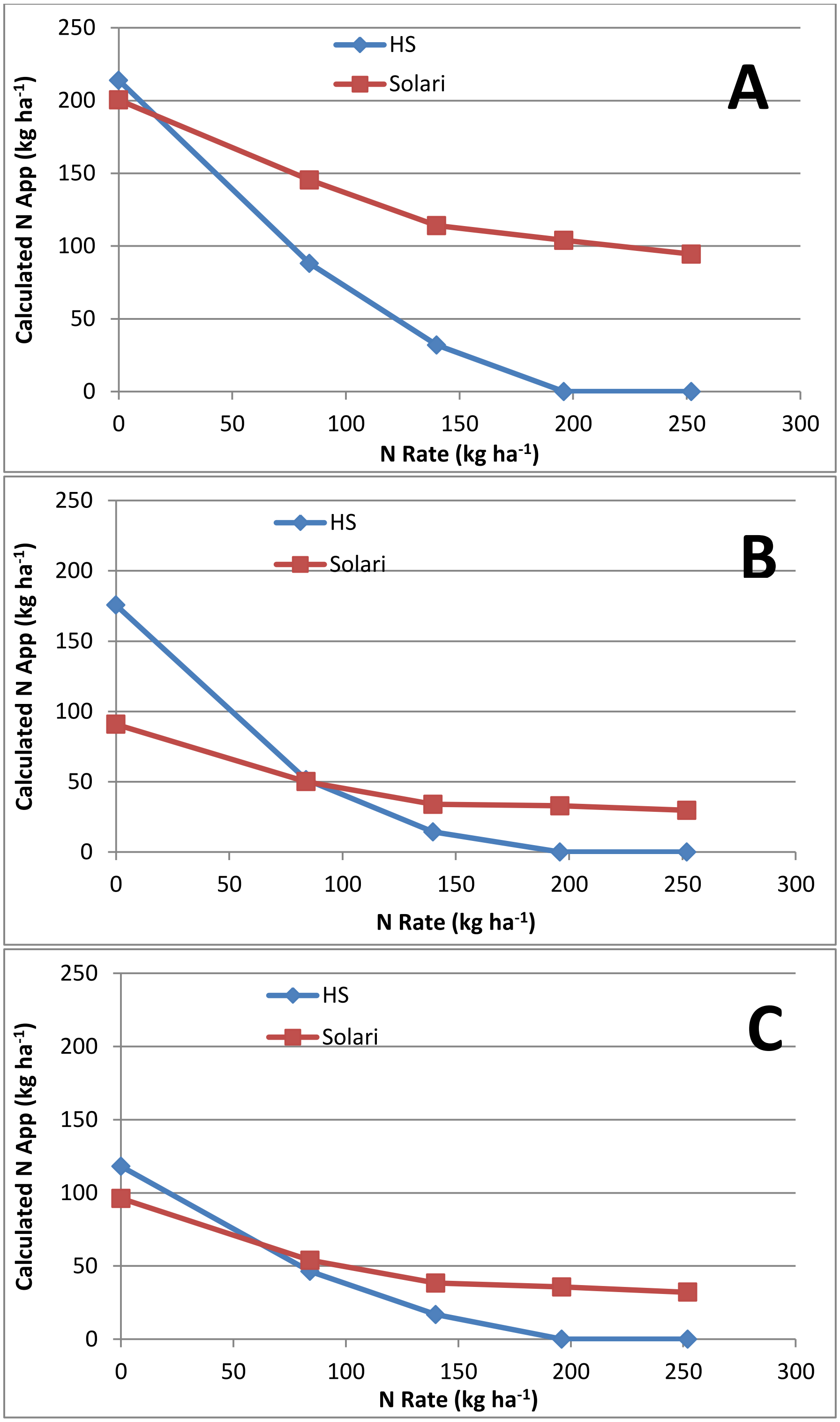

Figure 2-29 Three-way interaction between VI (A: CIRE, B: NDVI and C: DATT), N treatment and algorithm on calculated N side dress rates for SCAL 2012 site year. The CIRE resulted in the highest calculated N rates across all N treatments and algorithm approaches. The NDVI and DATT resulted in similar calculated N rates for both algorithm approaches.

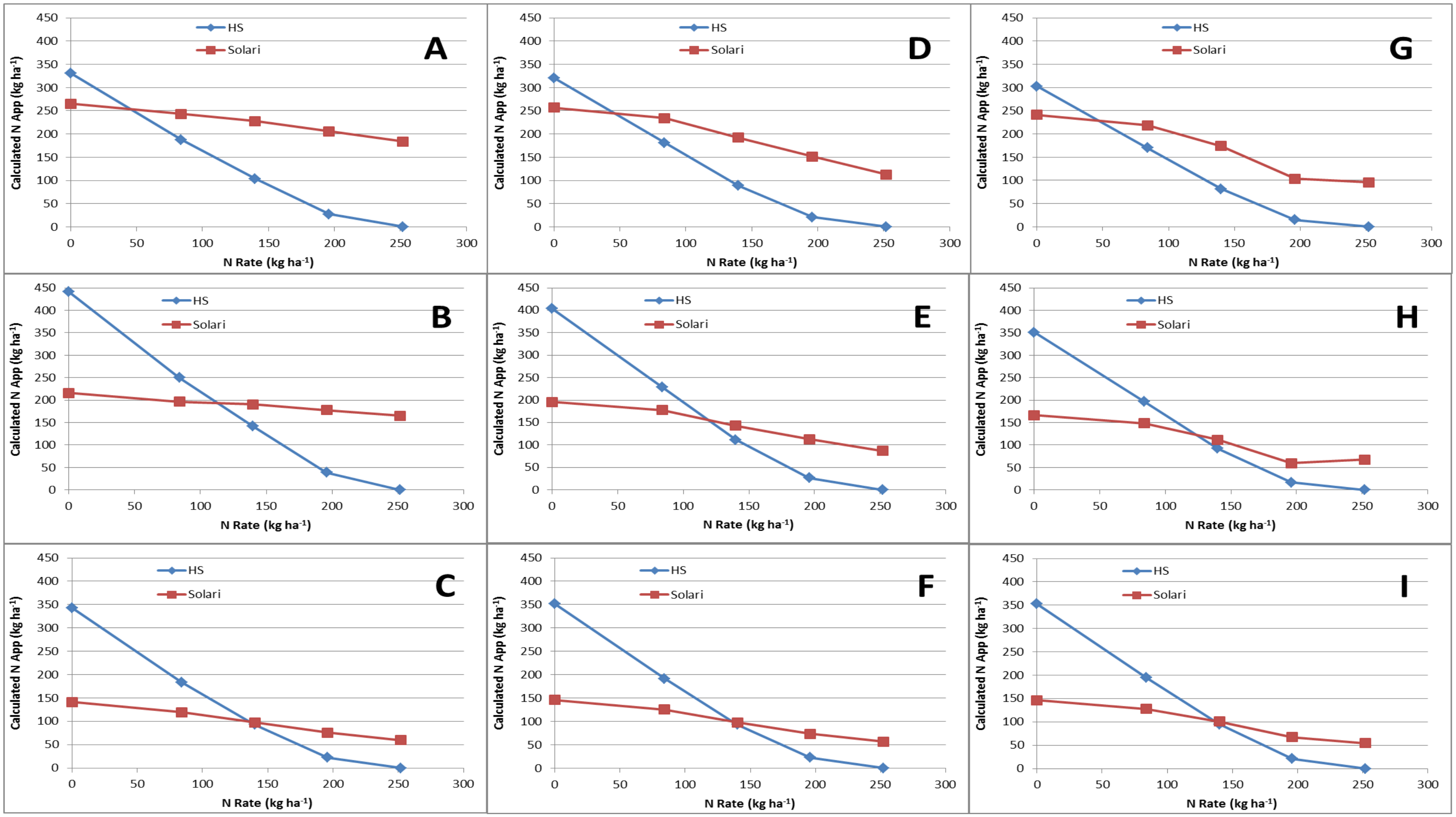

Figure 2-30The four-way interaction between irrigation, N treatment, VI and algorithm on calculated side-dress N rates for the SCAL 2013 site year. Rain fed (column 1): CIRE (A), NDVI (B) and DATT (C); 75% of Full irrigation (column 2): CIRE (D), NDVI (E) and DATT (F); Full irrigation (column 3): CIRE (G), NDVI (H) and DATT (I).

Table 2-1 Planting date, hybrid and seeded populations for study site years.

	BWL		SCAL		
	2012	2013	2011	2012	2013
	8-May	10-May	4-May	25-Apr	16-May
	Pioneer 3544	Pioneer 1151	Pioneer 541AM	Pioneer 1498HR	Pioneer 876CHR
Irrigated	79,200	79,200	74,100	74,100	74,100
Dry land	n/a	n/a	64,300	64,300	64,300

Table 2-2 Vegetation index formulas with sensor wavebands used in for calculations.

Indices	Wavebands (mm)	Equation	Source
NDVI	670, 760	$NDVI = \frac{NIR_{760} - Red_{670}}{NIR_{760} + Red_{670}}$	Rouse, 1974
CIRE	720, 760	$CIRE = \frac{NIR_{760}}{RedEdge_{720}} - 1$	Gitelson et al, 2005
DATT	670, 720, 760	$DATT = \frac{NIR_{760} - RedEdge_{720}}{NIR_{760} - Red_{670}}$	Datt et al, 1999

Table 2-3 Date and crop growth stage of sensing data used for theoretical N side dress application calculations.

	BWL		SCAL		
	2012	2013	2011	2012	2013
Date	17-Jul	9-Jul	28-Jun	25-Jun	12-Jul
Growth Stage	V12/V13	V10	V8/V9	V12	V11/V12

Table 2-4. Grain yield analysis for all site years of this study. The BWL 2012 site responded to irrigation treatment with no response to N fertilizer while the BWL 2013 site year experience significant N rate effects. The SCAL 2011 site year did not see a significant response to irrigation, while 2012 and 2013 both experienced a significant effect (α<0.05) of irrigation. All three SCAL sites experience significant responses to N fertilizer and interactions between N rate and irrigation treatment.

	BWL 2012		BWL 2013		SCAL 2011		SCAL 2012		SACL 2013	
Effect	Num DF	Pr > F	Num DF	Pr > F	Num DF	Pr > F	Num DF	Pr > F	Num DF	Pr > F
Irrigation	2	<.0001	NA	NA	2	0.1174	2	0.0290	2	0.0041
N Rate	2	0.7619	2	<.0001	3	<.0001	4	<.0001	4	<.0001
Irrigation*N Rate	4	0.7541	NA	NA	6	<.0001	8	0.0005	8	<.0001

Table 2-5 Nitrate concentrations in irrigation water used at study sites.

Site	Date Sampled	NO_3 - N (mg kg^{-1})
BWL	27-Aug-2010	18.9
	29-May-2013	17.8
SCAL	10-Aug-2011	3.3
	19-Jul-2012	4.2
	8-Aug-2013	3.8

Table 2-6. Analysis of AOS data collected at the optimal sensor directed N side-dress timing. The BWL 2012 site had a significant irrigation and index response, along with and irrigation by index interaction. The SCAL

	BWL				SCAL					
	17-Jul-12		9-Jul-13		28-Jun-11		25-Jun-12		12-Jul-13	
Effect	Num DF	Pr > F	Num DF	Pr > F	Num DF	Pr > F	Num DF	Pr > F	Num DF	Pr > F
Irrigation	2	<.0001	NA	NA	2	<.0001	2	<.0001	2	<.0001
N Rate	2	0.2796	2	<.0001	3	<.0001	4	<.0001	4	<.0001
Irrigation*N Rate	4	0.4317	NA	NA	6	0.3342	8	<.0001	8	0.0021
Index	2	<.0001	2	<.0001	2	<.0001	2	<.0001	2	<.0001
Irrigation*Index	4	0.0213	NA	NA	4	0.0061	4	<.0001	4	<.0001
N Rate*Index	4	0.7404	4	0.0003	6	0.2471	8	<.0001	8	<.0001
Irrig*N Rate*Index	8	0.9914	NA	NA	12	0.9982	16	0.0039	16	0.8382

Table 2-7. Analysis of calculated N application rates from AOS data at side-dress timing.

	BWL				SCAL					
	17-Jul-12		9-Jul-13		28-Jun-11		25-Jun-12		12-Jul-13	
Effect	Num DF	Pr > F	Num DF	Pr > F	Num DF	Pr > F	Num DF	Pr > F	Num DF	Pr > F
Irrigation	2	<.0001	-	-	2	<.0001	2	<.0001	2	<.0001
N Rate	2	<.0001	2	<.0001	3	<.0001	4	<.0001	4	<.0001
Irrigation*N Rate	4	0.3953	-	-	6	0.0356	8	<.0001	8	0.009
Index	2	<.0001	2	<.0001	2	<.0001	2	<.0001	2	<.0001
Irrigation*Index	4	0.0058	-	-	4	0.0002	4	<.0001	4	<.0001
N Rate*Index	4	0.6467	4	<.0001	6	<.0001	8	<.0001	8	0.0004
Irrig*N Rate*Index	8	0.8382	-	-	12	0.9815	16	0.0024	16	0.7876
Algorithm	1	0.0087	1	<.0001	1	<.0001	1	<.0001	1	<.0001
Irrigation*Algorithm	2	0.0424	-	-	2	<.0001	2	<.0001	2	<.0001
N Rate*Algorithm	2	<.0001	2	<.0001	3	<.0001	4	<.0001	4	<.0001
Irrig*N Rate*Algorithm	4	0.0121	-	-	6	0.2774	8	<.0001	8	<.0001
Index*Algorithm	2	<.0001	2	<.0001	2	<.0001	2	<.0001	2	<.0001
Irrig*Index*Algorithm	4	0.8574	-	-	4	0.1072	4	<.0001	4	0.0022
N Rate*Index*Algorithm	4	0.8589	4	<.0001	6	0.0197	8	<.0001	8	<.0001
Irrig*N Rate*Index*Algo	8	0.972	-	-	12	0.9989	16	0.2538	16	0.0162

Chapter 3. Nitrogen Fertility's Effect on Maize Canopy Temperature

Abstract

Detecting and correcting plant stresses are crucial management needs for supplying the world with food, fiber and fuel. Plant canopy temperature is a primary method used by researchers and practitioners alike for quantifying plant water stress but could be useful for additional diagnostic work such a nutrient deficiencies. The objective of this study was to quantify the effect of N fertility on plant canopy temperature and determine if functions of canopy temperature could be useful for detecting apparent N stress. A study was conducted from 2012 to 2013 with corn (Zea mays L.) at two sites in Nebraska. Treatments consisted of irrigation (Full, 75% of Full, and rain fed) and N fertilizer rate (0, 84, 140, 196, and 252 kg N ha^{-1}). Crop canopy temperature data were collected at multiple growth stages by a machine-mounted infrared temperature sensor. Plant canopy temperatures changed with sensing date and generally decreased as crop leaf area increased with growth stage. The difference between air and canopy temperatures was also affected by sensing date although this was more a function of sensing date than canopy size or age. One site-year showed significant canopy and temperature difference response to fertilizer N rate, with another site-year showing a strong trend for canopy temperature response to N. This study showed plant canopy temperature can be affected by stresses other than plant water and that more research on the subject would prove useful as canopy temperature data are used more on a spatial scale.

Introduction

The biophysical process of transpiration plays a vital role on earth that helps drive plant life. When plants transpire, water evaporates at the leaf cell and atmosphere interface. This exothermic process releases energy into the atmosphere, thereby cooling the plant at times of normal evaporation (Sadras and Calderini, 2009). It is this phenomenon that makes temperature of leaves or plant canopies useful as an indicator of plant health or stress.

The first cases of measuring leaf temperature were carried out by Miller and Saunders (1923) measuring leaf temperature of alfalfa (*Medicago sativa* L.) and Eaton and Belden (1929) on cotton (*Gossypium hirsutum* L.). Both studies showed that leaf temperatures were cooler than air temperature under field conditions. Moran (2004) noted that these early studies were highly criticized since instrumentation was touching the leaf surface and calculations at that time indicated impossibly high transpiration rates. These drawbacks and criticisms can be overcome with remote sensing of surface temperature. The released energy from evaporation or from any object can be related to surface temperature based on its emissivity or the ability to emit energy by radiation. Therefore sensing radiation will allow measurement of surface temperatures. Fuchs and Tanner (1966) described some of the early experiments using crude instrumentation to measure surface temperatures with remote sensing and the troubles incurred.

Modern, hand-held infrared thermometers (IRTs) were developed in the mid-1960s to early 1970s (Jackson et al., 1981). These devices detect thermal radiation in the mid to far-infrared region (8 to 14 μm) and then convert that digital number into temperature without direct physical contact between the leaf and the thermometer. One of the great advantages that IRTs provide is the ability to measure temperature from the leaf to canopy scale, but the question as to which measurement is best for analysis of plant stress remains. To help answer that question, Idso and Baker (1967) considered the three methods of heat transfer (radiation, convection and transpiration) to better understand heat dissipation in plants. Moran (2004) stated that the Idso and Baker study suggested that temperature measurements at the canopy scale would be useful for management activities like irrigation scheduling and monitoring plant health.

Much of the first work with IRT measurements focused on plant water and irrigation. Idso et al. (1977) and Jackson et al. (1977) measured canopy and air temperatures to develop an index of crop water status. They termed the difference of canopy minus air temperature as the 'stress-degree-day'. Jackson et al. (1981) refined this approach by fixing the assumption that other environmental factors such as vapor pressure deficit, net radiation and wind were manifested in the temperature difference. The inclusion of vapor pressure deficit (VPD), the driver of transpiration, resulted in what is known as "Crop Water Stress Index" (CWSI). Many other derivatives of canopy temperature measurements and their relation to crop water stress have been published: Stress Degree Day (Idso et al. 1977 and Jackson et al. 1977), Canopy Temperature Variability (Clawson and Blad 1982), Temperature Stress Day (Gardner et al. 1981) and Water Deficit Index (Moran et al. 1994).

Not all IRT work with plant temperature has focused on plant water. Seligman et al. (1983) examined how N deficiency in wheat hastened maturity. Their study noted that N deficient plants generally had higher canopy temperatures which would increase the rate of crop maturity. A study of phenological characteristics of rice (Oryza sativa L.)

examined how N fertilizer affected leaf temperature (Yan et al. 2010). This work showed significant effects of N fertilizer in which higher N fertilizer applications resulted in lower leaf temperatures. Hegde (1986) concluded that the additions of N fertilizer lead to decreased canopy temperatures in onion (Allium cepa L.).

In general, there is little canopy temperature work on factors other than plant/soil water and water stress. However, this subject is the focus of new ideas thanks in part to technological advances that makes temperature sensing easier and less expensive.

This study set out to test two main hypotheses: (i) a crop's N fertility status will affect plant canopy temperature and derivatives of canopy temperature; (ii) the canopy/air temperature difference will be more sensitive to detecting N fertility status than canopy temperature alone.

Materials and Methods

Experimental Design and Site Description

Field experiments were established in 2012 at the West Central Water Lab (BWL; 41.0294 ° N, -101.958292 ° W) near Brule, Nebraska and at the South Central Agriculture Lab (SCAL; 40.58145 ° N, -98.14147 ° W) near Clay Center, Nebraska. The BWL has variable soils across the experiment location; dominant soil series were Satanta loam (fine-loamy, mixed, superactive, mesic Aridic Argiustolls) 3 to 6% slope, Bankard loamy sand (sandy, mixed, mesic Ustic Torifluvents) channeled and Bayard very fine sandy loam (coarse-loamy, mixed, superactive, mesic Torriorthentic Haplustolls) 1 to 3% slope. In 2012, treatment design consisted of a split-plot replicated Latin square (3 replications); in 2013 the design was simplified to a randomized complete block (6 replications). In 2012, irrigation (Full, 75% of full, 40% of full) served as the main plot and N rate (0, 84, and 252 kg N ha^{-1}) as the sub plot. In 2013, variable irrigation failed so N rate became the main plot with no subplots. For both years, plots were 6.1 meters wide (8 rows) and 37.5 to 53.6 meters in length depending on distance from the pivot point. The dominant soil series at SCAL is Hastings silt loam (fine, smectitic, mesic Udic Argiustolls), 0 to 1% slope. Treatment design consisted of a split-plot randomized complete block with irrigation (Full, 75% of full, and rain fed) as the main plot and N rate (0, 84, 140, 196, and 252 kg N ha^{-1}) as the sub plot; treatments were replicated 4 times at this site. Plot size was 6.1 meters wide (8 rows) by 53.3 meters long. For both sites, the study was no-till, continuous corn with the previous year's corn managed uniformly. Planting date and plant population were based on local best management practices (BMPs) for each respective site (Table 3.1). Fertilizer was applied after crop emergence as 28% urea ammonium nitrate solution (UAN) at all sites. The UAN for BWL was surface-banded by a high clearance applicator equipped with drop tubes placing UAN on 152 cm centers. The SCAL site used subsurface coulter application of UAN on 76 cm centers. Irrigation events at BWL site were triggered by the station manager when a visual inspection of the crop indicated stress was present. For SCAL, irrigations were started when soil matric potential became lower than a pre-determined value based on the soil texture at the experiment site. Weed and pest management also followed BMPs for each site.

Canopy Sensing

Canopy temperature was measured with a PSC SSS LT20 (Process Sensors Corp., Milford, MA) non-contact infrared temperature sensor with a sensing range of 0-500 °C and accuracy of 0.5 °C at object temperatures > 20 °C. The sensor field of view was 20:1 and emissivity was set at 0.97. The sensor was oriented at nadir position over the row and placed approximately 40-60 cm above the uppermost leaves. At 60 cm above the crop canopy, the sensor had a circular field of view of approximately 7.07 cm^2. Fuchs et al. (1966) noted that viewing angles near zero result in lower temperatures since the IRT looks deeper into the canopy, thus integrating shaded vegetation. They also noted that as long as incidence angle stayed constant, variations stayed within ±0.3 °C. Ambient air temperature was collected simultaneously with canopy data by a sensor within the PSC-SSS IR optic. A GPS receiver was mounted next to the sensor optics to record spatial position. Sensor and GPS measurements were recorded using customized LabView software (National Instruments, Austin, TX) and then filtered based on spatial location to remove points outside of plot boundaries with ArcGIS 10.1 (ESRI, Redlands, CA). Additionally, a clip function was established to remove any data points within 3 m of the front or back of the plot. Since the GPS receiver was mounted with the sensor optic this method was able to eliminate possible border effects.

Crop Yield

Corn grain yield was determined by machine harvest at the Brule site for both study years. A combine equipped with a yield monitor harvested field-length strips that included the plot area. Yield data were then filtered using Yield Editor v1.02 BETA (USDA-ARS Cropping Systems and Water Quality Unit, Columbia, MO) and clipped (ArcGIS 10.1) of border area and a 10 meters buffer entering and exiting plots for a final plot harvest length of approximately 15 to 30 meters depending on distance from the pivot point. At the SCAL site, the full length of the plot was machine harvested with a plot combine equipped with a weigh bucket. In 2013, a severe hail event occurred; to confirm machine grain yield data, an additional area was hand harvested, shelled, and weighed. The hand and machine harvest data were combined for final grain yield analysis.

Data Analysis and Statistics

For data analysis, N treatments within the full irrigation main plot were analyzed using the PROC GLIMMIX procedure for SAS 9.2 (SAS Institute Inc., Cary NC). This was done so a baseline of canopy temperature could be established without the complication of irrigation level influence. Blocks were treated as a random effect with sensing dates compared within a year. No cross-year analysis was performed due to the large weather variations over the duration of the experiment.

Results and Discussions

Growing season weather summaries for BWL and SCAL were presented earlier in this paper (Figures 1.2 to 1.5). Overall, temperatures were similar for sites within a year, with 2012 being warmer than average May through August; and 2013 being cooler to normal early and warmer late. Rainfall was low for both sites in 2012, triggering early irrigations at BWL on 10-May and SCAL received the first irrigation on 7-July. The BWL required less frequent irrigation in 2013 than 2012 because of higher rainfall. Sensing dates and weather station information at the time of field entry are presented in Table 3.2.

Air Temperature Acquisition Comparison

Since this study involved temperature calculations between the ambient air and those of the crop canopy, the relationship between air temperature collected via the on-the-go sensor unit and those by a static on-site weather station were studied. Weather stations at both study sites were part of the High Plains Regional Climate Center (Lincoln, NE USA), within 0.4 km of field site and collected hourly temperature data. For each date of collection the sensor's head temperature (HT) was plotted with hourly station temperature (ST) to the closes hour of the sensing passes in Figures 3.1 through 3.13.

For all dates of data collection, HT was higher than ST. This difference changed both during collection and from date to date of data collection. For dates in which there were large temperature changes, Figure 3.1 and Figure 3.9, HT change lagged behind that of ST.

Grain Yield Response to Nitrogen

The BWL site did not show a statistically significant grain yield response to N fertilizer rate in 2012 (Figure 3.14). Several factors could have contributed to a lack of response and will be discussed later. For 2013, the BWL site produced above average grain yields compared to irrigated county average (USDA-NASS 2014) and showed significant responses to added N fertilizer (Figure 3.15). The grain yield response to N fertilization can be attributed to cool conditions early in the year, slowing N mineralization, which were very much opposite conditions to those encountered in 2012.

Additionally, frequent rainfall events during late vegetative and early reproductive growth stages reduced chances of crop water stress.

The SCAL site showed significant grain yield response to N fertilization in both 2012 (Figure 3.16) and 2013 (Figure 3.17). For SCAL in 2013, grain yields were lower than 2012 due to a significant hail event as mentioned earlier. Although damage was severe, significant grain yield responses were seen to applied N fertilizer over the non-fertilized check.

Canopy Temperature Response to Nitrogen

Analysis of variance for canopy temperature and the canopy/air temperature difference are presented in Table 3.4 and 3.5, respectively. First looking at canopy temperature (Table 3.4), all site years had a significant date response. This response is shown graphically in Figure 3.18 (BWL 2012 and 2013) and 3.19 (SCAL 2012 and 2013). In Figures 3.18 and 3.19, canopy temperature, in general, decreased as sensing date progressed through the season. This response was harder to detect for SCAL 2012 (Figure 3.19) with only two sensing dates but was very prevalent for the SCAL 2013.

There are several possible reasons for canopy temperature to decrease with growth stage. The first being that each sampling date had its own unique weather conditions, although the sensing passes occurred over the same rows of corn. A growing canopy is dynamic so expecting to see the same leaf arrangement and evapotranspiration scenario is not realistic. Secondly, as the canopy increases in size its ability to cool itself through transpiration increases, making it possible for more mature plants to create cooler canopies.

There was one site that showed a significant plant canopy temperature response to N rate (SCAL 2013), while another, BWL 2012, showed a strong trend for N response. Plant canopy temperature response to N rate for the SCAL 2013 site is displayed in Figure 3.20. As N fertility increased from the check plot to 196 kg N ha^{-1}, canopy temperature decreased by approximately 1.5° C. The BWL 2012 site showed the same trend (Figure 3.21) but was not pronounced (alpha=0.059). For both site years, linear functions were fitted to the data showing R^2 values of 0.55 and 0.70 for SCAL in 2013 and BWL in 2012, respectively. There were no significant interactions between sensing date and fertilizer N rate on canopy temperature.

The canopy/air temperature difference analysis resulted in similar results as canopy temperature alone. All site years had a significant response to sensing date (Table 3.5), with differences ranging from 1 to nearly 6 °C between crop canopy and ambient air. Date affects results are displayed in Figures 3.22 (BWL site) and 3.23 (SCAL site). There does not appear to be any pattern associated with sensing date and temperature difference. The temperature difference is probably more a function of weather condition at the time of sensing than growth stage dependent at canopy temperature alone.

Once again, the SCAL 2013 site showed a significant N fertilizer effect on temperature difference with higher N rates leading to a decreased gap between air and canopy temperatures. A linear function was fitted to the data with an R^2 of 0.75. No other site years showed this strong N response trend.

Conclusions

For certain sites, BWL 2012 and SCAL 2013, canopy temperature increased with decreased N fertilizer rate. Additionally, the difference of canopy and air temperatures showed similar results for the SCAL 2013 site year. When examining canopy reflectance data collected at the same time (Chapter 1), this confirms that an N response was visible and the temperature effect can be correlated with N status. Overall, canopy temperature alone was no better than the canopy/air difference in detecting differences in N rates. In fact, the canopy/air difference slightly increased sensitivity (Figure 3.24).

The effect of N fertility may be caused by several factors seen in N stressed canopies. First, the reduced growth and vigor results in smaller plants which would as a result may not be able to meet optimal transpiration rates. Smaller canopies with reduced leaf area will also result in a potential for higher soil reflectance of energy causing temperature to rise within the plant canopy or allowing for more soil background interference. The results of this study show the potential and pitfalls of canopy temperature data collected on a spatial scale.

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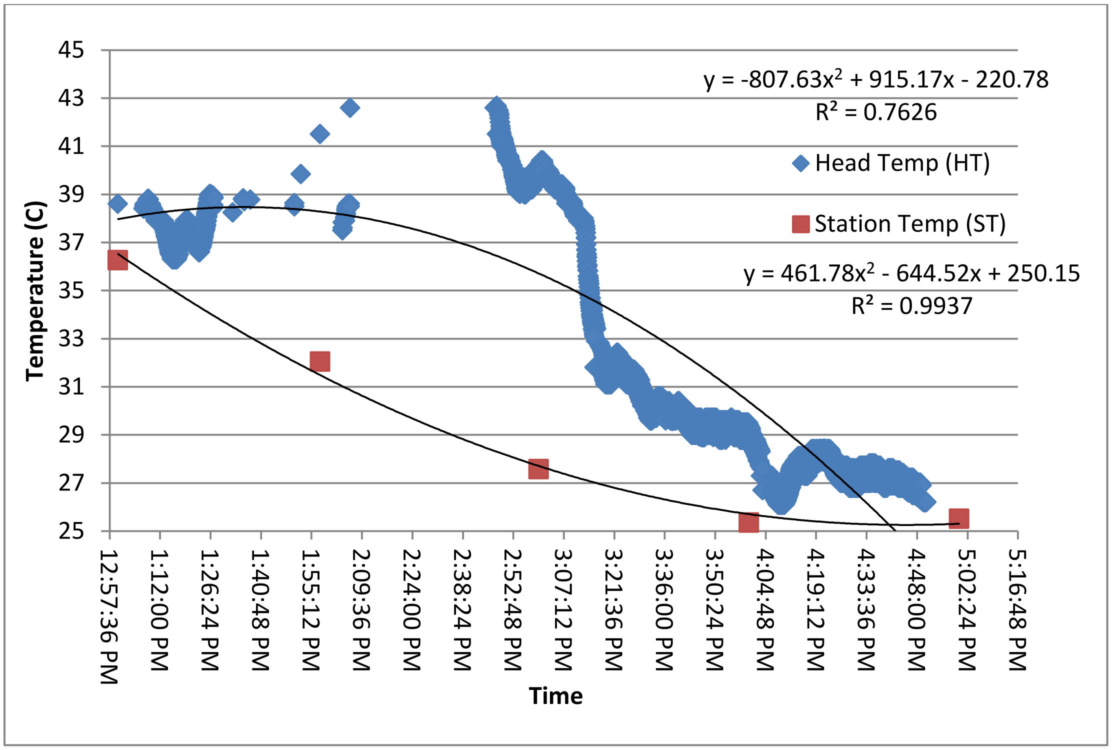

Figure 3-1 Diurnal temperature variations in the IRT head temperature and station temperature for 7 July for the BWL 2012 site year.

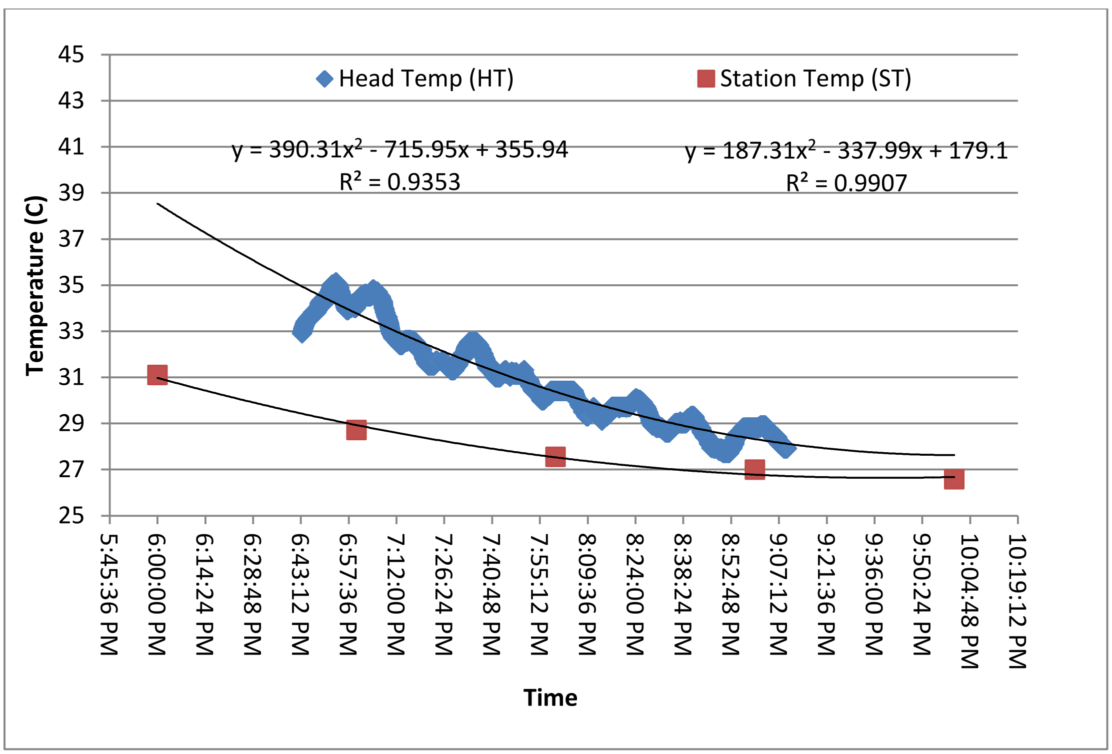

Figure 3-2 Diurnal temperature variations in the IRT head temperature (HT) and station temperature (ST) for 31 July for the BWL 2012 site year.

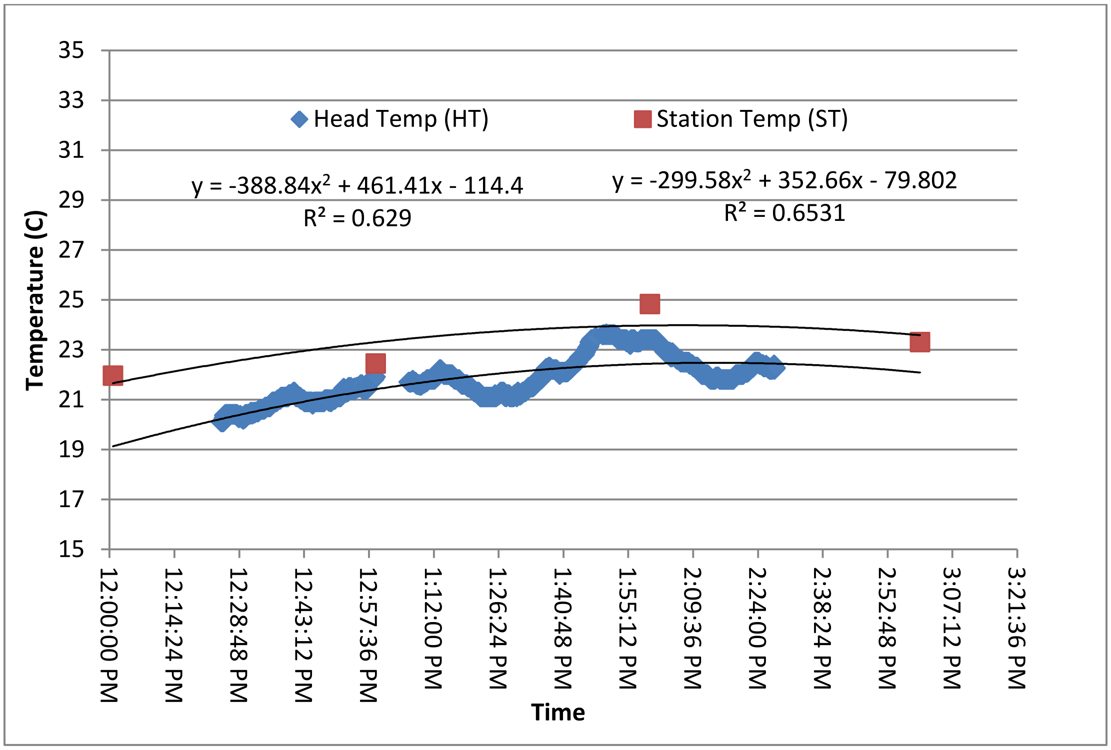

Figure 3-3 Diurnal temperature variations in the IRT head temperature (HT) and station temperature (ST) for 13 August for the BWL 2012 site year.

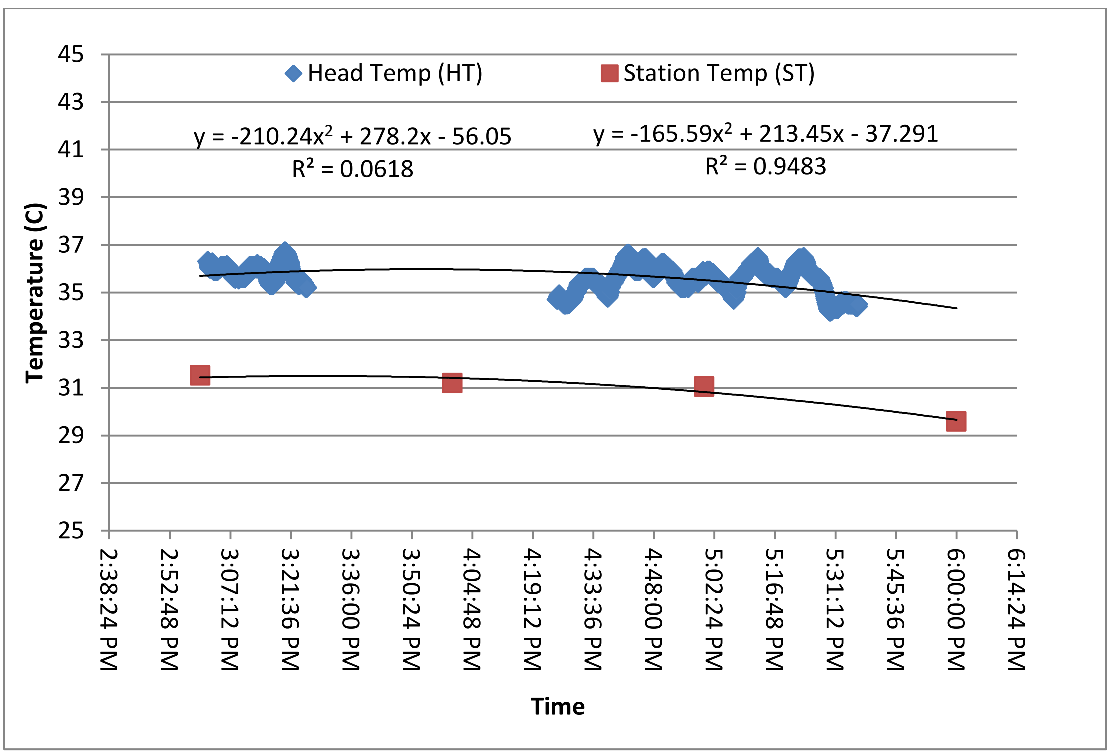

Figure 3-4 Diurnal temperature variations in the IRT head temperature (HT) and station temperature (ST) for 12 July for the SCAL 2012 site year.

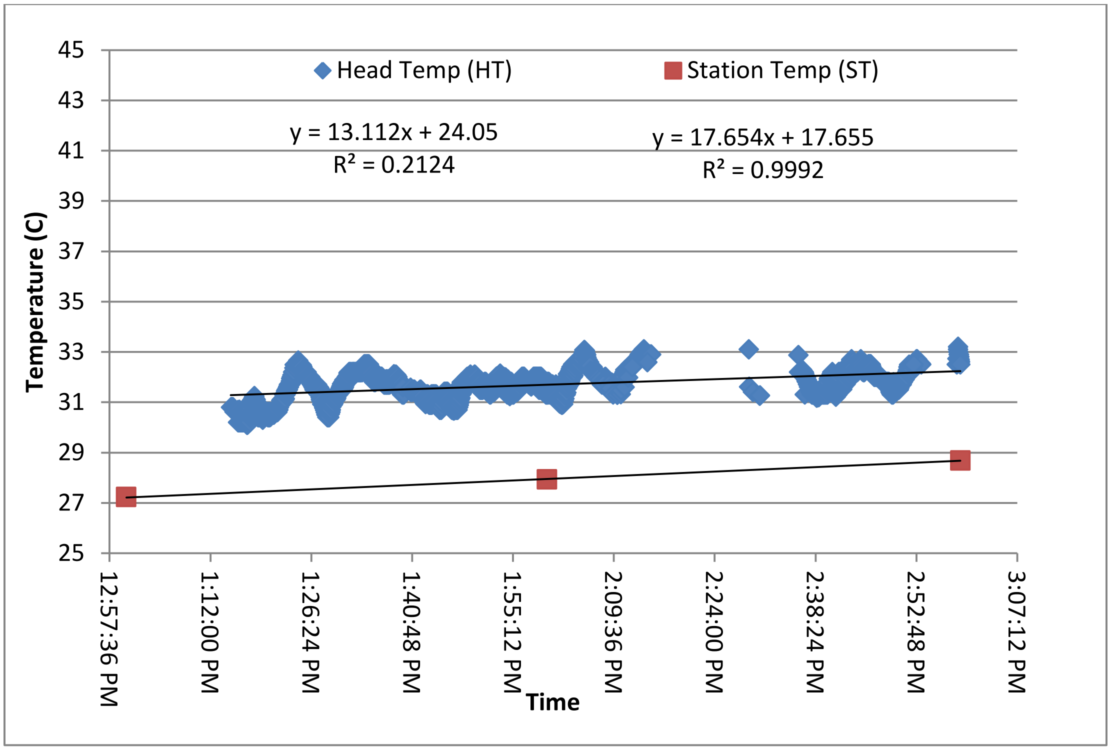

Figure 3-5 Diurnal temperature variations in the IRT head temperature (HT) and station temperature (ST) for 27 July for the SCAL 2012 site year.

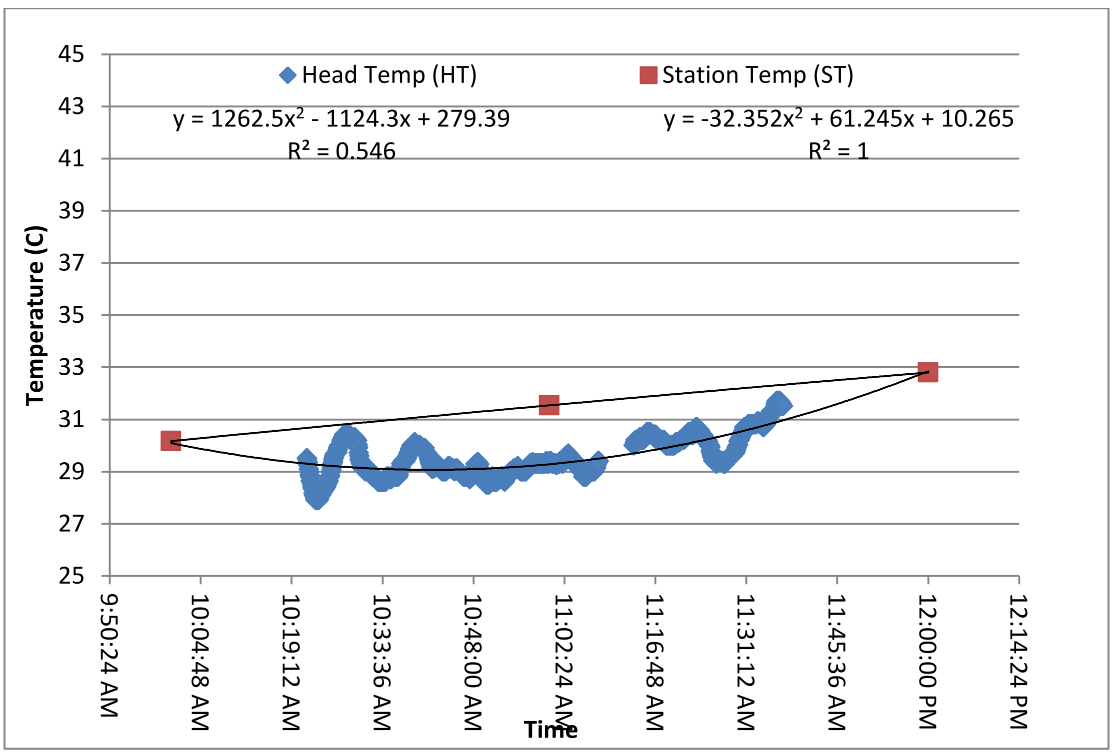

Figure 3-6 Diurnal temperature variations in the IRT head temperature (HT) and station temperature (ST) for 9 July for the BWL 2013 site year.

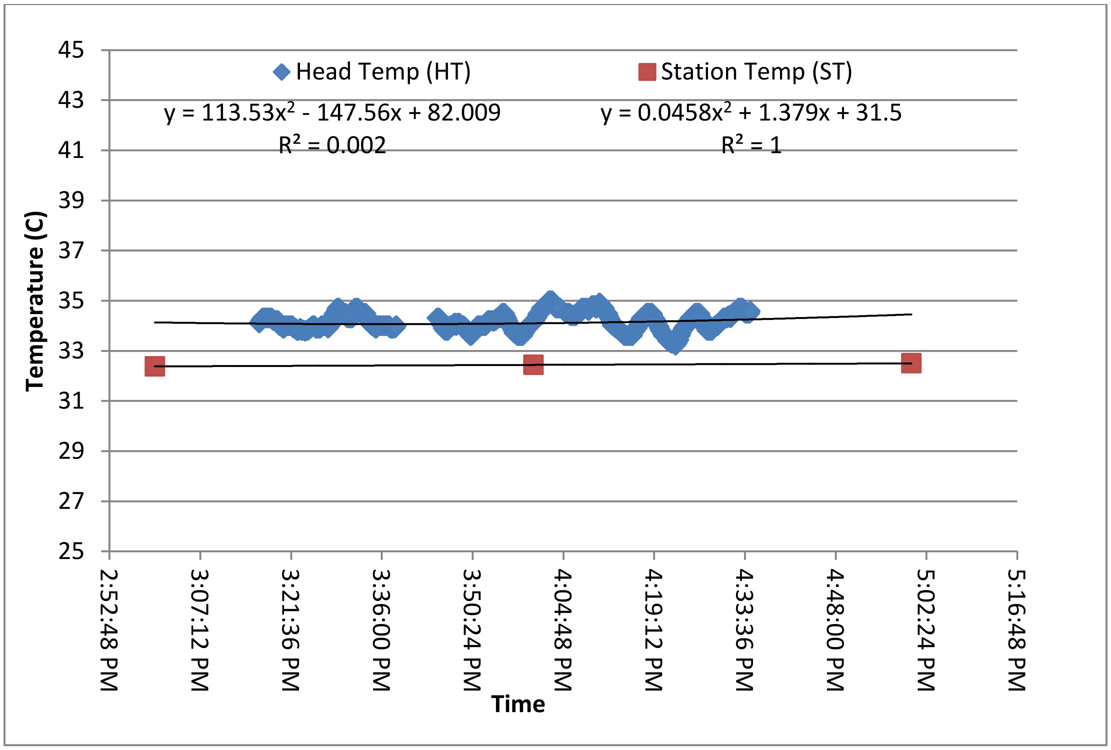

Figure 3-7 Diurnal temperature variations in the IRT head temperature (HT) and station temperature (ST) for 18 July for the BWL 2013 site year.

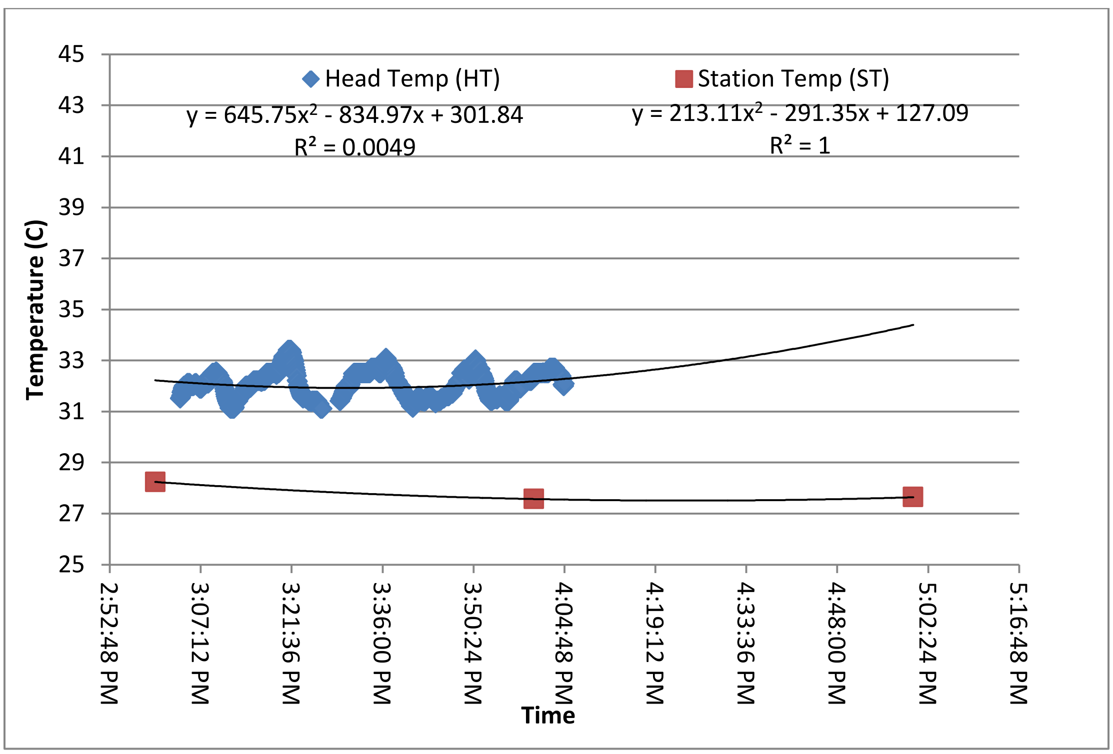

Figure 3-8 Diurnal temperature variations in the IRT head temperature (HT) and station temperature (ST) for 31 July for the BWL 2013 site year.

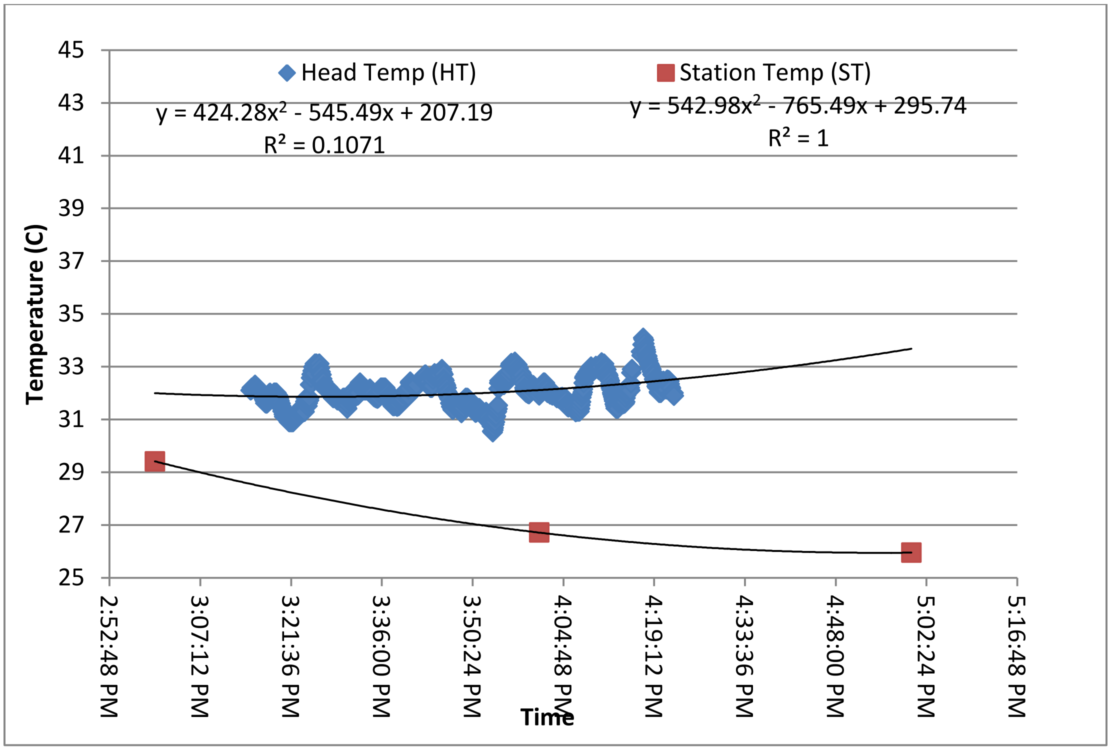

Figure 3-9 Diurnal temperature variations in the IRT head temperature (HT) and station temperature (ST) for 14 August for the BWL 2013 site year.

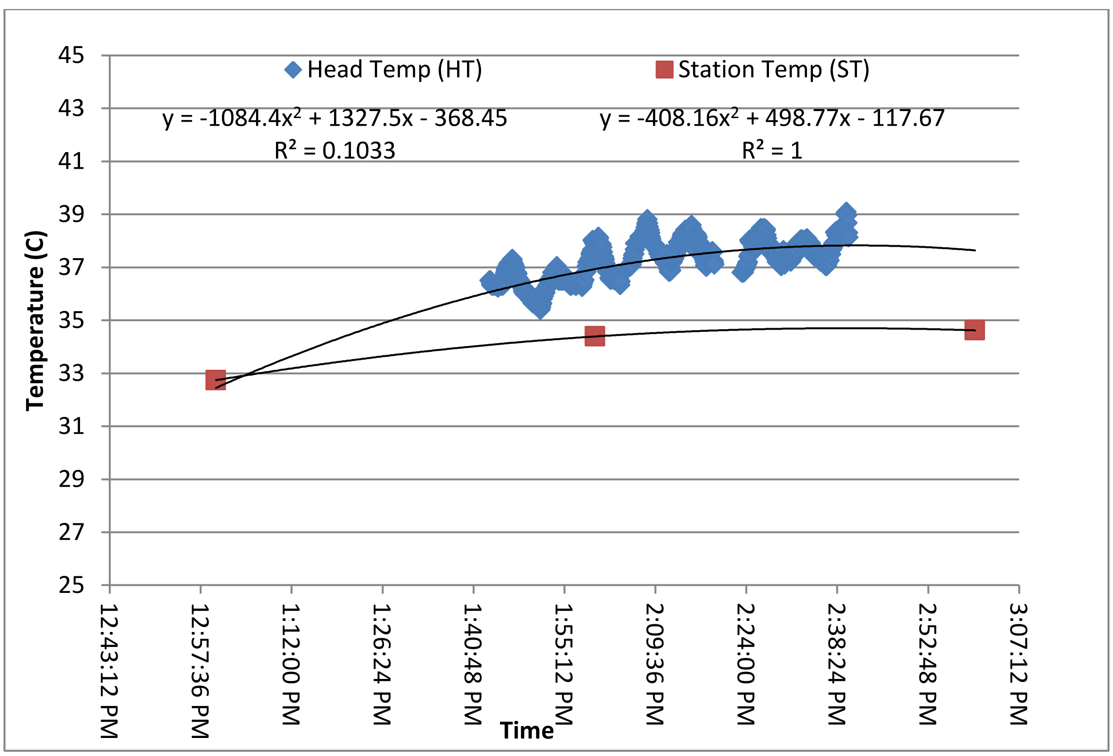

Figure 3-10 Diurnal temperature variations in the IRT head temperature (HT) and station temperature (ST) for 21 June for the SCAL 2013 site year.

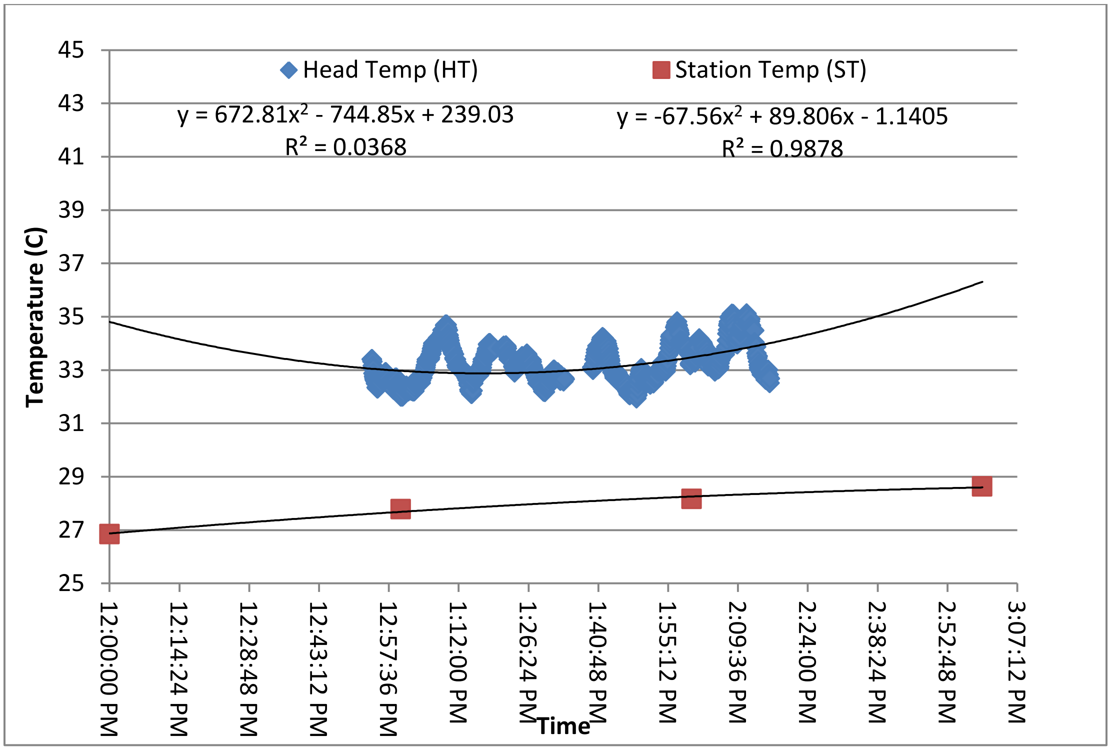

Figure 3-11 Diurnal temperature variations in the IRT head temperature (HT) and station temperature (ST) for 3 July for the SCAL 2013 site year.

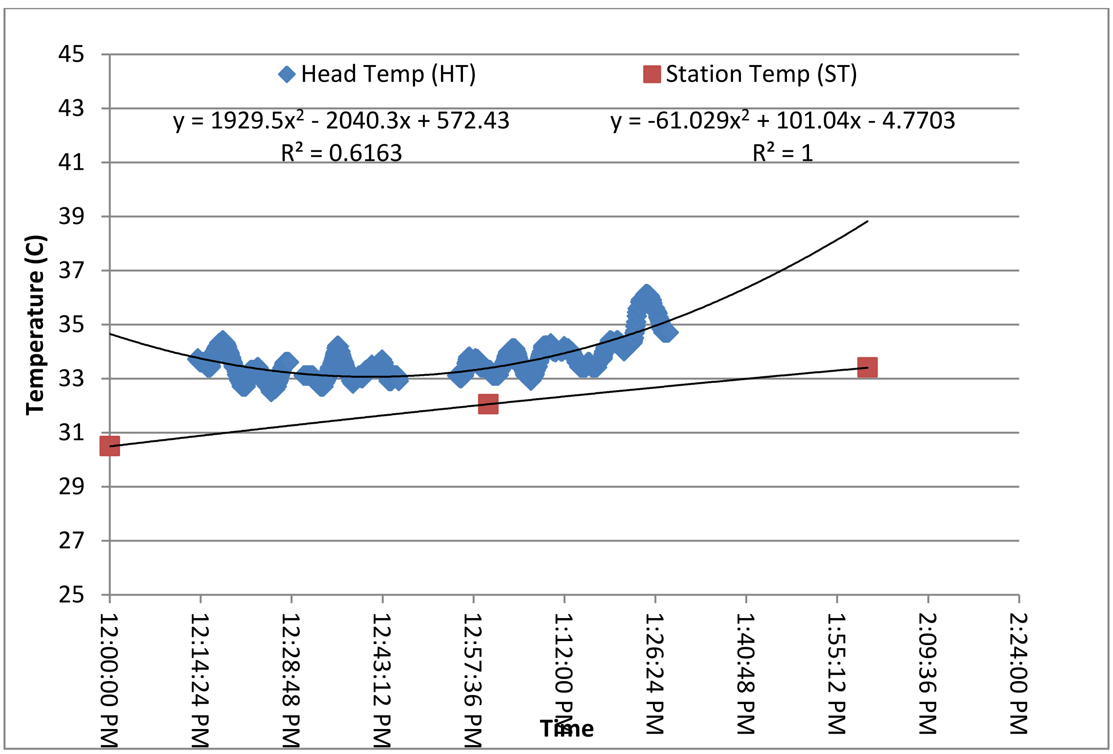

Figure 3-12 Diurnal temperature variations in the IRT head temperature (HT) and station temperature (ST) for 12 July for the SCAL 2013 site year.

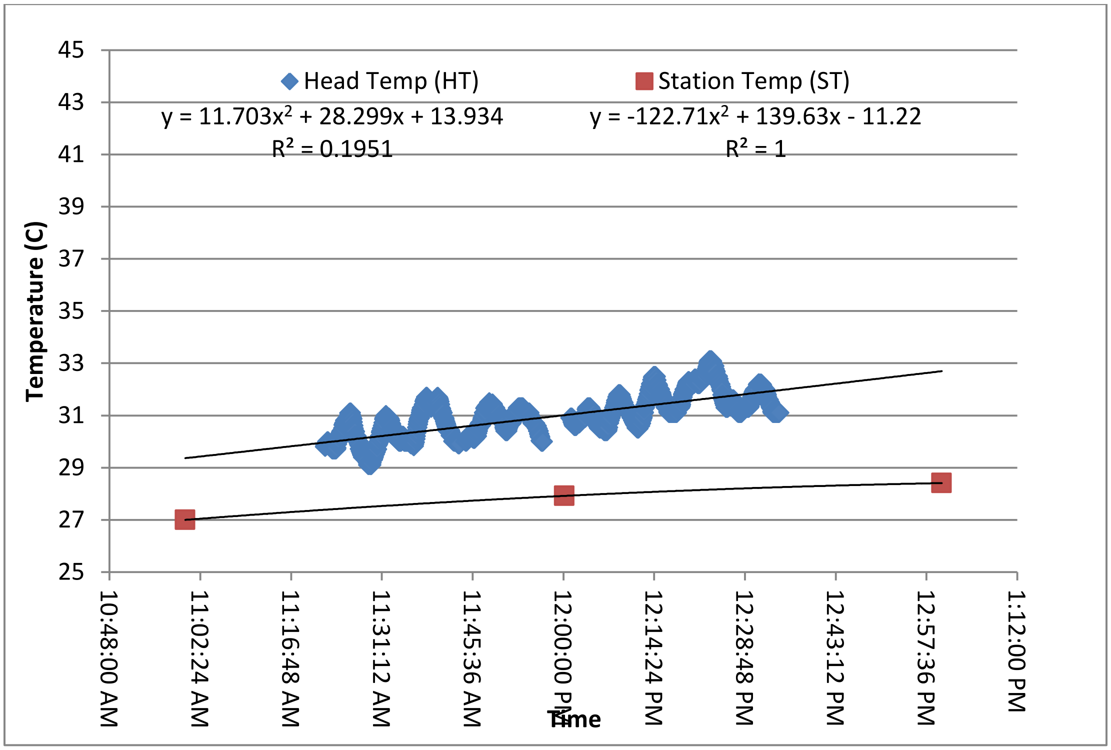

Figure 3-13 Diurnal temperature variations in the IRT head temperature (HT) and station temperature (ST) for 1 August for the SCAL 2013 site year.

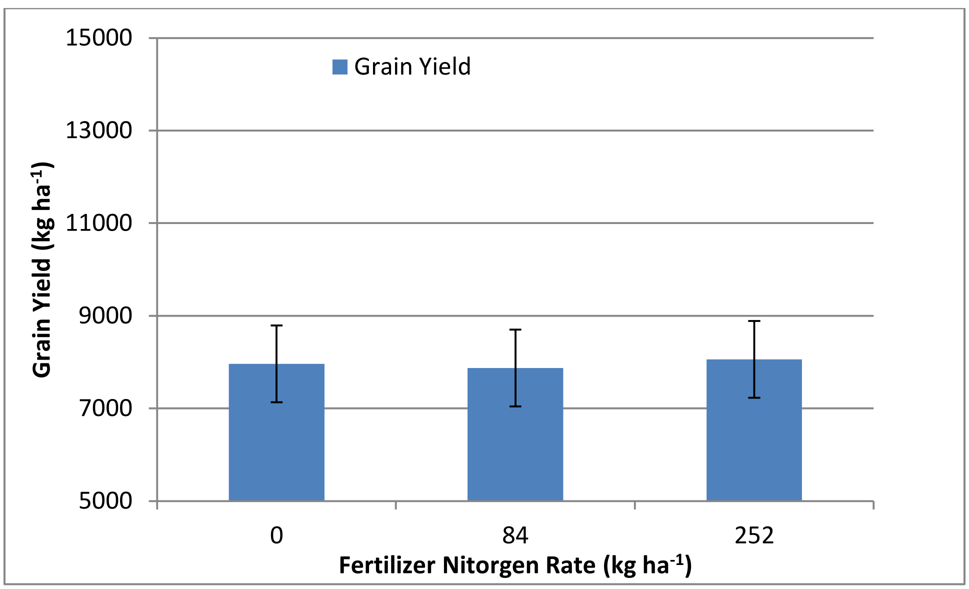

Figure 3-14 Corn grain yield for the BWL site in 2012, no significant response to N fertilizer was seen. Error bars represent standard error.

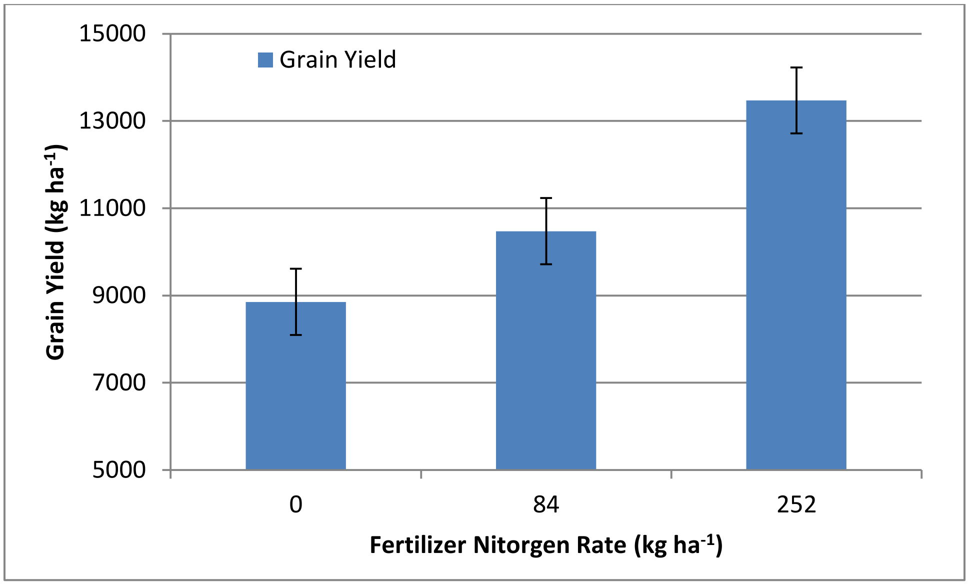

Figure 3-15 Corn grain yield for the BWL site in 2013, yields were substantially higher than the same site in 2012. A significant response to fertilizer N was observed from the 84 and 252 kg ha^{-1} rates. Error bars represent standard error.

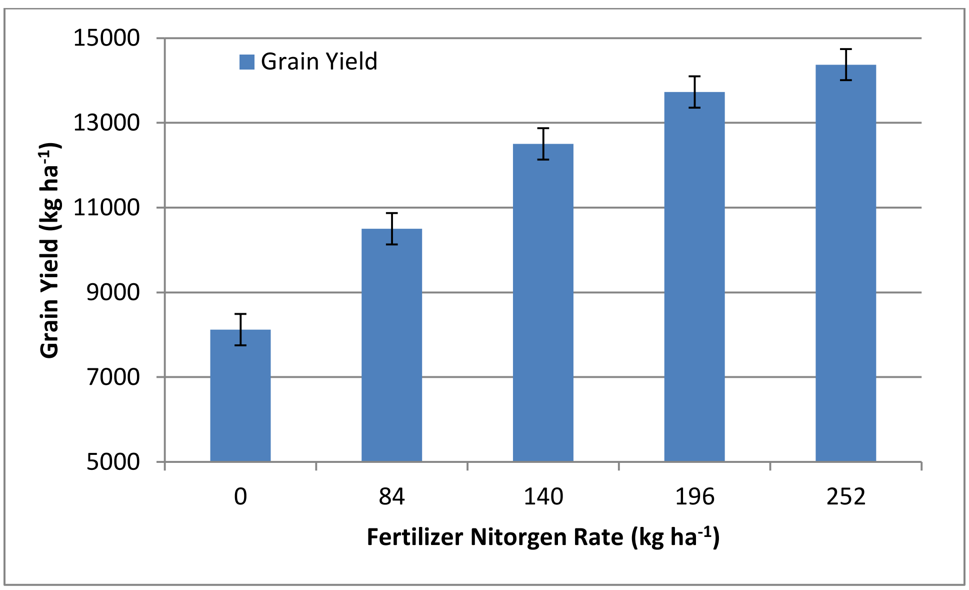

Figure 3-16 Corn grain yield for the SCAL site in 2012. A Significant response was seen for each level of N fertilizer added above the 0 N rate treatment. Error bars represent standard error.

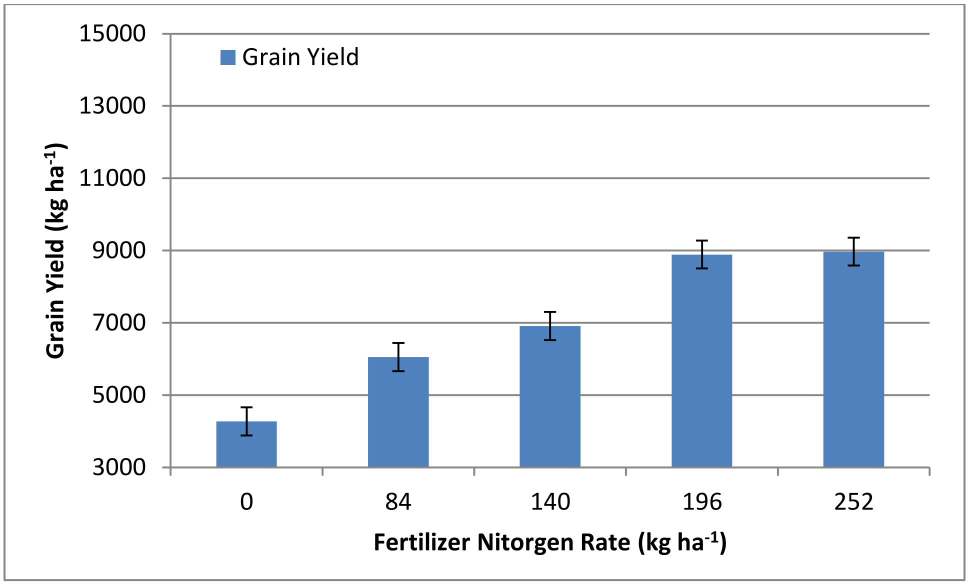

Figure 3-17 Corn grain yield for the SCAL site in 2013 were much lower than 2012 due to hail storm damage. A significant response was seen to the 84, 140 and 196 kg ha^{-1} N rates. The 196 and 252 kg ha^{-1} treatments yielded the same. Error bars represent standard error.

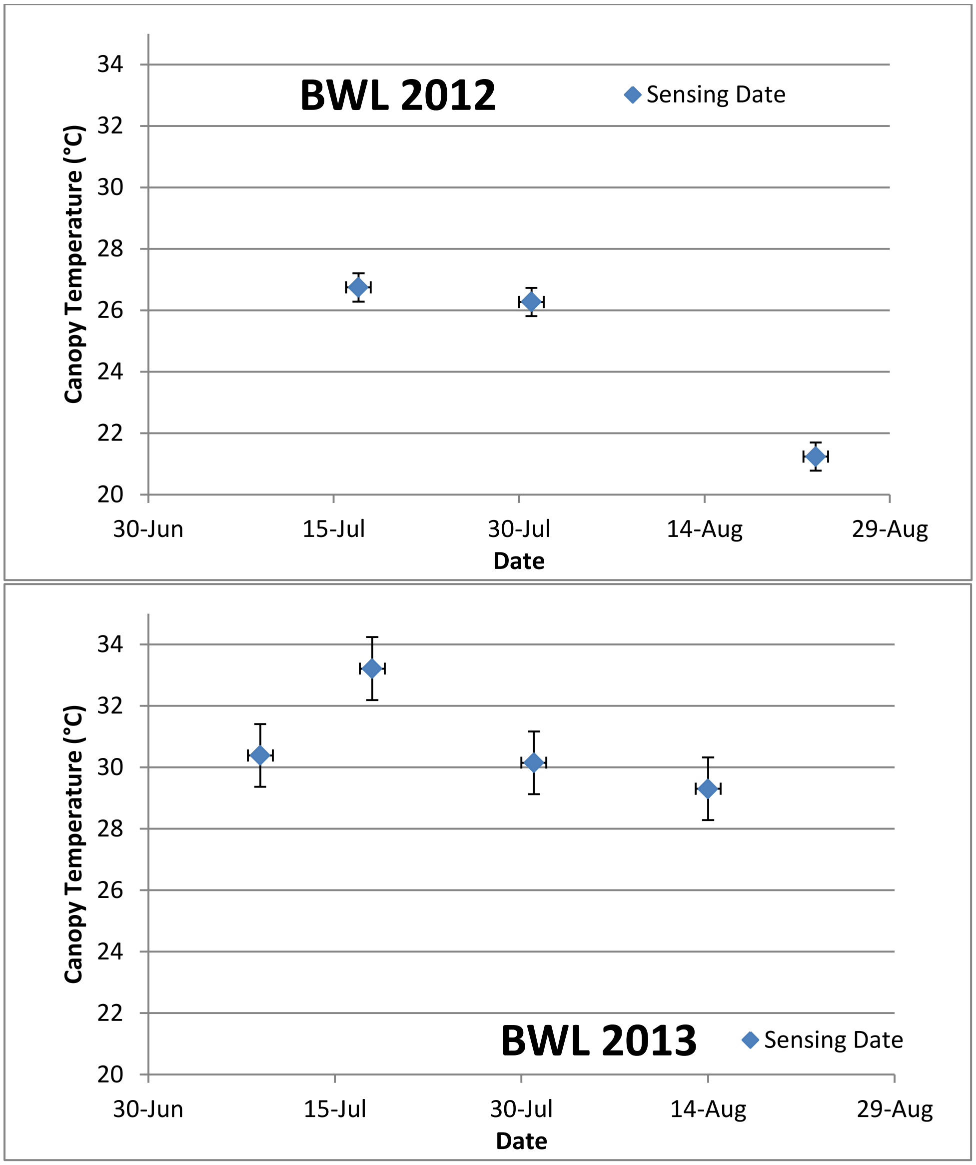

Figure 3-18 Canopy temperature affect from sensing date for BWL 2012 (top) and 2013 (bottom). Sensing dates were significantly different in 2012, with dates differeing in 2013. In general, canopy temperatures cooled as the growing season progressed. Error bars represent standard error.

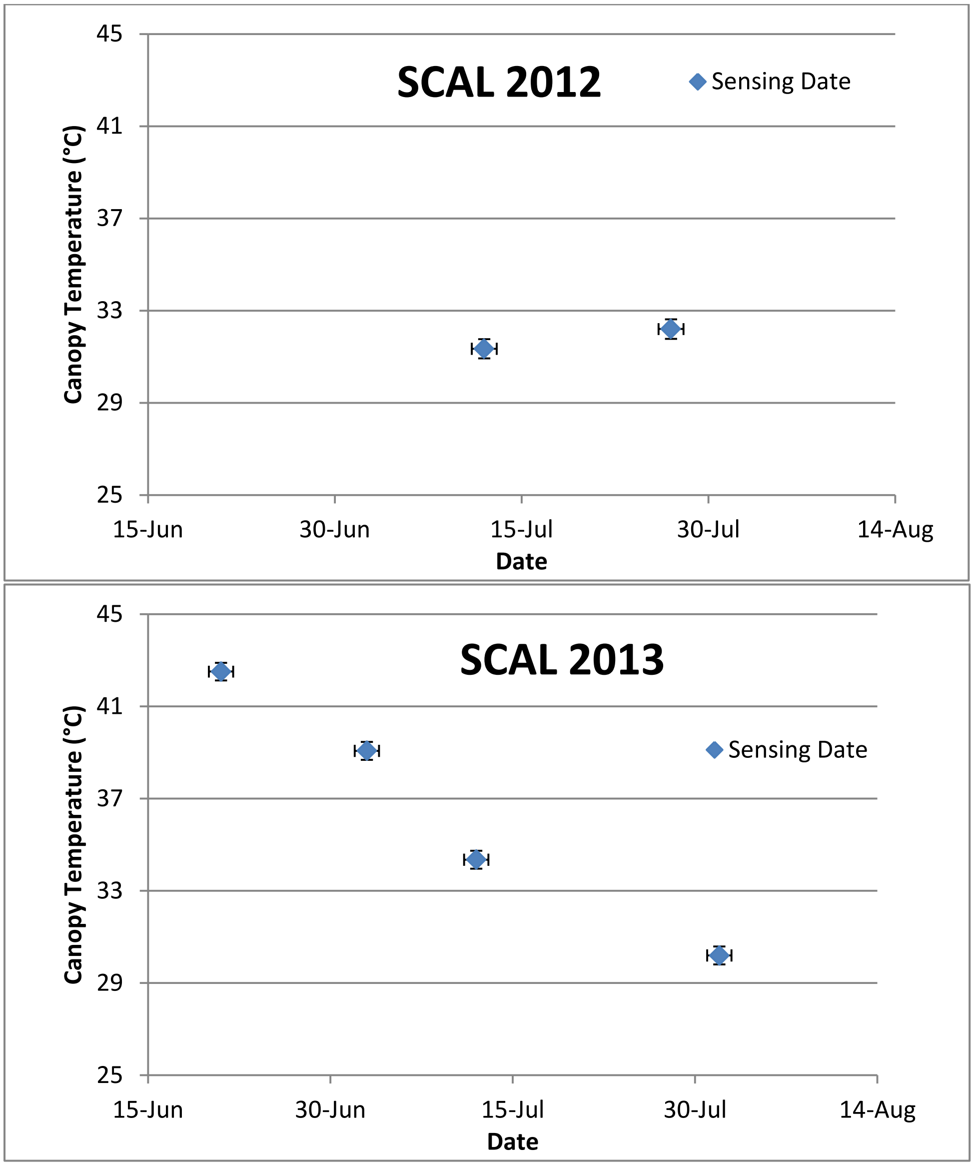

Figure 3-19 Canopy temperature affect from sensing date for SCAL 2012 (top) and 2013 (bottom). Sensing dates were significantly different for the two data collection times in 2012. In 2013, each date was significantly cooler than the previous time. Canopy temperature cooled as the growing season progress. Error bars represent standard error.

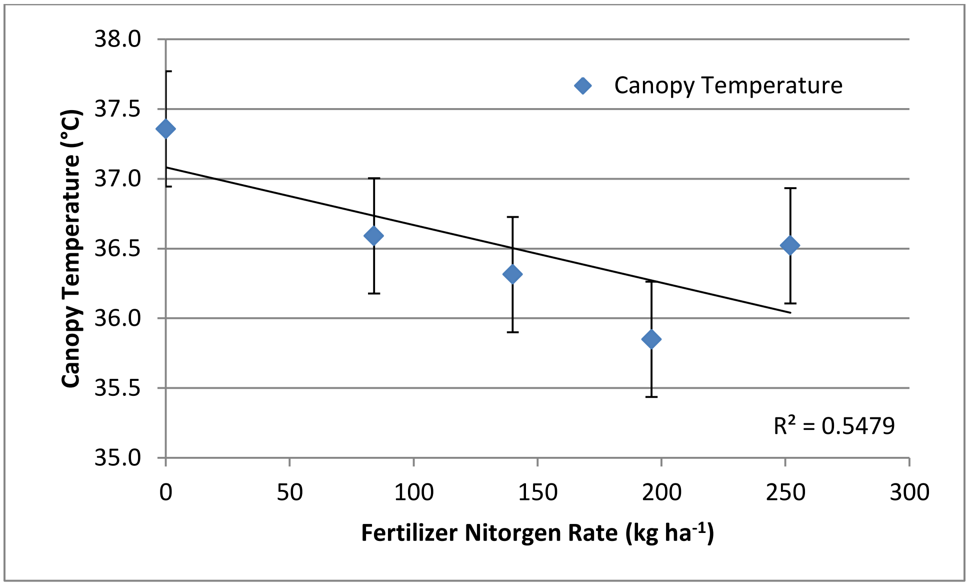

Figure 3-20 Canopy temperature response to N fertilizer rate fot the SCAL 2013 site year. Temperature decresease with increasing N rate, a linear model is fitted with an R^2 of 0.55. Error bars represent standard error.

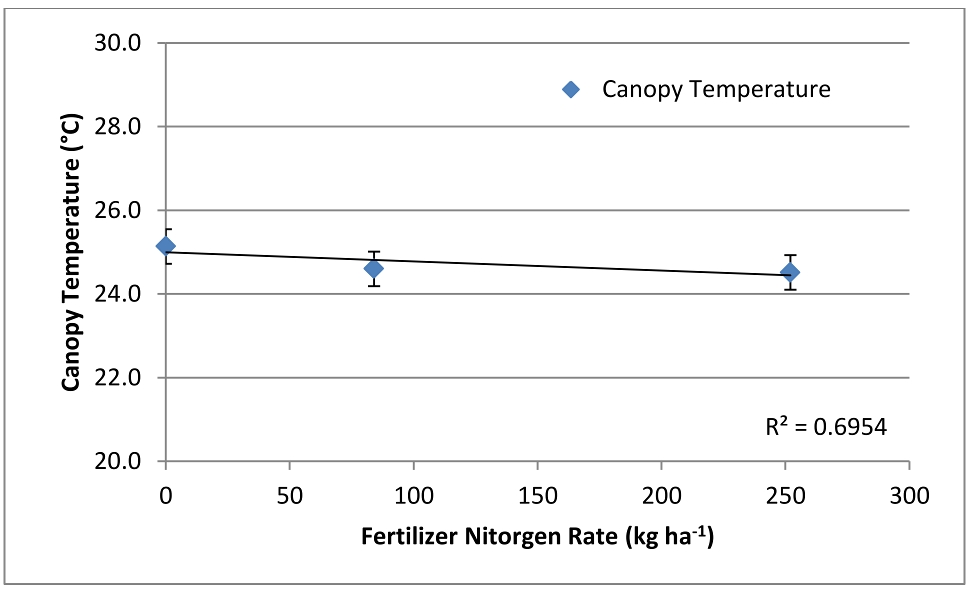

Figure 3-21 Canopy temperature response to N fertilizer rate for the BWL 2012 site year. Although not significant at alpha=0.05, the data shows the same trend as SCAL 2013 site year with a R^2 of 0.70. Error bars represent standard error.

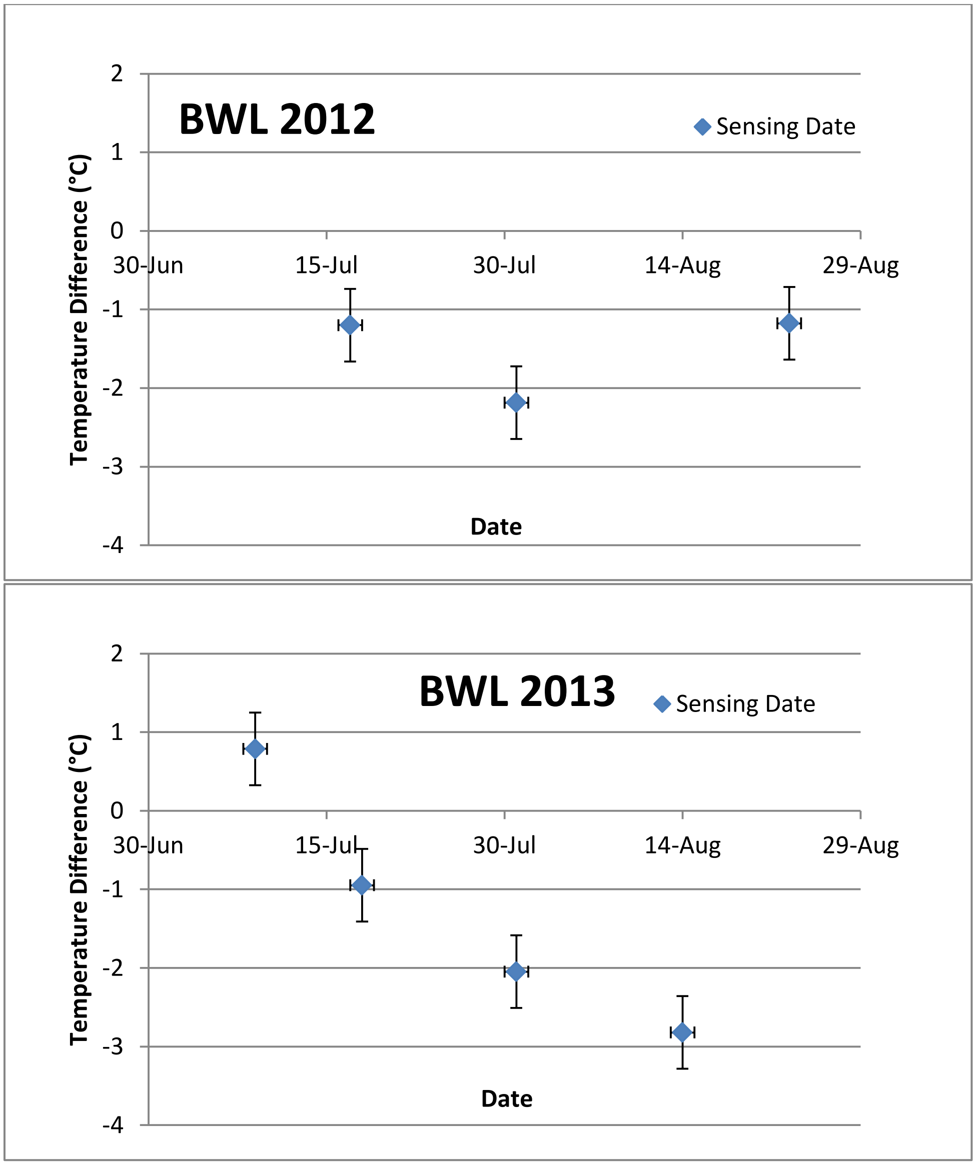

Figure 3-22 Temperature difference by date for the BWL 2012 (top) and 2013 (bottom) site. A significant effect was seen in both years. Error bars represent standard error.

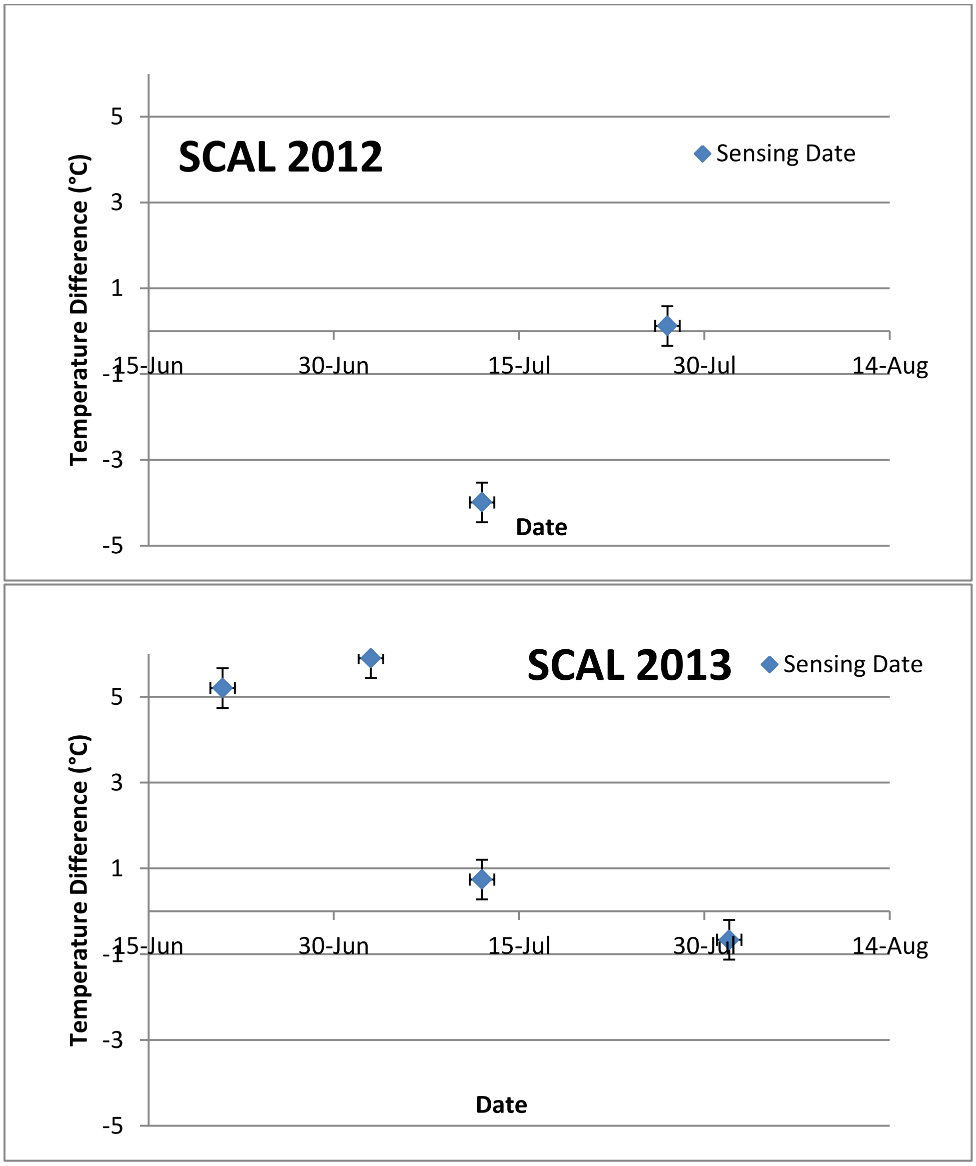

Figure 3-23 Temperature difference by date for the SCAL 2012 (top) and 2013 (bottom) site. A significant effect was seen in both years. Error bars represent standard error.

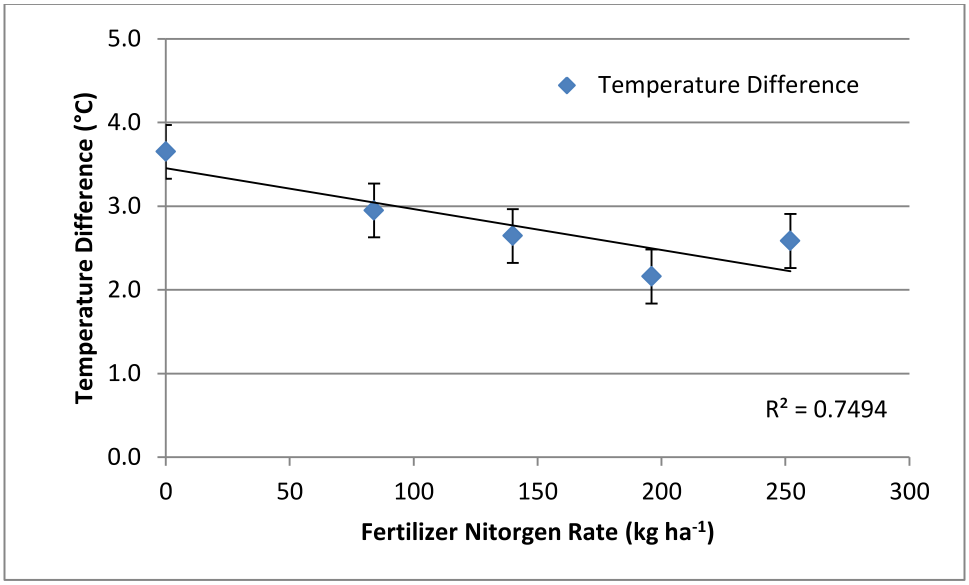

Figure 3-24 Canopy/air temperature difference response to N fertilizer rate fot the SCAL 2013 site year. The difference in temperature decresease with increasing N rate, a linear model is fitted with an R^2 of 0.75. This same trend was seen for the canpy temperature variable. Error bars represent standard error.

Table 3-1 Planting characteristics at the Brule Water Laboratory (BWL) and South Central Ag Lab (SCAL).

	BWL		SCAL	
	2012	2013	2012	2013
Planting Date	8-May	10-May	25-Apr	16-May
Hybrid	Pioneer 3544	Pioneer 1151	Pioneer 1498HR	Pioneer 876CHR
Plant Population (plants ha^{-1})	79200	79200	74100	74100

Table 3-2 Grain yield analysis for effect of N treatment for the sites of this study. All but the BWL 2012 site year experienced significant effects of N treatment on grain yield.

	BWL 2012		BWL 2013		SCAL 2012		SACL 2013	
Effect	Num DF	Pr > F	Num DF	Pr > F	Num DF	Pr > F	Num DF	Pr > F
N Rate	2	0.9751	2	<.0001	4	<.0001	4	<.0001

Table 3-3 Crop canopy sensing dates with corresponding weather data at the time of data collection.

Location	Date	Start Time	Air Temperature °C	Relative Humidity %	Wind speed M s^{-1}	Wind Vector °
			2012			
BWL	17-Jul	1:10 PM	36.26	24.18	1.83	72.8
	31-Jul	6:40 PM	34.85	28.61	2.55	136.6
	23-Aug	12:25 PM	21.96	80.4	1.57	138.7
SCAL	12-Jul	3:00 PM	31.51	45.69	1.91	180.1
	27-Jul	1:15 PM	27.23	87.04	1.99	49.16
			2013			
BWL	9-Jul	10:21 AM	30.17	49.9	2.88	356.2
	18-Jul	3:15 PM	32.38	35.29	4.95	2.3
	31-Jul	3:05 PM	28.24	55.17	3.05	100.2
	14-Aug	3:15 PM	29.41	39.79	1.60	97.1
SCAL	21-Jun	1:45 PM	34.39	35.77	8.67	179.1
	3-Jul	12:55 PM	27.78	34.32	1.93	172.8
	12-Jul	12:15 PM	32.05	50.56	5.86	147.0
	1-Aug	11:20 AM	27.00	69.11	3.55	151.5

Table 3-4 Canopy temperature analysis for all site years. All site years had a significant date effect while only SCAL 2013 showed a significant response (a<0.05) to N fertilizer rate. No site year had a sensing date by N rate interaction.

	BWL 2012		BWL 2013		SCAL 2012		SACL 2013	
Effect	Num DF	Pr > F	Num DF	Pr > F	Num DF	Pr > F	Num DF	Pr > F
Date	2	<.0001	3	0.0015	1	0.0268	3	<.0001
N Rate	2	0.0590	2	0.3909	4	0.1410	4	0.0154
Date*N rate	4	0.5802	6	0.9806	4	0.9277	12	0.1608

Table 3-5 Canopy/air temperature difference for all site years. All site years had a significant date effect while only SCAL 2013 showed a significant response (a<0.05) to N fertilizer rate. No site year had a sensing date by N rate interaction.

	BWL 2012		BWL 2013		SCAL 2012		SACL 2013	
Effect	Num DF	Pr > F	Num DF	Pr > F	Num DF	Pr > F	Num DF	Pr > F
Date	2	<.0001	3	0.0025	1	<.0001	3	<.0001
N Rate	2	0.9094	2	0.3348	4	0.1615	4	0.0280
Date*N rate	4	0.3080	6	0.9982	4	0.9849	12	0.4126

General summary and future suggestions

The overall objective of the research presented was to test new strategies and uses of canopy level electromagnetic sensor data for use in precision agriculture management.

The first chapter investigated the potential differences of reference strategy and vegetation index when using active optical crop sensors for nitrogen management. We found that the 'virtual reference' concept was equal to or better than the traditional approach of a high N fertility reference strip. This could help eliminate extra time and resources need to set up high N plot areas in farmer's fields which potentially make optical sensors more appealing. Additionally, the selection of different vegetation indices does not affect the performance of these different reference strategies.

The second chapter investigated the interactions of different vegetation indices and nitrogen application algorithms when calculating side-dress nitrogen rates as well as what affect water stress might play in nitrogen rate determination. We found that vegetation indices respond significantly different to nitrogen fertility and apparent water stress. This work provides data to illustrate the saturation issues with NDVI in large biomass crops such as corn. The use of different application algorithms with varying vegetation indices will result in vastly different nitrogen side-dress rates. This study really indicates the level of care needed when setting up an optical sensor side-dress program.

The final chapter investigated what affect nitrogen fertility would have on corn canopy temperature and if using a deviation of canopy temperature would be more or less sensitive. We found that canopy temperature will change with changes in a plant's nitrogen fertility and that a canopy air temperature difference is no more or less sensitive to this change that canopy temperature alone. This study would suggest that when using thermal imagery on a spatial scale it is important to know that stresses other than water will cause variations in plant canopy temperature.

Future work on optical sensors should be focused on extension, promoting and educating farmers about what optical sensors are and how it can be used across many situations. The technology should not be presented as a simple plug-and-play technology since there is such an extensive knowledge base behind both the concept of detecting stress as well as that of making an N recommendation. Also, other site-specific management tools like thermal imagery are not without their own limitations and should be used with that idea in mind.

Appendix A

Site locations and corresponding plot maps for each site year, along with additional figures of importance that pertain to the work presented.

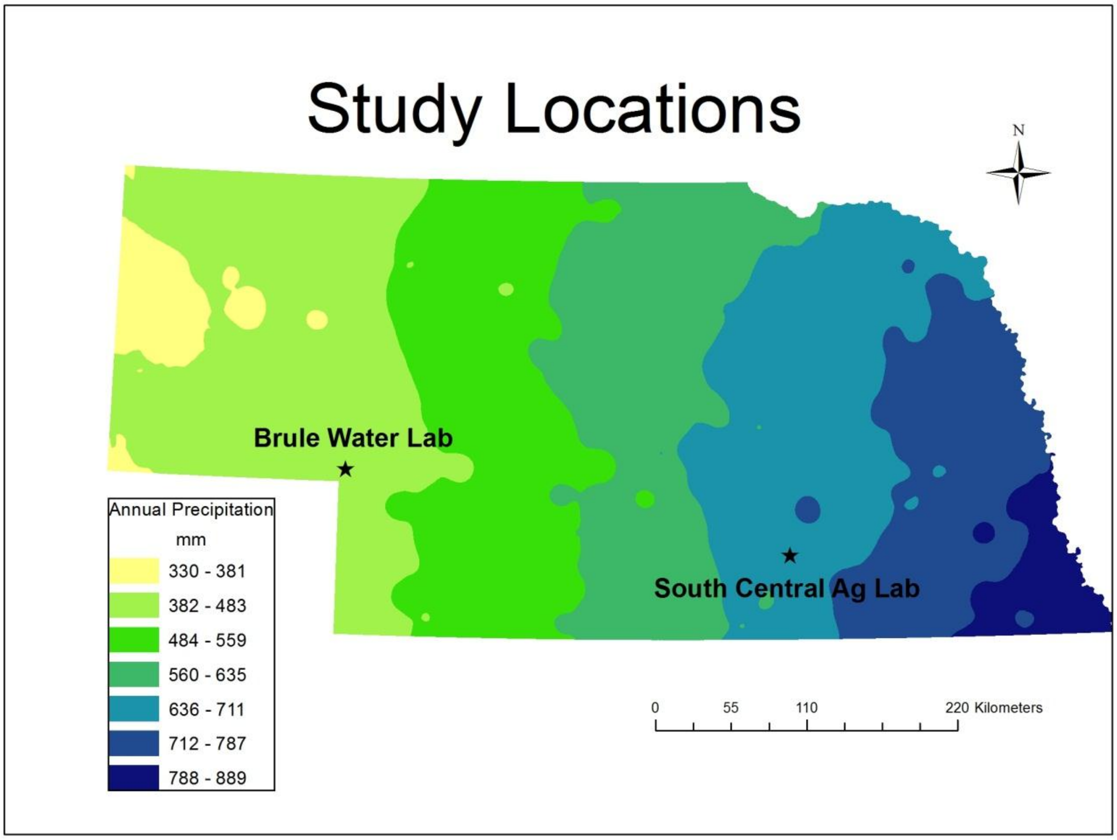

Figure A-1The two Study locations across the State of Nebraska.

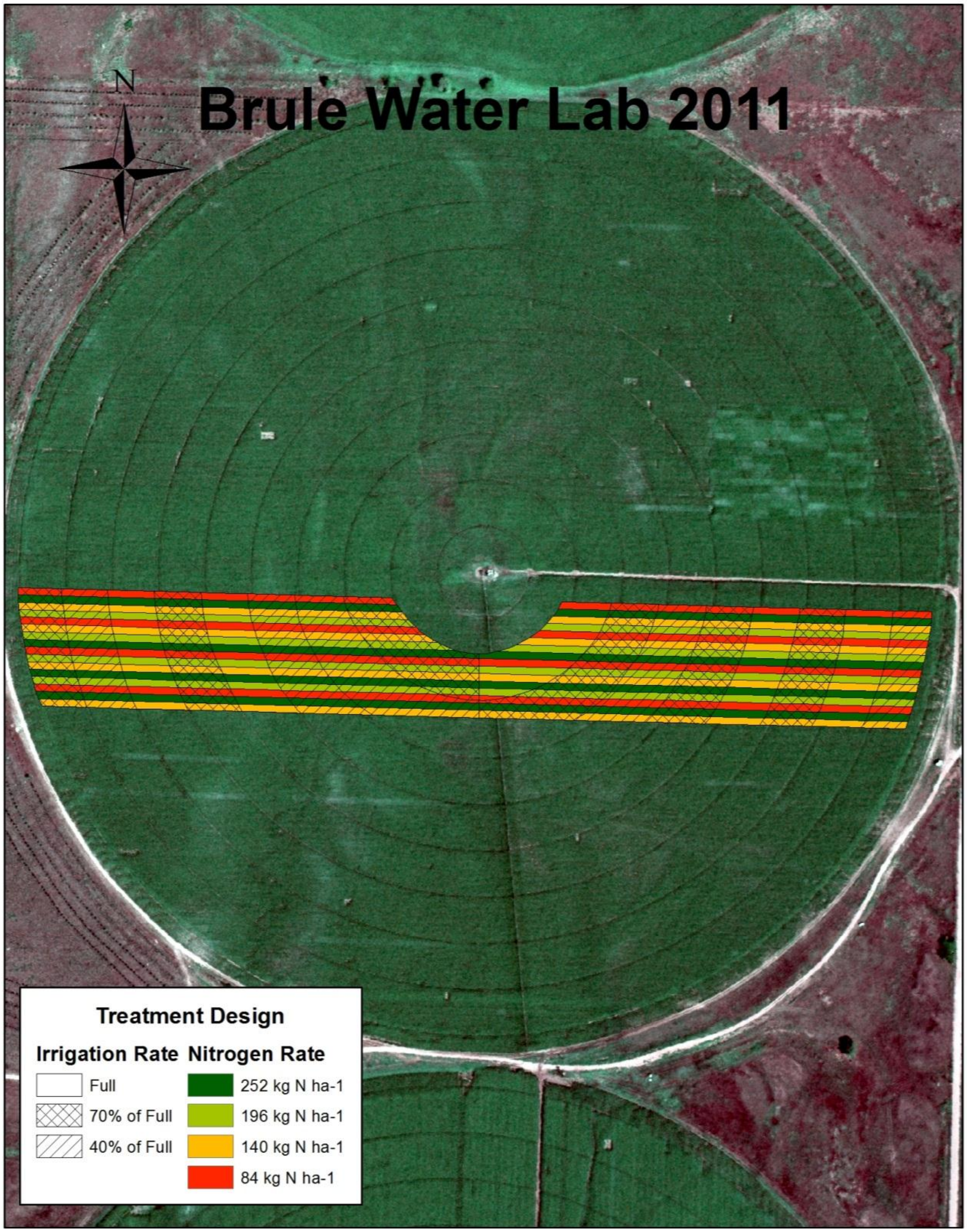

Figure A-2 Brule Water Lab experimental design for the 2011 site year.

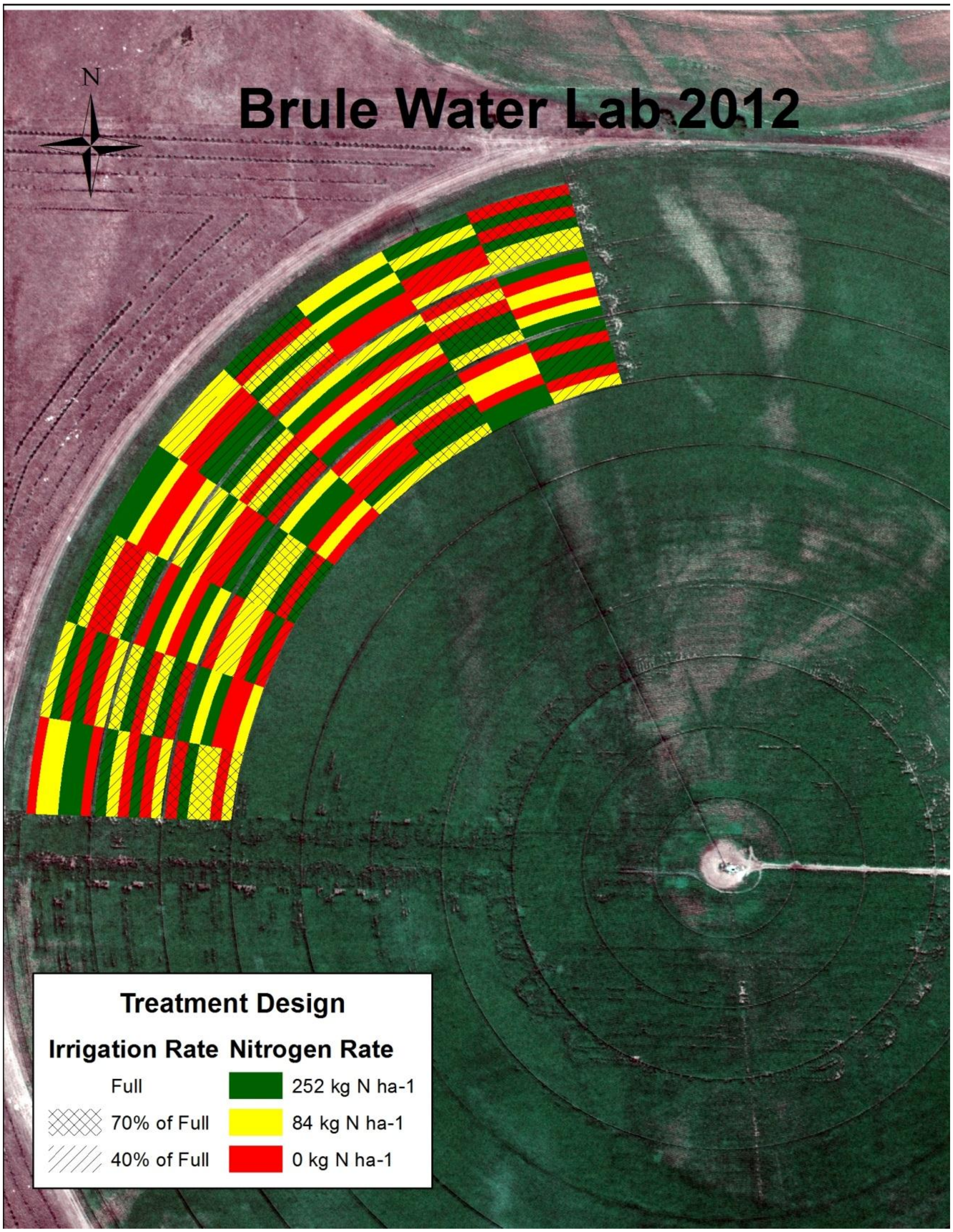

Figure A-3 Brule Water Lab experimental design for the 2012 site year.

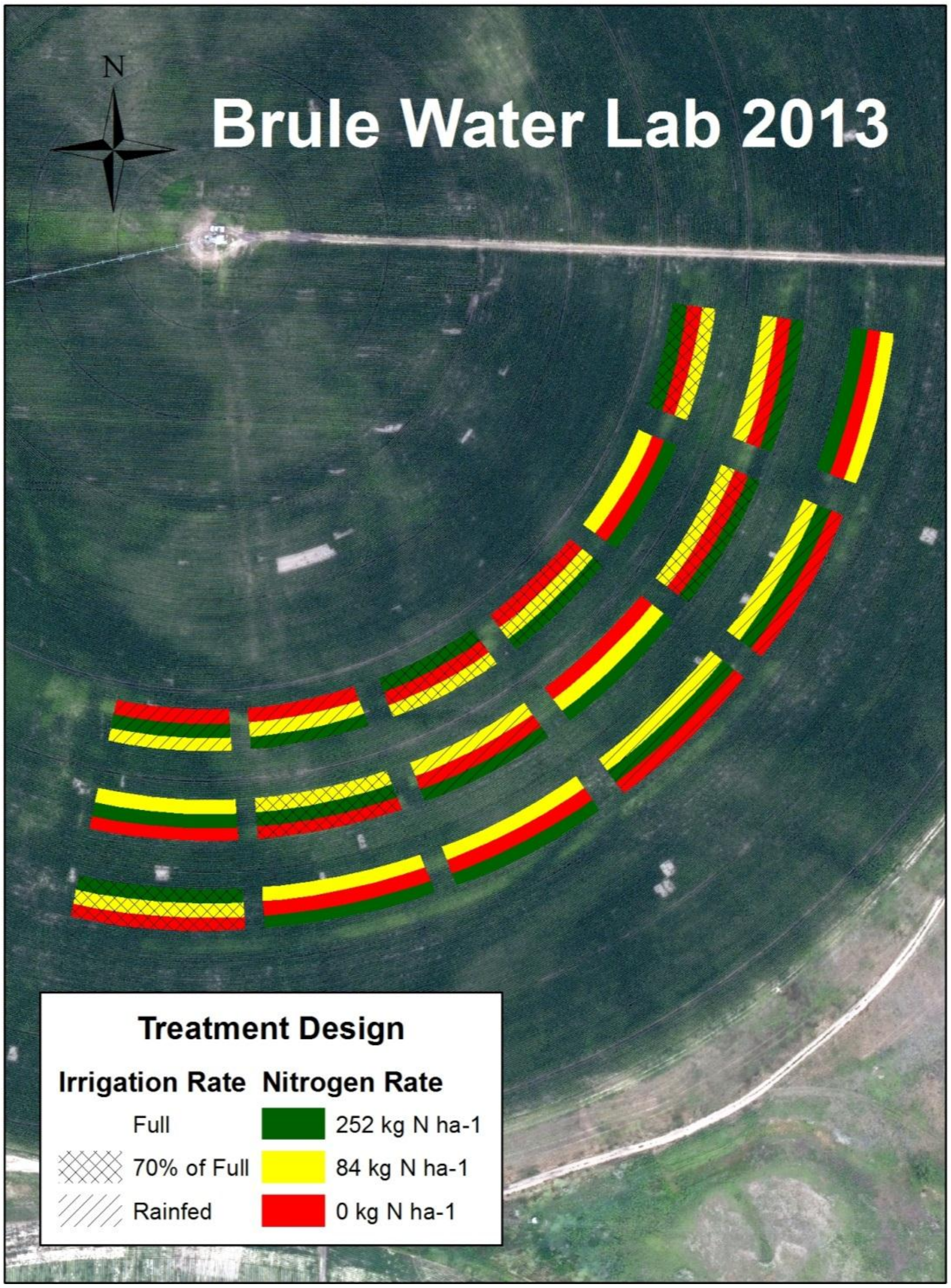

Figure A-4 Brule Water Lab experimental design for the 2013 site year.

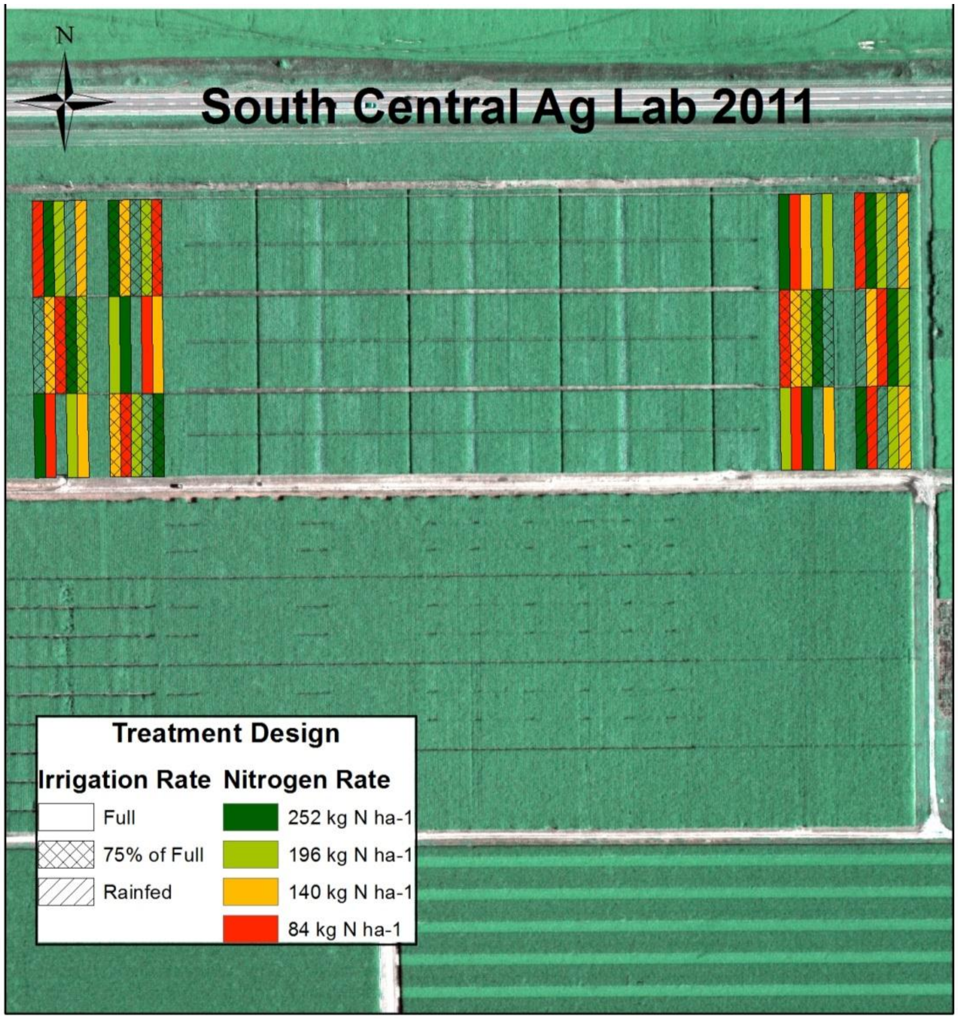

Figure A-5 South Central Ag Lab experimental design for the 2011 site year.

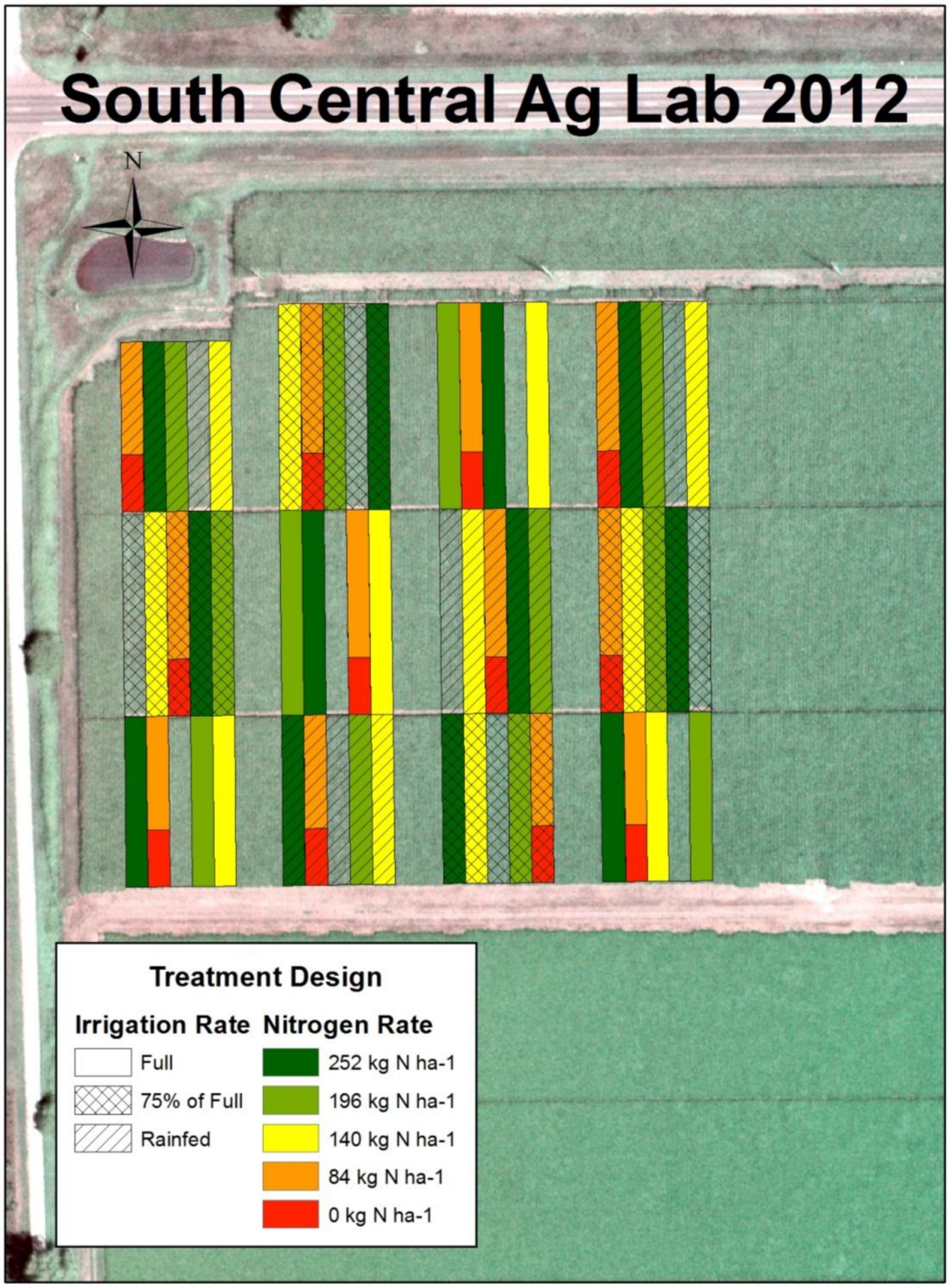

Figure A-6 South Central Ag Lab experimental design for the 2012 site year.

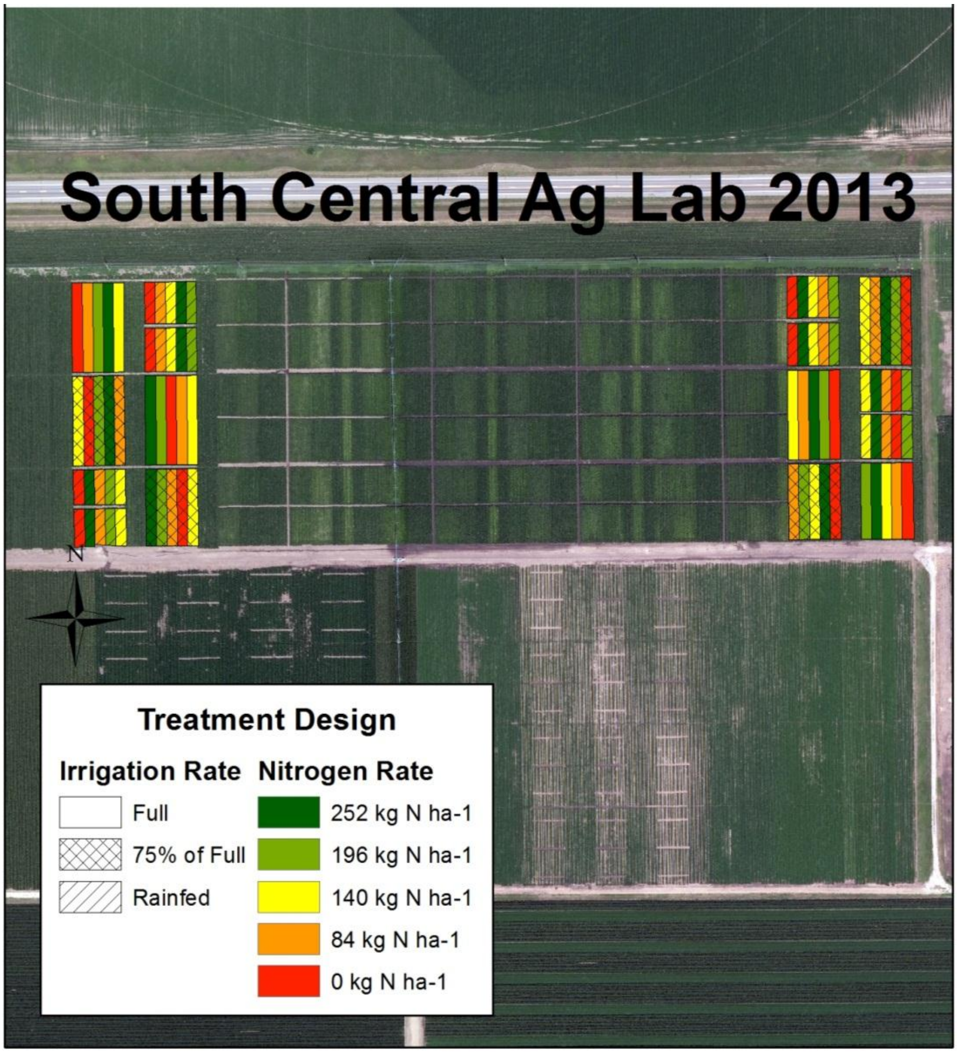

Figure A-7 South Central Ag Lab experimental design for the 2013 site year.

Figure A-8 Image of high clearance machine used to collect data in 2012 and 2013 (above) and high clearance machine with sensors attached collecting data at the Brule Water Lab site in 2013 (below).

Figure A-9 Hail damage to the 2013 South Central Ag Lab site. Top image shows extent of defoliation, while bottom shows "goose necking" and stock injury due to hail stones.