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Potential for Optical Sensor-Based Nitrogen Fertilization in Grain Sorghum (*Sorghum bicolor* L. Moench) in Arkansas

Potential for Optical Sensor-Based Nitrogen Fertilization in Grain Sorghum (*Sorghum bicolor* L. Moench) in Arkansas

A thesis submitted in partial fulfillment
of the requirements for the degree of
Master of Science in Crop, Soil, and Environmental Science

by

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Bachelor of Science in Agriculture, 2003

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This thesis is approved for recommendation to the Graduate Council.

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Abstract

Ground-based active-optical (GBAO) crop sensors have become an effective tool to improve nitrogen (N) use efficiency and to predict yield early in the growing season, particularly for grass crops. Commercially available canopy sensors calculate the normalized difference vegetative index (NDVI) by emitting light in the red and near infrared range of the electromagnetic spectrum. The NDVI is used to evaluate vigor status and to estimate yield potential. However, few studies have been conducted to compare the performance of commercially available sensors. Therefore, a study was conducted using the most common crop canopy sensors: i) N-Tech's GreenSeeker™ (GS), ii) Holland Scientific's Crop Circle™ (CC), and iii) Minolta's SPAD-502 chlorophyll content meter (CCM). The objective of this study was to find the optimum time for sensing and compare the relative performance of the sensors in estimating the yield potential of grain sorghum (*Sorghum bicolor* L. Moench). Treatments included six levels of N fertilization (0, 37, 74, 111, 148, and 185 kg N/ ha), applied in a single split 20 days after planting (DAP). Treatments were arranged in a randomized complete block design with five replications, in four locations in Arkansas, during 2012 and 2013. Sensors readings at vegetative growth stages V3, 4, 5 and 6. Results from simple regression analysis showed that the V3-V4 growth stage correlated better with grain yield than readings collected and any other time. In season estimated yield (INSEY) obtained at V3 captured 41, 57, 78, and 61% of the variation in grain sorghum yield when red NDVI of GS, red NDVI of CC, red edge for CC and CCM, respectively, were used. Results from these studies suggest that the CC sensor has a better potential for in-season site-specific N application in Arkansas than the GS sensor. The GS reflectance values appear to saturate after the V3 stage, in contrast with CC values that allow for discrimination past the V3 Stage. Therefore, the red edge wavebands of CC appear to

be better suited to develop relationships between spectral vegetation indices and agronomic parameters.

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Introduction

The trend for world population growth over the next three decades demand that food production doubles to meet minimum requirements for human consumption (FAO, 2008). Today's intensive use of nitrogen (N) fertilizers, besides providing the most vital plant nutrient for obtaining high yields, is a key input component in the budget of any agriculture operation. Even though N fertilizer consumption and cereal grain production have both increased over the last 50 years, N use efficiency in grain crops production has remained low at 33% worldwide (Raun and Johnson, 1999). The demand for N fertilizer changes from season to season, even in long-term studies where similar N rates are applied to the same plots. Management practices that influence N efficiency take into account the rate of N applied, timing, and placement, and use of urease inhibitors. Work still needs to be done to more accurately quantify the contribution of N mineralization to plant available N, as well as to develop management practices to accurately determine the need for N supplementation during the season, so it can be included in the development of N recommendations (Espinoza et al., 2005).

Grain sorghum (*S. bicolor*) is the third main cereal crop in the United States and the fifth cereal crop grown in the world. Acreage for grain sorghum has decreased substantially since 2007, from 7.7 million acres to 5.5 million in 2011 due to drought conditions in key growing states like Kansas and Texas, which in turn lead to subsequent price rationing-related changes in its 2012 U.S grain sorghum supply-demand balance and price forecasts (FAS/USDA, 2011). According to USDA's 2012 Crop Production Summary, in Arkansas sorghum yielded an average of 84 bu/acre, compared with 56.2 bu/acre in 2006.

Current N fertilizer applications for grain sorghum in Arkansas are based on the expected yield of the crop, irrigation regime and soil type (Espinoza et al., 2005). They represent the average grain response to varying N rates across locations and years. The total amounts of N is normally applied in a two-way split, with 30-50 % applied pre-plant or at planting and the remainder applied 30-35 days after planting (DAP). Timing of N application appears to be important in sorghum. Research in Kansas showed no significant grain yield response when N was applied beyond 40 DAP (Tucker, 2009). While the same rate of N is typically used each year, the probability that lower or higher N rates are required to optimize yield potential during a particular season is probably large. Such discrepancy is due in part to the varying weather patterns common to the Mid-south Mississippi River Delta region.

Nitrogen management based on active optical sensors may offer an alternative to fine tune nitrogen recommendations and improve N fertilizer use, by providing recommendations specific for the growing conditions in a given season and in a particular field. The use of active optical sensors has contributed to the development of fertilizer algorithms to be used in a number of crops (Raun et al., 2001). Knowing the potential yield of a crop in a given season is fundamental for calculating total N demand of cereal crops (Raun et al., 2001). The normalized difference vegetative index (NDVI) is the commonly used vegetative index developed and implemented in the late 1970's (Deering, 1975). The pre-plant application of N is essential because early-season NDVI readings can be used to predict yield potential (Teal et al. 2006; Raun et al., 2001). Mullen et al. (2003), showed that N responsiveness or response index (RI) can be estimated from early-season NDVI readings in crops.

Estimating yield potential early in the season and identifying the optimum sensing window are key factors for success towards judicious management of N, from both, an environmental and economic perspective. Raun et al. (2001) demonstrated that estimated yield (EY) was an excellent predictor of winter wheat grain yield across locations and seasons. This indicator was later adapted as an in-season estimate of yield (INSEY) and quantified as the ratio of NDVI readings to number of growing degree-days (GDD) from planting to time of measurement greater than zero (GDD>0) (Raun et al., 2002).

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Chapter I

Literature Review

Literature Review

Grain Sorghum Production and Importance

Crop description and production

Grain Sorghum is a C4 plant currently classified as *S. bicolor*, in the past known as *S. vulgare* Pers. It belongs to the genus of grasses graminae with about 30 species (Greenwood et al., 1990). Sorghum is in the Poaceae family, and the Panicoideae subfamily (Ayana and Bekele, 1998). Although, sorghum is commonly used as a forage source, is also used as food in many countries (Dover et al., 2004).

Grain sorghum is an alternative for areas that are likely to dry gradually in the spring and require afterward planting dates that are more appropriate to sorghum than other crops. According to Kelley et al. (2004), grain sorghum can be planted over a broad range of dates. However, it is commonly recommended that it be planted as early in the spring as possible under Arkansas conditions. Particularly, planting should be delayed until the soil temperature in the early morning reaches 20 °C at 5 cm below the soil surface. Early planting may also help to avoid insect pressure and create a broad window for rainfall and the negative effect of high temperature later in the season. Grain sorghum is more adaptable to dry conditions than corn (*Zea mays L.),* making it a practical opportunity for fields that are exposed to drought. Under irrigated conditions, a population of 185,000 plants/ha is recommended while, under non-irrigated conditions, a plant population of 124,000 plants/ha is normally used (Espinoza et al., 2005).

According to Sarrantonio (1994), grain sorghum would require 22 % less water to produce similar corn yield. In Arkansas, the amount of water needed will be around 400 to 610 mm. The amount of irrigation water required will change depending on the initial soil moisture and the amount of rainfall during a particular season (Kelley et al., 2004).

Grain sorghum requires less N than corn and will achieve similar yields to corn on poor soils. Sorghum will adapt well in a wide range of soil types from heavy clays to soils of sandy texture (Kramer and Ross, 1970). The optimum soil pH ranges between 5.8 and 6.5, which is the where the majority of nutrients are more easily accessible to plant roots.

According to a report by USDA (2013), grain sorghum’s global production in the last decade has increased from 60 to 65 million metric tons. Worldwide, over half of the grain sorghum is grown for human consumption. Although the United States, Argentina and Australia account for only 20 to 30 % of this production, they remain the top exporters of sorghum accounting for around 93% of total world exports. The United States is the major exporter of grain sorghum worldwide, exporting around 2.4 million tons in the 2010-2011 trade years. Mexico and Japan are the leading importers of sorghum (FAS-USDA, 2011). In the United States, 26,242 farms grow grain sorghum designated for industrial products that utilize sorghum for industrial purpose including wallboard and biodegradable packaging materials. Arkansas ranked as the eight largest grain sorghum producing US state in 2011, with a total value of production of over 71 million dollars in 2012 (FAS/USDA, 2013). Under Arkansas conditions, grain sorghum may grow well but is not widely grown in the state. St. Francis and Lee counties led Arkansas in sorghum acreage planted, and represented nearly half of the sorghum planted in 2012. In the majority of counties about 75% of the sorghum acreage was irrigated (USDA/ NASS, 2012).

Importance of N in Cereal Crops

The Food and Agricultural Organization (FAO) anticipated that the global trend for demand for N fertilizer would increase by 1.5 % each year since 2008, that equals to an increase of 7.3 million metric tons (MT) (FAO, 2008). Cereal grains accounted for 54.8 % of the total N fertilizer applied globally in 2007 (IFA, 2009). The fact that N plays an important role in protein formation, plus economic and environmental reasons demand that agricultural inputs be managed efficiently, especially during periods of high production. The amount of N supplied by soil from the organic pool has not been well determined because it is very active and unpredictable. If this organic fraction and the process of mineralization in season were better understood, significant advances in N use efficiency would be possible.

The amount of N fertilizer needed to produce a given yield is defined as NUE (Nitrogen Use Efficiency). A major factor limiting improvements in NUE, in a traditional N management schemes, may include incorrect rates of N early in the season before the root system can effectively utilize it. This portion of N fertilizer not being absorbed by the plant is a significant risk to ecological losses according to a review by Raun and Johnson (1999). They made emphasis to earlier research indicating that NUE could be significantly increased by focusing on mid-season applications of N fertilizer, and using rates that in fact improve the in-season N status of the crop.

Nitrogen fertilizer recommendations have typically been developed on a state or regional scale and are intended to be used as a general guide, so it is debatable if this approach can be used for variable-rate N that in theory will consider variability of season and soil properties (Ferguson et al., 2002). A number of studies have found significant differences in crop yield and crop N response within specifics fields (Carr et al., 1991). Farmers normally use uniform rates for N based on expected yield that could be inconsistent according to location and time. This situation requires the development of methods to produce specific N recommendations for each particular area (Ferguson et al., 2002).

According to Pierce and Nowak (1999), there are basic approaches currently being tested for variable-rate N application. The first involves determining plant available N status of the soil from field sampling and interpreting N rates based on current recommendations. The second approach bases N rates on observed crop N responses in reference strips, with different N rates across a representative area of the field. The third method involves determining the vigor of the plant by monitoring with active optical sensors over the canopy.

In Arkansas, the development and implementation of a soil N test for rice on silt loams (N-STaR) seems to improve N fertilizer management for Midsouth U.S. rice producers (Roberts et al., 2009). This soil test relies on the capacity of a soil to supply N. Research results suggest that the amino sugars can be correlated and calibrated to quantify the potential N mineralization in a given soil, which leads to the development of site-specific N recommendations. The amino sugars appear to be a stable pool of plant available N in a soil, which are not susceptible to leaching or denitrification losses.

Environmental Concerns

The current hypoxic region affecting the northern Gulf of Mexico, bordering the Mississippi River and the states of Louisiana and Texas, is the second largest hypoxic region worldwide. Recent reports show an increase in the concentration of N and phosphorus in the Lower Mississippi River. The cause of this increase is accredited to the growing use of N and phosphorus fertilizers, and N fixation by leguminous crops. Arkansas is listed as the fifth contributor to the hypoxia in the Gulf of Mexico related to N (USGS, 2009).

According to Battaglin (2010), the average dimension of the Gulf of Mexico's hypoxic zone has significantly increased in a period of 10 years. While the annual loading of total N to the Gulf of Mexico has decreased, the nitrate-N fraction of that load has gradually increased to15%, in the last 30 years.

Using adequate N rates in cereal production is one of the keys to succeed in every season since N inputs require careful management not only for economic reason, but for environmental concerns, as well. Mueller et al. (1995), reported that fertilizer N is the main source of nitrate contamination in a significant portion of groundwater in the Midwest. For such reason, there is a significant effort to improve the efficiency of fertilizer N use to reduce the total amount of N that can potentially become a contaminant. According to Peterson et al. (1993), factors like weather that affect N efficiency are out of a farmer's control. Fertilizer N price tends to fluctuate unpredictably every year, and N deficiencies can result in significant loss of yield potential and associated profit. As a result, producers are learning to manage fertilizer N to maximize yield potential, while reducing potential contamination.

Sorghum N Requirements in Arkansas

In Arkansas, N recommendations for irrigated grain sorghum range between 110 and 200 kg N/ha, depending on soil texture and yield potential, and between 110 and 150 kg N/ha for non-irrigated production. As a rule of thumb, 2 lbs of N are required to produce 45.5 kg of grain (Espinoza et al., 2005).

It appears that the plant does not take up much N during the first 3 weeks after emergence, but by the time the plant is 60 days old, it has taken up close to 60% of its total N. ”Consequently, a third to one-half of the total N is usually applied pre-plant". The remainder should be side dressed around 22-26 DAP (Espinoza et al., 2005).

Nitrogen fertilizer recommendations represent the average response of grain sorghum to varying N rates at different locations, during several years. They are defined by fitting a regression model to the relationship between N rates and relative yields, with the maximum N rate recommended being that rate which intersects the line at 95% relative yield. While an specific N rate is provided, in reality the optimum rate changes from season to season and according to location (Espinoza et al., 2005).

Raun et al. (2001), reported that the N rate required to maximize yields changes every single year in wheat production. The chance that the N rate would be the same from one year to the next is less than 1%. The variability of the N requirements to maximize yields in wheat during a given year can range from 22.5 kg N /ha N to135 kg N/ha fertilizer for a given year. According to Peterson et al. (1993), researchers have been studying ways to improve N use efficiency. Using a soil test to correct fertilizer N rates for residual nitrate does not work well all the time due to the dynamic nature of N. However, the potential exists to fine-tune N management decisions during the growing season to react to changing weather and crop conditions.

Nitrogen Efficiency in Sorghum

Grain sorghum is a C4 plant, which uses N, water and CO_2 more efficiently than C3 species (Greenwood et al., 1990). According to work by Espinoza et al. (2005), N is without doubt the most limiting nutrient in grain sorghum production in Arkansas, with almost 50% of the N removed with the grain, in contrast with 67 % and 17 % for phosphorus and potassium, respectively. Currently, NUE of grain and forage production ranges from 33% to 45%, respectively (Raun and Johnson, 1999). Voss (1998), distinguished improvements in fertilizer recommendations in many states through the calibration of a soil nitrate test for corn (*Zea mays L.)* to base fertilizer N recommendations. In Arkansas, the development of a soil test for rice called N-STa-R (Roberts, 2010) has been used successfully to provide site-specific N rates for specific fields. The potential exists to implement this methodology for upland crops, including grain sorghum.

Spectral reflectance and plants

Color is one of the properties that define plant matter. It is a reflection and absorption of specific wavelengths in the electromagnetic spectrum that gives the properties of color (Huete, 1988). Crop reflectance is defined by the ratio of radiation reflected to total incident radiation on an object (Huete, 1988). Plants absorb more of the visible wavelengths (blue and red) and reflect more of the green in the visible spectrum. Near infrared is strongly reflected from plant surfaces as a function of leaf tissue (Carter, 1991). The Beer-Lambert Law gives details about the relationship between the proportion of light penetrating a plant canopy and the leaf area index (LAI), measuring the portion of incident photons absorbed by unit of leaf area (Foroutan-pour et al., 2001), while the shape or distribution of leaf area appears to affect the capacity of a plant to capture light (Duncan, 1971). Work by Thomas and Gausman (1977), showed the coefficient for a linear correlation of carotenoid with chlorophyll was highly significant ($p=0.01$) for grain sorghum and other crops. Leaf reflectance values in the range 400 nm to 750 nm showed a strong correlation to N status, with a $R^2= 0.80$ in grain sorghum. Furthermore, this interaction showed that N deficiency reduced the chlorophyll and carotenoid concentration. Canopies with erectophile leaves (e.g. sorghum) and high leaf angles to the horizontal plane, have a lower foliar absorption coefficient and intercept less light per unit of foliage compared to canopies with planophile leaves (Lang et al., 1986). Studies in corn have shown that N concentration decreases with crop development due to dilution. While 50% of total N is associated with chloroplasts, more N supply can increase leaf chlorophyll concentration that results in more light absorbed and reduced reflectance of visible wavebands (Dwyeret al., 1995; Heege et al., 2008). Therefore, reflectance data can be used to evaluate a variety of vegetative indices that have good level of agreements with agronomic parameters (Adamsen et al., 1999).

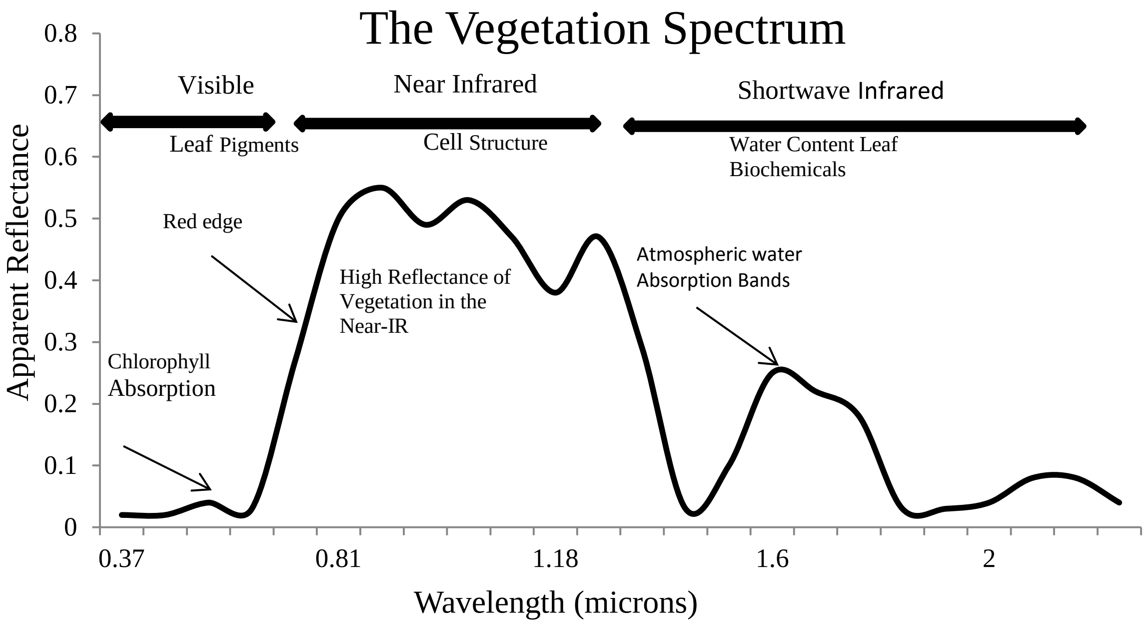

Figure 1.Typical spectral reflectance pattern for green vegetation (Killo, 2003).

Remote Sensing and Vegetation indices

Remote sensing was initially used in natural resources for land cover, biomass estimation, and to evaluate changes in land uses (Deering et al., 1975; Sala et al., 2000; Kogan et al., 2004; Henebry et al., 2005). Spectral reflectance sensors are classified as passive and active. Passive sensors use energy emitted by the sun and then record the amount that is reflected. In contrast, active optical sensors (AOS) have their own source of light emitted by diodes over the crop canopy, with the amount that is reflected being quantified by the sensor and transformed into numerical values called indices (Erdle et al., 2011). The principal advantages of actives sensors include using a modified light, the reflectance can be discriminated from natural source of light, and allowing collection at any time, regardless of cloud conditions. New sensing technologies are constantly being developed to measure plant properties by the reflected light, at specific wavelengths. One of the most common applications of AOS is their use to develop indices that help fine tune N fertilizer recommendations, with the main objective being the optimization of yield potential. The use of this technology has excellent potential in improving profit by reducing the cost of N and reducing environmental risk.

Some of the most common vegetation indices used in grain crops include the normalized difference vegetative index (NDVI), the Red edge index (NDRE) and the Chlorophyll Content Meter (CCM index) (Li et al., 2014). These indices are calculated from a broad wavelength range by directing visible light (VIS) (400–700 nm) as well as near infrared (NIR) (700–1300 nm). Where VIS reflectance is dependent on the chlorophyll contained in the palisade layer and NIR reflectance depends on the structure of the mesophyll cells (Inman et al., 2005).

The NDVI (R_{760}-R_{730})/(R_{760}+R_{730}) (Rouse et al.,1974), has been correlated with final yield and aboveground biomass in different grain crops (Raun et al., 2001). This correlation can be improved by normalizing the NDVI through dividing it by the number of GDD from planting to time of sensing or commonly referred as INSEY (In Season Estimate of Yield) (Lukina et al., 2001). The red edge index ($R_{790} - R_{720}$)/ ($R_{790} + R_{720}$) (Gitelson, 2004) has been found to be linearly related to N supply in grain crops and is less sensitive to biomass accumulation (Heege et al., 2008). Chlorophyll Content Meters (Minolta Camera Co., Ltd., Japan) have been used to manage crops such as corn, grain sorghum, wheat, cotton, rice, as well as other agricultural species (Schlemmer et al., 2005). Research has focused on the application of CCM to understanding nutrient content, in particular N, but also phosphorus in a wide range of plant species (Markwell et al., 1995; Hawkins et al., 2007). The CCM instrument uses two wavelength emitting diodes and receptors to calculate the chlorophyll content index (CCI), which is defined as the ratio of percent transmission at 931 nm and 653 nm through a leaf sample. CCI units are extrapolated to transmission measurements made with spectroradiometer measurements (Richardson et al., 2002).

N Tech Industries (2007) and Holland Scientific (2004) state that the GreenSeeker® and Crop Circle, respectively, measure NDVI by the use of red and NIR light. Red light is absorbed by a plant’s chlorophyll as an energy source for the period of photosynthesis. Therefore, vigorous plants absorb more red light and reflect larger amounts of NIR than those that are less vigorous (Bula et al., 1991). The NDVI is a good indicator of biomass (living plant tissue) (Deering et al., 1975). Also, the NDVI combined with GDD>0 or DAP is used to accurately project yield potential (Raun et al., 2005). These three active sensors are very convenient since they emit and receive a pulsed light source and do not use the passive light source of the sun.

This attribute means that the unit can be used under varying conditions, without interference of existing light or cloud conditions (NTech Industries, 2007).

Voss (1998), stated that research approaches using precision agriculture technology could provide a large database on which to base nutrient recommendations across a wide range of soils and crops. This and other reports (Verhulst et al., 2009), further noted the importance of simultaneously using soil and plant productivity indicators to make site-specific crop production decisions. Girma et al. (2006), showed that the mid-season NDVI calculated from optical sensors measurement and plant height were good predictors of final winter wheat grain yield. According to work by Lukina et al. (2001), NDVI alone was an excellent predictor of total winter wheat grain yield.

The GreenSeeker® sensor unit has its own energy source that emits light in both the red (650±10 nm full width half magnitude (FWHM)) and near infra-red (NIR) (770±15 nm FWHM) bands. The device measures the portion of the emitted light in the sensed area that is returned to the sensor from the canopy reflectance (NTech Industries, 2007). These portions are used within the sensor to calculate NDVI, which is equivalent to: NDVI =NIR–VIS/NIR+VIS (N Tech Industries, 2007).

The NDVI has been the traditional index used to develop in-season N fertilization for several crops. However, Gitelson et al. (2004), proposed the use of green normalized difference vegetation index (GNDVI) where the green band replace the red band in the NDVI equation, which may be more useful to evaluate canopy variation in green biomass.

Mid-Season N Fertilization Algorithm

According to Raun et al. (2001), when developing an algorithm for a crop, one needs to incorporate sensor readings that are transformed into a NDVI and a time/temperature component from a particular growth stage that correlates well to yield potential. Typically a “reference strip” (an area with non-limiting amount of N) is established in a representative area of a given field. Sensor readings, collected at the proper growth stage from the rest of the field, are compared to those from the reference strip. The yield potential is then used to back-calculate, based on a Response Index (RI), which define how much additional N fertilizer is needed to maximize yield potential in that particular season. A fertilizer use efficiency factor is incorporated into the algorithm to make the recommendation more robust and reflect the realities of N utilization by the crop. According to Raun et al. (2001), the approach to N management has increased NUE by 15% in initial studies with wheat, by accounting for missing plants, and small-scale differences in plant vigor.

The RI for the NDVI equation also applies to INSEY calculation and is presented below:

RIAlgorithm = NDVI N plot / NDVI 0 N plot

Where: NDVI N plot = NDVI readings from N applied plots > 0

NDVI 0 N plot = NDVI readings from 0 kg N/ha

According to Inman et al. (2005), the general idea with and algorithm is that a RI can be based on N application differences. An RI of 1.0 was used at the 0 kg N/ha application rate assuming that if the NDVI reference was divided by the NDVI target and a RI of 1.0 was recorded no additional N would be needed because the target area and reference area would have the same N status. When mineralization is large, crop N uptake will be large, and the amount of side-dress N is also reduced.

Chlorophyll Content Meters (CCM)

The CCM estimates the status of chlorophyll present in a plant leaf by positioning the meter over the leaf to receive an indexed chlorophyll content reading (0-99.9) (Konica, 2003). This chlorophyll content shows a good correlation with N concentrations in the leaf. This concept is an estimate of the “spoon feeding” N to the crop on an “as needed” basis (Schepers et al., 1996) with the objective to improve efficiency of N fertilization in a particular crop. According to Peterson et al. (1993), the CCM index technique allows improvement in N management under field conditions and avoids low yields caused by N deficiencies. The CCM used to determine the remained amount of fertilizer needed to reach maximum yield. This device enhances the ability to make N management program decisions, but does not replace other aspects for a good N management. In corn, it is recommended that at least one-half to three-quarters of the total fertilizer N be applied to the total field prior to the six-leaf stage to ensure the chlorophyll meter technique is effective (Shapiro et al., 2006). Wood et al. (1992), concluded that tissue N concentration at the V10 stage and mid-silk were good indicators of corn yield, noting that field chlorophyll measurements using a CCM were highly correlated with tissue N concentrations at both of these growth stages. Work by Blackmer et al. (1994), indicated that readings reflectance close to 550 nm detect N deficiencies in corn leaves. Varvel et al. (1997), used CCM readings to calculate a sufficiency index defined as a ratio between needed treatment/well-fertilized treatments. Results estimating plant N status concentration in corn evaluated with reading of CCM showed a linear relationship with $R^2 = 0.79$ (Rorie et al., 2011).

Limitations of Optical Sensors

The N Recommendation Systems

According to Espinoza et al. (2005), N recommendations for sorghum, as with many other systems implemented in the U.S agriculture, includes several components to calculate N recommendations. The most common components include an expected yield term to determine general N need by the crop and the texture of soil. In Arkansas, farmers commonly rotate sorghum with other crops, including soybeans which can provide a substantial amount of N to the following sorghum crop. However, N provided through mineralization and biological fixation are both strongly affected by in-season weather and the N loss mechanisms such as denitrification, ammonia volatilization; and surface runoff. The final issue with the current N recommendation systems for grains crops used in the US is that it assumes that sorghum will respond like corn does to N fertilization.

Another component of a recommendation is N fertilizer recovery or N use efficiency (NUE). Currently, NUE assumes a fertilizer recovery of 50% in spring barley (Foster et al., 2012). A Significant amount of studies have shown that NUE change as a function of N rate, timing, type of fertilizer, method of application and several other factors. Thus allowing for adjustments of the N rate use, which may result in more efficient N management practices (Raun et al., 2001).

The NDVI Saturation

The GS and CC are very good tools for differentiating management zones or prescription maps based on NDVI early and late in the growing season. However, NDVI exhibits gradual problems especially with canopy cover variations. At mid-season, when the entire field is covered by a solid green canopy, NDVI values become “saturated” and are of limited use for creating plant growth regulators (PGR) management zones in cotton (Vellidis et al., 2009). According to Vellidis et al. (2009), at midseason more than 90% of NDVI values exceeded 0.8 and nearly half were above 0.9 in cotton. Those readings values show that by mid-season plants have uniform green canopies across the fields. This close clustering of NDVI values limits this vegetation index as a tool for discriminating biomass differences during mid-season in cotton. However, the biomass differences were driven primarily by plant size, which NDVI was not able to discriminate effectively by mid-season. Despite its extensive use, the main disadvantage of NDVI, or similar indices, is the natural nonlinear relationship with such biophysical characteristics as vegetation fraction (VF), leaf area index (LAI) and aboveground biomass (Sellers, 1985; Huete et al., 2002). The nonlinear relationship between the NDVI and LAI has a physical basis as described in Myneni et al. (1995). According to Gitelson (2004), the NDVI sensitivity is significantly affected when the Leaf area index (LAI) exceeds about 2. The reduction of the ability to capture differences means narrow ranges of NDVI are observable.

When the LAI is much larger than 2, even a large change in the LAI may be barely visible using the NDVI. This has implications for land use change studies and land cover classification as well. Leaf area index values less than 1 work best for characterizing differences in vegetation. Therefore, the most important feature to improve this index should be "extended linearity to the biophysical parameters over a wide range of vegetation conditions" (Huete et al., 2002).

Work conducted by Gitelson (2004), showed that green vegetation displays more absorption in the red zone of the spectrum (around 670 nm), with red reflectance in this zone being between 3–5 %. In the near infrared (NIR) zone of the spectrum, green vegetation reflects a larger portion of the incident irradiation; reflectance in this section reaches from 40 to 60 %.

Option for NDVI Saturation (Red edge)

To overcome the issue of "saturation" in the NDVI index, research has focused in others zones of the spectrum that generate readings essentially independent of chlorophyll content and other pigments concentrations, despite variability of cover crop levels or canopy development (Girma et al., 2006). There is enough evidence that show the relationship between the biological status of plants and their spectral responses, particularly in the red edge zone. This zone is found within wavelengths 690 to 740 nm and is less sensitive to vegetation cover (Barber and Horler 1981; Ferns et al., 1984). The normal ratio use for red edge is $(R_{760}-R_{730})/ (R_{760}+R_{730})$ (Rouse et al., 1974). This zone, in particular, contains the maximum slope change from the visible to the near infrared spectrum. Experiments in corn have showed that red edge readings are sensitive at detecting small chlorophyll changes even in dark green leaves, providing good information for early detection of stress (Horler et al., 1983). Work by Meer and Jong (2006), showed that red edge points situated in that slope are influenced by the concentration of chlorophyll content, LAI and leaf mesophyll structure. In contrast, leaf orientation and soil background had only a small influence in red edge readings. These researchers found that red edge readings combined with plant growth models in sugar cane *(Saccharum edule),* improved the estimation of the yield based on N status of the plant. Similarly, Li et al. (2014) demonstrated the implication of red edge vegetation indices for estimating summer maize N status.

Procedure and Algorithm for Calculating Spatial and Temporal N Fertilizer Rates.

Reflectance data is used for the generation of vegetation indices (VIs), such as NDVI. The NDVI is calculated from reflectance measurements in the red and NIR portion of the spectrum (Stone et al., 1996):

NDVI = (NIR-Red) / (NIR+Red)

A study on winter wheat *(Triticum spp.)* evaluated the relationship of the coefficients of variation (CVs), determined from NDVI readings derived from spectral radiance measurements. “Results showed that the CV from NDVI readings was a good predictor of early season plant stand.” The relationship between vegetative RI (RI_{NDVI}) and harvest RI ($RI_{Harvest}$) was shown to improve with increasing CV values (Arnall et al., 2006; Raun et al., 2002). $RI_{Harvest}$ may be a good index with RI_{NDVI} for CV of spectral radiance (Tucker, 2009). Work by Raun et al. (2002), demonstrated that RI in winter wheat can be used to estimate N application rates. The wider the difference in reflectance values from the check and plots with different N rates, result in a RI higher with an N recommendation based on RI's relationship with plant N, grain yield and other agronomic factors.

Regression models are used to estimate the correlation between grain yield and NDVI (Raun, et al., 2002). In addition, an in-season estimated yield (INSEY) equation for yield potential prediction was established, which is comparable to that proposed by Raun et al. (2002). Several indices were evaluated, however only two had a high combined R^2 when compared to the other indices tested. The days from planting to sensing (DFP) INSEY (Raun et al., 2002) was calculated as:

DFP INSEY = NDVI/DFP

Where: DFP - days from planting to sensing

In addition, the cumulative growing degree days (GDD) INSEY was calculated as:

GDD INSEY = NDVI/GDD

Whereas: GDD - cumulative growing degree days (GDD) from planting to sensing and calculated using the "optimum day method" (Barger, 1969).

GDD= T max + T min/2 - Base Temperature

Whereas: base temperature for grain sorghum is 7 ºC (Sauer, 2012).

According to Teal et al. (2006), the equation derived from the best line that explains the relationship between actual corn grain yield and INSEY (both DFP INSEY and GDD INSEY) was fitted and the equation was used for predicting yield potential for corn. Also, the yield potential plus one standard deviation method (Raun et al., 2005) was use to evaluate yield potential.

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Chapter II

Potential for Optical Sensor-Based Nitrogen Fertilization in Grain Sorghum (*Sorghum bicolor* L. Moench) in Arkansas

Abstract

Ground-based active-optical (GBAO) crop sensors have become an effective tool to improve nitrogen (N) use efficiency and to predict yield early in the growing season, particularly for grass crops. Commercially available canopy sensors calculate the normalized difference vegetative index (NDVI) by emitting light in the red and near infrared range of the electromagnetic spectrum. The NDVI is used to evaluate vigor status and to estimate yield potential. However, few studies have been conducted to compare the performance of commercially available sensors. Therefore, a study was conducted using the most common crop canopy sensors: i) N-Tech's GreenSeeker™ (GS), ii) Holland Scientific's Crop Circle™ (CC), and iii) Minolta’s SPAD-502 chlorophyll content meter (CCM). The objective of this study was to find the optimum time for sensing and compare the relative performance of the sensors in estimating the yield potential of grain sorghum (*Sorghum bicolor* L. Moench). Treatments included six levels of N fertilization (0, 37, 74, 111, 148, and 185 kg N/ ha), applied in a single split 20 days after planting (DAP). Treatments were arranged in a randomized complete block design with five replications, in four locations in Arkansas, during 2012 and 2013. Sensors readings at vegetative growth stages V3, 4, 5 and 6. Results from simple regression analysis showed that the V3-V4 growth stage correlated better with grain yield than readings collected and any other time. In season estimated yield (INSEY) obtained at V3 captured 41, 57, 78, and 61% of the variation in grain sorghum yield when red NDVI of GS, red NDVI of CC, red edge for CC and CCM, respectively, were used. Results from these studies suggest that the CC sensor has a better potential for in-season site-specific N application in Arkansas than the GS sensor. The GS reflectance values appear to saturate after the V3 stage, in contrast with CC values that

allow for discrimination past the V3 Stage. Therefore, the red edge wavebands of CC appear to be better suited to develop relationships between spectral vegetation indices and agronomic parameters.

Introduction

Ground-based active-optical (GBAO) crop sensors have become an effective tool to improve nitrogen (N) use efficiency and to predict yield early in the growing season, particularly for grass crops. Commercially available canopy sensors calculate the normalized difference vegetative index (NDVI) by emitting light in the red and near infrared range of the electromagnetic spectrum and assessing the nature of the reflected light. The NDVI is used to evaluate vigor status and to estimate yield potential. However, a few studies have been conducted to evaluate comparative performance of commercially available canopy sensors for sorghum. Therefore, a study was conducted using three most common crop canopy sensors (NTech's GreenSeeker™ (GS), Holland Scientific's Crop Circle™ (CC), and Minolta Co. Spad-502 chlorophyll content meter (CCM)) for finding optimum time for sensing and compare the relative performance of the sensors and associated vegetation indices in estimating the yield potential of grain sorghum (*Sorghum bicolor* L. Moench). In season supplementation with N, when needed, is fundamental for high yield performance, Therefore, the estimation of grain yield potential based on NDVI and CCM readings will provide the basis for a N prescription to be used in season. The NDVI is a good indicator of biomass (amount of living plant tissue), and is used in conjunction with growing degree days greater than zero (GDD>0), or days from planting, to accurately project yield potential. Readings at growth stage V3 (growing point differentiation) should be highly correlated to final grain yield, and measurements must be carried out at growth stages of significant biomass production and nutrient demand.

Materials and Methods

Site Description

The study was conducted at three different locations the first year (2012): Lon Mann Cotton Research Station (Central AR) in a soil mapped as Calloway silt loam Thermic fine silt, mixed, active, Aquic Fraglosiudalfs, Rohwer Research Station Center (SE AR) in a soil mapped as a Desha silt loam thermic Vertic Hapludolls, and the Northeast Research and Extension Center (NE AR) in a soil mapped as a Sharkey clay soil very fine, smectitic, thermic Chromic Epiaquert. In 2013, an additional location was included at the Rice Research and Extension Center near Stuttgart (RREC) in a soil mapped as Dewitt silt fine, smetic thermic Typic Albaqualfs.

Study Design

Pioneer 84G62 was the grain sorghum cultivar used for the studies as it is one of the most widely used cultivars planted in Arkansas. Seeds were sown at a rate of 220,000 plants/ha at all the locations under conventional tillage and irrigated conditions. Test plots consisted of four rows wide, each spaced 0.76 m apart and 7.62 m in length. The N fertilizer (Urea coated with Agrotain®) was broadcast applied with a spreader distributor 15-20 days after planting.

Grain sorghum at all location was grown using the same management practices following the Grain Sorghum Production Handbook from the Cooperative Extension Service of the University of Arkansas (Espinoza and Kelley, 2004).

Statistical Analysis

Treatments were arranged in the field using a randomized complete block design (RCB), with six N rate treatments (0, 37, 74, 111, 148, 185 kg N/ ha) and five replications. Final plot grain yield was obtained from the two middle rows 7.62 meter long, using a plot combine set with an automatic scale and moisture meter. The GS and CC readings consist of a mean between 40 to 60 readings from each row. The CCM readings were based in a mean of 20 samples by plot. In general, means for each N treatment of each sensor were processed in Microsoft Excel-2007. Grain yields were adjusted to 15.5 % moisture. Yields at each location were converted to relative yield to reduce the variability associated with years and locations. Relative yield (RY) was calculated as the ratio of a particular treatment yield divided by the highest yield times 100 at a given site-year. The optimal N uptake, INSEY, aboveground dry matter and leaf N percent were calculate based in N fertilizer rates by fitting a linear, quadratic and exponential regression model analysis with intercept for each location and year using JMP Version 11 (SAS Institute Inc. 2011, Cary, NC) and Microsoft Excel-2007, choosing the best model as determined by the adjusted R^2, and solving for the N rate in function of the agronomic parameters previous mentioned by location and year. Treatments means for total grain yield were calculated across five replicates and six N rates for each site-year. Additionally, least square means of relative yield for all locations combined were separated using Fisher's protected LSD and statistical significance at the 0.10 probability level was interpreted. These analyses were conducted using PROC GLM of SAS 9.1 (SAS Institute Inc. 1999, Cary, NC).

GreenSeeker (GS) Hand Held Optical Sensor (NTech Industries, Inc.)

A GS unit was used to collect sensor measurements within the red zone (660±15nm) and near infrared zone (NIR) (770 nm ±15 nm)) light. The sensor uses a patented technique to measure crop reflectance and to calculate NDVI (Raun et al**.,** 2005; Stone et al., 2005). The unit senses with a light dimension of 106 x 4 cm area in a linear shape, when held at a distance of about 1.0 m from the illuminated surface. Sensors readings were collected manually at an approximate speed of 3 km/hr, resulting in approximately fifty to sixty average NDVI readings per row.

Holland Scientific‘s Crop Circle (CC) Sensor-470A.

The CC emits three bands: visible (670 ± 5.5 nm), red edge (730 ± 10 nm), and near infrared (760 ± 10 nm). The CC emitted a light of about 87 x 18 cm area in an oblong shape. Around 40 to 50 readings were collected with each pass. The illuminations covered the same area for both wavebands the CC provides a number of classic vegetative indices and incorporates three wavebands from 420 to 800 nm. Spectral configuration is performed via the use of standard 12.5 mm interference filters. Crop Circle measured reflectance at 730 nm allows for the calculation of a Red Index NDVI. The index R760/R730 is highly correlated with crop N uptake (Horler et al., 1983).

SPAD-502 chlorophyll content meter (CCM)

The CCM readings were taken from the most recently emerged developed leaf with a visible leaf collar with 20 plants sampled from the two middle rows. After selecting the leaf to be sampled, it was important to take the reading on about the same location on each leaf (half the distance from the leaf tip to the collar and halfway between the leaf margin and the leaf midrib). These readings were averaged by plot. A sufficing response index was calculated by considering the CCM readings of the highest N rate and dividing this by the CCM readings of the lower N treatments. Calculation of response index grain yield (RIGY) was done by taking the grain yield of the highest treatment N-rate and dividing this by the grain yield of the other lower N treatments.

Data Collection

Both single hand sensors (CC and GS) were passed holding the sensor approximately 75 to 100 cm above the crop canopy. The sensor readings were collected from the two middle rows of each plot in a nadir position, beginning at growth stage V2 (appendix 11); at weekly intervals in a time frame around 10:30 am to 12 pm to avoid moisture and temperature effects in the readings (Heinemann et al., 2002).

Total biomass accumulation was calculated by harvesting, at ground level, plants in 1 m of row from each treatment in 4 of the 5 replications. Plants were collected 70-80 DAP. Plant samples were dried (70 ^{o}C for 75 hours) or until the material reached a constant weight and later ground to pass a 110-mesh sieve. The N was analyzed following standard Method Kjeldahl Nitrogen and Phosphorous (Jones et al., 1991). The N in the soil was analyzed following standard procedures for NO_3-N based in the Specific Ion Electrode method (Donahue, 1992). Each block was sampled to a 15, 30, and 45 centimeters depth. Other nutrients were applied based on soil test results for each year.

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Results and Discussion

Total Grain Yield and N rates

There was a good yield response to N rates at each location in 2012 and 2013, except at SE AR in 2012 where 75 mm of rain were recorded in a period of three days that may have affected NUE. During 2012, yields were maximized at 148 kg N /ha at all the locations. In 2013 yields were maximized at 111 kg N/ha at SE AR, while at the NE AR location yield appeared to follow a linear trend. Yields at the RREC location were maximized at 148 kg N/ha. Yields at the Central AR location reached their maximum potential at 148 kg N/ha (Figure 2). Due to the lack of yield response at the SE AR location in 2012 (R^2=0.03), this site was removed from further analysis (Table 1). To reduce the effect of yield variability across locations and years, grain yield was converted to relative yield. When relative yields were combined across locations and years, they were statistically maximized at 148 kg N/ha (Table 2).

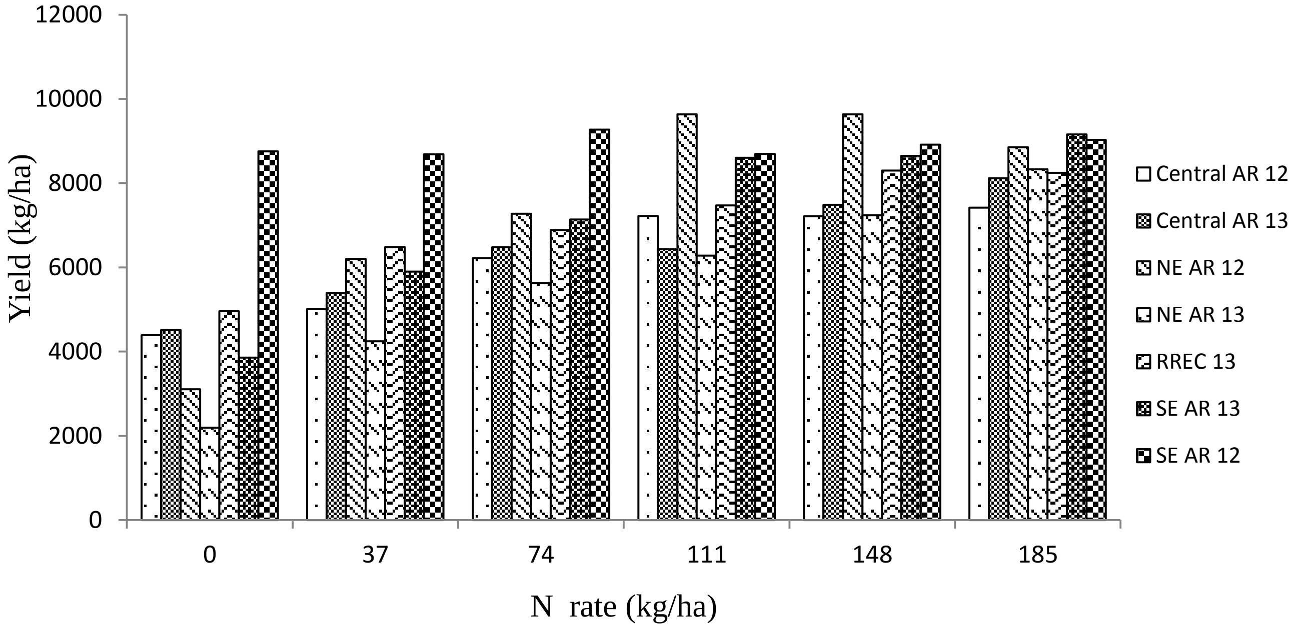


Figure 2. Average yield response of grain sorghum to varying nitrogen (N) rates across all locations and years.

Table 1. Equations describing the relationship between relative grain yield and nitrogen (N) rate for all the sites-years.

Location and Year	**Equations**	**R square**
NE AR- 12	$y = 0.2881 + 0.0096x - 4E\text{-}05x^2$	0.79
NE AR- 13	$y = 0.2366 + 0.0078x - 2E\text{-}05x^2$	0.82
Central AR12	$y = 0.4998 + 0.0056x - 2E\text{-}05x^2$	0.58
Central AR-13	$y = 0.5327 + 0.003x + 1E\text{-}06x^2$	0.74
SE AR-12	$y = 0.8952 + 0.0003x - 1E\text{-}06x^2$	0.03
SE AR-13	$y = 0.3577 + 0.0073x - 3E\text{-}05x^2$	0.76
RREC-13	$y = 0.6389 + 0.0053x - 2E\text{-}05x^2$	0.82

Table 2. Relationship between relative grain yield and nitrogen (N) rate for all the locations and years (n=160).

N rate (kg/ha)	Significance*	Relative Grain Yield (Mean %)
185	A	85.5
148	A B	79.8
111	B	77.9
74	C	66.9
37	D	57.5
0	E	37.9
	LSD = 6.43%	CV= 17.2%

* Means not followed by the same letter are significantly different ($p \leq 0.1$)

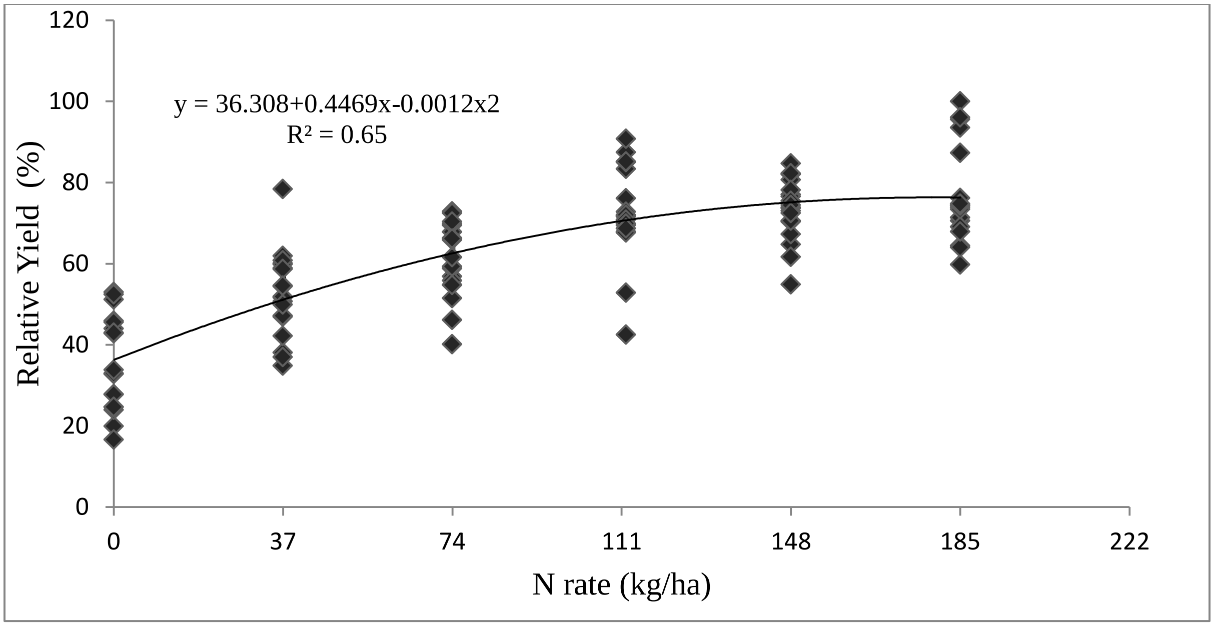


Figure 3. Relative yield response to fertilizer nitrogen (N) rates across location and years.

Table 3. Selected soil chemical parameters at the study locations for 2012 and 2013 (0 to 15 cm)

Year	**Loc**	**pH**[†]	**CEC**	**OM (%)**	**NO_3-N**[‡]	**P**	**K**	**Mg**
					mg/kg			
	SE AR	6.6	18.5	1.1	8	25	83	338
2012	Central AR	7.3	11.4	0.9	12	23	81	219
	NE AR	6.8	20.1	0.9	13	20	110	305
	SE AR	7	20	0.9	18	28	111	268
2013	Central AR	5.9	12	0.9	12	50	90	200
	NE AR	6.5	26	1.4	16	30	160	516
	RREC	4.9	11	0.8	71	39	92	219

[†] Soil pH was measured in a 1:2 (weight: volume) soil-water mixture

[‡] NO_3-N was measure with an ion specific electrode, and P, K, and Mg by Mehlich 3.

Predicting Grain Sorghum yield and N response in Arkansas from sensor data 2012 results.

At the Central AR site, reflectance readings were collected at 23, 31, 36, 43, and 50 days after planting, while at the NE AR site reflectance readings were collected at 25, 31, 38 and 47 days after planting. Reflectance values were used to calculate NDVI and then correlated with final grain yield, using an exponential equation. The relationships found between NDVI at each individual sampling time and grain yield at harvest resulting from the combination of N mineralized and applied fertilizer N in this experiment are presented in Figure 5. It is evident from the data that correlation between NDVI and yield improves as the plant develops. At NE AR, the coefficient of determination was 0.29 at 23 DAP and 0.63 at 33 DAP. After such time R^2 remains relatively constant for the next 10 days and then decreases to a R^2 of 0.14. NDVI calculated from the Central AR site showed a coefficient of 0.32 at 29 days after planting and reached a coefficient of 0.65 at 45 days after planting. Both locations showed higher R^2 in the window between 32 to 45 DAP, suggesting this as the best time to collect readings and develop yield prediction equations.

Table 4. Regression equations describing the relationship between nitrogen (N) rates and GreenSeeker- Normalized Difference Vegetation Index (NDVI) values at different days after planting in NE AR during 2012.

GS-NDVI	Days After Planting	Equations	R Squares
	25 DAP	$y = -0.6447 + 4.4294x - 3.7751x^2$	0.05
	31 DAP	$y = -9.3231 + 29.965x - 22.272x^2$	0.29
	38 DAP	$y = 15.177 - 45.119x + 33.97x^2$	0.65
	47 DAP	$y = -17.853 + 38.235x - 18.905x^2$	0.74

Table 5. Regression equations describing the relationship between GreenSeeker-Normalized Difference Vegetation Index (NDVI) values and relative grain yield at the NE AR location during 2012.

GS-NDVI	Days After Planting	Equations	R Squares
	25 DAP	$y = 2.52x^{5.4477}$	0.14
	31 DAP	$y = 6.6439x^{9.4746}$	0.63
	38 DAP	$y = 10.186x^{12.874}$	0.77
	47 DAP	$y = 3.4791x^{3.6085}$	0.29

2013 Results

The research was expanded by adding the Crop Circle sensor (CC) and an additional site (RREC) with the goal of assessing the relative performance of both GS and CC. During the 2013 season, all locations showed a good yield response to applied N rates. Results from the 2013 season showed similar trends to those observed in 2012. Reflectance data collection began around 25 DAP, with weekly reading taken until plants were midhead (55-60 DAP).

Time for Sensing in grain sorghum with GS and CC

NDVI readings values showed weak correlation with N rates early in the season for both sensors (Figure 3), with the relationship improving with crop age. Early in the season, sensor readings are influenced by background soil reflection and low Leaf Area Index (LAI) (Huete, 1988). Table 6 shows the regression equations and associated R-squares for the relationship between N rates and indices values. The R^2 values range between a low of 0.06 for GS-NDVI to a high of 0.58 for CC-red edge based on a quadratic model at 25 DAP. These responses improved with readings collected at 31 DAP; with a maximum response for both sensors at 38 DAP.

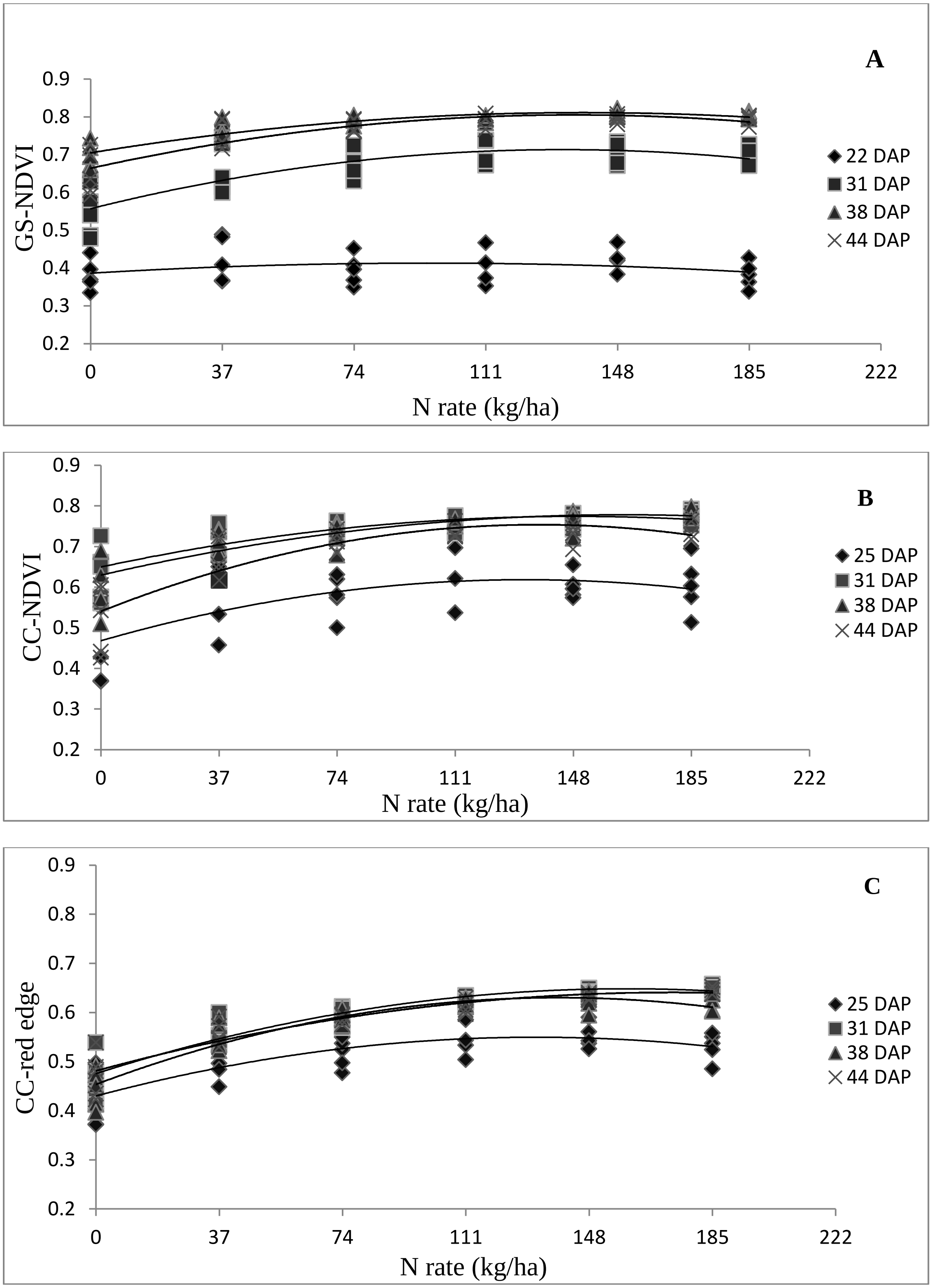


Figure 4. Relationship between GS-Normalized Difference Vegetation Index (NDVI) (**A**), CC-NDVI (**B**), CC-red edge index (**C**) with nitrogen (N) rates at different days after planting in NE AR-2013.

Table 6. Equations describing the relationship between nitrogen (N) rates and Normalize Difference Vegetation Index (NDVI) values at different days after planting in NE AR-2013.

SENSOR	Days after planting	Equations	R Squares
GS-NDVI			
	25 DAP	$y = 0.3864+ 0.0006x -3E\text{-}06x^2$	0.06
	31DAP	$y = 0.557+ 0.0024x -9E\text{-}06x^2$	0.61
	38 DAP	$y = 0.0015x + 0.7049 -6E\text{-}06x^2$	0.80
	44 DAP	$y = 0.6641+ 0.0021x -8E\text{-}06x^2$	0.72
CC-NDVI			
	25 DAP	$y = 0.4681+ 0.0023x-8E\text{-}06x^2$	0.41
	31 DAP	$y = 0.6496+ 0.0017x-6E\text{-}06x^2$	0.65
	38 DAP	$y = 0.6296+ 0.0018x -6E\text{-}06x^2$	0.68
	44 DAP	$y = 0.5405+ 0.0031x -1E\text{-}05x^2$	0.74
CC-red edge			
	25 DAP	$y = 0.4313+ 0.0018x-7E\text{-}06x^2$	0.58
	31 DAP	$y = 0.4756+ 0.0022x -7E\text{-}06x^2$	0.87
	38 DAP	$y = 0.4537+ 0.0025x -9E\text{-}06x^2$	0.88
	44 DAP	$y = 0.4811+ 0.0018x -5E\text{-}06x^2$	0.79

This trend was consistent across locations during the 2013 season. Under the conditions of this study, it appears that these relationships slightly improved late in the season for CC and decreased for GS. This effect has been previously reported and it appears to be related to the effect that canopy development has over NDVI values (Li et al., 2014).

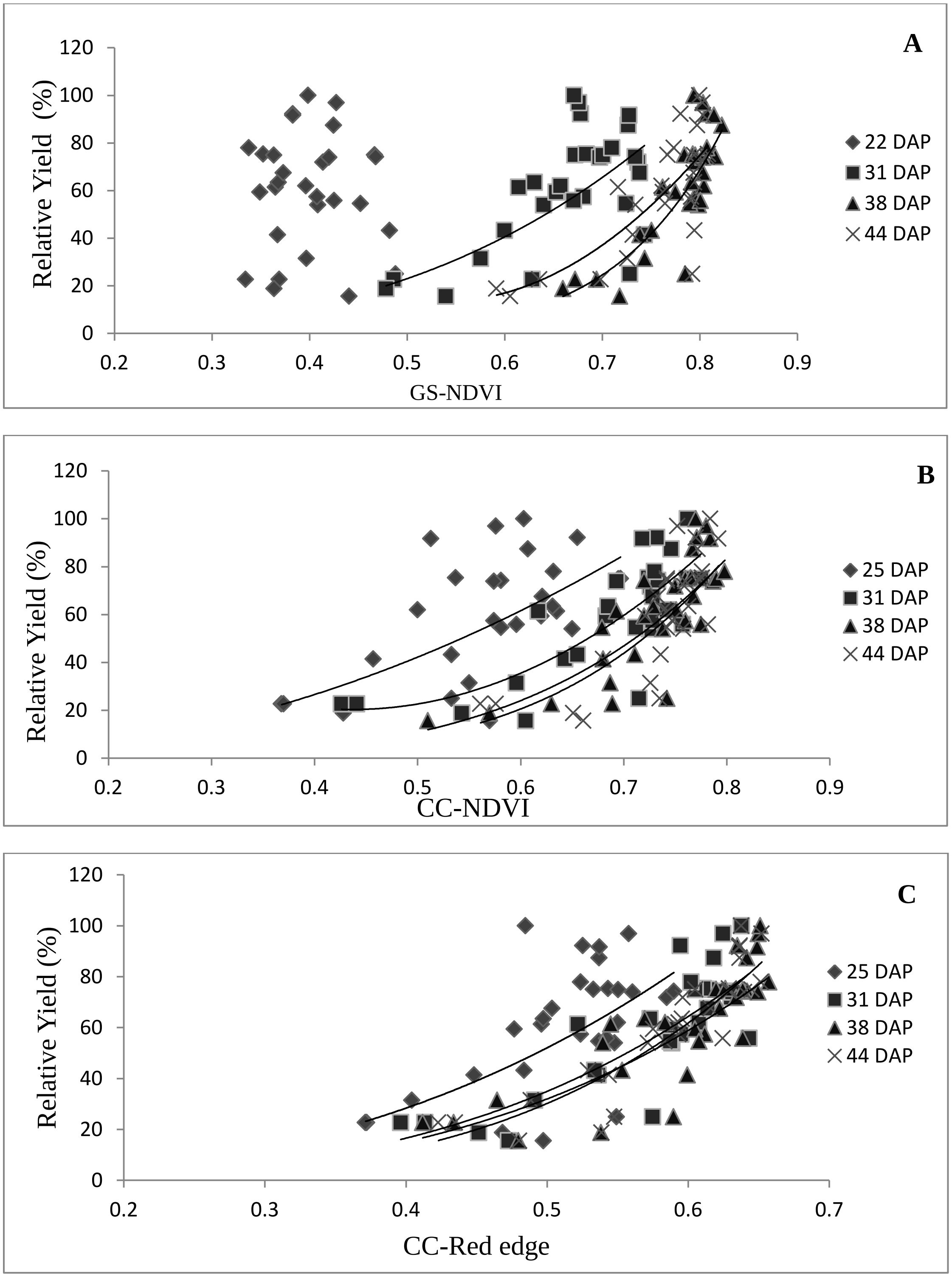


Figure 5. Relationship between GreenSeeker-Normalized Difference Vegetation Index (NDVI) (**A**), Crop Circle-NDVI (**B**), Crop Circle-red edge index (**C**) with relative grain yield at different days after planting in NE AR-2013.

Table 7. Regression equations describing the relationship between sensors indexes and relative grain yield at the NE AR location during 2013.

SENSOR	Days After planting	Equations	R squares
GS_NDVI			
	22 DAP	-	-
	31 DAP	$y = 198.73x^{3.1092}$	0.48
	38 DAP	$y = 384.78x^{7.7094}$	0.73
	44 DAP	$y = 222.66x^{5.072}$	0.67
CC_NDVI			
	25 DAP	$y = 177.51x^{2.0715}$	0.41
	31 DAP	$y = 146.45x^{2.5919}$	0.57
	38 DAP	$y = 219.46x^{4.3259}$	0.69
	44 DAP	$y = 252.65x^{4.9087}$	0.62
CC_red edge			
	25 DAP	$y = 343.46x^{2.7221}$	0.38
	31 DAP	$y = 355.66x^{3.3473}$	0.71
	38 DAP	$y = 459.14x^{3.9271}$	0.77
	44 DAP	$y = 325.56x^{3.3488}$	0.66

The relative performance of the different indices is shown clearly in Figure 5. These relationships agree with results shown in Figure 4, with reference to the optimum dates to collect sensor readings in grain sorghum. They confirm that, based simply on the coefficients of determination, readings collected between 38-44 DAP more closely correlate with the final yield of grain sorghum, independent of the type of sensor used (Table 7). This time frame corresponds approximately to the growing point differentiation (V3 stage). Previously reported results agree with our results (Moges et al., 2007; Tucker, 2009). The observed relationship for GS-NDVI beyond 38 DAP losses predictive ability (R^2=0.73 to R^2=0.67). In contrast with CC readings for both indices (NDVI and red edge index) which decrease slightly or remain fairly constant. The use of red edge NDVI can be useful to extend the narrow window of conventional sensors readings and associated indices calculations. Table 6 shows the equations associated with each index and corresponding coefficients of determination. This table underscores the suitability of sensing in the time frame of 38-44 DAP. The trends presented in Table 6 are consistent with those observed at the other locations. There is a general improvement in predictability with crop age to 38-44 DAP, with the relationship later weakening when using GS-NDVI and remaining fairly consistent when red edge NDVI is used.

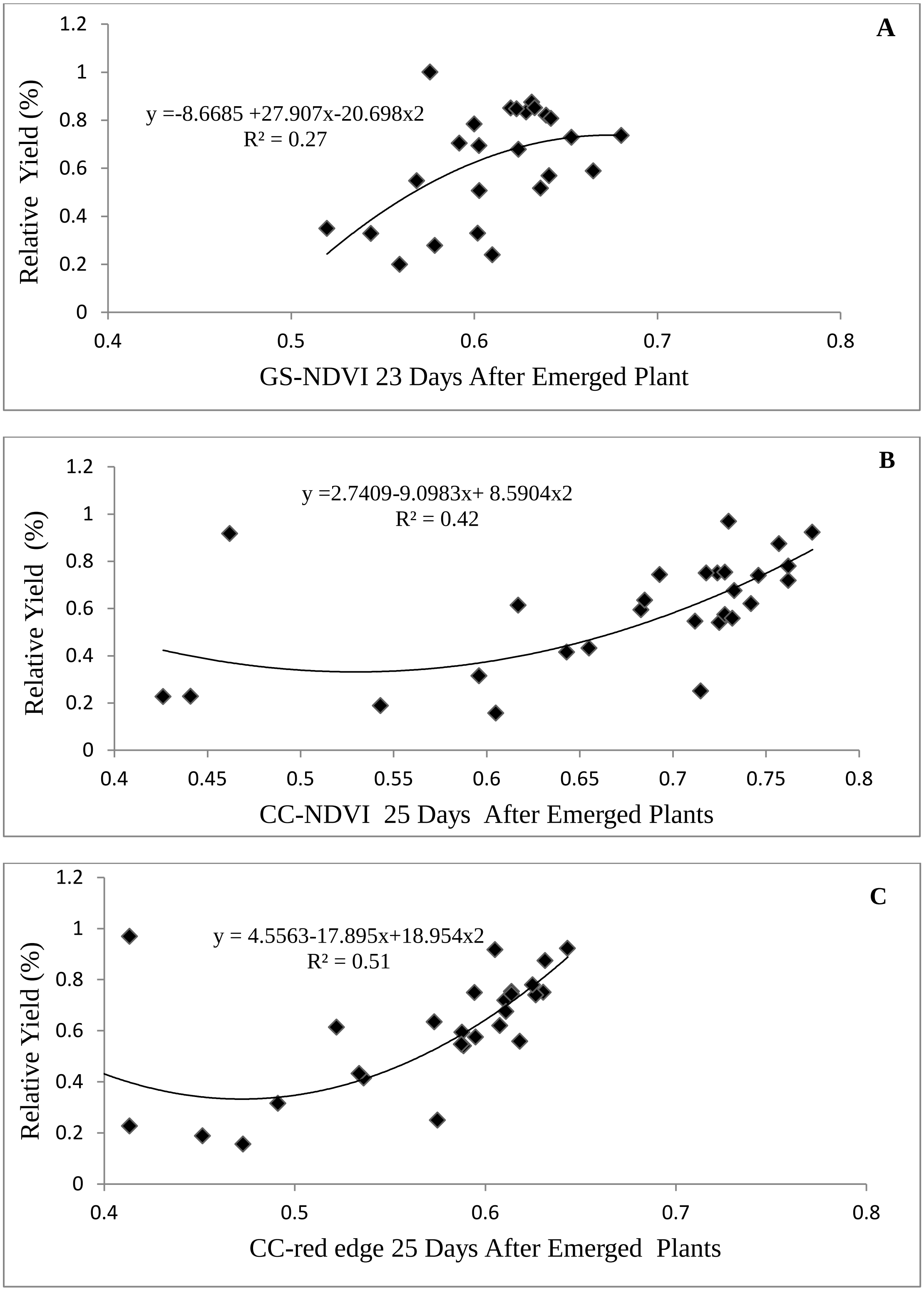


Figure 6. Relationship between GreenSeeker-Normalized Difference Vegetation Index (NDVI) (**A**), Crop Circle-NDVI (**B**), Crop Circle-red edge index (**C**) and relative grain yield at 23-25days after planting in NE AR-13.

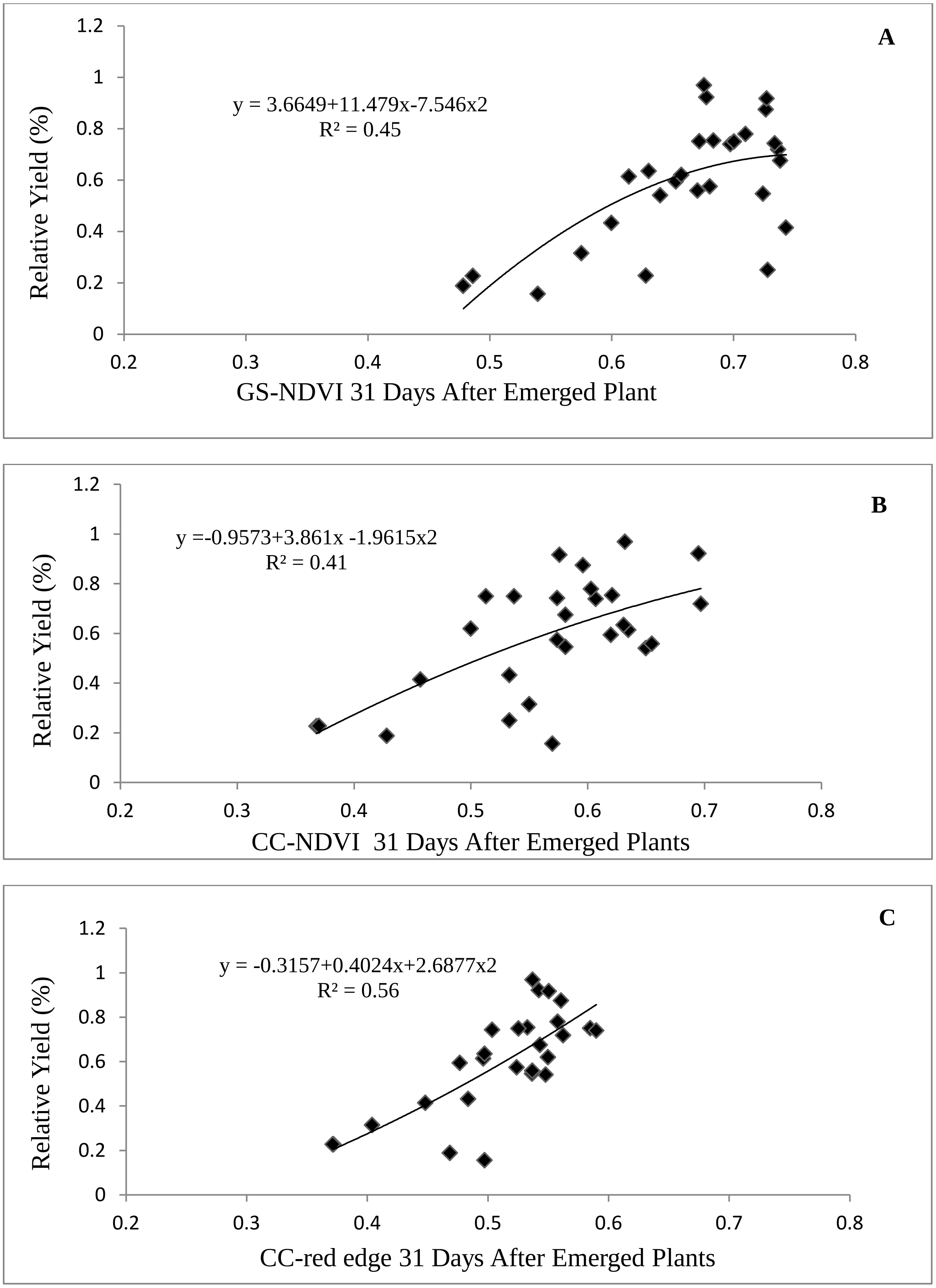


Figure 7. Relationship between GreenSeeker-Normalized Difference Vegetation Index (NDVI) (**A**), Crop Circle-NDVI (**B**), Crop Circle-red edge index (**C**) and relative grain yield at 31 days after planting in NE AR-13.

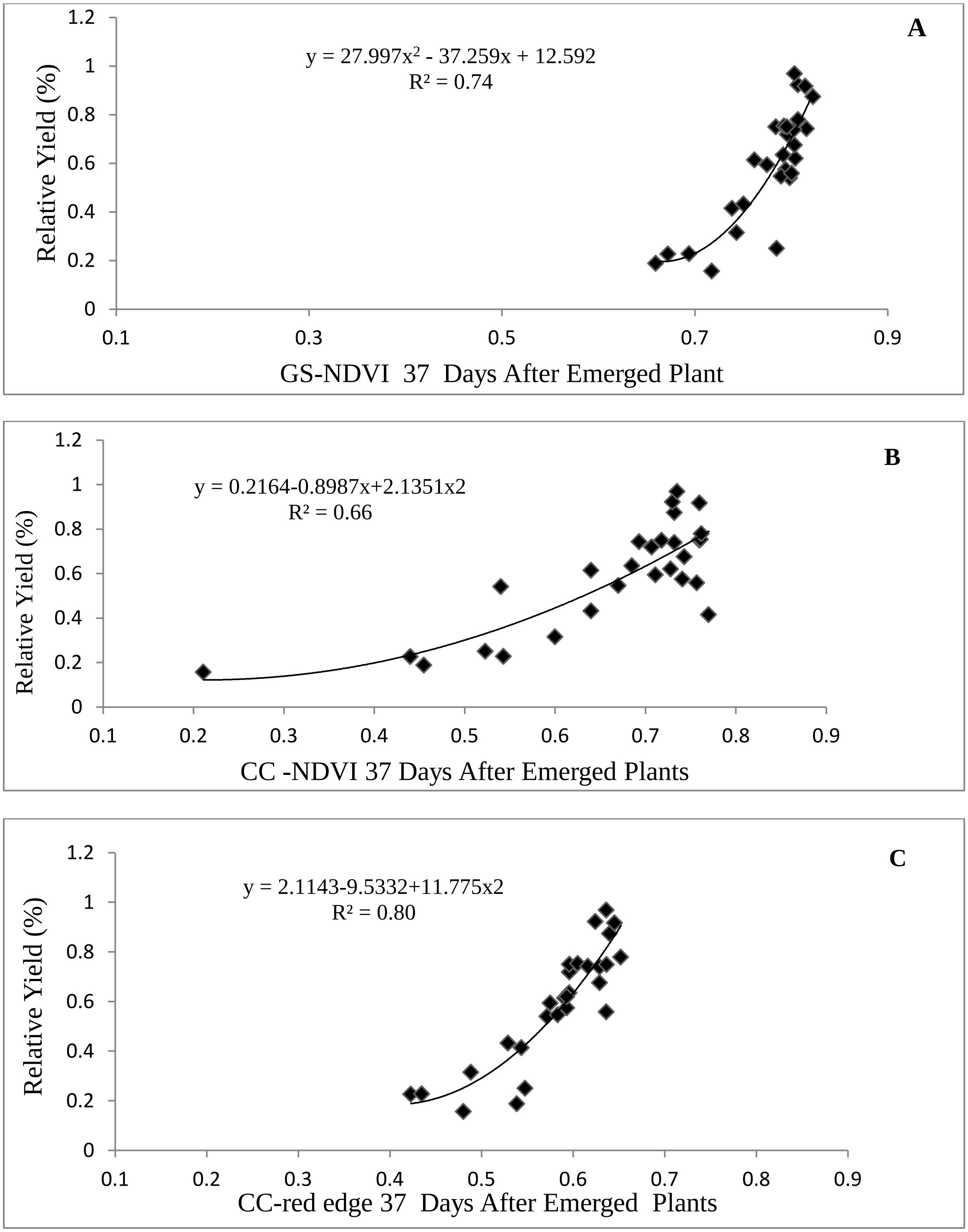


Figure 8. Relationship between GreenSeeker-Normalized Difference Vegetation Index (NDVI) (**A**), Crop Circle-NDVI (**B**), Crop Circle-red edge index (**C**) and relative grain yield at 37 days after planting in NE AR-13.

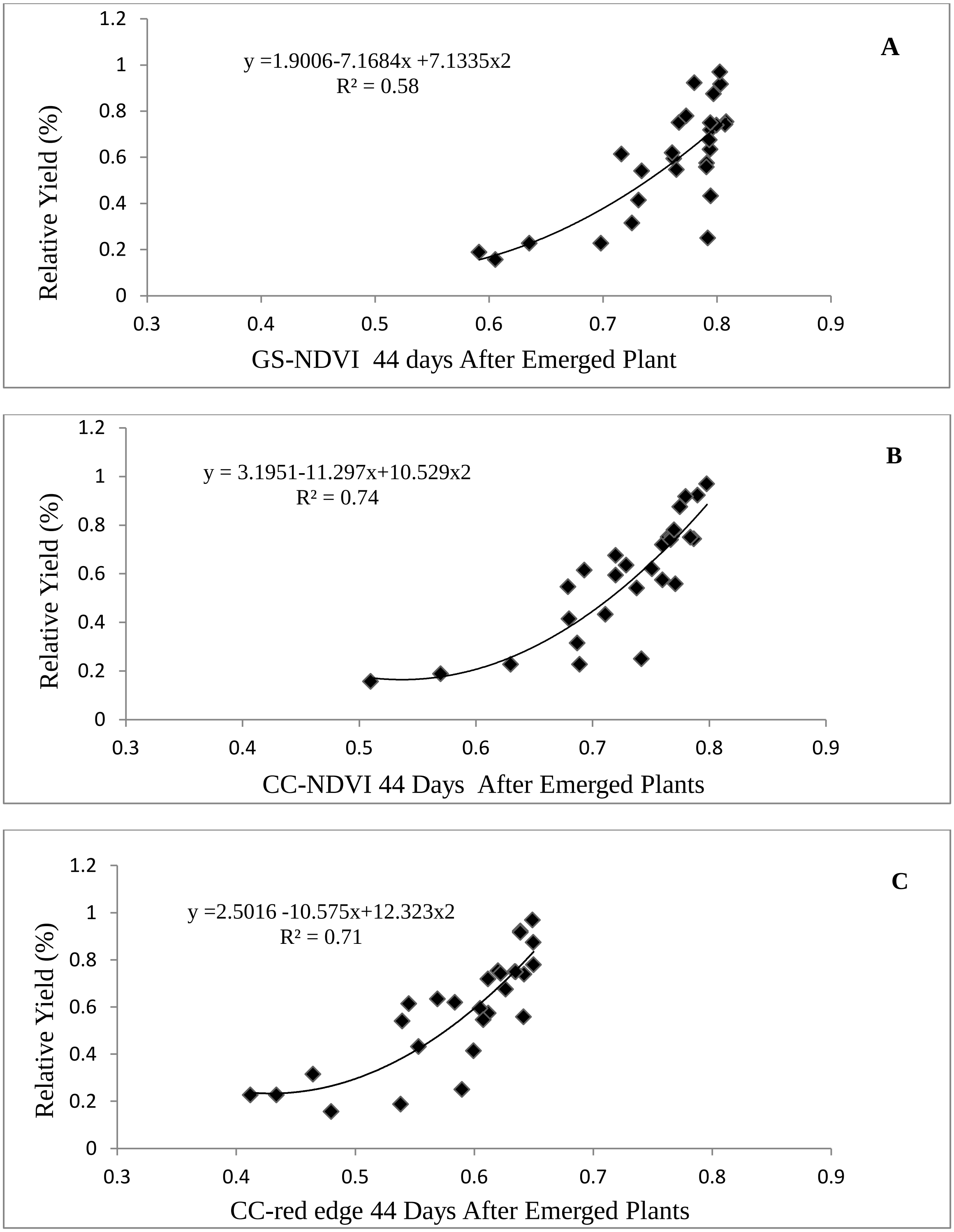


Figure 9. Relationship between GreenSeeker-Normalized Difference Vegetation Index (NDVI) (**A**), Crop Circle-NDVI (**B**), Crop Circle-red edge (**C**) index and relative grain yield at 44 days after planting in NE AR-13.

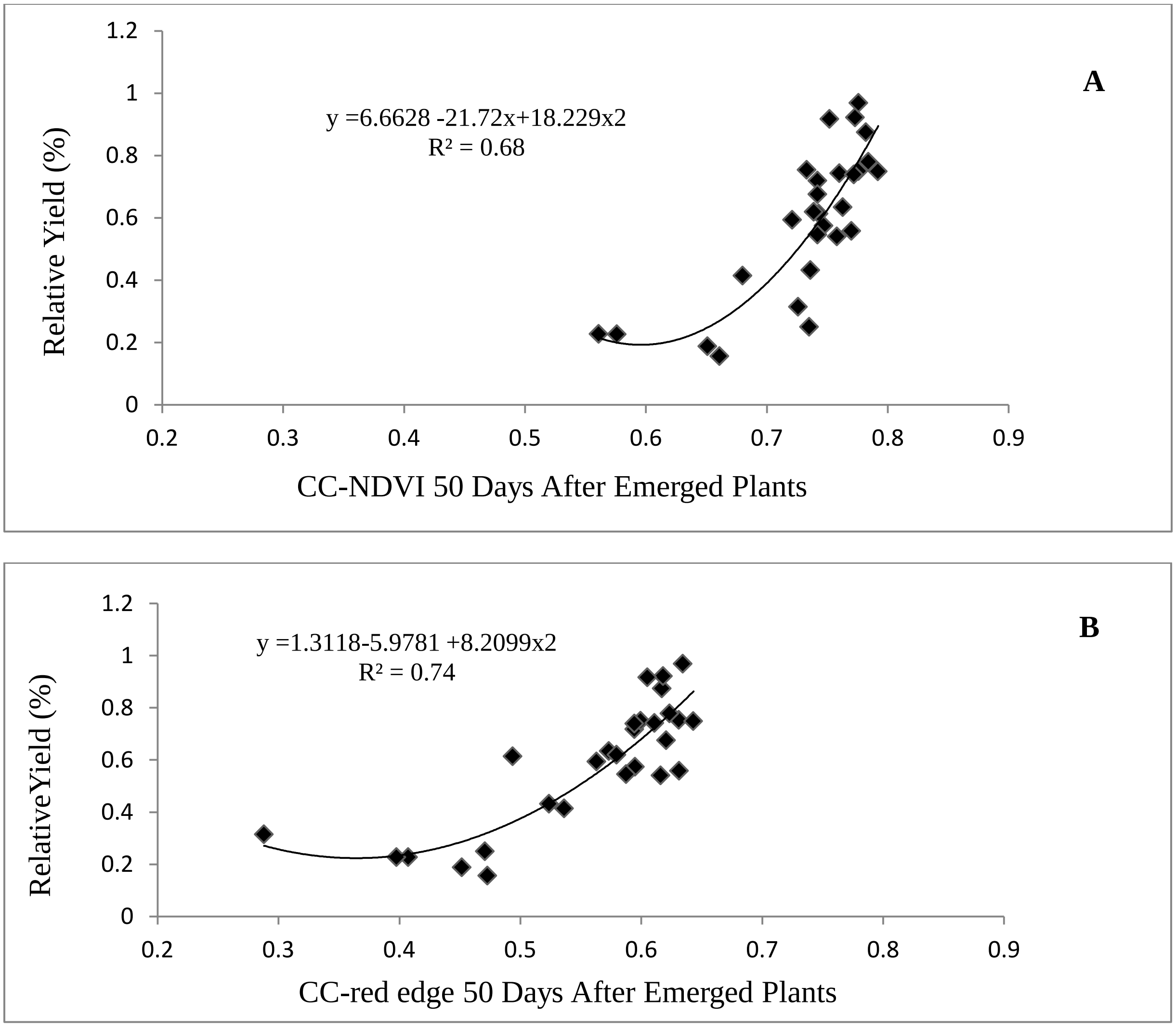


Figure 10. Relationship between Crop Circle-Normalized Difference Vegetation Index (NDVI) (**A**), Crop Circle-red edge index (**B**) with relative grain yield at 50 days after planting in NE AR-13.

Results from the NE AR Location

Results from this location show that GS and CC-NDVI, and CC-red edge index can potentially predict yield potential and provide guidance for the need of supplemental N in the 12 day windows between 33 and 45 DAP (Fig. 8 & 9) based on a single location. At 25 DAP, the CC-red edge shows 50% of the variability in relative yield, compared to only 28% and 42% showed by the GS-NDVI and CC-NDVI respectively (Figure 7). At 31 DAP, there was an improvement in the relationship between GS and relative yield, while such relationship for CC-NDVI and CC red edge index remained practically unchanged (Figure 7). At 38 DAP, the resulting regression models for all sensors and associated vegetation indices showed good yield prediction capability (Figure 8). At 44 DAP, the values for the coefficient of determination drop drastically for the GS- NDVI, but increased for CC-NDVI and CC-red edge index decreased slightly (Figure 9). The main disadvantage of NDVI or similar indices is the reported saturation with increasing aboveground biomass. Generally, NDVI approaches saturation asymptotically under moderate-to-high biomass conditions and for certain ranges of leaf area index (Huete et al., 2002). Despite the fact that NDVI values under high biomass tend to saturate, the CC red edge remains consistently high at 44 DAP, which means that it is less susceptible to being saturated.

In summary, in early growth stages, GS-NDVI (Figures 6A & 7A) seems to do a better work at discriminating among N treatments, but later in the season CC-NDVI appears to more closely correlate to relative yield than GS-NDVI.

In contrast, CC-red edge readings produced higher R^2 values in each of the sensing dates than those obtained when using the NDVI index (Figure 9). This means that the CC-red edge index, under the conditions of this study, was able to predict final yield better than the NDVI index independent of what sensor was used. Li (2012), compared the red edge index with NDVI and CCM-index in corn; his results show significantly higher R^2 values when using the red edge index. Red edge is more sensitive to absorbance related to crop chlorophyll concentration because this spectral index penetrates deeper into the crop canopy and produces more reflectance of the real pigment concentration level. Therefore, to a certain level, red edge overcomes saturation problems. Figures 10 (A&B) validate those previous reports, showing that the CC-red edge waveband readings were not affected as much as CC-NDVI by grain sorghum plants reaching full canopy development (boot stage).

Trends Followed by the Coefficient of Variations.

Figure 11 shows the trend followed by the coefficient of variations (CV) calculated based on average NDVI at different N rate of each one of the indexes. Regardless of the index used, the calculated CVs follow similar trends. Also, there were significantly higher CVs for the control treatments regardless of sampling date, except sampling date 25 DAP. This is probably due to natural soil variability. In general, the CV for the three sensors tended to decrease as a function of N rate. Later sensing showed that as the canopy began to close (more crop cover variability) the CV declined, independently of the N rate. The variability in biomass accumulation in plots with lower N rates was higher than plots where N was non-limiting. Treatments that received an N application showed more uniform plant development and that is probably what the sensor was reflecting. Less variability was generally observed at 38 DAP or later, possibly due to the plants actively taking up N from the fertilizer.

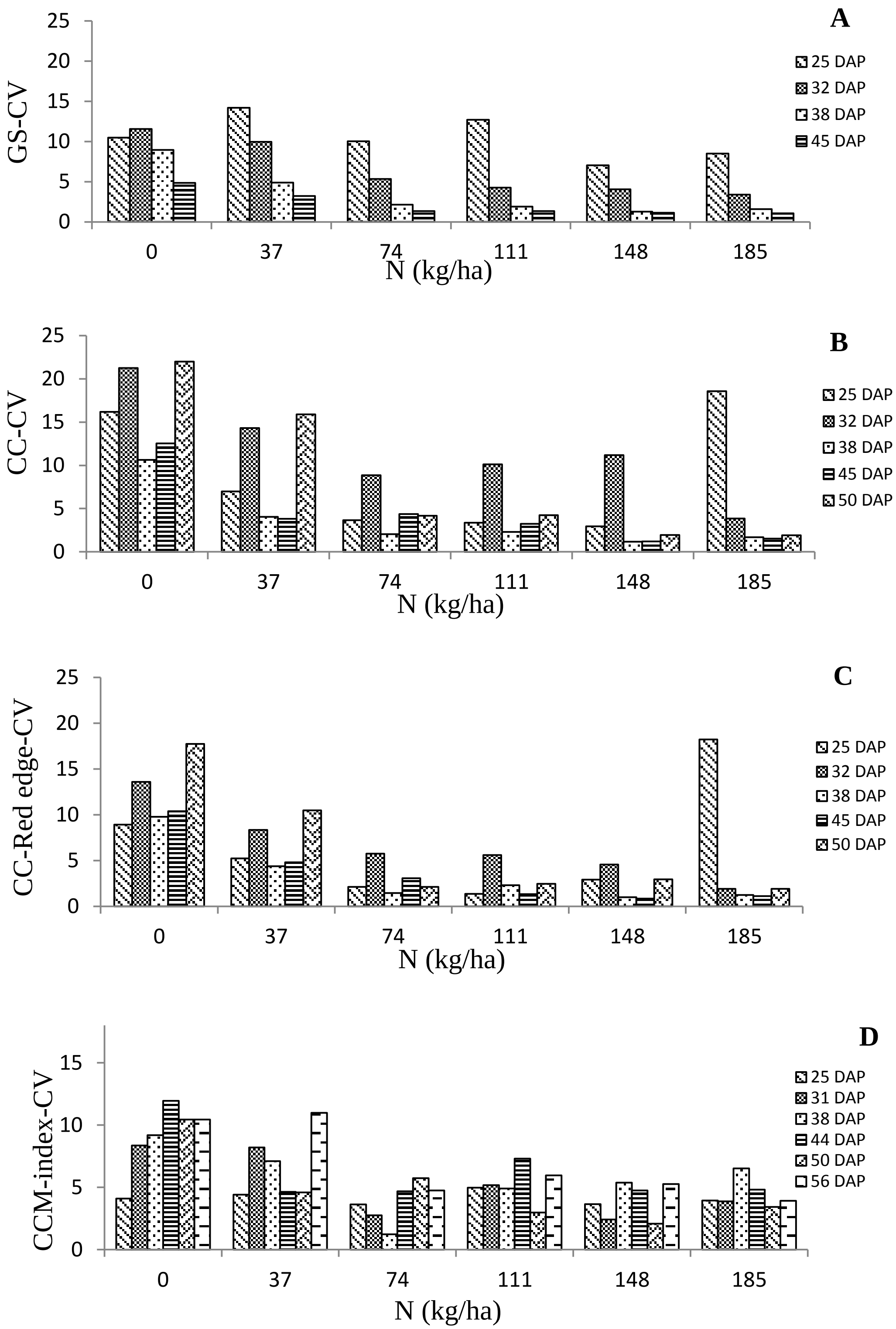


Figure 11. Relationship between Coefficient of Variation for GreenSeeker-Normalized Difference Vegetation Index (NDVI) (**A**), Crop Circle-NDVI (**B**), Crop Circle-red edge (**C**), chlorophyll content meter-index (**D**) and nitrogen (N) rate NE AR-13.

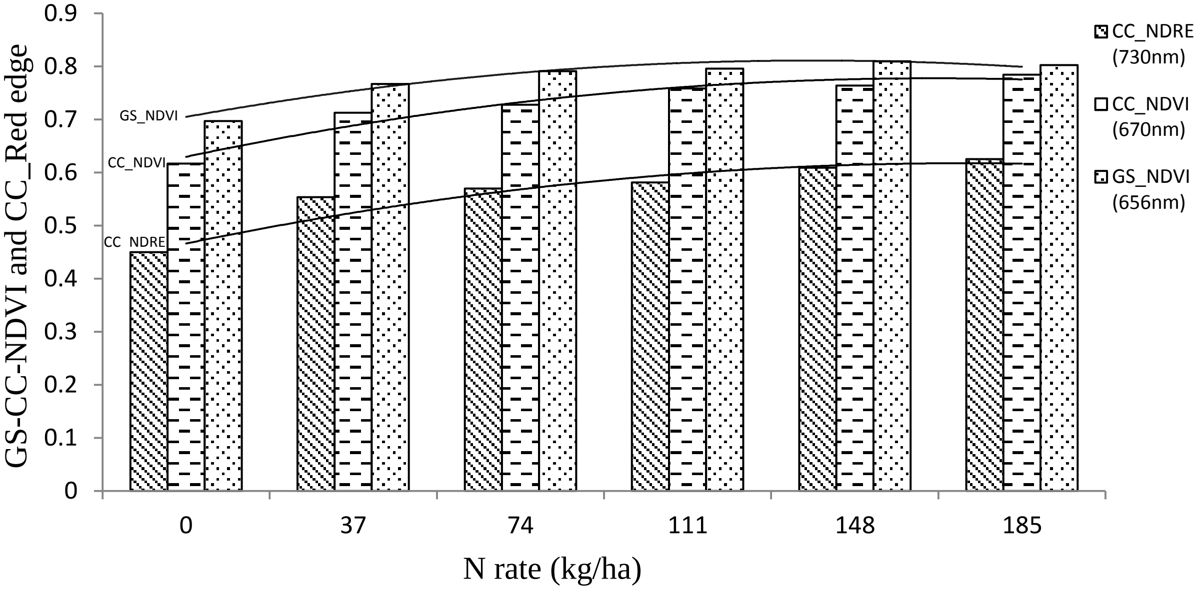


Figure 12.Relationship between GreenSeeker-Normalized Difference Vegetation Index (NDVI), Crop Circle-NDVI and Crop Circle-red edge index and nitrogen (N) rates at 32-44 days after planting (V3 stage) in SE AR-2013.

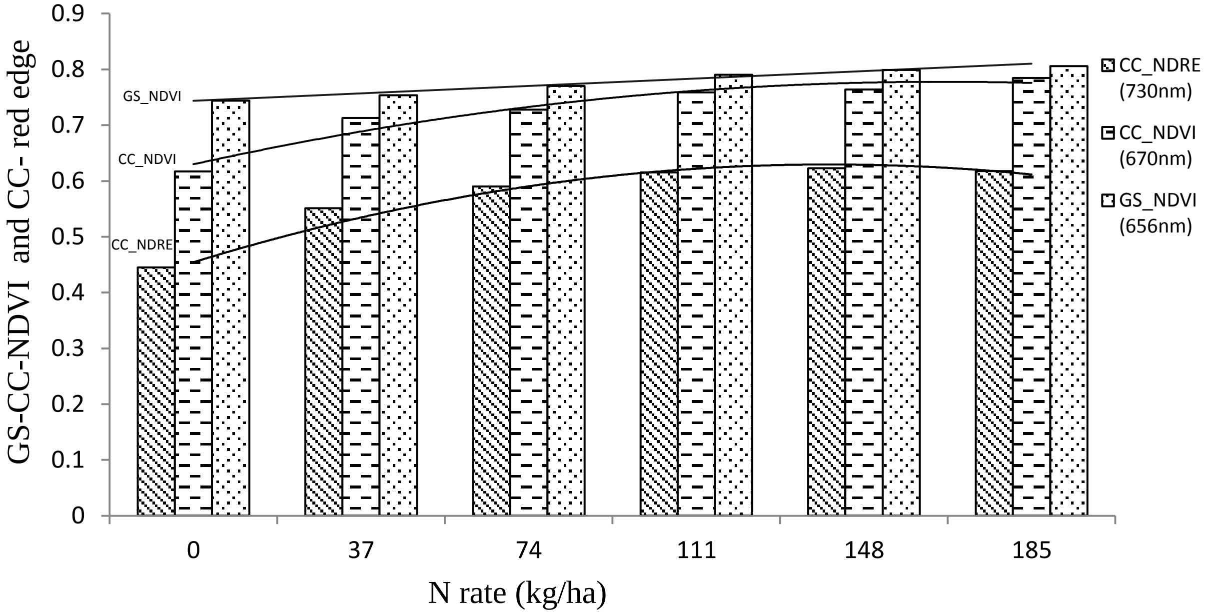


Fig 13. Relationship between GreenSeeker-Normalized Difference Vegetation Index (NDVI), Crop Circle-NDVI and Crop Circle-red edge index and nitrogen (N) rates after 50 days after planting (Before boot stage) in SE AR-2013.

The readings from both sensors started to show a good relationship based on R^2 from 32 to 44 DAP (Fig. 12). Red edge wavelength from CC produced the highest $R^2=0.91$ of all the sensor readings. Figure 13 shows the relationship between N rates and calculated values for the two sensors 12 days after this "optimum" sensing window had passed showing that CC and GS NDVI values remain unchanged due to the quick saturation of the red absorption band, as reported by Gitelson (1996). By 50 DAP the NDVI values are not able to distinguish among N rates. The GS-NDVI reaches maximum values at lower N rates more rapidly than CC-NDVI, but in general show the same trend towards a lower R^2 by the time the grain sorghum crop is transitioning into the reproductive stage as previously shown (Vanderlip, 1993). In contrast, the red edge, NDVI relationship with N rate stays relatively strong, even beyond the optimum sensing window. The red edge band look like it is independent or less sensitive of crop cover variability based on the observed trend and associated R^2 during different periods of fertilization.

Results from all Locations Combined.

The INSEY concept is useful to predict crop yield across locations and years. It standardizes the data to account for variability in weather conditions and agronomic factors (Raun, 2001). The INSEY estimates the relationship between NDVI and GDD. The relationship between relative yield and GS and CC INSEY at the V3 stage was evaluated across locations. Yield prediction equations presented in the Figures 14, 15 and 16 shows the relationship of GS and CC INSEY index with RY.

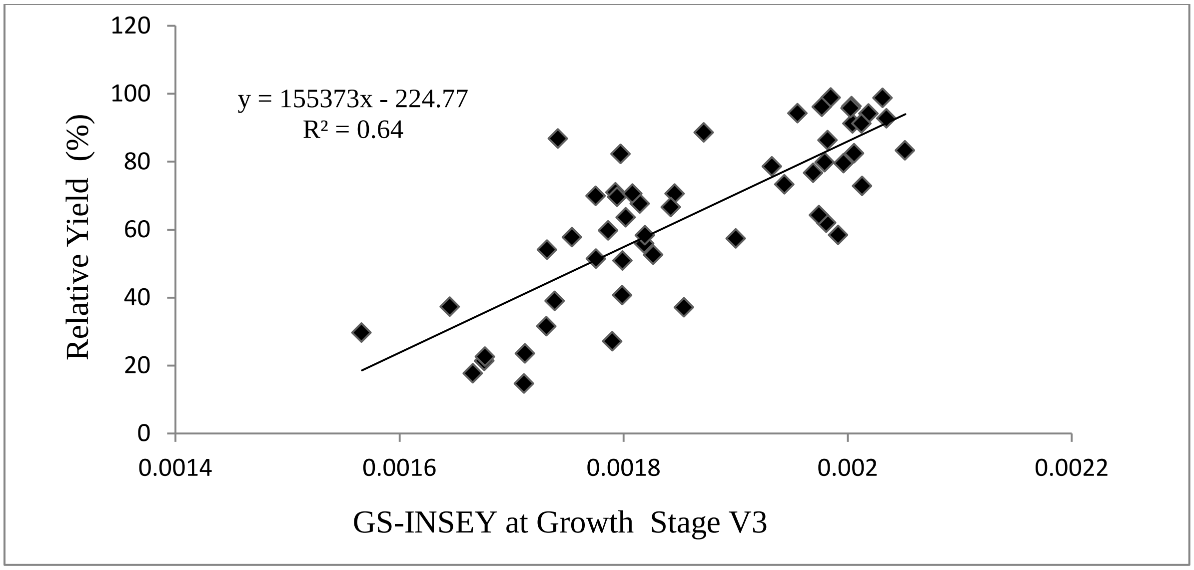


Figure 14. Relationship between GreenSeeker-In season estimated yield (INSEY) and relative yield at 40 DAP (V3) all sites 2013.

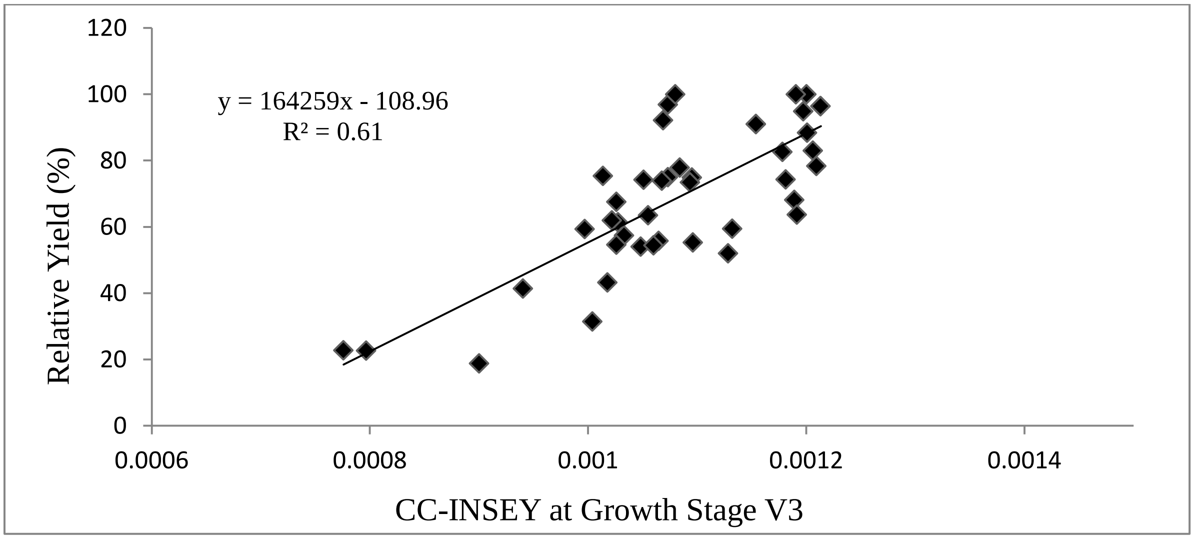


Figure 15. Relationship between Crop Circle-In season estimated yield (INSEY) and relative yield at 40 DAP (V3) all sites 2013.

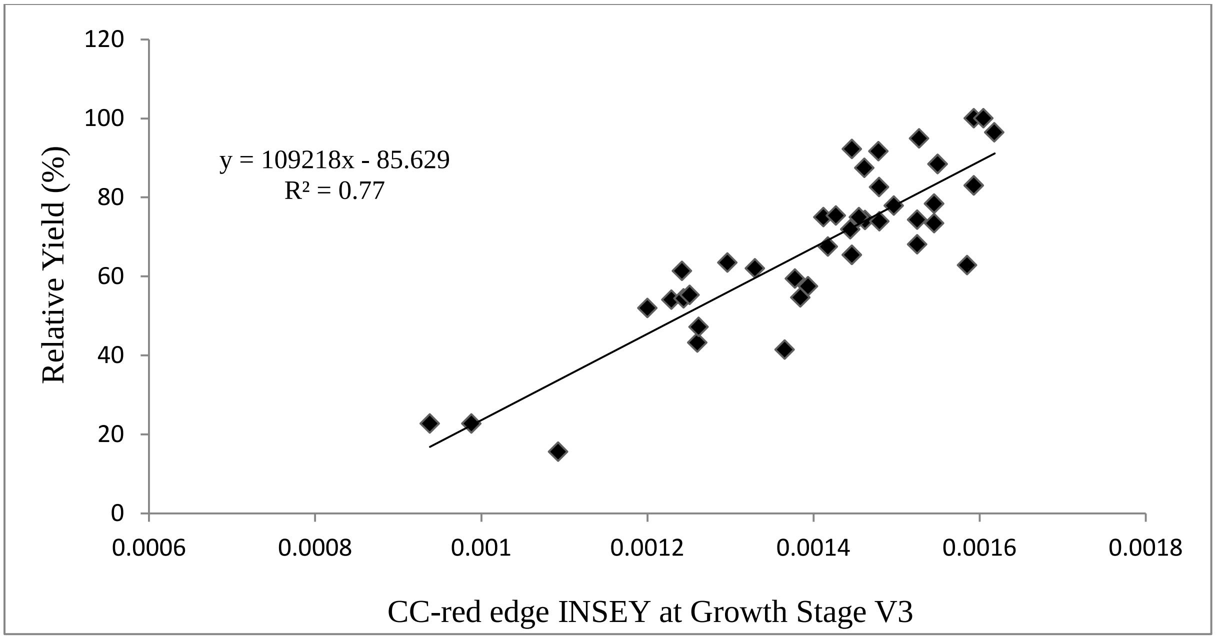


Figure 16. Relationship between Crop Circle-red edge-In season estimated yield (INSEY) and relative yield at 40 DAP (V3) for all sites 2013.

Figure 14 and 15, independent of the sensors used (GS or CC), show similar coefficients of determination, $R^2= 0.64$ for GS NDVI compared to $R^2= 0.61$ for CC-NDVI. However, the CC in the red edge index spectrum shows a better agreement, with R square of 0.77 (Fig. 16). The trend observed during the season show that in the early (<V3) and late growth stages (>boot stages), such relationships have a low R square ($R^2 <0.45$) (see appendix). In contrast, the R squares for both sensors show the red-NDVI spectrum beginning to decrease after 40 DAP. Despite this tendency, the R^2 values of the CC- red edge (INSEY) do not show a significant reduction (based in the resultant R square) (Figure 16). This further validates our findings that CC readings and the calculated index in the red edge spectrum decrease proportionally less than the other indices after the "optimum" period.

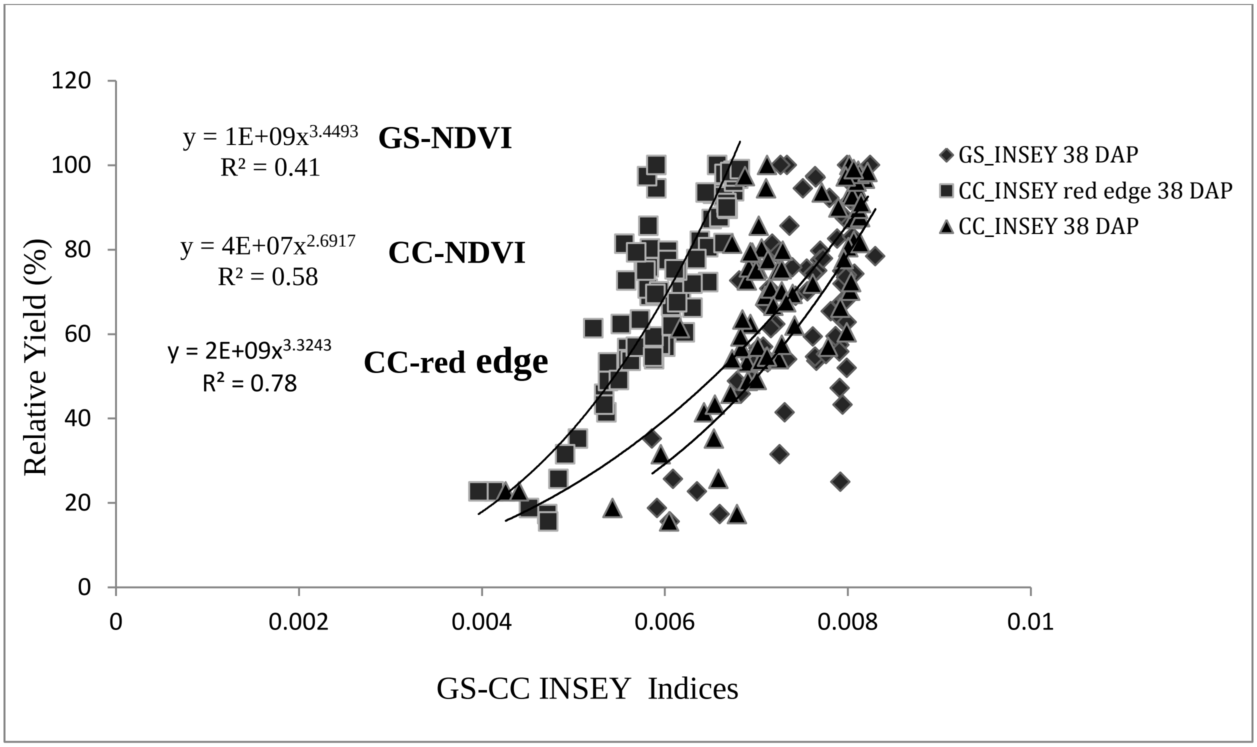


Figure 17. Relationship between sensors (GreenSeeker and Crop Circle) INSEY indices and relative grain yield at NE AR, SE AR and Central AR-2013 at 38 DAP.

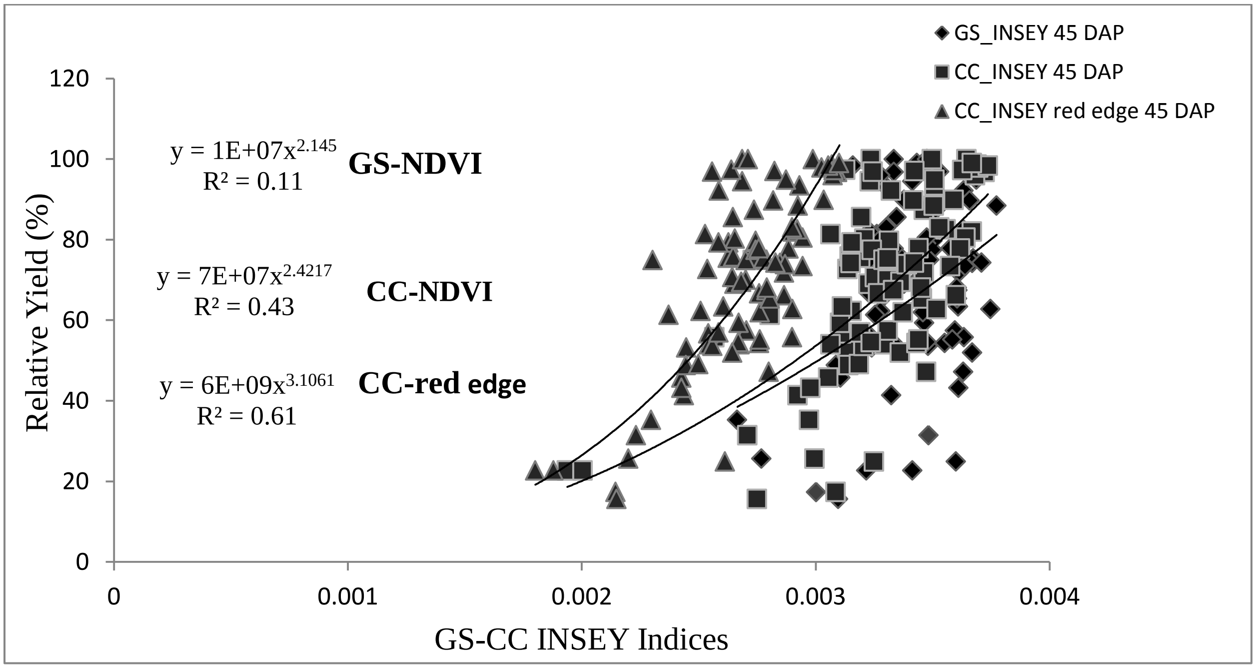


Figure 18**.** Relationship between sensors (GreenSeeker and Crop Circle) INSEY indices and relative grain yield at NE AR, SE AR and Central AR-2013 at 45 DAP.

Figure 17 shows regression models for INSEY at early growth stages for GS and CC NDVI indexes having similar R² with CC-red edge index better explaining the variability during such early stages. Figure 18 shows regression models for INSEY and RY at 45 DAP for all the indices. The trend observed is consistent with early growth stages, with red NDVI having the highest R square. However, the regression model developed with GS-NDVI and Relative Yield (RY) fails to explain the variability in the data, as seen with the resulting low R² values. Again, this is related to the early saturation observed by GS sensor that limits the ability of this sensor to distinguish among treatments. At RREC and SE AR the canopy developed at a faster rate than at the Central AR and NE AR locations, resulting in the GS sensor being saturated earlier.

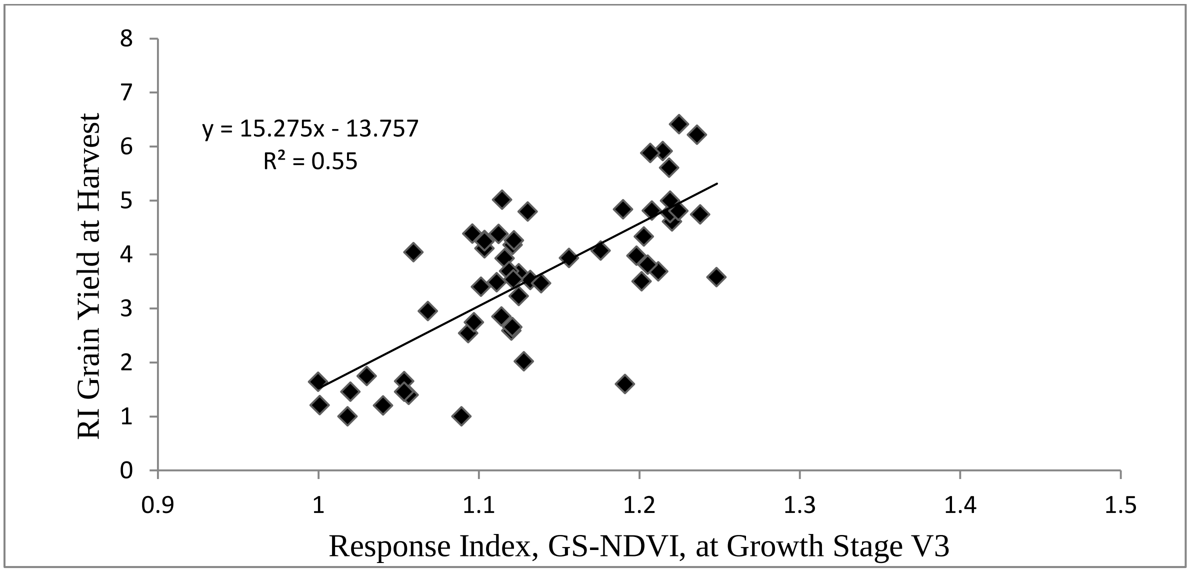


Figure 19. Relationship between the Response index (RI) grain yield and response index for GreenSeeker-Normalized Difference Vegetation Index (NDVI) at the V3 stage.

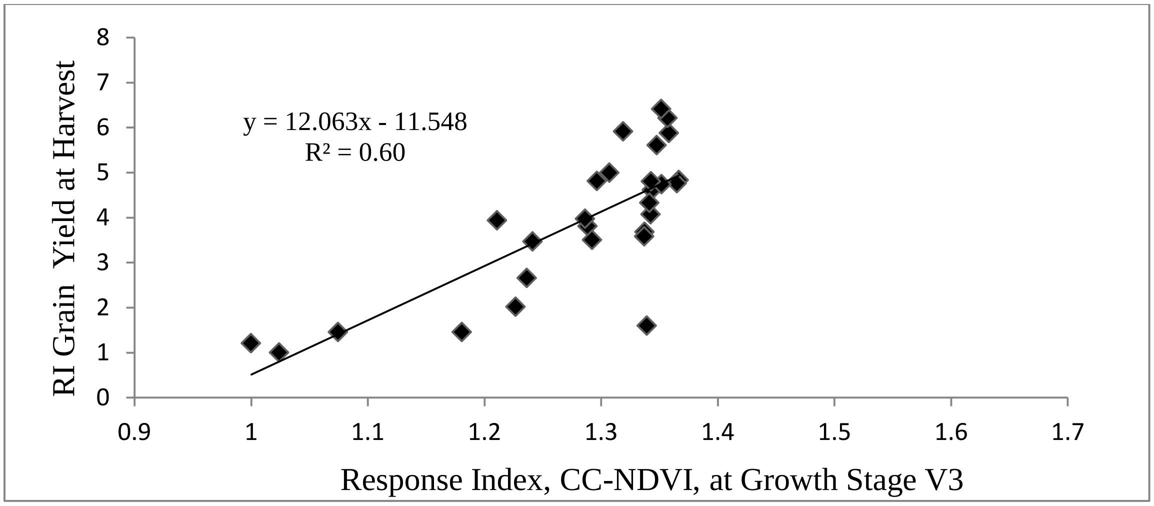


Figure 20. Relationship between the Response Index (RI) grain yield and RI Crop Circle-Normalized Difference Vegetation Index (NDVI) at the V3 stage.

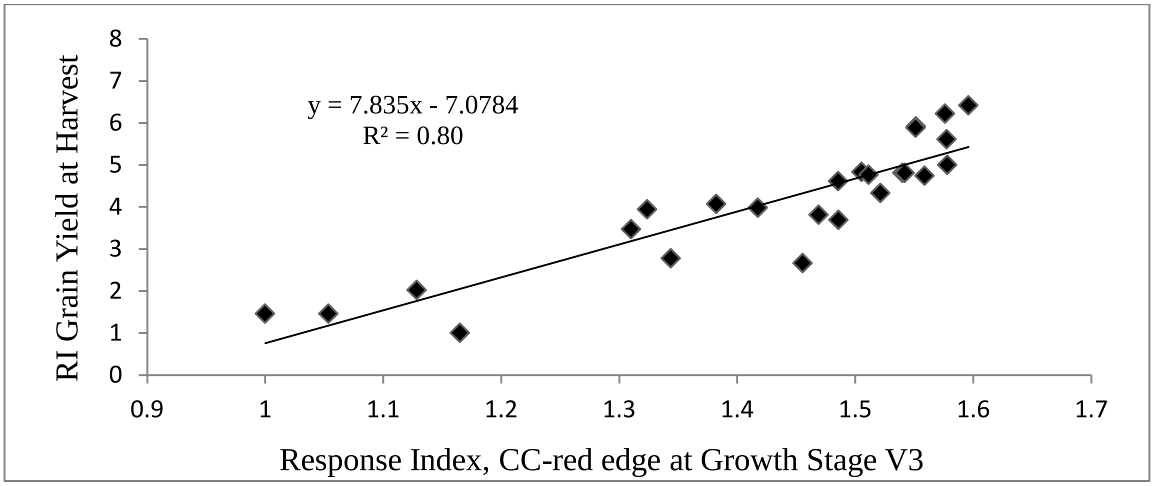


Figure 21. Relationship between the Response Index (RI) grain yield and RI Crop Circle-red edge at the V3 stage.

The Response Index (RI) is a measure of the expected yield response to additional nitrogen fertilizer. It is used to estimate the amount of supplemental N needed. N recommendations based in RI, using only the sensor readings as a response ratio and avoiding yield response as a factor in the equation, can provide a better relation to know the additional N fertilizer that is needed to maximize yield potential in a given season. A delta N time is used as a predictable NUE in the target area compared to the reference area. A value of 1means that no additional N would be required. Perhaps, this can be an index more suitable for Arkansas weather conditions, particularly with variability in the heat unit accumulation observed at each location and other agronomic factors. The results show that RI at the "optimum" sensing time (40 DAP) for the GS reduces the relationship based in R^2 alone (Figure 19) in contrast with the CC NDVI that maintains (Figure 20) and improves this relationship in the red edge wavelength. These results match the INSEY index with similar values based on R^2, and confirm the ability of red edge NDVI to produce a good relationship with an $R^2= 0.80$ (Figure 21). The data suggest that RI based on CC-red edge NDVI still provides useful information even beyond 50 DAP, contrary to CC and GS-NDVI based RI. The CC-red edge index is a better predictor of N response and yield potential for grain sorghum than CC and GS-NDVI, and can potentially increase nitrogen use efficiency.

Sensor comparison and wavelengths (NDVI, red edge and CCM)

There are studies that have evaluated the performance of several of the commercially available active sensors such GS and CC in cereal crops across all the vegetation stages (Erdle et al., 2011; Solari et al., 2008). These sensors provide different values, even when using the same indexes and sensing time as reported in Figure 6, 7 and 8. In 2013, we evaluated both sensors, side by side, across different locations for both, NDVI and red edge indices. Figure 22 shows a 1:1 relationship between CC-NDVI and GS-NDVI across growth stages and locations. The graph shows that values for GS-NDVI tend to be higher than those of CC-NDVI, because of the difference in the red wavelength each sensor uses. GreenSeeker senses at 650 nm, while CC senses at 670 nm. However, there is a good level of agreement between both sensors, based in a linear relationship with a $R^2=0.74$. It seems that at early growth stages and low N rates values from both sensors differ significantly.

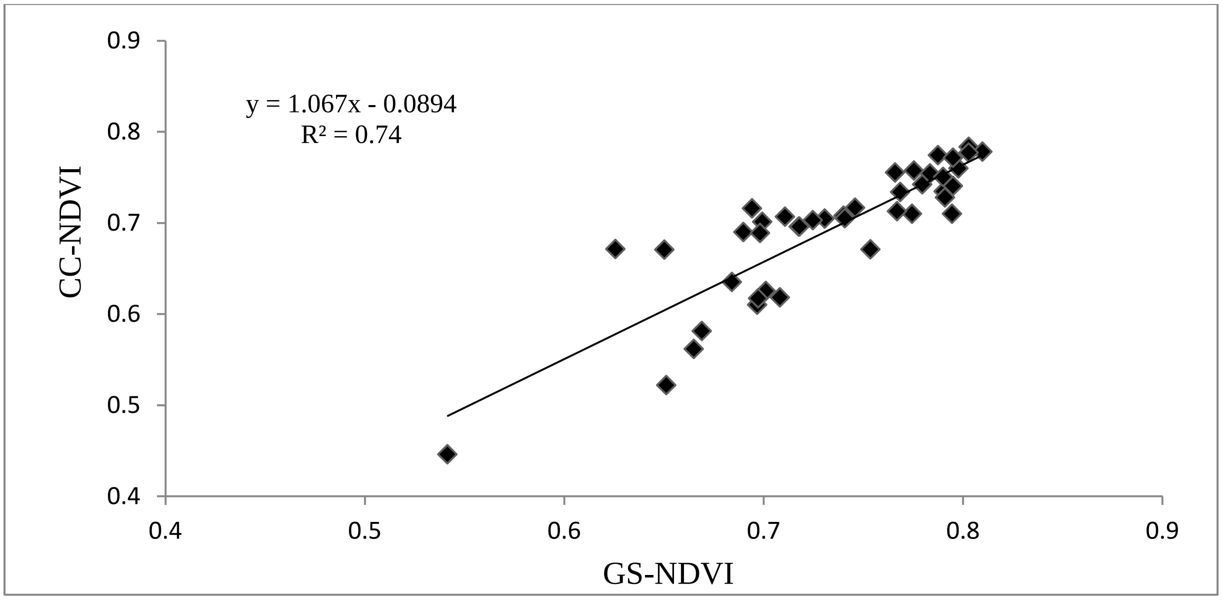


Figure 22. Relationship between average Crop Circle-Normalized Difference Vegetation Index (NDVI) and Crop Circle-red edge index collected across SE AR , Central AR and NE AR sensing dates and locations in 2013.

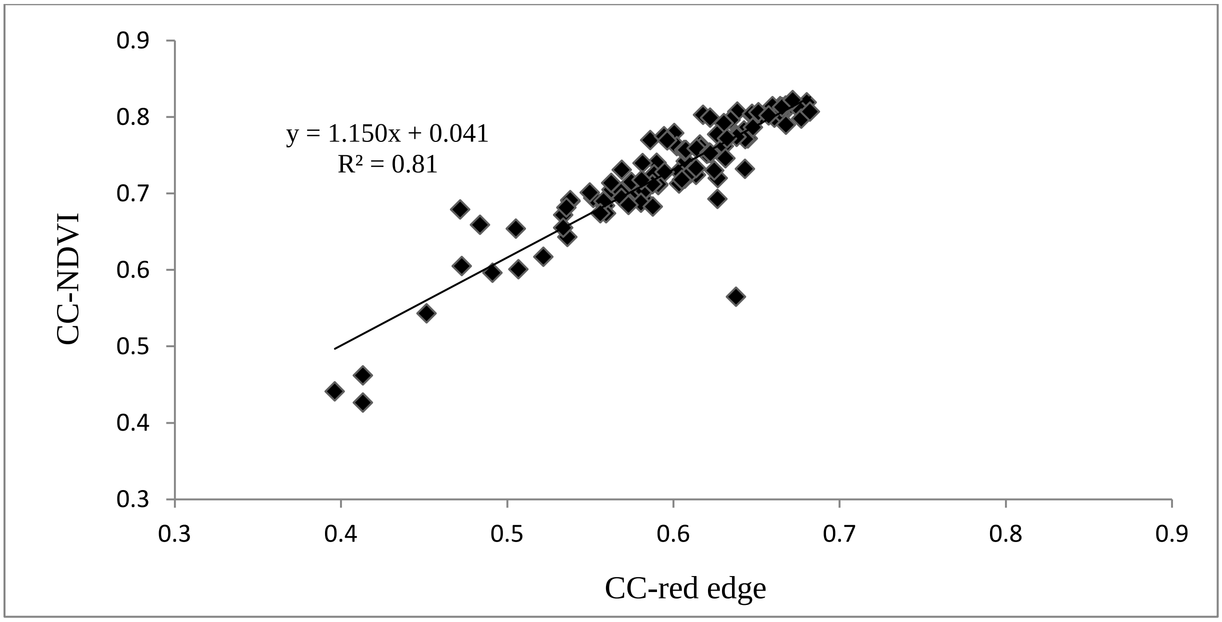


Figure 23. Relationship between average Crop Circle-Normalized-Difference Vegetation Index (NDVI) and Crop Circle-red edge index collected across SE AR, Central AR and NE AR sensing dates and locations in 2013.

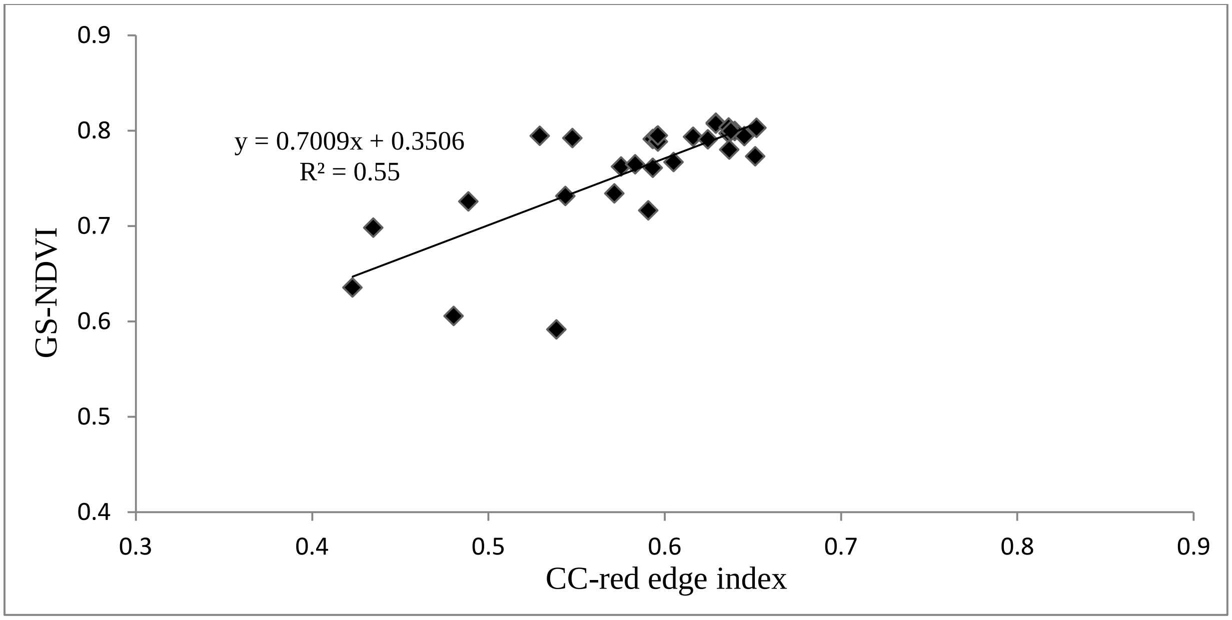


Figure 24. Relationship between average GreenSeeker-Normalized Difference Vegetation Index (NDVI) and Crop Circle-red edge index collected across SE AR , Central AR and NE AR sensing dates and location in 2013.

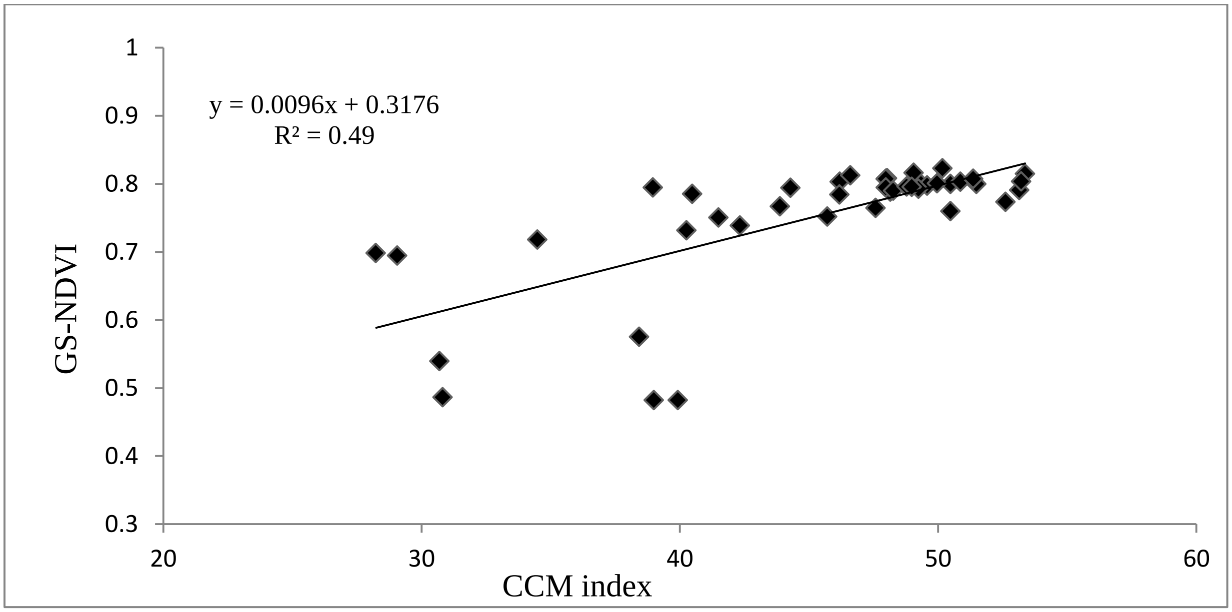


Figure 25. Relationship between average GreenSeeker-Normalized Difference Vegetation Index (NDVI) and chlorophyll content meter (CCM) index collected across SE AR, Central AR and NE AR sensing dates and location in 2013.

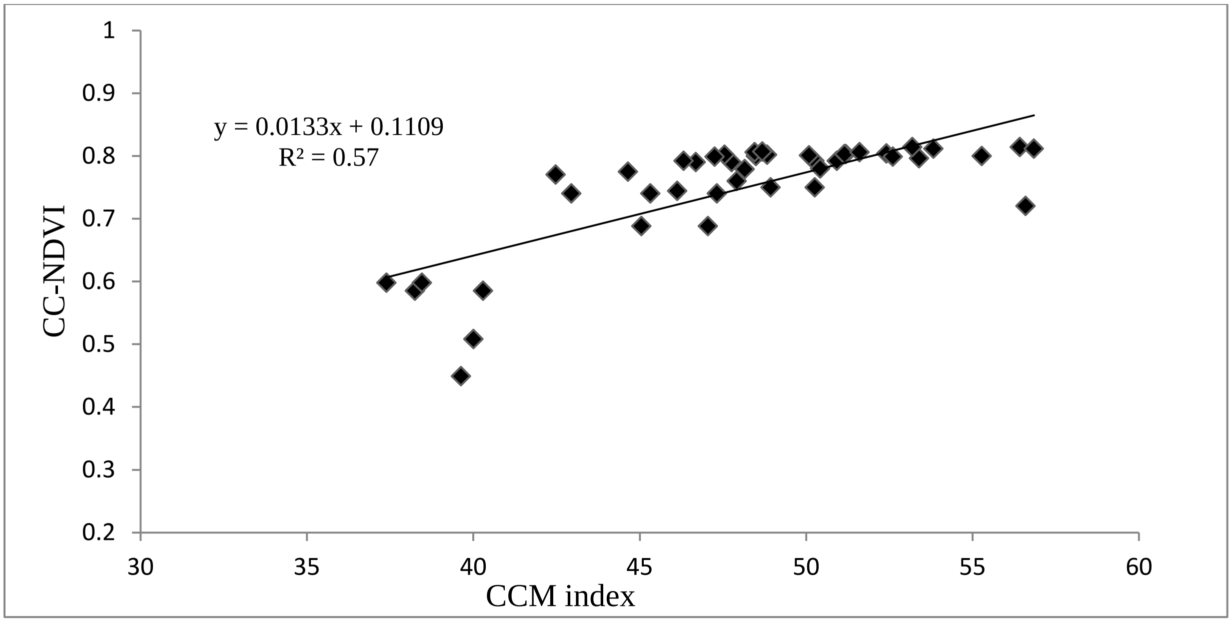


Figure 26. Relationship between average Crop Circle-Normalized Difference Vegetation Index (NDVI) and chlorophyll content meter (CCM) index collected across all sensing dates and location in 2013.

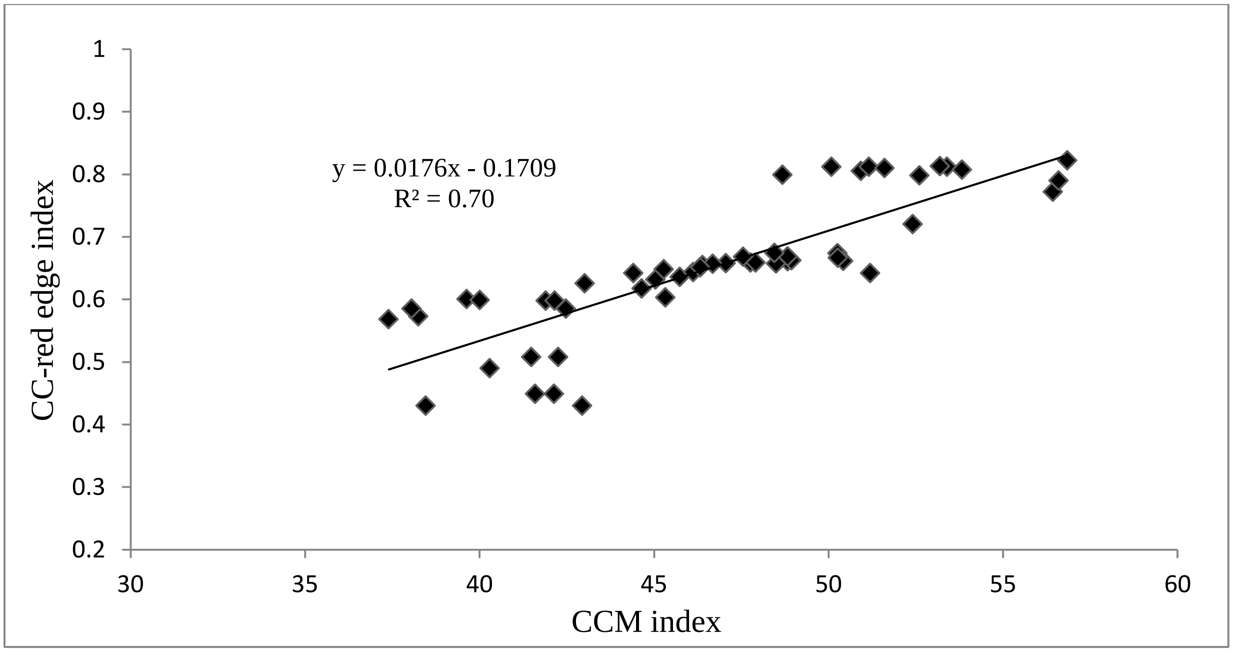


Figure 27. Relationship between average Crop Circle-red edge index and chlorophyll content meter (CCM) index collected across all sensing dates and locations in 2013.

That relationship shift gradually with increasing N rates and growth stages. The NDVI readings for CC-NDVI and CC-red edge index are shown in Figure 23. A high coefficient of determination ($R^2=0.81$) was observed even at earlier growth stages and lower N rates than those shown in Figure 22. A strong correlation was observed with NDVI values of 0.74 or higher when comparing GS-NDVI and CC-NDVI index. When CC-NDVI and CC-red edge index were compared a R^2 of 0.5 or higher was observed (Figure 24). The reason for this improvement in correlation is a later saturation and smoother line of NDVI readings from CC compared to GS (Figure 13). This ability may be based on the narrow difference in the wavelength of visible and red edge spectrum. These characteristics have important implications for future algorithm development. It is reasonable to consider the development of separate algorithms to improve accuracy of in-season N recommendations.

The CCM index was also correlated with GS and CC indices using a 1:1 relationship of the sensor readings (Figure 25, 26 & 27). Highest correlation was observed between CCM readings and red edge NDVI, with a coefficient of determination of $R^2=0.70$ based on a linear regression model, regardless of N rate and growth stage. However, when comparing CCM index with GS and CC NDVI a poor correlation was observed, particularly with GS-NDVI due to the early saturation of the sensor (44 DAP) and more vigorous growth (SE AR and RREC). Figure 25 shows poor correlation for the low N rates treatments during the season, with the relationship improving with increasing N rates.

Potential Application of the CCM

The CCM index produces different ranges of values across vegetative stages in grain sorghum. The range in CCM index during these studies was 28 to 61, and are similar to those reported in grain sorghum in previous studies (Yamamoto et al., 2002). Figure 28 shows the regression model explaining the relationship between N rates and CCM index collected in NE AR during each of the sensing dates. Table 8 shows simple regression models associated with Figure 28 for each of the sensing dates for NE AR. Data obtained with CCM validates the previous findings that show an optimum sensing windows at 38-44 DAP with coefficient of determinations of 0.72 and 0.83, respectively. Even at 31 DAP, there was a good correlation between N rate and CCM index (R^2=0.68). The CCM index show a strong relationship with RY earlier in the season (5 leaf stage) than similar relationship based on GS and CC NDVI values (Fig. 29 & Table 9). This effect is expected as CCM values represent direct single leaf readings, contrary to the GS and CC which provide an estimate of the average canopy reflectance readings of the whole plot. The coefficient of determination at 31 DAP for CCM is significantly higher (0.80) (Table 9), compared to coefficients of determination for CC and GSNDVI of 0.41 and 0.45, respectively, and close to the R^2=0.71 obtained with the CC red edge (Figure 7). However, the coefficients are very similar for the models generated from readings collected within the optimum sensing window (38-44 DAP).

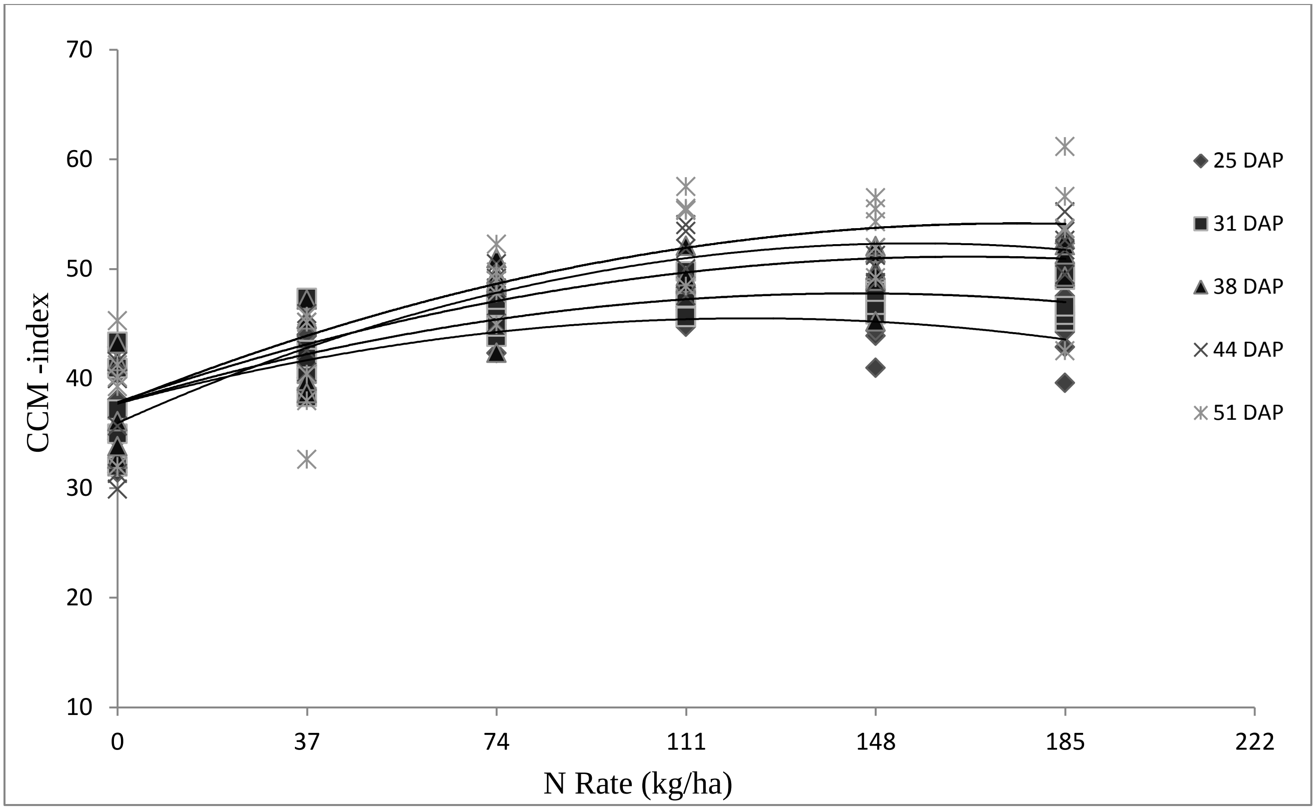


Figure 28. Relationship between chlorophyll content meter (CCM) index and nitrogen (N) rates at SE AR in 2013.

Table 8. Equations describing the relationship between chlorophyll content meter (CCM) index and nitrogen (N) rates.

Days after Planting	Equations	R squares
25 DAP	$y = 37.708+0.1261x-0.0005x^2$	0.55
31 DAP	$y = 37.747+0.1389x-0.0005x^2$	0.68
38 DAP	$y = 37.85+0.1605x-0.0005x^2$	0.72
44 DAP	$y = 35.942+0.2107x-0.0007x^2$	0.83
51 DAP	$y = 37.706+0.1874x-0.0005x^2$	0.62

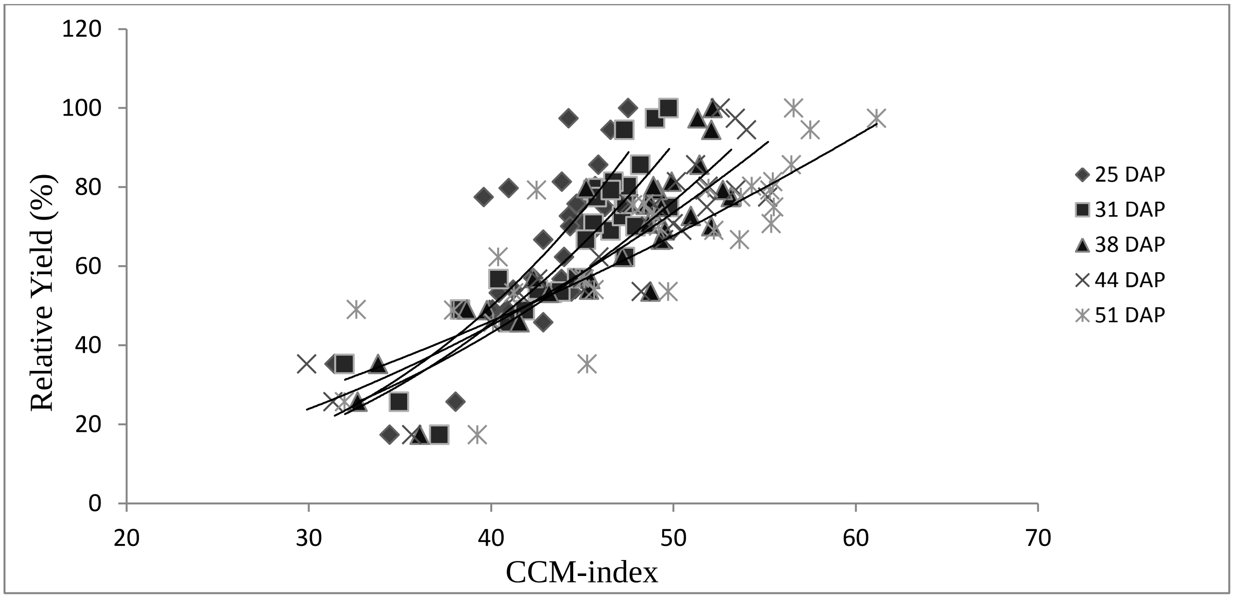
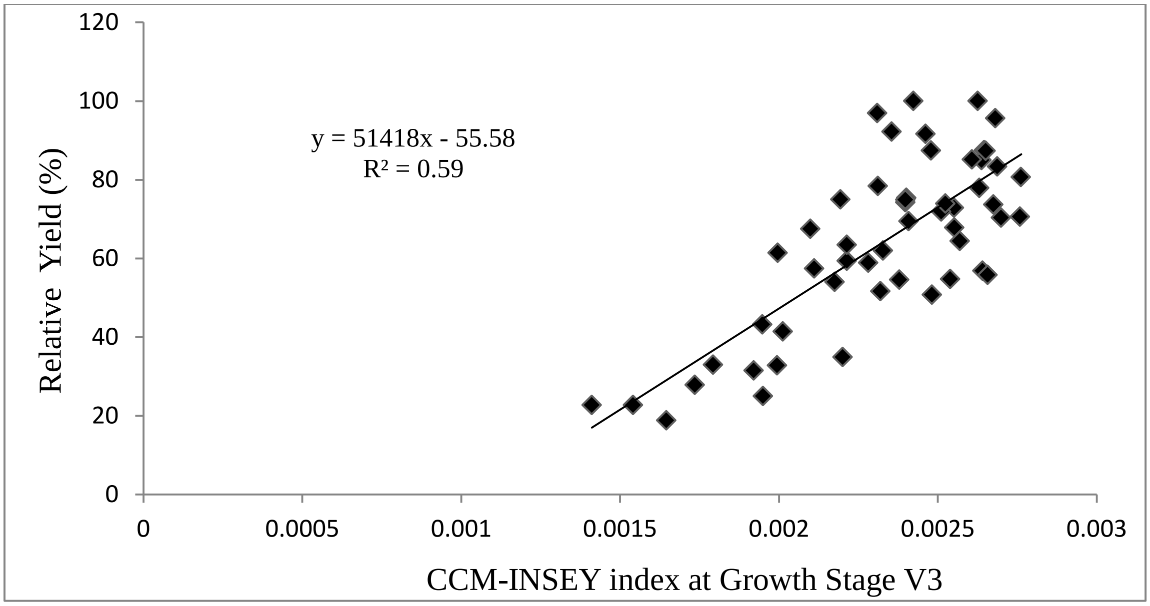


Figure 29. Relationship between chlorophyll content meter (CCM) index and relative yield in SE AR in 2013.

Table 9. Equations describing the relationship between chlorophyll content meter (CCM) index and relative grain yield.

Days after planting	**Equations**	**R squares**
25 DAP	$y = 162.77-9.7798x+0.1742x^2$	0.62
31 DAP	$y =161.42-9.2525x+0.1583x^2$	0.80
38 DAP	$y = 39.882-1.3435x+0.0198x^2$	0.78
44 DAP	$y = 29.682-1.6321x+0.0504x^2$	0.84
51 DAP	$y = 24.193-0.5515x+0.0287x^2$	0.67



30. Relationship between the grain yield and chlorophyll content meter (CCM)-In season estimated yield (INSEY) index at the V3 stage.

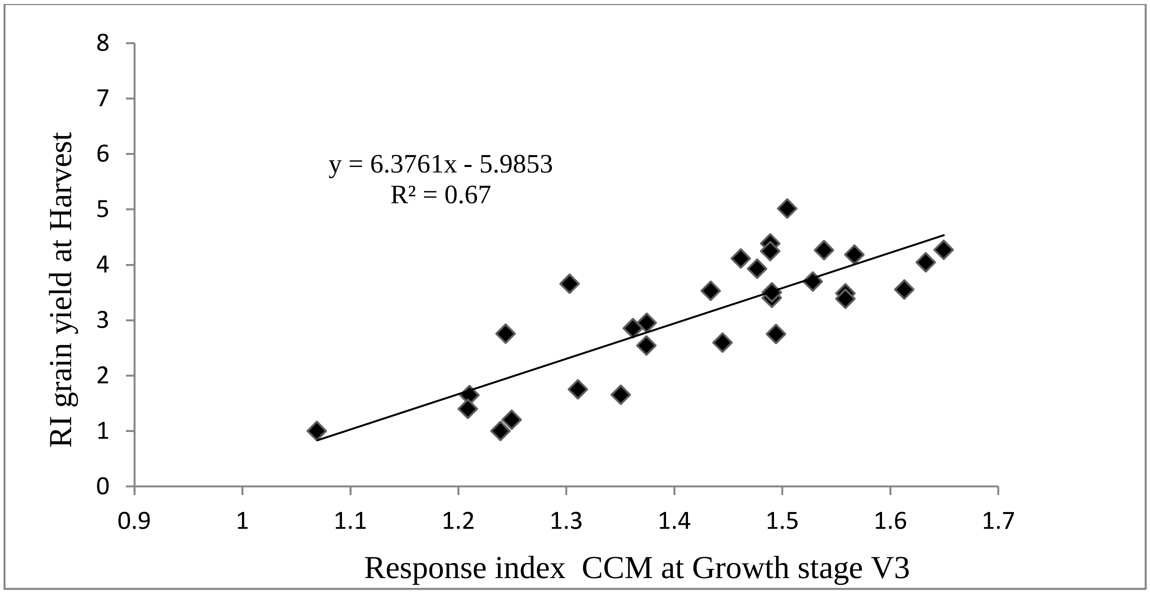


Figure 31. Relationship between the Response index (RI) grain yield and Response index chlorophyll content meter (CCM) at the V3 stage.

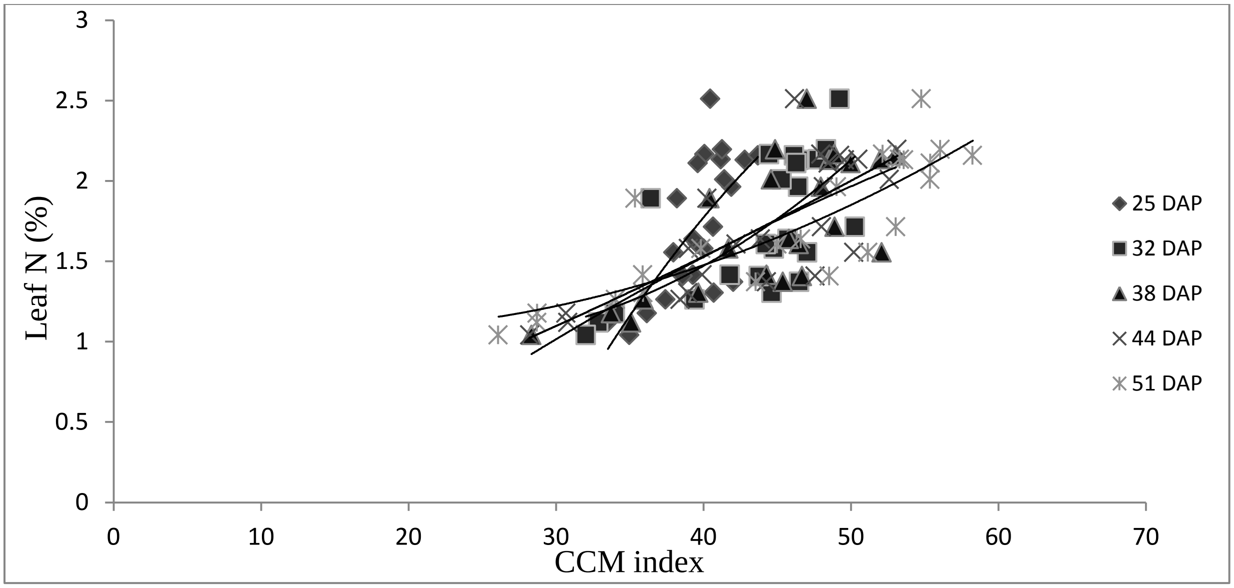


Figure 32. Relationship between chlorophyll content meter (CCM) index and leaf nitrogen (N) percent in NE AR in 2013.

Table 10. Equations describing the relationship between chlorophyll content meter (CCM) index and leaf nitrogen (N) percent in NE AR in 2013.

Days after planting	**Equations**	**R squares**
25 DAP	$y = -16.129+24.462x-5.9749x^2$	0.46
31 DAP	$y = -4.701+50.086x-12.094x^2$	0.58
38 DAP	$y = -23.467+71.05x-17.407x^2$	0.70
44 DAP	$y = -27.161+72.272x-17.096x^2$	0.75
51 DAP	$y = -12.34+54.27x-11.647x^2$	0.76

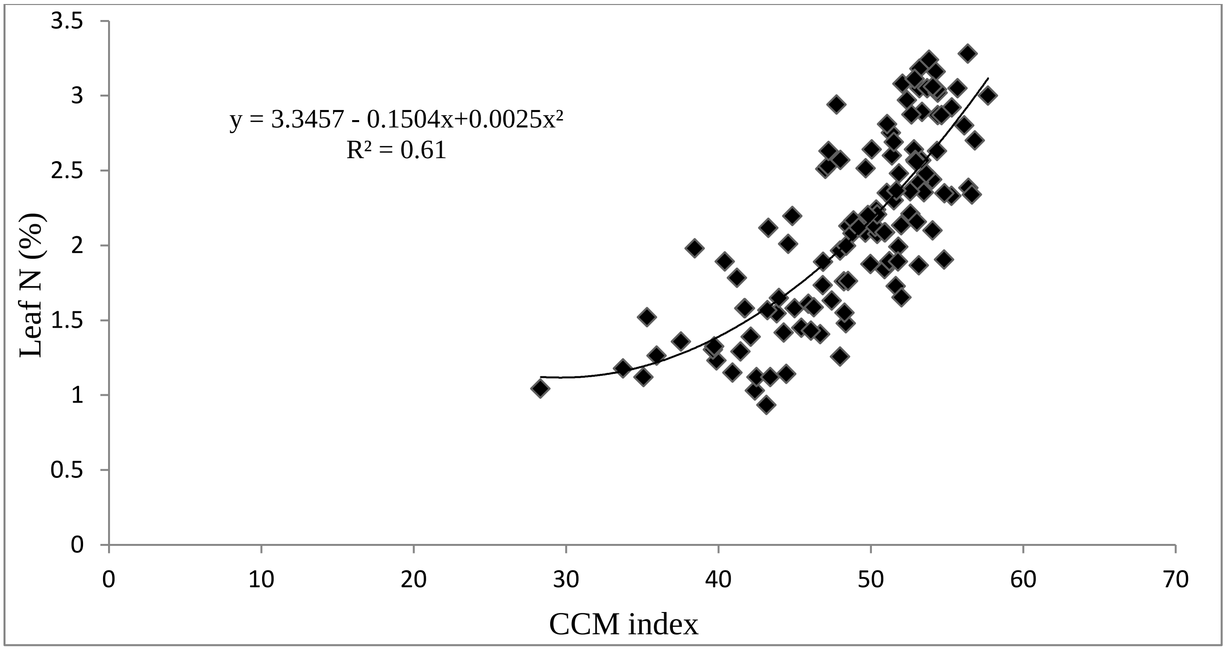


Figure 33. Relationship between chlorophyll content meter (CCM) index and leaf nitrogen (N) percent at 44 DAP (V3 Stage) across all locations in 2012 and 2013 (except SE AR).

Figure 32 shows the regression model for the relationship between Leaf N (%) and CCM index for NE AR at different growth stages during 2013. The fitness of the model improves with increasing growth stage, and remains constant after 44 DAP (Table 10).

Figure 33 shows leaf N (%) across locations, except SE AR, at the "optimum" sensing stage. Multiple regression models were fitted with CCM index as independent variable and percent leaf N as the dependent variable. The resulting regression equation was $y = 3.3457 - 0.1504x+0.0025x^2$. The fitted regression model is able to explain 61% of the total variation in N leaf (%).

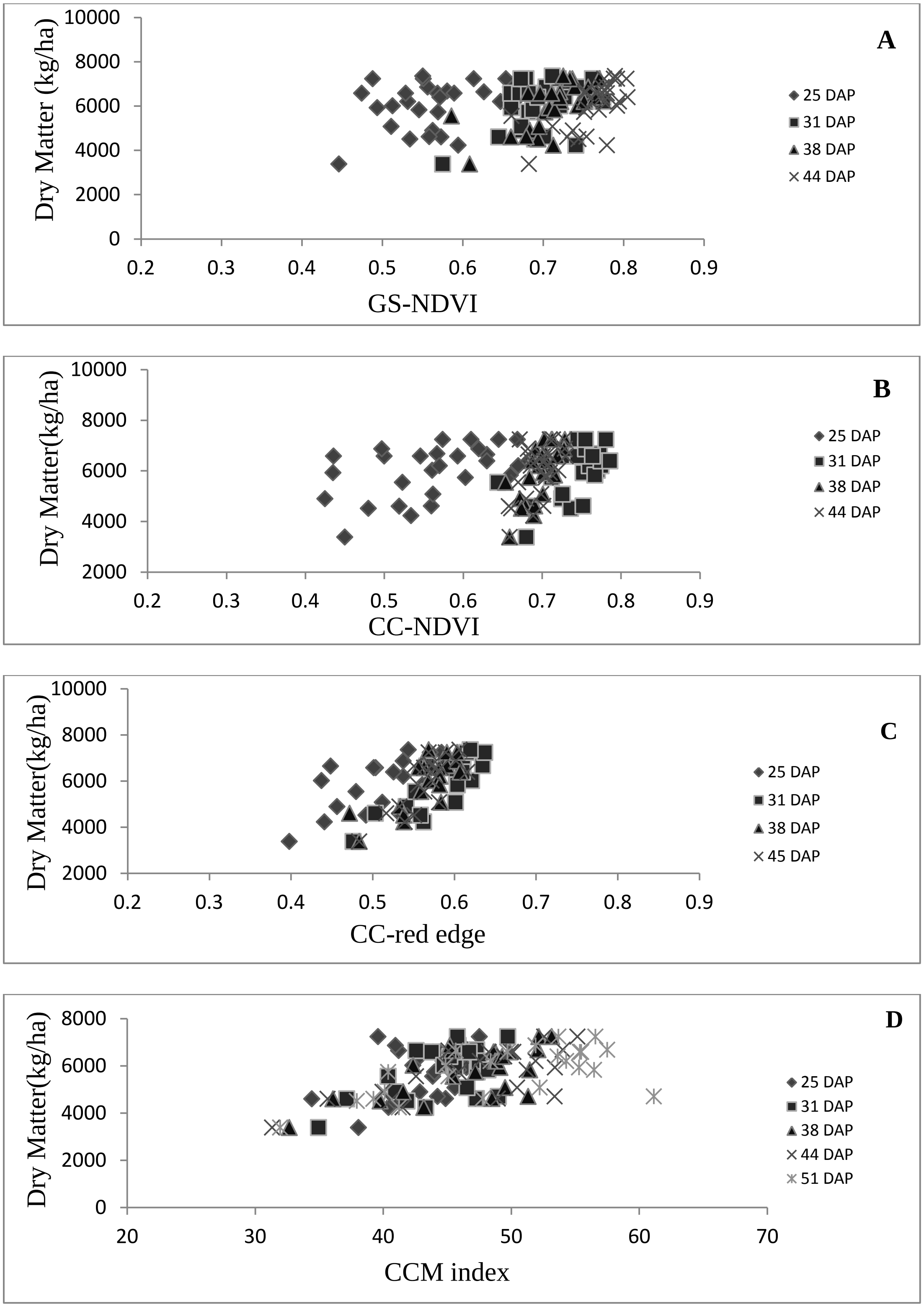


Figure 34. Relationship between GreenSeeker-Normalized Difference Vegetation Index (NDVI) (**A**), Crop Circle NDVI (**B**), Crop Circle red edge index (**C**), chlorophyll content meter index (**D**) and dry matter at all vegetative stages at NE AR-2013.

Table 11. Equations describing the relationship between sensors (GreenSeeker, Crop Circle and chlorophyll content meter) indices and dry matter at NE-AR in 2013.

Sensor	Days After Planting	Equations	R Squares
GS-NDVI			
	25 DAP	y = 6115.1x + 2615	0.11
	31 DAP	y = 11601x – 2038	0.20
	38 DAP	y = 16230x - 5548.5	0.47
	44 DAP	y = 20021x - 9223.2	0.41
CC-NDVI			
	25 DAP	y = 6644.8x + 2255.6	0.24
	31 DAP	y = 17409x - 6910.8	0.33
	38 DAP	y = 38417x – 20788	0.47
	44 DAP	y = 27342x – 13084	0.33
CC-red edge			
	25 DAP	y= 13715-1089.1	0.43
	31 DAP	y= 28602x-10248	0.63
	38 DAP	y= 21769x-6834.3	0.68
	44 DAP	y=23893x -7541.1	0.59
CCM-index			
	25 DAP	y = 141.55x - 354.7	0.17
	31 DAP	y = 160.13x - 1412.9	0.32
	38 DAP	y = 136.63x - 620.28	0.47
	44 DAP	y = 120.86x + 36.722	0.51
	51 DAP	y=87.916x+1450.6	0.41

The relationship, as described by the linear regression model, between dry matter and NDVI for GS and CC did not explain well the variability across sites and dates (Fig. 34 (A & B)) (Table 11). Direct comparison was also performed with the CCM sensor with similar results (Fig. 34 D). There was better agreement when using CC red edge (Fig. 34 C), particularly at 38 DAP (Table 11). The coefficients of determination at 38 DAP were 0.47, 0.47, 0.68 and 0.47 for GS- NDVI, CC- NDVI, CC-red edge index, and CCM-index respectively. Regardless of sensor used, the relationship decreases after 38 DAP. Previous research in grain sorghum has shown that once the crop has accumulated about 5000 kg/ha of dry matter this relationship is weak (Gitelson et al., 1996; Tucker, 2009). According to data obtained with these studies, the sensing time which a best correlates with dry matter production is 38 DAP corresponding to growth stage V3.

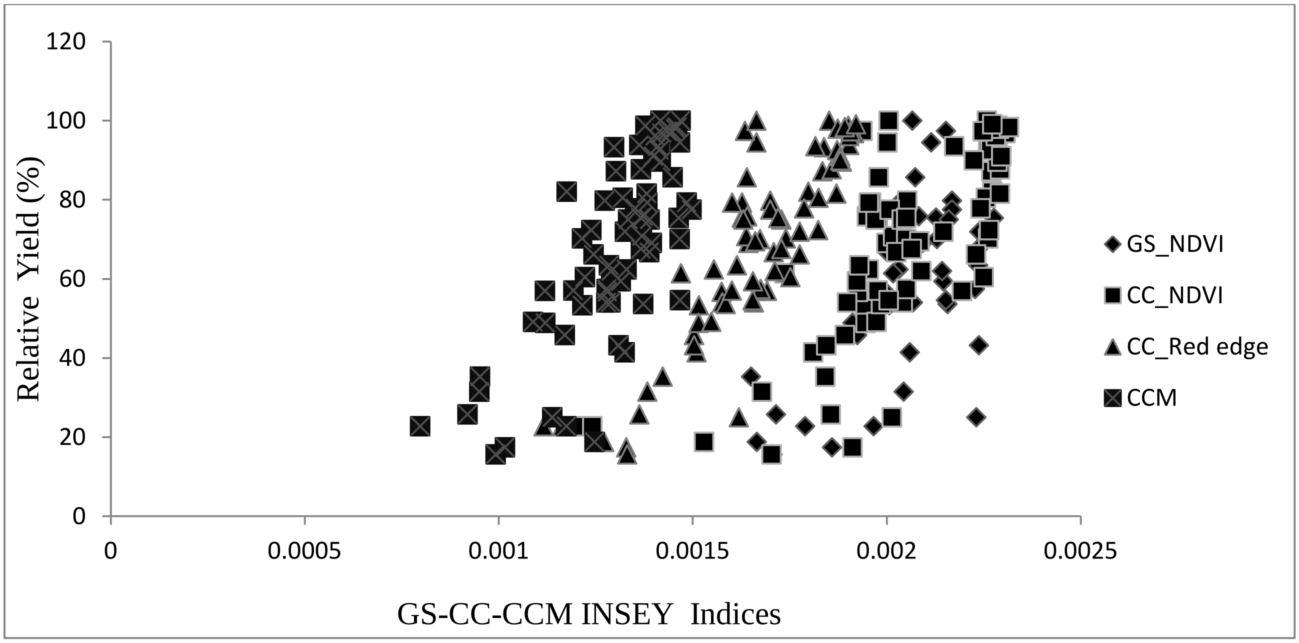


Figure 35. Relationship between sensors (GreenSeeker, Crop Circle and chlorophyll content meter) In season estimated yield (INSEY) indices and relative grain yield at NE AR, SE AR and Central AR 2013.

Table 12. Equations describing the relationship between sensors GreenSeeker, Crop Circle and chlorophyll content meter) In season estimated yield (INSEY) indices and relative grain yield at NE AR, SE AR and Central AR.

SENSOR	**Equations**	**R square**
GS-NDVI	$y=1E+09x^{3.4493}$	0.41
CC-NDVI	$y=4E+07x^{2.6917}$	0.57
CC-red edge	$y=2E+09x^{3.3243}$	0.78
CCM index	$y=7E+09x^{2.7881}$	0.61

Figure 35, shows the relationship between GS and CC indices and relative yield under the concept of INSEY, with the figure also including the CCM index as well. As expected, the coefficient of determination for the INSEY model that includes all site-years was lower than for individually (site-year) regressed data (Appendix 1-6). This loss in predictive capability is of lower magnitude when using red edge. For example, data from these studies shows that when GS-INSEY across locations was used, it explained 30 % less of the variability compared to the coefficient obtained when averaging the coefficients for individual years and locations (Appendices 1-6). However, the drop in accuracy was only half (15%), when the CC-red edge index was compared under similar conditions. The ability of the CCM index model to explain the observed variability also decreased when the data was combined, with such decrease being around 20 %, when compared to individual sites. The reason for this observed decrease in model accuracy, when the data was pooled across locations (Table 12), is probably due in part to more vigorous plants observed at selected locations, independent of N treatment.

Residual nitrate-N values for the first 45 cm across locations and years (Appendices 7 & 8) do not show a trend for higher levels at SE AR and RREC, however, more vigorous plants were observed at such locations (Appendix 6). Perhaps a significantly higher N mineralization rate at such locations is the reason for the observed difference in plant vigor. This has important implications for algorithm development. Estimates of N mineralization at a given location should be included as reported by other researchers (Tucker, 2009).The CC-red edge index appears to be less sensitive to this variability introduced by increased plant vigor at a particular location.

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Appendix 1. Regression equations describing the relationship between sensors (GreenSeeker and chlorophyll content meter) indices and relative grain yield at the Central-AR location during 2012.

SENSOR	Days After planting	Equations	R squares
GS-NDVI			
	23 DAP	$y = 24.331- 64.528x + 44.013x^2$	0.16
	31 DAP	$y = - 1.0561+ 6.6729x-5.8869x^2$	0.28
	36 DAP	$y = 0.5043 - 3.1956x +4.6602x^2$	0.47
	43 DAP	$y = 73.859-186.5x +118.57x^2$	0.64
	50 DAP	$y = - 1.8328+ 4.7687x -1.6376x^2$	0.40
CCM-index			
	23 DAP	$y = - 1.5439+ 0.0808x -0.0006x^2$	0.31
	31 DAP	$y = - 11.682+ 0.4739x -0.0045x^2$	0.52
	36 DAP	$y = - 1.1267+ 0.0462x -0.0002x^2$	0.54
	43 DAP	$y = - 1.5162+ 0.0617x -0.0003x^2$	0.55
	50 DAP	$y = - 0.58+ 0.0276x+ 6E-07x^2$	0.53

Appendix 2. Regression equations describing the relationship between sensors (GreenSeeker and chlorophyll content meter) indices and relative grain yield at the NE-AR location during 2012.

SENSOR	Days After planting	Equations	R squares
GS-NDVI			
	25 DAP	$y = -0.6447 + 4.4294x - 3.7751x^2$	0.05
	31 DAP	$y = -9.3231 + 29.965x - 22.272x^2$	0.29
	38 DAP	$y = 15.177 - 45.119x + 33.97x^2$	0.65
	45 DAP	$y = -17.853 + 38.235x - 18.905x^2$	0.74
	52 DAP	$y = -13.878 + 30.56x - 15.436x^2$	0.58
CCM-index			
	25 DAP	$y = 37.817 + 17.157x - 6.5137x^2$	0.48
	31 DAP	$y = 27.604 + 46.644x - 25.837x^2$	0.78
	38 DAP	$y = 28.428 + 49.863x - 24.293x^2$	0.81
	45 DAP	$y = 21.529 + 68.013x - 35.286x^2$	0.84
	52 DAP	$y = 22.162 + 69.597x - 39.289x^2$	0.73

Appendix 3. Regression equations describing the relationship between sensors (GreenSeeker, Crop Circle and chlorophyll content meter) indices and relative grain yield at the Central-AR location during 2013.

SENSOR	Days After planting	Equations	R squares
GS-NDVI			
	23 DAP	$y =- 13.818+ 32.857x +18.295x^2$	0.21
	31 DAP	$y = 1.9313 - 5.6699x +5.9736x^2$	0.37
	36 DAP	$y = 15.769x^2 - 19.364x + 6.4831$	0.64
	43 DAP	$y = 24.998- 69.226x +48.931x^2$	0.46
	50 DAP	$y = 18.693- 49.963x + 34.4x^2$	0.31
CC-NDVI			
	25 DAP	$y = 0.3544+ 3.1953x -6.4903x^2$	0.05
	31 DAP	$y = 6.9691- 20.694x +16.663x^2$	0.39
	38 DAP	$y = 11.289- 33.186x +25.441x^2$	0.48
	44 DAP	$y = 27.875- 76.541x +53.613x^2$	0.54
CC- red edge			
	25 DAP	$y = 2.86- 15.065x + 26.504x^2$	0.06
	31 DAP	$y = 0.9571- 4.8515x + 7.2488x^2$	0.59
	38 DAP	$y= 7.5564- 27.705x +27.283x^2$	0.60
	44 DAP	$y = 7.1898- 25.835x + +24.952x^2$	0.57
CCM-index			
	23 DAP	$y = 3.1597- 0.1599x +0.0024x^2$	0.40
	31DAP	$y= 0.4847- 0.0194x +0.0005x^2$	0.56
	38 DAP	$y= 2.9547- 0.1252x +0.0016x^2$	0.58
	44 DAP	$y = 3.6935- 0.1581x+0.002x^2$	0.75
	52 DAP	$y =1.2411- 0.0531x + +0.0009x^2$	0.57

Appendix 4. Regression equations describing the relationship between sensors (GreenSeeker, Crop Circle and chlorophyll content meter) indices and relative grain yield at the SE-AR location during 2013.

SENSOR	Days After planting	Equations	R squares
GS-NDVI			
	23 DAP	$y = 0.461 - 0.3201x + 1.2243x^2$	0.13
	31 DAP	$y = -0.57 + 1.5109x + 0.3993x^2$	0.32
	38 DAP	$y = -2.3231 + 5.0522x - 1.2153x^2$	0.54
	43 DAP	$y = 11.916 - 35.751x + 27.48x^2$	0.70
	50 DAP	$y = -2.458 + 6.0522x - 1.5653x^2$	0.44
CC-NDVI			
	23 DAP	$y = -70.438 + 200.54x - 141.24x^2$	0.33
	32 DAP	$y = -53.678 + 150.74x - 104.34x^2$	0.38
	38 DAP	$y = 11.362 - 34.075x + 26.431x^2$	0.54
	45 DAP	$y = 1.9423 - 6.3831x + 7.1853x^2$	0.40
CC- red edge			
	23 DAP	$y = 1.9219 - 6.3831x + 6.297x^2$	0.32
	32 DAP	$y=1.9548 - 7.58x + 9.9304x^2$	0.39
	38 DAP	$y = -2.3264 + 5.9695x - 1.2x^2$	0.60
	45 DAP	$y = -5.5796 + 17.517x - 11.4x^2$	0.72
CCM-index			
	23 DAP	$y = 28.417 + 33.277x - 15.736x^2$	0.65
	31 DAP	$y = 27.425 + 35.401x - 13.281x^2$	0.79
	38 DAP	$y = 23.204 + 49.849x - 20.212x^2$	0.81
	43 DAP	$y = 21.03 + 52.01x - 17.97x^2$	0.85
	50 DAP	$y = 132.722 + 12.503x + 5.34x^2$	0.67

Appendix 5. Regression equations describing the relationship between sensors (GreenSeeker, Crop Circle and chlorophyll content meter) indices and relative grain yield at the RREC location during 2013.

SENSOR	Days After planting	Equations	R squares
GS -NDVI			
	25 DAP	$y = 1.7986- 3.3679x +2.9922x^2$	0.09
	31 DAP	$y = - 42.814+ 120.22x-82.646x^2$	0.14
	38 DAP	$y = 15.635- 44.014x +31.635x^2$	0.66
	45 DAP	$y = 33.223- 87.632x +58.455x^2$	0.61
	51 DAP	$y= - 1.2819+ 1.0907x +2.0236x^2$	0.29
CC-NDVI			
	25 DAP	$y = 2.6683- 6.5548x+3.1492x^2$	0.23
	31 DAP	$y= - 0.0864+ 2.2603x-1.1831x^2$	0.29
	38 DAP	$y = 22.4-60.658x_+ 42.247x^2$	0.63
	45 DAP	$y = 43.041-111.67x +73.629x^2$	0.32
CC-red edge			
	25 DAP	$y = -5.4783+ 17.726x -12.163x^2$	0.22
	31 DAP	$y = -5.1231+ 20.91x -18.122x^2$	0.54
	38 DAP	$y = 4.1533 - 14.986x +15.202x^2$	0.75
	45 DAP	$y = 2.0856 - 8.1562x + 9.7159x^2$	0.81
CCM-index			
	25 DAP	$y = -2.2797+ 0.1141x-0.001x^2$	0.13
	31 DAP	$y = 0.0362+ 0.0055x+0.0003x^2$	0.32
	38 DAP	$y = 2.3062- 0.095x +0.0014x^2$	0.71
	45 DAP	$y = -1.8449+ 0.0978x -0.0009x^2$	0.82
	51 DAP	$y =-2.9866+ 0.1415x -0.0013x^2$	0.66

Appendix 6. Regression equations describing the relationship between sensors (GreenSeeker, Crop Circle and chlorophyll content meter) indexes and nitrogen (N) leaf percent at the RREC location during 2013.

SENSOR	Days After planting	Equations	R squares
GS-NDVI			
	25 DAP	$y = -8.0271 + 48.994x - 60.81x^2$	0.09
	31 DAP	$y = 12.833 - 78.14x + 134.59x^2$	0.14
	38 DAP	$y = -1.4758 + 5.5464x - 1.1174x^2$	0.44
	45 DAP	$y = 29.234 - 81.958x + 59.762x^2$	0.63
	51 DAP	$y = 12.2 - 35.205x + 28.005x^2$	0.47
CC -NDVI			
	25 DAP	$y = 3.6196 - 9.3059x + 9.488x^2$	0.28
	31 DAP	$y = 10.183 - 30.831x + 26.164x^2$	0.50
	38 DAP	$y = 10.874 - 33.432x + 28.436x^2$	0.72
	45 DAP	$y = 5.9001x^2 - 4.1789x + 1.8012$	0.52
CC-red edge			
	25 DAP	$y = 1.5413 - 4.6941x + 9.706x^2$	0.46
	31 DAP	$y = 2.7326 - 8.829x + 12.328x^2$	0.57
	38 DAP	$y = 7.1427 - 26.319x + 28.669x^2$	0.77
	45 DAP	$y = 4.128 - 15.1x + 18.791x^2$	0.65
CCM-index			
	25 DAP	$y = 16.129 + 24.462x - 5.9749x^2$	0.46
	31 DAP	$y = -4.701 + 50.086x - 12.094x^2$	0.58
	38 DAP	$y = -23.467 + 71.05x - 17.407x^2$	0.70
	44 DAP	$y = -27.161 + 72.272x - 17.096x^2$	0.75
	51 DAP	$y = -12.34 + 54.27x - 11.647x^2$	0.76

Appendix 7. Selected soil chemical parameters for soil samples for six nitrogen (N) in grain sorghum collected prior to planting during the 2012 season.

Loc (depth)	pH	CEC	OM (%)	NO_3-N	P	K	Mg
				mg/kg			
SE AR (15cm)	6.6	18.5	1.1	8	25	83	338
SE AR (30cm)	6.8	19.2	0.9	7	28	88	235
SE AR(45cm)	6.7	20.8	0.9	7	50	90	147
Central AR (15cm)	7.3	11.4	0.9	12	23	81	219
Central AR (30cm)	5.8	8	0.9	9	39	92	146
Central AR (45cm)	5.7	8.2	0.8	2	26	92	127
NE AR (15cm)	6.8	20.1	0.9	13	20	110	305
NE AR (30cm)	5.3	19.9	0.8	6	14	156	580
NE AR (45cm)	6.1	22.1	0.9	7	12	173	736

NO_3-N ion specific electrode; P, K, and Mg Mehlich 3 extraction; pH – 1:1 soil water ratio.

Appendix 8. Selected soil chemical parameters for soil samples for six nitrogen (N) rates in grain sorghum collected prior to planting during the 2013 season.

Loc (depth)	pH	CEC	OM (%)	NO_3-N	P	K	Mg
				mg/kg			
SE AR (30cm)	5.3	19	0.9	6	14	152	531
SE AR (45cm)	4.7	30	1	8	16	179	707
Central AR (15cm)	5.9	12	0.9	12	40	90	200
Central AR (30cm)	5.4	10	0.9	4	50	88	235
Central AR (45cm)	5.3	7	0.9	4	102	90	147
NE AR (15cm)	6.5	26	1.4	16	30	160	516
NE AR (30cm)	6.6	30	1.4	10	32	82	197
NE AR (45 cm)	6.7	35	1.6	18	31	76	168
RREC (15 cm)	6.1	8	0.8	3	39	81	219
RREC (30cm)	5.5	6	0.9	11	23	92	146
RREC (45 cm)	5.6	6	0.8	18	26	92	127

NO_3-N ion specific electrode; P, K, and Mg Mehlich 3 extraction; pH – 1:1 soil water ratio.

Appendix 9. Monthly precipitation (mm) during the 2012 and 2013 growing seasons for all the locations.

Precipitation in Millimeters (mm)

Location		April	May	June	July	August	Sept.	**Total**
	2013	141	185	17.5	70	47.5		460
Central AR	Average	127	127.5	98.5	95	65		510
	Departure	15.5	58.5	-81	-25	-17.5		-50
	2013	195	195	120	100	117.5		725
NE AR	Average	120	135	100	100	60		512.5
	Departure	77.5	60	22.5	0	60		215
	2013	152.5	142.5	52.5	47.5	40.5		435
SE AR	Average	120	127.5	95	93	62.5		495
	Departure	32.5	15	-42.5	42.5	22.5		60
	2013	167.5	107.5	37.5	20	37.5	7.5	375
RREC	Average	150	155	90	77.5	77.5	75	627
	Departure	17.5	-47.5	-56.5	57.5	-40	-67.5	-253
	2012	27.5	37.5	20	65	2.5		152.5
Central AR	Average	125	127.5	97.5	95	65		510
	Departure	-97.5	-90	-77.5	-30	-62.5		-360
	2012	30	105	62.5	60	30		285
NE AR	Average	120	135	100	100	60		512.5
	Departure	-90	30	-37.5	-40	-30		-227.5
	2012	75	17.5	105	65	177.5		437.5
SE AR	Average	120	127.5	95	92.5	62.5		495
	Departure	-45	-110	12.5	-27.5	115		-57.5

Appendix 10. Temperature based in Heat unit (**Hu**) with Days After Planting (**DAP**) sensing time by location in 2012and2013growing season Sampling date by location in 2012 and 2013 growing season.

Location	**Year**	**DAP**	**Date**	**Hu**
Central AR	2013	23	6/19/2013	491
Central AR	2013	31	6/29/2013	655
Central AR	2013	38	7/4/2013	760
Central AR	2013	45	7/10/2013	802
SE AR	2013	23	6/11/2013	180
SE AR	2013	31	6/17/2013	385
SE AR	2013	38	6/26/2013	535
SE AR	2013	45	6/30/2013	630
NE AR	2013	25	6/20/2013	311
NE AR	2013	31	6/27/2013	439
NE AR	2013	38	7/3/2013	557
NE AR	2013	45	7/8/2013	631
NE AR	2013	52	7/16/2013	768
RREC	2013	24	6/12/2013	370
RREC	2013	31	6/18/2013	490
RREC	2013	38	6/28/2013	672
RREC	2013	46	7/8/2013	758
Central AR	2012	23	5/21/2012	267
Central AR	2012	31	5/29/2012	389
Central AR	2012	36	6/4/2012	473
Central AR	2012	43	6/9/2013	541
Central AR	2012	50	6/15/2012	612
SE AR	2012	25	5/23/2012	389
SE AR	2012	31	5/30/2012	479
SE AR	2012	38	6/5/2012	575
SE AR	2012	48	6/15/2012	708
SE AR	2012	51	6/22/2012	817
NE AR	2012	24	5/30/2012	391
NE AR	2012	32	6/7/2012	499
NE AR	2012	38	6/14/2012	602
NE AR	2012	45	6/21/2012	720
NE AR	2012	52	6/28/2012	850

Appendix 11. Observed days after planting and associated growth stages for grain sorghum Pioneer 84G62 cultivar during 2012-2013.

Stages:	Name	Days After Planting (**DAP**)
	Vegetative Stages	
V0:	Emergence	4-8
V1:	Three-Leaf Stage Leaves	11-20
V2:	Five-Leaf Stage	27-30
V3:	Growing Point Differentiation	35-40
V4:	Flag Leaf Stage	49
V5:	Boot Stage	58
	Reproductive Stages	
V6:	Half-bloom	65
V7:	Soft-Dough Stage	78
	Maturity Stages	
V8:	Hard-Dough Stage	84
V9:	Physiological Maturity	90

Overall Conclusions

According to data from these studies, Ground-Based Active-optical (GBAO) crop sensors can be an effective tool to predict yield early in the growing season for grain sorghum in Arkansas. The ability of the sensors (GS, CC and CCM) to predict yield is affected, in different proportion, by the sensing date and perhaps by varying growing conditions at some locations. Early in the season (25 DAP) none of the sensors were able to produce a good correlation for yield prediction or other agronomic parameters. The reasons for this lack of relationship can be due to the fact that NDVI values are affected by soil reflection during earlier growth stages where plants cover less than 30 % of the area sensed, leaving open spaces where soil reflectance represents a portion of the NDVI values. The N uptake in grain sorghum before 21 DAP is not significant and that is reflected in limited canopy development at such crop age. After 31 DAP this relationship improves for all the sensors and indices because grain sorghum at 6 to 7 leaves has accumulated significant more biomass and readings are less affected by soil reflection. However, the CC-red edge index produces a better correlation across locations at this time, and has a better yield predictive capability than the other indices. In general, 38 DAP (V3 stage) was the optimum sensing date regardless of the sensor and index used. Readings and the resulting indices obtained at 45 DAP lost significant yield prediction capability, particularly when the GS or CC-NDVI were the indices of choice. However, when the red edge NDVI was used, its predictive capability remained relatively good (did not improve) when used at 45 DAP. This extension of the "optimum sensing window" is certainly a major advantage, especially when implementing this kind of technology in regions with variable weather patterns, logistics limitations, and to reduce conflicts with some planned cultural practices. The ability to cover more area when using this index is also a major benefit. In the case of GS and CC-NDVI, this sensing "window" is narrower or shorter. This is a result of the "saturation" in the NDVI values and the inability of the index to distinguish variations in green biomass or N status. This effect was clearly observed at SE AR and RREC, where canopy development or the overlapping of leaves occurred earlier due, perhaps, to better growing conditions. At such locations, the NDVI indices could not be correlated satisfactorily with grain yield beyond the "optimum" date (38 DAP). The CCM-index showed the best correlation with grain yield at earlier growth stages, of all the indices tested, and was not as affected by biomass accumulation as the other sensors were. The reason for the good performance of the CCM index is the fact that the sensor requires direct readings of individual plant samples. This situation eliminates the potential implications with biomass accumulation, but it requires significantly more time to acquire the data needed. The CCM index concept was developed in the 90s, and the time required to complete a task and issues with spatial variability has limited its commercial application.

All the sensors and indices distinguished, relative equal, N variability at 38 DAP that coincide with the growing point differentiation (V3) in grain sorghum, which seems to be the "optimum" sensing date. Despite the performance of all the indices at 38 DAP, only red edge index and CCM index maintain a relatively good correlation with grain yield beyond 38 DAP. It was also noted that the high CVs observed early in the season were followed by high CV’s as grain sorghum plants approached the reproductive stage. This was very consistent for all the sensors and indices.

The relative performance of each sensor and indices was evaluated, based in regression model parameters calculated for each location (NDVI) and across all locations combined (INSEY). Even thought the highest correlation observed for individual sites was produced by CC-red edge index (R^2=0.88), the R squares values for all the indices used were relatively close to each other, particularly when the variability in canopy development is higher as we observed in NE AR and Central AR. Contrary to the SE AR and RREC sites, where the variability was lower and the sensors readings and resulting NDVI indices showed lower R squares compared with the red edge and CCM index. This seems to be a "huge" impact when all the sites are pooled together, where the differences on R squares between indexes increases in different proportion. When the GS-NDVI was used for each location, the decrease in the correlation coefficient was on average 75 %, compared to 41% when pooling all the data. The decrease in predictive capability was of a lower magnitude when using CC-red edge and CCM index. The "saturation" effect over the GS-NDVI and CC-NDVI is probably the main cause for this lack of ability to correlate with grain yield. GS-NDVI showed no improvements on the relationship with grain yield at growth stages beyond 38 DAP. In the case of red edge index, the transition from individual site-years to a “pooled” model resulted in less than 10% loss of predictive ability. The red edge index produced the highest correlation with grain yield with a R^2=0.76 followed by CCM index (R^2=0.61), CC-NDVI (R^2=0.56) and GS-NDVI (0.41). This should have implications when developing algorithms using different sensors and crop species, particularly those crops that produce a significant amount of biomass.

Under the conditions of this study, the CC-red edge index sensor showed better potential in the determination of supplemental nitrogen fertilization needs than the other sensors and indices tested. The CC-red edge index and CCM index are better correlated to estimate agronomic variables, especially for the estimation of final yield than GS-NDVI and CC-NDVI. Even though the correlation of N leaf content and CCM index is the highest for all the sensors, such differences are not significantly different than CC-red edge index, but are significantly different when comparing to CC and GS NDVI.

In summary, the results of these studies show that there is a good potential for the development of an algorithm to improve N efficiency in grain sorghum grown under Arkansas conditions. The traditional approach of establishing an N-rich strip and compare sensor readings at 38 DAP, with the rest of the field that has received a base rate of 40 kg N/ha pre plant seems like a reasonable approach to continue with performance evaluation under field conditions. If the growing conditions during a particular growing season do not allow for the collection of readings at 38 DAP, then the CC-red edge should be the index of choice.

The results presented in this thesis are preliminary in nature, more extensive testing need to be carried out to categorically rank the sensors and indices tested. The opportunity exists for more adapted indices, using perhaps other bands and indices that can potentially improve the correlation with final yield under canopy variability and wide range of weather conditions. The development of a grain sorghum algorithm for Arkansas conditions should include more sites, with the differences in performance observed in these studies noted and considered. Further research is needed in order to estimate the site specific performance of these sensors and to determine if sensor methods and settings need to be adjusted depending upon the crop condition.