Different Approaches for Improvement of Nitrogen Management in Alabama Corn Grain Production

by

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ABSTRACT

Nitrogen (N) fertilization management in corn (*Zea mays* L.) production requires more consideration in Alabama. This is due to high spatial variability in soil texture across the state and within fields, and to the high temporal variability of rainfall patterns among growing seasons. Remote sensing using vegetation spectral indices (VIs) can be calculated from data collected using active remote sensors, providing the ability to perform on-the-go variable N rate application and to assess in-season N rate to achieve maximum economic yield potential. Analysis of N response under different rainfall scenarios was considered in this study as an additional tool to increase nitrogen use efficiency (NUE).

The objectives of this study were to: (i) identify VIs that best correlate with field measurements of plant leaf area index (LAI) and chlorophyll (Chl) content at early corn growth stages (V6); (ii) evaluate well-correlated VIs for in-season corn yield potential predictability; and, (iii) evaluate the impact that in-season changes in rainfall have on simulated corn yield, N leaching (NL), inorganic N in the soil at maturity (IN), and nitrogen use efficiency (NUE).

The data were collected in three different regions of Alabama; at Baldwin (south AL), Macon (central AL), and Limestone (North AL) counties. A complete randomized block design (r = 5) including different combinations of N rates at planting and side-dress N was implemented during 2009 to 2012. Canonical correlation analysis was performed to evaluate which VIs were best correlated with LAI and Chl at different growth stages. In addition, VIs were evaluated for their corn yield predictability goodness.

A crop simulation study was conducted for the same experiment at two of the locations in central and north Alabama. Soil and plant measurements were collected to calibrate and validate the CSM-CERES-Maize model. Different scenarios of rainfall amount and distribution were selected based on the abundant and well distributed rain index (AWDR) calculated for 61 years. The goal for using the AWDR

index was to characterize periods during the year that were either wet or dry. Having a better understanding of corn N response under different soil and weather conditions will assist producers in better decision making concerning the N rate and application timing. The CSM-CERES-Maize model was used to simulate and assess corn yield, N leaching, inorganic N in the soil at maturity, and grain N use efficiency for each rainfall scenario.

Results from the first study indicated that VIs including the red-edge wavelength are better at assessing LAI and Chl content at early growth stages than other VIs. Furthermore, the red-edge VIs performed better for mid-season yield predictability assessment. When comparing VI models for yield potential prediction, the normalized difference red-edge vegetation index (NDRE) resulted in higher yield potential predictability than the normalized difference vegetation index (NDVI). The NDRE exhibited R^2 of 0.37, 0.42, and 0.67 at V6, V8, and V10, respectively, while the NDVI resulted in 0.26 at V6, 0.30 at V8 and 0.36 at V10 growth stage. Other VIs including the RE resulted in similar yield potential prediction as the NDRE. Although the yield potential predictability in red-edge VIs was higher than NDVI at V6, the root mean square error (RMSE) were not considerably different between NDVI and red-edge indices.

Results from model simulation for years corresponding to either rainfall scenario indicated that corn response to N fertilization changed based on the rainfall conditions and soil type (silt loam in North and loamy sand in Central Alabama). In both locations, for *scenario A*, the crop response to N rates under wet May-June years was higher than the one during dry May-June years. In Central Alabama, the yield response curve under rainfall conditions reached a plateau at 56 and 112 kg N ha^{-1} at dry and wet May-June, respectively. The North Alabama location, also under rainfall conditions, resulted in higher N response. During dry May-June years no N was needed to achieve the maximum yield, while in wet May-June years, 56 kg N ha^{-1} was sufficient to reach the plateau where yield did not significantly increase with higher N rates. Rainfall patterns for *scenario B* (wet/dry March-June and dry/wet July-August) March-June wet and July-August dry combination resulted in higher N response given that plants were under to prolonged time under wet conditions as opposed to March-June dry and July-August wet combination.

Results from this study could be used by farmers as a decision support tool to improve N management in corn under the Alabama growing conditions.

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I. LITERATURE REVIEW

Nitrogen (N) is an essential element for life. Microorganisms, plants, animals and humans use N for metabolic processes that are crucial to the life cycle. Nitrogen is the most abundant component of the atmosphere occupying 78% by volume as a nontoxic, colorless, odorless, and tasteless gas. However, N in the atmosphere is mostly in the form of dinitrogen (N_2), a form that is not available to plants. The main N source for plants is soil organic matter. Soil organic N becomes plant available (inorganic N) as microorganisms decompose soil organic matter. Plants can also uptake N through a symbiotic relationship with microorganisms. Nitrogen-fixing plants, such as legumes, make symbiotic relationships with Rhizobium sp. During symbiosis, a strong plant-microorganism association takes place and atmospheric N is fixed by microbes and provided to the plant. The plant role in this association is to provide sugars to the associated microbe.

Soil N is taken up by plants and converted into organic forms as amino acids, nucleic acids, enzymes, chloroplasts, and other vital components in the plant structure. Some N is returned to the soil after the plant senesces and the residues are decomposed into organic matter. This is a small part of the N cycle involving inorganic N present in the atmosphere and soil as well as organic N present in living organisms (Johnson et al., 2005; Porter, 2013; Wagner, 2012).

Nitrogen is the most limiting nutrient for most crops, particularly cereal crops. Sixty percent of total fertilizer applied worldwide is used in cereal crop production. The average N use efficiency (NUE) for cereal grains is approximately 33%. In corn (*Zea mays* L.) production worldwide, low NUE is associated with release of N by plant tissue (52 to 73% of the unaccounted N using ^{15}N in corn research), gaseous N losses due to denitrification (22% in no-till), urea losses on surface applications (more than 40%), excess N application due to yield potential overestimation, and excess N applications as a strategy for high yield (Raun and Johnson, 1999). However, most of these losses can be minimized by combining agronomic practices and precision agriculture technology.

Crop rotation is a practice proven to improve NUE in the southeastern US. Hubbard et al. (2013) reported higher NUE in fields that incorporated cover crops compared to those left fallow. Contrasting results indicated that incorporating residues with high carbon:N ratio (C:N) reduced NUE due to soil N immobilization (Shaffer and Ma, 2001). However, residue retention under weather and soil conditions of the Southeast (high temperature, humidity and low C content in the soil) may be a desirable practice to prevent N leaching. Under these conditions, N undergoes net immobilization and organic matter mineralization is enhanced. Through this process, plant available N is released for the following crop (Hubbard et al., 2013).

Soil N conservation can also be improved with no-tillage practices. Tillage practices aerate soils and create a more oxidative environment in which nutrients are more susceptible for mineralization. As a result, soil capacity to immobilize and conserve N is decreased under tillage practices which negatively affects NUE (Spargo et al., 2008).

Corn hybrid selection can help improve NUE. Differences between hybrids have been observed specifically with N accumulation before anthesis, showing NUE differences between hybrids (Moll, Kamprath, et al., 1982). Well-managed irrigation systems are another way to improve NUE (Pandey et al., 2000; Szeles et al., 2012). Reduced water supply during plant growth and development limit the development of stem and leaf cells, resulting in reduced crop biomass and leaf area (Szeles et al., 2012). Hence, having a crop with sufficient water supply will enhance plant growth, nutrient uptake, and yield.

Nitrogen use efficiency can also be increased by managing fertilizer timing. In-season N applications have resulted in higher NUE as compared to pre-plant N applications in several experiments (Miller et al., 1975; Olson et al., 1986; Randall et al., 2003; Tremblay et al., 2012). Side-dress N applications are recommended for sandy soils with low cation exchange capacity (CEC) and for fine textured, poorly drained soils (Murrell, 2006). These soils tend to be more susceptible to leaching and denitrification. Therefore, N fertilizer recommendations for Alabama corn grain production suggest splitting N in at least two applications, one third of the total N at planting and the remaining two thirds as a side-dress when plants have about six fully developed leaves (Mask and Mitchell, 2012).

Finally, precision agriculture technologies are now available to support N management and increase NUE. Variable rate application technologies and remote sensing are some of the precision agriculture technologies used to better estimate and apply N rates based on temporal and spatial changes within a field resulting in increased NUE. Successful results in assessing N need at mid-season were found in several studies (Kitchen et al., 2010; Mullen et al., 2003; Raun and Johnson, 1999; Raun et al., 2002; Samborski et al., 2009; Solie et al., 2012; Teal et al., 2006)

Nitrogen fertilization represents approximately 40% of corn production costs (Varco, 2013) However, farmers sometimes give N cost less importance when a substantial yield increase is achieved. Nonetheless, increasing input use efficiency is key, especially for N stewardship, and enhancing environmental sustainability. Currently, uniform application of side-dress N on corn is a common practice among farmers, even though the high variability of corn N-response exists within a field resulting in low NUE. Tremblay et al. (2012) when studying N fertilized fields, found yield increased by factors of 1.6 and 2.7 at medium and fine soil textures, respectively, compared with the control treatment (zero N applied). However, they also reported low yields at low and high N rates indicating the high variability in corn N response.

Precise estimation of optimum N fertilizer rate is key to increase NUE and reduce N leaching losses. Howarth (2008), studying coastal N pollution, related the increase of global coastal eutrophication to the increase in N fixation from agriculture, synthetic N fertilizer use, and fossil fuel consumption. From these three processes, synthetic fertilizer use was found to be the main N source of pollution (100 Tg year^{-1}).

Nitrogen recommendations have traditionally followed the mass-balance approach (Stanford, 1973). By this method, N rates were back-calculated based on yield goal and grain N concentration. It accounts for non-fertilizer N sources such as N mineralized from soil organic matter (SOM), preceding crops, and organic amendments. Scharf et al. (2006) found that the mass balance approach was not accurate in estimating the right N rate because it is based on historical data, N mineralization, and plant N uptake which are highly variable within a field and between years. Recent studies have shown that by accounting for temporal and spatial within-field variability of plant chl content and biomass through the use of remote sensors, it is possible to better estimate the yield potential and N rate needed to achieve it (Raun and Johnson, 1999; Raun et al., 2002; Teal et al., 2006).

Nevertheless, it is important to recognize that NUE varies from year to year depending on weather and soil spatial variability (Hollinger and Hoeft, 1986; Raun and Johnson, 1999; Tremblay et al., 2012). Therefore, it is not always an easy task to determine how much N should be applied at a given time. Several methods attempt to measure plant status with the aim of estimating the right in-season N rate. For instance, the use of Chl meters like SPAD-502 (Konica Minolta, Osaka, Japan) has been successfully used for estimation of plant N status and estimate the N rate to be applied in several studies (Hurtado et al., 2011; Wood et al., 1992; Ziadi et al., 2008). The handheld SPAD-502 sensor clips on the leaf blade and indirectly measures Chl content. It emits light in the form of light emitting diode (LED) and measures light transmittance across the leaf blade as a ratio of near infrared and red wavelengths. The degree of N deficiency can be calculated from the SPAD readings as a ratio between a non-limiting and an N limited plant (Ziadi et al., 2008). Although this approach improves NUE, it is not possible to do on-the-go variable rate application using SPAD. Variable rate application using SPAD requires first geo-referenced field data collection and prescription map development which results in a very time consuming procedure.

For large fields, a more effective N content assessment and fertilizer application is possible through remote sensing (Samborski et al., 2009). The concept of remote sensing relies on the leaf absorbance and reflectance properties (Gates et al., 1965). The amount of light absorbed by a leaf is a function of its photosynthetic activity and is directly related to the photosynthetic pigment content. Since Chl are photosynthetic pigments and contain a significant amount of N, it is feasible to estimate the N content based on Chl content indirectly assessed by spectral reflectance measurements (Hatfield et al., 2008).

There are specific wavelengths in the electromagnetic spectrum that are most suitable for plant status spectral reflectance assessment based on the Chl reflectance properties. Within the visible portion, the blue (400-500 nm) and the red (670 nm) absorbance can reach 90% with increase of Chl content (Lichtenthaler, 1987). Thus, absorption at these wavelengths becomes saturated with low amounts of pigments. In contrast, for the green (550 nm) and red edge (700 nm) portions, the absorption coefficients are very low and sensitivity of absorption to Chl content is much higher than in the blue and red (Hatfield et al., 2008). On the other hand, the maximum reflectance was found to be in the near infrared (NIR) with slight variability among Chl contents levels (Hatfield et al., 2008) and independent of leaf senescence stages (Gitelson and Merzlyak, 1994). The combination of reflectance at different wavelengths in the form of vegetation indices (VIs), which comprise wavelength ratios or ratios of normalized differences, have been used to enhance differences among objects or to assess health levels on vegetation.

Several VIs have been developed to extract information about specific crop characteristics such as leaf area index (LAI), biomass, and Chl content (Hatfield et al., 2008; Myneni et al., 1995; Viña et al., 2011). For instance, normalized difference vegetation index (NDVI) corresponds to the normalized difference between the near infrared (NIR) and red (Red) wavelengths, and is widely used to estimate green biomass (Weier and Herring, 1999).

Spectral reflectance data in the form of VIs can be used to indirectly assess in-season yield potential as well as determine a specific N fertilizer rate required to achieve the crops potential yield (Kitchen et al., 2010; Raun et al., 2005; Solie et al., 2012). Many sensors are available in the market, such as GreenSeeker (Trimble, Sunnyvale, CA, USA) or CropCircle (Holland Scientific, Inc, Lincoln, NE) to calculate NDVI. Remote sensed data and yield data for different N rates are used in regression models or algorithms to develop a yield potential curve and calculate the N rate needed to achieve the yield potential. These algorithms estimate the N rate based on a response index or sufficiency index (SI) as the ratio of spectral measurements from a non-limited N strip and the N deficient areas within a field. For instance, a value of SI = 1 would indicate no N deficiencies within the field relative to the N rich strip, while a SI = 0.5 would indicate an N stressed crop within the field. Nitrogen variable rate is then estimated based on the SI or response index and the yield potential curve. Algorithms developed by Raun et al. (2005) and Kitchen et al. (2010) are currently used for N variable rate application (VRN). Most of the current approaches for VRN application are based on remote sensing readings but restrict their use to a specific growth stage. Plant N needs, remote sensors' sensitivity to crop status and in-season yield prediction are the main factors influencing that window. Scharf et al. (2002) in Missouri found no evidence of yield reduction when N applications were delayed until V11corn growth stage. Therefore, N fertilizer could be applied any time before V11 growth stage. However, N applications assisted by remote sensors are restricted to a narrower window. Certain VIs such as NDVI are inaccurate for estimating yield potential at the V6 corn growth stage (Teal et al., 2006) and are not sensitive at advanced growth stages when LAI > 2 (Gitelson et al., 2003). Variable rate N application assisted by active remote sensors is usually conducted after V8 corn growth stage in the Midwest (Teal et al., 2006). Nonetheless, plant N stress at early corn growth stages (V6) can be irreversible, affecting final yield when certain combinations of weather, climate and soil conditions take place (Binder et al., 2000). Delaying N application to V8 or later corn growth stages in Alabama may result in N stress, due to the sandy soils and high rainfall that characterize the Coastal Plain region of the state. Farmers in Alabama usually apply N fertilizer as early as the V4-6 growth stage (Charles C. Jr. Mitchell, personal communication, 2011).

Variable rate N application at early corn growth stages is less precise compared to applications at later growth stages. A weak relationship between NDVI at V6 corn growth stage and yield has been reported in Oklahoma (Teal et al., 2006). This can be attributed to less spatial and temporal variability of corn plants early in the growing season. Hence, early season N content assessment and VRN application are only feasible if there are tools for in-season weather assessment to help reduce the uncertainties and better estimate the yield potential. Corn production in the southeast USA is influenced by climate conditions characterized by high temperatures and relative humidity, as well as highly variable rainfall. In the Alabama Gulf Coast regions, average annual rainfall reaches 1500 mm a year. However, rainfall events are extremely variable in terms of distribution and amount (Kunkel et al., 2013). Due to inconsistent weather and climate patterns throughout the growing season, crop yields vary among years.

Along with impact of inter-annual climatic conditions on the Southeast corn yield, changes in soil type across the region impose another challenge for N management. Common soils in the Southeast are Spodosols, Alfisols, and Ultisols, the latter being the predominant soil type on the Piedmont and Gulf Coastal Plains regions. Ultilsols are highly weathered, acid soils, with low CEC and high pH dependent charges (Shaw et al., 2010). These conditions create an opportunity for further research on corn N fertilizer recommendations, taking into account soil type and in-season weather and climate conditions.

Properly calibrated and validated, simulation models can play an important role in assessing N fertilizer requirements by taking into account interactions between management and environmental conditions. Some examples of existing models used for supporting N fertilizer management and yield estimation are Maize-N (Setiyono et al., 2011), ADAPT-N (Melkonian et al., 2008) and the crop system model (CSM)-CERES-Maize model (Jones and Kiniry, 1986; Jones et al., 2003; Ritchie et al., 1998). The first two models, Maize-N and ADAPT-N, were developed for pre-plant and in-season N rate estimation by accounting for presiding crops, mineralized N, organic fertilizers (manure), in-season weather (site specific) and N-corn market prices (only Maize-N). The CSM-CERES-Maize model was developed for research and extension purposes. The CSM-CERES-Maize is part of the Decision Support System for Agrotechnology Transfer (DSSAT) which includes a set of 16 different crops simulation models. It has a main driver program (land unit module) with five primary modules (weather, soil, plant, soil-plant-atmosphere interface, and management components). Those modules allow the description of a specific environment or land unit module (Jones et al., 2003). In the model, soil water is simulated on a daily basis accounting for rainfall, irrigation, infiltration, vertical drainage, unsaturated flow, soil evaporation and plant water uptake (Ritchie et al., 1998). The N balance is also simulated accounting for mineralization, immobilization, denitrification, leaching, and plant N uptake (Goodwin and Singh, 1998). The CSM-CERES-Maize has been used in several experiments assessing corn yield and N cycling (He et al., 2011; Liu et al., 2011; Pang et al., 1997; Persson et al., 2009), and corn irrigation and fertilization (Asadi and Clemente, 2001; Popova and Kercheva, 2004).

Two studies are included in this thesis.

The objectives of the first study were to:

1. Identify the VI that best correlates with field plant measurements of LAI and Chl content at early corn growth stages (V6).
2. Evaluate the selected VI for in-season yield potential predictability.

The objective of the second study was to:

1. Evaluate the impact of in-season changes in rainfall on simulated corn yield, N leaching, inorganic N in the soil at maturity and NUE.

II. EVALUATION OF VEGETATION INDICES FOR IN-SEASON VARIABLE RATE NITORGEN APPLICATION USING ACTIVE ROMOTE SENSORS

Abstract

The use of crop canopy sensors for variable rate nitrogen (N) application in corn (*Zea mays* L.) grain production in the southeastern US requires identification of the relationship between plant status and sensor spectral reflectance, as well as the level of sensor's data predictability of in-season yield potential. The objectives of this study were to identify vegetation indices (VIs) that best correlate with field plant measurements of leaf area index (LAI) and chlorophyll (Chl) content at early corn growth stages and to evaluate selected VI for in-season yield potential prediction. An N test was conducted between 2010 and 2012 at three locations in Alabama. Six N fertilizer rates (0, 56, 112, 168, 224, 280 kg N ha^{-1}) of urea ammonium nitrate were applied at planting. In each location, data collected at the V6, V8, V10 vegetative growth stages were leaf Chl content measured with a Chl meter SPAD-502, LAI, and canopy spectral reflectance using the Greenseeker 505 and CropCircle ACS-470 sensors. Ten VIs that used red, near-infrared (NIR), and red-edge (RE) wavelengths were calculated with data collected from each location and growth stage. A canonical correlation analysis was conducted to identify the VIs best correlating with field-measured crop status variables (SPAD and LAI). Results indicated that VIs including de RE wavelength were more sensitive to changes in leaf Chl content and biomass than VIs including the red wavelength. The normalized difference red-edge (NDRE), Chl index red-edge [CI (RE)], simple ratio red-edge [SR (RE)], and inverse simple ratio red-edge [ISR (RE)] were most highly correlated to Chl content and biomass. When canopy sensor data from multiple location-years were combined for evaluation of in-season yield predictability, the yield prediction equation including the NDRE index had a higher coefficient of determination and a lower root mean square error when compared to equations including the NDVI index. The NDRE equation exhibited coefficient of determination (R^2) values of 0.37, 0.42, and 0.67 at the V6, V8, and V10 growth stages, respectively. Coefficients of determination values for the NDVI equation were 0.26 at V6, 0.30 at V8, and 0.36 at the V10 growth stage. Even though models for mid-season yield prediction of NDVI and NDRE performed similar at V6, the NDRE, the CI (RE) and SR (RE) resulted in overall higher yield predictability for all growth stages. Therefore, our finding suggest

that the NDRE and VIs including the RE wavelength can help improving mid-season yield potential prediction for VRN application between V6 and V10 growth stages.

Introduction

Nitrogen fertilizer is considered the most important nutrient in corn production because of its high impact on yield and production costs (Stone et al., 2010). The use of N as an inorganic fertilizer has been a subject of several agronomic, environmental, and economic studies. From an agronomic perspective, N applications can be under- or over- estimated if plant N uptake and N application timing are not synchronized. Raun and Johnson (1999) reported a 33% worldwide N use efficiency (NUE) for cereal grain production, highlighting the variables influencing NUE and implying the need to improve N management.

Low NUE is directly related to the current increase in coastal eutrophication (Howarth, 2008). Eutrophication has resulted in habitat degradation, widespread hypoxia and anoxia, loss of biodiversity, and increase in harmful algal blooms in coastal areas. Cost of N fertilizer, which has risen 130 percent from 2000 to 2007 (Huang, 2007), is another concern for farmers that pursue higher NUE to reduce production costs. Due to the current low NUE and high prices, several approaches have been evaluated to better estimate crop N requirements. However, additional refinement is required for current N applications to better account for soil and plant environmental conditions.

Nitrogen fertilizer recommendations are site-specific based on soil and climate conditions. Traditionally, fertilizer recommendations have been based on a yield goal, N in the soil, and N concentration in grain (Stanford, 1973). For example, recommendations from Northern Western States Extension Agencies, such as Iowa State University Extension (ISUE), recommend soil N analyses to account for soil N available to the plant (Johnson, 1997). In contrast, southern states, such as Alabama, do not include N soil testing for fertilizer recommendations because soil N at planting time is considered low due to the predominant sandy soils in the region, and high precipitation and ambient temperature during the spring-summer season (Charles C. Jr. Mitchell, personal communication, 2011). Soils in Alabama are also low in organic matter and have low cation exchange capacity (CEC) (Shaw et al., 2010). For corn grain production in Alabama, the recommendation for N fertilizer application is 134 kg N ha^{-1}. In order to increase NUE, the Alabama Cooperative Extension system (ACES) recommends splitting the N into at least two applications, one-third of the total N at planting and the remaining N at the V6 growth stage. Moreover, the N rate can be modified by a factor based on preceding crop and irrigation (Mask and Mitchell, 2012).

Recent studies have indicated that by accounting for spatial within-field variability of plant Chl content and biomass through the use of remote sensors, it is possible to increase NUE (Kitchen et al., 2010; Raun and Johnson, 1999; Raun et al., 2002; Teal et al., 2006). However, it is important to recognize that NUE varies from year to year due to dependency on weather and soil spatial variability (Hollinger and Hoeft, 1986; Raun and Johnson, 1999; Tremblay et al., 2012). Therefore, it may be difficult to determine how much N should be applied at a given time.

Several methods attempt to measure plant N status with the aim of estimating the correct in-season N rate. For instance, the Chl meter SPAD-502 (Konica Minolta, Osaka, Japan) has been used for estimating plant N status (Hurtado et al., 2011; Wood et al., 1992; Ziadi et al., 2008). The handheld SPAD-502 sensor clips on the leaf blade and indirectly measures leaf Chl content. The degree of N stress can be calculated from SPAD readings ratio between a non-limiting and N limited plants (Ziadi et al., 2008). Although this approach can be used to improve NUE, assessment of within-field leaf N changes using SPAD might be labor and time intensive, therefore limiting its use for on-the-go variable rate nitrogen application. Variable rate nitrogen application using SPAD requires first geo-referenced field data collection and subsequently the generation of an N prescription map which might require time and specialized knowledge. Hence, for large fields, a more effective N content assessment for in-season fertilizer application is remote sensing (Samborski et al., 2009).

The concept of remote sensing relies on leaf absorbance and reflectance properties (Gates et al., 1965). The amount of light absorbed by a leaf is a function of its photosynthetic activity and is directly related to the photosynthetic pigment content. Since Chl are the main photosynthetic pigments and contain significant amount of N, it is feasible to estimate N content based on Chl content indirectly assessed by spectral reflectance measurements (Hatfield et al., 2008). Based on Chl reflectance properties, there are specific wavelengths in the electromagnetic spectrum (EMS) that are more suitable for plant status spectral reflectance assessment. Within the visible portion, from blue (400-500 nm) to red (670 nm) portion, absorbance can reach 90% with an increase in Chl content (Lichtenthaler, 1987). Therefore, absorption in those wavelengths becomes saturated with low pigments amount. In contrast, for the green (550 nm) and the red-edge (700 nm) wavelengths, the absorption coefficients are very low and sensitivity of absorption to Chl content is much higher than in the blue and red portions of the EMS (Hatfield et al., 2008). On the other hand, maximum reflectance values can be found in the near infrared (NIR) portion of the EMS with slight variability of Chl content levels (Hatfield et al., 2008) and independently of leaf senescence stages (Gitelson and Merzlyak, 1994). The combination of reflectance at different wavelengths in the form of vegetation indices (VIs), which comprise wavelength ratios or ratios of normalized differences, have been used to enhance differences among objects or to assess health levels on vegetation (Hatfield et al., 2008).

Several VIs have been developed to extract information of specific crop characteristics such as leaf area index (LAI), biomass, and Chl content (Hatfield et al., 2008; Myneni et al., 1995; Viña et al., 2011). For instance, the normalized difference vegetation index (NDVI) that corresponds to the normalized difference between the near infrared (NIR) and red (Red) wavelengths has been one of the most widely used VIs to estimate green biomass (Weier and Herring, 1999).

Spectral reflectance data in the form of VIs can be used indirectly to assess in-season yield potential as well as the specific N fertilizer rate required to achieve a crop’s potential yield (Kitchen et al., 2010; Raun and Johnson, 1999; Raun et al., 2005; Solie et al., 2012). Many sensors available in the market, such as the GreenSeeker (Trimble, Sunnyvale, CA, USA) or CropCircle (Holland Scientific, Inc, Lincoln, NE), calculate NDVI. Different nitrogen rate algorithms assisted by on-the-go active remote sensors have been developed for VRN application. Remote sensed data and yield data from different N rates are used in regression models or algorithms to develop a yield potential curve and calculate in-season the N rate needed to achieve the yield potential. These algorithms estimate the N rate based on a response index or sufficiency index (SI) as the ratio of spectral measurements from a non-limited N strip and the N deficient areas within a field. For instance, a SI = 1 would indicate no N deficiencies within the field relative to the N rich strip, while a SI = 0.5 would indicate an N stressed crop area within the field. Nitrogen variable rate is then estimated based on the sufficiency index or response index values calculated using the canopy sensor readings and the yield potential curve.

Algorithms developed by Raun et al. (2005) and Kitchen et al. (2010) are currently used for VRN application in corn production. These current in-season VRN applications restrict their use to a specific window during the growing season (V8 to V12 growth stage). Plant N needs, remote sensors' sensitivity to crop status and in-season yield prediction are the main factors influencing that window. Scharf et al. (2002) found no evidence of yield reduction when N applications were completed at the V11 stage suggesting that N fertilizer could be applied any time before V11. However, N applications assisted by remote sensors are restricted to a narrower window. Certain VIs, such as NDVI, are inaccurate in estimating yield potential at the V6 corn growth stage (Teal et al., 2006), and are non-sensitive at advanced growth stages when LAI > 2 (Gitelson et al., 2003). Variable rate N application using active remote sensors is usually conducted after the V8 corn growth stage in the Midwest (Teal et al., 2006). Delaying N application to V8 or later corn growth stages in Alabama may result in N stress due to sandy soils and high rainfall that characterize the Coastal Plain region of the state. Therefore, farmers in Alabama usually apply N fertilizer as early as the V4-6 growth stage (Charles C. Jr. Mitchell, personal communication, 2011). According to Binder et al. (2000), plant N stress at early corn growth stages (V6) can be irreversible affecting final yield when certain combinations of weather, climate and soil conditions take place. Previous studies have reported limitations on the use of the canopy sensors for N assessment early in the growing season. Teal et al. (2006), using data from Oklahoam reported a low correlation between NDVI and final yield when data collected at the V6 corn growth stage was used. The edaphic and environmental conditions of the Southeast suggest N in-season application much earlier than the Midwest, therefore, assessment of plant N status early in the season is needed in order to take advantage of the current precision agriculture technologies and management approaches.

Currently, research that compares the most used VI (NDVI) with other indices for the assessment of crop status at early corn growth stages is limited in the Southeast. Therefore, the objectives of this study were to (1) identify the VIs that best correlate with field plant measurements of LAI and leaf Chl content at early corn growth stages (V6); (2) evaluate the selected VIs for in-season yield potential predictability.

Materials and Methods

Experimental Site and Treatments

This three-year study took place at three Auburn University Research Stations in Alabama (AL) between 2010 and 2012. The research stations were the Gulf Coast Research and Extension Center (GCS) in Fairhope, AL (30°32’09.21”N, 87°52’39.15”W, 34 m elevation), E.V. Smith Research Center (EVS) in Shorter, AL (32°25’43.43”N, 85°53’34.81”W, 69 m elevation) and Tennessee Valley Research and Extension Center (TVS) in Belle Mina, AL (34°41’05.37N, 86°53’18.04”W, 187 m elevation). Soil series were: Compass loamy sand (coarse-loamy, siliceous, subactive, thermic Plinthic Paleudults) at the EVS site under irrigation, Marvyn sandy loam (fine-loamy, kaolinitic, thermic Typic Kanhapludults) at the EVS site under rainfed conditions, Decatur silt loam (fine, kaolinitic, thermic Rhodic Paleudults) at the TVS site under irrigation, and Marlboro very fine sandy loam (fine-loamy, siliceous, subactive, thermic Plinthic Paleudults) at the GCS site (rainfed). Locations, years, experiments, planting and sensing dates are presented in Table 1.1.

Irrigated tests at the EVS and TVS sites will be referred to as EVS-I and TVS, respectively. Rainfed tests at GCS and EVS sites will be referred as GCS and EVS-R, respectively. Irrigation management was conducted according to plant needs and research station practices. At each site-year, a randomized complete block design (r = 5) with six N treatments (0, 56, 112, 168, 224, 280 kg ha^{-1}) of urea ammonium nitrate (liquid, 28 % N) incorporated at planting were implemented. Plots received a pre-plant application of P, K, and lime based on recommendations of the Soil Testing Laboratory at Auburn University and the Alabama Cooperative Extension Systems (ACES) (Mask and Mitchell, 2012). Each plot was 3.66 m wide by 10 m long with 0.9 m row spacing resulting in a total of four rows. The corn hybrid used was a Pioneer 31P42 sown at 70,000 seeds ha^{-1} at GCS and EVS sites and at 80,000 seeds ha^{-1} at the TVS site during the three years of the study.

Data collection

Spectral reflectance, leaf Chl content and LAI were collected at the V6, V8, and V10 corn growth stages. All readings were collected from the two middle rows of each plot. The leaf Chl content and LAI data were collected as ground truth measurement of plant status. Leaf Chl content can be indirectly assessed thought the use of a Chl meter SPAD-502 (Konica Minolta, Osaka, Japan) (Hurtado et al., 2011; Rorie et al., 2011; Wood et al., 1992; Zhao et al., 2007; Ziadi et al., 2008). Ten random SPAD values per plot were collected. Each SPAD value consisted on the average of three readings from the most recently collared leaf on each corn plant. Leaf area index was assessed with an LAI-2200 plant canopy analyzer (LI-COR Biosciences, Lincoln, NE) (Rover and Koch, 1995; Wilhelm et al., 2000; Wu et al., 2007). Three readings per plot were collected with the LAI-2200 sensor. Each of the three readings consisted of five measurements, one reading above canopy and four bellow canopy (in the row, 25%, 50%, and 75% of the row width). The LAI-2200 calculated LAI by measuring the blue light range (320-490 nm) at five zenith angles (148º field-of-view).

Spectral reflectance data were measured using a GreenSeeker GS-505 (Trimble, Sunnyvale, CA, USA) and a CropCircle ACS-470 (Holland Scientific, Inc, Lincoln, NE) active remote sensors. Both sensors were placed at a height of 0.82 m from the canopy during data collection. The GreenSeeker (GS-505) measured spectral reflectance using modulated light emitting diodes in the visible (Red, 660 nm) and in near-infrared (NIR, 770 nm) wavelengths at a sample output rate of 50 Hz (NTech Industries, 2007). Normalized difference vegetation index (NDVI) was automatically calculated by the GS-505 sensor using the red and NIR sensor readings. The CropCircle ACS-470 sensor used a modulated polychromatic light emitting diode (LED) array emitting light in the range between 430 to 850 nm. It contains of three silicon photodiode channels for photodetection that range from 320 to 1100 nm. The optical measurement bands were user-definable and range from 430 to 800 nm via 12.5 mm interference filters. For this study, the CC-470 sensor was calibrated for three wavelength combinations in the Red (670nm), near infrared (NIR, 760nm), and Red-edge (RE, 730nm) portions of the electromagnetic spectrum using a 5 Hz sample output rate (Holland Scientific, 2011). Both sensors, GS-550 and CC-470, were mounted on a customized bicycle. The modification consisted of two extra side-wheels and a structure based on a mast with a platform where the sensors were mounted. This configuration allowed a consistent height above the target plant for the readings. The bicycle was pulled or pushed at walking speed though the second and third rows of each plot. Vegetation indices were calculated from the sensors' readings, giving priority to indices with high Chl content correlation. Normalized difference vegetation index collected by the GreenSeeker (GS-NDVI) and ten additional VIs were calculated using data from the CC-470 sensor. The VIs calculated using the CC-470 sensor's data were NDVI, NDVI red-edge (NDRE), simple ratio (SR), simple ratio red-edge [SR(RE)], inverse simple ratio (ISR), inverse simple ratio red-edge [ISR(RE)], Chl index red-edge [CI-(RE)], Datts index (Datt), MERIS terrestrial Chl index (MTCI), and modified simple ratio (MSR) (Table 1.2).

Vegetation indices are often used to enhance specific plant properties. For instance, NDVI has been regularly used to assess differences in Chl content as well as crop yield prediction (Solari et al., 2008). A healthy plant absorbs and reflects more energy in the visible (e.g. Red) and NIR, respectively, as compared to an unhealthy (Chl reduced) plant (Hatfield et al., 2008; Ollinger, 2011). Therefore, healthy plants generate higher NDVI values compared to unhealthy plants. One disadvantage of the NDVI is that it becomes saturated on high biomass crops, LAI > 2 for corn (Gitelson et al., 2003). Indices with the same wavelengths as NDVI but with different combinations of the Red and NIR wavelengths are the SR, ISR and MSR indices. The NDRE index uses the same equation as the NDVI but replaces the Red with the Red-edge wavelength. According to Gitelson and Merzlyak (1994), the red-edge wavelength is more sensitive to Chl content at higher biomass levels compared to NDVI. Analogous indices to the NDRE are the SR (RE), ISR (RE), and CI (RE). The Datt index that combines the Red, RE, and NIR wavelength removes the interferences caused by leaf scatter, and is therefore considered a good estimator of Chl content at regional and global scales (Datt, 1999). Similar to the Datt index, the MERIS terrestrial Chl index is also reported as being sensitive to a wide range of Chl content at the regional and global scale. This index also combines the Red, RE, and NIR wavelengths (Dash and Curran, 2004).

Statistical Analysis

A canonical correlation analysis (CCA) was conducted by year-site-growth stage to identify the VIs that best correlated with field-measured crop status variables. This statistical analysis examined the relationship between two sets of variables, creating independent pairs of new variables called canonical variates (X and Y). Each canonical variate (X and Y) results from the linear combination of the original variables within each set. The association between the two sets of variables was maximized by aggregating multiple associations into a few significant ones (Martín et al., 2005). Then correlations are analyzed in terms of intra-set structure correlation (strength of the association between the original variables and their canonical variate) as well as in terms of inter-set structure correlation (strength of the interrelationship between canonical variates of a measurement domain and the observed variables of the other domain) (Ortiz et al., 2011).

Before the CCA was run, data for each vegetation index value was standardized to a zero mean and unit variance. The first step for data standardization was to take the difference between each independent VI value and the VI average of the dataset (site-year-growth stage). Then, the result from the difference was divided by the standard deviation of the VI dataset (site-year-growth stage). This ensured that the VIs comparison was under the same range of values. The CCA was conducted using the PROC CANCORR procedure of SAS (SAS Institute, 2008). Plant status canonical variate (PSV) and vegetation index canonical variate (VIV) were designated as the canonical variates for the analysis. The PSV resulted from the linear combination of ground truth measurements of LAI and SPAD data. The VIV resulted from the linear combination of the eleven VIs. The significance of the canonical correlation was assessed using Wilkes-Lambda statistic. Canonical variates are significantly associated by a canonical correlation if $P < 0.05$ for the Wilkes-Lambda statistic (Gittins, 1985). Standardized cumulative variance (SVC) values reported in the CCA were used to study the percent of total variance explained by each canonical variate within each data set. The simple linear relationships between the original variables and the canonical variates are explained by the loadings or correlations within each set. Variables having a high contribution to the canonical variate are those exhibiting large loadings for multivariate dependencies assessment (Ortiz et al., 2011). Since the goal of this study was to identify VIs best correlating with plant status assessed by LAI and leaf Chl content, canonical variates were analyzed in terms of inter-set structure correlation.

Identification of vegetation indices for in-season corn status discrimination

The inter-set correlation values allowed the identification of the VIs strongly correlated with plant status canonical variate. For every site-year-growth stage, VIs with the four highest inter-set correlation values were identified. Then, a frequency table by growth stage was developed including only the VIs with the top four highest correlations on each site-year. Indices with higher frequencies were those that resulted more times with the highest correlations by growth stage. Therefore, those VIs exhibiting the highest frequencies could be considered the best and most stable for an indirect prediction of leaf Chl content and LAI status.

Vegetation Index data for in-season corn yield potential estimation

A reliable VI that is sensitive to variations in leaf Chl content and LAI as early as V6 corn growth stage is needed for Alabama corn production systems. The VIs that strongly correlate with PSV were evaluated as predictors for corn yield. Linear regression models were used to determine the relationship between in-season (V6, V8, and V10 growth stage) crop growth assessment using vegetation index data and grain yield. Linear regression models by growth stage included multiple site-years. Those regression models were determined using the PROC REG procedure in SAS (SAS Institute, 2008). Because each model combined data of multiple site-years for a given growth stage, the in-season estimated yield (INSEY) equations were established as described by Raun et al. (2002). The INSEY values were computed dividing the VIs values by the cumulative growing degree days (GDD) calculated for each site-year-growth stage from planting to sensing date. This procedure normalized the VIs data allowing the combination of VIs into a single regression model (Teal et al., 2006). The GDD were calculated using the "optimum day method" (Barger, 1969) calculated as:

$$GDD = \frac{T_{max} + T_{min}}{2} - 10℃$$

Where: T_{max} and T_{min} are the minimum and maximum temperature, respectively

Values of coefficient of determination (R^2), the root mean square error (RMSE) and the coefficient of variation (CV) were used to evaluate and compare each yield potential prediction model. These parameters were used before by Peng and Gitelson (2011) to compare VIs models when evaluating crop gross primary productivity in corn. Yield prediction models, including a specific vegetation index as predictor variable, with the highest coefficient of determination (R^2), the lowest RMSE, and the lowest CV were more suitable for in-season yield potential estimation and therefore potential use for VRN application at a given growth stage.

Yield prediction equations were developed using linear and exponential regression models. After both models were evaluated for their fit, the linear regression model with intercept was found to be the best yield predictor because of the lowest RMSE and CV values. Linear regression models with intercept were successfully used in evaluating corn grain and stover yield prediction by Mourtzinis et al. (2013). Also, linear relationships between mid-season VIs assessment and grain yield were previously found appropriate for this type of datasets (Teal et al., 2006).

Results and Discussion

Canonical correlation analysis

The CAA between plant status variables and VIs resulted in two pairs of canonical variates for each site-year-growth stage (Table 1.3). The first pair of canonical variates (CC1) was significantly correlated ($p < 0.05$, Wilk's Lambda) for most site-year-growth stages combinations, except for EVS-I-V6-2010, GCS-V8-2010, and EVS-I-V6-2012. Canonical correlations between the first pair of canonical variates (CC1) ranged from 0.84 to 0.99. The second pair of canonical variates (CC2) resulted in a significant canonical correlation only at one site-year-growth stage (EVS-I-V10-2011).

The standardized cumulative variance (SCVP and SCVVI) explained by the canonical variates of the CC1 pair (PSV and VIV) varied by site-year-growth stage. Except for TVS-V8-2011 (SCVP =1), which did not include the LAI data in the analysis (data not available), the PSV canonical variate explained between 48% and 86% of the total variance in plant status data. An increase in total variance explained by the PSV canonical variate was observed as the plant growth progressed from the V6 to the V10 growth stage. For example, SCV_p for the V6 growth stage ranged from 50% to 67% but for the V10 growth stage ranged from 62% to 82%. The SCV_{VI} resulted in a similar trend among growth stages as the SCV_P. In four out of five cases the VIV canonical variate explained 62% to 65% at V6 and in four out of six cases it explained from 84% to 90% of the total variance in the VIs values at the V10 corn growth stage. Even though the VIV canonical variate resulted in higher variance explained when compared to the PSV canonical variate, results indicated that the percent variance explained by both canonical variates increased as the plant growth progressed from the V6 to the V10 corn growth stages.

Relationship between canonical variables and field measured data

Because the correlation between the first pair of canonical variates (CC1) was the highest and significant for most site-year-growth stages, the discussion of results herein is focused on the intra-set structure correlation coefficients of the first pair of canonical variates. The intra-set correlations are the correlations between canonical variates and the observed variables of the same domain. Tables 1.4-6 present the intra-set correlations between the PSV variate and the plant status variables (SPAD and LAI) evaluated at the V6, V8, and V10 growth stages, respectively. These correlations show the variable that affects the most their canonical variate and the direction of the effect (Gittins, 1985; Martín et al., 2005; Ortiz et al., 2011). Among the two plant status variables, SPAD had the highest intra-set correction with the PSV variate across site-year-growth stages with correlation values ranging from 0.68 (EVS-I-V8-2012) to 1.00 (GCS-V6-2010, TVS-V6-2010, TVS-V8-2011, and TVS-V10-2010). The intra-set correlation between LAI and PSV increased as the growth progressed with values ranging from -0.02 to 0.78, 0.16 to 0.95, and 0.49 to 0.84 at the V6, V8, and V10 growth stages, respectively. The high values observed for the intra-set correlations between plant status measurements (especially SPAD) and PSV suggest that VIs exhibiting a high correlation with PSV could be useful to assess plant differences with respect to SPAD and LAI.

The inter-set correlation (strength of the interrelationship between canonical variates of a measurement domain and the observed variables of the other domain) between each VI and the PSV canonical variate increased as the growth stages progressed for most site-year combinations. For example, the inter-set correlation values ranged from 0.56 to 0.78 for the V6 growth stage at the GCS site in 2012; however, at the same location the correlation values were in a range of 0.83 to 0.93 for the V10 growth stage (Tables 1.4 and 1.6).

Rainfed experiments exhibited a greater variation in inter-set correlation coefficients when compared to irrigated experiments. For the rainfed experiments at the V6 growth stage, the ranges of inter-set correlations between VIs and PSV were 0.67-0.86, 0.65-0.83, and 0.56-0.78 for the GCS-2010, EVS-R-2012, and GCS-2012 site-years, respectively. In contrast, for the irrigated site (TVS) at the V6 growth stage, the ranges of inter-set correlations were 0.57-0.73 and 0.82-0.84 during the 2010 and 2012 growing seasons, respectively. Under irrigated conditions corn N response is higher, which results in a more homogeneous plant stand among N rates. When VIs assessment is conducted under these conditions, lower variability in mid-sensor readings and VIs is observed when compared to same measurements in rainfed experiments. Variability among N fertilized plots was higher for rainfed conditions, therefore, variability in Chl content and LAI was better assessed by VIs. This results in greater variations among correlations.

At the V6 growth stage, the MTCI exhibited the strongest correlation with PSV for two out of the three rainfed site-years and the GS-NDVI exhibited the least correlation (Table 1.4). Moderate correlations were exhibited by the CI (RE), SR (RE), NDRE, ISR (RE), and Datt vegetation indices. The SR (RE), MTCI and CI (RE) were the VIs that more often exhibited the greatest correlations among site-years. The MTCI is known for its sensitivity to high Chl content levels (Boyd et al., 2011; Dash and Curran, 2004), and it has also been found to be unaffected by confounding effects of water stress (Shiratsuchi et al., 2011). In the same study, the MTCI was more sensitive to N rate levels at early and advance growth stages when compared to the NDVI. These results support the observed high correlations exhibited by the MTCI VI in two of the rainfed site-years at the V6 growth stage.

When inter-set correlation values corresponding to GS-NDVI and NDVI indices were compared, the one calculated using the CC-470 sensor (NDVI) had a higher correlation with PSV than the one calculated with the GS-505 sensor (GS-NDVI). This was observed across three rainfed site-years using data collected at theV6 growth stage. Although small differences were found in other studies, NDVI calculated by CC-470 could be more sensitive to differences in leaf Chl content and biomass than the same index calculated using data from the GS-505 sensor (Erdle et al., 2011; Perry et al., 2012).

When inter-set correlations were analyzed at theV8 growth stage also differences among site-years were found (Table 1.5). The range of variation of inter-set correlation coefficients was smaller for most irrigated sites compared with the rainfed sites. When the inter-set correlation coefficients for both irrigated sites (EVS-I and TVS) were compared, a small range of variation was observed at the TVS sites compare with the EVS-I site. Those differences could be related to differences in soil texture among sites. The soil texture at the TVS site was characterized as silt loam while at the EVS-I site as loamy sand. Since there is a higher N fertilization response in finer textural classes (Tremblay et al., 2012), the leaf Chl content and/or biomass variability among N treatments at the TVS site was not very pronounced at early growth stages compared with the EVS-I site. Therefore, more homogeneous leaf Chl content and

LAI conditions could explain the small range of inter-set correlation values at the TVS indicating low sensitivity of the VIs for discriminating small plant status differences. The GS-NDVI exhibited the highest correlations among VIs in two out of the three rainfed site-years. Across site-years, the VIs with the most frequent high correlation were NDRE, ISR (RE), SR (RE), and CI (RE).

At the V10 growth stage, inter-set correlations were the greatest compared with those at the V6 and V8 growth stages (Table 1.6). However, the variability of inter-set correlations for the VIs did not differ considerably when rainfed and irrigated tests were compared. Across site-years, the VIs with the most frequent high correlation were NDRE, ISR (RE), and the CI (RE).

The three indices that resulted in high correlation with plant status variables had in common the red edge wavelength. This portion of the electromagnetic spectrum (730 nm, measured in this experiment) has been proven to be more sensitive to leaf Chl content across a range of crops (Delegido et al., 2013). Their results also indicated that the NDRE is a more reliable VI because it does not saturate at high LAI values. The CI (RE) resulted in the strongest relationships between VIs assesstment and Chl content for maize, soybean, grass and potato (Clevers and Gitelson, 2013). The ISR using the Red wavelength was better in assessing N health differences compared to NDVI (Roberts, 2006). Therefore, the ISR (RE) was expected to be a good estimator of leaf Chl content and biomass as observed in this experiment.

Identification of vegetation indices for in-season corn status discrimination

The results from the frequency analysis were intended to rank the VIs based on the degree of inter-set correlation within and across corn growth stages (Table 1.7). For this analysis, only VIs with the highest four inter-set correlations per growth stage were taken into consideration. For instance, among the site-year combinations at the V6 growth stage, GS-NDVI was one time out of five site-year combinations in the top four highest correlations therefore; only one unit frequency was assigned to it in the frequency table. Hence, one unit frequency out of five possible events indicated that 20% of the times the GS-NDVI was within the top four highest correlations at the V6 corn growth stage.

At the V6 growth stage, indices SR (RE), ISR (RE) and CI (RE) exhibited high correlations with plant status canonical variate at most site-years (Table 1.4). Those indices were in the top four highest correlations in four out of five site-year combinations, 80% of cases (Table 1.7). Following those VIs, the NDRE and the MTCI were in the top four highest correlations in 60% of cases and Datt index in 40% of cases. The remaining VIs only were 20% of cases in the top four highest correlations. The VIs with higher frequency of high correlation with the PSV were better estimators of Chl content and LAI at V6 growth stage. Moreover, when VIs were separated according to their wavelengths; it was evident that VIs including the NIR and the RE wavelengths had a stronger correlation with plant status. The MTCI and Datt indexes ranked as the second best predictors of plant status after the three RE indices [SR (RE), ISR (RE) and CI (RE)] and those include the NIR, Red and RE wavelengths in the equations. From the group of VIs, the ones with the lowest prediction ability of plant status, low frequency of occurrence of being in the top four correlations, were the indices that included only the NIR and Red wavelengths.

The NDRE and the ISR (RE) indices exhibited the highest correlation frequencies at the V8 growth stage. Those indices were in the top four highest correlations in six out of seven site-year combinations, 86% of cases. The second best predictors of plant status were the SR (RE) and CI (RE) indices with correlations in the top four groups in five out of seven cases (71%) and the MTCI in 57% of cases. The other VIs evaluated exhibited < 50% frequency of correlation with plant status. Even though both NDVI indices were ranked low in terms of their indirect assessment of plant status, GS-NDVI had higher frequency of occurrence of being in the top four correlations than CC-NDVI, 43% and 14% of cases, respectively. The indices with the top four highest correlations were the same as for the V6 growth stage. The VIs containing the NIR and RE resulted with the highest frequencies among vegetation indices. Moderate frequencies resulted in those VIs containing the NIR, Red and RE wavelengths.

At the V10 growth stage, the NDRE and ISR (RE) were in the top four highest collections in 100% of cases. The CI (RE) was ranked as the second with the highest correlation frequency in 83% of the cases. The SR (RE) and the MTCI resulted in the third place as best predictors of plant status in the 67% of cases. The other VIs in the group exhibited a correlation frequency below 50%. The results at the V10 growth stage in terms of VIs suitable for indirect prediction of plant status were similar to those observed at the V6 and V8 growth stages.

Overall, the highest frequencies among site-years-growth stages were exhibited by those VIs including only the NIR and RE wavelengths. The second highest frequencies among site-years-growth stages were for those VIs combining three wavelengths in the equation (MTCI and Datt).The remaining VIs, which only included the Red and the NIR wavelengths, resulted in the lowest frequencies calculated in the correlations rank.

Overall, among the VIs evaluated, the NDVI exhibited the lowest frequency of high correlation with plant status variables at the V6 corn growth stage. However, the replacement of the Red by RE wavelength in the NDVI equation improved the correlations considerably. Thus, VIs containing the RE wavelength can improve leaf Chl content and LAI assessment resulting in better VIs for VRN application. A wider application window for VRN application is possible using the RE wavelength. The RE is more sensitive to leaf Chl content and biomass and it does not saturates at high biomass levels (Delegido et al., 2013; Gitelson et al., 2003; Viña et al., 2011). Moreover, results from this experiment show that the RE is also sensitive to leaf Chl content and biomass at early corn growth stages indicating the potential use of this wavelength for early season N fertilizer applications.

Vegetation Index data for In-season corn yield potential estimation

The VIs more often exhibiting highest correlations with the plant status variate (Table 1.7) and the NDVI calculated using data from the CC-470 sensor were selected to evaluate their ability predicting yield potential. Yield prediction equations were computed for the following VIs: NDVI, NDRE, CI (RE), SR (RE), and ISR (RE).

Results of mid-season VIs assessment, where sensor measurements considerably described variability among different N fertilized plots, were used to develop linear regression models with final grain yield. Results are shown in Table 1.8.

Models for the selected VIs and grain yield resulted significant ($p < 0.0010$) for each VI and growth stage evaluated. When evaluating the relationship between mid-season VIs assessments and final yield, an improvement in yield predictability was observed as the growth stages progressed from the V6 to the V10.

Among the five models evaluated across the three growth stages, the ISR (RE) and the NDVI resulted in the lowest R^2, the highest RMSE and the highest CV for all growth stages. However, when the ISR (RE) was evaluated for yield predictability using independent site-years by growth stage (not combining multiple locations into one regression model), the R^2 resulted among the strongest relationship to grain yield for all site-years as compared to the NDVI and the other VIs assessed (data not shown).

At the V6 growth stage, the five different VIs linear regression models included data from four site-years. The R^2 ranged from 0.12 to 0.43 for ISR (RE) and SR (RE), respectively. The NDVI resulted in the second lowest R^2 (0.26) after the ISR (RE) with the lowest R^2 value. The NDRE, which comprised the same equation as NDVI, but replacing the Red by the RE wavelength, resulted in a higher R^2 (0.37) than NDVI. However, the RMSE and the CV were not considerably lower. The RMSE resulted in 2247 and 2080 kg ha^{-1} for NDVI and NDRE, respectively. Results for the CV were 30 % and 28 % for NDVI and NDRE, respectively. The CI (RE) exhibited R^2 of 0.34 and RMSE of 2129 kg ha^{-1}, while the SR (RE), had highest R^2, and a RMSE of 1982 kg ha^{-1}. Looking at the CV, the CI (RE) resulted in 28% (same than NDRE), and the SR (RE) in 26 %.

Five site-years were combined for regression models comparisons at the V8 growth stage. An increase in yield potential predictability was observed for all VIs compared with the yield prediction models generated with data from the V6 growth stage. The same tendency than in the V6 was observed, the NDVI and the ISR (RE) resulted in the lowest yield prediction with R^2 values of 0.30 and 0.32, respectively. Other VIs including the RE wavelength resulted in $R^2 > 0.40$. The NDRE, CI (RE) and SR (RE) had similar RMSE and CV values. The CV was 32 % for the NDRE, CI (RE), and SR (RE) indices, but 35 % for the NDVI and the ISE (RE) indices. Although, the NDVI has been successfully used in algorithms for VRN application at the V8 growth stage (Teal et al., 2006), our data shows that the NDRE had a higher yield predictability (high R^2 and low RMSE) than the yield prediction equation using NDVI as predictor variable. A VIs with higher yield predictability results in more accurate prediction of in-season N rates.

At the V10 growth stage, five site years were also combined for regression models comparisons. Overall, the yield predictability increased when compared with models using data collected either at the V6 or V8 growth stages. This was expected because as the growth stages progresses to the V10, variability in plant status was enhanced. This was also observed in the CCA when the V10 resulted in higher correlations with PSV (Chl and LAI) variate. For instance, those plots that received high N rates responded to N fertilizer showing higher Chl contents and biomass than plots receiving low N rates. The variability in plant status resulted in grain yield differences. Since higher differences in N response were observed later in the season, measurements at the V10 resulted in more accurate yield predictability. For this growth stage, the ISR (RE) also resulted in the lowest R^2 (0.09), the highest RMSE (3071 kg ha^{-1}) and the highest CV (45%).

Differences in yield predictability between the NDVI and the NDRE were greater than those observed at the V6 and V8 growth stages. The NDVI exhibited $R^2 = 0.36$, while the NDRE resulted in $R^2 = 0.67$. Also, the RMSE and the CV were considerably lower for the NDRE, and resulted in 1850 kg ha^{-1} and 27 %, respectively. The NDVI exhibited a RMSE of 2568 kg ha^{-1} and a CV of 37 %. The rest RE VIs [CI (RE) and SR (RE)], as the NDRE, also exhibited high R^2, low RMSE and low CV, > 0.67, < 1861 kg ha^{-1}, and 27 % respectively. Overall, results indicated a higher performance of the RE VIs [except for ISR (RE)] with respect to in-season yield prediction. The NDVI saturation reported in several studies (Delegido et al., 2013; Gitelson et al., 2003; Viña et al., 2011) was also validated in these results when the NDVI did not significantly increase yield predictability compared to the RE VIs at the V10 corn growth stage.

However, at early growth stages (V6), the only indication that the NDRE, the CI (RE), and the SR (RE) performed better than the NDVI were provided by the higher R^2. Differences in RMSE and CV at the V6 growth stage were not considerably high. Therefore, there is not sufficient evidence to conclude that the NDRE, the CI (RE), and the SR (RE) are better VIs than NDVI in yield potential prediction at early growth stages.

Conclusions

The ability to indirectly assess biomass and leaf Chl content was assessed for ten VIs. The use of the canonical correlation analysis allowed the combination of multiple variables into canonical variates to evaluate the correlation between plant status and vegetation indices canonical variates. High correlations were found between canonical variates suggesting that VIs could be used for indirect assessment of biomass and leaf Chl content. A frequency table by growth stage was developed including only the VIs with the top four highest correlations on each site-year. Indices with higher frequencies were those that appeared more often within the four highest correlations by growth stage. Vegetation indices that included the RE wavelength were more often among the highest correlations.

Yield prediction equations were developed for NDVI, NDRE, CI (RE), SR (RE) and ISR (RE). Linear regression models were evaluated for their yield potential predictability using the R^2, the RMSE, and the CV %. The NDRE, the CI (RE) and the SR (RE), resulted in the highest yield predictability at V6 growth stage showing consistency in high predictability as the growth stages progressed from V6 to V10. Therefore, the NDRE, SR (RE), and the CI (RE) are potential VIs to be included in algorithms combining multiple site-years for VRN application between V6 and V10 growth stage. However, further research is needed for better assessment of RE VIs yield predictability at early growth stages.

Table 1.1 Planting and sensing date by site and year.

Year	Site†	Plating Date	Sensing Date¶		
			V6	V8	V10
2010	EVS-R‡	31-Mar	-	18-May	-
	EVS-I§	13-Apr	18-May	-	-
	GCS‡	29-Mar	28-Apr	10-May	24-May
	TVS§	2-Apr	13-May	-	4-Jun
2011	EVS-I	7-Apr	-	23-May	3-Jun
	TVS	7-Apr	-	27-May	-
2012	EVS-R	27-Mar	1-May	11-May	-
	EVS-I	27-Mar	1-May	11-May	21-May
	GCS	21-Mar	27-Apr	10-May	14-May
	TVS	2-Apr	4-May	16-May	23-May

† EVS, E. V. Smith Research Center; TVS, Tennessee Valley Research and Extension Center; GCS, Gulf Coast Research and Extension Center.

‡Rainfed experiments.

§Irrigated experiments.

¶Sensing date by growth stage. Accounting from the first leaf to the last fully developed (collared) leaf. Six (V6), eight (V8), and ten (V10) leaves per plant.

Table 1.2 Vegetation indices (VIs) formulas used in this study.

VIs†	Equation‡	Source
NDVI	(NIR-Red)/(NIR+Red)	Rouse et al. (1973), Tucker (1980)
NDRE	(NIR-RE)/(NIR+RE)	Gitelson, A.A. and M.N. Merzlyak, (1994)
SR	NIR/Red	Jordan, (1969)
SR (RE)§	NIR/Red edge	-
ISR	Red/NIR	Gong et al., (2003)
ISR (RE)§	RE/NIR	-
Cl (RE)	(NIR/RE)-1	Gitelson et al., (2003b) and Gitelson et al., (2005)
Datt	(NIR-RE)/(NIR-Red)	Datt, (1999)
MTCI	(NIR-RE)/(RE-Red)	Dash and Curran (2004)
MSR	$(NIR/Red-1)/((NIR/Red)^{1/2}+1)$	Chen (1996)

†VIs: NDVI, normalized difference vegetation index; NDRE, normalized difference vegetation index; SR, simple ratio; SR(RE), simple ratio red-edge; ISR, inverse simple ratio, ISR(RE), inverse simple ratio red-edge; CI(RE), chlorophyll index red-edge; Datt, Datt index; MTCI, MERIS terrestrial chlorophyll index; MSR, modified simple ratio.

‡Red, 670nm; RE, 730nm; NIR, 760nm.

§Vegetation indices calculated in this study.

Table 1.3 Canonical Correlation by year, site and growth stage.

Year	Site†	GS‡	Canonical Correlation				Wilk's.L	SCV	
			CC1§	Pr > F	CC2§	Pr>F	Pr > F	$SCV_{P¶}$	$SCV_{VI\#}$
2010	EVS-R‡‡	V8	0.93	0.003	0.69	0.303	0.003	0.63	0.65
	EVS-I¥	V6	0.91	0.110	0.83	0.232	0.110	0.70	0.48
	GCS‡‡	V6	0.96	0.003	0.36	0.986	0.003	0.50	0.62
		V8	0.84	0.196	0.54	0.783	0.196	0.67	0.56
		V10	0.97	0.000	0.81	0.121	0.000	0.73	0.57
	TVS¥	V6§§	0.88	0.020	0.78	0.130	0.020	0.56	0.62
		V10	0.97	0.003	0.68	0.509	0.003	0.62	0.22
2011	EVS-I	V8	0.94	<0.0001	0.45	0.688	<0.0001	0.48	0.69
		V10	0.92	<0.0001	0.67	0.003	<0.0001	0.77	0.87
	TVS	V8ǂ	0.90	<0.0001	ND₩	ND	<0.0001	1.00	0.92
2012	EVS-R	V6	0.93	0.010	0.66	0.479	0.010	0.51	0.64
		V8	0.95	0.010	0.58	0.748	0.010	0.79	0.66
	EVS-I	V6	0.99	0.227	0.82	0.717	0.227	0.46	0.58
		V8	0.93	0.001	0.81	0.052	0.001	0.68	0.74
		V10	0.98	0.002	0.92	0.056	0.002	0.82	0.86
	GCS	V6	0.89	0.006	0.78	0.099	0.006	0.67	0.65
		V8	0.94	0.002	0.70	0.289	0.002	0.76	0.52
		V10	0.97	<0.0001	0.80	0.064	<0.0001	0.74	0.84
	TVS	V6	0.90	0.027	0.62	0.546	0.027	0.58	0.85
		V8	0.90	0.010	0.72	0.235	0.010	0.86	0.91
		V10	0.98	<0.0001	0.77	0.178	<0.0001	0.81	0.90

† EVS, E. V. Smith Research Center; TVS, Tennessee Valley Research and Extension Center; GCS, Gulf Coast Research and Extension Center.
‡GS, corn growth stage.
§CC, canonical correlation.
¶Standardized cumulative variance in plant status variables.
#Standardized cumulative variance in vegetation indices.
‡‡Rainfed.
¥Irrigated.
₩ND, non-data available.

Table 1.4 Intra-set and inter-set correlations generated through the CCA. Data collected at the V6 growth stage.

Variables†\sites‡	2010		2012		
	GCS§	TVS¶	EVS-R	GCS	TVS
Correlation between field-measured plant status variables and plant status canonical variate (PSV)					
SPAD (Chl)	1.00	0.98	0.98	0.86	1.00
LAI	-0.02	0.07	0.26	0.78	-0.41
Correlation between vegetation indices and plant status canonical variate (PSV)					
GS-NDVI	0.67	-	0.65	0.70	0.84
NDRE	0.77	0.72	0.81	0.74	0.82
NDVI	0.71	0.70	0.69	0.72	0.83
SR	0.69	0.70	0.69	0.78	0.82
SR (RE)	0.77	0.73	0.81	0.75	0.82
ISR	-0.72	-0.65	-0.68	-0.69	-0.84
ISR (RE)	-0.77	-0.71	-0.81	-0.72	-0.83
MTCI	0.86	0.70	0.83	0.70	0.83
MSR	0.70	0.70	0.69	0.77	0.82
CI (RE)	0.77	0.73	0.81	0.75	0.82
Datt	0.85	0.57	0.66	0.56	0.83

†Variables: SPAD, chlorophyll content; LAI, leaf area index; GS-NDVI, Greenseeker normalized difference vegetation index; NDRE, normalized difference vegetation index red-edge; NDVI, Cropcircle normalized difference vegetation index; SR, simple ratio; SR(RE), simple ratio red-edge; ISR, inverse simple ratio, ISR(RE), inverse simple ratio red-edge; MTCI, MERIS terrestial chlorophyll index; MSR, modified simple ratio; CI(RE), chlorophyll index red-edge; Datt, Datt index.

‡EVS, E. V. Smith Research Center; TVS, Tennessee Valley Research and Extension Center; GCS, Gulf Coast Research and Extension Center.

§Rianfed.

¶Irrigated.

Table 1.5 Intra-set and inter-set correlations generated through the CCA. Data collected at the V8 growth stage.

Variables†\sites‡	2010	2011		2012			
	EVS-R§	EVS-I¶	TVS¶	EVS-R	EVS-I	GCS§	TVS
Correlation between field-measured plant status variables and plant status canonical variate (PSV)							
SPAD (Chl)	0.97	0.96	1.00	0.99	0.68	0.99	0.96
LAI	0.57	0.16	-	0.79	0.95	0.74	0.89
Correlation between vegetation indices and plant status canonical variate (PSV)							
GS_ NDVI	0.85	0.71	0.87	0.65	0.75	0.85	0.85
NDRE	0.75	0.83	0.88	0.82	0.82	0.77	0.87
NDVI	0.76	0.71	0.86	0.72	0.76	0.67	0.84
SR	0.70	0.69	0.84	0.77	0.79	0.70	0.86
SR (RE)	0.73	0.81	0.87	0.84	0.82	0.76	0.87
ISR	-0.78	-0.70	-0.86	-0.68	-0.75	-0.60	-0.83
ISR (RE)	-0.76	-0.83	-0.88	-0.80	-0.82	-0.77	-0.86
MTCI	0.70	0.87	0.87	0.85	0.81	0.32	0.86
MSR	0.73	0.70	0.85	0.76	0.78	0.71	0.86
CI (RE)	0.73	0.81	0.87	0.84	0.82	0.76	0.87
Datt	0.72	0.89	0.87	0.76	0.82	0.05	0.85

†Variables: SPAD, chlorophyll content; LAI, leaf area index; GS-NDVI, Greenseeker normalized difference vegetation index; NDRE, normalized difference vegetation index red-edge; NDVI, Cropcircle normalized difference vegetation index; SR, simple ratio; SR(RE), simple ratio red-edge; ISR, inverse simple ratio, ISR(RE), inverse simple ratio red-edge; MTCI, MERIS terrestrial chlorophyll index; MSR, modified simple ratio; CI(RE), chlorophyll index red-edge; Datt, Datt index.

‡EVS, E. V. Smith Research Center; TVS, Tennessee Valley Research and Extension Center; GCS, Gulf Coast Research and Extension Center.

§Rianfed.

¶Irrigated.

Table 1.6 Intra-set and inter-set correlations generated through the CCA. Data collected at the V10 growth stage.

Variables†\sites‡	2010		2011	2012		
	GCS§	TVS¶	EVS-I¶	EVS-I	GCS	TVS
Correlation between field-measured plant status variables and plant status canonical variate (PSV)						
SPAD (Chl)	0.97	1.00	0.99	0.98	0.98	0.96
LAI	0.72	0.49	0.74	0.82	0.72	0.84
Correlation between vegetation indices and plant status canonical variate (PSV)						
GS_ NDVI	0.75	0.48	0.70	0.84	0.87	0.87
NDRE	0.85	0.61	0.89	0.94	0.91	0.97
NDVI	0.61	0.28	0.85	0.88	0.86	0.88
SR	0.61	0.33	0.84	0.91	0.83	0.91
SR (RE)	0.86	0.67	0.89	0.95	0.89	0.97
ISR	-0.60	-0.28	-0.85	-0.87	-0.85	-0.85
ISR (RE)	-0.85	-0.57	-0.89	-0.93	-0.92	-0.97
MTCI	0.50	-0.23	0.89	0.93	0.90	0.97
MSR	0.61	0.31	0.85	0.90	0.85	0.91
CI (RE)	0.86	0.67	0.89	0.95	0.89	0.97
Datt	0.87	0.23	0.88	0.91	0.93	0.98

†Variables: SPAD, chlorophyll content; LAI, leaf area index; GS-NDVI, Greenseeker normalized difference vegetation index; NDRE, normalized difference vegetation index red-edge; NDVI, Cropcircle normalized difference vegetation index; SR, simple ratio; SR(RE), simple ratio red-edge; ISR, inverse simple ratio, ISR(RE), inverse simple ratio red-edge; MTCI, MERIS terrestrial chlorophyll index; MSR, modified simple ratio; CI(RE), chlorophyll index red-edge; Datt, Datt index.
‡EVS, E. V. Smith Research Center; TVS, Tennessee Valley Research and Extension Center; GCS, Gulf Coast Research and Extension Center.
§Rianfed.
¶Irrigated.

Table 1.7 Ranking of occurrence of vegetation indices having the highest intra-set correlation.

VIs†	V6		V8		V10	
	Sensing times year-location (5)		Sensing times year-location (7)		Sensing times year-location (6)	
	Freq (VI)‡	%§	Freq (VI)	%	Freq (VI)	%
GS_ NDVI	1	20	3	43	0	0
NDRE	3	60	6	86	6	100
NDVI	1	20	1	14	0	0
SR	1	20	1	14	0	0
SR (RE)	4	80	5	71	4	67
ISR	1	20	1	14	0	0
ISR (RE)	4	80	6	86	6	100
MTCI	3	60	4	57	4	67
MSR	1	20	1	14	0	0
CI (RE)	4	80	5	71	5	83
Datt	2	40	3	43	3	50

†VIs: GS-NDVI, Greenseeker normalized difference vegetation index; NDRE, normalized difference vegetation index red-edge; NDVI, Cropcircle normalized difference vegetation index; SR, simple ratio; SR(RE), simple ratio red-edge; ISR, inverse simple ratio, ISR(RE), inverse simple ratio red-edge; MTCI, MERIS terrestrial chlorophyll index; MSR, modified simple ratio; CI(RE), chlorophyll index red-edge; Datt, Datt index.

‡Frequency of occurrence in top four highest correlations (times by growth stage a VI is in the top four higher correlations).

§Percent Frequency (number of times in the top four higher correlations divided by total sensing times at V6 times100).

Table 1.8 Performance evaluations of five linear regression models as predictors of corn yield potential at the V6, V8, and V10 corn growth stages.

Growth Stage	Parameter	Vegetation Index†				
		NDVI	NDRE	CI(RE)	SR(RE)	ISR(RE)
V6	R^2†	0.26	0.37	0.34	0.43	0.12
	RMSE‡	2247	2080	2129	1982	2452
	CV§	30	28	28	26	33
V8	R^2	0.30	0.42	0.40	0.41	0.32
	RMSE	2497	2270	2303	2289	2462
	CV	35	32	32	32	35
V10	R^2	0.36	0.67	0.67	0.68	0.09
	RMSE	2568	1850	1861	1814	3071
	CV	37	27	27	26	45

† The values under each vegetation column represent three different model performance indicators of good-need of fit. Every model included a single vegetation index as independent/predictor variable.
†R^2, Coefficient of determination.
‡RMSE, root mean square error (kg ha^{-1}).
§CV, coefficient of variation (%).

III. NITROGEN FERTILIZER RESPONSE OF CORN AS AFFECTED BY RAINFALL PATTERNS IN ALABAMA

Abstract

Nitrogen (N) fertilization is an important practice for increasing yield in corn (*Zea mays* L.). However, plant-soil interactions with in-season climatic variability result in different site-specific responses of corn to N fertilizer rates. The objectives of this study were to evaluate the Cropping System Model (CSM)-CERES-Maize for its ability to simulate growth, development, grain yield and grain N of corn planted in Alabama, and to evaluate the impact that in-season changes in rainfall have on simulated corn yield, N leaching (NL), inorganic N in the soil at maturity (IN), and nitrogen use efficiency (NUE). The crop model was calibrated and evaluated using data collected from an N fertilization study conducted at two locations in Alabama (AL) between 2009 and 2012.Three N treatments from a randomized complete block design of 16 N rate treatments (r =5) were selected for this study. The N treatments used were 0, 168, and 224 kg N ha^{-1}. The N rates were split at planting and side-dress in 56-112 and 67-157, for 168 and 224 kg N ha^{-1}, respectively. Two rainfall scenarios used for the simulation modeling study were established by analyzing values of the abundant and well distributed rain index (AWDR) which assesses rainfall amount and evenness for a given period. Weather data of 61 years was used to calculate AWDR values index corresponding to two different corn growing scenarios; i) Scenario A:dry/wet May-June years and ii) Scenario B: years having dry/wet March-June period and wet/dry July-August period. Results from a seasonal analysis indicated that corn response to N fertilization changed based on the in-season rainfall conditions and soil type (Silt loam in North and Loamy sand in Central AL). For scenario A, the crop response to N rates under wet May-June years period was higher that dry years at both locations. For Central AL, the N rate yield response curve under rainfall conditions reached a plateau at 56 and 112 kg N ha^{-1} during a dry and wet May-June, respectively. For the conditions of North AL, when the model was run under rainfed conditions, corn N response was higher. During dry May-June years no N fertilizer was needed to achieve the maximum yield, while in wet May-June years, 56 kg N ha^{-1} was sufficient to reach the plateau where yield did not significantly increase with higher N rates. For scenario B, when the model was run for EVS rainfed using years characterized as wet March-June period and dry July-August period, higher yield were observed. A prolonged period under wet conditions favored higher

yield. However, under irrigation, no significant differences between wet-dry and dry-wet combination were observed at EVS. In contrast, at TVS no significant differences were observed between dry-wet and wet-dry conditions under rainfed conditions, but significant differences were found under irrigation. For rainfed conditions the silt loam at TVS was able to hold more water during the dry period and prevent yield losses. However, when irrigated, yield was negatively affected in the silt loam during the wet-dry combination due to excessive water. Farmers could use results from this study as a decision support tool to improve N management in corn under Alabama growing conditions.

Introduction

Nitrogen fertilization in corn has been a subject of extensive research due to its significant impact on corn biomass and grain yield production. Nitrogen fertilization represents 40% of the total corn production cost (Varco, 2013). However, farmers sometimes give N cost less importance when a substantial yield increase is achieved. Nonetheless, increasing NUE is key to reduce environmental pollution and enhance sustainability in the long term. Uniform application of N at side-dress in corn is a common practice among farmers in the southeast US, even though high variability of corn N-response driven by soil and weather conditions results in low N use efficiency (NUE). Tremblay et al. (2012) found yield increased by a factor of 1.6 and 2.7 due to N fertilization at medium and fine soil textures, respectively, compared with the control treatment (zero N applied) . However, they also reported low yields at low and high N rates evidencing the high variability in corn N response.

Precise estimation of optimum N fertilizer rates is key to increasing NUE and reducing N leaching losses. Raun and Johnson (1999) reported a worldwide average NUE of 33% in cereal grain production implying the need to understand and control the N cycle for reducing negative environmental impacts of N over-application. Howarth (2008), studying coastal N pollution, related the increase of global coastal eutrophication to the increase in N fixation from agriculture, synthetic N fertilizer use, and fossil fuel consumption. From these three processes, synthetic fertilizer use was found to be the main N source of pollution (100 Tg year^{-1}).

Nitrogen recommendations have traditionally followed the mass-balance approach (Stanford, 1973). By this method, N rates were back-calculated based on yield goal and grain N concentration. It accounts for non-fertilizer N sources such as N mineralized from soil organic matter (SOM), preceding crops, and organic amendments. Scharf et al. (2006) found that the mass balance approach is not accurate in estimating the right N rate because it was based on historical data, N mineralization, and plant N uptake, which are highly variable within a field and between years.

Methods for variable rate N (VRN) application attempt to increase NUE by accounting for within-field spatial N need variations, but does not account directly for temporal climate and weather variability (Kitchen et al., 2010; Mullen et al., 2003; Solie et al., 2012; Teal et al., 2006). Soil properties such as texture, water holding capacity, SOM, as well as ambient temperature and precipitation, have a significant impact on soil N dynamics, which directly affects NUE and crop yield (Zhu et al., 2009).

Nitrogen use efficiency was found to be affected by soil texture when comparing N response across different soil types and locations (Tremblay et al., 2012). Soils with finer textures tend to hold more N due to higher cation exchange capacity (CEC) and to have higher SOM contents (Gaines and Gaines, 1994; Van Es et al., 2002). Therefore, fine textured soils typically have higher NUE than course textured soils. This difference was evidenced when significant lower economic optimal N rates were needed to maximize yield in a silt loam and silty clay loam soils as compared to irrigated sandy soils (Oberle and Keeney, 1990). Moreover, Kim et al. (2008) indicated that N and water in the soil are synergistically related. In this association, water additions enhanced NUE while N additions enhanced water use efficiency. Temperature is also important for N dynamics because it affects N mineralization rate. Tremblay et al. (2012) reported that temperature plays an important role affecting NUE from 30 days before side-dress (SD) to 15 after side-dress. They also found that rainfall was key from 15 days before SD to 30 days after side-dress. The higher temperatures before SD will promote N mineralization, while the higher rainfall after SD will enhance water and nutrient uptake. The NUE improvements require decision tools for N rates estimation that take into account the influence of weather on this process. Therefore, an understanding of the role of weather and climate on NUE combined with in-season assessment spatial N needs can improve N management.

Corn production in the southeastern US is influenced by climate conditions, characterized by high temperatures and relative humidity as well as highly variable rainfall. In the Alabama Gulf Coast region, average annual rainfall reaches 1500 mm a year. However, rainfall events are extremely variable in terms of distribution and amount (Kunkel et al., 2013). Due to inconsistent weather and climate patterns throughout the growing season, crop yields vary among years. Along with the impact of inter-annual climatic conditions on the Southeast corn yield, changes in soil type across the region impose another challenge on N management. Common soils in the Southeast are Spodosols, Alfisols, and Ultisols, with the latter being the predominant soil type in the Piedmont and Gulf Coastal Plains regions. Ultilsols are highly weathered, acids, with low CEC and high pH dependent charges (Shaw et al., 2010). These conditions open an opportunity for further research on corn N fertilizer recommendations taking into account soil type and in-season weather and climate conditions.

When properly calibrated and validated simulation crop growth models can play an important role in assessing N fertilizer requirements by taking into account interactions between management and environmental conditions. Some examples of existing models used for supporting N fertilizer management and yield estimation are Maize-N (Setiyono et al., 2011), ADAPT-N (Melkonian et al., 2008), and the crop system model (CSM)-CERES-Maize model (Jones and Kiniry, 1986; Jones et al., 2003; Ritchie et al., 1998). The first two models, Maize-N and ADAPT-N, were developed for pre-plant and in-season N rate estimation by accounting for previous crops, mineralized N, organic fertilizers (manure), in-season weather (site specific) and N-corn market prices (only Maize-N). The CSM-CERES-Maize model was developed for research and extension purposes. The CSM-CERES-Maize is part of the Decision Support System for Agrotechnology Transfer (DSSAT) which includes a set of 16 different crops simulation models. It has a main driver program (land unit module) with five primary modules (weather, soil, plant, soil-plant-atmosphere interface, and management components). Together, the modules describe a specific environment or land unit module (Jones et al., 2003). In the model, soil water is simulated on a daily basis accounting for rainfall, irrigation, infiltration, vertical drainage, unsaturated flow, soil evaporation and plant water uptake (Ritchie et al., 1998). The N balance is also simulated with the model accounting for mineralization, immobilization, denitrification, leaching, and plant N uptake (Goodwin and Singh, 1998). The CSM-CERES-Maize has been used with successful results in several studies (Kovács et al., 1995; Pang et al., 1997; Singh et al., 1993). For instance, Pang et al. (1997) successfully simulated grain yield and N uptake under irrigation with $R^2 = 0.94$ and $R^2 = 0.95$, respectively. Also, NO_3-N leaching for no-till lysimeters, under corn-alfalfa rotation, was well simulated by Gerakis et al. (2006).

The objective of this this study was to evaluate the impact of in-season changes in rainfall on simulated corn yield, N leaching (NL), inorganic N in the soil at maturity (IN), and nitrogen use efficiency (NUE). The results from this study will be used to understand plant N response and improve current N recommendations rates for southeastern US climate conditions.

Materials and Methods

Experimental data

A field N experiment was conducted at two Alabama Agricultural Experiment Stations during a period of four years (2009, 2010, 2011, and 2012). The research stations were, the E.V. Smith Research Center (EVS) in Shorter, AL (32°25’43.43”N, 85°53’34.81”W, 69 m elevation) and Tennessee Valley Research and Extension Center (TVS) in Belle Mina, AL (34°41’05.37N, 86°53’18.04”W, 187 m elevation). Both experiments were sprinkler irrigated according to plants need and research stations practices.

In each site-year, a randomized complete block design (r = 5) with 16 N treatments was implemented. Nitrogen was applied as liquid urea ammonium nitrate (28 % N). Three N treatments, 0, 168, 224 kg N ha^{-1} were selected for this study. Nitrogen rate was split, 1/3 of total N applied at planting and the remainder in a side-dress application at the V6 growth stage. The N rates for planting and side-dress were 0-0, 56-112 and 67-157 for 0, 168 and 224 kg N ha^{-1} treatments, respectively. Plots received a pre-plant application of P, K, and lime based on recommendations of the Soil Testing Laboratory at Auburn University and the Alabama Cooperative Extension Systems (ACES) (Mask and Mitchell, 2012). Each four rows plot was 3.66 m wide by 10 m long with 0.9 m row spacing. The corn hybrid Pioneer 31P42 was sown at 70,000 seeds ha^{-1} at the EVS site and 80,000 seeds ha^{-1} at the TVS site during the four years of the study. Planting dates by year and location are shown in Table 2.1.

Plant, soil, and weather data

Model calibration and validation data for crop phenology parameters of emergence, anthesis, and physiological maturity dates were collected following crop the physiology parameters as described by Ritchie et al. (1992)(Table 2.1). Biomass was collected at midseason (R1 growth stage) and physiological maturity from four replications on each study site over an area of 0.91 and 0.76 m^2 in each plot at EVS and TVS respectively. Samples were separated into leaves, stems, and ears; oven dried (with air circulating at 70 °C) to constant weight. Leaves and steams were weighted separately and ears were counted and segregated into husk, kernels, and cobs and weighed independently. Kernel number and moisture content were determined and dry matter weight was calculated. Yield components derived from the biomass samples were number of kernels per ear, number of kernels per m^2, and average kernel mass (yield). Yield was corrected to 0% of moisture.

Soil series at the study sites were Compass loamy sand (coarse-loamy, siliceous, subactive, thermic Plinthic Paleudults) at the EVS site and Decatur silt loam (fine, kaolinitic, thermic Rhodic Paleudults) at the TVS site. At both locations volumetric soil water content ($cm^3\ cm^{-3}$) was measured at 15 and 30 cm soil depths. At the EVS site, soil moisture was also measured at 60 cm depth. The EC-5 (Decagon Devices Inc., USA) soil sensors were used to record volumetric soil water content at four hour intervals throughout the growing season. The soil moisture data was used to calibrate the soil-water holding characteristics. Nitrogen content in the soil (%) for the treatment 168 kg N ha^{-1} at four replications was measured at 20cm depth at EVS and TVS after harvest in 2012. Each treatment sample was the combination of 15 soil subsamples across the plot. Subsamples collection was divided into three sets of five subsamples per plot. The first set was collected between the first and the second row, the second set between the second and the third row, and the third set between the third and the fourth row. Within each set, the first subsample was collected in the row and the subsequent subsamples were collected in the mid-row in a diagonal direction towards the following row where the fifth subsample was collected. Nitrogen content (%) was determined by total combustion using a Vario Elementar macro CNS analyzer (Elementar Analysensysteme Gmblt, Hanau, Germany).

Weather input data for model calibration and validation for the period 2009-2012, including rainfall and temperature (maximum and minimum), was obtained from the CRONOS Database (North Carolina Climate Retrieval and Observations Network Of the Southeast Database, http://www.nc-climate.ncsu.edu/cronos). Daily solar radiation was estimated using the method described by Hargreaves and Samani (1982).

Daily weather input data for the seasonal analysis simulation was obtained from the Cooperative Observer Program (COOP) network of the national weather service (http://www.nws.noaa.gov/om/coop/) for a period of 61 years data available (1950-2010). Daily solar radiation was estimated with the WGER generator (Hodges et al., 1985) and then adapted for the south-eastern USA conditions (Garcia y Garcia et al., 2008).

In-season rainfall variability

Rainfall changes in the growing-season were studied for assessment of their impact on yield, grain NUE, IN and NL. By site-year, historic records of 61 years of daily rainfall were analyzed in terms of rainfall amount and distribution over different periods within each growing season. The abundant and well distributed rainfall (AWDR) index representing optimal water availability (abundant rainfall, well distributed in time) over a specific time period was selected for this analysis. The AWDR index was calculated following the methodology proposed by Tremblay et al. (2012) using equation 1. The AWDR assesses and combines rainfall amount (PPT) and frequency (SDI) for a given period (n).

$$AWDR = PPT \times SDI \qquad (1)$$

Where PPT is the cumulative daily rainfall (mm) over the study period [Σ(Rain)], and the SDI corresponds to the Shannon diversity index defined by equation 2. The SDI ranges from 0-1. SDI = 1 implies equal amount of rain in each day of the year, while SDI = 0 implies extreme unevenness in rainfall distribution.

$$SDI = [-\Sigma pi \ln(pi)]/\ln(n) \quad (2)$$

Where pi = Rain/PPT and n corresponded to the number of days in the given period (Bronikowski and Webb, 1996).

Annual differences on daily AWDR were studied for two different periods during the corn growing season: i) *Scenario A*, corresponding to either dry or wet condition during the May-June period and ii) *Scenario B*, corresponding to dry/wet March-June and dry/wet July-August periods. The May and June months represent important condition for corn growth and development in Alabama. During this period, N side-dress application, corn tasseling, and silking normally occur. Tremblay et al. (2012) when studying corn N uptake response to soil texture and weather, found that rainfall was most critical for N uptake from 15 days before to 30 days after N side-dress. Those results show a higher N response when high rainfall occurred during this 45 days period because water supply enhances plant growth and nutrient uptake. Additionally, avoiding water stress during the flowering period was important. Nesmith and Ritchie (1992) when studying tassel development and yield in corn as affected by water-deficits, reported 46% yield losses when corn was under water stress for 19 subsequent days starting just before tasseling. Water stress during the flowering period negatively affected the plant reproductive stage resulting in poor synchronization in flower organ appearance (Freier et al., 1984; Herrero and Johnson, 1981) and embryo abortion (Westgate and Boyer, 1986).

Using rainfall data representing dry and wet conditions for the May-June period will help to understand its impact on N side-dress on final yield and NUE. With *scenario B*, the goal was to evaluate the impact of water either during the growth and development period or grain filling period affecting yield and NUE the most. Our hypothesis was that if a wet March-June combined with dry July-August occurs, N side-dress application could be favored. Plus, corn plants may be less impacted during the silking and initiation of the grain filling period, but the opposite might occur if the rainfall scenario corresponds to a dry March-June and wet July-August period. For *scenario A*, the AWDR was calculated for the May-Jun period corresponding to each of the 61 years of weather data. The AWDR index values that were below the 25th quantile and above the 75th quantile of the distribution were then grouped into two sets of years defined as dry and wet years for the May-June time frame.

Scenario B conditions consisted in selecting years characterized as dry March-June and wet July-August conditions or wet March-June and dry July-August conditions occurring within the same year. The first AWDR values corresponded to the period from March-June and the second value corresponded to the July-August period. These AWDR values were used to identify years with AWDR values below the 25th percentile (driest years) and years with AWDR values above the 75th percentile (wettest years) for each specific time period. Years were selected if they consisted of a dry March-June and a wet July-August or vice versa.

Model Calibration

Field data collected at the EVS and TVS sites in 2012 was used to calibrate the CSM-CERES-Maize model of DSSAT 4.5 (Hoogenboom, 2010) and to generate the cultivar coefficients for the Pioneer

31P42 corn hybrid (Pioneer Hi-Bred International, Johnston, Iowa). Only treatments with sufficient N (168 and 224 kg N ha^{-1}) were used for calibration. This procedure was needed in order to account for the specific environmental conditions of corn grown in the southeastern US.

Soil-Water Holding Characteristics and Nitrogen assessment

The crop model required estimation of specific soil-water holding characteristics in order to estimate soil plant-available water. For each horizon in the soil profile, the soil water holding characteristics required by the model include permanent wilting point or lower limit (LL, cm^3 cm^{-3}), field capacity or drained upper limit (DUL, cm^3 cm^{-3}), saturated water content (SAT cm^3 cm^{-3}), saturated hydraulic conductivity (KSAT, cm h^{-1}), and root growth factor (SRGF, ranging from zero to one) (Table 2.4). The SBuild program of DSSAT Verison 4.5 was used to estimate initial values of those parameters using basic soil characteristics for each layer that were input into the model. The estimated KSAT value for each horizon was replaced by data from the Web Soil Survey (USDA-NRCS, http://websoilsurvey.nrcs.usda.gov/app/WebSoilSurvey.aspx).

Using a preliminary set of cultivar coefficients, the soil water holding characteristics were calibrated for the first two or three soil horizons by adjusting the LL, DUL, and SAT simulated values to the measured values. A quality calibration was reached by minimizing the root mean square error (RMSE) between simulated and observed volumetric soil water content for the specific soil horizons depths of the 168 kg N ha^{-1} treatment. The SBuild program was also used to estimate soil drainage, soil albedo, and runoff curve number based on soil color, drainage, slope and runoff potential for each experimental location. Soil profile calibration improves the soil crop model simulation by minimizing the error between simulated and measured soil profile characteristicsCultivar Coefficients

Coefficients calibration using 2012 data from EVS and TVS for the corn hybrid Pionner 31P42 was done following the procedures described by Boote (1999). The variables considered for this procedure were crop phenology parameters, plant biomass partition, grain yield, as well as plant tissue and grain N content. Crop phenology was calibrated using observed emergence, anthesis, and physiological maturity dates. Biomass partitioning data was collected at flowering and physiological maturity. After soil water holding characteristics were calibrated, the new cultivar coefficients were estimated using the GLUE (generalized likelihood uncertainty estimation) analysis tool (He, Porter, et al., 2010). The coefficients calibrations were performed in a sequential order from phenology parameters to growth and development parameters. Sensitivity analysis for phenology parameters, biomass components, yield, and N variables were conducted to estimate the cultivar coefficient values that minimized the RMSE between simulated and observed values for the N fertilized treatments (168 and 224 kg N ha^{-1}). Cultivar coefficients descriptions and coefficients for the corn hybrid Pioneer 31P42 are shown in Table 2.5.

Model Evaluation and Statistical Methods for Performance Assessment

Model calibration and validation assessment for the corn hybrid Pioneer 31P42 was done by comparing simulated phenology parameters, biomass components, grain yield, and N variables to observed values. Five site-years of data were used for model validation including data collected from the EVS site during 2009 and 2010, and the TVS site from the period 2009-2011. The simulated values deviation with respect to the measured values was evaluated by assessing results from three statistical parameters included in the DSSAT package. Those parameters were: root mean square error (RMSE), percentage prediction deviation (PD), and the index of agreement, d-statistic (Willmott, 1982). Values for each index were calculated using the following equations:

$$RMSE = \left[N^{-1} \sum_{i=1}^{n} (P_i - O_i) \right]^{0.5}$$

$$PD\ (\%) = \left(\frac{P_i - O_i}{O_i} \right) x\ 100$$

$$d = 1 - \left[\frac{\sum_{i=1}^{n} (P_i - O_i)^2}{\sum_{i=1}^{n} (|P'_i| + |O'_i|)^2} \right], 0 \leq d\ \leq 1$$

N = number of observed values.

P_i = predicted value. $P_i = P_i – O$.

O_i = observed value. $O'_i = O'_i – O$.

O = Mean of observed values.

The RMSE measures the difference between the observed and predicted values. A lower error between simulated and observed values is observed when the RMSE approaches zero. For the d-statistic the closer it is to one, the better prediction of the simulated over the measured values. The percent prediction deviation assesses model under- or over- prediction, with negative or positive PD values, respectively.

Model application

After model calibration and validation, an analysis was conducted to assess corn yield, grain NUE, NL, and IN at the EVS and TVS sites under contrasting climate scenarios with respect to rainfall amount and distribution. Sixty one years (1950-2010) of historical weather data from weather stations located were for the model simulation analyses. A seasonal analysis within DSSAT was conducted for simulating corn response to six different N rates under irrigated and rainfed conditions (Thornton and Hoogenboom, 1994). Irrigation parameters were set to 50 % threshold of maximum water holding capacity, 0.4 m management depth, and 85 % efficiency. Nitrogen rates ranging from 0 to 280 kg ha^{-1} were established in order to simulate a wide range of possible N rates applied by farmers in the area. The N rates were 0-0, 0-56, 34-78, 67-157, 140-140 and 280-0 kg N ha^{-1} with the first number of the rate combination corresponding to the N rate applied at planting and the second number corresponding to the N side-dress rate. For the seasonal analysis, specific planting date and N fertilizations dates were established based on the management practices implemented on the field experiment for the 2009-2012 period at each site. The planting and first N fertilization application dates were 2 April and 12 April at TVS and EVS sites, respectively. The side-dress N application date was set at 40 days after planting, corresponding to 12 May and 22 May, for the TVS and EVS sites, respectively.

Once the seasonal analysis was completed, the simulated data for the years identified on the rainfall analysis corresponding to rainfall *scenarios A* and *B* were grouped and analyzed separately to study the impact of rainfall condition on corn N responses in terms of dry grain yield (kg ha^{-1}), total N applied (N rate, kg ha^{-1}), NL (kg ha^{-1}), IN (kg ha^{-1}), and grain NUE (%).

Grain N use efficiency (fertilizer N recovery) was calculated for both scenarios (A and B) under rainfed and irrigated conditions using the following formula (Pomares-Garcia and Pratt, 1978):

$$PFR = (NF)\text{-}(NC) / R$$

NF = total N uptake in corn from N fertilized plots (kg ha^{-1})

NC = total N uptake in corn from unfertilized plots (kg ha^{-1})

R = rate of fertilizer N applied (kg ha^{-1})

PFR = percent fertilizer recovery (%)

Statistical Analysis

For each scenario, differences between dry and wet conditions with respect to AWDR, yield, NUE, NL, and IN values were analyzed. Yield, NUE, NL, and IN differences between N rates were analyzed within each scenario (A and B) under rainfed and irrigated simulation conditions. The statistical analysis was conducted using the procedure linear mixed models (PROC MIXED) implemented in SAS (SAS Institute, 2008). Nitrogen treatments and weather scenarios (AWDR) were considered fixed effects. Mean separation between N treatments for yield, NUE, NL and IN were obtained by a Tukey’s significant difference test ($P < 0.05$).

Results and Discussion

Calibration and evaluation of the CSM-CERES-Maize model

The corn hybrid 31P42's cultivar coefficients providing the lowest RMSE and highest d-statistic for the group of study variables measured at both sites are presented in Table 2.5. After calibration, the RMSE between simulated and observed anthesis dates corresponding to N-fertilization/site combinations was 1.6 days with a d-statistic value of 0.94 (Fig. 2.1.a). The physiological maturity date was simulated earlier at TVS and later at EVS resulting in 2.5 days RMSE, for both sites combined (Fig. 2.1.b). Above ground biomass and yield resulted in d-statistic value above 0.8 with RMSE values of 2341 and 1188 kg ha^{-1}, respectively (Fig. 2.1.c and 2.1.d). The d-statistic for above ground biomass and grain N were 0.77 and 0.55, respectively. The RMSE for the same variables were 37 and 30 kg ha^{-1}, respectively (Fig. 2.1.e and 2.1.f).

Validation results including anthesis (DAP), above ground biomass (kg ha^{-1}), yield (kg ha^{-1}), and grain N (kg ha^{-1}) variables for all site-years shown in Fig. 2.2. There were no differences between simulated and measured anthesis days for the EVS-2009 and TVS-2010 site-years. The highest difference between simulated and measured anthesis days was observed at EVS-2009 [PD = (-12.5%), 10 days difference]. Overall, The RMSE between simulated and measured anthesis dates across all site-years was 6 days with a d-statistic value of 0.88. Above ground biomass weight and grain yield were well simulated for all fertilized treatments at the EVS and TVS site in 2009 and 2010. The PD values ranged from (-4.8) to 34.1 %, and from (-1.3) to 38.1 % for above ground biomass and grain yield, respectively. The above ground biomass resulted in 3650 kg ha^{-1} RMSE and a d-statistic value of 0.86 (data from three site-years). Yield was well simulated. It resulted in 2091 kg ha^{-1} RMSE and 0.87 d-statistic value calculated using five site-years data. At TVS, 2011grain yield resulted in 56.4% PD and 82.4% PD for the 150 and 200 kg N ha^{-1} treatments, respectively. Finally, grain N calculated with data from EVS-2009 resulted in 79 kg N ha^{-1} RMSE and a d-statistic value of 0.6.

Climatic Analysis

Sixty one years were used to calculate the AWDR index values for two different weather growing scenarios: May to June rainfall (*Scenario A*) and March-June rainfall conditions combined with July-August rainfall conditions (*Scenario B*). For *scenario A*, 15 years exhibited the lowest AWDR index values. These were classified as years with May-June months exhibiting low and not well distributed rainfall (dry May-June conditions). There were also 15 years that showed the highest AWDR index values, therefore they were classified as years with May-June months exhibiting higher than average and well distributed rainfall (wet May-June conditions). It is important to state that the years selected for each location were different given that the AWDR index was calculated by location using local weather data (Table 2.2). For instance, for the EVS site, the AWDR index values ranged from 24 to 65 for dry years and 134 to 290 for wet years, respectively. When the AWDR values for the TVS site were compared with the EVS site, a wider range of AWDR index values (13 -76) for the dry years group compared with a narrower range of AWDR values (163- 294) for the wet years was observed. Average values for AWDR in wet years were at least two times higher than AWDR values in dry years for each location ($P < .0001$) (Table 2.2). For *scenario B*, only four years matched the rainfall selection criteria (Table 2.3). The year selection under this scenario was more complex because the goal was to identify years that combined an extremely wet period (AWDR values above 75th quartile, March to June period) followed by an extremely dry period (AWDR values below 25th quartile, July to August period) and vice versa. Average values for AWDR in wet years were significantly different from dry years for each location ($P < .0001$) and at least twice high. When comparing the AWDR index values between July-August wet years and July-August dry years, differences in AWDR index values were statistically significant ($P < .0001$). Significant differences between AWDR values in dry and wet periods are important for evaluation of crop yield, NUE, NL, and IN and NUE under contrasting rainfall amount and distribution.

Model Application

The years selected through the analysis of AWDR index values corresponding to the climate *scenarios A* and *B* were used for simulating corn yield response to supplemental N under rainfed and irrigated conditions. The corn response to N application was evaluated in terms of grain yield (kg ha^{-1}), NL (kg N ha^{-1}), IN (kg N ha^{-1}), and NUE (%). Overall, independently of the climate scenario, an increase in yield and IN and a decrease in NUE were observed as the N rate increased. The N leaching was mainly dependent on the rainfall conditions, dry or wet conditions, and was not significantly affected by N rate changes.

Tremblay et al. (2012) found that the N-rich rate (178 kg N ha^{-1}) resulted in significant lower yield than the one produced by the split application [34 and 134 kg N ha^{-1} at planting and side-dress (median: V7), respectively]. They reported higher yield for the split application in several cases with different soil textures, at low and high AWDR values. However, in our study for both scenarios, there were no significant differences in yield and NUE between the split (140-140 kg N ha^{-1}) and the N-rich starter of 280 kg N ha^{-1}. The 280 kg N ha^{-1} treatment was a considerable amount of N that was not affected by changes in rainfall amount and distribution.

Scenario A - Rainfed

Grain yield was significantly influenced by rainfall amount and distribution, dry and wet May-June periods based on AWDR values, at the EVS ($P < .0001$) and TVS ($P < .0001$) sites (Table 2.2).

During the May-June wet years, a 100% yield increase was observed in both locations with respect to dry conditions during the same growing period (Tables 2.6-7). At the EVS site, corn yield response curve reached a plateau at 4021 and 8320 kg ha^{-1} during dry and wet May-June years, respectively. When dry May-June conditions occurred, the plateau was reached when N-application rate exceeded 56 kg N ha^{-1}. In contrast, during wet May-June periods, the plateau was reached with a rate of 112 kg N ha^{-1}. At the TVS site, there were no significant yield differences ($P = 0.14$) between N rates during dry May-June years and the average yield among N treatments was 4573 kg ha^{-1}. During wet May-June years, yield differences existed only between the zero and the N fertilized treatments ($P < .0001$), but there were no differences among N fertilized treatments. The plateau for the yield response function was reached with less N amount at the TVS site when compared to the EVS site. The higher N response could be associated with differences in rainfall amount and distribution, soil texture and organic matter. At the

TVS site, the average AWDR index value for the dry May-June years was 213 compared to the 185 AWDR index value at the EVS site, which indicated a higher amount and well distributed rainfall during that period. The silt loam soils at the TVS site favored N uptake compared to the loamy sand soils in the EVS site. Tremblay et al. (2012) found a higher N response on soils with a clay content above 30% when studying the impact of weather and soil texture on N response at 51 locations in the United States, Mexico and Canada. Soil with higher clay content retain more water and tend to have higher soil organic matter contents than sandy soils (Baldock and Skjemstad, 2000; Denef et al., 2004). Moreover, Oberle and Keeney (1990), when studying the factors affecting corn fertilizer N requirements in the U.S. Corn Belt, found that silt loam and silty clay loam soils had lower economic optimal N rates than irrigated sandy soils.

Beside yield, significant differences between dry and wet May-June years existed for NUE, IN, and N leaching (Tables 2.6-7). Higher NUE was observed in wet years compared to the same treatments under dry conditions (low AWDR values). Independent of location, the highest value of NUE was observed in the control treatment (0 Kg N ha^{-1}); NUE decreased significantly with increasing N amount. At the EVS site, the NUE values ranged from 100 to 18% under dry May-June years and from 100 to 42% for wet May-June years. At TVS, the NUE also followed the same trend; it ranged from 100 to 20% and from 100 to 44% at dry and wet years respectively, with significant differences among N rates as well. The water available in the soil through rainfall might be related to NUE differences between dry May-June years (low NUE) and wet May-June years (high NUE). Under low soil moisture conditions, the applied N does not move downward promptly into the soil, and thereby not taken up by the plant. Similar findings were reported by Kim et al. (2008) when analyzing relationships between water and N in the soil. They found that a synergistic relationship existed between water and N and that NUE was enhanced by water additions with water use efficiency enhanced by N additions.

In this study, three N pathways for N were studied. These included IN, NL below root zone, and plant N uptake (calculated as NUE). Even though, the amount of NL differed between the dry and the wet years ($p < .0001$ and $p < .0023$ at EVS and TVS, respectively), there were no significant differences among N rates in dry or wet years for both locations. For instance, at the EVS site, the NL resulted in 17 and 31 kg N ha^{-1} during dry and wet years, respectively. At the TVS site, the mean NL values were 2 and 5 kg N ha^{-1} for the dry and wet years, respectively. Differences in NL between EVS and TVS could be attributed to soil texture and organic matter. The silt loam soil at the TVS site has higher clay and organic matter content (higher CEC) which results in higher potential for N absorption (Gaines and Gaines, 1994; Van Es et al., 2002). When looking at the simulated values for NUE and inorganic N in the soil, a negative correlation was observed (r = -0.8). As the NUE decreased, the IN increased in all cases. This negative correlation indicated that the N not taken up by the plant remained in the soil. High values of IN together with the low NUE were observed during dry years at the EVS and TVS sites. At the EVS site, the IN in the soil was lower for all N rates compared to values observed at the TVS site. This low IN at EVS could be explained by a higher NL as compared to the TVS site. At TVS, no N fertilizer applications were necessary to achieve maximum yield. While at EVS, the maximum yield was achieved with 56 kg N ha^{-1} and resulted in 62 % NUE. For the wet years, the most efficient N rates were 112 and 56 kg N ha^{-1} with 69 and 80 % NUE at the EVS and TVS sites, respectively. From these results, it is important to note that those N rates were the most efficient based on statistical significant differences, but there are absolute differences that may be more important from a practical perspective. For instance, at the TVS site during wet years, there were no statistical significant differences between the grain yield resulting from N rate 112 and the 168 kg N ha^{-1}, however, the absolute difference in grain yield between both rates was 1871 kg ha^{-1} favoring the 168 kg N ha^{-1} rate. Depending on N rate and corn market prices, almost 2000 kg ha^{-1} could be a significant profit increase for a producer. In this study, the N fertilizer rate 56 kg N ha^{-1} (zero N at planting and 56 kg N ha^{-1} side-dress) for dry years and the 112 kg N ha^{-1} (split 30% at planting and 70% at side-dress) for wet years were the most efficient N rates. Based on rates evaluated in this study, NUE may be maintained above 62 % by using N rates that were selected according to the weather scenario.

Scenario A - Irrigated

The statistical differences for AWDR corresponding to *scenario A – rainfed* apply to this scenario as well. However, no statistical significant differences between dry and wet May-June with respect to yield, IN, and NUE were observed in either site (Tables 2.8-9). This occurred because irrigation water supply was sufficient and plants were maintained under optimal water conditions. Differences between May-June dry and wet years were only observed for NL at each location ($P < .0001$). Nevertheless, there were no significant differences in NL among N rates for the TVS and EVS sites. Mean NL values at the EVS site were 18 and 42 kg N ha^{-1} for the dry and wet years, respectively. At the TVS site, NL was 2 kg N ha^{-1} for dry years and 6 kg N ha^{-1} for wet years. Under the conditions of wet years, NL was significantly higher compared to dry years mainly because higher rainfall amounts promote water movement thought the soil profile and N is leached out of the root zone.

Nitrogen leaching resulted higher at EVS than TVS. These results were also observed in *scenario A – rainfed*. Those differences were probably due to soil texture and higher organic matter content (Gaines and Gaines, 1994). Since there were no significant differences in yield, IN and NUE between May-June dry and wet years, data were combined and analyzed for differences by N rates. For both locations, the yield response function reached a plateau above 112 kg N ha^{-1} and yielded an average of 10290 and 11748 kg ha^{-1} at EVS and TVS, respectively. The NUE was higher under irrigated conditions compared with the rainfed conditions described earlier. For instance, during rainfed dry years at EVS, the NUE ranged from 100 to 18% while for the same years but under irrigated conditions the NUE ranged from 100 to 52%. A higher NUE is enhanced using irrigation because water supply promotes plant growth and nutrient uptake (Kim et al., 2008; Szeles et al., 2012). Under irrigated conditions, results from this study at both locations indicated that an N rate of 112 kg N ha^{-1} (30% of the N and planting and 70% at side-dress) was optimal to achieve maximum yield.

Scenario B - Rainfed

The first studied climate scenario (wet-dry) included four years that were characterized by a wet period from March to June months and a dry period for July-August months. The second climate scenario (dry-wet) was characterized by a dry period from March to June and a wet period for July-August. Significant differences in AWDR ($p < .0001$) between dry and wet March to June, as well as, significant differences ($p < .0001$) between wet and dry July-August were found at EVS and TVS (Table 2.3).

Grain yield at EVS exhibited statistically significant differences at ($p < 0.0244$) between wet-dry and dry-wet years, but there were not significant differences at the TVS site ($p < 0.6266$) (Tables 2.10-11). When yield from the wet-dry compared with the dry-wet climatic conditions were compared at the EVS site, yield under wet-dry conditions was higher 5326 kg ha^{-1} than the dry-wet (4332 kg ha^{-1}) conditions. However, for both climatic conditions (dry-wet and wet-dry) there were no significant yield differences among N rates. Yield under the wet-dry climate scenario could be much higher because the soil profile held some water from the wet period into the dry one, and also the crop was able to develop more biomass during vegetative stages resulting in more photoassimilates for grain filling.

Nitrogen leaching differences between both climate scenarios, wet/dry March-June and dry/wet July-August, were observed at the EVS and TVS sites ($p < .0001$ and $p < .0002$, respectively). Similar to the results from the *scenario A*, there were no significant differences among N rates for either combination; however, wet-dry years exhibited significantly higher NL than the dry-wet years. The NL at the EVS site was 30 and 14 kg N ha^{-1} at wet-dry and dry-wet years, respectively. In contrast, at TVS site the NL resulted in 10 kg N ha^{-1} in wet-dry years and in 1 kg ha^{-1} at dry-wet years. The period of time that fields were exposed to wet conditions was significantly longer (more days) in the wet-dry than in the dry-wet combinations. Therefore, differences in NL may be attributed to the longer period of time (from March to June) the wet-dry years were exposed to wet conditions as compared to the dry-wet combination (exposed to wet conditions only in July-August). Also, as observed before, the NL was higher at the EVS site compared to the TVS site. Because of limited rainfall, plants did not develop sufficiently and no N fertilizer was needed to achieve the highest possible yield at EVS under *scenario B*. Under rainfed conditions the silt loam at TVS was able to hold more water during the dry period and prevent yield losses. Therefore, at TVS, no significant differences in yield between dry-wet and wet-dry years were found. As a result, total averages (between wet-dry and dry-wet combinations) by N rate were computed to evaluate differences in IN and NUE. Significant differences in yield ($p < .0001$) were found between zero and 56 kg N ha^{-1}. Over 56 kg N ha^{-1} the yield response curve reached a plateau resulting in an average of 7768 kg ha^{-1}. Maximum yield using the most efficient N rate was achieved with 56 kg N ha^{-1} and resulted in 83% NUE.

Scenario B - Irrigated

The same conditions for the AWDR (significantly different between periods) corresponding to *scenario B – rainfed* apply to this scenario. At the EVS site there were no significant differences with respect to yield, NUE and IN between wet-dry and dry-wet climate scenarios (Tables 2.12-13). Significant differences between climate scenarios were only found for NL ($P < .0001$). Nitrogen leaching resulted in 34 and 19 kg N ha^{-1} during the wet-dry and dry-wet climate scenarios, respectively. A similar trend was also observed before in *scenario B – rainfed*, where the wet-dry period resulted in higher NL. This was probably due to the prolonged period under wet conditions as opposed to the dry-wet combination. Looking at the average yield between wet-dry and dry-wet yield at EVS, the yield response curve reached a plateau at 112 kg N ha^{-1}. Above this N rate, there are no significant differences in yield which resulted in a mean 11054 kg ha^{-1} yield. Applying 112 kg N ha^{-1} and splitting 30% at planting and 70% at side-dress for EVS wet-dry or dry-wet conditions under irrigation, resulted in a high NUE (85%). At the TVS site, significant differences were found in yield ($P < .00001$), NL ($P < 0.0001$), IN ($P < 0.0433$), and NUE ($P < .0036$) (Table 2.14). Yield ranged between 4336-9593 and 4818-12737 kg ha^{-1} for wet-dry and dry-wet combinations, respectively. Lower yield in the wet-dry combination could be attributed to cloudy days with excessive rainfall for prolonged periods (high AWDR index values) causing occasional water flooding. This affects roots respiration and reduces yield as a consequence (Lizaso and Ritchie, 1997; Meyer et al., 1987). Yield response curve reached a plateau at 56 and 112 kg N ha^{-1} for the wet-dry and dry-wet combination respectively. The 56 and 112 kg N ha^{-1} rates resulted in 84 and 71% NUE, respectively. Nitrogen leaching resulted in similar trend as described above in *scenario B-rainfed*. Higher NL was observed in the wet-dry combination due to prolonged time exposed to wet conditions as compared to dry-wet combination.

Conclusions

The CSM-CERES-Maize model was successfully used to model yield, NUE, IN in the soil at maturity and NL under different rainfall scenarios. Two different scenarios, *A* and *B*, were developed to assess the impact of rainfall amount and distribution on the simulated variables. *Scenario A*, corresponded to years with either dry or wet conditions during the May-June period, while *Scenario B*, consisted of years with dry/wet March-June and dry/wet July-August periods. Using a dataset of 61 years, each specific period during the year was assessed for rainfall amount and distribution using the AWDR index. Only years that qualified for the specific rainfall scenario were used for model simulation. Corn growth and development was simulated for the selected years of each scenario using the CSM-CERES-Maize. Simulated results were analyzed according to rainfall scenario. Results from the simulation indicated an overall increase in yield and IN in the soil at maturity and a decrease in NUE as N rates increased. Corn N response was affected by rainfall patterns and by soil texture. In North Alabama, where soils were characterized as silt loam, corn N response was higher when compared to Central Alabama, where soil texture was characterized as sandy loam. Moreover, N rate prescriptions should be changed annually according to possible rainfall scenarios expected for the season. For instance, at EVS, 56 and 112 kg N ha^{-1} were the optimal N rates for years under dry and wet May-June, respectively. A good decision for N application rate could save a producer half of the N applied for a dry year compared to a fixed annual N rate of 112 kg N ha^{-1}. If the N rates can be changed according to the weather scenarios, the NUE would be maintained above 62% even in the worst conditions affecting this variable. Nevertheless, a reliable rainfall forecast is needed to better predict in-season precipitation variations affecting yield and NUE to develop better decisions tools on the proper N rate to be applied.

Table 2.1 Planting, anthesis, physiological maturity, and side-dress dates by site-year.

Year	Site†							
	EVS				TVS			
	Planting	Anthesis	P. Maturity‡	N Side-dress	Planting	Anthesis	P. Maturity	N Side-dress
2009	20-Apr	1-Jul	-	19-May	24-Mar	28-Jun	-	12-May
2010	13-Apr	16-Jun	-	27-May	2-Apr	14-Jun	-	14-May
2011	-	-	-	13-May	7-Apr	-	-	12-May
2012	27-Mar	1-Jun	19-Jul	3-May	2-Apr	13-Jun	3-Aug	7-May

†EVS, E.V. Smith Research Center; TVS, Tennessee Valley Research and Extension Center (both irrigated).

‡P. Maturity: Physiological Maturity.

Table 2.2 Abundant and well distributed rain (AWDR) values for May-June period, *scenario A*.

Site†	May-June (Dry)		May-June (Wet)	
	Years	AWDR‡	Years	AWDR
EVS	1951	60	1955	180
	1954	40	1957	168
	1964	57	1970	161
	1965	57	1973	171
	1968	52	1976	135
	1977	40	1978	210
	1986	65	1980	153
	1988	63	1983	147
	1990	63	1987	205
	1993	65	1989	290
	1995	37	1991	284
	1996	31	1992	146
	2000	43	1999	188
	2002	31	2004	202
	2007	24	2009	134
Average	-	48***	-	184
TVS	1952	32	1959	200
	1954	60	1967	213
	1958	72	1974	177
	1962	65	1976	262
	1964	40	1983	255
	1965	76	1984	181
	1968	64	1986	177
	1971	71	1989	294
	1988	13	1991	185
	1995	66	1994	215
	1996	72	1997	178
	1998	57	1999	163
	2000	76	2001	263
	2005	70	2003	240
	2007	27	2009	198
Average	-	57***	-	213

†EVS, E.V. Smith Research Center; TVS, Tennessee Valley Research and Extension Center (both irrigated).
‡AWDR = PPT x SDI. PPT (cumulative precipitation) = Σ(Rain), where Rain is the daily rainfall (mm). SDI (Shannon diversity index) = [-Σpi ln(pi)]/ln(n), where pi = Rain/PPT and n is the number of days in that period.
***Significant at the 0.001 probability level.

Table 2.3 Abundant and well distributed rain (AWDR) values for March-June wet/dry and July-August wet/dry, *scenario B*.

Site†	Mar-Jun(Dry) & Jul-Aug(Wet)			Mar-Jun(Wet) & Jul-Aug(Dry)		
	Years	AWDR†		Years	AWDR	
		Mar-June	Jul-Aug		Mar-June	Jul-Aug
EVS	1974	187	277	1957	389	70
	1985	156	165	1962	330	96
	1996	188	236	1976	345	81
	2008	183	254	1980	460	54
Average	-	179***	233	-	318	75
TVS	1986	216	146	1983	526	25
	1971	216	146	1991	526	55
	2005	227	161	1963	421	78
	1985	233	155	1997	350	82
Average	-	223***	152	-	456	60

†EVS, E.V. Smith Research Center; TVS, Tennessee Valley Research and Extension Center (both irrigated).

‡AWDR = PPT x SDI. PPT (cumulative precipitation) = Σ(Rain), where Rain is the daily rainfall (mm). SDI (Shannon diversity index) = [-Σpi ln(pi)]/ln(n), where pi = Rain/PPT and n is the number of days in that period.

***Significant at the 0.001 probability level.

Table 2.4 Soil properties for the experiment conducted at the two study sites in Alabama.

Site†	Soil series	Horizon	Depth	Clay	Silt	CEC‡	LL§	DUL¶	SAT#	SSKS‡‡
			cm	%	%	cmol kg^{-1}	----------	cm^3 cm^{-3}	--------	cm h^{-1}
		fine, kaolinitic, thermic Rhodic Paleudult								
TVS	Decatur	Ap1	19	31	54	8.9	0.21	0.33	0.52	3.2
		Ap2	30	35	52	10.0	0.21	0.33	0.49	3.2
		Bt1	46	51	39	11.9	0.27	0.34	0.47	3.2
		Bt2	110	54	36	10.5	0.30	0.44	0.46	3.2
		Bt3	150	63	28	10.9	0.34	0.47	0.48	3.2
		coarse-loamy, siliceous, subactive, thermic Plinthic Paleudult								
EVS	Compass	Ap	17	4	16	2.3	0.08	0.15	0.43	33.1
		BE	42	7	20	1.9	0.13	0.24	0.42	20.2
		Bt1	80	7	21	1.4	0.20	0.33	0.42	9.9
		Bt2	99	8	20	1.6	0.20	0.32	0.41	3.2
		Btv	122	8	18	1.6	0.24	0.34	0.40	3.2
		BC	140	12	15	2.3	0.09	0.16	0.39	3.2
		C	150	14	15	2.9	0.10	0.18	0.38	3.2

†EVS, E.V. Smith Research Center; TVS, Tennessee Valley Research and Extension Center (both irrigated).
‡CEC, cation exchange capacity.
§LL, lower limit or permanent wilting point.
¶DUL, drained upper limit or field capacity.
#SAT, saturation.
‡‡SSKS, saturate hydraulic conductivity.

Table 2.5 Cultivar coefficients (CC) of the CSM-CERES-Maize model.

CC	Unit	Definition	31P42†
P1	C° days > 8 C°	Thermal time from emergence to juvenile phase.	240
P2	Unitless (0 - 1)	Photoperiod coefficient.	0.60
P5	C° days > 8 C°	Thermal time from silking to physiological maturity.	913
G2	kernels $plant^{-1}$	Maximum number of kernels per plant.	780
G3	mg $kernel^{-1}$ d^{-1}	Kernel growth rate in optimum conditions.	8.1
PHINT	C° days > 8 C°	Thermal interval between successive leaf tip appearances.	41.5

† Corn hybrid, Pioneer Hi-Bred International.

Table 2.6 Yield, nitrogen leaching (NL), inorganic nitrogen in the soil at maturity (IN), and nitrogen use efficiency (NUE) differences for E.V, Smith Research Center under rainfall conditions of *Scenario A* (May-June).

Nitrogen treatment (kg ha^{-1})	Dry (May-June)								Wet (May-June)							
	Yield§		NL§		IN§		NUE§		Yield		NL		IN		NUE	
	Mean	SD#	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
	kg ha^{-1}						%		kg ha^{-1}						%	
0-0	2230 a‡	576	18†	15	27 a	5	100 a	0	3050 a	722	34†	16	23 a	2	100 a	0
0-56	4021 b	950	17†	14	30 a	11	62 b	20	6245 b	1607	31†	14	24 a	3	67 b	16
34-78	4350 b	1095	17†	14	51 a	29	45 c	13	8320 bc	2058	29†	12	26 a	11	69 b	16
56-112	4241 b	1015	17†	14	95 b	35	30 d	9	8616 bc	2309	29†	13	35 a	18	64 bc	16
67-157	4213 b	996	17†	14	148 c	34	22 d	7	8410 bc	2292	30†	13	63 b	33	51 cd	16
140-140	4274 b	902	17†	13	201 d	33	18 d	5	8446 bc	2199	32†	15	109 c	39	42 d	13
280-0	4303 b	930	17†	14	198 d	35	18 d	5	8614 c	2282	35†	19	106 c	40	42 d	13

†No statistical significant difference.

‡Means followed by the same letter do not differ at α = 0.05.

§Significant different from the contrasting weather condition (P <0.05).

#Standard deviation.

Table 2.7 Yield, nitrogen leaching (NL), inorganic nitrogen in the soil (IN), and nitrogen use efficiency (NUE) differences for Tennessee Valley Research and Extension Center under rainfall conditions of *Scenario A* (May-June).

Nitrogen treatment (kg ha^{-1})	Dry (May-June)								Wet (May-June)							
	Yield§		NL§		IN§		NUE§		Yield		NL		IN		NUE	
	Mean	SD#	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
	kg ha^{-1}						%		kg ha^{-1}						%	
0-0	2824†	1149	2†	5	28 a‡	7	100 a	0	4380 a	948	5†	8	24 a	5	100 a	0
0-56	4841†	2253	2†	5	38 a	29	63 b	36	8046 b	1460	5†	8	23 a	4	80 b	17
34-78	5100†	2873	2†	6	60 ab	44	50 bc	33	9771 b	1862	5†	8	24 a	4	77 b	16
56-112	4927†	2788	2†	6	103 bc	55	34 cd	24	9917 b	2266	5†	9	34 a	14	67 bc	16
67-157	4853†	2750	2†	6	156 cd	57	25 cd	18	9483 b	2439	5†	9	69 b	35	53 cd	17
140-140	4869†	2684	2†	6	208 d	56	20 d	15	9410 b	2274	5†	9	113 c	42	43 d	14
280-0	4892†	2801	2†	6	202 d	59	20 d	15	9556 b	2323	6†	11	107 c	41	44 d	14

†No statistical significant difference.

‡Means followed by the same letter do not differ at α = 0.05.

§Significant different from the contrasting weather condition (P <0.05).

#Standard deviation.

Table 2.8 Yield, nitrogen leaching (NL), inorganic nitrogen in the soil at maturity (IN), and nitrogen use efficiency (NUE) differences for E.V, Smith Research Center under irrigated conditions of *Scenario A* (May-June).

Nitrogen treatment ($kg\ ha^{-1}$)	Dry (May-June)		Wet (May-June)		Average¶		
	NL§		NL		Yield	IN	NUE
	Mean	SD#	Mean	SD	Mean	Mean	Mean
	------------------------------- $kg\ ha^{-1}$ -------------------------------						%
0-0	19†	15	36†	15	3515 a‡	24 a	100 a
0-56	18†	15	37†	15	7336 b	24 a	79 b
34-78	18†	15	39†	15	9840 c	24 a	82 b c
56-112	18†	14	42†	17	10381 c	28 a	75 c
67-157	18†	14	43†	19	10409 c	44 b	64 d
140-140	18†	14	47†	23	10409 c	82 c	52 e
280-0	19†	16	50†	28	10409 c	81 c	52 e

†No statistical significant difference.

‡Means followed by the same letter do not differ at $\alpha = 0.05$.

§Significant difference from the contrasting weather condition ($P < 0.05$).

¶Variables that were not statistically different were averaged to evaluate differences between nitrogen rates.

#Standard deviation.

Table 2.9 Yield, nitrogen leaching (NL), inorganic nitrogen in the soil (IN), and nitrogen use efficiency (NUE) differences for Tennessee Valley Research and Extension Center under irrigated conditions of *Scenario A* (May-June)

Nitrogen treatment (kg ha^{-1})	Dry (May-June)		Wet (May-June)		Average¶		
	NL§		NL		Yield	IN	NUE
	Mean	SD#	Mean	SD	Mean	Mean	Mean
	------------------------------		kg ha^{-1}	------------------------------			%
0-0	2†	5	5†	8	4631 a‡	25 a	100 a
0-56	2†	5	5†	8	9044 b	25 a	91 b
34-78	2†	5	5†	9	11363 c	25 a	90 b
56-112	2†	4	6†	9	11823 c	28 a	80 c
67-157	2†	4	6†	9	11851 c	42 b	68 d
140-140	2†	4	6†	9	11850 c	75 c	57 e
280-0	2†	5	7†	10	11851 c	71 c	57 e

†No statistical significant difference.

‡Means followed by the same letter do not differ at $\alpha = 0.05$.

§Significant difference from the contrasting weather condition ($P < 0.05$).

¶Variables that were not statistically different were averaged to evaluate differences between nitrogen rates.

#Standard deviation.

Table 2.10 Yield, nitrogen leaching (NL), inorganic nitrogen in the soil (IN), and nitrogen use efficiency (NUE) differences for E.V. Smith Reseach Center under rainfall conditions for *Scenrio B* [March (M) to June (J) wet/dry, and July (Ju) to August (A) wet/dry].

Nitrogen treatment ($kg\ ha^{-1}$)	Wet (M-J) - Dry (Ju-A)				Dry (M-J) -Wet (Ju-A)				Average¶	
	Yield§		NL§		Yield		NL		IN	NUE
	Mean	SD#	Mean	SD	Mean	SD	Mean	SD	Mean	Mean
	------------------------------ $kg\ ha^{-1}$ ------------------------------									%
0-0	2594†	596	34†	7	2930†	729	14†	13	25 a‡	100 a
0-56	4629†	1555	34†	6	4727†	814	13†	12	26 a	61 b
34-78	6132†	2477	30†	3	4684†	590	14†	11	40 a b	51 bc
56-112	6004†	2312	28†	5	4430†	1175	14†	11	76 b	37 cd
67-157	5954†	2236	27†	4	4525†	1098	14†	11	126 c	28 cd
140-140	5972†	1920	28†	3	4532†	983	14†	9	179 d	23 d
280-0	5996†	2243	30†	3	4498†	1160	14†	11	176 d	23 d

†No statistical significant difference.

‡Means followed by the same letter do not differ at $\alpha = 0.05$.

§Significant difference from the contrasting weather condition ($P < 0.05$).

¶Variables that were not statistically different were averaged to evaluate differences between nitrogen rates.

#Standard deviation.

Table 2.11 Yield, nitrogen leaching (NL), inorganic nitrogen in the soil (IN), and nitrogen use efficiency (NUE) differences for Tennessee Valley Research and Extension Center under rainfall conditions for *Scenario B* [March (M) to June (J) wet/dry, and July (Ju) to August (A) wet/dry].

Nitrogen treatment (kg ha^{-1})	Wet (M-J) - Dry (Ju-A) NL§		Dry (M-J) -Wet (Ju-A) NL		Average¶ Yield	IN	NUE
	Mean	SD#	Mean	SD	Mean	Mean	Mean
	Kg ha^{-1}						%
0-0	10†	14	1†	1	4147 a‡	26 a	100 a
0-56	10†	14	1†	1	7339 b	25 a	83 ab
34-78	10†	15	1†	1	8321 b	27 a	77 bc
56-112	10†	15	1†	1	8097 b	47 a	59 c
67-157	10†	15	1†	1	7603 b	102 b	42 d
140-140	11†	15	1†	1	7577 b	154 c	33 d
280-0	13†	19	1†	1	7671 b	148 c	34 d

†No statistical significant difference.

‡Means followed by the same letter do not differ at $\alpha = 0.05$.

§Significant difference from the contrasting weather condition ($P < 0.05$).

¶Variables that were not statistically different were averaged to evaluate differences between nitrogen rates.

#Standard deviation.

Table 2.12 Yield, nitrogen leaching (NL), inorganic nitrogen in the soil (IN), and nitrogen use efficiency (NUE) differences for E.V. Smith Reseach Center under irrigated conditions for *Scenrio B* [March (M) to June (J) wet/dry, and July (Ju) to August (A) wet/dry].

Nitrogen treatment (kg ha^{-1})	Wet (M-J) - Dry (Ju-A)		Dry (M-J) -Wet (Ju-A)		Average¶		
	NL§		NL§		Yield	IN	NUE
	Mean	SD#	Mean	SD	Mean	Mean	Mean
	kg ha^{-1}						%
0-0	34†	7	16†	12	3830 a‡	24 a	100 a
0-56	35†	7	16†	12	7860 b	24 a	80 b
34-78	35†	7	17†	12	10548 c	25 a	85 b
56-112	34†	7	19†	12	11181 c	27 a	80 b
67-157	34†	8	21†	14	11181 c	37 a	69 c
140-140	33†	5	21†	10	11181 c	78 b	56 d
280-0	35†	8	21†	13	11181 c	77 b	56 d

†No statistical significant difference.
‡Means followed by the same letter do not differ at α = 0.05.
§Significant difference from the contrasting weather condition (P <0.05).
¶Variables that were not statistically different were averaged to evaluate differences between nitrogen rates.
#Standard deviation.

Table 2.13 Yield, nitrogen leaching (NL), inorganic nitrogen in the soil (IN), and nitrogen use efficiency (NUE) differences for Tennessee Valley Research and Extension Center under irrigated conditions for *Scenario B* [March (M) to June (J) wet/dry, and July (Ju) to August (A) wet/dry].

Nitrogen treatment (kg ha^{-1})	Wet (M-J) - Dry (Ju-A)								Dry (M-J) -Wet (Ju-A)							
	Yield§		NL§		IN		NUE§		Yield		NL		IN		NUE	
	Mean	SD#	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
	kg ha^{-1}						%		kg ha^{-1}						%	
0-0	4336 a‡	912	10†	14	21 a	1	100 a	0	4818 a	428	1†	1	29 a	5	100 a	0
0-56	7921 b	1089	10†	14	21 a	1	85 b	9	9700 b	350	1†	1	29 a	6	95 a	4
34-78	9394 b	665	11†	14	23 a	1	81 b	4	12133 c	757	1†	1	29 a	5	89 ab	13
56-112	9571 b	581	11†	15	31 a	2	68 c	4	12701 c	354	1†	1	30 a	4	83 ab	10
67-157	9593 b	600	11†	15	68 b	13	52 d	3	12737 c	291	1†	1	33 ab	3	75 bc	4
140-140	9592 b	520	11†	13	114 c	11	42 d	3	12737 c	290	1†	1	56 c	17	63 c	2
280-0	9589 b	605	13†	17	108 c	16	42 d	3	12736 c	291	1†	1	54 bc	6	63 c	2

†No statistical significant difference.
‡Means followed by the same letter do not differ at α = 0.05.
§Significant difference from the contrasting weather condition (P <0.05).
#Standard deviation.

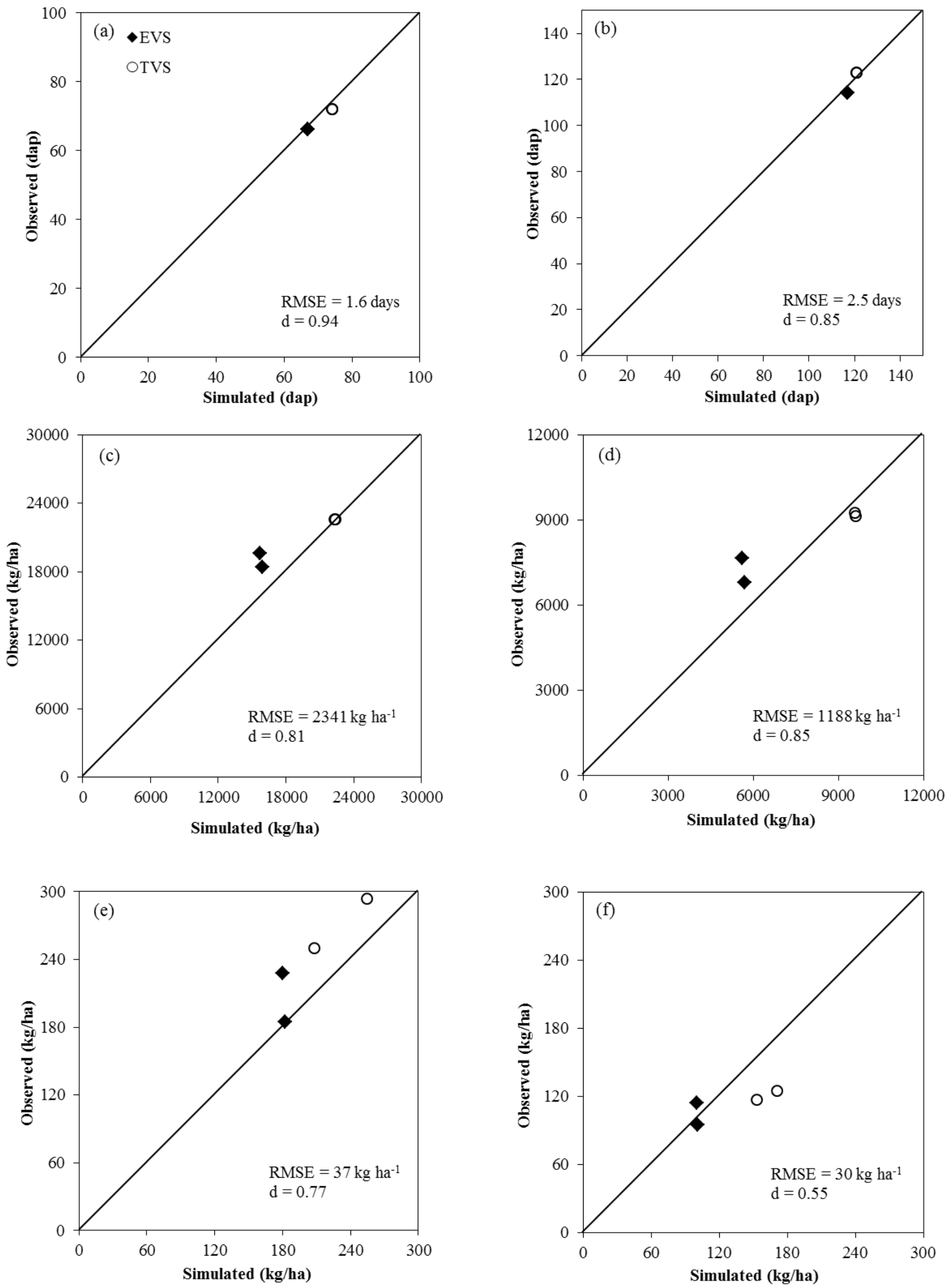

Figure 2.1. Observed and simulated data (treatments 168 and 224 kg N ha^{-1}) for the CSM-CERES-Maize model calibration: (a) anthesis day (dap, days after planting); (b) physiological maturity day (dap, days after planting); (c) tops weight (kg ha^{-1}); (d) yield (kg ha^{-1}); (e) above biomass nitrogen (kg N ha^{-1}); grain nitrogen (kg N ha^{-1}).

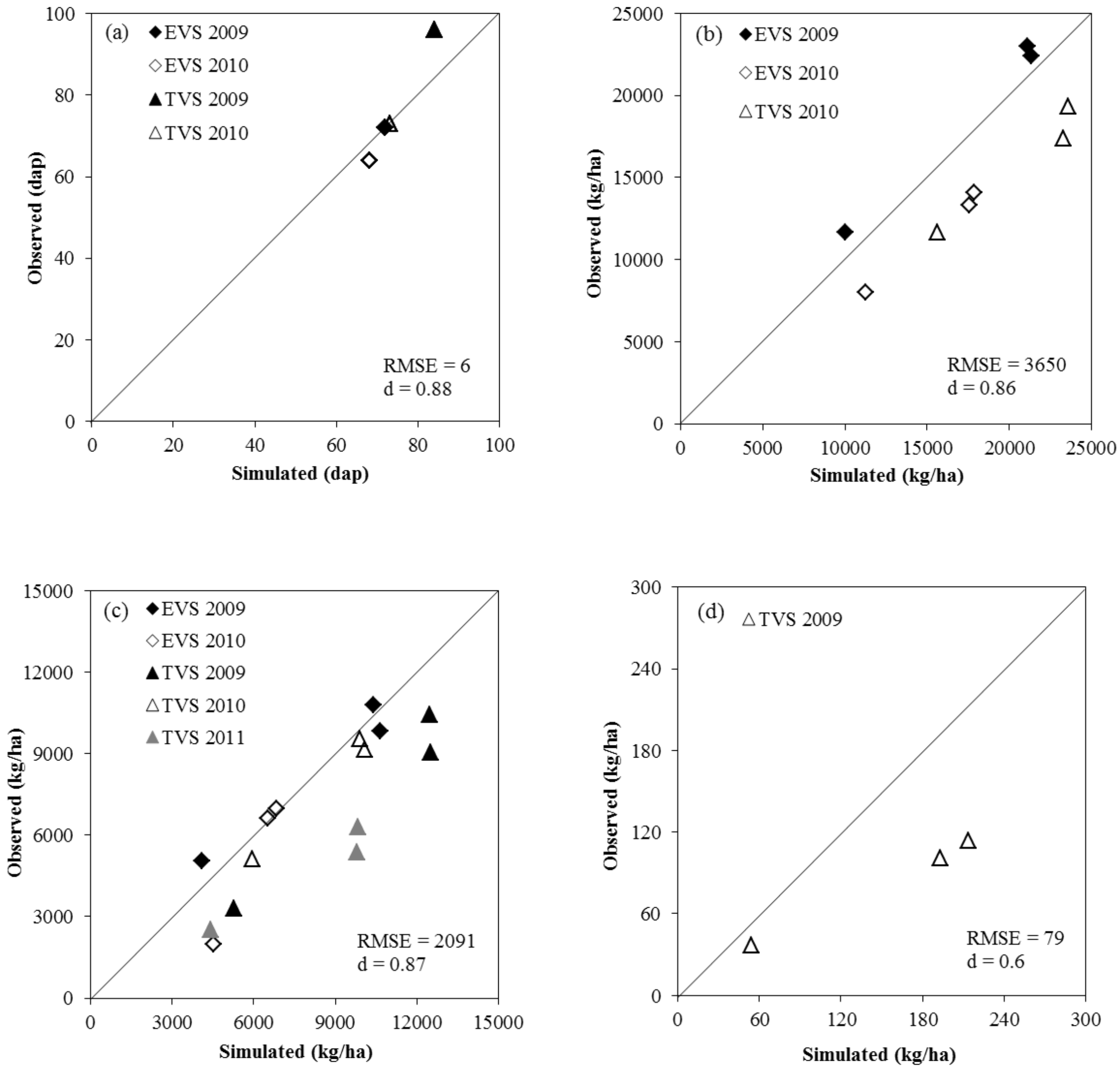

Figure 2.2. Observed and simulated data (treatments 0, 168, and 224 kg N ha^{-1}) for the CSM-CERES-Maize model validation: (a) anthesis (dap, days after planting); (b) above ground biomass (kg ha^{-1}); (c) yield (kg ha^{-1}); (d) grain nitrogen (kg N ha^{-1}).

IV. SUMMARY AND CONCLUSIONS

Nitrogen is a nutrient that impacts corn growth, development, and grain yield. Understanding the N cycle, which is a complex system including soil (inorganic and organic portions), plants, animals and atmosphere, can help improving NUE in agricultural ecosystems. Corn NUE can be improved by combining good agronomic management practices with technology (precision agriculture, hybrid selection, irrigation, climate and weather forecasts, among others).

This thesis focused on evaluating the potential of using precision agriculture tools together with climate data for improving NUE in Alabama. The first study objectives were to (1) identify the VIs that best correlate with field plant measurements of LAI and leaf Chl content at early corn growth stages (V6), and (2) evaluate the selected VIs for in-season yield potential predictability. The second study objective was to evaluate the impact that in-season changes in rainfall have on simulated corn yield, NL, IN in the soil at maturity, and NUE.

Results from the first study suggest that VIs including the red-edge (730 nm) wavelength were better estimators of Chl content and biomass than VIs including the red wavelength (670 nm). The NDRE, SR (RE), ISR (RE), and CI (RE) resulted on the highest frequency (> 60% of cases) of strongest correlation with plant status measured variables of SPAD and leaf area index (LAI). Those VIs and the traditionally used NDVI index were evaluated for mid-season yield potential predictability. For the V6, V8, and V10 growth stages, five linear regression models including a single VI as an independent variable were generated for in-season grain yield prediction. Performance evaluation of the five models per growth stage was conducted by comparing the performance indicator of good-need of fit of coefficient of determination (R^2), root mean squared error (RMSE), and the coefficient of variation (CV). When comparing vegetation indices based-yield prediction models, the NDRE resulted in higher yield potential predictability as compared the NDVI-based yield models. The NDRE-based models exhibited R^2 of 0.37, 0.42, and 0.67 at V6, V8, and V10 growth stages, respectively, while the NDVI-based models resulted in R^2 0.26 at V6, 0.30 at V8 and 0.36 at V10 growth stage. Other VIs including the RE resulted on similar yield potential prediction as the NDRE. Even though the yield potential predictability using red-edge VIs was higher than NDVI at V6, there were not large differences in RMSE different between the models including the NDVI and red-edge indices. Nevertheless, at the V8 and V10 growth stages the yield potential predictability was considerably higher using the NDRE index as predictor than the prediction using NDVI index. The higher percentage of the yield variability explained by the model using the NDRE as independent variable indicated that this VI and other red-edge VIs could potentially be used to increase NUE when developing algorithms for VRN application. However, further research is needed to develop and evaluate yield potential prediction at early growth stages using red-edge VIs.

The results from the second study, evaluation of the impact that in-season changes in rainfall on simulated corn yield, NL, IN in the soil at maturity, and NUE in Central and North Alabama, showed that the crop response to N fertilizer differed among rainfall scenarios and soil type (Silt loam in North and Loamy sand in Central AL). At both locations, the crop response to N rates under a wet May-June (*scenario A*) period was higher compared to years with a dry May-June period. Furthermore, in North Alabama, where soils were characterized as silt loam, corn N response resulted higher when compared to Central Alabama, where soil texture was characterized as sandy loam. For Central Alabama (EVS), the yield response curve under rainfed conditions reached a plateau at 56 and 112 kg N ha^{-1} for dry and wet May-June rainfall conditions, respectively. Based on our findings, farmers should apply 56 kg N ha^{-1} side-dress at V6 growth stage to achieve maximum yield in dry May-June years. If the May-June period is wet, an N rate of 112 kg N ha^{-1} (30 % at planting, and 70 % at side-dress) might be enough to achieve maximum yield. At the North AL location, no N is needed to be applied during dry May-June years. During dry years there is not water in the soil, and the N applied cannot be taken up by the plant. In contrast, for wet May-June years, 56 kg N ha^{-1} applied at the V6 was required to achieve maximum yield.

When the CSM-CERES-Maize model were run under irrigated conditions, results indicated that 112 kg N ha^{-1}, for EVS and TVS, was sufficient to achieve for maximum yield. Data from this study showed that if supplemental water through irrigation is available, the N fertilizer to achieve the highest yield in each location should be applied spitted on 30 % of the total nitrogen at planting and 70 % at side-dress (V6). Using 112 kg N ha^{-1}, the NUE under irrigated conditions could be kept above 82 % for both locations.

Results for *scenario B* also indicated variations in yield and N uptake under different rainfall conditions. Under rainfall conditions corresponding to a wet March-June period and late dry conditions during the July-August period, a higher N response was observed at EVS as compared to years with March-June dry and July-August wet. Those conditions provided a prolonged time under sufficient water for plant growth, development, and flowering, plus enhancing N uptake. However, no N was needed to achieve maximum yield under rainfall conditions for either combination (wet-dry or dry-wet). Water stress in either situation (wet-dry or dry wet), limits growth and development (dry-wet combination) or grain filling (wet-dry combination) which results in low amounts of N (no fertilizer) required to achieve maximum yield. In contrast, at the TVS rainfed, corn N response was only observed for the 56 kg ha^{-1} N rate. There was no yield response to higher N rates due to limited rain on the dry period of either combination (dry-wet and wet-dry).

Under *scenario B- Irrigated* for EVS, no significant differences between dry-wet and wet-dry combinations were observed. From the average between dry-wet and wet-dry combinations was possible to conclude that 112 kg N ha^{-1} spitted on 30 % at planting and 70 % at side-dress was the optimum N rate to achieve maximum yield. For TVS irrigated under the wet-dry combination, 56 kg N ha^{-1} applied at side-dress (V6) was sufficient to achieve maximum yield. However, for the dry-wet combination, achieving higher yield than the wet-dry combination the N rate of 112 Kg N ha^{-1} was optimum for maximum yield. Lower yield in the wet-dry combination was attributed to cloudy days with excessive rainfall for prolonged periods (high AWDR index values) causing occasional water flooding which affects roots respiration reducing crop yield.

Results from these studies could be used by farmers as decision support tools to improve N management in corn under the growing conditions of Central and North Alabama. However, better climate and weather forecasts for in-season rainfall changes is needed in order for the farmers to use the information about the rainfall amount and distribution as decision tools for assessment of in-season N management.

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