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MAIZE NITROGEN MANAGEMENT USING REACTIVE SENSOR AND PROACTIVE MAIZE-N MODEL VIA FERTIGATION

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by

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Applying a portion of total nitrogen (N) during the growing season has the potential to improve nitrogen use efficiency (NUE) by achieving greater synchrony between N supply and crop N demand, allowing for responsive adjustments to actual field conditions. Three studies from 2017-2019 evaluated using reactive sensor and proactive Maize-N model for determining in-season N requirements via fertigation in corn. The first study evaluated the integration of reactive sensor and proactive Maize-N model for determining the timing and rate of in-season N via fertigation. Overall, reactive and proactive fertigation treatments reduced total N applied by 35 to 65 kg N ha^{-1} thus increasing NUE and profit compared to the University of Nebraska-Lincoln (UNL) algorithm and Holland and Schepers (H-S) algorithm treatments with no significant difference in yields. The second study evaluated Maize-N model for predicting economic optimum N rate (EONR), N uptake, and soil nitrate-N. Overall, Maize-N underestimated N rate recommendations by 47 kg N ha^{-1} compared to the calculated actual EONR with no significant differences in yield. However, the Maize-N EONR reduced profit by 33.5 $ ha^{-1}. Maize-N underestimated N uptake by 24.7 kg N ha^{-1}. Additionally, Maize-N overestimated soil nitrate-N, but a calibrated model improved agreement between predicted and observed soil nitrate-N by 67.5%. The third study evaluated the

performance of active and passive crop canopy sensors compared to the SPAD meter in terms of assessing in-season corn N status. Reasonable correlation at any growth stage did not always lead to the same fertigation decision, as the same decision for two sensors can be achieved if both sensor's SI values are greater than 0.95 thresholds or both less than or equal to 0.95. The overall fertigation decisions that matched between SPAD SI and active sensor SI across all growth stages and site years was 72%, and 37 to 48% between SPAD SI and passive sensor SI. Crop canopy sensor and Maize-N model integration will likely result in more accurate N rate and timing decisions.

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Corn Production and Nitrogen Fertilizer Consumption

Corn (Zea mays L.) is among the most commonly grown crops in the United States with 36.1 million ha. The U.S. is the biggest corn producer in the world with 366.3 million metric tons of grain in 2018 (USDA-NASS, 2019). In Nebraska, corn is the most important crop with 3.9 Million ha (2.2 Million ha irrigated, which representing 57% of total corn planted area) and the third-largest corn producer in the U.S. with 45.4 million metric tons of grain in 2018. Corn is the biggest N consumer with 47.5% of total N fertilizer applied to the crop in the US in 2014 (USDA-ERS, 2019).

Nitrogen (N) is an essential plant growth element and the most limiting nutrient in crop production (Fageria and Baligar, 2005; Ladha et al., 2005). To achieve optimal corn yields, high amounts of N fertilizer application are required. In 2017, the total worldwide consumption of N fertilizer was 113.6 million Mg to meet the global growth in food demand (FAO, 2017). Nitrogen (applied or indigenous) in the soil that is not taken up by the crop can be converted to different forms, such as ammonium and nitrate. Thus, if N is unused by the crop, it can be lost via many pathways, such as ammonia volatilization, nitrate denitrification, and leaching, which has a high potential for groundwater contamination (Raun and Johnson, 1999; Quemada et al., 2013).

Nitrate Groundwater Contamination

Nitrate and ammonium are the main forms of inorganic N that exist in the soil and available to be taken up by the plant. Ammonium in the soil is formed from applied fertilizer or manure and also from the mineralization of soil organic matter (SOM). Ammonium is converted to nitrate in warm and moisture conditions by the nitrification process. Thus, nitrate is the more dominant form of inorganic N in most agricultural soils. Nitrate carries a negative charge and clay minerals and SOM also carry a negative charge on their surfaces. Thus, nitrate is not held by cation exchange sites as ammonium is. Also, nitrate is a highly water-soluble form of N, and a mobile anion thus it is readily leached or moved below the crop root zone (Exner et al., 2014). High inputs of N fertilizer applied to row crop production along with surplus precipitation or irrigation in irrigated cropland can result in nitrate leaching below the crop root zone (Frank et al., 1991; Spalding et al., 2010). Additionally, poor synchrony between soil N supply and crop N demand results in inefficient use of fertilizer N and is one of the major causes of nitrate groundwater contamination (Ferguson, 2015). Commercial N fertilizer is a major source of groundwater contamination when it converts to nitrate and moves out of the crop root zone to groundwater (Exner et al., 2014). Both the amount and timing of N and water applications are closely related to N leached to the groundwater when the amount and timing does not match crop demand, resulting in inefficient N use (Frank et al., 1991).

Nitrogen Use Efficiency

Crop N fertilizer utilization by crops is historically inefficient (Ladha et al., 2005; Sharma and Bali, 2018). According to Raun and Johnson (1999), global nitrogen use efficiency (NUE) has been estimated to be only 33% for several crops including corn. Three important components can be used to measure NUE, including partial factor productivity for N (PFP_N), the recovery efficiency of N (RE_N), and the agronomic efficiency of applied N (AE_N) (Table 1.1).

Partial factor productivity for N) represents the ratio of grain yield produced per unit of N fertilizer applied (Cassman et al., 2002; Sharma and Bali, 2018). Cassman et al. (2002) reported that PFP_N for corn production in the U.S. increased from 42 in 1980 to 57 kg kg^{-1} in 2000. They stated that increases in PFP_N related to increasing RE_N because N uptake is closely associated with dry matter accumulation and grain yield. Corn grain yield has steadily increased without significant increases in N rate, which can be contributed to a consistent increase in PFP over time. Ferguson (2015) reported that NUE as PFP has steadily increased from 49 to 67 kg grain kg N^{-1} from 1988 to 2012 for corn production in Nebraska statewide. Increased efficiencies have been attributed largely to the adoption of N management practices that include accounting for N credits from SOM, irrigation water, manure, and other sources besides N from fertilizer.

The RE_N is defined as the difference between fertilized N uptake and unfertilized N uptake dividing by N applied (Dobermann, 2005). Therefore, the unfertilized check is subtracted from fertilized to identify RE_N from fertilizer alone. The unfertilized check is also important to NUE to identify N uptake from indigenous sources including residual soil nitrate-N, mineralized N from SOM, deposition of atmospheric ammonium, and nitrate-N from irrigation water (Wortmann et al., 2011). The RE_N has been estimated to be between 35 to 75% of N applied to corn (Morris et al., 2018). Likewise, N fertilizer-recovery efficiency was estimated to be 37% in the major six-corn producing U.S. Midwest states through 1995 to 1999 across 55 on-farm experiments (Cassman et al., 2002).

The AE_N is defined as the difference between fertilized grain yield and unfertilized grain yield dividing by N applied (Dobermann, 2005; Thompson et al., 2015). The grain yield of the fertilized plot and yield of the unfertilized check plot is required to measure AE_N due to fertilizer alone. The AE_N is a short-term indicator of the impact of applied N fertilizer on productivity and related directly to economic return (Fixen et al., 2014). As NUE increases, the economic benefit to the producers increases while minimizing negative environmental impacts. Therefore, further increases in corn NUE and decreases in N losses are needed to identify factors contributing to low NUE.

Table 1.1. Measurements and calculations of nitrogen use efficiency (NUE) and related parameters and their typical ranges in cereals according to (Dobermann, 2005; Naser, 2012).

NUE Measurement	Calculation	Interpretation	Common values
PFP_N = Partial Factor Productivity of applied N (kg grain yield per kg N applied)	$PFP_N = Y_N/F_N$	• PFP_N integrates the use efficiency of both indigenous and applied N resources: $PFP_N = (Y_0/F_N) + AE_N$ • Increasing indigenous soil N (Y_0) and the efficiency of applied N (AE_N) are equally important for improving PFP_N	40–70 kg grain kg^{-1} N >70 kg grain kg^{-1} N at low rates of N or in very efficiently managed systems. However, in many cases with high PFP_N that has a low N rate resulted in reduced yield. Thus, AE_N and RE_N should be considered in the evaluation and effectiveness of an N strategy.
AE_N = Agronomic efficiency of applied N (kg yield increase per kg N applied)	$AE_N = (Y_N - Y_0)/F_N$	• AE_N is the product of the efficiency of N recovery from applied N and the efficiency with which the plant uses each additional unit of N acquired: $AE_N = RE_N \times PE_N$ • AE_N can be increased by N, crop, and soil management practices that affect RE_N, PE_N, or both.	10–30 kg grain kg^{-1} N >30 kg kg^{-1} in well-managed systems or at low levels of N use or low soil N supply
RE_N = Crop recovery efficiency of applied N (kg increase in N uptake per kg N applied)	$RE_N = (U_N - U_0)/F_N$	• RE_N depends on the congruence between plant N demand and the quantity of N released from applied N.	0.30–0.50 kg kg^{-1} 0.50–0.80 kg kg^{-1} in well-managed systems or at low levels of N use or low soil N supply

• RE_N is affected by the N levels of N use or low timing, placement, N form) as well as by factors that determine the size of the crop N sink (genotype, climate, plant density, abiotic/biotic stresses).

F_N is the amount of (fertilizer) N applied (kg ha^{-1})
Y_N is crop yield with applied N (kg ha^{-1})
Y_0 is crop yield (kg ha^{-1}) in a check treatment with no N
U_N is the total plant N uptake in aboveground biomass at maturity (kg ha^{-1}) in a plot that received N
U_0 is the total N uptake in aboveground biomass at maturity (kg ha^{-1}) in a plot that received no N
PE_N is a Physiological efficiency of applied N (kg yield increase per kg increase in N uptake from fertilizer).

Factors Contributing to Low Nitrogen Use Efficiency

Poor synchrony between N supply and crop N demand is one main factor for low NUE in corn production (Shanahan et al., 2008; Ferguson, 2015; Thompson et al., 2015; Sharma and Bali, 2018). Inappropriate timing of N fertilizer application between N supply in the soil and crop N uptake is the major reason for poor synchronization (Ferguson, 2015). Cassman et al. (2002) stated that about 75% of the N fertilizer application is applied prior to planting and only 25% of N fertilizer is applied after planting. This resulted in high levels of inorganic N, such as nitrate in the soil profile before significant crop N demand, which increases the risk of N loss. In-season applications of N fertilizer between V8 to R2 have been proposed by Shanahan et al. (2008) to coincide N supply with the period of rapid N uptake, resulting in a greater NUE and minimizing N losses compared to pre-plant N applications.

Another factor contributing to low NUE is uniform N application instead of spatially varying rates within the field (Shanahan et al., 2008). Mamo et al. (2003) reported that a uniform N rate applied to the whole field results in sub-field areas that are either under or over-fertilized. They concluded that under-fertilization limits yield and over-fertilization increases the risk of nitrate leaching below the crop root zone. Several studies have reported that uniform application discounts the fact that soil N mineralization supply and crop N needs and responses differ spatially within fields (Inman et al., 2005b; Shanahan et al., 2008; Roberts et al., 2010; Thompson et al., 2015; Sharma and Bali, 2018). Thompson et al. (2015) stated that the N mineralization of SOM varied spatially according to differences in soil temperature and water availability, which varies with landscape position. Likewise, Roberts et al. (2010) observed that soil N levels and N mineralization vary spatially within fields and between fields. Inman et al. (2005b) observed that using variable N rate application reduced total N applied by 22 kg ha^{-1} without a reduction in corn grain yield compared to uniform N application. Thus, managing N applications based on spatial soil variability can decrease the risk of under and overfertilization and increase profit compared to uniform N applications (Mamo et al., 2003).

A third factor contributing to low NUE is temporal variability. Temporal variations in N response and N mineralization can be linked to environmental factors (Thompson et al., 2015). This represents changing environmental conditions and how they interact with N management practice (Mamo et al., 2003). Cassman et al. (2002) stated that the interactions between climate and crop management can result in variations of corn N requirement and yield from year to year. Varied N need by year can be attributed to weather differences that cause a different rate of soil N mineralization depending on temperature and moisture differences (Krienke, 2015). Accounting for temporal variability and effects of weather on the crop N needs during the growing season reduces the risk of N loss and improves NUE (Lory and Scharf, 2003).

4Rs of Nutrient Stewardship

Managing N fertilizer in corn production to achieve both profitability and environmental benefits is extremely difficult for producers (Tao et al., 2018). The authors proposed to promote the 4Rs of Nutrient Stewardship to support producers in developing and implementing better nutrient management strategies. They stated that 4Rs incorporating the right rate, right source, right timing, and right place for fertilizer management is essential to develop nutrient management strategies. Practically, it is difficult to use 4Rs to improve field-based fertilizer decisions due to a limited number of studies that have quantified the influences of these 4Rs factors and their interactions on N status, yield, and profitability in producer's fields (Tao et al., 2018). They found that N source and timing, previous crop, tillage practice, and drainage class were driving variables affecting N availability to corn and not only N rate in the growing season. Several field studies have shown that the impact of one or more of the 4Rs on corn grain yield and N losses affect NUE as well (Quemada et al., 2013; Halvorson and Bartolo, 2014; Anderson and Kyveryga, 2016; Tao et al., 2018). Tao et al. (2018) concluded that the adaptive management program and the 4Rs of Nutrient Stewardship management are useful to support and improve field-based fertilizer decisions. Furthermore, an increase in NUE and a decrease in N losses could be employed by developing, adopting, and implementing next-generation management practices and techniques such as fertigation, controlled-release N fertilizers, and spatially variable in-season N application using crop canopy sensors (Ferguson, 2015).

Approaches for Determining N Requirement

Nitrogen management practices can generally be categorized as:

- Predictive approach
- Reactive approach
- Proactive approach

Predictive Approach

There are many N recommendation approaches or algorithms developed over time to assist producers in determining the right rate of N to achieve optimum yields. A predictive approach includes various methods of determining the N rate at the beginning of the growing season (Ping et al., 2008). An initial N recommendation approach was developed based on mass balance theory developed by Stanford (1973) to determine the N rate from research in the early 1970s. Morris et al. (2018) stated that N fertilizer recommendation approaches from the 1970s until 2005 in 34 U.S. states were based on yield goal ideas developed by Stanford (1973). Stanford found that approximately 0.544 kg N ha^{-1} was required to produce 25.5 kg ha^{-1} of corn grain yield (1.2 lbs N bu^{-1} grain). This approach calculates N rate pre-plant through the use of this ratio, and multiplying it with the desired yield goal or expected yield, then subtracting N credits, such as soil residual nitrate, N mineralization from SOM, manure, legume credits, and N from irrigation water for a specific field. Morris et al. (2018) reported the yield goal-based approach is more suitable in arid environments where year-to-year differences in grain yield, N mineralization, and N loss vary little as soil moisture is managed by irrigation. Because of wet springs in the Corn Belt, which can cause loss of pre-plant N fertilizer, N deficiency, and yield loss, the current best management practices (BMPs) for N management recommend split N application, which is more efficient than single large pre-plant doses (Shapiro et al., 2008; Morris et al., 2018).

One example of a yield goal approach that considers splitting N rate application is developed by the University of Nebraska-Lincoln (UNL algorithm) as a current BMP to split N application in irrigated corn (Shapiro et al., 2008). This algorithm estimates economic optimum N rate (EONR) (the N rate which optimizes profit) based on expected yield (105 percent of the average yield for the previous five years), soil test results (SOM and residual soil nitrate), and other N credits (N from legumes, manure, previous crop, and N from irrigation water). The algorithm is adjusted for the classification of soil texture and also includes a correction factor based on corn and N price and timing of N application as shown in Equation 1 as follows (Shapiro et al., 2008):

N rate recommendation (kg N ha^{-1}) =

1.12 x [35 + (1.2 x EY) - (8 x Nitrate-N ppm) - (0.14 x EY x OM) - other N credits] x Price$_{adj}$ x Timing$_{adj}$ [1]

Where,

1.12 is used to convert N recommendations from lbs N ac^{-1} to kg N ha^{-1}.

1.2 lb N per 1 bu corn yield

EY is expected yield (bu ac^{-1})

Nitrate-N ppm is an average nitrate-N concentration in the root zone (30-120 cm depth) in parts per million

OM is the percent organic matter

Other N credits are the N from legumes, manure, other organic materials, and N from irrigation water

Price$_{adj}$ is the adjustment factor for prices of corn and N

Timing$_{adj}$ is the adjustment factor for fall, spring, and split applications

Work by Dobermann et al. (2011) indicated that the UNL algorithm resulted in an effective prediction of EONR with high NUE and low residual soil nitrate in irrigated corn across Nebraska. Ferguson et al. (2002) used the UNL algorithm to apply N rate as variable rate N application based on the spatial variability in the field. The authors concluded that applying N rates depending on spatial variability showed no advantage compared to when applying N rates depending on uniform application using UNL algorithm.

Several limitations have been noted in this approach including uncertainties at the time of fertilization of predicting yield, soil N mineralization, internal N efficiency, and soil and fertilizer use efficiency resulting from the interaction of corn hybrid, cropping system management, weather, landscape, and soil properties (Morris et al., 2018). Thus, the yield goal approach may result in under or over-fertilization compare to an optimal N rate (ONR) required to maximize yield, resulting in poor economic return (Ransom, 2018).

Reactive Approach

To overcome the limitations of yield goal-based or predictive approaches, researchers have used various reactive sampling techniques to increase N management options for corn producers (Barker and Sawyer, 2012). Various reactive sampling techniques can include soil tests (Magdoff et al., 1984; Scharf, 2001), destructive plant tissue tests (Schröder et al., 2000; Scharf, 2001), and non-destructive measuring of crop canopy light characteristics using a crop sensor-based approach to determine N requirements (Samborski et al., 2009; Holland and Schepers, 2010; Schlemmer et al., 2013). The crop sensor-based approach has the potential to provide a rapid, larger sample size that is an inexpensive and accurate technique compared to destructive sampling to monitor crop N status (Inman et al., 2005; Morris et al., 2018; Naser et al., 2020). Crop canopy reflectance can be used to detect N status using a crop sensor during the growing season. A strong linear relationship exists between leaf N content and leaf chlorophyll content (Shaver et al., 2011; Naser et al., 2020), which makes sense because the majority of leaf N is contained in chlorophyll molecules (Daughtry et al., 2000). As a result, a reactive approach can be focused on using crop sensors to quantify leaf chlorophyll content. Reactive sensor-based approaches can be an effective indicator of in-season crop N need that integrates crop growing conditions including weather effects on the crop from the time of planting to the time of sensing (Thompson et al., 2015). A reactive approach responds to measured crop N needs and determines the timing of additional N requirements based on the indication of the crop N sufficiency status.

SPAD Chlorophyll Meters

Handheld SPAD Chlorophyll Meters (SPAD CM) (Spectrum Technologies Inc.) measures light transmittance properties of leaves in two wavelengths (650 and 940 nm) by clamping the sensor on the crop leaf and emitting its own light to assess leaf greenness. Samborski et al. (2009) reported that SPAD CM operation is based on the amount of red light absorbed that indicates the amount of chlorophyll, and the amount of NIR light transmitted serves as an internal reference to compensate for leaf thickness and water content. They indicated that a very strong, nonlinear relationship between SPAD CM readings and leaf chlorophyll content exists in corn. Likewise, Schröder et al. (2000) found that SPAD CM readings have a strong correlation with leaf chlorophyll concentration and leaf N concentration. Several studies have shown that SPAD CM can be used to monitor leaf greenness and N status through the corn growing season as a simple to use, reliable, and accurate tool to detect N deficiency (Dwyer et al., 1991; Bullock and Anderson, 1998; Scharf and Lory, 2006). Other studies utilized SPAD CM readings to measure leaf greenness and detect crop N status at early stages to correct in-season N deficiency without reducing yields (Peterson et al., 1993; Varvel et al., 1997, 2007; Daughtry et al., 2000; Samborski et al., 2009; Schmidt et al., 2009). Chlorophyll measurements with handheld tools, such as the SPAD CM, were used to create information on plant N status as a convenient alternative to destroying plant tissue and laboratory N analysis (Blackmer and Schepers, 1995; Schröder et al., 2000).

The SPAD CM is unitless, indicating leaf greenness and plant N status at a specific time, it does not predict plant status in the future or how much N fertilizer will be needed by the crop (Bullock and Anderson, 1998; Samborski et al., 2009). Additionally, several studies have shown that calibration of SPAD CM measurements is required for different hybrids, crop growth stage, the timing of N fertilizer application, N source, site, leaf thickness, and environmental conditions (Schepers et al., 1992; Blackmer and Schepers, 1995; Bullock and Anderson, 1998; Schröder et al., 2000; Samborski et al., 2009). Because these sources of variation affect SPAD CM measurements, a non-limiting N fertilizer area or high N reference has been used to normalize sensor data to a specific situation to assure N adequacy at the time of sensor measurements. Murdock et al. (1997) suggested that as much as possible, reference areas should represent the entire field, but not poorly drained areas. Then, sensor measurements can be collected from unknown chlorophyll concentration (target area or bulk treatment) and compared to non-limited N fertilizer or reference area to calculate a sufficiency index (SI), which has the following equation (Peterson et al., 1993):

$$\boldsymbol{SI} = \frac{\textbf{VI Unknown}}{\textbf{VI Reference}} \qquad \textbf{[2]}$$

Where,

SI = sufficiency index,

VI Unknown is a sensor vegetation index obtained from target chlorophyll concentration,

VI Reference is a sensor vegetation index obtained from non-limited N fertilizer or high N reference.

Several studies have demonstrated the requirements of non-limiting or high N reference to calibrate SPAD CM measurements (Blackmer and Schepers, 1995; Daughtry et al., 2000; Samborski et al., 2009; Schmidt et al., 2009). Hawkins et al. (2007) and Varvel et al. (2007) found that there is a strong relationship between relative SPAD CM values and the optimal N rate when SPAD CM values are compared to high N reference values. Thus, the most accurate N rate recommendations can be produced using a high N reference area (Morris et al., 2018). Peterson et al. (1993) and Blackmer and Schepers (1995) used sufficiency index (SI) to normalized SPAD CM measurements and to detect and correct corn N stress via fertigation when SI values were 0.95 or below, indicating N deficiency. They found that N deficient state at early growth stages can be corrected, but may not achieve maximum yields. Treatments that started with adequate N fertilizer and then became deficient were corrected, and maximum yields were attained. Blackmer and Schepers (1995), confirmed by Varvel et al. (1997), that the SPAD CM can be effective to detect in-season N stress and additional N rate can apply to correct crop deficiency at the V8 growth stage for maximizing yield if there is no severe N deficiency at an early stage.

However, Schmidt et al. (2009) reported that although SPAD CM has been suggested to provide a rapid in-season assessment of the corn N status to recommend N fertilizer, one shortcoming is that the SPAD CM measurements are taken by hand and for specific plants, making this a non-realistic approach for variable rate N management at the field level. Additionally, SPAD meter use is labor-intensive and time-consuming with smaller sample sizes than canopy reflectance sensors (Morris et al., 2018).

Crop Canopy Sensors

Proximal and remote sensing have been used extensively for in-season N management that provides an estimate of crop N status over a large field area that accounts for spatial variability and supports decisions on N supplements (Morris et al., 2018; Thompson and Puntel, 2020). The properties of canopy light reflectance can be measured by proximal sensors or by sensors mounted on aerial platforms, such as airplanes, drones, and satellites. Crop canopy sensors can be divided into two categories, active and passive sensors, according to their light sources (Muñoz-Huerta et al., 2013).

Passive sensors use sunlight as their energy source and measure reflected light from the target emitted from the sun (Souza et al., 2017). Passive sensors can be carried and used by satellites, aircraft, or drones to obtain agricultural imagery. Unmanned aerial systems (UAS) have become a common platform for carrying and using passive sensors for agricultural research as well as commercial purposes. Several studies have shown that useful information such as crop N status can be obtained from crop canopies with passive sensors mounted on satellite or airborne platforms (Inman et al., 2005; Shaver et al., 2010, 2014; Erdle et al., 2011; Krienke et al., 2017; Thompson and Puntel, 2020). However, the angles of the sun, time of day, and cloud cover will influence reflectance and vegetation indices measured from the corn canopy (Souza et al., 2010). Consequently, UAV passive sensors require calibration and specialized software to analyze and interpret imagery.

Active sensors have their own light source and measure reflected light from the target emitted from the sensor. Tubaña et al. (2011) documented that active sensors were developed to overcome the limitations of passive sensors and to minimize the impacts of ambient light conditions on crop canopy reflectance readings. Active sensors can be used at any time of day or night. They are relatively inexpensive, easy to use, and small enough to mount on a fertilizer application boom or tractor and on UAS (Inman et al., 2005a; Shaver et al., 2011; Krienke, 2015). The use of small platforms, such as active sensors (on-the-go) on the N applicator can immediately provide information to assess corn N status and apply varying N rates based on real-time reflectance data (Inman et al., 2005a; Schmidt et al., 2009). Many active sensors have been used in agriculture applications, but the most common active sensors used are GreenSeeker (NTech Industries Inc., Ukiah, CA, USA), and the Crop Circle sensor family such as RapidScan-CS-45 and OptRx sensor (Holland Scientific, Lincoln, NE, USA).

Vegetative Indices

Passive and active crop canopy sensor reflectance values are expressed as vegetation indices (VIs) that were developed to link reflectance from leaves or canopies with canopy characteristics (Hatfield et al., 2008). Canopy reflectance sensor measurements can be used to normalize sensor data to generate VIs. The VIs are combinations of reflectance from two or more wavelengths. For example, the normalization of the red and NIR wavelength bands using light reflectance from a crop canopy generates the Normalized Difference Vegetation Index (NDVI) to estimate canopy biomass. The NDVI is one of the most widely adopted VIs proposed by Rouse et al. (1974). The NDVI is determined by normalizing the ratio of the difference between

NIR (correlated to leaf structure) and red (correlated to chlorophyll content) wavelength bands to the sum between NIR and red wavelength bands, which has the following equation:

$$\boldsymbol{NDVI} = \frac{\textbf{NIR}-\textbf{Red}}{\textbf{NIR}+\textbf{Red}} \qquad \textbf{[3]}$$

Where,

NIR is the reflectance in the near-infrared wavelength band

Red is the reflectance in the red wavelength band

NDVI values range between -1.0 and 1.0. and NDVI values from bare soil reflectance normally range between 0.1 and 0.2. The NDVI has been used successfully to direct variable N applications during the growing season and has the potential for improving N management (Solari et al., 2008; Samborski et al., 2009; Kitchen et al., 2010). The NDVI reading fails to discern differences under high canopy coverage conditions due to the saturation of red region reflectance. Sims and Gamon (2002) stated that relatively low chlorophyll contents are sufficient to saturate absorption in the red region, reducing sensitivity to high chlorophyll contents. Red edge band (700-740 nm)-based spectral indices can overcome the limitation of the saturation of the red band observed in NDVI, and is more sensitive to crop canopy chlorophyll and N status under high canopy coverage conditions such as corn (Li et al., 2014). They concluded that the red band can be replaced by a red edge band to create the Normalized Difference Red Edge (NDRE) index previously suggested by Buschmann and Nagel (1993), which is a reliable indicator of chlorophyll or N status. The NDRE using red edge and NIR bands are more sensitive to maize canopy N indicators than those using NIR and red bands, and has the following equation (Li et al., 2014):

$$NDRE = \frac{\textbf{NIR}-\textbf{Red Edge}}{\textbf{NIR}+\textbf{Red Edge}} \qquad \textbf{[4]}$$

Where,

NIR is the reflectance in the near-infrared wavelength band

Red Edge is the reflectance in the red edge wavelength band

High N Reference

To account for some factors influencing VIs other than N-related factors, a high N reference (non-limited N) has been developed. The high N reference area in the field receives a non-limiting N rate at planting to be above crop needs to ensure that total N is sufficient throughout the entire growing season. Thus, the high N reference is used to calculate crop N SI (VI Unknown / VI Reference) as earlier mentioned in Equation 2 to assess crop N status. Unknown or target VIs is the field area to be fertilized while reference VIs is the field area with non-limited N. Shapiro et al. (2013) recommended establishing appropriate reference strips in each field to represent conditions or variability for the entire field. The reference crop needs to be managed identically to the rest of the field or treatments except that sufficient N is applied to ensure that plants do not show N deficiency at the time of sensing. However, using a high N reference area can be inconvenient and may be restricted in some countries or situations (Holland and Schepers, 2013). Moreover, a high N reference area should be moved to a different area of the field every year to ensure that the nutrient status of the rest of the field is represented accurately. Franzen et al. (2016) stated that using a high N reference area for calibration of active sensors can be problematic. They concluded that establishing high N reference may induce a sulfur deficiency in corn as a result of a nutrient imbalance between N and sulfur. A virtual reference concept was proposed by Holland and Schepers (2013) as a method to overcome the limitations of using a high N reference approach and to identify adequately fertilized plants whose reflectance serves as a reference without applying high amounts of N fertilizer. In this approach, reference values are obtained utilizing the 95-percentile cumulative values from a histogram of sensor VI values to generate SI. This SI values can then be used to calculate in-season N rates recommendation using an algorithm.

In-season N Recommendation Algorithm

Several corn N recommendation algorithms with different inputs have been developed that use the high N reference for translating crop canopy sensor information into in-season N rates (Holland and Schepers, 2010; Solari et al., 2010). Holland and Schepers (2010) developed a universal algorithm as an alternative to current uniform N application practices. The algorithm developed a generalized approach that can be used with crop canopy sensors to detect spatial variability that exists within fields. This algorithm calculates the N rate based on a yield response function (quadratic or quadratic plateau) to N and SI (Franzen et al., 2016). The algorithm inputs include EONR or the maximum N rate that producers expect will maximize yield, and provides for credit for N fertilizer applied before crop sensing, N credits (from previous crops, manure application, nitrate content in irrigation water), SI, and delta SI to determine the in-season sidedress N application rate between V8-V14 growth stages. This algorithm has the following equation (Holland and Schepers, 2010):

$$N_{APP} = (N_{OPT} - N_{PreFert} - N_{CRD} + N_{COMP}) \cdot \sqrt{\frac{(1 - SI)}{\Delta SI \cdot (1 + 0.1 \cdot e^{m(SI_{Threshold} - SI)})}} \qquad \textbf{[5]}$$

Where,

N_{APP} is N application rate

N_{OPT} is EONR or the maximum N rate prescribed by producers

$N_{PreFert}$ is the total N fertilizer applied before crop sensing and /or in-season N application

N_{CRD} is N credit for the previous season's crop, nitrate in irrigation water, or manure application

N_{COMP} is N in excess of N_{OPT} required by the crop under soil limiting conditions at a given growth stage

SI is the sufficiency index of the target crop

M is back-off rate variable (0 < m < 100)

$Th_{reshold}$ is the back-off cut-on point

ΔSI is the difference between where SI equals 1 and the point where the response curve intersects the y-axis (1-SI (0))

Improving N rate recommendations can be achieved through remote sensing techniques to detect crop N status and spatially adjusted in-season N fertilizer to improve NUE and increase profit (Ferguson et al., 2002). Shanahan et al. (2008) reported that additional soil, climate, and management factors are required to refine recommendation algorithms to better predict EONR and improve NUE. Improving NUE and decreasing N losses can result from developing, adopting, and implementing next-generation management practices and techniques (Ferguson, 2015). One of the next-generation precision N management practices and techniques is simulating crop N requirement models (Thompson et al., 2015).

Proactive Approach

A proactive approach attempts to predict N demand and supplement N to the crop before N deficiency occurs that will reduce yield potential. Crop simulation models attempt to account for spatial variability among fields and temporal variability between years by combining soil, crop, and management information with current and long-term weather to estimate corn N demands (Setiyono et al., 2011; Sela et al., 2016). They have the potential to provide information for farmers to adjust in-season N application to synchronize soil N fertilizer application with crop N demand (Cassman et al., 2002; Li et al., 2006; Thompson et al., 2015; Jin et al., 2017). Several crop simulation models have been developed to investigate soil-crop-weather dynamics (Puntel et al., 2016), such as a WOrld FOod STudies (WOFOST) (Supit et al., 1994), the Decision Support System for Agrotechnology Transfer (DSSAT) (Jones et al., 2003), and a System Approach to Land Use Sustainability (SALUS) (Basso et al., 2006). However, these models typically are not designed to support decisions about pre-plant or in-season N rate recommendations (Thompson et al., 2015).

A number of specific simulation models have been developed to recommend pre-plant and in-season N management in corn (Jin et al., 2017). These models include Quantitative Evaluation of the Fertility of Tropical Soils (QUEFTS) (Janssen et al., 1990), the Agricultural Production Systems sIMulator (APSIM) (Holzworth et al., 2006;

Puntel et al., 2016), Adapt-N (Melkonian et al., 2008), and Maize-N (Setiyono et al., 2011).

The Adapt-N model is a tool developed at Cornell University to provide an in-season N recommendations tool to optimize split application N management for corn production based on simulation of soil N dynamics and maize N uptake for conditions in the Northeast U.S. (Melkonian et al., 2008; Sela et al., 2016). Rutan and Steinke (2017) reported that the Adapt-N model is built on the Precision N Management (PNM) model (Melkonian et al., 2007, 2008) which integrated and enhanced the combination of the LEACHN model and a corn N uptake, growth, and yield model (Sinclair and Muchow, 1995). Users provide site-specific soil properties, manure application, irrigation, land management, crop species, and N management information while the model has dynamic accesses to gridded, near real-time (1d lag), high-resolution regional weather data (4 by 4 km) for site-specific N recommendations. This high-resolution weather data enables simulations of soil N levels in the early season, which can improve estimates of in-season N requirements. A recent study evaluated Adapt-N and compared it with grower-selected (conventional) corn sidedress N rates during 2011-2014 across 113 New York and Iowa on-farm strip trials (Sela et al., 2016). The authors found that Adapt-N reduced N rates 53 and 31 kg N ha^{-1} compared to grower-selected rates without significant grain yield reductions for New York and Iowa, respectively, and increased grower profits \$65 ha^{-1} and reduced environmental N losses by 28 kg ha^{-1}. In contrast, Laboski et al. (2014) found that the Adapt-N model trend was to under-recommend N to a great extent and be less profitable than the Maximum Return to Nitrogen (MRTN) approach in Indiana and Iowa using retroactively generated sidedress N rates. They concluded that the model failed to adequately account for excessive spring rainfall, N mineralization, and subsequent availability of manure N.

The Maize-N model is another precision N management tool developed at the University of Nebraska-Lincoln for estimating EONR for corn (Setiyono et al., 2011). Thompson et al. (2015) stated that the Maize-N model is based on functions from the Hybrid-Maize simulation model (Yang et al., 2006) for maize growth and yield prediction under rainfed and irrigated conditions, and from a mono-component model (Yang and Janssen, 2000) for simulating C and N mineralization from SOM and crop residuals. The model inputs include long-term weather, planting date, previous crop, tillage, soil information (SOM, pH, texture, bulk density), other N credits such as soil residual nitrate, manure, N fertilizer source and application, and grain and fertilizer prices (Setiyono et al., 2011). Setiyono et al. (2011) reported that in addition to EONR, attainable yield, N uptake, and daily rate of C and N mineralization were simulated by the Maize-N model. Additionally, the Maize-N model simulates indigenous N supply and relates it to yield through yield vs. N uptake relationship using a research and farmer field trial database (Morris et al., 2018). Determining EONR by the Maize-N model depends on the prediction of N mineralization from SOM as it is affected by weather conditions such as temperature and precipitation (Thompson et al., 2015; Banger et al., 2019; Yin et al., 2020).

The model was validated and simulated EONR showed a good agreement to measured EONR based on experiments conducted in western Corn Belt states in both irrigated conditions (central Nebraska and eastern South Dakota) and rainfed conditions (eastern South Dakota and western Nebraska) (Setiyono et al., 2011). The EONR simulated by Maize-N showed greater accuracy with lower root mean square error (RMSE) and mean error (ME) values than current university N recommendation approaches. A more recent field study by Thompson et al. (2015) conducted across 12 sites in Nebraska, Missouri, and North Dakota found that the Maize-N model, in general, recommended more N than a sensor-based approach in-season recommendations, but was better at protecting yield potential. However, recent research conducted across eight US Midwest Corn Belt states at 49 sites and three growing seasons showed that the Maize-N model performance in predicting EONR was lower than some other current N recommendation models (Ransom et al., 2020). A summary of features and inputs for Maize-N vs. Adapt-N is presented in Table 1.2

Table 1.2. Summary of features and inputs for Adapt-N and Maize-N simulation models. Table adapted from Morris et al., (2018).

Feature/Input	Adapt-N (Version 2015)	Maize-N (Version 2016)	Comments
Time scale	Real-time, daily high-resolution weather data. Uses historical climate data for post-date estimates	Long-term using historical daily climate data inputs for yield estimation and N mineralization with the option of in-season weather data for N mineralization	Key difference between the tools
Optimum N estimation	Mass balance: deterministic (pre)-stochastic (post) with crop-fertilizer price ratio	Response curve-N credits-efficiency, with crop-fertilizer price ratio	Adapt-N incorporates pre-set seasonal crop-fertilizer price ratios; Maize-N employs user inputs
Climate-weather inputs	Near-real-time: Solar radiation; Evapotranspiraton (ET); max-min temperature; precipitation	Solar radiation, max-min temperature; precipitation; ET	Solar radiation and ET are (or can be) estimated in both tools.
Soil inputs	Soil type or series name related to NRCS database; rooting depth; slope; soil organic carbon (SOC)	SOC; texture; bulk density; acidity; measured soil nitrate before planting (opt.)	Default values available for some inputs
Crop inputs	Cultivar (grain, silage, sweet); maturity class; population; expected yield	Maturity rating; date of planting; population; grain price	Adapt-N uses user-defined yield; Maize-N estimates yield, with possible user modification
Management inputs	Tillage (type, time, residue level); irrigation (amount, date); manure applications (type, N & solid contents, rate, timing, incorpo-ration method); previous crop characteristics	Tillage (type, time); irrigation; manuring (type, N and moisture contents, rate, timing); previous crop and yield	
N Fertilizer inputs	Multiple: Type, rate, time of	Basal and in-season: Type, price,	

	application, placement depth	rate, time of application, N from irrigation	
Graphical outputs	N contributions and uptake; N losses (total, NO3 leaching and N2O); N content dynamics; crop development; weather inputs	Soil C–N dynamics; yield response curve; N contributions and uptake; yield indicators; efficiency indicators; weather inputs	
Other	Web-accessible; option for automatic daily updates by email or text message; batch data upload capability. Available for 18 U.S. states in the Northeast and Midwest.	Purchased and downloaded to PC. Input/output features. Tested for conditions in the western Corn Belt	Both tools have diagnostic and reporting features, and facilitate evaluation of management alternatives

Integration of Crop Sensor and Crop Model Approaches

A reactive approach based on crop leaf or crop canopy sensors and a proactive approach based on crop simulation models are effective and useful tools for N management in corn. Crop sensors based on canopy reflectance provide a great value to assess crop N status (Morris et al., 2018). However, complex interactions that exist in the dynamic soil-plant-atmosphere system and uncertainty in weather make it challenging to manage N and estimate ONR (Puntel et al., 2016). Crop simulation models accounting for soil-plant-atmosphere system interaction over space and time may greatly improve EONR estimates and minimize N leaching without affecting farmer's profits (Basso et al., 2016).

Finding approaches for improving corn N recommendations are important to provide optimal yield and profit for producers while reducing N loss to the environment (Morris et al., 2018). In recent research conducted over 49 sites through eight states and three growing seasons, integrating two N recommendation tools, such as Yield Goal and Maize-N model to generate an N recommendation improved the performance of these tools, and decreased RMSE compared to using a single N recommendation tool (Ransom, 2018). Likewise, Thompson et al. (2015) recommended integrating or combining crop sensors and model information could increase the accuracy of N rate recommendations to match EONR, thus improving NUE and increasing or maintaining yield and profit while reducing N losses and minimizing environmental consequences. Because in-season N sidedress application takes place once at a specific growth stage range, the method is limited by labor, weather, and availability of high clearance applicator equipment. To overcome these limitations under irrigated conditions, a desirable alternative method is to apply N via fertigation.

What is Fertigation?

Fertigation is a method to apply fertilizers through the irrigation system, which is a common and cost-effective means to apply multiple small doses of in-season fertilizer application. Fertigation has consistently been shown to increase fertilizer efficiency and crop growth through closely controlling the rate and timing of nutrients and water supply compared with traditional application methods (Mikkelsen et al., 2015). Blackmer and Schepers (1995) found that SPAD CM measurements can be used to schedule fertigation in irrigated corn, which resulted in maintaining yield and profit, reducing N rate, and protecting the environment. Likewise, Schepers et al. (1995) demonstrated that using a spoon-feeding strategy based on SPAD CM SI to schedule fertigation saved 168 kg N ha^{-1} for the first year and 105 kg N ha^{-1} for the second year without reducing yield . However, spatial variability in N status observed for the second year made it difficult to meet crop N needs.

Using fertigation has many advantages, such as increasing flexibility in nutrient supply and splitting fertilizer doses to be synchronized with crop nutrient uptake, and improving fertilizer distribution in the root zone to improve crop uptake (Incrocci et al., 2017). Also, fertigation can provide high uniformity of fertilizer (depending on the uniformity of water application), reduce soil compaction, less labor, and reduce N run-off thus minimizing environmental pollution. However, fertigation has some challenges, including inefficiency during a wet season and required training and experience (Mikkelsen et al., 2015).

Conclusion

Reactive and proactive approaches via fertigation are considering next-generation precision N management practices and techniques. Both approaches can address in-season N crop need in response to current growing season conditions, with the potential to improve NUE and decrease N losses. Integrating sensor and model information increase the accuracy of in-season decision support for N recommendation. Thus, the integration of reactive and proactive approaches to determine the timing and rate of N requirement via fertigation in corn will be considered in the second chapter of this dissertation.

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Chapter 2: Integration of Reactive Sensor and Proactive Maize-N Model Approaches for Determining Nitrogen Requirements Via Fertigation in Corn

Introduction

Low nitrogen use efficiency (NUE) has been attributed to several causes including poor synchrony between soil N supply and crop N demand, unaccounted for spatial soil variability, and temporal variation in crop N requirements (Cassman et al., 2002; Shanahan et al., 2008; Solari et al., 2008; Thompson et al., 2015). Inappropriate timing of N fertilizer application between N supply in the soil and crop N uptake is the major reason for poor synchronization (Ferguson, 2015). Cassman et al. (2002) stated that about 75% of the N fertilizer application is applied prior to planting and only 25% of N fertilizer is applied after planting. This can result in high levels of inorganic N, such as nitrate in the soil profile before rapid crop N demand, which increases the risk of N loss. In-season applications of N fertilizer between V8 to R2 have been proposed by Shanahan et al. (2008) to coincide N supply with the period of rapid N uptake, resulting in greater NUE and minimizing N losses compared to pre-plant N applications.

Uniform N application rates instead of spatially variable application rates within the field can be a second factor that contributes to low NUE (Shanahan et al., 2008; Thompson et al., 2015). Mamo et al. (2003) reported that a uniform N rate applied to the whole field resulted in either under or over-fertilized for sub-field areas. Roberts et al. (2010) observed that soil N levels and N mineralization vary spatially within fields and between fields. Likewise, Mamo et al. (2003) reported that N mineralization of SOM varies spatially across a field due to variation in soil characteristics. Several studies have reported that uniform applications within the field discounts the fact that soil N mineralization supply, crop N needs, and responses are not the same spatially, resulting in a greater risk of N loss (Inman et al., 2005b; Shanahan et al., 2008; Roberts et al., 2010; Thompson et al., 2015). Managing N applications based on spatial soil variability can decrease the risk of under and overfertilization and increase profit compared to uniform N applications (Mamo et al., 2003).

Unaccounted for temporal variability, which is temporal variation in N mineralization and N response related to environmental conditions, is another factor that leads to lower NUE. This represents changing environmental conditions and how they interact with N management practices (Mamo et al., 2003). The interactions between climate and management can impact N mineralization, crop N demand, and yield variations from year to year (Thompson et al., 2015). Accounting for temporal variability and effects of weather on the crop N needs during the growing season reduces the risk of N loss and improves NUE (Lory and Scharf, 2003). Spatial and temporal variability combined create uncertainty and decrease the ability to accurately estimate the optimal N rate (ONR) for any given year (Roberts et al., 2010). Thus, it is critical to determine the timing and rate of crop N needs that vary spatially and temporally within a field to improve NUE and minimize N loss to the environment.

There are two major strategies to manage N, reactive and proactive approaches, with the potential to increase synchrony between soil N supply and crop N demand and account for spatial soil variability and temporal variation in crop N requirements that cause low NUE. A proactive approach attempts to predict N demand and supplement N to the crop before additional N application is required, to avoid crop N deficiency. In contrast, the reactive approach attempts to detect crop N deficiency based on the indication of the real-time crop N sufficiency status to determine additional N supply requirements. Both approaches are employed in various combinations, such as a proactive approach that predicts N demand at pre-season and a reactive approach that reactively detects in-season crop N status and determines if additional N requirements are needed.

A proactive approach can include an empirical prediction algorithm that incorporates historical productivity (yield goal) or crop simulation models. One example of a yield goal approach is the University of Nebraska-Lincoln corn N recommendation algorithm (UNL algorithm) that considers splitting N rate application, which proactively predicts total N requirements (Shapiro et al., 2019). This algorithm aims to estimate N requirements and minimize residual soil nitrate using yield goal, SOM, residual soil nitrate as well as various N source credits such as legumes or manure, and irrigation water nitrate content. Crop simulation models attempt to account for spatial variability between fields and temporal variability between years by combining soil, crop, and management information with current and long-term weather to estimate N demands for corn (Setiyono et al., 2011; Sela et al., 2016). Although many crop simulation models exist, such as DSSAT (Jones et al., 2003), APSIM (Holzworth et al., 2006), CropSyst (Stöckle et al., 2003), SALUS (Basso et al., 2006), and others that have been used to investigate soil-crop-weather dynamics (Puntel et al., 2016), they were not designed to support pre-plant or in-season N rate recommendations (Thompson et al., 2015). A number of specific simulation models, such as Adapt-N (Melkonian et al., 2008) and Maize-N models (Setiyono et al., 2011) have been developed to recommend pre-plant and in-season N rate applications in corn (Jin et al., 2017). Adapt-N model was developed at Cornell University to provide an in-season N recommendations tool to optimize split application nutrient management for corn production based on simulation of soil N dynamics and maize N uptake under conditions in the Northeast US (Melkonian et al., 2008; Sela et al., 2016).

The Maize-N model was developed at the University of Nebraska-Lincoln to predict economic optimal N rate (EONR) based on functions from the Hybrid-Maize model (Yang et al., 2006) for corn growth and yield prediction and a mono-component model (Yang and Janssen, 2000) for SOM mineralization and yield response to N uptake. The Maize-N model attempts to account for variability among fields and years by combining current and long-term weather data, current and last crop information, soil information, tillage system, various N credits, and prices for grain and N fertilizer to estimate EONR (Setiyono et al., 2011). The model was validated and EONR simulated by the Maize-N model showed a good agreement to measured EONR based on experiments conducted in western Corn Belt states in both irrigated conditions (central Nebraska and eastern South Dakota) and rainfed conditions (eastern South Dakota and western Nebraska) (Setiyono et al., 2011). Likewise, Thompson et al. (2015) reported that the EONR simulated by the Maize-N model showed greater accuracy with lower root mean square error (RMSE) and mean error (ME) values compared with the current university N recommendation approach, such as the UNL algorithm.

In contrast, the reactive approach can include responding to measured crop N requirements that have been calibrated to different sampling techniques, such as soil tests (Magdoff et al., 1984; Scharf, 2001), destructive plant tissue tests (Schröder et al., 2000; Scharf, 2001), and non-destructive measuring of crop canopy light characteristics using a crop sensor-based approach to determine N requirements (Samborski et al., 2009;

Holland and Schepers, 2010; Schlemmer et al., 2013). The crop sensor-based approach has the potential to provide a rapid, large sample size that is a more inexpensive and accurate technique compared to destructive sampling to monitor crop N status (Inman et al., 2005; Morris et al., 2018; Naser et al., 2020). A strong linear relationship exists between leaf N content and leaf chlorophyll content (Shaver et al., 2011; Naser et al., 2020), which makes sense because the majority of leaf N is contained in chlorophyll molecules (Daughtry et al., 2000). Sensors using either light reflectance or transmittance properties of canopies or leaves can be used to detect spectral characteristics (Morris et al., 2018), which relates to plant chlorophyll content and N content (Erdle et al., 2011). Sensors can be divided into two broad categories: active and passive.

Passive sensors utilize ambient light (sunlight) as their source of energy to illuminate their targets, whereas active sensors use their own source of light (Erdle et al., 2011; Shaver et al., 2011). Using active sensor reflectance measurements of corn canopy has been shown to be effective to estimate N status and improve NUE (Solari et al., 2008; Holland and Schepers, 2010; Thompson et al., 2015). An example of a sensor that uses light transmittance is (Soil Plant Analysis Development) SPAD 502 Chlorophyll Meters (SPAD CM) (Spectrum Technologies Inc. Aurora, Illinois, USA), which is also considered an active crop leaf sensor. SPAD CM measures light transmittance properties of leaves in the red (650 nm) and near-infrared (940 nm) spectral bands (Solari et al., 2008), which is strongly correlated with leaf chlorophyll content. Thus, SPAD CM has been used as an N management tool to provide rapid and nondestructive estimates of crop chlorophyll content and monitor corn N status (Peterson et al., 1993; Varvel et al., 1997), which eliminates the need to use conventional plant tissue sampling to quantify N content

(Naser et al., 2020). Shapiro et al. (2013) provided guidelines for the use of chlorophyll meters for fine-tuning N management decisions during the growing season, increasing NUE, and maintaining the yield of corn. However, to monitor crop N status, it is required to have a high N reference area (non-limiting N) to determine the sufficiency index (SI) by normalizing data in the field to avoid the site and sampling date effects. This is described in detail by Peterson et al. (1993).

A recent review by Morris et al. (2018) showed that using either a crop canopy sensor or crop leaf sensor as a reactive approach for N management is effective and has greater accuracy than a proactive approach. This greater accuracy translates to reduced N rate, improved NUE, increased or maintained yield, and reduced N loss. Likewise, a recent field study by Thompson et al. (2015) found that a reactive approach using crop canopy sensor-based Holland-Schepers algorithm (H-S algorithm) (Holland and Schepers, 2010) was effective in reducing in-season N rate, increasing NUE as measured by PFP_N and AE with little to no reduction in yield compared with a proactive approach across 12 sites in Nebraska, Missouri, and North Dakota. The sensor-based approach relied on applying a sufficient base rate of N application at planting followed by a reactive one-time in-season assessment of the crop N deficiency informed by the sensor (Holland and Schepers, 2010). Although the use of a sensor-based approach attempts to detect spatial variability that exists within fields and generate SI, the method does not need to set a threshold to detect the timing of the N application. Because the in-season N sidedress application takes place once at a specific growth stage range, the method is limited by labor, weather, and availability of high clearance applicator equipment.

To overcome the limitations of labor, weather, and availability of high clearance applicator equipment under irrigated conditions, a desirable alternative method is to apply N via fertigation. Fertigation is a method to apply fertilizers through the irrigation system, which is a common and cost-effective means to apply multiple small doses of in-season fertilizer application. Applying multiple small N doses when N uptake by corn is highest can result in greater NUE and less N loss. For example, Blackmer and Schepers, (1995) and Schepers et al. (1995) found that a reactive approach using SPAD CM can be a valuable tool to monitor corn N status and schedule fertigation for corn resulting in lower N rates, higher NUE without reducing yield compared with a proactive approach, which resulted in higher N rates without increased grain yield.

However, there are no previous studies that have integrated a reactive approach using crop N sensors and a proactive approach using the Maize-N model to determine the timing and rate of in-season N requirements via fertigation. The objective of this research was to evaluate and develop a new N application method using the integration of reactive sensor and proactive Maize-N model approaches via fertigation in corn.

Material and Methods

Site Description

This study was conducted during the 2017 and 2018 growing seasons at two sites of the University of Nebraska-Lincoln: (i) South Central Agriculture Laboratory (SCAL), near Clay Center, Nebraska (44.6° N, 98.1° W; elevation: 552 m above mean sea level) and (ii) West Central Research and Extension Center (WCREC) (41°5' N, 100°45' W; elevation: 861 m above mean sea level), North Platte, Nebraska. The soil at the SCAL site was classified as Hasting silt loam (fine, montmorillonitic, mesic Udic Argiustolls) soil series with 0 to 1 percent slopes (Hammer et al.,1981). Whereas, the soil at the WCREC site was classified as Cozad silt loam (fine, silty, mixed, mesic Typic Haplustolls) soil series with 0 to 1 percent slopes (Bowman et al., 1978).

The SCAL site is characterized as a transition zone between sub-humid and semi-arid climates, with average precipitation received during the crop growing season from April 1 to September 30, 2017 of 450.9 mm and the average daily temperature was 18.98°C. For 2018, the average precipitation received during the crop growing season from April 1 to September 30, 2018 was 505.5 mm and the average daily temperature was 18.88°C (HPRCC, 2019). The WCREC site is characterized as a semi-arid climate, with average precipitation received during the crop growing season from April 1 to September 30, 2017 of 457.4 mm and the average daily temperature was 18.37°C. For 2018, the average precipitation received during the crop growing season from April 1 to September 30, 2018 was 453.5 mm and the average daily temperature was 17.72°C (HPRCC, 2019).

Soil samples were collected at each site to characterize soil chemical properties and residual soil nitrate. Initial spring soil samples for the topsoil layer (0-20 cm) were composited from four to six soil cores to obtain one sample and two samples for each replication to obtain eight soil samples for each site. Four to five soil cores were composited for the deep soil layers to 180 cm with 30 cm increment and two samples for each replication to obtain 48 soil samples. The previous crop and a summary of soil properties for the topsoil layer across two site years are presented in Table 2.1.

Table 2.1. Summary of soil properties for spring soil samples acquired at depths of 0-20 cm for SCAL and WCREC sites in 2017 and 2018.

Site Year ID	Soil Texture	pH†	SOM‡ %	CEC* meq $100g^{-1}$	NO_3-N⋆ mg kg^{-1}	P-M3ᵟ mg kg^{-1}	K§ mg kg^{-1}	Previous crop
SCAL17	SiL⁺	6.8	3.4	15.0	8.3	29.3	360.4	soybean
WCREC17	SiL	7.9	2.0	17.8	7.0	53.1	516.4	soybean
SCAL18	SiL	6.6	3.3	15.8	11.8	32.6	334.3	corn
WCREC18	SiL	7.8	2.1	17.2	8.5	49.4	451.9	soybean

⁺SiL is silt loam, †pH is 1:1 soil: water, ‡SOM is soil organic matter LOI %, *CEC is cation exchange capacity, ⋆NO_3-N is nitrate-nitrogen, ᵟP-M3 is Mehlich-3 soil phosphorus, §K is potassium extracted by 1 N ammonium acetate.

Experimental and Treatments Design

The experimental design was a randomized complete block design with eight treatments and four replications. At the SCAL site, plot dimensions were 6.1 m wide by 36.6 m long with eight rows at 0.76 m row width. At the WCREC site, plot dimensions were 12.2 m wide by 27.9 m long with 16 rows in 2017 and 10.7 m wide by 32 m long with 14 rows at 0.76 m row width in 2018. Planting at the SCAL site was on April 24, 2017, and May 2, 2018, while planting at the WCREC site was on May 8 in both years. A planting population of 84,000 plants ha^{-1} using hybrid Fontanelle 6A327RBC was used for both site years.

Other than N fertilizer, all other agronomic activities, including pest control were managed according to the University of Nebraska Extension Guidelines (Shapiro et al., 2019). All site years were irrigated with a linear sprinkler irrigation system at the SCAL site and a center-pivot irrigation system at the WCREC site. Both irrigation systems were used for applying irrigation water and were capable of applying N fertilizer to crops through irrigation water (fertigation). Irrigation management was conducted according to the method developed by Irmak et al. (2005). Irrigation timing and amount were determined from a combination of soil moisture content and crop growth stage monitoring with the use of a Watermark soil moisture sensors (model 200SS) with a range of measurements from 0-239 (kPa) (IRROMETER Company, Inc., Riverside, CA, USA) at the SCAL site and using a neutron moisture meter (model CPN 503DR Hydroprobe) (Campbell Pacific Nuclear International Inc., Concord, CA, USA) at WCREC site. At both sites, fertilizer was applied according to UNL extension guidelines. Starter fertilizer was applied as ammonium polyphosphate 10-34-0 (NPK) (6.5 kg N ha^{-1} and 22 kg P_2O_5 ha^{-1}) and 0.32 kg ha^{-1} 20% Zn for SCAL site and as ammonium polyphosphate 10-34-0 (NPK) (6.5 kg N ha^{-1} and 22 kg P_2O_5 ha^{-1}) and phosphorus applied to plots deficient in soil test P as triple superphosphate ranged between 83 to 184 kg ha^{-1} using a dry fertilizer spreader (Barber Engineering Company, Spokane, WA, USA) in 2017 only for WCREC site. The fertilizer was banded over the seed via the planter in both site years (Table 2.2).

Eight treatments representing current best management practices (BMP) for N management in Nebraska as well as potential new practices were evaluated. The treatments were broadly categorized as the following: check, calibration, proactive, and reactive. The check (unfertilized) treatment received only starter fertilizer to supplement the recommended phosphorus and zinc needs. This treatment is important to identify N uptake from indigenous sources, including residual soil nitrate-N, mineralized N from SOM, crop residues, deposition of atmospheric ammonium, and nitrate-N from irrigation water (Wortmann et al., 2011). A non-N-limiting reference treatment was used as a calibration treatment to determine the relative N sufficiency status by normalizing sensor data and calculating the relative SI of target treatments (Blackmer and Schepers, 1995). The reference treatment was also used to represent maximum yield. The reference treatment received a non-limiting N rate (280 kg ha^{-1}) at planting to be above crop needs to ensure that total N was sufficient throughout the entire growing season.

Six treatments were labeled according to Timing-Application Method-Rate-N Source. Timing was either proactive or reactive. A reactive approach responds to measured crop N needs and determines the timing of additional N requirements based on the indication of the crop N sufficiency status. In contrast, a proactive approach attempts to predict N demand and supplement N to the crop before N deficiency occurs. The application method was either sidedress or fertigation. The rate was arbitrarily fixed or calculated by the UNL algorithm and H-S algorithm or predicted by the Maize-N model. The N source for all but one treatment was a urea-ammonium nitrate (UAN) solution (32%N) as a base rate and additional N applied via fertigation and thus omitted from the description. One treatment used Environment Smart Nitrogen (ESN), a polymer-coated controlled-release N source as a base rate and additional N applied via fertigation as UAN (32%N) (Table 2.2).

The proactive treatments consisted of: (i) the proactive-sidedress-UNL algorithm (P-SD-UNL) treatment, (ii) the proactive-fertigation-model (P-F-Model) treatment. The P-SD-UNL treatment was considered as the current non-sensor-based BMP, which proactively predicted seasonal N rate requirements. The N rate is an empirically fit prediction algorithm that incorporates historic productivity (expected yield), SOM, residual soil nitrate as well as various N source credits such as from legumes or manure and irrigation water nitrate content. The algorithm was recommended to be a one-time in-season sidedress application informed by yield goal and N credits. It included price and application timing adjustment factors (Shapiro et al., 2019) as follows:

N rate recommendation (kg N ha^{-1}) =

$$\mathbf{1.12 \times [35 + (1.2 \times EY) - (8 \times Nitrate\text{-}N\ ppm) - (0.14 \times EY \times OM) - other\ N\ credits] \times Price_{adj} \times Timing_{adj}} \quad \mathbf{[2.1]}$$

where,

1.12 is used to convert N recommendations from lbs N ac^{-1} to kg N ha^{-1}.

EY is expected yield (bu ac^{-1})

Nitrate-N ppm is weighted average soil nitrate down to 120 cm

OM is the percent soil organic matter

Other N credits include previous legume credit, manure, other organic materials, and irrigation water nitrate

$Price_{adj}$ is the adjustment factor for prices of corn and N

$Timing_{adj}$ is the adjustment factor for fall, spring, and split applications

The P-F-Model treatment was not sensor guided, but was informed by the Maize-N model, which proactively predicted N rate requirements according to expected crop N supply and demand for the next three weeks using long-term weather data, current and previous crop information, current soil information, and N credits (Setiyono et al., 2011).

The reactive treatments consisted of: (i) reactive-sidedress-H-S algorithm (R-SD-HS), (ii) reactive-fertigation-fixed (R-F-Fixed) treatment, (iii) reactive-fertigation-model (R-F-Model) treatment, and (iv) reactive-fertigation-model-slow release (R-F-Model-SR). The R-SD-HS treatment was considered as the current sensor-informed BMP, informed by the active sensor to calculate in-season sidedress N applications. The calculation of N application took into account EONR (calculated using UNL algorithm) or the maximum N rate prescribed by the producers, total N fertilizer applied before crop sensing, N credits as well as sensor SI value (Holland and Schepers, 2010) as follows:

$$\boldsymbol{N_{APP}} = (\boldsymbol{N_{OPT}} - \boldsymbol{N_{PreFert}} - \boldsymbol{N_{CRD}} + \boldsymbol{N_{COMP}}) \cdot \sqrt{\frac{(\boldsymbol{1} - \boldsymbol{SI})}{\Delta \boldsymbol{SI} \cdot (\boldsymbol{1} + \boldsymbol{0.1} \cdot \boldsymbol{e}^{\boldsymbol{m}(\boldsymbol{SI_{Threshold}} - \boldsymbol{SI})})}} \quad \textbf{[2.2]}$$

where,

N_{APP} is N application rate to be applied as sidedress

N_{OPT} is EONR or the maximum N rate prescribed by producers

$N_{PreFert}$ is the total N fertilizer applied before crop sensing and/or in-season N application

N_{CRD} is N credit for the previous season’s crop, nitrate in water, and manure application

N_{COMP} is N above N_{OPT} required by the crop under soil limiting conditions at a given growth stage

SI is the sufficiency index of the target crop

M is back-off rate variable ($0 < m < 100$)

$Th_{reshold}$ is the back-off cut-on point

ΔSI is differences between where SI equals one and the point where the response curve intersects the y-axis (1-SI (0))

Three reactive fertigation treatments included R-F-Fixed, R-F-Model, and R-F-Model-SR informed by the sensor as reactive to crop N deficiency. N rates were either arbitrarily fixed-rate (34 kg ha^{-1} as the typical rate of N to be applied via fertigation without injuring corn plants) (Blackmer and Schepers, 1995) for R-F-Fixed treatment or were determined by Maize-N for R-F-Model and R-F-SR-Model treatments. The base rate of N fertilizer for all site years was applied at planting as UAN (Table 2.2), banded to the soil between crop rows (knife was spaced in the middle of the row and fertilizer was injected below the soil surface) for all treatments except for R-F-SR-Model treatment. For R-F-SR-Model treatment, the base rate of N fertilizer was applied at planting as ESN (Table 2.2), which was surface broadcast using a dry fertilizer drop spreader (3m wide).

Table 2.2. Site year, treatment, planting date, starter N rate, application date, base N rate, N application date, N source, and method of application for eight N fertilizer decision strategies for SCAL and WCREC sites in 2017 and 2018.

Site Year ID	Treatment	Planting Date	Starter[+] N Rate (kg N ha^{-1})	Application Date	Base N Rate (kg N ha^{-1})	N Application Date	N Source	Method of Application
SCAL17	**Check**	24 Apr.	6.5	24 Apr.	0	-	-	-
	Reference				280	8 May	UAN32%†	Banded
	P-SD-UNL				84			
	R-SD-HS				84			
	R-F-Fixed				84			
	R-F-Model				84			
	R-F-SR-Model				95		ESN‡	Broadcast
	P-F-Model				84		UAN32%	Banded
WCREC17	**Check**	8 May	6.5	8 May	0	-	-	-
	Reference				280	4 May	UAN32%	Banded
	P-SD-UNL				78.5			
	R-SD-HS				78.5			
	R-F-Fixed				78.5			
	R-F-Model				78.5			
	R-F-SR-Model				64	3 May	ESN	Broadcast
	P-F-Model				78.5	4 May	UAN32%	Banded
SCAL18	**Check**	2 May	6.5	2 May	0	-	-	-
	Reference				280	11 May	UAN32%	Banded
	P-SD-UNL				78.5			
	R-SD-HS				78.5			

	R-F-Fixed				78.5			
	R-F-Model				78.5			
	R-F-SR-Model				147	10 May	ESN	Broadcast
	P-F-Model				78.5	11 May	UAN32%	Banded
WCREC18	**Check**	8 May	6.5	8 May	0	-	-	-
	Reference				280	16 May	UAN32%	Banded
	P-SD-UNL				87	17 May		
	R-SD-HS				87	17 May		
	R-F-Fixed				78.5	16 May		
	R-F-Model				78.5	16 May		
	R-F-SR-Model				84	17 May	ESN	Broadcast
	P-F-Model				78.5	16 May	UAN32%	Banded

+ Indicates Liquid ammonium polyphosphate (10-34-0) (NPK) banded for all treatments as starter N.
† Indicates Urea-Ammonium Nitrate solution (32%N) as a base rate.
‡ Indicates Environment Smart Nitrogen (ESN) coated urea (44% N) as a base rate.

Active Crop Sensors and Data Collection

SPAD CM and RapidScan CS-45 (RS) crop canopy sensor (Holland Scientific, Lincoln, NE, USA) were used to monitor crop and detect corn N status. The SPAD CM was used to validate the method previously developed by Peterson et al. (1993) and Blackmer and Schepers, (1995) to compare with RS whether or not using the RS would result in the same management decisions. The RS is capable of rapid data collection with the capacity to sense a much larger area than the SPAD CM (Krienke et al., 2017). However, fertigation decisions relied solely on the SI calculated using the SPAD CM.

The SPAD CM is an active handheld crop leaf sensor (contact sensor) that measures light transmittance properties of leaves in two wavelengths (650 and 940 nm) by clamping it on the crop leaf and emitting its own light to measure N status. In the field, fifteen readings per row from the middle two rows (total of thirty readings) were collected (from the sensing area as described above). Sensor measurements were taken from halfway between the leaf margin and the leaf midrib from the newest fully expanded leaf before the tassel (VT) growth stage, and from the ear leaf after the VT growth stage. SPAD CM values were generated and averaged to obtain one mean value for each plot.

The RS is an active handheld crop canopy sensor (proximal sensor) that integrates a data logger, GPS, crop sensor, and power source into one small unit with a modulated polychromatic light source and three measurement channels: 670 nm, 730 nm, and 780 nm. Reflectance from these three channels was used to obtain the normalized difference red edge index (NDRE) (Li et al., 2014). Sensing was conducted in the middle of each plot (sensing area). The sensing area of each plot consisted of the two middle rows of each plot with 9 m length by holding the RS unit in the nadir position at the recommended height of approximately 1 meter above the corn and walking directly over each row for each plot. Measurements with the sensor were moved to between three rows instead of directly over the two rows after the VT growth stage through physiological maturity (R6) growth stages. NDRE values were generated and averaged for each row to obtain one mean value for each plot.

SPAD CM measurements were used to calculate SI by normalizing the target vegetation index versus the reference vegetation index to limit the effects of growth stages, hybrid, environmental conditions, and disease. The SI is defined as follows:

$$\boldsymbol{SI} = \frac{\textbf{VI Target}}{\textbf{VI Reference}} \qquad \textbf{[2.3]}$$

Where,

SI = sufficiency index,
VI Target is a sensor vegetation index obtained from unknown or target chlorophyll concentration,
VI Reference is a sensor vegetation index obtained from non-limited N fertilizer or high N reference.

When the SI value was equal to or less than 0.95, supplement N via fertigation was applied. N needs were reassessed after two weeks using sensor SI information to determine if an additional N application is needed. This procedure was repeated to assess crop N status until late season at the R2 growth stage, which was suggested by Hawkins et al. (2007) to avoid fertigation loss efficiency (Figure 2.1).

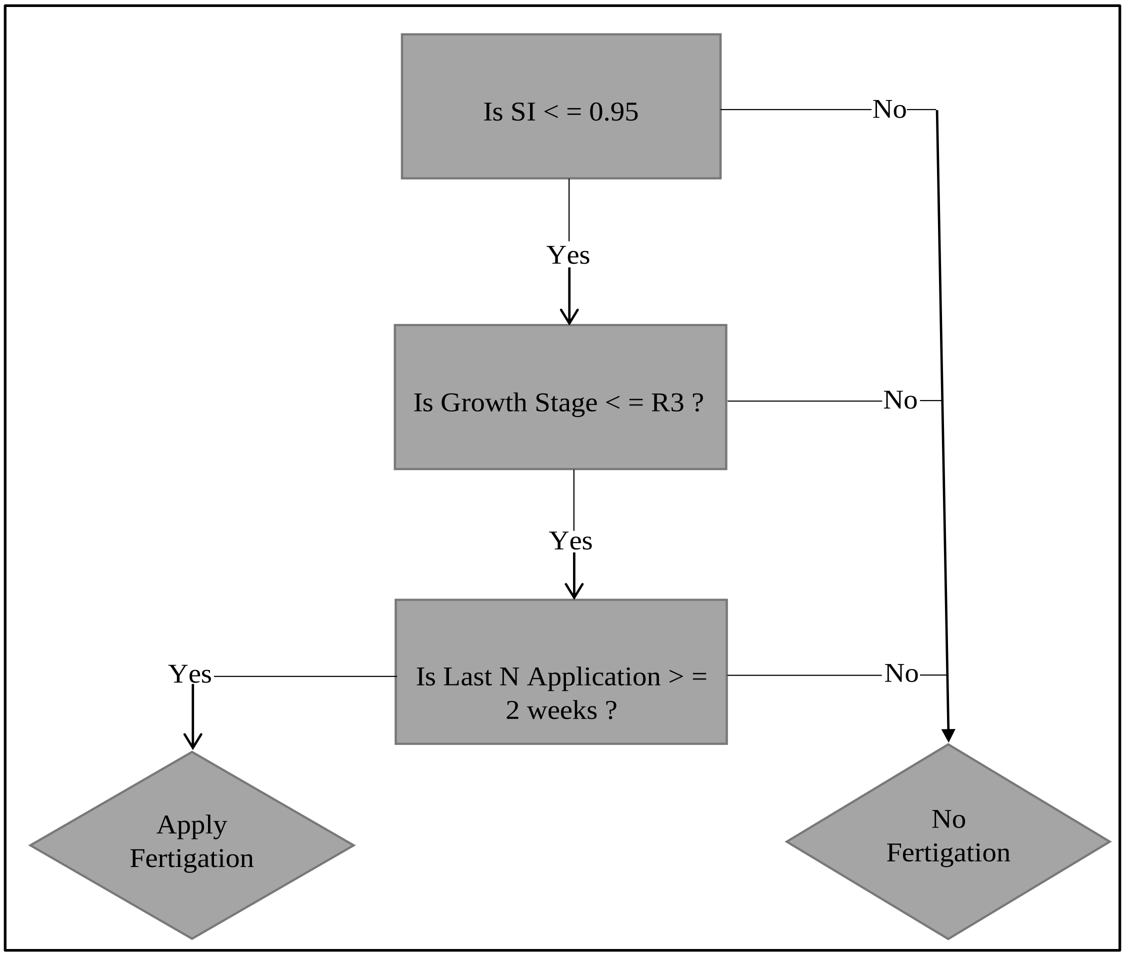

Figure 2.1. Timing decision logic of fertigation application.

Model N Rates

The N rate for treatments based on the model was determined using the Maize-N model. The Maize-N model was developed to estimate EONR of fertilizer to apply for corn by taking into account current and long-term weather, current and previous crop information, crop rotation, N fertilizer information, tillage system, soil properties, N credits, and indigenous soil N supply (Setiyono et al., 2011). All these input values were entered into the model to predict EONR. Maize-N model version 2017 was used for the 2017 and 2018 growing seasons. Current weather data was incorporated with other inputs into the model to estimate the amount of N mineralization from the period of the last crop to the time of running the model for the current crop. In contrast, long-term weather data based on historical trends were incorporated with other inputs into the model to estimate the amount of N mineralization for the remainder of the season. The input and output values of the Maize-N model prediction for each site are shown in Appendix A.

Biomass Samples, Grain Yield, NUE, and Partial Profit

Whole plant (aboveground biomass) samples were collected at physiological maturity (R6). Six plants were sampled randomly for each plot by collecting three plants from each adjacent row to each row of the sensing area (two rows were selected in the middle of each plot with 9 m length). Then, the plant was separated from the ear, bagged, weighed, chopped, placed into an oven to dry at 70°C until reaching constant weight. The ear was air-dried, shelled, and weighed. Total aboveground biomass samples (stover and grain) were analyzed for total N to calculate total aboveground N uptake. Plots (sensing area with two rows for 9 m length) were hand-harvested on September 28, 2017, and October 3, 2018, for the SCAL site to obtain grain yield. Grain was shelled, weighed, and adjusted to 0.155 g g^{-1} moisture content. At the WCREC site, grain yield was measured using a three-row plot combine on November 8, 2017, and October 11, 2018, and adjusted to 0.155 g g^{-1} moisture content.

PFP_N, AE_N, and RE_N were calculated to represent NUE. The PFP_N was calculated by dividing grain yield produced by total N fertilizer applied. AE_N was calculated by dividing the difference in grain yield between the fertilized treatment and the check treatment by total N fertilizer applied. RE_N was calculated by dividing the difference in aboveground biomass N uptake between the fertilized treatment and the check treatment by total N fertilizer applied. Partial profit was calculated as the total corn revenue subtracted by fertilizer costs. The total corn revenue was calculated as the yield for each plot multiplied by the yield price. The yield was sold for \$0.14 kg^{-1} and \$0.15 kg^{-1} corn for 2017 and 2018, respectively. Fertilizer cost was calculated as the amount of total N fertilizer applied to each plot multiplied by the cost of the N fertilizer source. The N fertilizer cost was \$1.30 kg^{-1} ESN fertilizer for both years and \$0.99 kg^{-1} and \$0.90 kg^{-1} UAN fertilizer for 2017 and 2018, respectively.

Residual Soil Nitrate-N (RSN-N)

Deep soil samples (30 cm increments to 150 cm for 2017 and 180 cm for 2018) for quantifying residual soil nitrate post-harvest were collected on November 27 and December 1, 2017, and November 7 and November 14, 2018, respectively, at the SCAL site. At the WCREC site, deep soil samples (30 cm increments to 180 cm) were collected on October 17 and October 22, 2018. Three to four soil cores were composited to make one sample per depth, five and six samples per replication to obtain 160 and 192 soil samples, respectively. Soil samples were collected from two rows between rows of the sensing area.

Statistical Analysis

Analysis of variance (ANOVA) was conducted using PROC GLIMMIX in Statistical Analysis System (SAS) version 9.4. Grain yield, PFP_N, AE_N, RE_N, partial profit, and RSN-N were analyzed as response variables. A mean separation test was performed using Tukey's Multiple Comparison Test.

Results and Discussion

Weather

Table 2.3 shows total precipitation, total irrigation, and average temperature for historic average weather data for 30 years and 2017-2018 through the growing season from April to September at SCAL and WCREC sites. Figure 2.2 shows weather data for the same period for each site year from April to September (growing season) for comparison, including mean daily temperature, total precipitation, and total irrigation. At SCAL17, the average precipitation during the growing season was less than the 30-year historical average, but was higher than the 30-year historical average in May, which has a high potential for leaching of nitrate by precipitation. At SCAL18, the average precipitation during the growing season was higher than the 30-year historical average, especially in June, which has a high potential for leaching of nitrate. At WCREC, the average precipitation during the 2017 and 2018 growing seasons was higher than the 30-year historical average (HPRCC, 2019), especially in July in 2017 and in May, June, and July in 2018, which has the potential for leaching of nitrate.

Total irrigation at the SCAL site through the 2017 and 2018 growing seasons was less than the total irrigation at the WCREC site for both years (Table 2.3). The average temperature for both SCAL (18.98 ^{o}C in 2017 and 18.88 ^{o}C in 2018) and WCREC (18.37 ^{o}C in 2017 and 17.72 ^{o}C in 2018) sites was very close to 30 years historical average temperature for SCAL (18.76 ^{o}C) and for WCREC (17.95 ^{o}C) during the 2017 and 2018 growing season for the same periods from April to September.

Table 2.3. A summary of annual total precipitation (mm), total irrigation (mm), and average temperature (^{0}C) through the growing season for historic 30 years average weather data and for 2017 and 2018 for sites in SCAL and WCREC.

Site Year ID	Apr.	May	Jun.	Jul.	Aug.	Sep.	
			Precipitation (mm)				Total
SCAL17	81.28	153.92	22.61	50.80	89.64	52.68	450.93
WCREC17	52.07	70.61	28.70	104.39	81.79	119.84	457.40
SCAL18	13.67	48.46	158.72	76.71	84.58	123.37	505.51
WCREC18	28.52	172.62	108.64	129.11	7.75	6.83	453.47
SCAL-Hist.†	59.36	111.28	93.90	89.26	83.31	55.74	492.85
WCREC-Hist.†	53.94	75.85	86.90	63.89	56.77	38.34	375.69
			Irrigation (mm)				Total
SCAL17	0	0	44.45	57.15	31.75	0	133.35
WCREC17	0	0	55.88	142.24	45.72	40.64	284.48
SCAL18	0	0	0	12.70	31.75	0	44.45
WCREC18	0	0	0	132.08	76.20	0	208.28
			Average Temperature (°C)				Avg
SCAL17	10.40	15.60	22.75	24.83	20.74	19.56	18.98
WCREC17	10.21	13.83	21.95	25.20	20.80	18.24	18.37
SCAL18	5.72	19.27	23.81	23.18	22.29	19.04	18.88
WCREC18	5.46	16.83	21.50	22.78	21.26	18.49	17.72
SCAL-Hist.	9.89	16.11	21.83	23.82	22.69	18.20	18.76
WCREC-Hist.	8.95	14.78	20.73	23.52	22.33	17.40	17.95

†Historic 30 years average weather data for SCAL and WCREC.

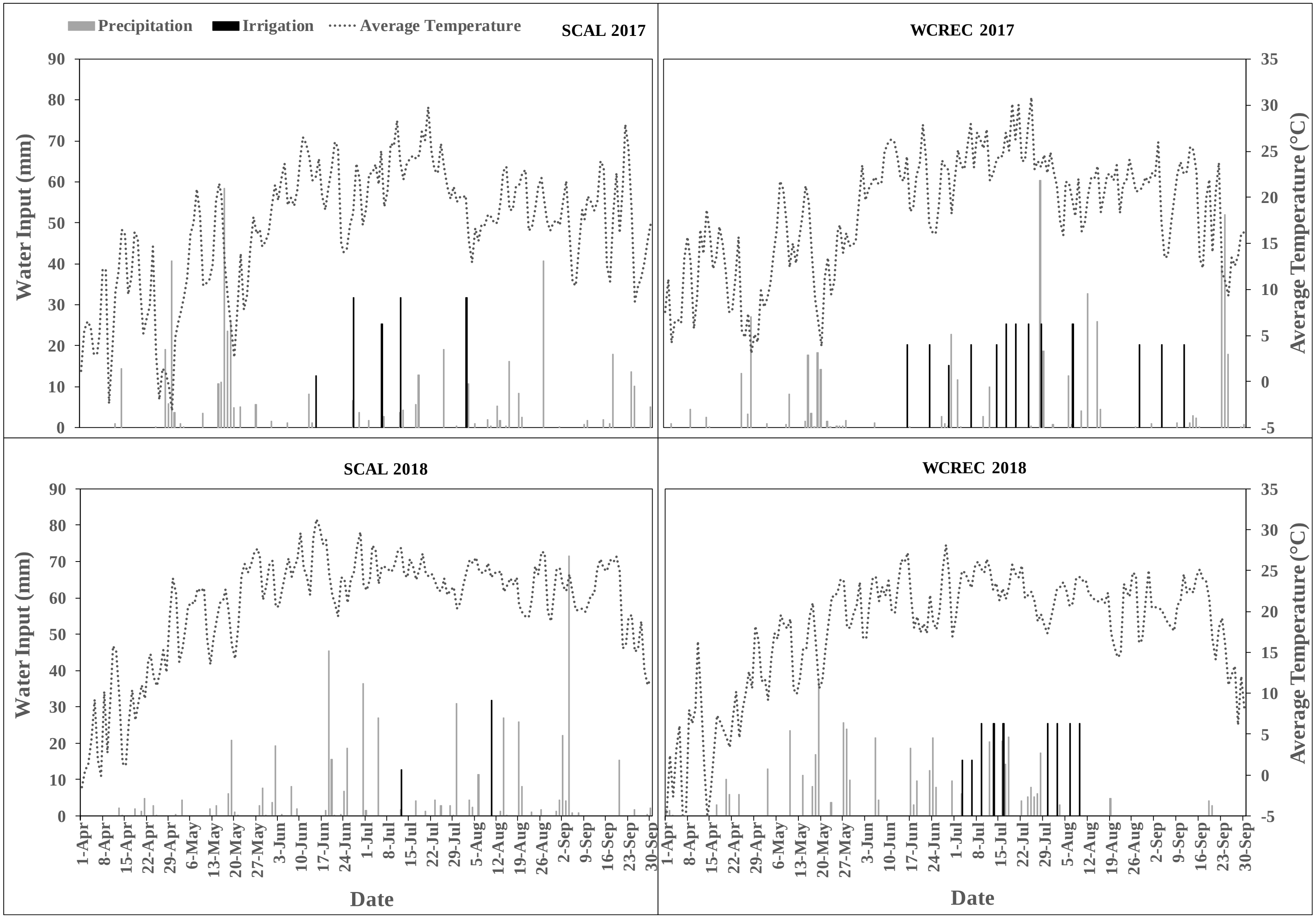

Figure 2.2. Total water (mm) and mean daily temperature (°C) through the growing season for each site in SCAL and WCREC in 2017 and 2018.

In-Season Nitrogen Application Rates

Table 2.4 summarizes sensor timing, SI values, and in-season N application rates for eight treatments for SCAL and WCREC sites in 2017 and 2018. At SCAL17, the in-season N application rate for the R-F-SR-Model treatment (based on sensor and model with initial ESN fertilizer) was lower than the in-season N rate for all other treatments. At WCREC17, no in-season N was applied for the R-F-Fixed (based on the sensor only) treatment compared to in-season N rates for other treatments. The reference treatment also received the in-season N application rate. At SCAL18, no in-season N was applied for the R-F-Fixed, R-F-Model (based on sensor and model), and R-F-SR-Model treatments. At WCREC18, the in-season N application rate for the R-SD-HS treatment was lower than the in-season N rates for all other treatments. In-season N rate for R-F-Model treatment was lower than in-season N rates for fertigation treatments.

At the SCAL17 site, the R-F-SR-Model treatment had a lower in-season N rate due to a higher initial N rate applied (95 kg N ha^{-1}) as ESN slow-release N being input into the Maize-N model. This resulted in reducing the in-season N rate predicted by the Maize-N model for R-F-SR-Model treatment without reducing yield as it was among the highest-yielding treatments. At WCREC17, the R-F-Fixed treatment did not receive additional in-season N application since the SI values were greater than 0.95 during all growth stages (V6-R6), without limiting yield as it was among the highest-yielding treatments (not significantly lower than any other). Also, the seasonal average SI value (0.98) for this treatment was greater than the SI values for all other treatments. To assure the sufficiency of plant N at the time of sensing, the in-season N rate was also applied for the reference treatment at WCREC17.

At SCAL18, the R-F-Fixed, R-F-Model, and R-F-SR-Model treatments did not receive additional in-season-N applications since SI values were greater than 0.95 during all growth stages (V6-R6), without limiting yield as it was among the highest-yielding treatments (not significantly lower than any other). Also, the seasonal average SI values (0.99) for these three treatments were slightly different than SI values for the reference during all growth stages at sensor timing. At WCREC18, a relatively low in-season N rate was recommended using the H-S algorithm for R-SD-HS treatment since it had a higher SI value (0.98). The R-F-Model treatment had a lower in-season N rate than fertigation treatments due to a higher seasonal average SI value (0.98) (V6-R6) than other fertigation treatments except for P-F-Model treatment (based on the model only) which received multiple in-season N applications. However, the lower in-season N rate applied for R-F-Model treatment did not impact yield, as it was among the highest-yielding treatments.

Across all site years, on average, in-season N application rates were lower for reactive fertigation treatments (R-F-Fixed, R-F-Model, and R-F-SR-Model treatments) compared to the proactive sidedress UNL algorithm (P-SD-UNL treatment) and reactive sidedress H-S algorithm (R-SD-HS treatment). The R-F-Fixed, R-F-Model, and R-F-SR-Model treatments reduced in-season N rates by 62, 55, and 59 kg N ha^{-1} compared to the P-SD-UNL treatment and by 25, 18, and 22 kg N ha^{-1} compared to the R-SD-HS treatment. In contrast, the proactive fertigation treatment (P-F-Model) reduced in-season N rates by 32 kg N ha^{-1} compared to the P-SD-UNL treatment, but it increased in-season N rates by 5 kg N ha^{-1} compared to the R-SD-HS treatment. This is consistent with the finding of Thompson et al. (2015) that reported the reactive approach-based-sensor recommended lower in-season N rates than the proactive approach-based Maize-N model across 9 of 11 sites. The results showed that reactive fertigation treatments (R-F-Fixed, R-F-Model, and R-F-SR-Model treatments) reduced the in-season N rates application due to the ability of the sensor to detect and respond to crop N status. This resulted in better synchronization between N supply and crop demand. However, the proactive fertigation treatment (P-F-Model) reduced the in-season N rate compared to the proactive sidedress UNL algorithm (P-SD-UNL treatment) and did not reduce the in-season N rate compared to reactive sidedress H-S algorithm (R-SD-HS treatment). This is because the proactive fertigation treatment (P-F-Model) did not have the ability to detect and respond to current crop N status as did reactive treatments.

Table 2.4. Site year, treatment, sensor timing, sufficiency index, in-season N rate, N recommendation method, and method of N application for eight N fertilizer decision strategies for SCAL and WCREC sites in 2017 and 2018.

Site Year ID	Treatment	Growth stage at Sensor Timing	Sufficiency Index (SI)	In-Season N Rate (kg ha^{-1})	N Recommendation Method	N Application Method
SCAL17	Check	V6-R6	0.82	0	-	-
	Reference	-	-	0	-	-
	P-SD-UNL	V6	0.95	84	UNL algorithm	Sidedress
	R-SD-HS	V11	0.93	56	H-S algorithm	Sidedress
	R-F-Fixed	V11	0.92	34	Fixed rate	Fertigation
	R-F-Model	V11	0.93	37	Model rate	Fertigation
	R-F-SR-Model	V11	0.93	20	Model rate	Fertigation
	P-F-Model	V9	0.97	30	Model rate	Fertigation
WCREC17	Check	V6-R6	0.89	0	-	-
	Reference	VT	-	34	Calibration	Fertigation
	P-SD-UNL	V6	0.97	41	UNL algorithm	Sidedress
	R-SD-HS	V13	0.90	46	H-S algorithm	Sidedress
	R-F-Fixed	V6-R6	0.98	0	-	-
	R-F-Model	V8	0.92	46	Model rate	Fertigation
	R-F-SR-Model	V8	0.93	33	Model rate	Fertigation
	P-F-Model	V8	0.94	43	Model rate	Fertigation
SCAL18	Check	V6-R6	0.85	0	-	-
	Reference	-	-	0	-	-
	P-SD-UNL	V6	0.95	136	UNL algorithm	Sidedress
	R-SD-HS	VT	0.99	58	H-S algorithm	Sidedress

	R-F-Fixed	V6-R6	0.99	0	-	-
	R-F-Model	V6-R6	0.99	0	-	-
	R-F-SR-Model	V6-R6	0.99	0	-	-
	P-F-Model	VT	1.01	30	Model rate	Fertigation
WCREC18	Check	V6-R5	0.73	0	-	-
	Reference	-	-	0	-	-
	P-SD-UNL	V6	0.94	64	UNL algorithm	Sidedress
	R-SD-HS	V18	0.98	17	H-S algorithm	Sidedress
	R-F-Fixed	V10	0.95	17	Fixed rate	Fertigation
		R1	0.95	25		
	R-F-Model	V12	0.97	12	Model rate	Fertigation
		R1	0.97	10		
	R-F-SR-Model	V10	0.97	13	Model rate	Fertigation
		V12	0.94	7		
		R1	0.95	18		
	P-F-Model	V10	0.99	34	Model rate	Fertigation
		R1	0.99	47		
		R2	1.01	12		

The red color of SI values indicates SI values were equal to or less than the 0.95 thresholds.

Grain Yield

Table 2.5 shows Type III tests of fixed effects of site, year, and treatment on grain yield at SCAL and WCREC sites in 2017 and 2018. There were significant site, year, and treatment main effects on grain yield. There were significant site x treatment and year x treatment interactions effects on grain yield at SCAL and WCREC sites in 2017 and 2018. Because of the significant interactions effect of site x treatment and year x treatment, the simple effect of treatment on grain yield will be explored by site and year as shown in Figure 2.3 and Figure 2.4.

Table 2.5. Type III tests of fixed effect of site, year, and treatment on grain yield at SCAL and WCREC sites in 2017 and 2018.

Grain Yield				
Effect	**Numerator DF**	**Denominator DF**	**F Value**	**Pr > F**
site	1	12	23.08	0.0004
year	1	12	30.62	0.0001
site*year	1	12	0.05	0.8319
Trt	7	84	26.25	<.0001
site*Trt	7	84	2.15	0.0473
year*Trt	7	84	2.59	0.018
site*year*Trt	7	84	1.72	0.1149

Grain yield ranged from 8.49 at WCREC18 to 16.18 Mg ha^{-1} at SCAL17 as shown in Appendix A (Table A.1). Figure 2.3 and Figure 2.4 show the mean estimates by site and year for average grain yield and total N applied at SCAL and WCREC sites in 2017 and 2018 arranged by treatment. At SCAL17, the highest grain yield was observed with the reference treatment (16.18 Mg ha^{-1}), which was not significantly different from grain yield of other treatments except for the check treatment. The lowest grain yield was observed with the check treatment (11.17 Mg ha^{-1}), which was significantly different from the grain yield of other treatments (Figure 2.3). At WCREC17, the highest grain yield was observed with the reference treatment (14.14 Mg ha^{-1}), which was not significantly different from the grain yield of other treatments. The lowest grain yield was observed with the check treatment (12.74 Mg ha^{-1}), which was not significantly different from the grain yield of other treatments (Figure 2.3).

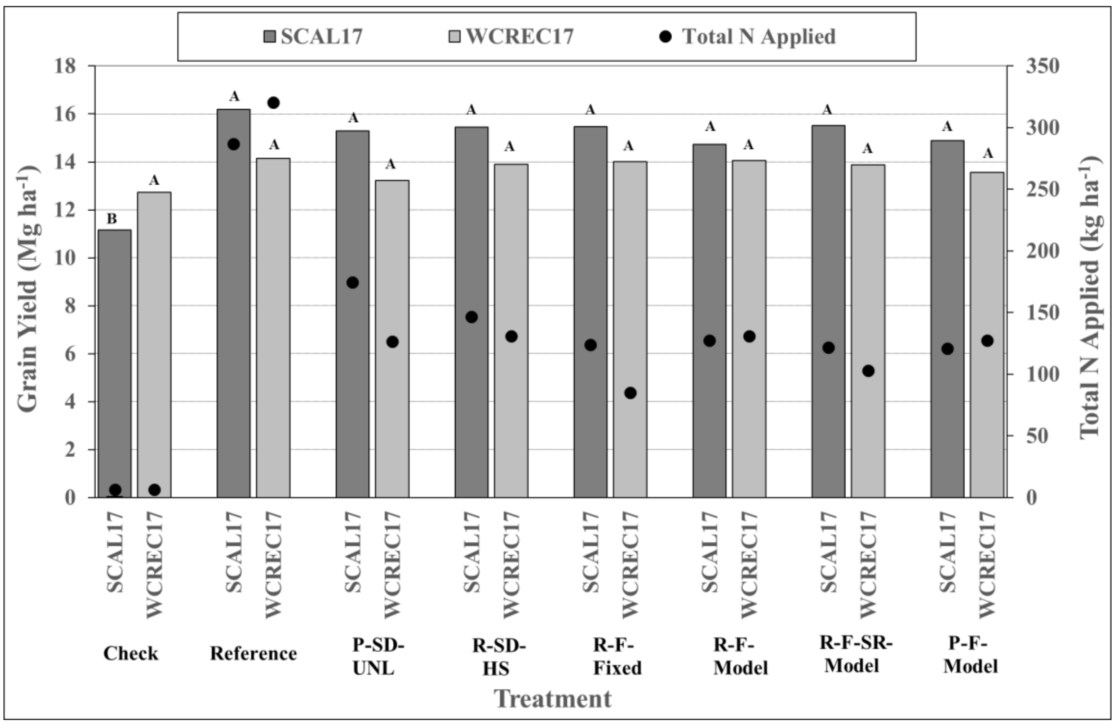

Figure 2.3. Mean estimates by site and year for average grain yield and total N applied at SCAL and WCREC sites in 2017 arranged by treatment. Different letters indicate a significant difference at the 95% confidence level (alpha = 0.05) within the site.

At SCAL18, the highest grain yield was observed with the R-F-Fixed treatment (14.56 Mg ha^{-1}), which was not significantly different from the grain yield of other treatments except for the check treatment. The lowest grain yield was observed with the check treatment (9.33 Mg ha^{-1}), which was significantly different from other treatments

(Figure 2.4). At WCREC18, the highest grain yield was observed with the P-F-Model treatment (13.28 Mg ha^{-1}), which was not significantly different from grain yield for other treatments except for the check treatment. The lowest grain yield was observed with the check treatment (8.49 Mg ha^{-1}), which was significantly different from other treatments (Figure 2.4).

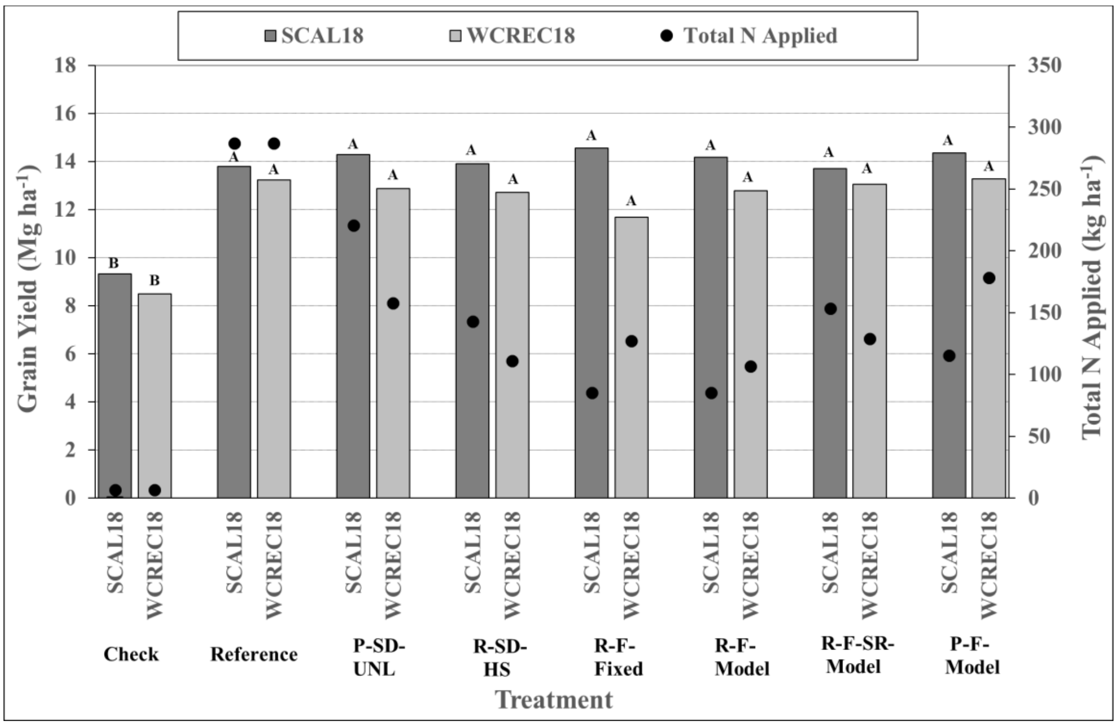

Figure 2.4. Mean estimates by site and year for average grain yield and total N applied at SCAL and WCREC sites in 2018 arranged by treatment. Different letters indicate a significant difference at the 95% confidence level (alpha = 0.05) within the site.

High grain yield observed for the check treatment at WCREC17 is explained by the large contribution of N from other sources such as N mineralization, which provided sufficient N to the crop and avoided N deficiency that limited response to N fertilizer for other treatments. Higher grain yield was also observed for the R-F-Fixed treatment at SCAL18 site year although it did not receive additional in-season-N applications. Similar results were observed by Thompson et al. (2015) that found high yields for check treatment for two sites in Nebraska in 2012. Results showed that the reactive fertigation treatments (R-F-Fixed, R-F-Model, and R-F-SR-Model) maintained or increased grain yield and reduced total N application compared to currently recommended approaches including proactive sidedress UNL algorithm (P-SD-UNL treatment) and reactive sidedress H-S algorithm (R-SD-HS treatment), which resulted in higher applied N rates, but neither treatment increased grain yield. The proactive fertigation treatment (P-F-Model) maintained or increased grain yield compared to P-SD-UNL and R-SD-HS, and reduced total N application rates compared to P-SD-UNL, but did not reduce total N application compared to R-SD-HS.

Nitrogen Use Efficiency (PFP, RE, and AE)

The partial factor productivity of N (PFP_N), agronomy efficiency (AE_N), and recovery efficiency (RE_N) were used as agronomic indices to measure nitrogen use efficiency (NUE). Table 2.6 shows Type III tests of fixed effect of site, year, and treatment on PFP_N, AE_N, and RE_N at SCAL and WCREC sites in 2017 and 2018. There were significant site, year, and treatment main effects on PFP_N and AE_N and significant year and treatment main effects on RE_N. There were significant site x year x treatment interaction effects on PFP_N, AE_N, and RE_N at SCAL and WCREC sites in 2017 and 2018. Due to significant interaction effects of site x year x treatment, the simple effect of treatment on PFP_N, AE_N, and RE_N will be explored by site and year as shown in Figure 2.5 through Figure 2.10.

Table 2.6. Type III tests of fixed effect of site, year, and treatment on three measures of NUE (PFP_N, AE_N, and RE_N) at SCAL and WCREC sites in 2017 and 2018.

Effect	Numerator DF	Denominator DF	F Value	Pr > F
Partial Factor Productivity of Nitrogen (PFP_N)				
site	1	12	4.52	0.055
year	1	12	5.92	0.0316
site*year	1	12	12.44	0.0042
Trt	6	72	100.49	<.0001
site*Trt	6	72	10.53	<.0001
year*Trt	6	72	13.23	<.0001
site*year*Trt	6	72	14.55	<.0001
Agronomic Efficiency of Nitrogen (AE_N)				
site	1	12	18.11	0.0011
year	1	12	23.85	0.0004
site*year	1	12	4.33	0.0596
Trt	6	72	16.47	<.0001
site*Trt	6	72	5.06	0.0002
year*Trt	6	72	4.51	0.0006
site*year*Trt	6	72	5.16	0.0002
Recovery Efficiency of Nitrogen (RE_N)				
site	1	12	0.19	0.6715
year	1	12	11.55	0.0053
site*year	1	12	4.75	0.05
Trt	6	72	2.3	0.0432
site*Trt	6	72	1.34	0.2526
year*Trt	6	72	1.89	0.0948
site*year*Trt	6	72	3.17	0.0081

PFP_N ranged from 44.11 at WCREC17 site year to 171.33 kg grain kg N applied^{-1} at SCAL18 as shown in Appendix A (Table A.1). Figure 2.5 and Figure 2.6 show the mean estimates by site and year for average PFP_N at SCAL and WCREC sites in 2017 and 2018 arranged by treatment. At SCAL17, the highest PFP_N was observed with the R-F-SR-Model treatment (127.13 kg grain kg N applied^{-1}), which was not significantly different from other treatments except for the reference and P-SD-UNL treatments. The lowest PFP_N was observed with the reference treatment (56.40 kg grain kg N^{-1}), which was significantly different from other treatments (Figure 2.5). At WCREC17, the highest PFP_N was observed with the R-F-Fixed treatment (164.93 kg grain kg N^{-1}), which was significantly different from other treatments. The lowest PFP_N was observed with the reference treatment (44.11 kg grain kg N^{-1}), which was significantly different from other treatments (Figure 2.5).

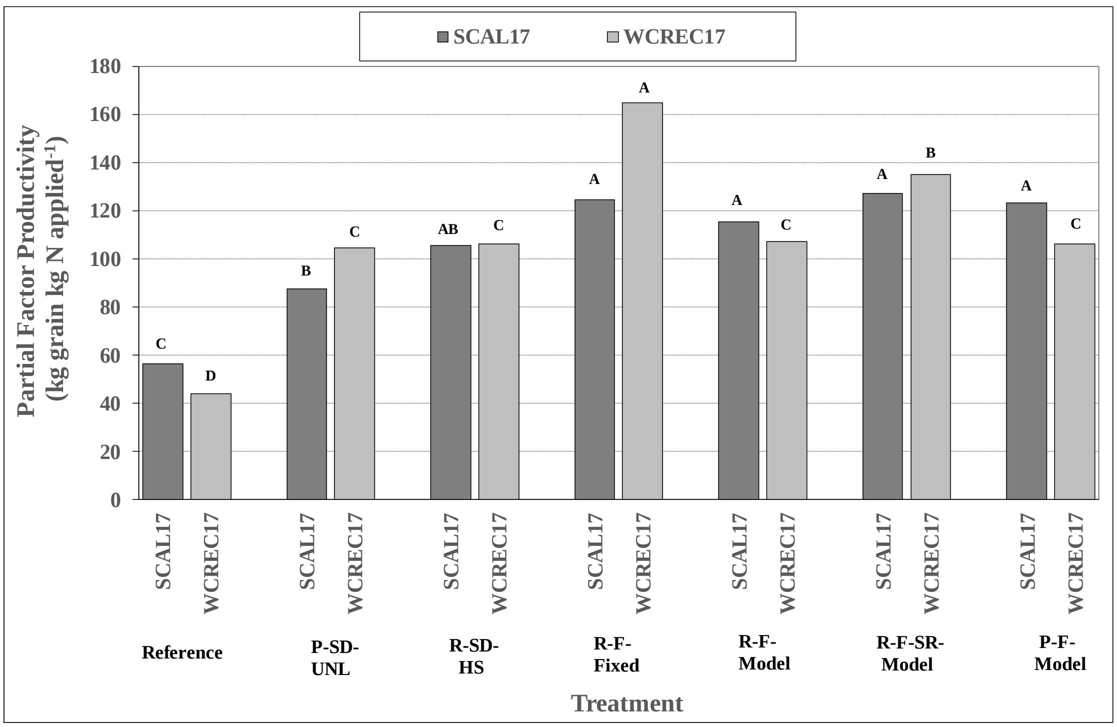

Figure 2.5. Mean estimates by site and year for average partial factor productivity of N (PFP_N) at SCAL and WCREC sites in 2017 arranged by treatment. Different letters indicate a significant difference at the 95% confidence level (alpha = 0.05) within the site.

At SCAL18, the highest PFP_N was observed with the R-F-Fixed treatment (171.33 kg grain kg N^{-1}), which was significantly different from other treatments except for the R-F-Model treatment. The lowest PFP_N was observed with the reference treatment

(48.09 kg grain kg N^{-1}), which was significantly different from other treatments except for the P-SD-UNL treatment (Figure 2.6). At WCREC18, the highest PFP_N was observed with the R-F-Model treatment (125.67 kg grain kg N^{-1}), which was significantly different from other treatments except for R-SD-HS and R-F-SR-Model treatments. The lowest PFP_N was observed with the reference treatment (46.13 kg grain kg N^{-1}), which was significantly different from other treatments (Figure 2.6).

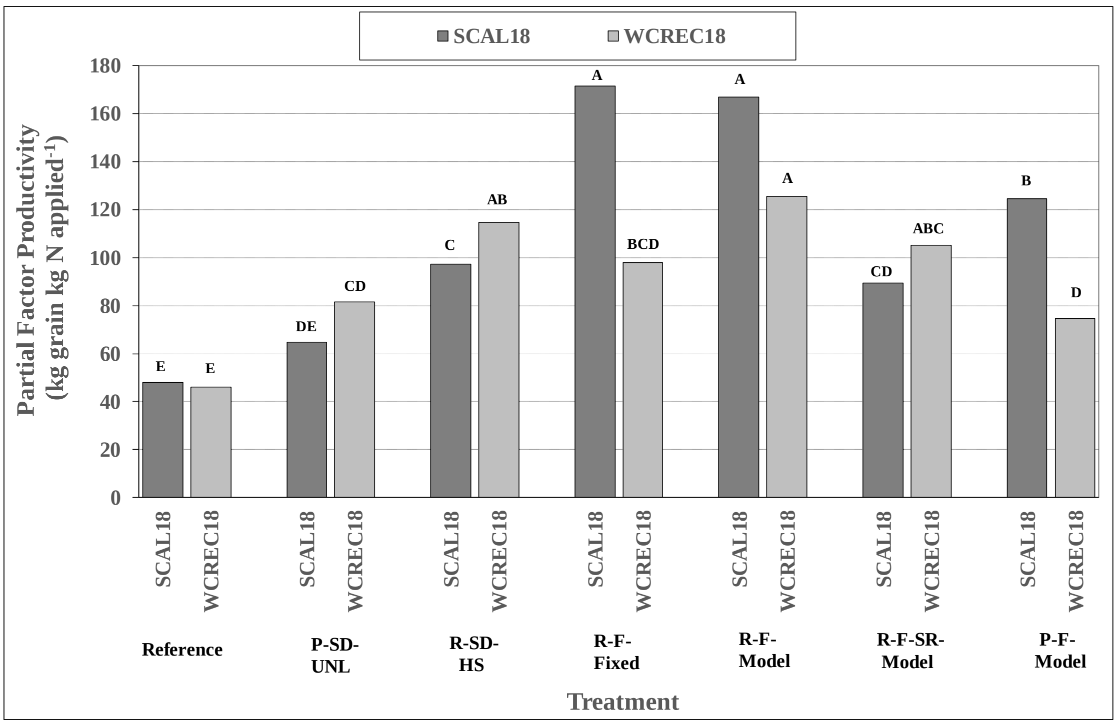

Figure 2.6. Mean estimates by site and year for average partial factor productivity of N (PFP_N) at SCAL and WCREC sites in 2018 arranged by treatment. Different letters indicate a significant difference at the 95% confidence level (alpha = 0.05) within the site.

AE_N ranged from 3.95 at WCREC17 site year to 61.60 kg grain increase kg N^{-1} at SCAL18 site year as shown in Appendix A (Table A.1). Figure 2.7 and Figure 2.8 show the mean estimates by site and year for average AE_N at SCAL and WCREC sites in 2017 and 2018 arranged by treatment. At SCAL17, the highest AE_N was observed with the R-

F-SR-Model treatment (35.59 kg grain increase kg N^{-1}), which was not significantly different from other treatments except for the reference treatment. The lowest AE_N was observed with the reference treatment (17.46 kg grain increase kg N^{-1}), which was not significantly different from other treatments except for R-F-Fixed and R-F-SR-Model treatments (Figure 2.7). At WCREC17, the highest AE_N was observed with the R-F-Fixed treatment (15.09 kg grain increase kg N^{-1}), which was not significantly different from other treatments. The lowest AE_N was observed with the P-SD-UNL treatment (3.95 kg grain increase kg N^{-1}), which was also not significantly different from other treatments (Figure 2.7).

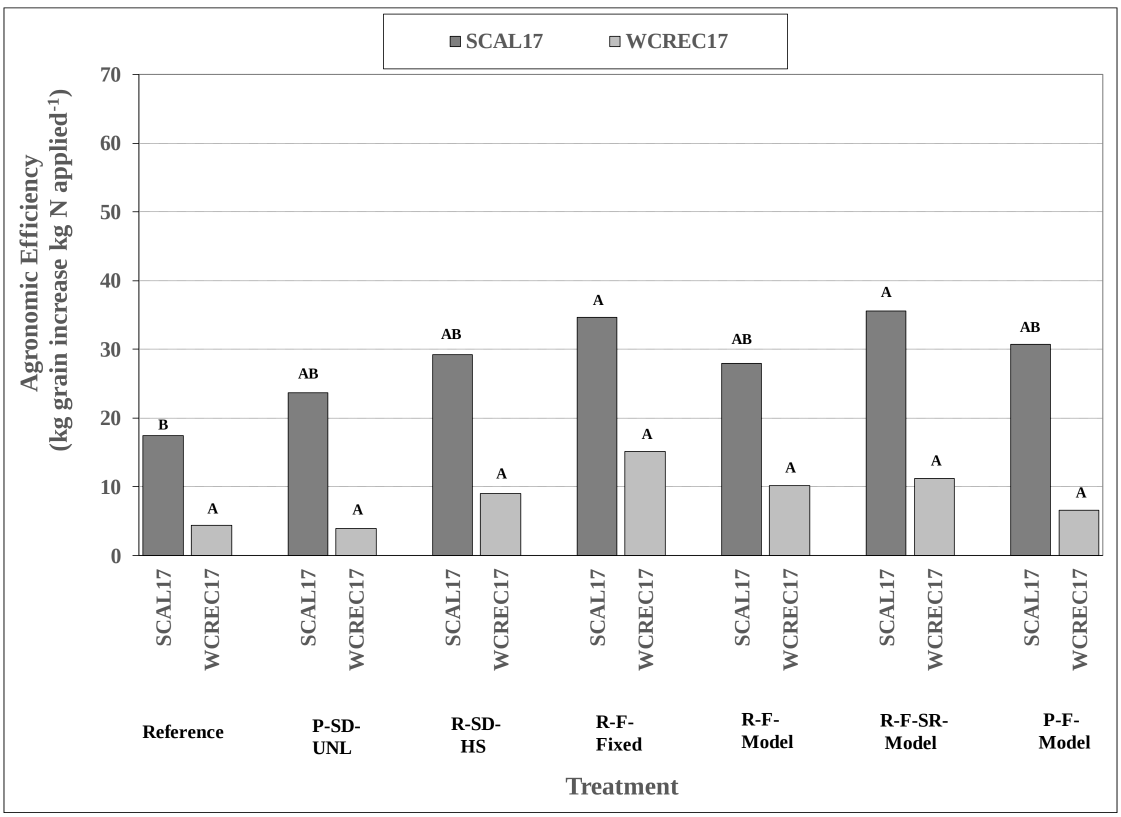

Figure 2.7. Mean estimates by site and year for average agronomic efficiency of N (AE_N) at SCAL and WCREC sites in 2017 arranged by treatment. Different letters indicate a significant difference at the 95% confidence level (alpha = 0.05) within the site.

At SCAL18, the highest AE_N was observed with the R-F-Fixed treatment (61.60 kg grain increase kg N^{-1}), which was significantly different from other treatments except for the R-F-Model treatment. The lowest AE_N was observed with the reference treatment (15.58 kg grain increase kg N^{-1}), which was not significantly different from other treatments except for R-F-Fixed, R-F-Model, and P-F-Model treatments (Figure 2.8). At WCREC18, the highest AE_N was observed with the R-F-Model treatment (39.75 kg grain increase kg N^{-1}), which was not significantly different from other treatments except for the reference treatment. The lowest AE_N was observed with the reference treatment (16.53 kg grain increase kg N^{-1}), which was not significantly different from other treatments except for R-SD-HS, R-F-Model, and R-F-SR-Model treatments (Figure 2.8).

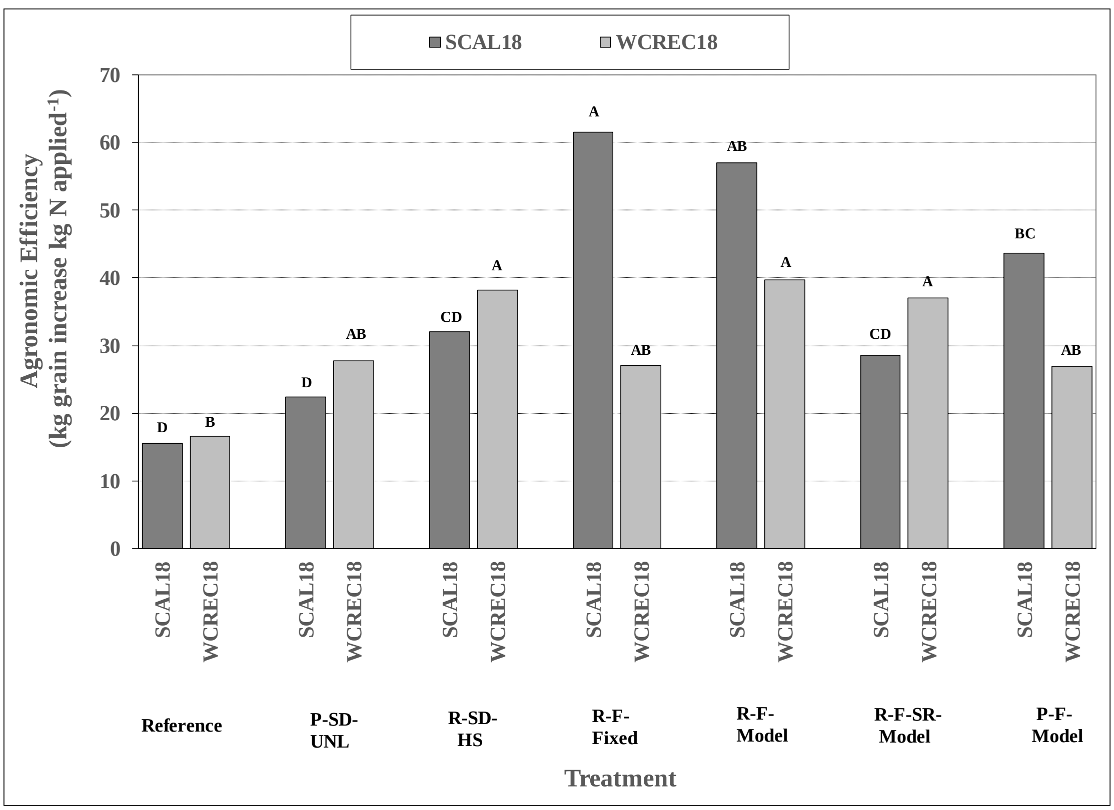

Figure 2.8. Mean estimates by site and year for average agronomic efficiency of N (AE_N) at SCAL and WCREC sites in 2018 arranged by treatment. Different letters indicate a significant difference at the 95% confidence level (alpha = 0.05) within the site.

RE_N ranged from 0.19 at WCREC17 to 1.17 kg increase in N uptake kg N^{-1} at WCREC18 as shown in Appendix A (Table A.1). Figure 2.9 and Figure 2.10 show the mean estimates by site and year for average RE_N at SCAL and WCREC sites in 2017 and 2018 arranged by treatment. At SCAL17, the highest RE_N was observed with R-F-Model, R-F-SR-Model, and P-F-Model treatments (0.60 kg N uptake increase kg N^{-1}), which was not significantly different from other treatments. The lowest RE_N was observed with reference and P-SD-UNL treatments (kg 0.48 N uptake increase kg N^{-1}), which was also not significantly different from other treatments (Figure 2.9). At WCREC17, the highest RE_N was observed with the R-F-SR-Model treatment (0.57 kg N uptake increase kg N^{-1}), which was not significantly different from other treatments. The lowest RE_N was observed with the R-F-Model treatment (kg 0.19 N uptake increase kg N^{-1}), which was also not significantly different from other treatments (Figure 2.9).

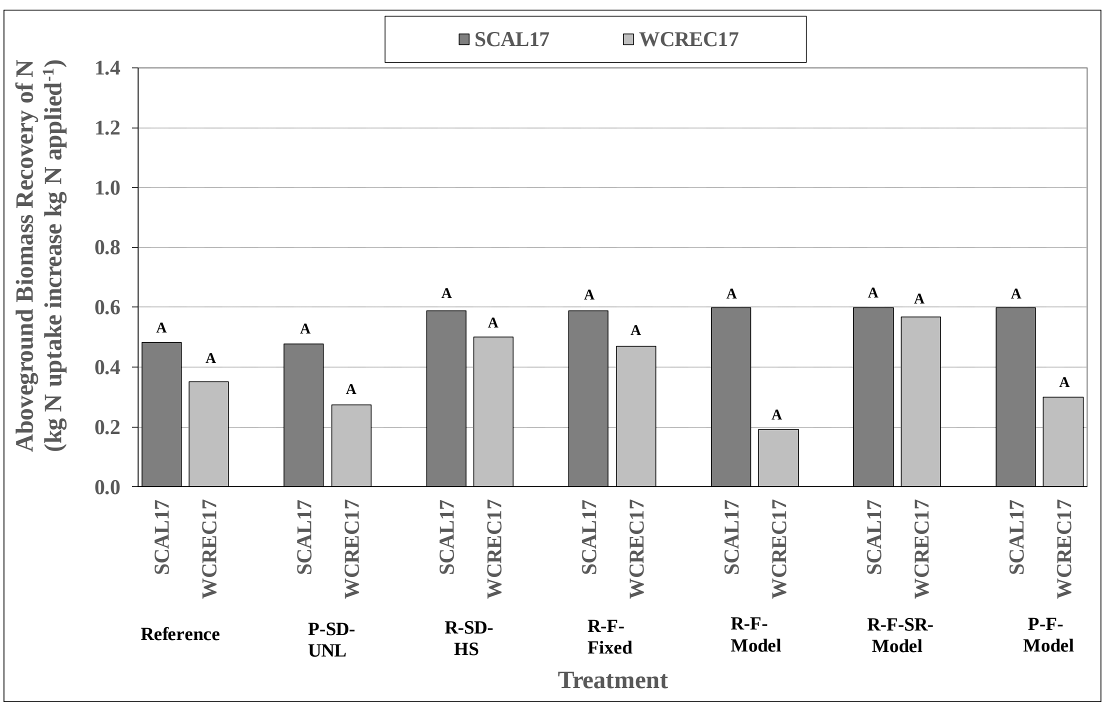

Figure 2.9. Mean estimates by site and year for average aboveground biomass recovery efficiency of N (RE_N) at SCAL and WCREC sites in 2017 arranged by

treatment. Different letters indicate a significant difference at the 95% confidence level (alpha = 0.05) within the site.

At SCAL18, the highest RE_N was observed with the R-F-Fixed treatment (0.79 kg N uptake increase kg N^{-1}), which was not significantly different from other treatments. The lowest RE_N was observed with the reference treatment (0.51 kg N uptake increase kg N^{-1}), which was not significantly different from other treatments (Figure 2.10). At WCREC18, the highest RE_N was observed with the R-F-Model treatment (1.17 kg N uptake increase kg N^{-1}), which was not significantly different from other treatments except reference, R-F-Fixed, and R-F-SR-Model treatments. The lowest RE_N was observed with the reference treatment (0.45 kg N uptake increase kg N^{-1}), which was not significantly different from other treatments except R-SD-HS and R-F-Model treatments (Figure 2.10).

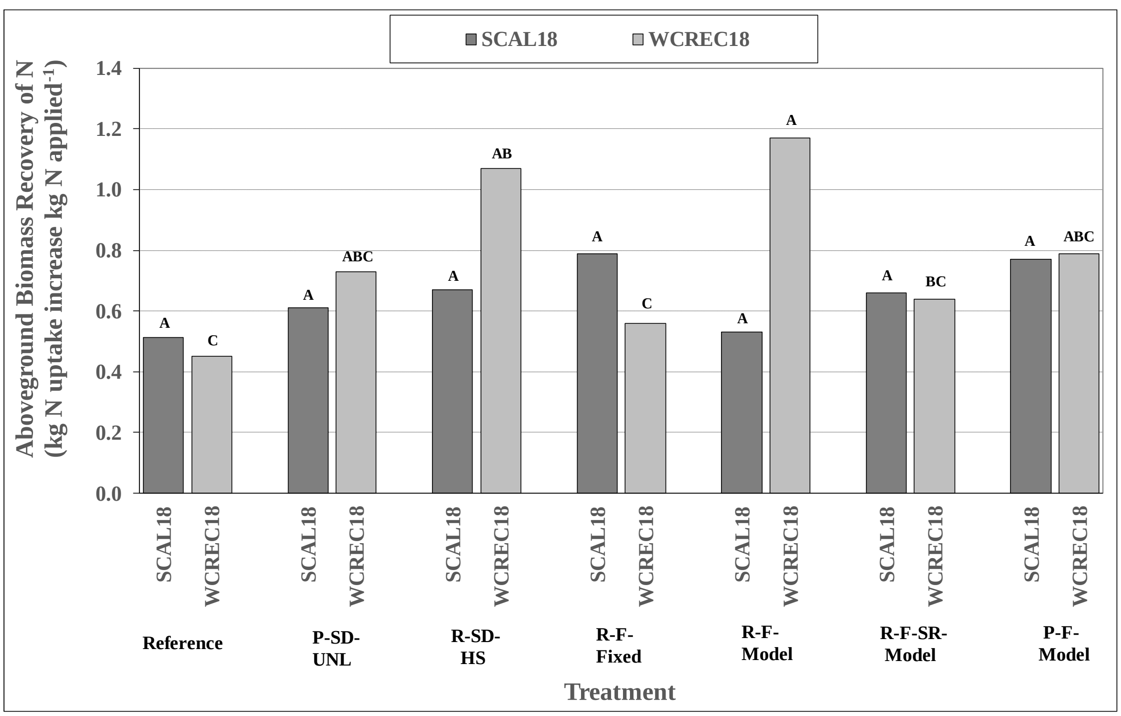

Figure 2.10. Mean estimates by site and year for average aboveground biomass recovery efficiency of N (RE_N) at SCAL and WCREC sites in 2018 arranged by treatment. Different letters indicate a significant difference at the 95% confidence level (alpha = 0.05) within the site.

Overall, PFP_N, AE_N, and RE_N were lower with the reference, P-SD-UNL, R-SD-HS, and P-F-Model treatments than with reactive fertigation treatments (R-F-Fixed, R-F-Model, and R-F-SR-Model treatments). This was expected for the reference treatment since it received a higher amount of N than the crop needed, as well as for P-SD-UNL, R-SD-HS, and P-F-Model treatments which resulted in higher N rates. The treatment with the highest PFP_N, AE_N, and RE_N had the lowest N rate application, while the lowest PFP_N, AE_N, and RE_N had the highest N rate application. This is consistent with findings by Roberts et al. (2010) and Thompson et al. (2015) that reported the higher PFP_N, AE_N, and RE_N obtained with the lower amounts of N rate applied for treatment. Likewise, Cassman et al. (2002) observed that RE_N increased as the amount of N application decreases, especially with high N rate applications. They stated that increases in PFP related to increases in RE_N as N uptake is closely related to dry matter accumulation and grain yield. Thus. if the yield is not reduced, the higher NUE measured by PFP_N and AE_N is desirable (Thompson et al., 2015). Results demonstrated that reactive fertigation treatments (R-F-Fixed, R-F-Model, and R-F-SR-Model) improved NUE as measured by PFP_N, AE_N, and RE_N compared to proactive sidedress treatment (P-SD-UNL) and reactive sidedress treatment (R-SD-HS), by reducing in-season N application without reducing yield. This is attributed to the ability of the sensor to detect and respond to crop N status resulting in increased synchrony between N supply and crop demand. However, the proactive fertigation treatment (P-F-Model) improved PFP_N, AE_N, and RE_N compared to the P-SD-UNL treatment, but did not improve PFP_N, AE_N, and RE_N compared to the R-SD-HS treatment.

Partial Profit

Total yield revenue was calculated as the yield for each plot multiplied by grain price, and fertilizer cost was calculated as the amount of N fertilizer applied to each plot multiplied by the cost of the N fertilizer. Partial profit was calculated as the total corn revenue subtracted by the fertilizer costs.

Table 2.7 shows Type III tests of fixed effect of site, year, and treatment on partial profit at SCAL and WCREC sites in 2017 and 2018. There were significant site and treatment main effects on partial profit. There were significant year x treatment interactions effect on partial profit at SCAL and WCREC sites in 2017 and 2018. Because of the significant interaction effects of year x treatment, the simple effect of treatment on partial profit will be explored by site and year as shown in Figure 2.11 and Figure 2.12.

Table 2.7. Type III tests of fixed effect of site, year, and treatment on partial profit at SCAL and WCREC sites in 2017 and 2018.

Partial Profit				
Effect	**Numerator DF**	**Denominator DF**	**F Value**	**Pr > F**
site	1	12	19.47	0.0008
year	1	12	1.84	0.1995
site*year	1	12	0.24	0.6329
Trt	7	84	14.38	<.0001
site*Trt	7	84	1.94	0.0736
year*Trt	7	84	3.01	0.0072
site*year*Trt	7	84	2.03	0.0606

Partial profit ranged from 1236.46 at WCREC18 to 2054.10 \$ ha^{1} at SCAL18 as shown in Appendix A (Table A.1). Figure 2.11 and Figure 2.12 show the mean estimates by site and year for average partial profit at SCAL and WCREC sites in 2017 and 2018 arranged by treatment. At SCAL17, the highest partial profit was observed with the R-F-Fixed treatment (1982.05 \$ ha^{-1}), which was not significantly different from other treatments except for the check treatment. The lowest partial profit was observed with the check treatment (1513.37 \$ ha^{-1}), which was significantly different from other treatments (Figure 2.11). At WCREC17, the highest partial profit was observed with the R-F-Fixed treatment (1823.55 \$ ha^{-1}), which was not significantly different from other treatments. The lowest partial profit was observed with the reference treatment (1606.14 \$ ha^{-1}), which was also not significantly different from other treatments (Figure 2.11).

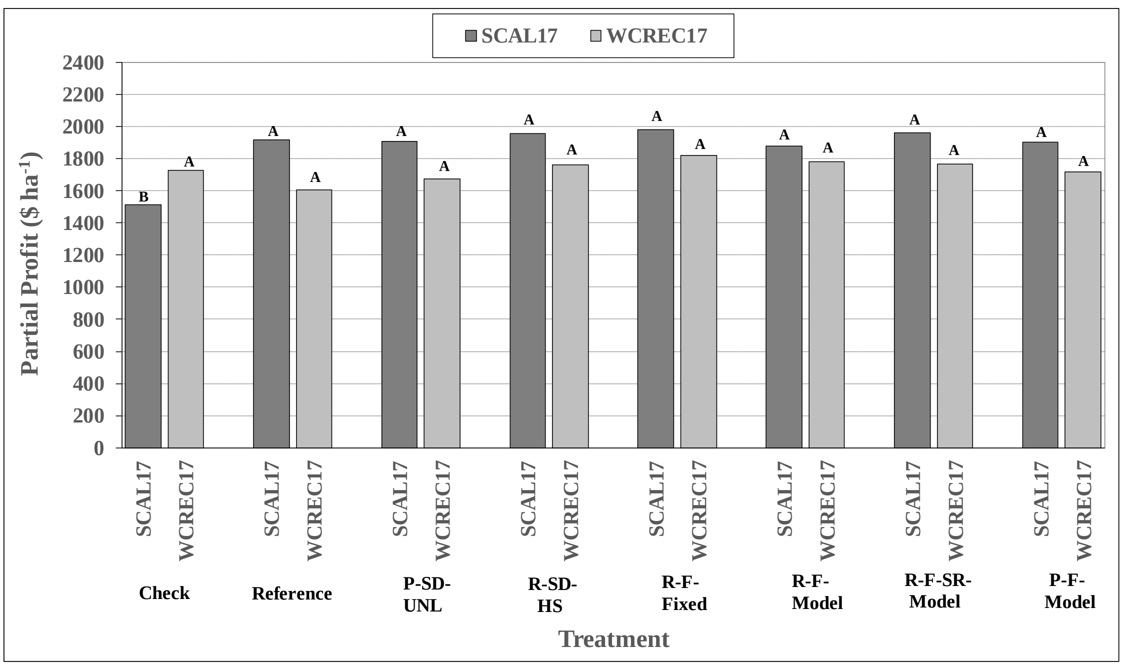

Figure 2.11. Mean estimates by site and year for average partial profit at SCAL and WCREC sites in 2017 arranged by treatment. (Assuming grain was \$0.14 kg^{-1} corn and N fertilizer was \$1.30 kg^{-1} ESN fertilizer and \$0.99 kg^{-1} UAN fertilizer in 2017). Different letters indicate a significant difference at the 95% confidence level (alpha = 0.05) within the site.

At SCAL18, the highest partial profit was observed with the R-F-Fixed treatment (2054.10 \$ ha^{-1}), which was not significantly different from other treatments except for the check treatment. The lowest partial profit was observed with the check treatment (1358.90 \$ ha^{-1}), which was significantly different from other treatments (Figure 2.12). At WCREC18, the highest partial profit was observed with the P-F-Model treatment (1781.66 \$ ha^{-1}), which was not significantly different from other treatments except for the check treatment. The lowest partial profit was observed with the check treatment (1236.46 \$ ha^{-1}), which was significantly different from other treatments (Figure 2.12).

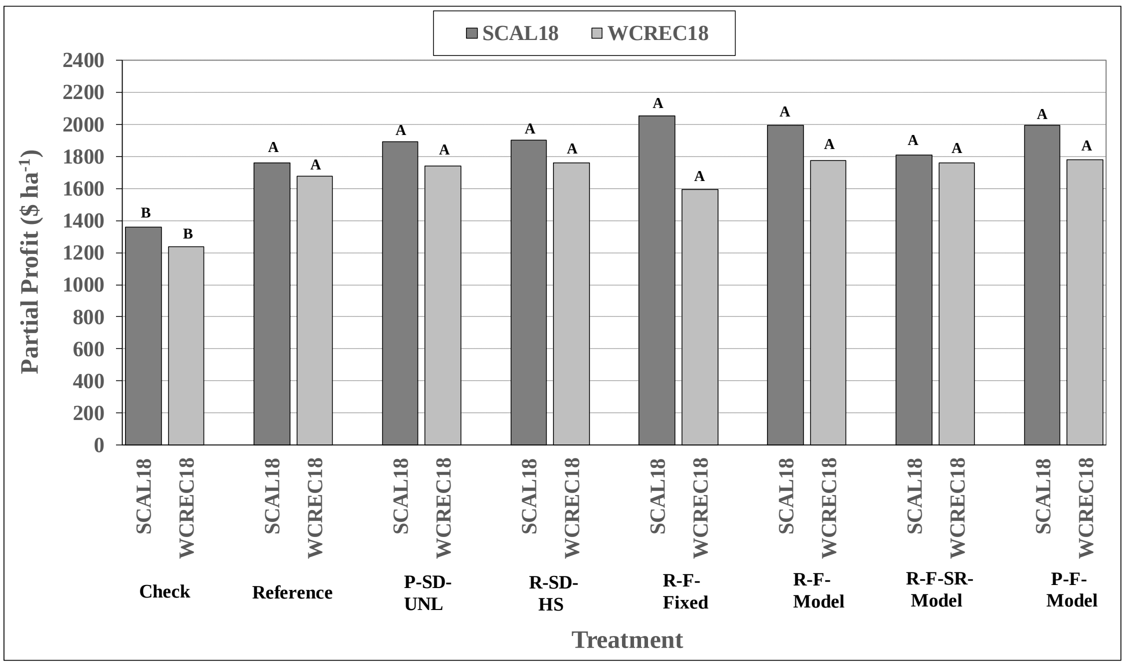

Figure 2.12. Mean estimates by site and year for average partial profit at SCAL and WCREC sites in 2018 arranged by treatment. (Assuming grain was \$0.15 kg^{-1} corn and N fertilizer was \$1.30 kg^{-1} ESN fertilizer and \$0.90 kg^{-1} UAN fertilizer in 2018). Different letters indicate a significant difference at the 95%confidence level (alpha = 0.05) within the site.

The higher partial profit observed for the check treatment at WCREC17 was attributed to higher yield (12.74 Mg ha^{-1}) due to the large contribution of N from other sources, such as N mineralization from SOM and crop residues (Wortmann et al., 2011), which provided sufficient N to the crop. The proactive and reactive fertigation treatments increased or maintained partial profit compared to proactive sidedress (P-SD-UNL) and reactive sidedress treatments (R-SD-HS). The increased partial profit of the reactive and proactive fertigation treatments over P-SD-UNL and R-SD-HS treatments was due to lower in-season N rates and equivalent yields. Similar results were observed by Thompson et al. (2015) who stated that lower in-season N recommendations and comparable yields increased profitability for reactive approach based-sensor compared to the proactive approach based Maize-N model.

Partial Profit and NUE Differences (Treatment – UNL)

Figure 2.13 shows the average partial profit (difference between each treatment and the P-SD-UNL treatment) versus average NUE as measured by PFP_N (difference between each treatment and P-SD-UNL treatment) for SCAL and WCREC sites in 2017 and 2018. At the SCAL site, the R-F-Fixed treatment had the highest average PFP_N (71.8 kg grain kg N^{-1}) and the highest average partial profit (118.4 \$ ha^{-1}) compared to other treatments. The reference treatment had the lowest average PFP_N (-23.9 kg grain kg N^{-1}) and the lowest average partial profit (-61.4 \$ ha^{-1}). At the WCREC site, the R-F-Fixed had the highest average PFP_N (38.3 kg grain kg N^{-1}) and the R-F-Model treatment had the highest average partial profit (69.8 \$ ha^{-1}) compared with other treatments. The reference treatment also had the lowest average PFP_N (-48.0 kg grain kg N^{-1}) and the lowest average partial profit (-67.1 \$ ha^{-1}). Figure 2.14 shows the overall average partial profit (difference between each treatment and the P-SD-UNL treatment) versus overall average

NUE as measured by PFP_N (difference between each treatment and P-SD-UNL treatment) across all site years. The R-F-Fixed treatment had the highest average PFP_N (55 kg grain kg N^{-1}) and the highest average partial profit (59.3 \$ ha^{-1}). The reference treatment also had the lowest average PFP_N (-35.9 kg grain kg N^{-1}) and the lowest average partial profit (-64.3 \$ ha^{-1}).

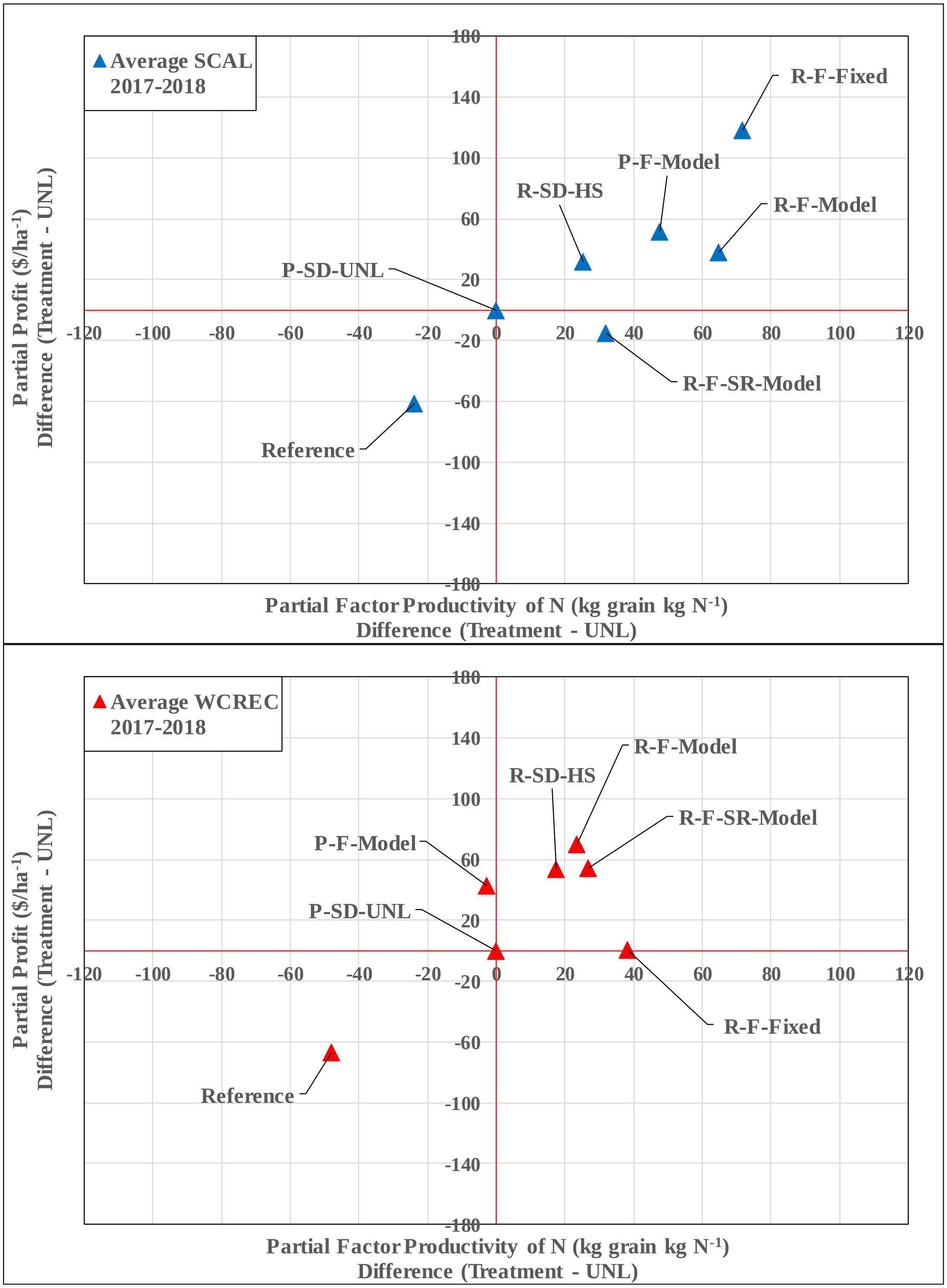

Figure 2.13. Average partial profit for the difference between treatment and UNL treatment versus average nitrogen use efficiency as partial factor productivity for N (PFP_N) for the difference between treatment and UNL treatment at SCAL (top) and WCREC (bottom) sites in 2017 and 2018.

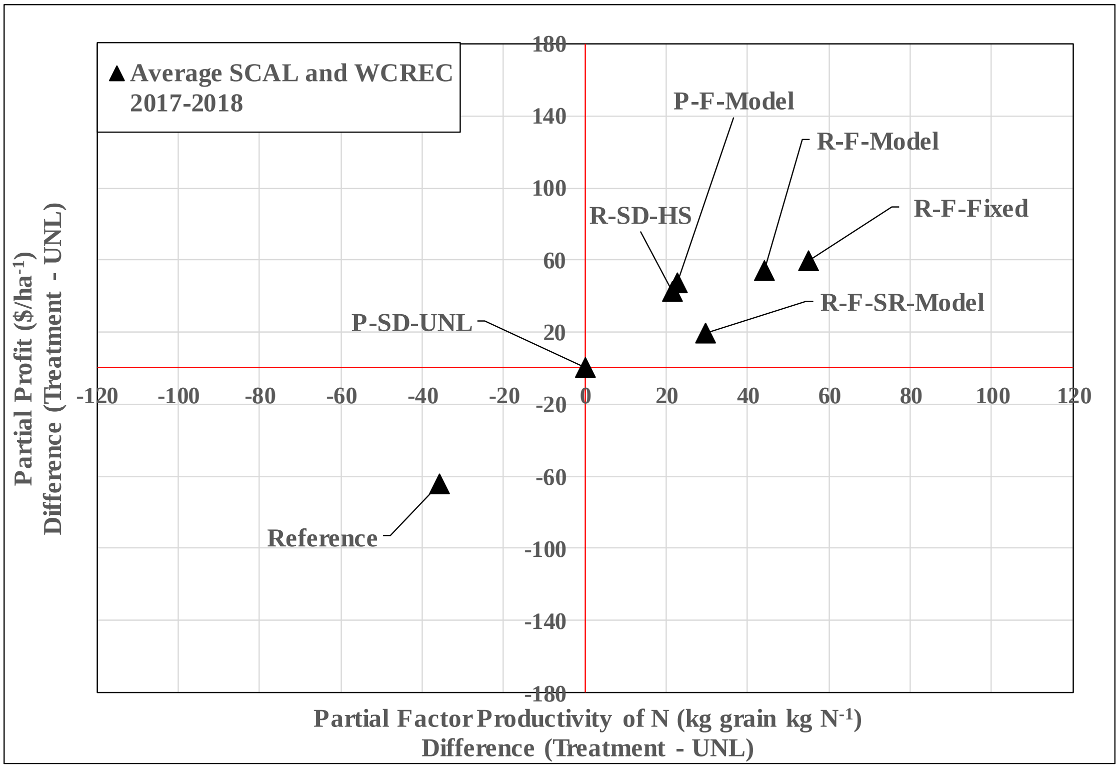

Figure 2.14. Overall average partial profit for the difference between treatment and UNL treatment versus overall average nitrogen use efficiency as partial factor productivity for N (PFP_N) for the difference between treatment and UNL treatment at SCAL and WCREC sites in 2017 and 2018.

Overall, the reactive fertigation treatments (R-F-Fixed, R-F-Model, and R-F-SR-Model) increased or maintained partial profit and improved NUE as measured by PFP_N compared to the proactive sidedress treatment (P-SD-UNL) and reactive sidedress treatment (R-SD-HS). The proactive fertigation treatment (P-F-Model) increased partial profit and improved PFP_N compared to the P-SD-UNL treatment, and it slightly improved partial profit and PFP_N over R-SD-HS treatment.

Residual Soil Nitrate-N (RSN-N)

Table 2.8 shows Type III tests of fixed effects of the environment, depth, and treatment on RSN-N for SCAL site in 2017 and 2018 and WCREC site in 2018. There were significant environment, depth, treatment main effects on RSN-N. There were significant environment x depth x treatment interaction effects on RSN-N. Due to the significant interaction effects of environment x depth x treatment, the simple effect of treatment on RSN-N will be explored by each environment as shown in Figure 2.15 through Figure 2.17.

Table 2.8. Type III tests of fixed effect of environment (site and year), depth, and treatment on RSN-N for SCAL site in 2017 and 2018 and WCREC site in 2018.

Residual Nitrate-N				
Effect	**Numerator DF**	**Denominator DF**	**F Value**	**Pr > F**
env	2	9	13.54	0.0019
Trt	7	63	22.08	<.0001
env*Trt	14	63	5.81	<.0001
Depth	5	42	40.76	<.0001
env*Depth	9	42	11.26	<.0001
Trt*Depth	35	294	2.76	<.0001
env*Trt*Depth	63	294	2.2	<.0001

Post-harvest average RSN-N ranged from 0.23 at SCAL18 to 61.11 kg ha^{1} at WCREC18. Figure 2.15 through Figure 2.17 shows the mean estimates by the environment for average RSN-N for SCAL site in 2017 and 2018 and WCREC site in 2018 arranged by depth for each treatment.

At SCAL17, the highest RSN-N was observed with the reference treatment (35.72 kg ha^{-1}) at a depth of 30 cm, which was not significantly different from other treatments at the same depth (Figure 2.15). The reference treatment also had the highest average RSN-N (17.99 kg ha^{-1}) for all depths (30-150 cm) of the soil profile as shown in Appendix A (Table A.1), which was significantly different from other treatments. The lowest RSN-N was observed with the check treatment (1.73 kg ha^{-1}) at a depth of 120 cm, which was also not significantly different from other treatments at the same depth (Figure 2.15). The check treatment also had the lowest average RSN-N (7.66 kg ha^{-1}) for all depths (30-150 cm) of soil profile as shown in Appendix A (Table A.1), which was not significantly different from other treatments except reference and R-F-Model treatments.

At SCAL18, the highest RSN-N was observed with the P-SD-UNL treatment (22.28 kg ha^{-1}) at a depth of 90 cm, which was significantly different from the check, R-SD-HS, R-F-Model treatments at the same depth (Figure 2.16). The P-SD-UNL treatment also had the highest average RSN-N (15.03 kg ha^{-1}) for all depths (30-150 cm) of the soil profile as shown in Appendix A (Table A.1), which was significantly different from other treatments. The lowest RSN-N was observed with the R-F-Model treatment (0.23 kg ha^{-1}) at a depth of 150 cm, which was not significantly different from other treatments at the same depth (Figure 2.16). The R-F-Model treatment also had the lowest average RSN-N (2.79 kg ha^{-1}) for all depths (30-150 cm) of the soil profile as shown in Appendix A (Table A.1), which was not significantly different from other treatments except reference and P-SD-UNL treatments.

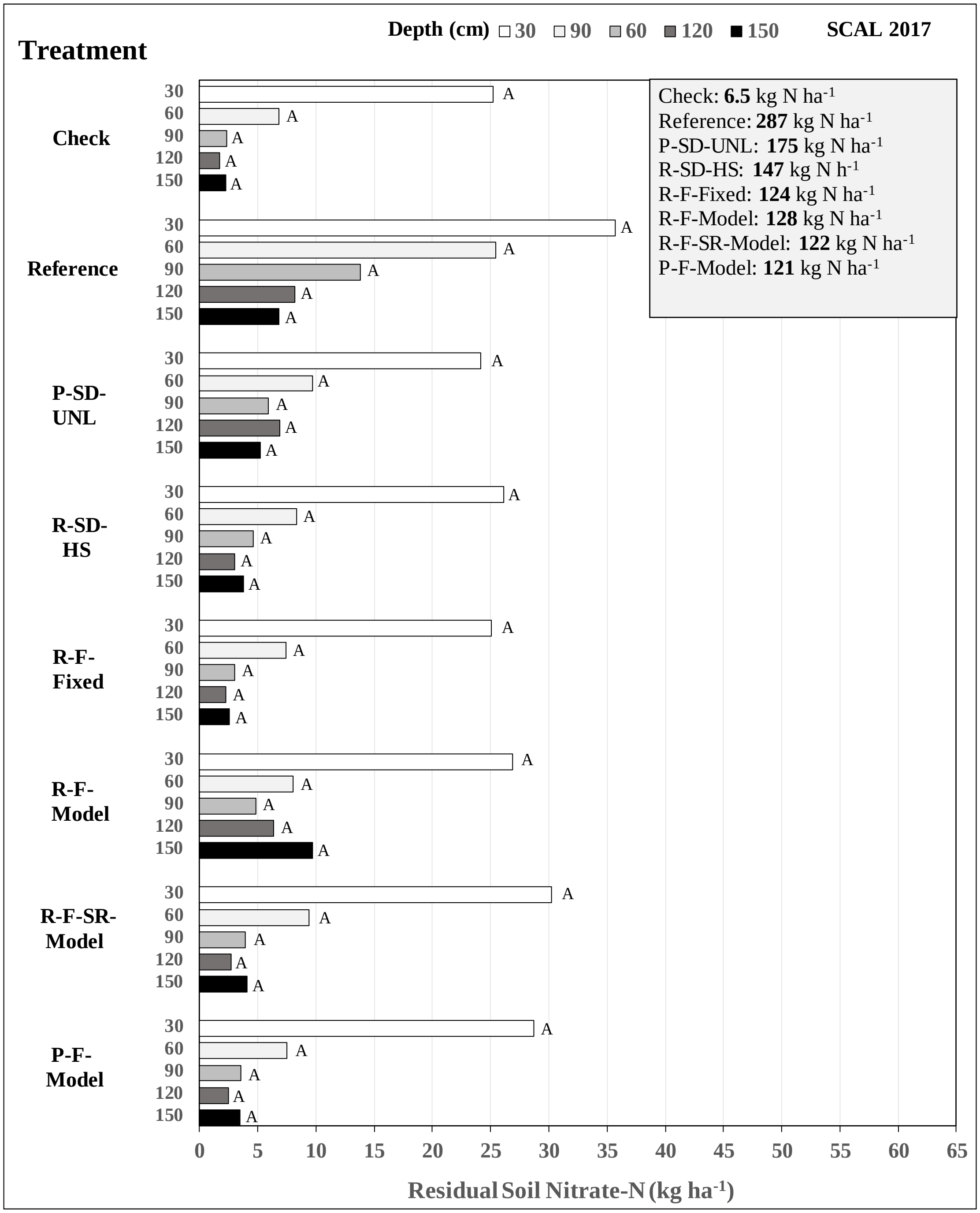

Figure 2.15. Mean estimates by the environment (site and year) for post-harvest average RSN-N for SCAL site in 2017 arranged by depth for each treatment. Different letters indicate a significant difference at the 95% confidence level (alpha = 0.05) within depth.

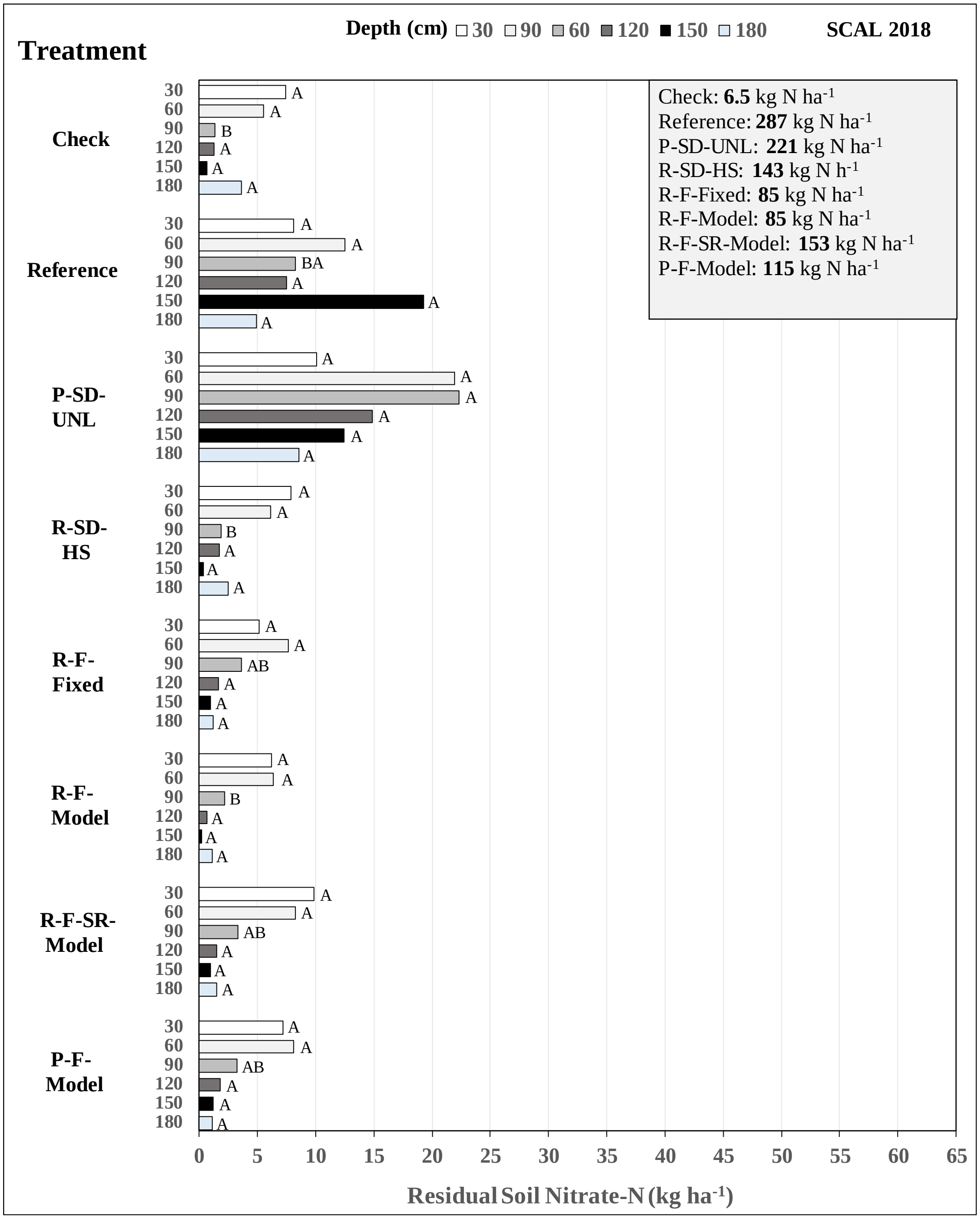

Figure 2.16. Mean estimates by the environment (site and year) for post-harvest average RSN-N for SCAL site in 2018 arranged by depth for each treatment. Different letters indicate a significant difference at the 95% confidence level (alpha = 0.05) within depth.

At WCREC18, the highest RSN-N was observed with the reference treatment (61.11 kg ha^{-1}) at a depth of 60 cm, which was significantly different from other treatments at the same depth. The reference treatment had the highest RSN-N (41.71 kg ha^{-1}) at a depth of 90 cm, which was also significantly different from other treatments at the same depth (Figure 2.17). Also, the reference treatment had the highest average RSN-N (24.23 kg ha^{-1}) for all depths (30-150 cm) of soil profile as shown in Appendix A (Table A.1), which was significantly different from other treatments. The lowest RSN-N was observed with the check treatment (1.15 kg ha^{-1}) at a depth of 120 cm, which was not significantly different from other treatments at the same depth (Figure 2.17). The check treatment had the lowest average RSN-N (3.59 kg ha^{-1}) for all depths (30-150 cm) of soil profile as shown in Appendix A (Table A.1), which was not significantly different from other treatments except the reference treatment.

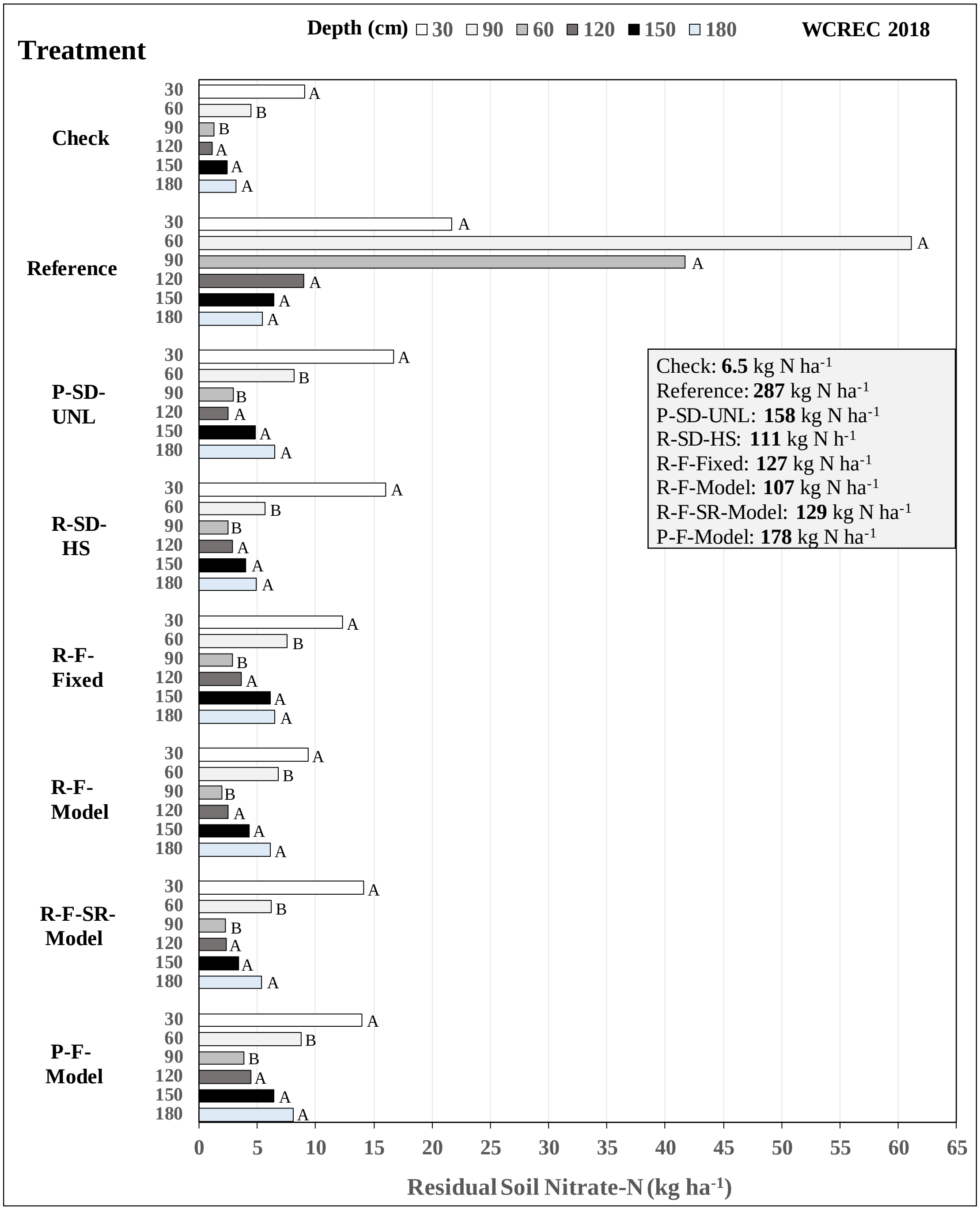

Figure 2.17. Mean estimates by the environment (site and year) for post-harvest average RSN-N for WCREC site in 2018 arranged by depth for each treatment. Different letters indicate a significant difference at the 95% confidence level (alpha = 0.05) within depth.

Across all site years, the reference treatment had the highest average post-harvest RSN-N (21.09 kg ha^{-1}) for effective root zone depth at 120 cm, which was significantly different from other treatments. This was expected since the reference treatment received the highest N application. The check treatment had the lowest average post-harvest RSN-N (5.65 kg ha^{-1}) at the same depth, which was not significantly different from other treatments except for reference and P-SD-UNL treatments. This was also expected since the check treatment did not receive N fertilizer except starter fertilizer.

Reactive fertigation treatments (R-F-Fixed and R-F-Model) reduced average post-harvest RSN-N for effective root zone depth at 120 cm by 5.33 kg ha^{-1} compared to the current recommended proactive sidedress UNL algorithm (P-SD-UNL treatment) and by 0.38 kg ha^{-1} compared to reactive sidedress H-S algorithm (R-SD-HS treatment). A similar result was also observed by Ferguson and Irmak, (2006) that reported a reactive approach guided by SPAD CM had lower residual nitrate-N than the currently recommended proactive sidedress UNL algorithm (P-SD-UNL treatment) in 60 cm depth of soil profile. The reactive fertigation treatment (R-F-SR-Model) and proactive fertigation treatment (P-F-Model) reduced average post-harvest RSN-N by 4.34 and 4.36 kg ha^{-1}, respectively, compared to P-SD-UNL treatment, but both treatments did not reduce RSN-N compared to R-SD-HS treatment at the same depth.

Overall Comparison Summary

Table 2.9. shows overall average total N applied, grain yield, PFP_N, AE_N, RE_N, partial profit, and RSN-N across SCAL and WCREC sites in 2017 and 2018. The overall results across all site years showed that the reactive fertigation treatments (R-F-Fixed, R-F-Model, and R-F-SR-Model) reduced total N applied by 65, 57, and 43 kg ha^{-1}, respectively, compared to the current recommended proactive sidedress UNL algorithm (P-SD-UNL treatment) and by 28, 20, and 6 kg ha^{-1}, respectively, compared to the current recommended reactive sidedress H-S algorithm (R-SD-HS treatment). The proactive fertigation treatment (P-F-Model) reduced total N applied by 35 kg ha^{-1} compared to the P-SD-UNL treatment and increased total N applied by 2 kg ha^{-1} compared to the R-SD-HS treatment. The reactive fertigation treatments (R-F-Fixed, R-F-Model, and R-F-SR-Model) and proactive fertigation treatment (P-F-Model) maintained grain yield compared to P-SD-UNL and R-SD-HS treatments.

The reactive fertigation treatments (R-F-Fixed, R-F-Model, and R-F-SR-Model) increased PFP_N by 55, 44, and 30 kg grain kg N^{-1}, respectively, compared to the P-SD-UNL treatment and by 34, 23, and 8 kg grain kg N^{-1}, respectively, compared to the R-SD-HS treatment. The proactive fertigation treatment (P-F-Model) increased PFP_N by 23 and 1 kg grain kg N $applied^{-1}$, respectively, compared to the P-SD-UNL and R-SD-HS treatments. The reactive fertigation treatments (R-F-Fixed, R-F-Model, and R-F-SR-Model) also increased AE_N by 15, 14, and 9 kg grain increase kg N^{-1}, respectively, compared to the P-SD-UNL treatment and by 7, 7, and 1 kg grain increase kg N^{-1}, respectively, compared to the R-SD-HS treatment. The proactive fertigation treatment (P-F-Model) increased AE_N by 8 (kg grain increase kg N^{-1}) compared to the P-SD-UNL treatment, but did not increase AE_N compared to the R-SD-HS treatment. The reactive fertigation treatments (R-F-Fixed, R-F-Model, and R-F-SR-Model) increased RE_N by 0.08, 0.10, and 0.10 kg N uptake kg N^{-1}, respectively, compared to the P-SD-UNL treatment, but was no more efficient than the R-SD-HS treatment. The proactive fertigation treatment (P-F-Model) increased RE_N by 0.09 kg N uptake kg N^{-1} compared to the P-SD-UNL treatment, but was no more efficient than the R-SD-HS treatment.

The reactive fertigation treatments (R-F-Fixed, R-F-Model, and R-F-SR-Model) increased partial profit by 59, 54, and 20 \$ ha^{-1}, respectively, compared to the P-SD-UNL treatment and by 17 and 11 \$ ha^{-1} for R-F-Fixed and R-F-Model, respectively, compared to the R-SD-HS treatment, but R-F-SR-Model treatment did not increase partial profit compared to R-SD-HS treatment. The proactive fertigation treatment (P-F-Model) increased partial profit by 47 and 4 \$ ha^{-1}, respectively, compared to P-SD-UNL and R-SD-HS treatments.

The reactive fertigation treatments (R-F-Fixed, R-F-Model, and R-F-SR-Model) reduced RSN-N by 4.8, 4.5, and 4.3 kg ha^{-1}, respectively, compared to the P-SD-UNL treatment, but did not reduce RSN compared to R-SD-HS treatment. In contrast, the proactive fertigation treatment (P-F-Model) reduced RSN by 3.96 kg ha^{-1} compared to the P-SD-UNL treatment but did not reduce RSN-N compared to the R-SD-HS treatment.

Table 2.9. Overall average total N applied, grain yield, partial factor productivity of N (PFP_N), agronomy efficiency (AE_N), recovery efficiency (RE_N), partial profit, and post-harvest residual soil nitrate-N (RSN-N) across two site years.

	Treatment							
	Check	Reference	P-SD-UNL	R-SD-HS	R-F-Fixed	R-F-Model	R-F-SR-Model	P-F-Model
Total N applied (kg ha^{-1})	6.5	295	170	133	105	113	127	135
Grain yield (Mg ha^{-1})	10.43b	14.34a	13.93a	14.00a	13.93a	13.94a	14.04a	14.02a
PFP_N (kg grain kg N^{-1})	-	48.68e	84.62d	105.94c	139.66a	128.81b	114.12c	107.15c
AE_N (kg grain kg N^{-1})	-	13.48d	19.46c	27.10b	34.58a	33.71a	28.08b	26.96b
RE_N (kg N uptake kg N^{-1})	-	0.45c	0.52bc	0.71a	0.60ab	0.62ab	0.62ab	0.61ab
Partial profit ($ ha^{-1})	1458.9c	1739.9b	1804.2ab	1846.8a	1863.4a	1858.2a	1823.9ab	1851.3a
RSN-N (kg ha^{-1})	4.7c	16.7a	10.6b	5.9bc	5.77bc	6.1bc	6.3bc	6.6bc

Conclusion

The integration of reactive sensor and proactive Maize-N model approaches were evaluated for determining N requirements via fertigation in corn. Results across all site years showed that the reactive fertigation treatments (R-F-Fixed, R-F-Model, and R-F-SR-Model) reduced total N applied by 65, 57, and 43 kg ha^{-1}, respectively, compared to the proactive sidedress UNL algorithm treatment and by 28, 20, and 6 kg ha^{-1} compared to the reactive sidedress H-S algorithm treatment with no significant difference in yield. The proactive fertigation treatment (P-F-Model) reduced total N applied by 35 kg ha^{-1} compared to the proactive sidedress UNL algorithm treatment only. Across all site years, both reactive and proactive fertigation treatments showed a higher NUE as PFP and partial profit than the proactive sidedress UNL algorithm treatment and the reactive sidedress H-S algorithm treatment. Additionally, residual soil nitrate-N was reduced by reactive and proactive fertigation treatments compared to the proactive sidedress UNL algorithm treatment. Either sensor or model approaches, or the combination of both approaches have the potential to be effective methods to direct fertigation to improve NUE while increasing profit and reducing environmental impact.

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Chapter 3: Testing The Maize-N Model for Nitrogen Fertilizer Rate, Nitrogen Uptake, and Soil Nitrate-N Predictions

Introduction

Crop simulation models integrate the current knowledge of plant growth and development from various disciplines, such as crop science, physiology, agrometeorology, soil science, and agronomy to simulate the behavior of a crop's growth and development, yield formation, and biomass partitioning among organs (roots, stems, leaves, and grains) (Yang et al., 2004; Sandhu and Irmak, 2020). They synthesize our current quantitative understanding of crop growth processes as influenced by genotype, environmental conditions, and crop management (Yang et al., 2006; Oteng-Darko et al., 2013). Crop simulation models have been widely used in research, teaching, and extension and have become an indispensable tool for supporting crop management decisions, scientific investigation, and to inform policymaking (Hammer et al., 2002; Yang et al., 2017).

Crop simulation models attempt to account for spatial variability among fields and temporal variability between years by combining soil, crop, and management information with current and long-term weather to estimate corn nitrogen (N) demands (Setiyono et al., 2011; Sela et al., 2016). They have the potential to provide information for farmers to adjust in-season N application to synchronize soil N fertilizer application with crop N demand (Cassman et al., 2002; Thompson et al., 2015; Jin et al., 2017). Although several crop simulation models exist, such as a WOrld FOod STudies (WOFOST) (Supit et al., 1994), the Decision Support System for Agrotechnology Transfer (DSSAT) (Jones et al., 2003), a Cropping Systems simulator (CropSyst)

(Stöckle et al., 2003), and a System Approach to Land Use Sustainability (SALUS) (Basso et al., 2006) have been used to investigate soil-crop-weather dynamics (Puntel et al., 2016). They typically are not designed to support decisions about pre-plant or in-season N rate recommendations (Thompson et al., 2015). Specific simulation models have been developed to recommend pre-plant and in-season N management in corn (Jin et al., 2017) such as the Quantitative Evaluation of the Fertility of Tropical Soils (QUEFTS) (Janssen et al., 1990), the Agricultural Production Systems sIMulator (APSIM) (Holzworth et al., 2006; Puntel et al., 2016), Adapt-N (Melkonian et al., 2008), and Maize-N (Setiyono et al., 2011).

In this study, the Maize-N model was used as it is simple, easy to run, and requires relatively fewer input parameters compared to other crop simulation models. Maize-N is built on functions from the Hybrid-Maize crop simulation model (Yang et al., 2004, 2006) for maize growth and yield prediction under rainfed and irrigated conditions, and from a mono-component model (Yang and Janssen, 2000) for simulating carbon (C) and N mineralization from soil organic matter (SOM) and crop residuals. Thus, the Maize-N model has been used as a useful tool for N management in corn that accounts for dynamic interactions between soil, crop management, and weather conditions (Setiyono et al., 2011; Thompson et al., 2015).

The Maize-N model attempts to account for variability among fields and years by combining historical weather, current season weather, previous and current crop information, soil information, tillage system, various N credits, and prices for grain and N fertilizer to estimate economic optimum N rate (EONR). Besides predicting EONR (the N rate which optimizes profit), the Maize-N model was also developed to predict available soil N supply and N uptake demand (Setiyono et al., 2011). Soil N mineralization from SOM, crop N uptake, and N losses can influence EONR (Puntel et al., 2016). Determining EONR by the Maize-N model depends on the prediction of N mineralization from SOM as it is affected by weather conditions such as temperature and precipitation (Leiros et al., 1999; Thompson et al., 2015; Banger et al., 2019; Yin et al., 2020). Several studies have shown that uncertainty of weather conditions, particularly temperature and precipitation, and their impact on N mineralization and N losses is the main challenge to predicting EONR prior to planting (Melkonian et al., 2007; Setiyono et al., 2011; Puntel et al., 2016; Sela et al., 2016; Yin et al., 2020). Other studies have shown that EONR can be well predicted using the Adapt-N model (Sela et al., 2016; Rutan and Steinke, 2017). Prediction of plant N uptake using the QUEFTS model showed a good agreement with a relative root mean square error (RRMSE) of 10-15% between predicted and observed N uptake (Setiyono et al., 2010). A more recent study by Yin et al. (2020) reported that the Simulateur mulTIdisciplinaire pour les Cultures Standard (STICS) model showed reasonable agreement in simulating N uptake and soil N mineralization with relatively low RRMSE of 20-24% for N uptake and 16-21% for soil N mineralization.

The Maize-N model has been used in simulating EONR in experiments conducted in western Corn Belt states in both irrigated conditions (central Nebraska and eastern South Dakota) and rainfed conditions (eastern South Dakota and western Nebraska) (Setiyono et al., 2011). The EONR simulated by Maize-N showed greater accuracy with lower root mean square error (RMSE) and mean error (ME) values than current university N recommendation approaches. A field study by Thompson et al. (2015)

conducted across 12 sites in Nebraska, Missouri, and North Dakota found that the EONR predicted by the Maize-N model was more closely estimated the linear-plateau derived ONR than a sensor-based approach. The model tended to overapply N, but better-protected yield. They also, reported that the Maize-N model underestimated N mineralization from SOM. However, recent research conducted across eight U.S. Midwest Corn Belt states at 49 sites and three growing seasons showed that the Maize-N model performance in predicting EONR was lower than some other current N recommendation models (Ransom et al., 2020). Thus, the ability to predict pre-season N requirements still needs improvement, and much applied N fertilizer is not accounted for by crop uptake (Shapiro et al., 2018). Additionally, the Maize-N model has not been evaluated sufficiently for predicting in-season soil nitrate-N supply and N uptake. Therefore, there are opportunities to test and evaluate the model performance to improve these deficiencies by improving the predictions of the Maize-N model.

The overall goal of this study was to test and evaluate the Maize-N model performance for predicting EONR, crop N uptake at V8 through R6, and soil nitrate-N supply at V8 through R5. The specific objectives were (i) to evaluate the EONR, crop N uptake, and soil nitrate-N supply predicted by the Maize-N model compare to the estimated ONR and calculated EONR, observed N uptake, and observed soil nitrate-N supply and (ii) to monitor crop N status and refine Maize-N model N uptake prediction using crop canopy sensor information.

Materials and Methods

Study Site

This study was conducted on two fields, over two corn growing seasons (2018 and 2019) at the University of Nebraska-Lincoln research site at the South-Central Agriculture Laboratory (SCAL), near Clay Center, Nebraska, USA, and are referred to as SCAL18 and SCAL19 site years, respectively. For SCAL18, the geo-coordinates of the field are latitude 40° 34' 50.4732" N, and longitude -98° 8' 40.7688" W. For SCAL19, the geo-coordinates of the field are latitude 40° 34' 50.5632" N, -98° 8' 40.504" W. The soil for both fields was classified as Hasting silt loam (fine, montmorillonitic, mesic Udic Argiustolls) soil series with 0 to 1 percent slopes (Hammer et al.,1981). The location of the study sites was characterized as a transition zone between sub-humid and semi-arid climates. For SCAL18, the total precipitation received during the crop growing season from April 1 to September 30, 2018 was 506 mm. The average daily temperature was 18.9°C and the average relative humidity was 74.6%. For SCAL19, the total precipitation received during the crop growing season from April 1 to September 30, 2019 was 599 mm. The average daily temperature was 19.1°C and the average relative humidity was 75.4% (HPRCC, 2019). The total precipitation received during the two growing seasons of the same period was higher than the thirty-year historical average (493 mm). The average temperature for both site years was slightly higher than the thirty-years historical average (18.7°C).

Soil samples were collected at each site each year to characterize soil chemical properties and residual soil nitrate. Initial spring soil samples for the topsoil layer (0-20 cm) were composited from four soil cores to obtain one sample for each replication. Four soil cores were composited for the deep soil layers from 0 to 180 cm with 30 cm increments and one sample per depth for each replication to obtain a total of 24 soil samples. A summary of soil properties for the topsoil layer and previous crop for both site years are presented in Table 3.1.

Table 3.1. Summary of soil properties for spring soil samples at depths of 0-20 cm and previous crop for SCAL18 and SCAL19 site years.

Site Year ID	Soil Texture	pH†	SOM‡ %	CEC* meq $100g^{-1}$	NO_3-N⋆ mg kg^{-1}	P-M3[δ] mg kg^{-1}	K§ mg kg^{-1}	Previous crop
SCAL18	SiL⁺	6.6	3.3	15.8	11.8	32.6	334.3	corn
SCAL19	SiL	6.5	3.3	16.0	8.2	29.8	315.3	corn

⁺SiL is silt loam, †pH is 1:1 soil: water, ‡SOM is soil organic matter LOI %, *CEC is cation exchange capacity, ⋆NO_3-N is nitrate-nitrogen, [δ]P-M3 is Mehlich-3 soil phosphorus, §K is potassium extracted by 1 N ammonium acetate.

Experimental and Treatment Design

This study was a part of a large fertigation project. The experimental design was a randomized complete block design with five treatments and four replications. Individual plots were 6.1 m wide by 23.1 m length with eight maize rows with 0.76 m row width between rows. Corn was planted on May 2 for SCAL18 and May 14 for SCAL19 at a population of 84,000 plants ha^{-1} using Hybrid Fontanelle 6A327RBC for the SCAL18 site and Hybrid Channel 209-15 STXRIB for the SCAL19 site.

Other than N fertilizer treatment, all other agronomic activities, including pest control were managed according to the University of Nebraska Extension Guidelines (Shapiro et al., 2019). Both site years were irrigated with a linear sprinkler irrigation system. Irrigation management was conducted according to the method developed by Irmak et al. (2005). Irrigation timing and amount were determined from a combination of soil moisture content and crop growth stage monitoring with the use of Watermark soil moisture sensors (model 200SS) with a range of measurements from 0-239 kPa (IRROMETER Company, Inc., Riverside, CA, USA). Also, soil temperature sensors (model 200TS) were used to measure soil temperature. For both SCAL18 and SCAL19, fertilizer was applied according to UNL extension guidelines (Shapiro et al., 2019). Starter fertilizer was applied as ammonium polyphosphate 10-34-0 (NPK) (6.5 kg N ha^{-1} and 22 kg P_2O_5 ha^{-1}) and 0.32 kg ha^{-1} 20% Zn for SCAL18 and as ammonium polyphosphate 10-34-0 (NPK) only with the same amount for SCAL19. The fertilizer was banded over the seed via the planter in both site years (Table 3.2).

Five treatments used the Maize-N model for N management in Nebraska. The treatments were categorized as the following: check, calibration, and three proactive treatments. The check (unfertilized) treatment received only starter fertilizer to supplement phosphorus and zinc needs. This treatment is important to identify N uptake from indigenous sources, including residual soil nitrate-N, mineralized N from SOM, crop residues, deposition of atmospheric ammonium, and nitrate-N from irrigation water (Wortmann et al., 2011). A non-N limiting reference treatment was used as a calibration treatment to determine the relative N sufficiency status by normalizing sensor data and calculating the relative sufficiency index (SI) of target treatments (Blackmer and Schepers, 1995). The reference treatment was also used to represent maximum yield. The reference treatment received a non-limiting N rate of 280 kg N ha^{-1} as urea-ammonium nitrate (UAN) solution (32%N) after planting to be above crop needs to ensure that total N was sufficient throughout the growing season. Three treatments were labeled according to the Timing-Application Method-Rate. A proactive approach attempts to predict N demand and supplement N to the crop before N deficiency occurs. The application method was sidedress by a backpack sprayer (ShurFlo SRS-600). The rate was predicted by the Maize-N model (Setiyono et al., 2011). The N source for all treatments was UAN 32% N. The proactive treatments consisted of: (i) proactive-sidedress-model (P-SD-model), (ii) proactive-sidedress-model minus 56 kg N ha^{-1} (P-SD-model - 56), and (iii) proactive-sidedress-model plus 56 kg N ha^{-1} (P-SD-model + 56) (Table 3.2).

Table 3.2. Site year, treatment, planting date, starter N rate, application date, N rate, application date, and N application method for five treatments for SCAL18 and SCAL19 site years.

Site Year ID	Treatment	Planting Date	Starter+ N Rate (kg N ha^{-1})	Application Date	Sidedress† N Rate (kg ha^{-1})	Application Date	Total N (kg ha^{-1})
SCAL18	**Check**	2-May	6.5	2-May	0	-	6.5
	P-SD-Model -56				78	25-May	85
	P-SD-Model				135		141
	P-SD-Model +56				191		197
	Reference				280		287
SCAL19	**Check**	14-May	6.5	14-May	0	-	6.5
	P-SD-Model -56				110	13-Jun	116
	P-SD-Model				166		172
	P-SD-Model +56				222		228
	Reference				280		287

+ Indicates Liquid ammonium polyphosphate (10-34-0) (NPK) banded for all treatments as starter N.

† Indicates Urea-Ammonium Nitrate (UAN) solution (32%N).

Maize-N Model-Determined Economically Optimal N Rate (EONR)

The N rate requirements for the P-SD-model treatment were determined by the Maize-N model. The Maize-N model was developed to estimate the EONR for corn by taking into account current weather (up to the time of application) and long-term average weather (from time of application to crop maturity), current and previous crop information, crop rotation, N fertilizer information, tillage system, soil properties, N credits, and indigenous soil N supply (Setiyono et al., 2011). All these input values were entered into the model to predict available soil nitrate, N uptake demand, and EONR (Table 3.3). Maize-N model version 2017 was used for both SCAL18 and 2019 growing seasons. The model uses real-time weather data from the end of the previous season to the current to estimate the amount of N mineralization and crop growth that had already occurred and uses long-term average daily weather data to predict N mineralization and crop growth for the rest of the season until crop maturity.

In order to improve Maize-N model predictions, inputs to the Maize-N model were adjusted and tested at the end of each season for nitrate-N prediction. In this study, the adjustment process used additional information as below:

- Default air temperature values were replaced with measured soil temperature during the growing season (from 19-June for SCAL18 and from 17-June for SCAL19 to the end of each growing season).
- Default values of bulk density and measured values of SOM for the top 20 cm were replaced with measured values of bulk density and measured values of SOM for the top 30 cm of soil.

- Default values of the ratio of SOC below topsoil to the amount of SOC in the topsoil (20 cm) replaced with measured values for the top 30 cm of soil.

Maize-N model inputs, processes, and outputs used to predict EONR are provided in Table 3.3 and the Maize-N model decision-making process to predict EONR is shown in Figure 3.1. The input and output values of the Maize-N model prediction for SCAL18 and SCAL19 are shown in Appendix B.

Table 3.3. Maize-N model inputs, processes, and outputs used to predict the economically optimal N rate (EONR). Table adapted from Setiyono et al., (2011).

Inputs	Processes	Outputs
➢ **Long-term weather data:** Daily maximum and minimum air temperature, solar radiation, relative humidity, precipitation, and evapotranspiration	Maize yield & variation **(Hybrid-Maize model)**	➢ **Economically optimal N rate** (EONR)
➢ **Current Maize Crop:** Irrigated or rainfed system, maturity, planting date, plant population, grain price, and yield history (optional)		➢ **N fertilizer:** N already applied, N to be applied, and fertilizer cost
➢ **Last Crop:** Type, yield, total N applied, date of maturity, amount of crop residue left in the field, root-zone soil moisture at crop maturity, and % of the field capacity	Soil C & N mineralization **(DK C & N model)**	➢ **N use efficiencies:** Recovery efficiency (RE), physiological efficiency (PE), and agronomic efficiency (AE)
➢ **Nitrogen Fertilizer Management:** N already applied, dates, amount, N to be applied, type of fertilizer, N content, price, and N from irrigation water		➢ **Yield:** Yield potential, yield at EONR, and yield without N fertilizer
➢ **Tillage:** Type and date of tillage operation	N use efficiencies **(QUEFTS, f (Ya, Y0))**	➢ **Total N uptake demand:** N uptake from indigenous sources, total: from N-leftover, SOM min., crop residues min., manure, slow-release fertilizer, and irrigation water
➢ **Soil properties:** Top-soil organic matter (SOM) content %, top-soil bulk density, soil texture, soil pH, and soil root zone depth	Maize yield response to N rate **(Spherical model)**	➢ **N leaching:** Season up to date N leaching, long-term average N leaching loss of the same period
➢ **Measured root zone soil nitrate:** The amount and date of sampling		➢ **Seasonal C & N mineralization dynamics**
➢ **Manuring:** Type, moisture content, amount, and date of application		➢ **Interactive yield response to N rate**

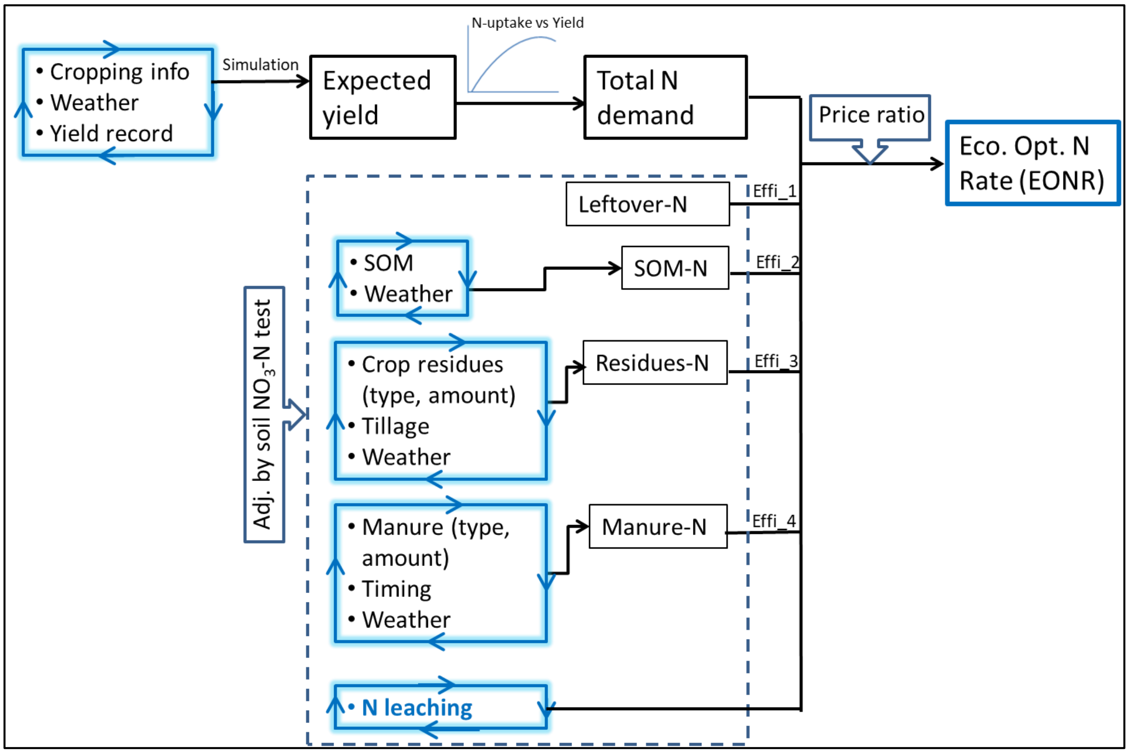

Figure 3.1. Maize-N model decision-making process to predict the economically optimal N rate (EONR). Figure adapted from personal communication with Dr. Haishun Yang (UNL).

Crop Canopy Sensing

The RapidScan CS-45 (RS) active crop canopy sensor (Holland Scientific, Lincoln, NE, USA) and SPAD chlorophyll meters (SPAD CM) (Spectrum Technologies Inc.) were used to monitor crop N status and refine Maize-N model N uptake prediction. The RS is an active handheld crop canopy sensor that integrates a data logger, GPS, crop sensor, and power source into one small unit with a modulated polychromatic light source and three measurement channels: 670, 730, and 780 nm. Reflectance from these three channels was used to obtain the normalized difference red edge index (NDRE) (Li et al., 2014). Sensing was conducted in the middle of each plot (sensing area). The sensing area of each plot consisted of the two middle rows of each plot with 9 m length from the vegetative six-leaf collar (V6) to tasseling (VT) growth stages by holding the RS unit in the nadir position at the recommended height of approximately 1 meter above the canopy and walking directly over each row for each plot. Measurements of the sensor were moved to be taken between three rows instead of directly over two rows from VT through physiological maturity (R6) growth stages. The NDRE values were generated and averaged for each row to obtain one mean value for each plot.

The SPAD CM is an active handheld crop leaf sensor (contact sensor) that measures light transmittance properties of leaves in two wavelengths (650 and 940 nm) by clamping it on the crop leaf and emitting its own light to monitor crop N status. In the field, fifteen readings per row from the middle two rows (total of thirty readings) were collected (from the sensing area as described above). Sensor measurements were taken from halfway between the leaf margin or edge and the leaf midrib from the newest fully expanded leaf before the VT growth stage, and from the ear leaf after the VT growth stage. The SPAD CM values were generated and averaged to obtain one mean value for each plot.

Biomass and Soil Samples

Whole plant samples (aboveground biomass) were collected six times for SCAL18 and five times for SCAL19 during the growing season at various growth stages. For SCAL18, biomass samples were collected at vegetative stages [eight leaf collar (V8) and fourteen leaf collar (V14)] and reproductive stages [silking (R1), milk (R3), dent (R5), and physiological maturity (R6)]. For SCAL19, biomass samples were collected at vegetative stages [seven leaf collar (V7), twelve leaf collar (V12), and VT] and reproductive stages [R3 and R6]. Six plants were sampled randomly for each plot by collecting three plants from each adjacent row of the sensing area (2 rows were selected in the middle of each plot with 9 m length). Plants were separated from the ear (for samples after silking), bagged, weighed, chopped, and dried at 70°C until constant weight. Ears were air-dried, shelled, and weighed. Total aboveground biomass samples (stover and grain) were analyzed for total N to calculate total aboveground N uptake.

Soil samples were collected five times for SCAL18 and four times for SCAL19 during the growing season at various corn growth stages to quantify soil nitrate-N. For SCAL18, soil samples were collected at vegetative stages [eight leaf collar (V8) and fourteen leaf collar (V14)] and reproductive stages [silking (R1), milk (R3), and dent (R5)]. For SCAL19, soil samples were collected at vegetative stages [seven leaf collar (V7), twelve leaf collar (V12), and tasseling (VT)] and reproductive stage [milk (R3)]. Soil samples were collected at four depths in 30 cm increments to 120 cm and four soil cores were composited for one sample per depth, four samples per treatment for each replication to obtain a total of 80 soil samples. Soil samples were collected in between two rows of the sensing area. Plots (sensing area with two rows for 9 m length) were hand-harvested on October 3, 2018, for SCAL18 and October 16, 2019, for the SCAL19 to obtain grain yield. Grain was shelled, weighed, and adjusted to 0.155 g g^{-1} moisture content.

Statistical Analysis

Estimation ONR and Calculation Actual EONR

An estimation of the ONR and calculation of actual EONR for SCAL18 and SCAL19 were required in order to compare it with the EONR predicted by the Maize-N model. The relationship between yield and N rate was determined using polynomial regression. Regression analysis was done using PROC GLIMMIX in Statistical Analysis System (SAS) version 9.4. A lack-of-fit term was used to determine whether orders higher than those stated in the model needed to be included. The quadratic regression model was used to fit the relationship between yield and N rate to determine ONR. Actual EONR was calculated from modeled yield including the cost of 32% UAN which was \$0.90 kg^{-1} for 2018 and \$0.88 kg^{-1} for 2019, and the price of corn which was \$0.14 kg^{-1} for 2018 and \$0.15 kg^{-1} for 2019. Fertilizer cost was subtracted from grain price to determine the partial profit in \$ ha^{-1}. Actual EONR was determined as the N rate with the highest partial profit for both site years.

Evaluation of Maize-N Model Performance

Statistical and graphical methods were used to evaluate the Maize-N model goodness of fit. The root mean square error (RMSE) and the relative root mean square error (RRMSE) were calculated for the statistical evaluation as below:

$$\text{RMSE} = \sqrt{\frac{\sum_{\mathrm{i=1}}^{\mathrm{n}}(\mathrm{Pi-Oi})^2}{n}} \qquad \textbf{[3.1]}$$

$$\text{RRMSE} = \frac{\text{RMSE}}{\bar{\mathrm{O}}} \times 100 \qquad \textbf{[3.2]}$$

where,

Pi is the Maize-N predicted value
Oi is the observed value
n is the number of data pairs
Ō is the mean observed value

The RMSE provides the average difference between predicted and observed values, whereas RRMSE provides the relative difference between predicted and observed values. A lower value of RMSE or RRMSE indicates better model performance. In this study, we considered RRMSE ≤ 15% as “good” agreement; 15–30% as “moderate” agreement; and ≥30% as “poor” agreement (Puntel et al., 2016, 2018; Yin et al., 2020).

Results and Discussion

Estimated ONR and Calculated Actual EONR Compared to Predicted EONR

There was no need to include a cubic term or higher in the analysis since the lack-of-fit (lof) term was not significant with a p-value of 0.4456 and 0.7092 for SCAL18 and SCAL19, respectively (Table 3.4 and Table 3.5).

Table 3.4. Type I Test of Fixed Effects for each term in the quadratic regression model for the SCAL18 site year.

Type I Tests of Fixed Effects				
Effect	**Num DF**	**Den DF**	**F Value**	**Pr > F**
N_rate	1	15	83.02	<.0001
N_rate*N_rate	1	15	33.95	<.0001
lof	2	15	0.85	0.4456

Table 3.5. Type I Test of Fixed Effects for each term in the quadratic regression model for the SCAL19 site year.

Type I Tests of Fixed Effects				
Effect	**Num DF**	**Den DF**	**F Value**	**Pr > F**
N_rate	1	15	225.87	<.0001
N_rate*N_rate	1	15	49.00	<.0001
lof	2	15	0.35	0.7092

Therefore, the regression quadratic predictors can be written as:

$$\hat{Y} = \beta_0 + \beta_1 X + \beta_2 X^2 \qquad \textbf{[3.3]}$$

where,

$\hat{Y}$ is estimated corn yield
X is the N rate
β_0 is the intercept
$\beta_1$is the linear coefficient
β_2 is the quadratic coefficient.

The estimates for the coefficients for SCAL18 and SCAL19 to determine ONR are shown in Table 3.6. The PROC RSREG from SAS was used to determine the optimal value of the N rate. The quadratic model using canonical analysis was used to estimate the N rate value that yields the maximum estimated yield as provided in Equations 3.4 and 3.5.

Table 3.6. The estimates of the coefficients for SCAL18 and SCAL19 sites are shown below:

SCAL18					
Parameter Estimates					
Effect	**Estimate**	**Standard Error**	**DF**	**t Value**	**Pr > |t|**
Intercept	8.8473	0.4016	17	22.02	<.0001
N_rate	0.05143	0.006179	17	8.32	<.0001
N_rate*N_rate	-0.00012	0.000020	17	-5.88	<.0001
Scale	0.6042	0.2072	.	.	.
SCAL19					
Parameter Estimates					
Effect	**Estimate**	**Standard Error**	**DF**	**t Value**	**Pr > |t|**
Intercept	6.2118	0.2625	17	23.66	<.0001
N_rate	0.04543	0.003933	17	11.55	<.0001
N_rate*N_rate	-0.00009	0.000013	17	-7.28	<.0001
Scale	0.2467	0.08461	.	.	.

The equations of the curves for SCAL18 and SCAL19 respectively are given by:

$$\text{Estimated Yield} = -0.00012\,\text{X}^2 + 0.05143\text{X} + 8.8473 \qquad \textbf{[3.4]}$$

$$\text{Estimated Yield} = -0.00009\,\text{X}^2 + 0.04543\text{X} + 6.2118 \qquad \textbf{[3.5]}$$

where X is the N rate.

An estimation of the ONR and calculation of actual EONR were required in order to compare with predicted EONR using the Maize-N model for SCAL18 and SCAL19 site years. The relationship between yield and N rate was fitted using the quadratic regression model as shown in Figure 3.2. The quadratic model well-described corn grain yield response to N fertilizer rate. The ONR estimated using the quadratic model and actual EONR using the modeled yield were compared to the EONR predicted by the

Maize-N model which represents the N rate applied for SCAL18 and SCAL19 (Table 3.2). The ONR values were estimated as the N rate needed to achieve maximum yield. Whereas the EONR values were calculated as the optimum economic N rate from modeled yield with fertilizer cost and corn price as inputs as same as fertilizer cost and corn price used to predict EONR by Maize-N. Therefore, the N rate recommendations for calculated actual EONR or predicted EONR were generally lower than the N rate recommendations for ONR.

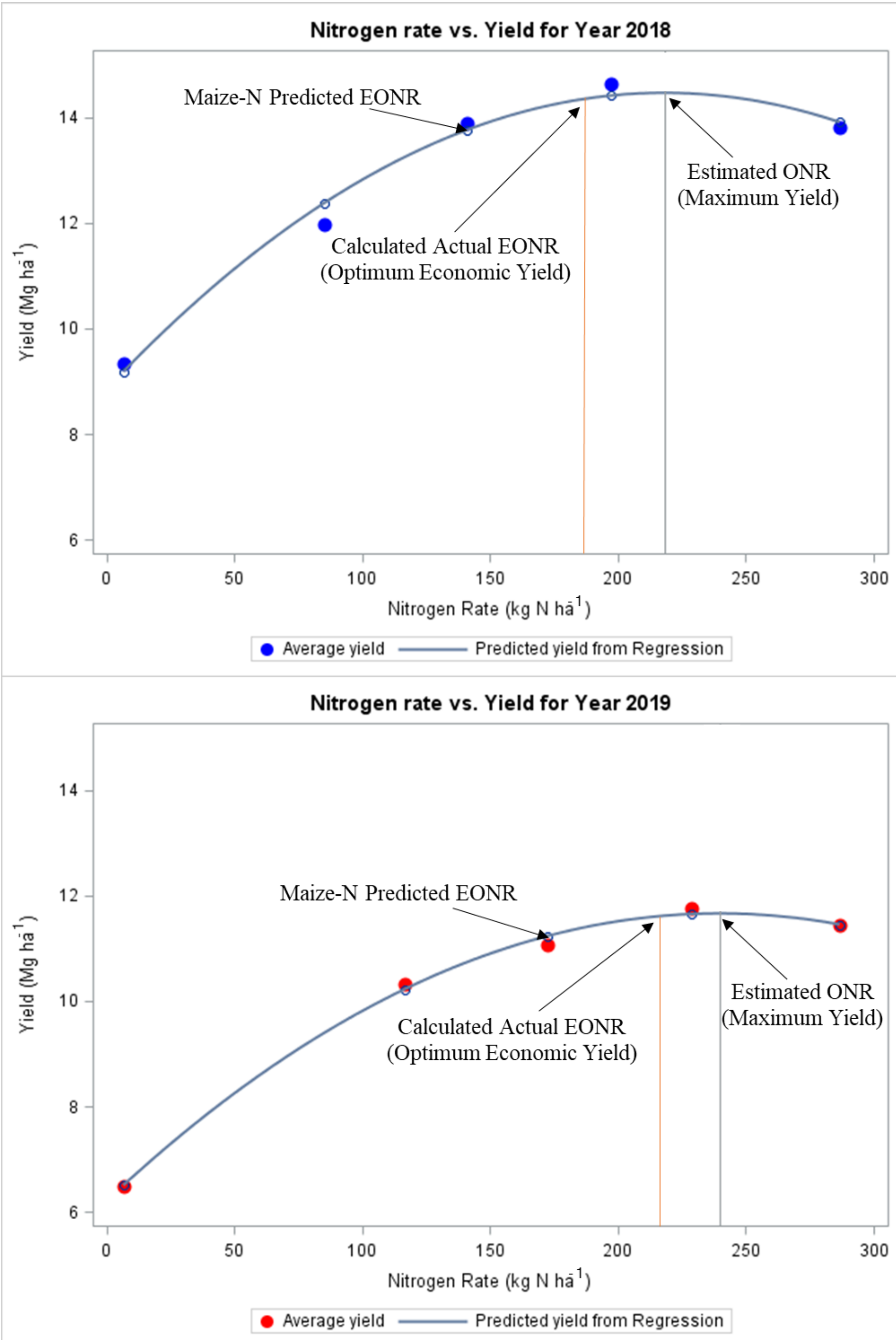

Figure 3.2. Corn grain yield response to N fertilizer rate for five treatments (Check, P-SD- model minus 56, P-SD-model rate, P-SD-model plus 56, and reference respectively). The vertical lines represent estimated ONR derived using the quadratic model, calculated actual EONR from modeled yield, and Maize-N predicted EONR including fertilizer cost and corn price for SCAL18 (Top) and SCAL19 (Bottom).

The EONR predicted by Maize-N as shown in Table 3.2 and Figure 3.2 (141 kg ha^{-1} for SCAL18 and 172 kg ha^{-1} for SCAL19) was compared with the ONR estimated by the quadratic model (218 kg ha^{-1} for SCAL18 and 239 kg ha^{-1} for SCAL19) (Figure 3.2) and with actual EONR calculated from modeled yield (187 kg ha^{-1} for SCAL18 and 220 kg ha^{-1} for SCAL19) (Figure 3.2).

The EONR predicted by Maize-N underestimated N recommendation compared to the estimated ONR by -77 and -67 kg N ha^{-1} for SCAL18 and SCAL19, respectively, and to the calculated actual EONR, by -46 and -48 kg N ha^{-1} for SCAL18 and SCAL19, respectively. A similar result was noted by Ransom et al. (2020) that the Maize-N model underestimated N recommendation by -70 kg ha^{-1} compared to EONR across 49 sites in US Corn Belt. In contrast, Thompson et al. (2015) reported that the EONR predicted by the Maize-N model closely estimated ONR when data was combined across 12 sites. They concluded that the Maize-N model tended towards the over-application of N. However, in this study, although there were no significant differences in the yields for calculated actual EONR, predicted EONR, and estimated ONR, the Maize-N predicted EONR reduced profit by 36 \$ ha^{-1} and 20 \$ ha^{-1} for SCAL18 and by 31 \$ ha^{-1} and 26 \$ ha^{-1} for SCAL19 compared to calculated actual EONR and estimated ONR, respectively.

Yield Response to Treatments

Grain yield tended to increase with the N rate, but not significantly. Yield with EONR predicted by the model was not different from the yield with model plus 56 kg N ha^{-1} and reference treatments as shown in Table 3.7. In general, the average corn yield for SCAL18 was higher for all N treatments compared to the average corn yield for SCAL19 (Table 3.7) due to hail and wind damage at the R2 growth stage in 2019 that affected yield.

Table 3.7. Site year, treatment, and yield for SCAL18 and SCAL19 site years. Means followed by the same letter are not significantly different at P≤0.05.

Site Year	Treatment	Yield (Mg ha^{-1})
SCAL18	**Check**	9.3 c
	P-SD-model -56	12.0 b
	P-SD-model	13.9 a
	P-SD-model +56	14.6 a
	Reference	13.8 a
SCAL19	**Check**	6.5 c
	P-SD-model -56	10.3 b
	P-SD-model	11.1 ab
	P-SD-model +56	11.8 a
	Reference	11.5 a

Monitoring Crop N Status

The SPAD CM sensor was used to monitor the crop and detect crop N status during the growing season. It was used to determine if additional N application was needed based on the sensor sufficiency index (SI) information that was computed during the growing season. No additional N needed since the SPAD SI values were above the threshold of 0.95 through the growing season until the R5 growth stage for SCAL18 and until the R3 growth stage for SCAL19. Earlier studies have shown that when the SI is above 0.95, there is little likelihood of yield increase with additional N. Also, applying additional N after R3 was not recommended as N application doesn't coincide with the period of rapid N uptake that results in a greater risk of N loss (Shanahan et al., 2008). These results supported the Maize-N prediction of EONR for both site years, with no need for in-season N.

Observed and Predicted Total N Uptake Comparison

The difference in observed and predicted total N uptake were derived for each growing season, then analyzed for correlation. Differences between predicted and observed values were treated as repeated measures. A linear regression of differences with an autoregressive (AR(1)) covariance structure was used to account for the repeated measures. The regression model was then used to construct 95% confidence intervals for each day that the plant N uptake and soil nitrate-N were measured.

Differences between observed and predicted crop N uptake gradually increased with time from the V12 growth stage to the R6 growth stage for SCAL18 (Figure 3.3 A). For SCAL19, the differences between predicted and observed N uptake did not have a consistent pattern for all growth stages (Figure 3.3 B). For SCAL18, the Maize-N underpredicted N uptake compared to observed N uptake for all growth stages. The model-predicted N uptake showed a significant difference from the observed N uptake values for all growth stages (V12, R1, R3, R5, and R6) except at the early growth stage (V8) as shown in Figure 3.3 A. For SCAL19, the model predicted N uptake slightly overestimated observed N uptake. The model predicted N uptake showed a non-significant difference from the observed N uptake values across all growth stages as shown in Figure 3.3 B.

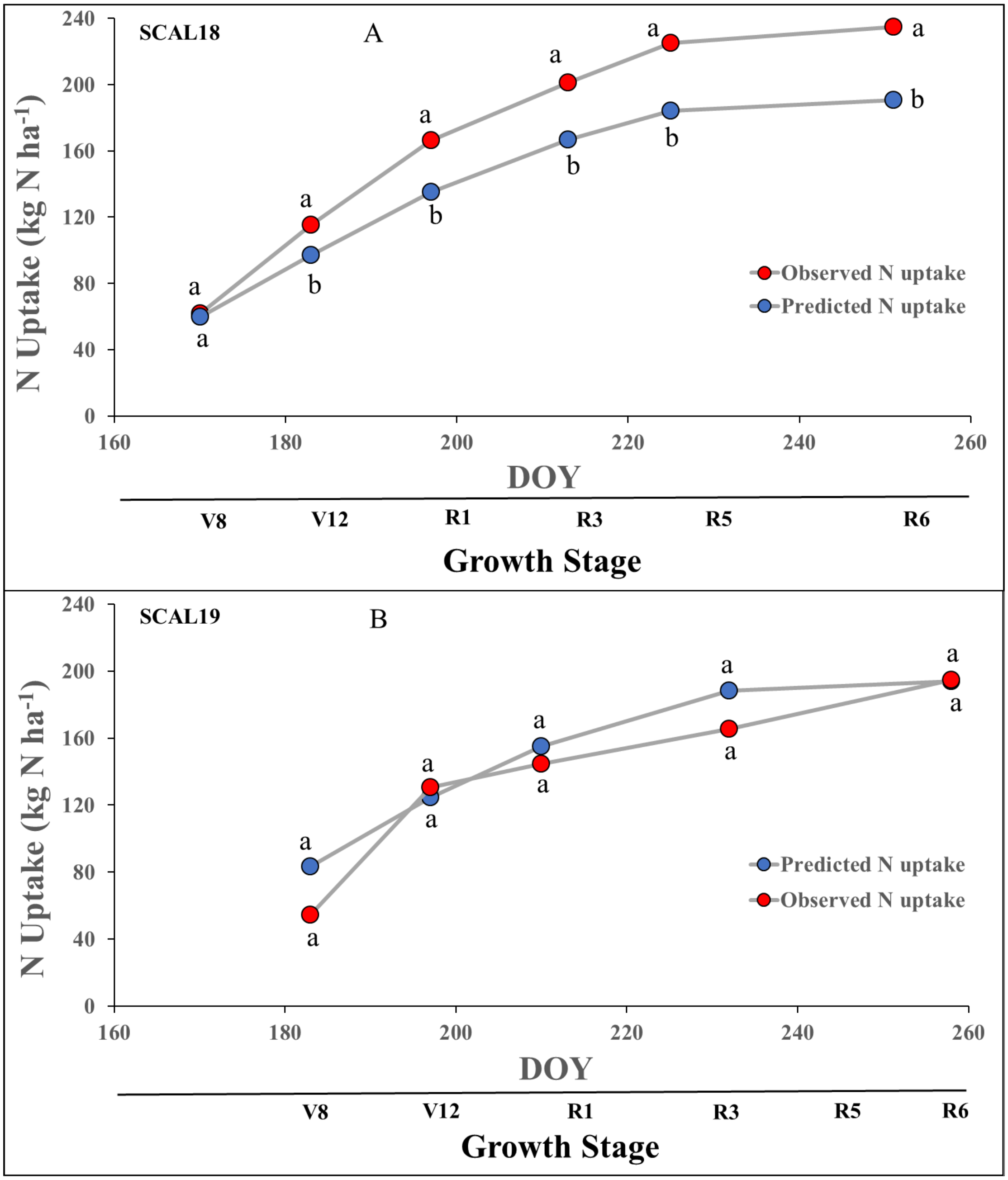

Figure 3.3. Predicted and observed N uptake for uncalibrated model treatment for SCAL18 (A) (n = 6) and SCAL19 (B) (n = 5) at V8, V12, R1, R3, R5, and R6 growth stages. Different letters indicate a significant difference from each other at the 95% confidence limits (alpha = 0.05).

Figure 3.4 shows the relationship between predicted and observed N uptake for the uncalibrated Maize-N model for SCAL18 and SCAL19 site years. The Maize-N model explained 99% and 92% of the observed variability in N uptake for SCAL18 and SCAL19, respectively. The model predicted N uptake underestimated N uptake for SCAL18 and overestimated N uptake for SCAL19. The difference in N uptake between predicted and observed values were larger for SCAL18 (RMSE= -31.9 kg N ha^{-1}) than SCAL19 (RMSE= 17.5 kg N ha^{-1}). Thus, a moderate agreement between predicted and observed N uptake was observed for SCAL18 (RRMSE= 19.1%) and good agreement was observed for SCAL19 (RRMSE= 12.7%) as shown in Figure 3.4. Overall results showed that the Maize-N model over the two years underestimated N uptake, with the difference in N uptake between predicted and observed values as RMSE was -24.7 kg N ha^{-1}. Consequently, the overall model showed moderate agreement (RRMSE 15.9%) between predicted and observed N uptake. Similar results were also reported from other crop model N uptake predictions (Setiyono et al., 2010). They showed that the RMSE was 37 kg N ha^{-1} between predicted and observed values and RRMSE was 15%, which is considered good agreement, similar to the overall RRMSE across two site years in the current study.

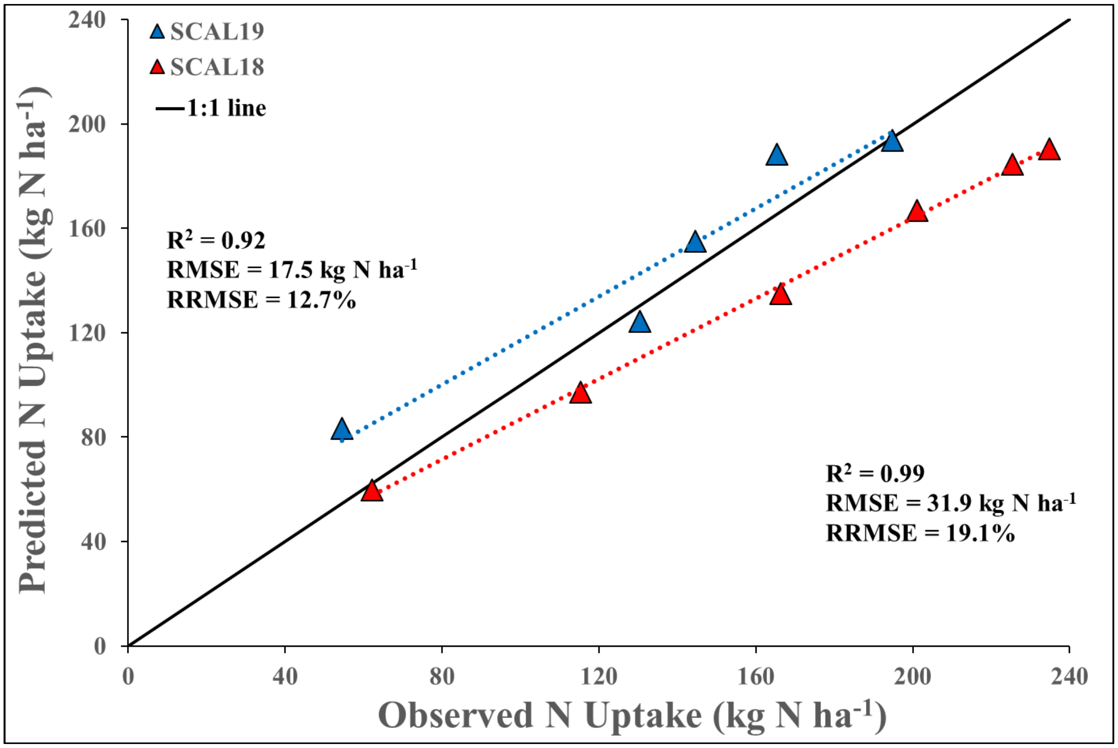

Figure 3.4. Predicted versus observed N uptake for uncalibrated model treatment. The coefficient of determination (R^2), root mean square error (RMSE), and relative root mean square error (RRMSE) are for SCAL18 (n = 6) and SCAL19 (n = 5). The dashed line is the linear regression and the continuous line is a 1:1 relationship.

Refining Model N Uptake Prediction using Sensor Information

Crop sensor information was used in order to refine the Maize-N model N uptake prediction. Based on a statistical analysis of the Type III Tests of Fixed Effects (Table 3.8), the p-values for SPAD and NDRE measurements were 0.3066 and 0.5740, respectively. These p-values indicate that treatments had no significant effect on SPAD or NDRE measurements, and therefore this information cannot be used to refine model predictions, at least for this study. This non-significant result could have arisen from the low number of observations used in the analysis. Increasing the number of observations is recommended to have a more powerful test to detect an effect for sensor measurements.

Table 3.8. Type III Test of Fixed Effects for site year, SPAD, and NDRE for the SCAL18 and SCAL19 site years.

Type III Tests of Fixed Effects				
Effect	**Num DF**	**Den DF**	**F Value**	**Pr > F**
SiteYear	1	5	10.33	0.0236
SPAD	1	5	1.30	0.3066
NDRE	1	5	0.36	0.5740

Observed and Predicted Soil Nitrate-N Before and After Calibration Comparison

Figure 3.5 and Figure 3.6 show observed and predicted soil nitrate-N for the uncalibrated and calibrated Maize-N model at the R6 growth stage (maturity) for SCAL18 and SCAL19. For SCAL18, the uncalibrated model prediction of soil nitrate-N differed from observed soil nitrate-N values for all growth stages. (Figure 3.5 A). For the calibrated model, the prediction of soil nitrate-N differed from the observed nitrate-N for all growth stages except the V8 growth stage. (Figure 3.5 B).

For SCAL19, the uncalibrated model prediction of soil nitrate-N differed from observed soil nitrate-N for all growth stages except the R3 growth stage (Figure 3.6 C). For the calibrated model, the model prediction of nitrate-N was not significantly different from the observed nitrate-N for all growth stages (Figure 3.6 D).

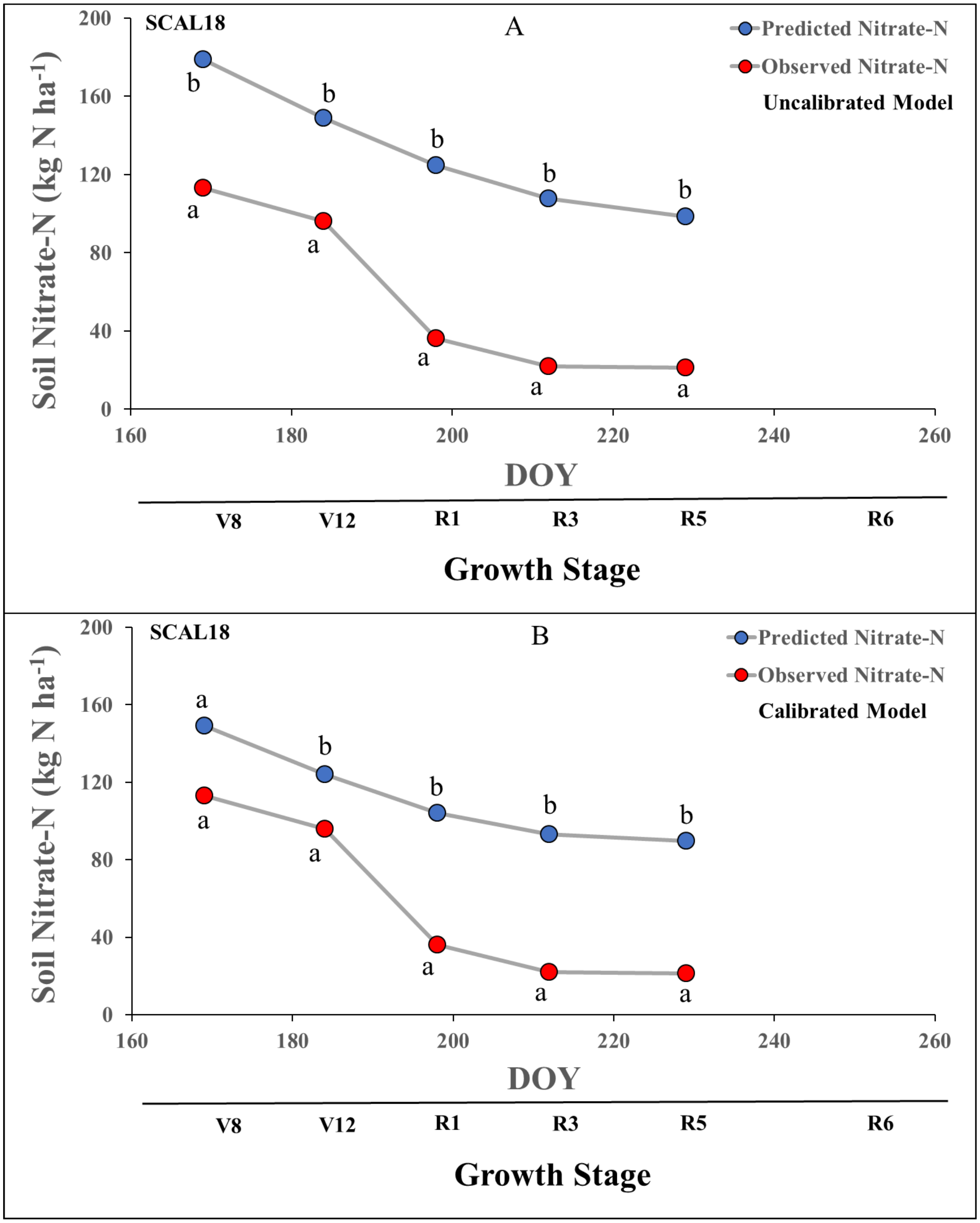

Figure 3.5. Predicted and observed soil nitrate-N for model treatment for SCAL18 (n = 5) at V8, V12, R1, R3, and R5 growth stages. Uncalibrated (A) and calibrated (B) model prediction at R6. Different letters indicate a significant difference at the 95% confidence limits (alpha = 0.05).

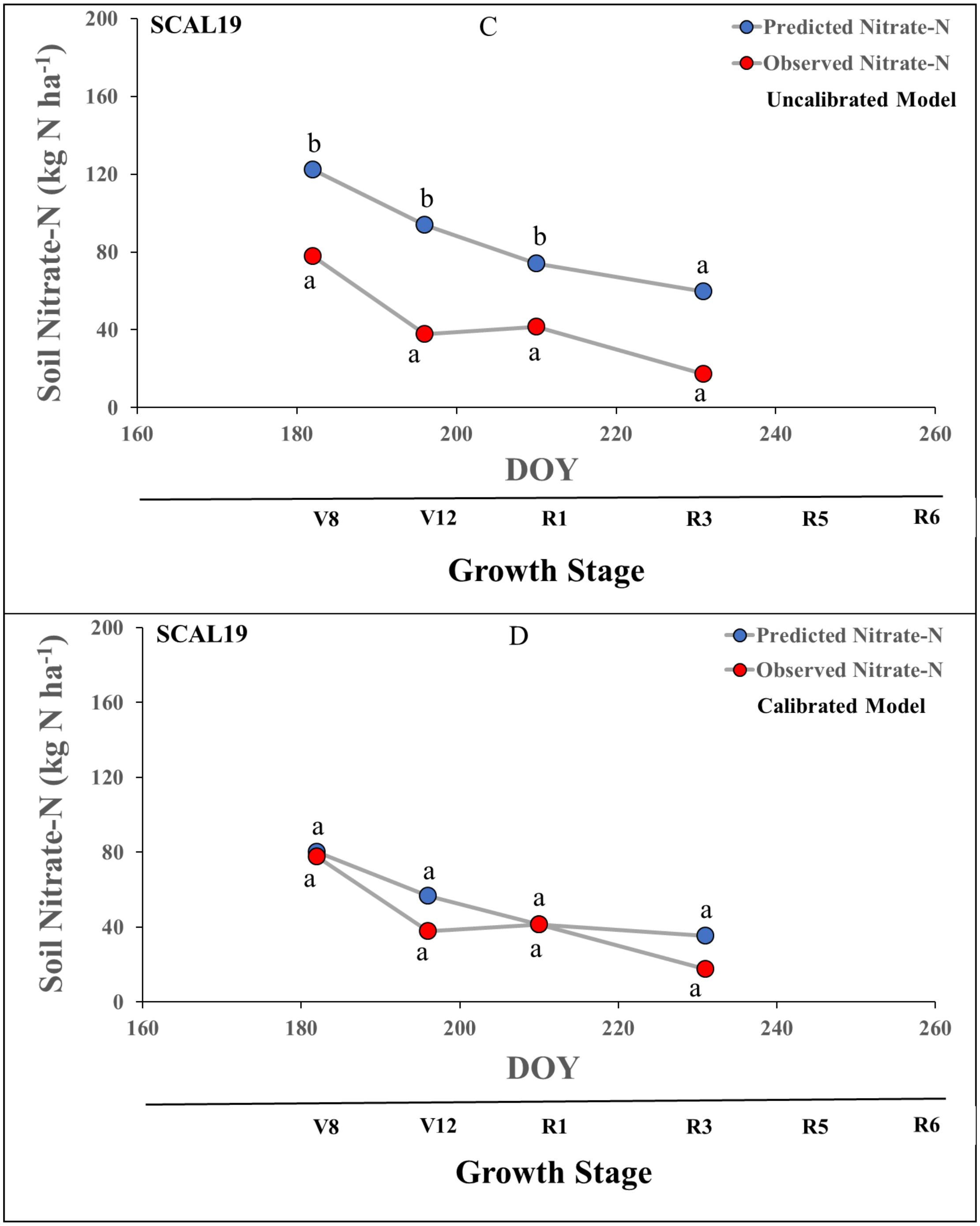

Figure 3.6. Predicted and observed soil nitrate-N for model treatment for SCAL19 (n = 4) at V8, V12, R1, and R3 growth stages. Uncalibrated (C) and calibrated (D) model prediction at R6. Different letters indicate a significant difference at the 95% confidence limits (alpha = 0.05).

Figure 3.7 shows the relationship between observed and predicted available soil nitrate-N for the uncalibrated and calibrated Maize-N model at the R6 growth stage for SCAL18 (top) and SCAL19 (bottom) site years. The Maize-N model explained 93% of variation in soil nitrate before calibration and 94% of variation in soil nitrate after calibration for SCAL18. For SCAL19, the Maize-N model explained 87% of variation in soil nitrate before calibration and 85% of the variation in soil nitrate after calibration.

Soil nitrate-N was overestimated by Maize N for both SCAL18 and SCAL19 site years. The differences in soil nitrate-N between predicted and observed values were greater before calibration than after calibration. For SCAL18, the RMSE ranged from 75.3 kg N ha^{-1} before calibration to 57.4 kg N ha^{-1} after calibration (Figure 3.7). For SCAL19, the RMSE ranged from 44.7 kg N ha^{-1} before calibration to 13 kg N ha^{-1} after calibration (Figure 3.7). Model predictions before and after calibration showed poor agreement (RRMSE >30%) for all uncalibrated and calibrated model predictions except the calibrated model for SCAL19, that showed moderate agreement (RRMSE <30%) as shown in Figure 3.7. The overall RMSE for both years reduced from 60 kg N ha^{-1} before calibration to 35.2 kg N ha^{-1} after calibration. Overall model prediction agreement as RRMSE improved from 116.6% before calibration to 64.7% after calibration.

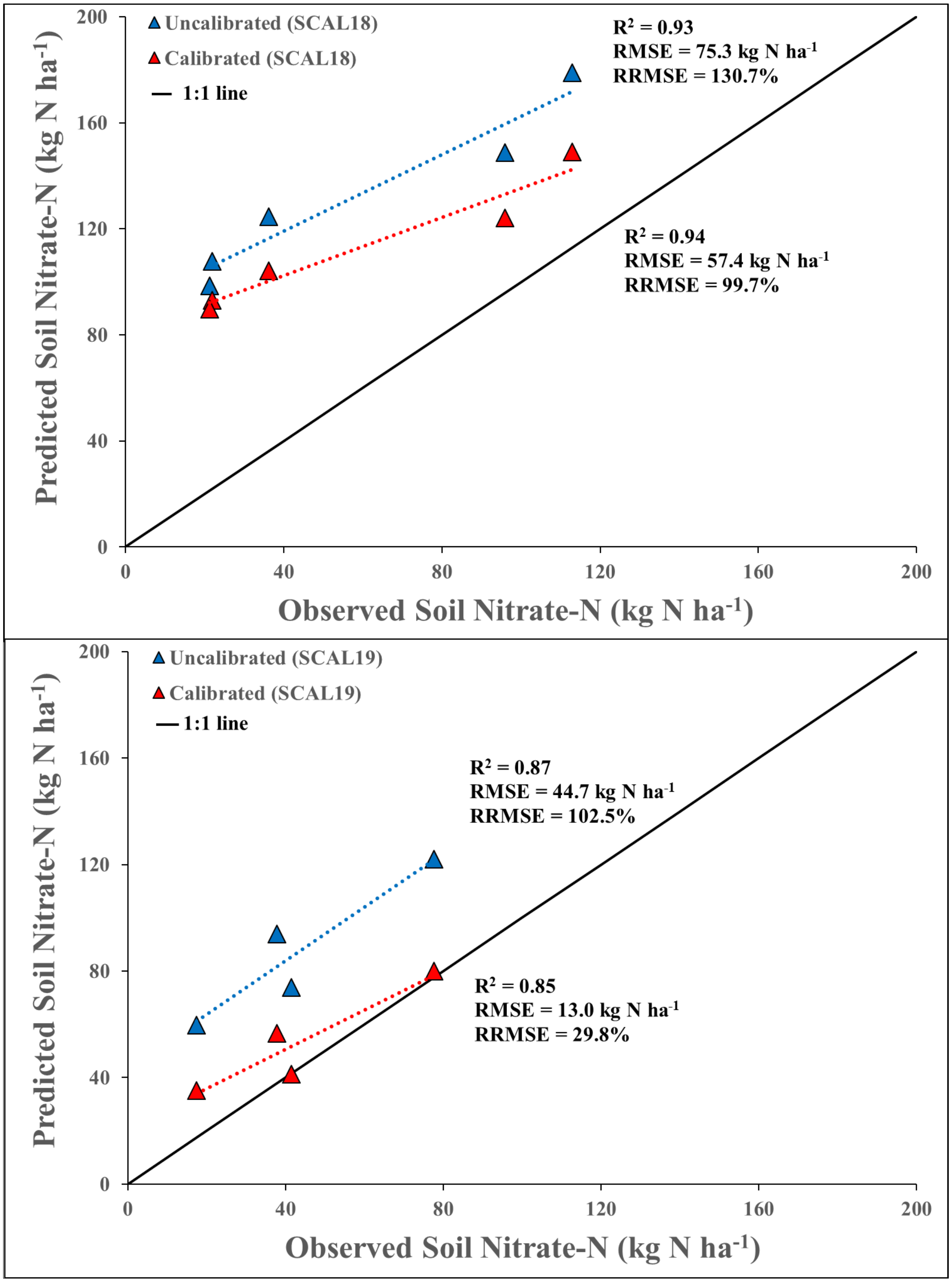

Figure 3.7. Predicted versus observed soil nitrate-N for an uncalibrated and calibrated model for SCAL18 (n=5) (top) and uncalibrated and calibrated model for SCAL19 (n=4) (bottom). The coefficient of determination (R^2), root mean square error (RMSE), and relative root mean square error (RRMSE) for both site years. The dashed line is the linear regression and the continuous line is the 1:1 relationship.

Factors Affecting N Mineralization (Soil Nitrate-N)

Maize-N model prediction of soil nitrate-N is based on mineralization of SOM. The amount of nitrate-N mineralized depends on the amount of SOM, the C: N ratio of SOM, and environmental factors such as temperature and moisture (Janssen, 1996; Leiros et al., 1999; Watson C.A. et al., 2002; Yin et al., 2020). In general, when the SOM of the site increases, predicted N mineralization increases (Myrold and Bottomley, 2008). In this study, SOM was the same for both SCAL18 and SCAL19 site years, with similar average daily air temperature. However, SCAL19 received approximately 93.6 mm more precipitation than SCAL18 during the growing season. Thus, N mineralization was expected to vary by year even when the SOM content was the same, since precipitation influences N mineralization and N loss (Thompson et al., 2015). The above-average precipitation for May and June for SCAL19 likely increased N loss, reduced N supply, and resulted in a higher EONR (Rutan and Steinke, 2017). The model-estimated EONR for SCAL19 was higher than SCAL18 by 31 kg N ha^{-1}. The N mineralization from SOM for SCAL19 was lower than in SCAL18 by 27 kg N ha^{-1}, and residual nitrate-N for SCAL19 was higher than in SCAL18 by 15 kg N ha^{-1}.

Results from the uncalibrated and calibrated model prediction showed that the predicted soil nitrate-N was overestimated for SCAL18 and SCAL19 site years (Figure 3.7). In contrast, Maize-N underestimated N mineralization in a similar study conducted across 12 site years (Thompson et al., 2015). In this study, after calibration, the differences in soil nitrate-N between predicted and observed values as RMSE were reduced by 17.9 kg N ha^{-1} for SCAL18 and by 31.7 kg N ha^{-1} for SCAL19. As a result, model prediction agreement as RRMSE improved by 31% for SCAL18 and 72.7% for

SCAL19. The overall RMSE over both site years was reduced by 24.8 kg N ha^{-1} with calibration; thus the overall model prediction agreement over both site years was improved by 51.9%.

The improvement in Maize N prediction of soil nitrate-N resulted from using actual values of specific input parameters instead of estimates. These included actual bulk density at a depth of 30 cm instead of estimated bulk density at a depth of 20 cm, and measured SOM for the top of 30 cm instead of measured SOM for the top 20 cm. Also, the calibrated model used the measured ratio of subsoil to topsoil SOM. Finally, the measured soil temperature (average of 15-106 cm depth) was used during the growing season from mid-June to the end of the season for each site year instead of air temperature. The use of measured soil temperature during the growing season with an uncalibrated model prediction at R6 reduced the differences in soil nitrate-N between predicted and observed values as RMSE by 3.4 kg N ha^{-1} and 6.9 kg N ha^{-1} for SCAL18 and SCAL19, respectively. Differences between predicted and observed soil nitrate-N improved by 5.9 and 15.9% for SCAL18 and SCAL19, respectively. The improvements of the RMSE and RRMSE between predicted and observed soil nitrate-N were higher for SCAL19 than for SCAL18 due to the effect of using soil temperature data for two growing seasons than using soil temperature for one growing season.

Conclusion

The Maize-N model was tested and evaluated for EONR, N uptake, and soil nitrate-N predictions. This study showed that Maize-N is a useful tool for the prediction of EONR and crop N uptake. The study provided evidence that the use of the calibrated Maize N model (using measured soil temperature, measured soil bulk density, measured SOM for the top 30cm, and the measured ratio of SOC in subsoil to topsoil) can improve the ability of Maize N to predict soil nitrate-N during the growing season. The Maize-N predicted EONR underestimated N rate recommendations by 46 kg N ha^{-1} for SCAL18 and by 48 kg N ha^{-1} for SCAL19 compared to the calculated actual EONR, but with no significant differences in the yield. However, the Maize-N predicted EONR reduced profit by 36 \$ ha^{-1} for SCAL18 and by 31 \$ ha^{-1} for SCAL19 compared to the calculated actual EONR. Crop N uptake errors were within the range of -31.9 for SCAL18 to +17.5 kg N ha^{-1} for SCAL19. Over the two site years combined, the model slightly underestimated observed N uptake with root mean square error (RMSE) of -24.7 kg N ha^{-1} and agreement as relative root mean square error (RRMSE) of 15.9%. Crop sensor information was useful to monitor crop N status, but could not be used to refine model N uptake prediction for this study. For soil nitrate-N, Maize N overestimated soil nitrate-N for both SCAL18 and SCAL19 site years. The calibrated Maize-N model reduced RMSE of soil nitrate-N prediction by 17.9 kg N ha^{-1} for SCAL18 and by 31.7 kg N ha^{-1}. The overall RMSE of soil nitrate-N prediction over two years was reduced by 24.8 kg N ha^{-1}. Additionally, the calibrated Maize-N model improved RRMSE agreement of soil nitrate-N prediction by 31% for SCAL18 and by 72.7% for SCAL19. The overall RRMSE of soil nitrate-N prediction improved by 51.9%.

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Chapter 4: Can an Active or Passive Crop Canopy Sensor Replace the SPAD Meter for Scheduling Fertigation?

Introduction

Applying a portion of N fertilizer during the growing season has the potential to improve N use efficiency (NUE) by attaining greater synchrony between N supply and crop N demand, and allows for responsive adjustments to actual field conditions (Thompson et al., 2015; Thompson and Puntel, 2020). Thus, in-season assessment of plant N status is an important component of N management to adjust additional N requirements. Various sampling techniques have been used to assess plant N status, such as destructive plant tissue testing (Fox and Walthall, 2008) and non-destructive measuring of crop canopy light reflectance using a crop sensor. A non-destructive reactive approach using a crop sensor has the potential to provide a rapid, larger sample size that is a more inexpensive and accurate technique than destructive sampling to monitor crop N status (Morris et al., 2018; Naser et al., 2020). Crop canopy reflectance can be used to detect N status using a crop sensor during the growing season. Because the majority of leaf N is contained in chlorophyll molecules, a strong linear relationship exists between leaf chlorophyll content and leaf N content (Shaver et al., 2010; Schmidt et al., 2011). As a result, a non-destructive reactive approach focused on using crop sensors to quantify leaf chlorophyll content to assess crop N status. Reactive approach-based crop sensors can be effective indicators of in-season crop N need that integrate crop growing conditions including weather effects on the crop from the time of planting to near the time of sensing (Thompson et al., 2015).

The SPAD (Soil and Plant Analysis Development) meter measures the light transmittance properties of leaves in two wavelengths (650 and 940 nm) (Solari et al., 2008), which is strongly correlated with leaf chlorophyll content (Samborski et al., 2009). Several studies have shown that the SPAD meter can be used as a tool to provide rapid and nondestructive estimates of crop chlorophyll content and N status through the entire corn growing season as a simple to use, reliable, and accurate tool to detect N deficiency (Al-Abbas et al., 1974; Scharf and Lory, 2006; Varvel et al., 2007; Scharf et al., 2011), which eliminates plant tissue sampling to quantify N content (Blackmer and Schepers, 1995). Although the SPAD meter has the potential to provide a rapid in-season assessment of crop N status to recommend additional N fertilizer, one shortcoming is that the SPAD meter measurements are taken by hand and for specific plants, making this a non-realistic approach for variable rate N management at the field level. Additionally, the SPAD meter approach is labor-intensive and time-consuming with smaller sample sizes than canopy reflectance sensors or aerial imagery.

Proximal and remote sensing have been used extensively for in-season N management that provides an estimate of crop N status over a large field area that accounts for spatial variability and efficiently supports decisions on N supplements (Morris et al., 2018; Thompson and Puntel, 2020). Canopy light reflectance properties can be measured by proximal sensors (active sensors) or by passive sensors mounted on an aerial platform. As a result, both active and passive crop canopy sensors can monitor and assess plant N status through the growing season.

Passive sensors use sunlight as their energy source and measure reflected light from the target emitted from the sun (Souza et al., 2017). Passive sensors can be carried and used by satellites, aircraft, and drones to obtain agricultural imagery. Several studies have shown that useful information such as crop N status can be obtained from crop canopies with passive sensors mounted on satellite or airborne platforms (Inman et al., 2005; Shaver et al., 2010, 2014; Erdle et al., 2011; Krienke et al., 2017; Thompson and Puntel, 2020). Unmanned aerial vehicles (UAV) have lately become a common platform for carrying and using passive sensors for agricultural research to estimate crop biomass and detect crop N stress. However, the angles of the sun, time of daylight, and cloud cover will influence reflectance and vegetation indices measured from the corn canopy (Souza et al., 2010). Consequently, UAV passive sensors require calibration and specialized software to analyze and interpret imagery.

Active sensors were developed to overcome passive sensors' limitations and minimize the impacts of ambient light conditions on crop canopy reflectance readings (Tubaña et al., 2011). Active sensors have their own energy source and measure reflected light from the target emitted from the sensor; thus they require close proximity to the target (Thompson and Puntel, 2020). As a result, active sensors can be used at any time of day or night as they are not affected by ambient radiation (Naser et al., 2020). They are relatively inexpensive, easy to use, and small enough to mount on a fertilizer application boom or tractor and low flying UAV (0.5-1.5 m) (Krienke et al., 2017). Thus, the use of small platforms, such as active sensors (on-the-go) on the N applicator can immediately provide information to assess corn N status and apply varying N rates based on real-time reflectance data.

Passive and active crop canopy sensor reflectance values in two or more wavelengths are expressed as vegetation indices (VIs) that were developed to link reflectance from leaves or canopies with canopy characteristics (Hatfield et al., 2008).

One of the most widely adopted VIs is the normalized difference vegetative index (NDVI) proposed by Rouse et al. (1974) to estimate canopy biomass. Another index, the normalized difference red-edge (NDRE) index suggested by Buschmann and Nagel (1993), is a reliable indicator of chlorophyll or N status because it is not subject to red waveband saturation as with NDVI when leaf area index is greater than three (Thompson et al., 2015; Naser et al., 2020). To monitor and compare crop N status across the field, normalizing the VIs of the target crop to the VIs of the field area receiving non-limiting N is required to calculate the N sufficiency index (SI) (Blackmer and Schepers, 1995; Thompson and Puntel, 2020).

Several studies have compared how different active crop canopy sensors can be used to detect crop N status (Barker and Sawyer, 2010; Shaver et al., 2010, 2011, 2014; Cao et al., 2015; Nogueira Martins et al., 2020), while a few studies have compared active sensors to passive sensors (Hong et al., 2007; Erdle et al., 2011). No previous studies have compared active or passive crop canopy sensors with SPAD meter based on SI to detect the onset of N stress in the crop canopy in time (weekly) to supplement N through the irrigation system (fertigation).

The overall goal of this study was to evaluate the possibility of replacing the SPAD meter by utilizing an active or passive crop canopy sensor-based SI to inform the decision of when to fertigate. The specific objectives were (i) to assess the correlation between active or passive crop canopy sensors and the SPAD meter based on sufficiency index (SI) values from V6 through R2 growth stages, and (ii) to determine the frequency of decisions that matched between active or passive crop canopy sensors and SPAD meter based on SI 0.95 thresholds from V6 through R2 growth stages

Materials and Methods

Site Description

This study was conducted at two sites over two growing seasons (2017 and 2018) at University of Nebraska-Lincoln research sites: (i) South Central Agriculture Laboratory (SCAL), near Clay Center, Nebraska, USA, referred to as SCAL17 and SCAL18 site years, respectively (ii) West Central Research and Extension Center (WCREC) North Platte, Nebraska, USA, and referred to as WCREC17 and WCREC18 site years, respectively. The geo-coordinates of the fields were latitude 40° 34' 50.4114" N and 40° 34' 50.4726" N, longitude -98° 8' 41.118" W and -98° 8' 40.7688" W for SCAL2017 and SCAL18, respectively. For WCREC17 and WCREC18, the geo-coordinates of the fields were latitude 41° 5' 22.8552" N and 41° 5' 22.8834" N, longitude -100° 45' 42.3714" W and -100° 45' 40.6836" W.

The soil for both SCAL17 and SCAL18 fields was classified as Hasting silt loam (fine, montmorillonitic, mesic Udic Argiustolls) soil series with 0 to 1 percent slopes (Hammer et al.,1981). The location of the SCAL sites was characterized as a transition zone between sub-humid and semi-arid climates, with the total precipitation received during the crop growing season from April 1 to September 30 of 451 mm for SCAL17 and 506 mm for SCAL18. The total precipitation received during the 2017 growing season of the same period was less than the thirty-year historical average (493 mm) and higher than the thirty-year historical average during the 2018 growing season. The average daily temperature was 18.98°C and 18.88°C for SCAL17 and SCAL18, respectively, the average temperature for both site years was slightly higher than the thirty-years historical average (18.76 ^{o}C). The average relative humidity was 69.62% and 74.60% for SCAL2017 and SCAL18 respectively (HPRCC, 2019).

The soil for both WCREC17 and WCREC18 sites was classified as Cozad silt loam (fine, silty, mixed, mesic Typic Haplustolls) soil series with 0 to 1 percent slopes (Bowman et al., 1978). The location of the WCREC sites was characterized as a semi-arid climate, with average precipitation received during the crop growing season from April 1 to September 30 of 457 mm for WCREC17 and 453 mm for WCREC18. The total precipitation received during the two growing seasons of the same period was higher than the thirty-year historical average (376 mm). The average daily temperature was 18.37^{o}C and 17.72^{o}C for WCREC17 and WCREC18 site years, respectively. The average temperature for WCREC17 was slightly less than the thirty-years historical average (17.95^{o}C) and higher than the thirty-year historical average for WCREC18. The average relative humidity was 61.41% and 65.65% for WCREC17 and WCREC18, respectively (HPRCC, 2019).

Soil samples were collected at each site each year to characterize soil chemical properties. Initial spring soil samples for the topsoil layer (0-20 cm) were composited from four to six soil cores to obtain one sample and two samples for each replication with a total of 8 soil samples for each site. A summary of soil properties for the topsoil layer and previous crop for both site years are presented in Table 4.1.

Table 4.1. Summary of soil properties for spring soil samples acquired at depths of 0-20 cm for SCAL and WCREC sites in 2017 and 2018.

Site Year ID	Soil Texture	pH†	SOM‡ %	CEC* meq $100g^{-1}$	NO_3-N⋆ mg kg^{-1}	P-M3$^{\delta}$ mg kg^{-1}	K§ mg kg^{-1}	Previous crop
SCAL17	SiL⁺	6.8	3.4	15.0	8.3	29.3	360.4	soybean
WCREC17	SiL	7.9	2.0	17.8	7.0	53.1	516.4	soybean
SCAL18	SiL	6.6	3.3	15.8	11.8	32.6	334.3	corn
WCREC18	SiL	7.8	2.1	17.2	8.5	49.4	451.9	soybean

⁺SiL is silt loam, †pH is 1:1 soil: water, ‡SOM is soil organic matter LOI %, *CEC is cation exchange capacity, ⋆NO_3-N is nitrate-nitrogen, $^{\delta}$P-M3 is Mehlich-3 soil phosphorus, §K is potassium extracted by 1 N ammonium acetate.

Experimental Design

This study was a part of a large fertigation project. The experimental design was a randomized complete block design with four treatments and four replications for each site each year. For the SCAL site years, individual plots were 6.1 m wide by 36.6 m length with eight maize rows with 0.76 m row width between rows. Dimensions of individual plots for the WCREC site were 12.2 m wide by 27.9 m length with sixteen rows for WCREC17 and 10.7 m wide by 32 m length with fourteen rows for WCREC18 with 0.76 m row width between rows for both site years. Corn was planted at a population of 84,000 plants ha^{-1} using Hybrid Fontanelle 6A327RBC on April 24 and May 2 for SCAL17 and SCAL18, respectively, and on May 8 for both WCREC17 and WCREC18 site years.

Other than N fertilizer treatment, all other agronomic activities, including pest control were managed according to the University of Nebraska Extension Guidelines (Shapiro et al., 2019). The SCAL sites were irrigated with a linear sprinkler irrigation system while the WCREC sites were irrigated with a center-pivot irrigation system. Both irrigation systems were used for applying irrigation water and were capable of applying N fertilizer to crops through irrigation water (fertigation). Irrigation management was conducted according to the method developed by Irmak et al. (2005). Irrigation timing and amount were determined from a combination of soil moisture content and crop growth stage monitoring with the use of a Watermark soil moisture sensor (model 200SS) with a range of measurements from 0-239 (kPa) (IRROMETER Company, Inc., Riverside, CA, USA) for SCAL site years. For WCREC site years, irrigation timing and amount were determined using a neutron moisture meter (model CPN 503DR Hydroprobe) (Campbell Pacific Nuclear International Inc., Concord, CA, USA). For all site years, fertilizer was applied according to UNL extension guidelines (Shapiro et al., 2019).

Starter fertilizer was applied as ammonium polyphosphate 10-34-0 (NPK) (6.5 kg N ha^{-1} and 22 kg P_2O_5 ha^{-1}) and 0.32 kg ha^{-1} 20% Zn for both SCAL site years. For the WCREC site, starter fertilizer was also applied as ammonium polyphosphate 10-34-0 (NPK) (6.5 kg N ha^{-1} and 22 kg P_2O_5 ha^{-1}) and phosphorus applied to plots deficient in soil test P as triple superphosphate ranged between 83 to 184 kg ha^{-1} using a dry fertilizer spreader (Barber Engineering Company, Spokane, WA, USA) in 2017 only) (Table 4.2). The fertilizer was banded over the seed via the planter in both site years.

Four treatments were evaluated as new N management practices in Nebraska. The treatments were categorized as a calibration treatment and three reactive treatments. A non-N limiting reference treatment was used as a calibration treatment to determine the relative N sufficiency status by normalizing sensor data and calculating the relative sufficiency index (SI) of target treatments (Blackmer and Schepers, 1995) as shown in equation 4.1. The SI is calculated as follows:

$$\boldsymbol{SI} = \frac{\textbf{VI Target}}{\textbf{VI Reference}} \qquad \textbf{[4.1]}$$

Where,

SI is sufficiency index,
VI Target is a sensor vegetation index obtained from unknown or target treatment,
VI Reference is a sensor vegetation index obtained from non-limited N fertilizer or high N reference.

The reference treatment was also used to represent maximum yield. The reference treatment received a non-limiting N rate of 280 kg ha^{-1} as urea-ammonium nitrate (UAN) solution (32%N) at planting to be above crop needs to ensure that total N was sufficient throughout the entire growing season.

Three reactive treatments consisting of: (i) reactive-fertigation-fixed (R-F-Fixed) (ii) reactive-fertigation-model (R-F-Model), and (iii) reactive-fertigation-model-slow release (R-F-Model-SR) were labeled according to the Timing, Application Method, Rate, and N Source. Timing is informed by the sensor as a reactive approach that responds to the measured crop N needs and determines the timing of additional in-season N rate requirements via fertigation based on the indication of the crop N sufficiency status. When the SI value was equal to or less than the threshold of 0.95, supplement N via fertigation was applied based on VIs of the SPAD CM. The N needs were reassessed after two weeks using sensor SI information to determine if an additional N application was needed. This procedure was repeated no later than the reproductive blister (R2) growth stage as suggested by Hawkins et al. (2007) to avoid fertigation losses after the R2 growth stage.

The N rate was arbitrarily fixed for R-F-Fixed treatment (34 kg ha^{-1} as the typical rate of N to be applied via fertigation without injuring corn plants) (Blackmer and Schepers, 1995) or predicted by the Maize-N model for R-F-Model and R-F-Model-SR treatments. The N source for R-F-Fixed and R-F-Model treatments was urea-ammonium nitrate (UAN) solution (32%N) (Table 4.2) as a base rate and an additional in-season N applied via fertigation. Whereas the R-F-Model-SR treatment used Environment Smart Nitrogen (ESN – a polymer-coated form of urea, Nutrien, Ltd.) (Table 4.2), and additional in-season N applied as UAN via fertigation. The base rate of N fertilizer for all site years was applied at planting as UAN, banded to the soil between crop rows (knife was spaced in the middle of the row and fertilizer was injected below the soil surface) for all treatments except for R-F-Model-SR treatment. For R-F-Model-SR treatment, the base rate of N fertilizer was applied at planting as ESN (Table 4.2), which was surface broadcast using a dry fertilizer spreader.

Table 4.2. Site year, treatment, planting date, starter N rate, application date, base N rate, N application date, N source, and method of application for N fertilizer decision strategies for SCAL and WCREC sites in 2017 and 2018.

Site Year ID	Treatment	Planting Date	Starter N+ Rate (kg N ha^{-1})	Application Date	Base N Rate (kg N ha^{-1})	N Application Date	N Source	Method of Application
SCAL17	**Reference**	24 Apr.	6.5	24 Apr.	280	8-May	UAN32%†	Banded
	R-F-Fixed				84			
	R-F-Model				84			
	R-F-Model-SR				95		ESN‡	Broadcast
WCREC17	**Reference**	8-May	6.5	8-May	280	4-May	UAN32%	Banded
	R-F-Fixed				78.5			
	R-F-Model				78.5			
	R-F-Model-SR				64	3-May	ESN	Broadcast
SCAL18	**Reference**	2-May	6.5	2-May	280	11-May	UAN32%	Banded
	R-F-Fixed				78.5			
	R-F-Model				78.5			
	R-F-Model-SR				147	10-May	ESN	Broadcast
WCREC18	**Reference**	8-May	6.5	8-May	280	16-May	UAN32%	Banded
	R-F-Fixed				78.5			
	R-F-Model				78.5			
	R-F-Model-SR				84	17-May	ESN	Broadcast

+ Indicates liquid ammonium polyphosphate (10-34-0) (NPK) banded for all treatments as starter N.
† Indicates Urea-Ammonium Nitrate solution (32%N) as a base rate.
‡ Indicates Environment Smart Nitrogen coated urea (44% N) as a base rate.

Crop Canopy Sensing

Crop canopy sensing information was obtained using three different sensors: SPAD chlorophyll meter (Spectrum Technologies Inc. Aurora, IL, USA), RapidScan CS-45 active crop canopy sensor (Holland Scientific, Lincoln, NE, USA), and Parrot Sequoia passive sensor (Parrot Inc., San Francisco, CA, USA). The SPAD meter used the method developed by Peterson et al. (1993) and Blackmer and Schepers, (1995) that used the SPAD meter to schedule fertigation of irrigated corn. Additionally, evaluating the possibility of replacing the SPAD meter by using an active or passive sensor would result in the same management decisions, as the active or passive sensors are capable of rapid data collection with a larger spatial scale (Krienke et al., 2017). However, in this study, fertigation decisions relied solely on the SI calculated using the SPAD meter.

SPAD Meter

The SPAD meter is an active handheld crop leaf sensor (active sensor using its own source of light and contact sensor according to the distance from the target) that measures light transmittance properties of leaves in two wavelengths (650 and 940 nm) by clamping it on the crop leaf and emitting its own light. Fifteen readings per row from the middle two rows (total of thirty readings) were collected (from sensing area of 9 m length) for each plot within each site year. Sensor measurements were taken from halfway between the leaf margin and the leaf midrib from the newest fully expanded vegetative six-leaf (V6) to vegetative tasseling (VT) growth stages, and from the ear leaf from VT through R2 growth stages. The SPAD meter reading values were generated and averaged to obtain one mean value for each plot.

Active Sensor

The RapidScan CS-45 is an active handheld crop canopy sensor (active sensor with its own source of light and a proximal sensor according to distance from the target) that integrates a data logger, GPS, crop sensor, and power source into one small unit with a modulated polychromatic light source and three measurement channels: 670 nm, 730 nm, and 780 nm. Reflectance from these three channels was used to obtain normalized difference red edge (NDRE) information. Sensing was conducted in the middle of each plot (sensing area). The sensing area of each plot consisted of the two middle rows of each plot with 9 m length from the V6 to VT growth stages by holding the sensor unit in the nadir position at the recommended height of approximately 1 meter above the corn, and walking directly over each row for each plot. Measurements of the sensor were moved to be taken between three rows instead of directly over the two rows from VT through R2 growth stages. The NDRE values were generated and averaged for each row to obtain one mean value for each plot. The NDRE calculated as follows:

$$\boldsymbol{NDRE} = \frac{\textbf{NIR}-\textbf{Red Edge}}{\textbf{NIR}+\textbf{Red Edge}} \qquad \textbf{[4.2]}$$

Where,

NIR is the reflectance in the near-infrared wavelength band

Red Edge is the reflectance in the red edge wavelength band

Passive Sensor

The Parrot Sequoia is a passive multispectral sensor (relying on sunlight as the energy source and a remote sensor according to distance from the target) that was mounted on an eBee SQ senseFly UAV (Lausanne, Switzerland) and flown to approxtmitly120 m. The UAV measurements were taken at the R2 growth stage for SCAL17; VT and R2 growth stages for SCAL18; and V18 growth stage for WCREC18. Reflectance measurements were collected in 4 bands (green, red, red-edge, and NIR); wavelengths centered at 550 ± 40 nm, 660 ± 40 nm, 735 ± 10 nm, 790 ± 40 nm. Images were acquired with overlapping regions over the entire study area with a spatial resolution of 6 cm. A downwelling radiation sensor (sunshine sensor installed on top of the UAV) was used for radiometric calibration. A reflectance panel was also used for calibration by holding the UAV sensor directly over the panel without causing shadows on the panel. Then, the Sequoia images were processed with Pix4D software (Lausanne, Switzerland). The remaining raster image processing steps were performed using ArcGIS 10.4 (ESRI, Redlands, CA). In ArcGIS, the polygon was drawn on the sensing area for each plot (average of two middle rows) according to GPS coordinates from the active sensor. These polygons were used to clip NDRE raster by the tool (Extract by Mask). Two methods were applied on the clipped raster to extract statistical values. The first was to calculate the average NDRE value for each plot using the Spatial Analyst tool (Zonal Statistics as a Table). The second method was to extract all NDRE pixel values for each plot by converting clipped raster pixel to points to obtain NDRE values as a table. The table was transferred to Excel to calculate the top 5th to 10th percentile of NDRE values. The top 5th to10th percentile of NDRE was calculated to see how different percentile ranges from the average of NDRE based passive sensor compare to the average of the SPAD meter.

The SI values were calculated from active and passive sensors based on NDRE values as well as from SPAD meter reading values to determine the relative N sufficiency status (equation 4.1) and to schedule fertigation.

Statistical Analysis

The linear regression analysis between SPAD SI versus active and passive sensor SI values and between active sensor SI versus passive sensor SI values was performed using Microsoft Excel for each growth stage within each site year. In addition, the percent of N fertilizer decisions that matched between the two sensor indices was calculated for each treatment and growth stage within each site year using Statistical Analysis System (SAS) version 9.4. The same decision for two sensors was achieved when the SPAD SI and active or passive sensor SI values were both greater than 0.95 thresholds or both less than or equal to 0.95 thresholds.

Results and Discussion

Correlation between SPAD SI and Active Sensor SI

The correlation between SPAD SI (average SPAD readings) and active sensor SI (average NDRE values) values for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments at V6 through R2 growth stages for SCAL17, SCAL18, WCREC17, and WCREC18 site years, respectively, are shown in Figures 4.1 through Figure 4.4.

For SCAL17, SPAD SI and active sensor SI values were weakly correlated at all crop growth stages except at the V11 stage, which showed a stronger correlation (r^2 = 0.52) as shown in Figure 4.1. For SCAL18, SPAD SI and active sensor SI values were weakly correlated at all crop growth stages except at the V10 and R1 growth stages, which showed a stronger and good correlation (r^2 = 0.48 and 0.63 respectively) as shown in Figure 4.2. For WCREC17, poor correlation between SPAD SI and active sensor SI values was observed at all crop growth stages except at the V6 stage, which showed some correlation (r^2 = 0.40) as shown in Figure 4.3. For WCREC18, SPAD SI and active sensor SI values were well correlated at all crop growth stages except at the V18 and R2 growth stages, which showed weaker correlation as shown in Figure 4.4. The r^2 of correlated values showed a high and good correlation of 0.90, 0.94, 0.85, 0.57, and 0.46 at V6, V8, V10, V13, and R1 growth stages, respectively, which explained 90%, 94%, 85%, 57%, and 46% of the variability in the active sensor SI values by SPAD SI values.

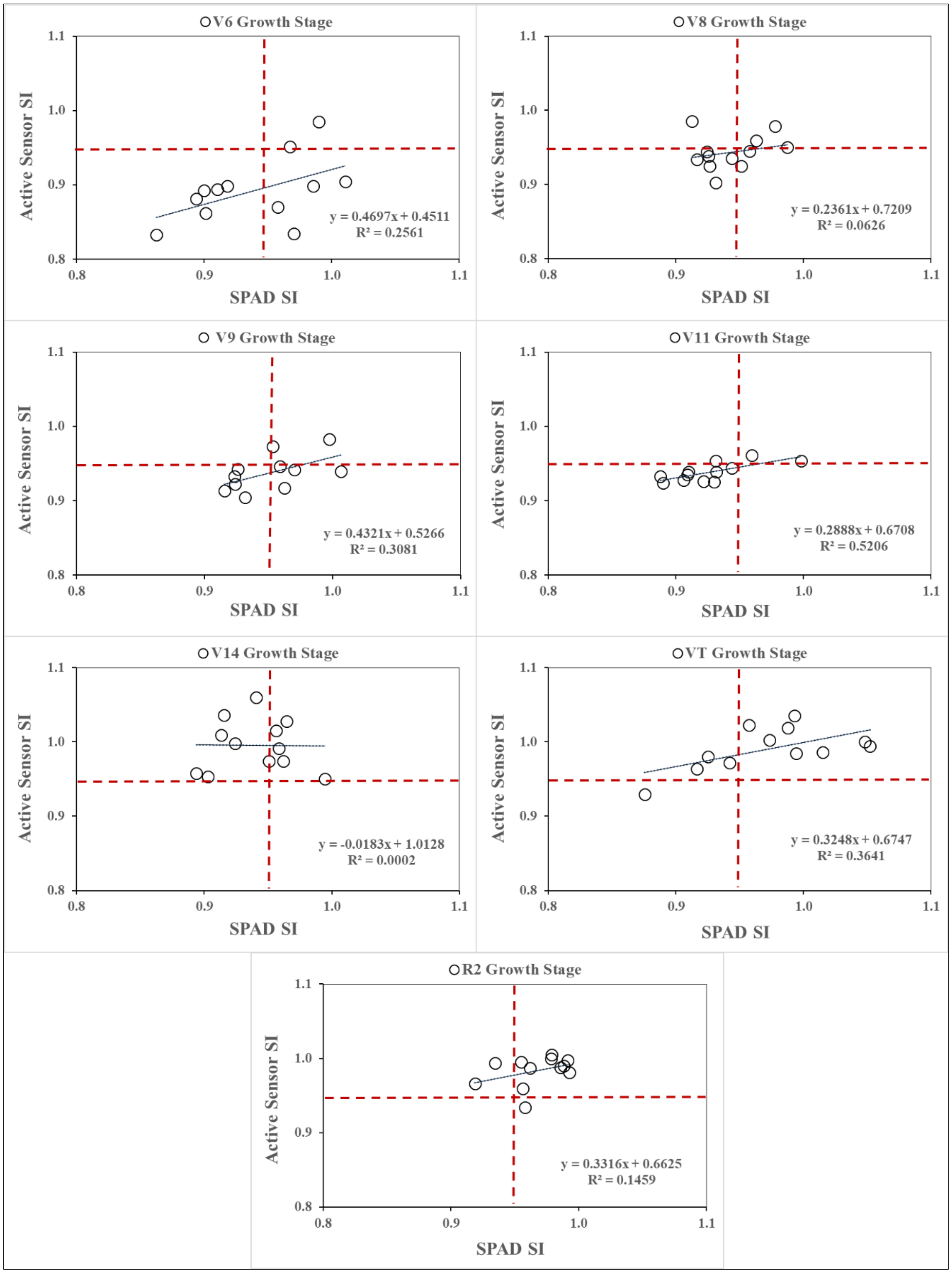

Figure 4.1. Correlation between SPAD sufficiency index (based on average SPAD readings) and active sensor sufficiency index (based on average NDRE values) values for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments (n=12) at V6, V8, V9, V11, V14, VT, and R2 growth stages for SCAL 2017.

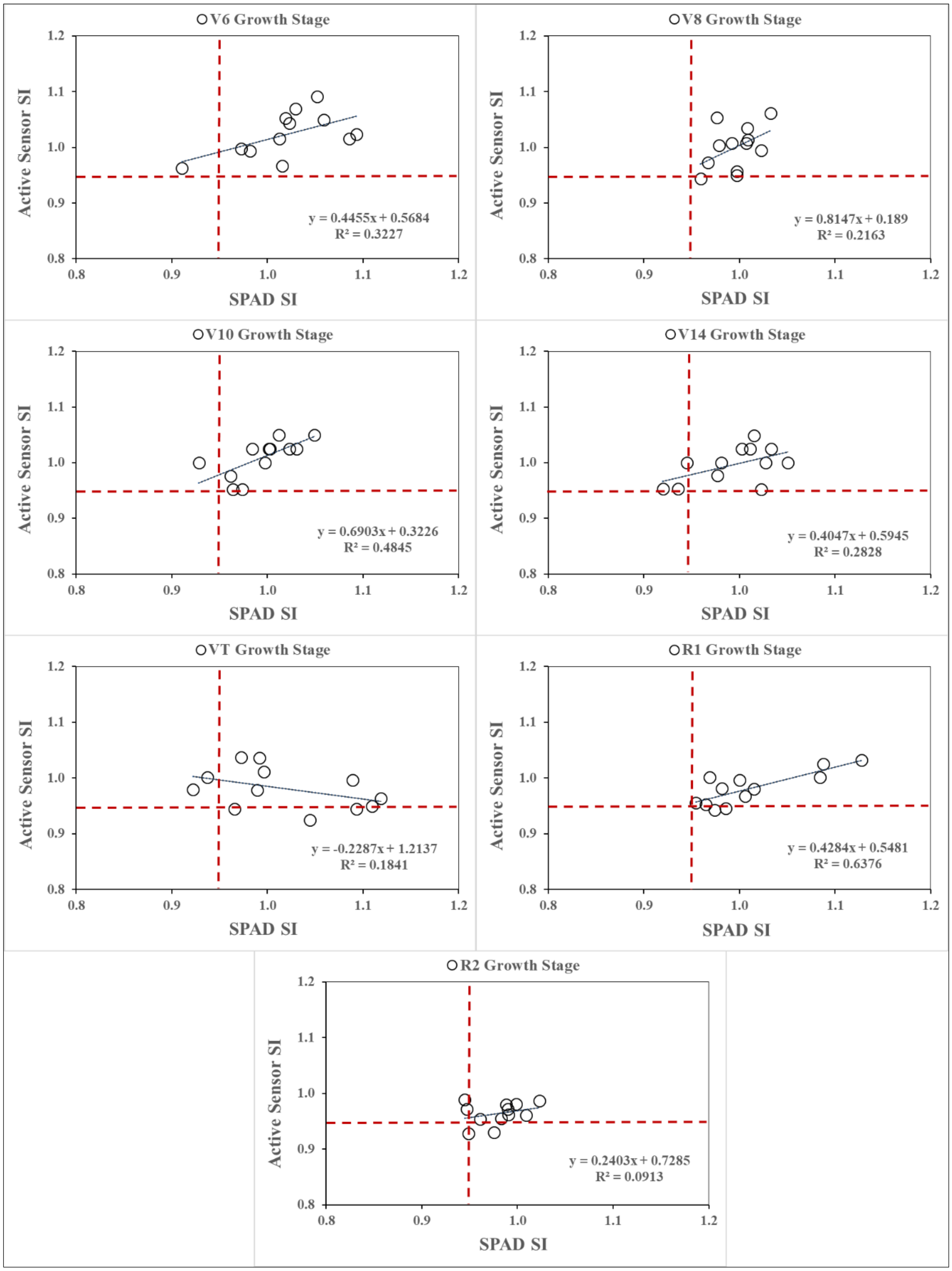

Figure 4.2. Correlation between SPAD sufficiency index (based on average SPAD readings) and active sensor sufficiency index (based on average NDRE values) values for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments (n=12) at V6, V8, V10, V14, VT, R1, and R2 growth stages for SCAL 2018.

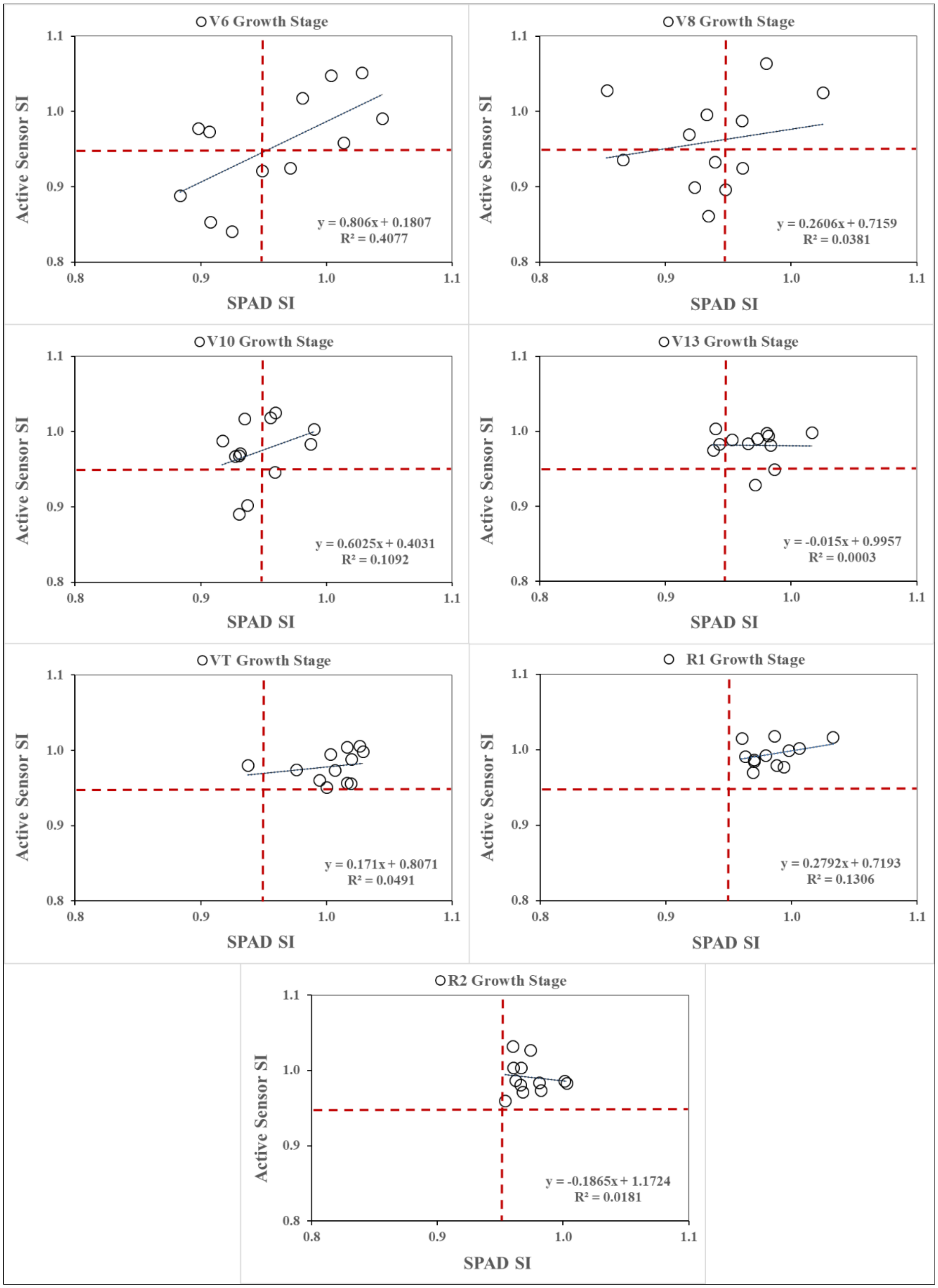

Figure 4.3. Correlation between SPAD sufficiency index (based on average SPAD readings) and active sensor sufficiency index (based on average NDRE values) values for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments (n=12) at V6, V8, V10, V13, VT, R1, and R2 growth stages for WCREC 2017.

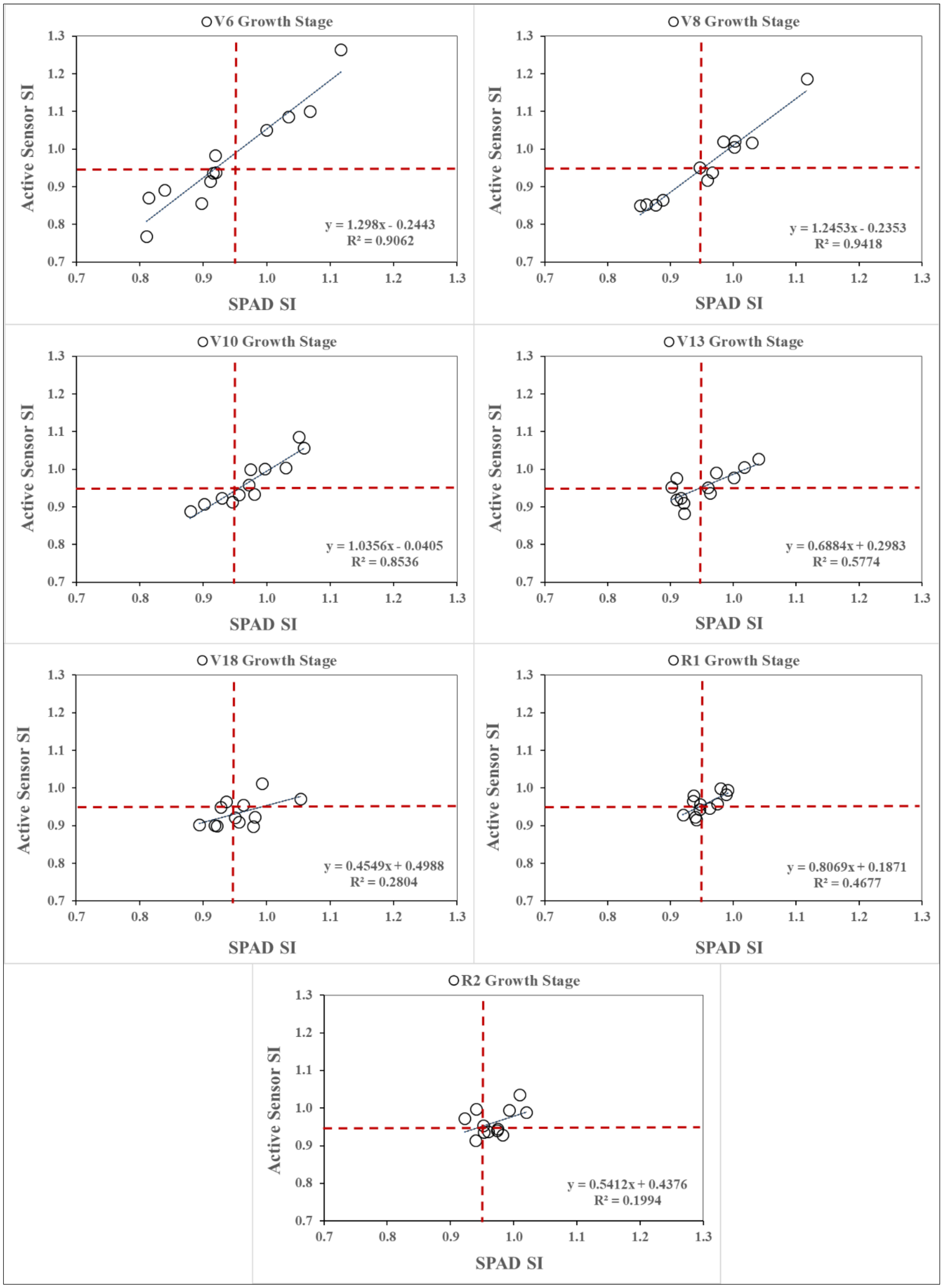

Figure 4.4. Correlation between SPAD sufficiency index (based on average SPAD readings) and active sensor sufficiency index (based on average NDRE values) values for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments (n=12) at V6, V8, V10, V13, V18, R1, and R2 growth stages for WCREC 2018.

Relationship between SPAD SI and Active Sensor SI Fertigation Decisions

The relationship between SPAD SI (based on average SPAD readings) and active sensor SI (based on average NDRE values) fertigation decisions for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments at V6 through R2 growth stages for SCAL17, SCAL18, WCREC17, and WCREC18 site years, respectively, are shown in Figure 4.5 through Figure 4.8.

For the SCAL17 site year, the relationship of fertigation decisions between SPAD SI and active sensor SI values was 100% for 1 out of 3 treatments at V8 and R2 growth stages and 2 out of 3 treatments at the V11 growth stage (Figure 4.5 A). The relationship of decisions was 75% for 1 out of 3 treatments at V6, V8, V11, V14, and R2 growth stages, respectively, 2 out of 3 treatments at the V9 growth stage, and 3 out of 3 treatments at the VT growth stage (Figure 4.5 A). Additionally, 50% of the decisions matched for 1 out of 3 treatments at V8, V14, and R2 growth stages and 2 out of 3 treatments at the V6 growth stage. There were only 1 out of 3 treatments at the V9 stage that showed a 25% match proportion and 1 out of 3 treatments at the V14 growth stage showed a 0% match proportion of the decisions (Figure 4.5 A).

The overall average relationship for the three treatments at each growth stage is shown in Figure 4.5 B. The overall average relationship of fertigation decisions was 92% at the V11 growth stage, 75% at the V8, VT, and R2 growth stages, 58% at the V6 and V9 growth stages, and 42% at the V14 growth stage. As a result, the average overall relationship of fertigation decisions that matched between SPAD SI and active sensor SI values for the three treatments across all growth stages was 68% for the SCAL17.

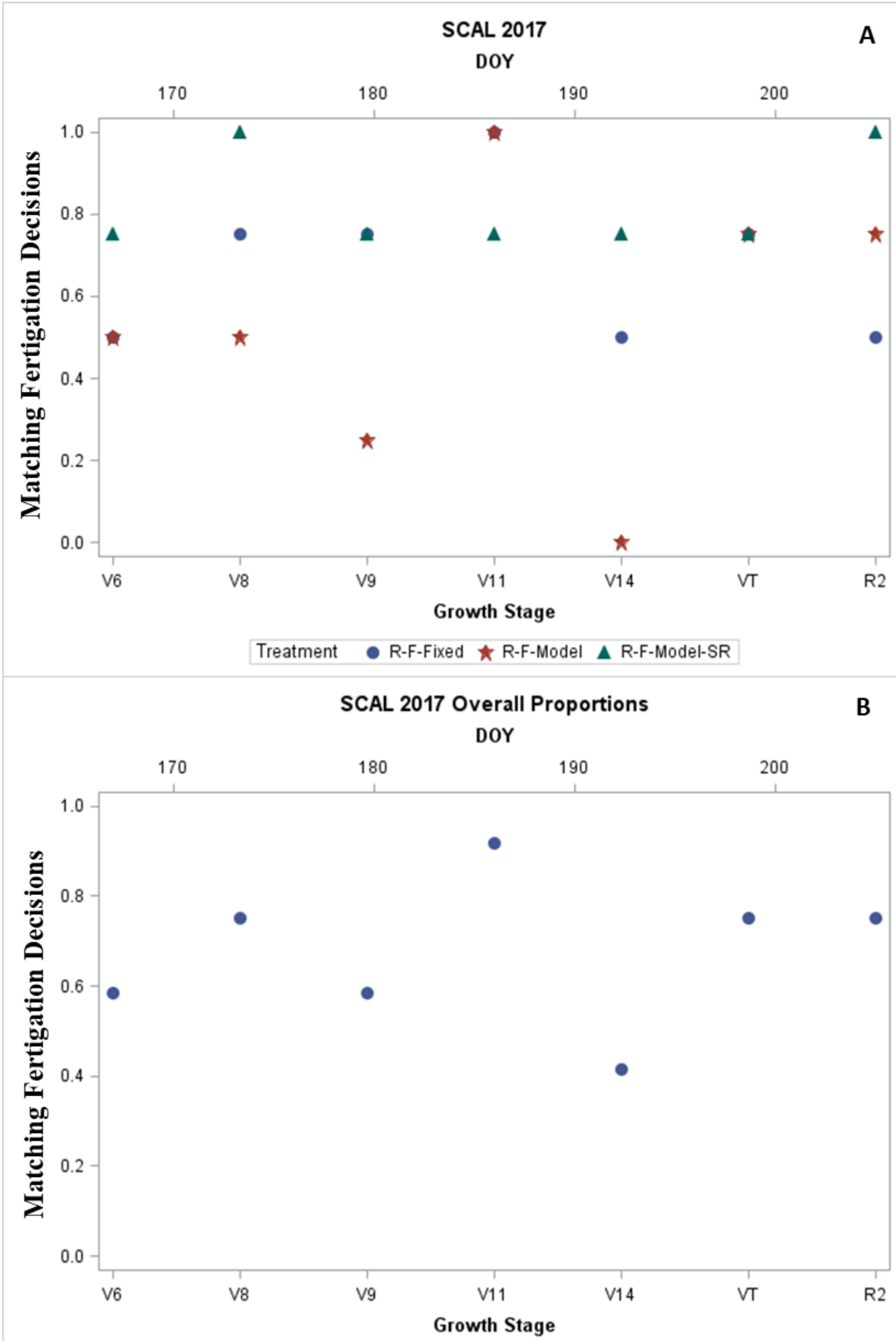

Figure 4.5. Relationship between the SPAD sufficiency index (based on average SPAD readings) and active sensor sufficiency index (based on average NDRE values) fertigation decisions at V6, V8, V9, V11, V14, VT, and R2 growth stages with day of year (DOY) for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments (A) and overall proportions (B) for SCAL 2017.

For SCAL18, the relationship of fertigation decisions between SPAD SI and active sensor SI values was 100% for 1 out of 3 treatments at V14 and R2 growth stages and 2 out of 3 treatments at the V6 and V8 growth stages (Figure 4.6 C). The relationship of decisions was 75% for 1 out of 3 treatments at the V6 growth stage, 2 out of 3 treatments at the V14 and R1 growth stages, and 3 out of 3 treatments at the V10 growth stage (Figure 4.6 C). 50% of the decisions matched for 1 out of 3 treatments at V8, R1, and R2 growth stages, and 3 out of 3 treatments at the VT growth stage. Only 1 out of 3 treatments at the R2 stage showed a 25% match proportion of the decisions (Figure 4.6 C).

The overall average relationship for the three treatments at each growth stage is shown in Figure 4.6 D. The overall average relationship of fertigation decisions was 92% at the V6 growth stage, 83% at the V8 and V14 growth stages, 75% at the V10 growth stage, 67% at the R1 growth stage, 58% at the R2 growth stage, and 50% at the VT growth stage. The average overall relationship of fertigation decisions that matched between SPAD SI and active sensor SI values for the three treatments across all growth stages was 73% for SCAL18.

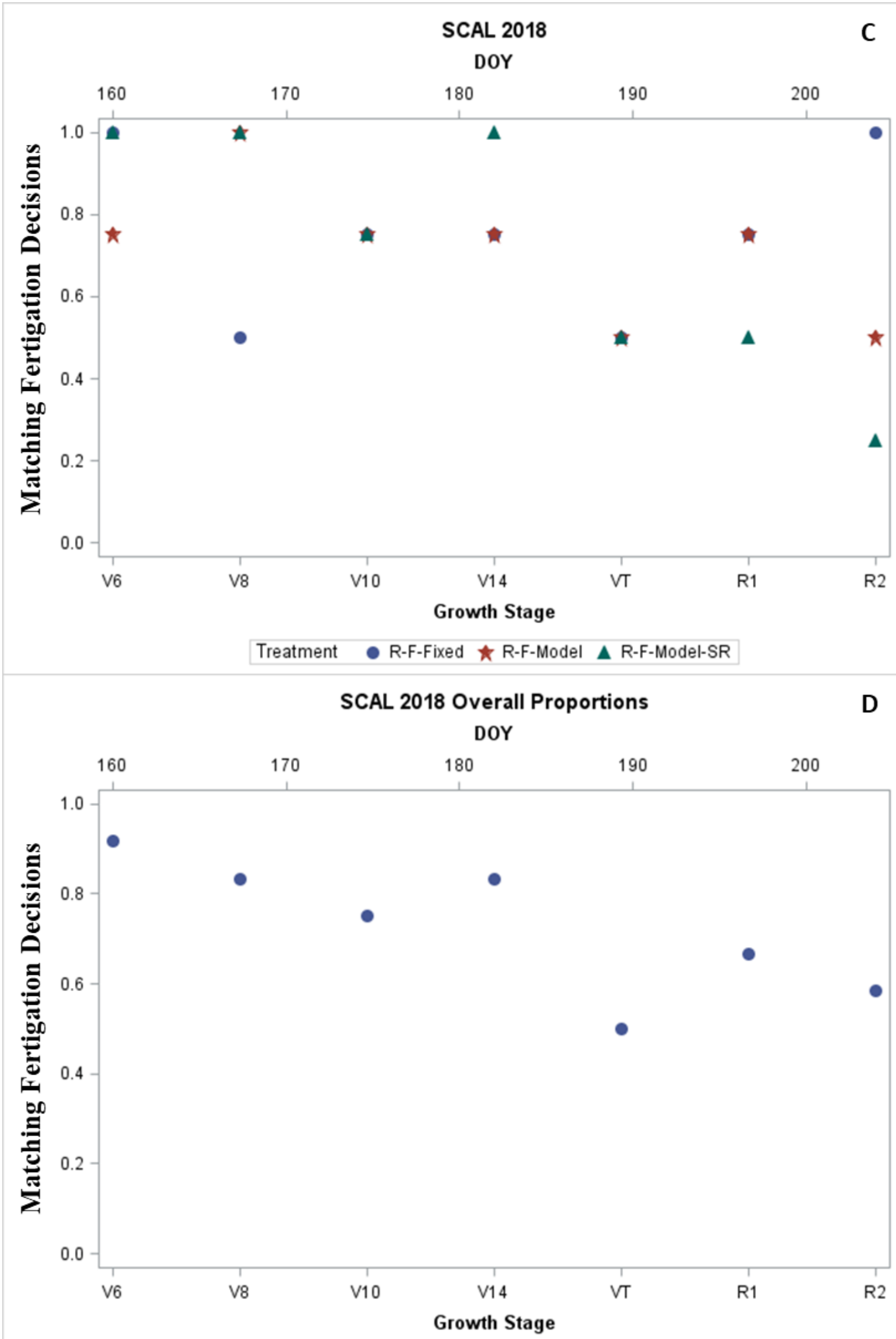

Figure 4.6. Relationship between the SPAD sufficiency index (based on average SPAD readings) and active sensor sufficiency index (based on average NDRE values) fertigation decisions at V6, V8, V10, V14, VT, R1, and R2 growth stages with day of year (DOY) for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments (C) and overall proportions (D) for SCAL 2018.

For WCREC17, the relationship of fertigation decisions between SPAD SI and active sensor SI values was 100% for 1 out of 3 treatments at V6, V8, and VT growth stages, 2 out of 3 treatments at the R2 growth stage, and 3 out of 3 treatments at R1 growth stage (Figure 4.7 E). A 75% match proportion of the decisions was observed for 1 out of 3 treatments at the V6, V8, V10, V13, and R2 growth stages and 2 out of 3 treatments at the VT growth stage (Figure 4.7 E). 1 out of 3 treatments at V6, V10, and V13 growth stages showed a 50% relationship of decisions. There were only 1 out of 3 treatments at V8, V10, and V13 growth stages which had a 25% relationship of decisions (Figure 4.7 E).

The overall average relationship for the three treatments at each growth stage is shown in Figure 4.7 F. The overall average relationship of fertigation decisions was 100% at the R1 growth stage, 92% at the R2 growth stage, 83% at the VT growth stage, 75% at the V6 growth stage, 67% at the V8 growth stage, and 50% at the V10 and V13 growth stages. As a result, the average overall relationship of fertigation decisions that matched between SPAD SI and active sensor SI values for the three treatments across all growth stages was 74% for WCREC17.

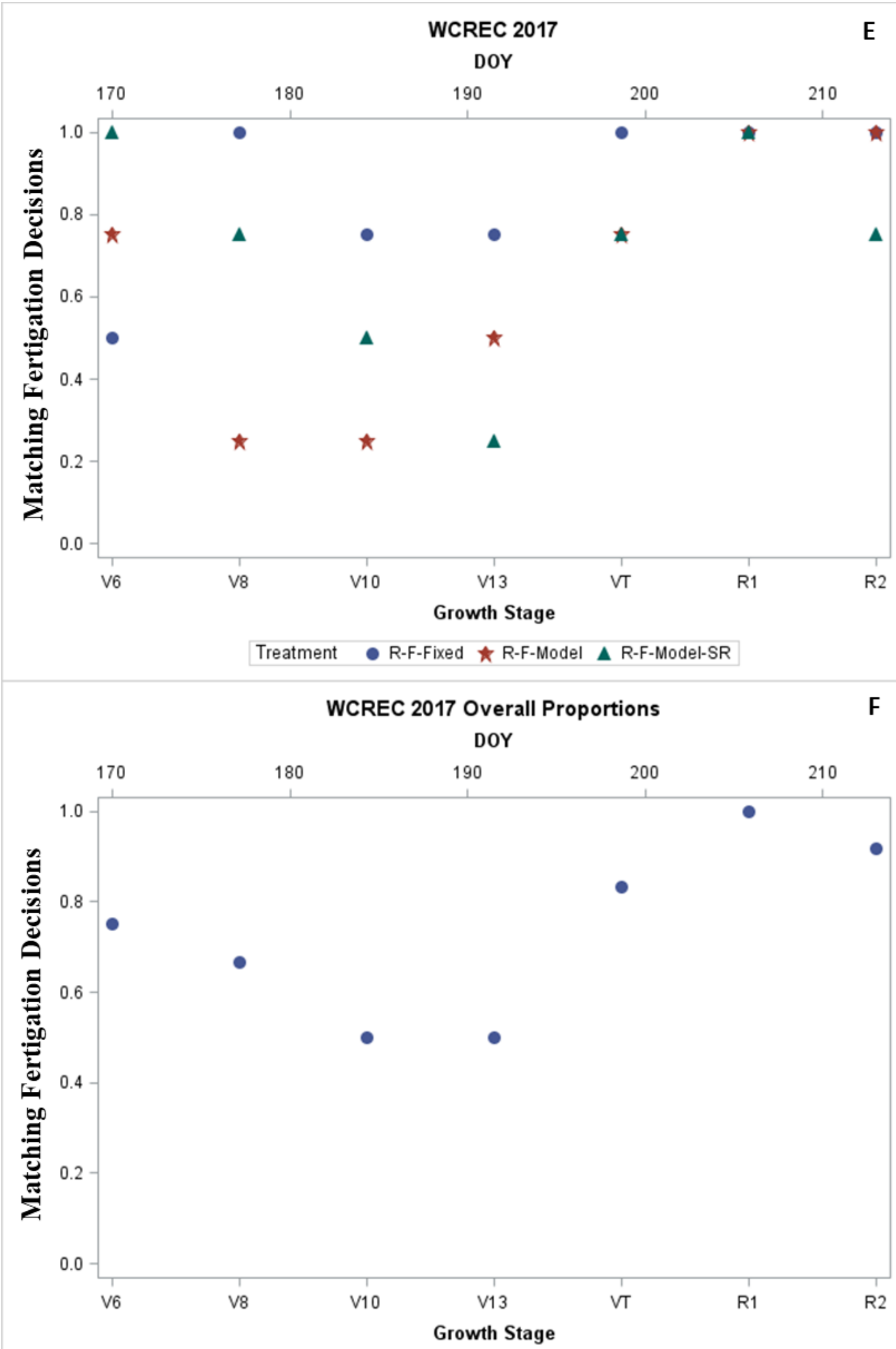

Figure 4.7. Relationship between the SPAD sufficiency index (based on average SPAD readings) and active sensor sufficiency index (based on average NDRE values) fertigation decisions at V6, V8, V10, V13, VT, R1, and R2 growth stages with day of year (DOY) for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments (E) and overall proportions (F) for WCREC 2017.

For WCREC18, the relationship of fertigation decisions between SPAD SI and active sensor SI values was 100% for 1 out of 3 treatments at V10, V13, and R1 growth stages and 2 out of 3 treatments at the V6 and V8 growth stages (Figure 4.8 G). The relationship of decisions was 75% for 1 out of 3 treatments at the V6, V13, and R2 growth stage and 2 out of 3 treatments at the V10 and V18 growth stages (Figure 4.8 G). Additionally, a 50% relationship of decisions was observed for 1 out of 3 treatments at V8, V13, V18, and R2 growth stages and 2 out of 3 treatments at the R1 growth stage. Only 1 out of 3 treatments at the R2 growth stage showed a 25% match proportion of the decisions (Figure 4.8 G).

The overall average relationship for the three treatments at each growth stage is shown in Figure 4.8 H. The overall average relationship of fertigation decisions was 92% at the V6 growth stage, 83% at the V8 and V10 growth stages, 75% at the V13 growth stage, 67% at the V18 and R1 growth stages, and 50% at the R2 growth stage. The average overall relationship of fertigation decisions that matched between SPAD SI and active sensor SI values for the three treatments across all growth stages was 74% for WCREC18.

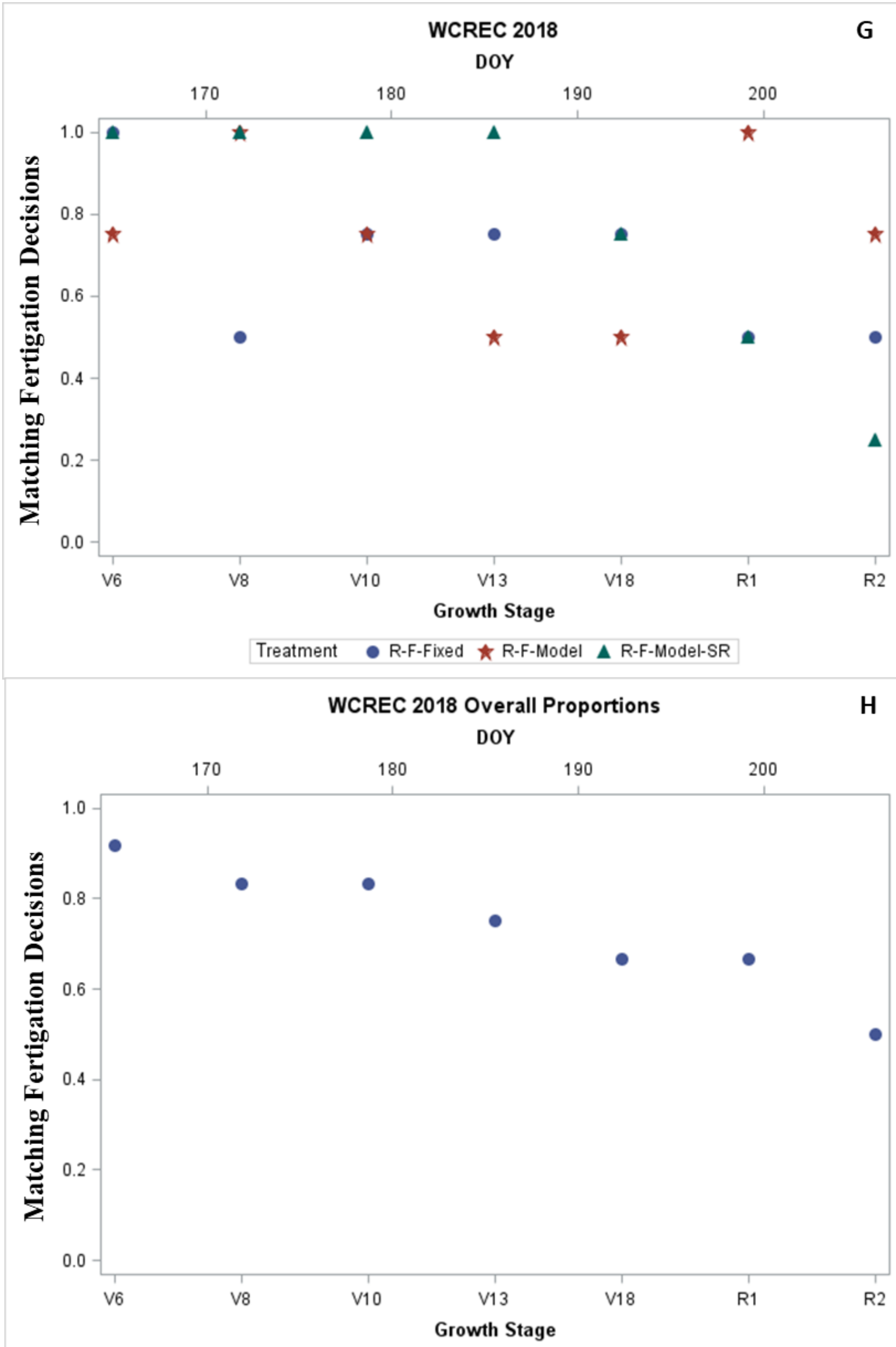

Figure 4.8. Relationship between the SPAD sufficiency index (based on average SPAD readings) and active sensor sufficiency index (based on average NDRE values) fertigation decisions at V6, V8, V10, V13, V18, R1, and R2 growth stages with day of year (DOY) for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments (G) and overall proportions (H) for WCREC 2018.

Correlation between SPAD SI and Passive Sensor SI

The correlation between SPAD SI (based on average SPAD readings) and passive sensor SI (based on average NDRE values and based on 90-95 percentile NDRE values) values for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments at R2 growth stage for SCAL17, at VT and R2 growth stages for SCAL18, and at the V18 growth stage for WCREC18, respectively, are shown in Figure 4.9 through Figure 4.11.

For SCAL17, poor correlation was observed between SPAD SI and passive sensor SI (based on average NDRE values) (Figure 4.9 A) and between SPAD SI and passive sensor SI (based on 90 percentile NDRE values) (Figure 4.9 B) at the R2 growth stage. For SCAL18, good correlation with r^2 = 0.61 and 0.71 was observed between SPAD SI and passive sensor SI (based on average NDRE values) (Figure 4.10 C) and between SPAD SI and passive sensor SI (based on 95 percentile NDRE value) (Figure 4.10 D), respectively at the VT growth stage. At the VT growth stage, 61% and 71% of the variability in the passive sensor SI values was explained by SPAD SI values. At the R2 growth stage, a weak correlation was observed between SPAD SI and passive sensor SI (based on average NDRE values) (Figure 4.10 E) and between SPAD SI and passive sensor SI (based on 90 percentile NDRE value) (Figure 4.10 F). Likewise, weak correlation was observed between SPAD SI and passive sensor SI (based on average NDRE values) (Figure 4.11 G) and between SPAD SI and passive sensor SI (based on 90 percentile NDRE value) (Figure 4.11 H) at the V18 growth stage for the WCREC18 site year. Percentile of 90-95 NDRE values was used to avoid tassel interference with canopy reflectance. This resulted in improving the correlation between SPAD SI and passive sensor SI values using 90-95 percentile NDRE values over average NDRE values for all site years except for SCAL17 as shown in Figure 4.9.

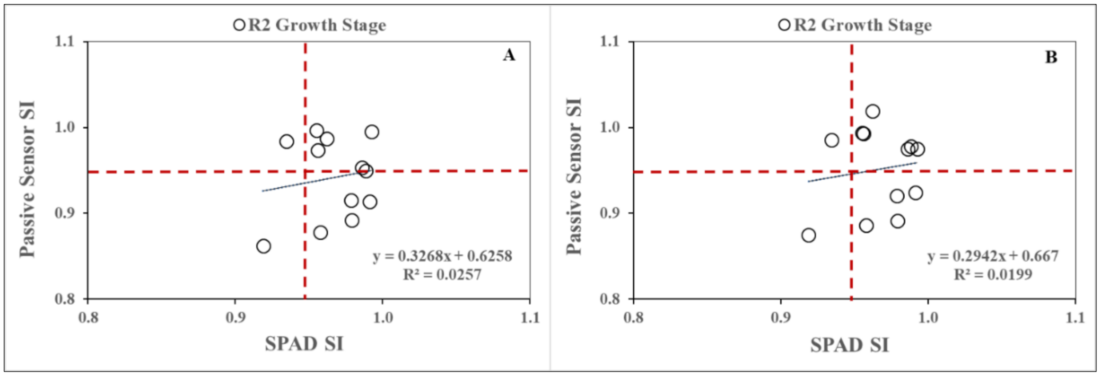

Figure 4.9. Correlation between SPAD sufficiency index (based on average SPAD readings) and passive sensor sufficiency index (based on average NDRE values) values (A) SPAD sufficiency index and passive sensor sufficiency index (based on 90 percentile NDRE value) values (B) for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments (n=12) at R2 growth stage for SCAL 2017.

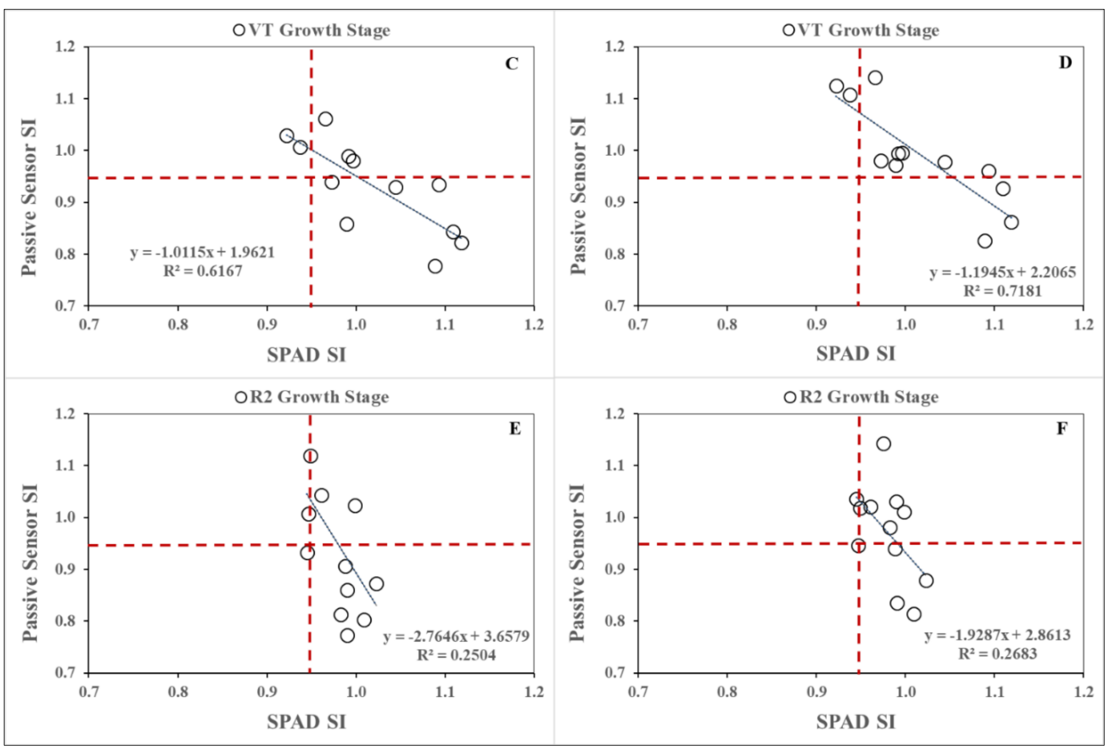

Figure 4.10. Correlation between SPAD sufficiency index (based on average SPAD readings) and passive sensor sufficiency index (based on average NDRE values) values (C and E) SPAD sufficiency index and passive sensor sufficiency index (based

on 95-90 percentile NDRE values) values (D and F) for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments (n=12) at VT and R2 growth stages for SCAL 2018.

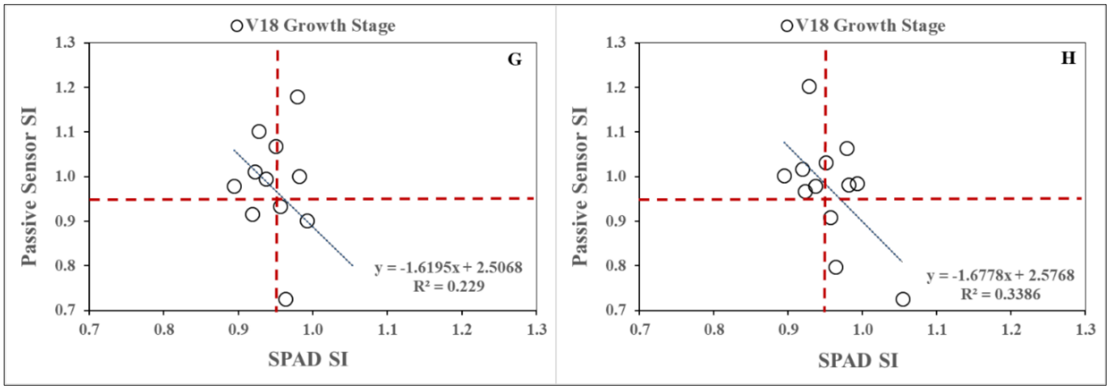

Figure 4.11. Correlation between SPAD sufficiency index (based on average SPAD readings) and passive sensor sufficiency index (based on average NDRE values) values (G) SPAD sufficiency index and passive sensor sufficiency index (based on 90 percentile NDRE value) values (H) for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments (n=12) at V18 growth stage for WCREC 2018.

Relationship between SPAD SI and Passive Sensor SI Fertigation Decisions

Table 4.3 shows the proportion of fertigation decisions that matched between SPAD SI (based on average SPAD readings) and passive sensor SI (based on average NDRE values) values for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments at R2, VT, R2, and V18 growth stages for SCAL17, SCAL18, and WCREC18, respectively. For SCAL17, the % of decisions that matched between SPAD SI and passive sensor SI values was 25% for 1 out of 3 treatments, 75% for 1 out of 3 treatments, and 50% for 1 out of 3 treatments, respectively at the R2 growth stage. As a result, the overall average of matched decisions was 50%. For the SCAL18 site year, 25% of decisions matched for 3 out of 3 treatments at the VT growth stage. Overall, 25% of decisions matched. At the R2 growth stage, 2 out of 3 treatments matched 25%, and 1 out of 3 treatments matched 50% of the time. Overall, 33% of decisions matched. Therefore, the overall average match for

VT and R2 growth stages was 29%. For WCREC18, 25% of decisions matched for 1 out of 3 treatments, 75% for 1 out of 3 treatments, and 0% for 1 out of 3 treatments, respectively at the V18 growth stage. As a result, overall 33% of decisions matched.

Table 4.3. **Relationship between SPAD sufficiency index (based on average SPAD readings) and passive sensor sufficiency index (based on average NDRE values) fertigation decisions for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments at R2, VT, R2, and V18 growth stages for SCAL2017, SCAL 2018, and WCREC 2018, respectively.**

		Treatment			
Site Year	Growth Stage	R-F-Fixed	R-F-Model	R-F-Model-SR	
		Matching Fertigation Decisions			Overall
SCAL 2017	**R2**	0.25	0.75	0.50	0.50
SCAL 2018	**VT**	0.25	0.25	0.25	0.25
SCAL 2018	**R2**	0.25	0.50	0.25	0.33
WCREC 2018	**V18**	0.25	0.75	0.00	0.33

Table 4.4 shows the proportion of decisions that matched between SPAD SI (based on average SPAD readings) and passive sensor SI (based on 90-95 percentile NDRE values) for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments at R2, VT, R2, and V18 growth stages for SCAL17, SCAL18, and WCREC18, respectively. For SCAL17, the match proportion of decisions that matched between SPAD SI and passive sensor SI values was 25% for 1 out of 3 treatments, 100% for 1 out of 3 treatments, and 50% for 1 out of 3 treatments, respectively at the R2 growth stage. Therefore, 58% of fertigation decisions matched. For SCAL18, 75% of decisions matched for 1 out of 3 treatments, and 50% matched for 2 out of 3 treatments at the VT growth stage. Overall, 58% of decisions matched. At the R2 growth stage,1 out of 3 treatments matched 25% of

the time, 1 out of 3 treatments 50%, and 1 out of 3 treatments matched 75% of the time. Overall, 50% of fertigation decisions matched. Therefore, the overall average match for VT and R2 growth stages was 54%. For WCREC18, the match proportion of decisions was 25% for 1 out of 3 treatments, 75% for 1 out of 3 treatments, and 0% for 1 out of 3 treatments respectively at the V18 growth stage. The overall relationship was 33%. Results showed that using 90-95 percentile NDRE values (Table 4.4) over average NDRE values (Table 4.3.) to obtain passive sensor SI improved the relationship between SPAD SI and passive sensor SI fertigation decisions except WCREC18.

Table 4.4. Relationship between SPAD sufficiency index (based on average SPAD readings) and passive sensor sufficiency index (based on 90-95 percentile NDRE values) fertigation decisions for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments at R2, VT, R2, and V18 growth stages for SCAL2017, SCAL 2018, and WCREC 2018, respectively.

		Treatment			
Site Year	**Growth Stage**	**R-F-Fixed**	**R-F-Model**	**R-F-Model-SR**	
		Matching Fertigation Decisions			**Overall**
SCAL 2017†	**R2**	0.25	1.00	0.50	0.58
SCAL 2018δ	**VT**	0.75	0.50	0.50	0.58
SCAL 2018†	**R2**	0.25	0.50	0.75	0.50
WCREC 2018†	**V18**	0.25	0.75	0.00	0.33

† Passive SI value-based on 90 percentile NDRE value
δ Passive SI value-based on 95 percentile NDRE value

Weak correlations were observed between SPAD SI and active sensor SI in different growth stages within each site year (Figure 4.1 through Figure 4.4) or SPAD SI versus passive sensor SI values (Figure 4.9 through Figure 4.11) and between active sensor SI or passive sensor SI values (Appendix C: Figure C.1 through Figure C.3). This depends on growth stages and is likely the result of the different sensor types, methods, and timing of measurement (Krienke et al., 2017). Also, this is expected as the field of view is different for the three types of sensors and the design is very different. SPAD measurements were taken from a single location of a small area on the leaf to represent a characteristic of the entire plant and the measurements did not incorporate any direct measure of plant architecture (Hong et al., 2007). In contrast, active or passive crop canopy sensor reflectance measurements were taken to integrate the entire canopy. Additionally, active or passive sensor measurements can be affected by the amount of non-plant pixels (soil pixels), especially early in the season. However, passive sensor measurements in this study were taken later in the season at V18 to R2 growth stages, with full crop canopies and for the most part eliminated the impact of soil pixels on passive sensor measurements. Nevertheless, passive sensor measurements can be impacted by multiple factors such as the time of day when the measurements were taken, cloud cover, and reflectance correction based on the quality of the downwelling radiation sensor (Souza et al., 2010). Similar results were observed by Bastos and Ferguson, (2016) that passive and active NDRE values were weakly correlated at V13, VT, and R4 growth stages. These results were different from a study conducted by Hong et al. (2007) that canopy reflectance measurements with passive and active sensors were closely correlated with SPAD meter measurements at V6-7, V8-9, and at flowering growth stages. However, the measurements of the study conducted by Hong et al. (2007) were collected with different active and passive sensors and different vegetation indices than active and passive sensors and vegetation indices used in this study to compare with the SPAD meter measurements.

The r^2 of the correlation between SPAD SI and active or passive sensor SI values measured how close the data was to the fitted regression line and how much variability was explained by the model. The high or weak correlation at any growth stage did not always lead to the same fertigation decision regarding N application as the same decision for two sensors can be achieved if both sensor's SI values are greater than 0.95 thresholds or both less than or equal to 0.95 thresholds. As a result, in general, for any correlation, all the points located in the top right quadrant or bottom left quadrant of each relationship led to the same fertigation decision. Otherwise, all the points for any correlation located in the top left quadrant or bottom right quadrant of each relationship led to different fertigation decisions. These results explained how correlation was different from matching fertigation decisions in terms of N application. The matching fertigation decisions between SPAD SI and active sensor SI were higher than the matching fertigation decisions between SPAD SI and passive sensor SI. Therefore, the matching of fertigation decisions between SPAD SI and active sensor SI has a greater potential of replacing the SPAD meter by utilizing an active crop canopy sensor to inform the decision of when to fertigate than passive sensor SI.

Conclusion

The performance of active (RapidScan CS-45) and passive (Parrot Sequoia) crop canopy sensors compared to SPAD meter were evaluated in terms of assessing in-season corn N status. The high or weak correlation at any growth stage did not always lead to the same fertigation decision regarding N application, as the same decision for two sensors can be achieved if both sensor's SI values are greater than 0.95 thresholds or both less than or equal to 0.95 thresholds. The overall proportion of fertigation decisions that matched between SPAD SI and active sensor SI values across all growth stages and site years was 72%. The overall proportion of fertigation decisions that matched between SPAD SI and passive sensor SI values across all growth stages and site years was 48% (for passive sensor SI calculated from 90-95 percentile NDRE values) and 37% (for passive sensor SI calculated from average NDRE values). The matching fertigation decisions between SPAD SI and active sensor SI were higher than the matching fertigation decisions between SPAD SI and passive sensor SI. However, one to two growth stages of passive sensor data were used compared to seven growth stages of active sensor data to evaluate sensor similarity in assessing crop N status. The matching of fertigation decisions between SPAD SI and active sensor SI has a greater potential than passive sensor SI of replacing the SPAD meter to inform the decision of when to fertigate.

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Chapter 5: General Summary and Future Suggestions

The overall objective for this research was to evaluate and develop a new strategy for in-season nitrogen (N) management using an integration of reactive sensor and proactive Maize-N model approaches via fertigation in corn. To address this overall objective, three studies were conducted to better understand crop canopy sensor and Maize-N model use and investigate the possibility of integrating a reactive sensor with a proactive Maize-N model.

The first study evaluated the integration of reactive sensor (SPAD meter) and proactive Maize-N model for determining the timing and rate of in-season N via fertigation in two site years. The SPAD meter was used weekly from V6 to R6 growth stages to monitor crop and determine the crop N sufficiency index (SI) to detect the onset of N stress in time to supplement N via fertigation. The N rate was fixed or calculated by the UNL algorithm and H-S algorithm or predicted by the Maize-N model.

Results from this study showed that either reactive or proactive fertigation approaches or a combination of both approaches reduced total N applied. This resulted in an increase in nitrogen use efficiency (NUE) and partial profit compared to the proactive sidedress UNL algorithm and the reactive sidedress H-S algorithm with no significant difference in yields. Additionally, both approaches reduced residual soil nitrate-N compared to the proactive sidedress UNL algorithm. These results suggest that using a sensor or model or an integration of both has the potential to be an effective approach to direct fertigation to improve NUE and profit while minimizing environmental impact.

The second study evaluated the Maize-N model for predicting economic optimum N rate (EONR), N uptake, and soil nitrate-N using default, measured parameters, and crop sensors. Optimum N rate (ONR) was estimated from yield response to N rate and actual EONR was calculated from modeled yield with cost of fertilizer and price of corn to compare with EONR predicted by Maize-N. Additionally, biomass was collected from V8 to R6 growth stages to calculate total aboveground N uptake to compare with predicted N uptake. Soil samples were collected from V8 to R5 growth stages to quantify soil nitrate-N to compare with predicted soil nitrate-N. To improve Maize-N soil nitrate-N prediction, measured soil temperature, measured soil bulk density, measured soil organic matter (SOM) for the top 30 cm, and the measured ratio of soil organic carbon (SOC) in the subsoil to topsoil was used to calibrate the model. A crop sensor was used to monitor and refine N uptake predictions.

Results from this study showed that Maize-N predicted EONR underestimated N rate recommendations compared to the calculated actual EONR, but with no significant differences in yield. However, Maize-N predicted EONR reduced profit compared to the calculated actual EONR. Results also showed that the model prediction slightly underestimated N uptake while overestimating soil nitrate-N. Crop sensor information was a useful tool to monitor crop N status, but could not be used to refine model N uptake predictions for this study. A calibrated model greatly reduced differences between predicted and observed soil nitrate-N, but still overestimated soil nitrate-N. This study showed that Maize-N is a useful tool for the prediction of EONR and crop N uptake.

The third study evaluated the performance of active and passive crop canopy sensors compared to the SPAD meter in terms of assessing in-season corn N status and managing N fertigation. Crop canopy reflectance measurements were taken using two crop canopy sensors: an active crop canopy sensor (RapidScan CS-45) from V6 to R2 growth stages and a passive crop canopy sensor (Parrot Sequoia) from V18 to R2 growth stages to compare with SPAD meter measurements. SI values were calculated from each sensor to assess crop N status. Results from this study showed that even reasonable correlation at any growth stage did not always lead to the same fertigation decision regarding N application, as the same decision for two sensors can be achieved if both sensor's SI values are greater than 0.95 thresholds or both less than or equal to 0.95 thresholds. There was a higher proportion of fertigation decisions that matched between SPAD SI and active sensor SI than between passive sensor SI and SPAD SI values. This indicates the matching of fertigation decisions between SPAD SI and active sensor SI has a greater potential of replacing the SPAD meter by utilizing an active crop canopy sensor to inform the decision of when to fertigate than passive sensor SI. This provided evidence of the possibility of replacing the SPAD meter by using an active crop canopy sensor that is capable of rapid data collection with a larger spatial scale.

The outcomes of this research showed that the reactive sensor approach was an effective indicator of in-season crop N needs that integrated crop growing conditions including weather effects on the crop from the time of planting to the time of sensing. The proactive Maize-N model approach showed great potential to account for spatial variability among fields and temporal variability between years by combining soil, crop, and management information with current and long-term weather to estimate corn N demands. This research developed new N application methods using either sensor or model approaches, or the combination of both approaches to determine the timing and rate of in-season N requirements via fertigation in corn resulted in improving NUE, increasing profit, and minimizing environmental impact.

The investigation of using a reactive sensor approach combined with a proactive Maize-N model approach should be continued to make more accurate N rate and timing decisions. Additionally, future investigations on using crop sensors and model simulation should be focusing on extension and educating farmers about what crop canopy sensors and model simulation are and how they can be used under different environmental conditions.

Appendix A

Table A.1. In-season N application rates for eight N application methods for all site years. Mean estimates by site and year for average grain yield, partial factor productivity of N (PFP_N), agronomic efficiency of N (AE_N), the aboveground biomass recovery efficiency of N (RE_N), partial profit, and residual soil nitrate-N (RSN) for all site years in SCAL and WCREC. All mean values in this table showed and explained in figure for each variable in chapter 2.

	Treatment							
Site Year ID	**Check**	**Reference**	**P-SD-UNL**	**R-SD-HS**	**R-F-Fixed**	**R-F-Model**	**R-F-SR-Model**	**P-F-Model**
	In-season N application rate (kg ha^{-1})							
SCAL17	0	0	84	56	34	37	20	30
WCREC17	0	34	41	46	0	46	33	43
SCAL18	0	0	136	58	0	0	0	30
WCREC18	0	0	64	17	42	22	38	93
	Grain Yield (Mg ha^{-1})							
SCAL17	11.17b	16.18a	15.30a	15.46a	15.47a	14.73a	15.51a	14.88a
WCREC17	12.74a	14.14a	13.24a	13.91a	14.02a	14.06a	13.89a	13.57a
SCAL18	9.33b	13.80a	14.28a	13.90a	14.56a	14.17a	13.71a	14.36a
WCREC18	8.49b	13.23a	12.88a	12.72a	11.68a	12.78a	13.04a	13.28a
	Partial Factor Productivity of N (PFP) (kg grain kg N applied^{-1})							
SCAL17	-	56.40c	87.59b	105.42ab	124.50a	115.46a	127.13a	123.12a
WCREC17	-	44.11d	104.64c	106.20c	164.93a	107.36c	134.89b	106.35c
SCAL18	-	48.09e	64.70de	97.35c	171.33a	166.74a	89.35cd	124.58b
WCREC18	-	46.13e	81.55cd	114.80ab	97.87bcd	125.67a	105.13abc	74.55d
	Agronomic Efficiency of N (AE_N) (kg grain increase kg N applied^{-1})							

SCAL17	-	17.46b	23.68ab	29.28ab	34.62a	27.94ab	35.59a	30.74ab
WCREC17	-	4.37a	3.95a	8.97a	15.09a	10.12a	11.18a	6.55a
SCAL18	-	15.58d	22.44d	32.00cd	61.60a	57.01ab	28.55cd	43.66bc
WCREC18	-	16.53b	27.77ab	38.16a	27.00ab	39.75a	37.02a	26.87ab
	Aboveground Biomass Recovery Efficiency of N (RE_N) (kg N uptake increase kg N applied^{-1})							
SCAL17	-	0.48a	0.48a	0.59a	0.59a	0.60a	0.60a	0.60a
WCREC17	-	0.35a	0.27a	0.50a	0.47a	0.19a	0.57a	0.30a
SCAL18	-	0.51a	0.61a	0.67a	0.79a	0.53a	0.66a	0.77a
WCREC18	-	0.45c	0.73abc	1.07ab	0.56c	1.17a	0.64bc	0.79abc
	Partial Profit (\$ ha^{-1})							
SCAL17	1513.37b	1917.14a	1909.56a	1958.86a	1982.05a	1878.63a	1960.46a	1905.68a
WCREC17	1726.80a	1606.14a	1675.94a	1763.28a	1823.55a	1783.81a	1768.05a	1720.55a
SCAL18	1358.90b	1759.46a	1889.87a	1904.30a	2054.10a	1997.07a	1808.78a	1997.12a
WCREC18	1236.46b	1676.96a	1741.35a	1760.89a	1594.06a	1773.09a	1758.17a	1781.66a
	Residual soil nitrate (kg ha^{-1})							
SCAL17	7.66c	17.99a	10.40bc	9.18bc	8.07c	11.17b	10.08bc	9.16bc
WCREC17	-	-	-	-	-	-	-	-
SCAL18	3.33c	10.10b	15.03a	3.42c	3.37c	2.79c	4.25c	3.79c
WCREC18	3.59b	24.23a	6.94b	5.99b	6.50b	5.17b	5.61b	7.58b

Table A.2. User input Maize-N model settings for model treatment for SCAL17 site year at planting.

SCAL17		
USER INPUT SETTINGS		
Weather data	20170424-SCAL-MaizeN_Weather_All_Trt.wth†	
The Maize Crop		
Hybrid relative maturity (days)	107	
Date of planting	04/24/17	
Plant population	34	x1000/acre
Price of maize	3.46	/bu
An average yield of last 5 years	N/A	
Last Crop		
Type of crop	Soybean	
Economic yield	70	bu/acre
Total N applied	0	lb/acre
User-set last crop fertilizer recover rate, %	N/A	
Date of maturity	09/30/16	
Amount of residues left in the field	All	
Soil moisture of entire rooting depth at maturity as % of field capacity	50%	
Nitrogen Fertilizer Management		
N already applied		
Dates	05/01/17	
Amount	6	lb N/acre
N to be applied		
Type of fertilizer for in-season applications	Urea ammonium nitrate (UAN32%)	
N content of the fertilizer	32	%
Price of the fertilizer	288	/ton
User-set overall fertilizer recover rate, %	N/A	
N from irrigation water	8	lb N/acre
Applied slow-release N fertilizer		
N/A		
Tillage		

Type of tillage	No-till	
Date of tillage operation	04/16/17	
Soil properties		
Top-soil organic matter content	3.3	%
Top-soil bulk density	1.3	g/cm3
Average soil texture of root zone	Silt Loam	
Soil pH	Neutral	
Soil root zone depth	48	inch
Manuring		
N/A		
Measured Soil Nitrate to 1.2 m Depth		
Amount	34	lb N/acre
Date of soil sampling	04/05/17	

† Long term weather data was used to predict the amount of N mineralization for the remainder of the season.

Table A.3. Maize-N model output for model treatment for SCAL17 site year at planting.

SCAL17		
N rate recommendation for maize		
Date: 04/26/17		
Overall economically optimal N rate (EONR)	113	(±29) lb N/acre
N doses:		
Total N already applied	6	lb N/acre
N to be applied	106	lb N/acre
Total fertilizer cost	51	/acre
Recovery Efficiency (RE) of fertilizer	0.6 0	N-uptake/N-applied
Physiological efficiency of N-uptake from fertilize (PE)	53	lb maize/lb N-uptake
Agronomic Efficiency of fertilizer-N (AE)	32	lb maize/lb fertilizer-N
Yield potential (Yp)	241	(±24) bu/acre
Attainable yield at EONR (Ya)	205	bu/acre
Yield without N fertilizer (Y0)	141	bu/acre
Total N uptake demand:	179	lb/acre
N uptake from indigenous sources, total:	112	lb/acre
From N-leftover	1	lb N/acre
From SOM mineralization	90	lb N/acre
From crop residues mineralization	15	lb N/acre
From manure	0	lb N/acre
From slow-release fertilizer	0	lb N/acre
From irrigation water	6	lb N/acre
This season up-to-date N leaching	0	lb N/acre
Long-term average N leaching loss of the same period	0	lb N/acre

Table A.4. User input Maize-N model settings for model treatment for WCREC17 site year at planting.

WCREC17		
USER INPUT SETTINGS		
Weather data	20170424-WCREC-MaizeN_Weather_All_Trts.wth	
The Maize Crop		
Hybrid relative maturity (days)	107	
Date of planting	05/01/17	
Plant population	34	x1000/acre
Price of maize	3.46	/bu
An average yield of last 5 years	N/A	
Last Crop		
Type of crop	Soybean	
Economic yield	60	bu/acre
Total N applied	0	lb/acre
User-set last crop fertilizer recover rate, %	N/A	
Date of maturity	10/03/16	
Amount of residues left in the field	All	
Soil moisture of entire rooting depth at maturity as % of field capacity	50%	
Nitrogen Fertilizer Management		
N already applied		
Dates	05/01/17	
Amount	6	lb N/acre
N to be applied		
Type of fertilizer for in-season applications	Urea ammonium nitrate (UAN32%)	
N content of the fertilizer	32	%
Price of the fertilizer	288	/ton
User-set overall fertilizer recover rate, %	N/A	
N from irrigation water	1	lb N/acre
Applied slow-release N fertilizer		
N/A		
Tillage		
Type of tillage	No-till	
Date of tillage operation	11/30/16	

Soil properties		
Top-soil organic matter content	2	%
Top-soil bulk density	1.3	g/cm3
Average soil texture of root zone	Silt Loam	
Soil pH	Alkaline	
Soil root zone depth	48	inch
Manuring		
N/A		
Measured Soil Nitrate		
Amount	67	lb N/acre
Date of soil sampling	04/14/17	

Table A.5. Maize-N model output for model treatment for WCREC17 site year at planting.

WCREC17		
N rate recommendation for maize		
Date: 04/26/17		
Overall economically optimal N rate (EONR)	114	(±43) lb N/acre
N doses:		
Total N already applied	6	lb N/acre
N to be applied	108	lb N/acre
Total fertilizer cost	51	/acre
Recovery Efficiency (RE) of fertilizer	0.54	N-uptake/N-applied
Physiological efficiency of N-uptake from fertilize(PE)	52	lb maize/lb N-uptake
Agronomic Efficiency of fertilizer-N (AE)	28	lb maize/lb fertilizer-N
Yield potential (Yp)	247	(±31) bu/acre
Attainable yield at EONR (Ya)	210	bu/acre
Yield without N fertilizer (Y0)	153	bu/acre
Total N uptake demand:	184	lb/acre
N uptake from indigenous sources, total:	122	lb/acre
From N-leftover	19	lb N/acre
From SOM mineralization	84	lb N/acre
From crop residues mineralization	19	lb N/acre
From manure	0	lb N/acre
From slow-release fertilizer	0	lb N/acre
From irrigation water	1	lb N/acre
This season up-to-date N leaching	0	lb N/acre
Long-term average N leaching loss of the same period	0	lb N/acre

Table A.6. User input Maize-N model settings for model treatment for SCAL17 site year at the V9 stage.

SCAL17		
USER INPUT SETTINGS (setting file: 20170625-SCAL-MaizeN_v2017_InputSettings_All-Trt-8.stg)		
Weather data	20170625-SCAL-MaizeN_Weather_All_Trt.wth	
The Maize Crop		
Hybrid relative maturity (days)	107	
Date of planting	04/24/17	
Plant population	34	x1000/acre
Price of maize	3.46	/bu
An average yield of last 5 years	N/A	
Last Crop		
Type of crop	Soybean	
Economic yield	70	bu/acre
Total N applied	0	lb/acre
User-set last crop fertilizer recover rate, %	N/A	
Date of maturity	09/30/16	
Amount of residues left in the field	All	
Soil moisture of entire rooting depth at maturity as % of field capacity	50%	
Nitrogen Fertilizer Management		
N already applied		
Dates	04/24/17, 05/08/17	
Amount	6, 75	lb N/acre
N to be applied		
Type of fertilizer for in-season applications	Urea ammonium nitrate (UAN 32%)	
N content of the fertilizer	32	%
Price of the fertilizer	288	/ton
User-set overall fertilizer recover rate, %	N/A	
N from irrigation water	8	lb N/acre
Applied slow-release N fertilizer		
N/A		
Tillage		
Type of tillage	No-till	
Date of tillage operation	04/16/17	

Soil properties		
Top-soil organic matter content	3.3	%
Top-soil bulk density	1.3	g/cm3
Average soil texture of root zone	Silt Loam	
Soil pH	Neutral	
Soil root zone depth	48	inch
Manuring		
N/A		
Measured Soil Nitrate		
Amount	34	lb N/acre
Date of soil sampling	04/05/17	

Table A.7. Maize-N model output for model treatment for SCAL17 site year at the V9 stage.

SCAL17		
N rate recommendation for maize		
Date: 06/26/17		
Overall economically optimal N rate (EONR)	108	(±29) lb N/acre
N doses:		
Total N already applied	81	lb N/acre
N to be applied	27	lb N/acre
Total fertilizer cost	49	/acre
Recovery Efficiency (RE) of fertilizer	0.6 0	N-uptake/N-applied
Physiological efficiency of N-uptake from fertilize (PE)	52	lb maize/lb N-uptake
Agronomic Efficiency of fertilizer-N (AE)	31	lb maize/lb fertilizer-N
Yield potential (Yp)	241	(±24) bu/acre
Attainable yield at EONR (Ya)	205	bu/acre
Yield without N fertilizer (Y0)	144	bu/acre
Total N uptake demand:	179	lb/acre
N uptake from indigenous sources, total:	115	lb/acre
From N-leftover	1	lb N/acre
From SOM mineralization	92	lb N/acre
From crop residues mineralization	15	lb N/acre
From manure	0	lb N/acre
From slow-release fertilizer	0	lb N/acre
From irrigation water	6	lb N/acre
This season up-to-date N leaching	0	lb N/acre
Long-term average N leaching loss of the same period	3	lb N/acre

Table A.8. User input Maize-N model settings for sensor + model-I treatment for SCAL17 site year at the V12 stage.

SCAL17		
USER INPUT SETTINGS		
Weather data	20170702-SCAL-MaizeN_Weather_All_Trt_6.wth	
The Maize Crop		
Hybrid relative maturity (days)	107	
Date of planting	4/24/2017	
Plant population	34.0	x1000/acre
Price of maize	3.46	/bu
An average yield of last 5 years	N/A	
Last Crop		
Type of crop	Soybean	
Economic yield	70	bu/acre
Total N applied	0	lb/acre
User-set last crop fertilizer recovery rate, %	N/A	
Date of maturity	9/30/2016	
Amount of residues left in the field	All	
Soil moisture of entire rooting depth at maturity as % of field capacity	50%	
Nitrogen Fertilizer Management		
N already applied		
Dates	4/24/2017, 5/8/2017	
Amount	6, 75	lb N/acre
N to be applied		
Type of fertilizer for in-season applications	Urea ammonium nitrate (UAN 32%)	
N content of the fertilizer	32	%
Price of the fertilizer	288	/ton
User-set overall fertilizer recovery rate, %	N/A	
N from irrigation water	8	lb N/acre
Applied slow-release N fertilizer		
N/A		
Tillage		
Type of tillage	No-till	

Date of tillage operation	4/16/2017	
Soil properties		
Top-soil organic matter content	3.3	%
Top-soil bulk density	1.3	g/cm3
Average soil texture of root zone	Silt Loam	
Soil pH	Neutral	
Soil root zone depth	48	inch
Manuring		
N/A		
Measured Soil Nitrate		
Amount	34	lb N/acre
Date of soil sampling	4/5/2017	

Table A.9. Maize-N model output for sensor + model-I treatment for SCAL17 site year at the V12 stage.

SCAL17		
N rate recommendation for maize		
Date: 07/02/2017		
Overall economically optimal N rate (EONR)	114	(±29) lb N/acre
N doses:		
Total N already applied	81	lb N/acre
N to be applied	33	lb N/acre
Total fertilizer cost	46	/acre
Recovery Efficiency (RE) of fertilizer	0.6 0	N-uptake/N-applied
Physiological efficiency of N-uptake from fertilize (PE)	52	lb maize/lb N-uptake
Agronomic Efficiency of fertilizer-N (AE)	31	lb maize/lb fertilizer-N
Yield potential (Yp)	241	(±24) bu/acre
Yield at EONR (Y_EONR)	205	bu/acre
Yield without N fertilizer (Y0)	148	bu/acre
Total N uptake demand:	179	lb/acre
N uptake from indigenous sources, total:	118	lb/acre
From N-leftover	0	lb N/acre
From SOM mineralization	98	lb N/acre
From crop residues mineralization	14	lb N/acre
From manure	0	lb N/acre
From slow-release fertilizer	0	lb N/acre
From irrigation water	6	lb N/acre
This season up-to-date N leaching	4	lb N/acre
Long-term average N leaching loss of the same period	7	lb N/acre

Table A.10. User input Maize-N model settings for sensor + model-II treatment for SCAL17 site year at the V12 stage.

SCAL17		
USER INPUT SETTINGS		
Weather data	20170702-SCAL-MaizeN_Weather_All_Trt_7.wth	
The Maize Crop		
Hybrid relative maturity (days)	107	
Date of planting	4/24/2017	
Plant population	34.0	x1000/acre
Price of maize	3.46	/bu
An average yield of last 5 years	N/A	
Last Crop		
Type of crop	Soybean	
Economic yield	70	bu/acre
Total N applied	0	lb/acre
User-set last crop fertilizer recovery rate, %	N/A	
Date of maturity	9/30/2016	
Amount of residues left in the field	All	
Soil moisture of entire rooting depth at maturity as % of field capacity	50%	
Nitrogen Fertilizer Management		
N already applied		
Dates	4/24/2017	
Amount	6	lb N/acre
N to be applied		
Type of fertilizer for in-season applications	Urea ammonium nitrate (UAN 32%)	
N content of the fertilizer	32	%
Price of the fertilizer	288	/ton
User-set overall fertilizer recovery rate, %	N/A	
N from irrigation water	8	lb N/acre
Applied slow-release N fertilizer		
Date applied	5/8/2017	
Amount	85	lb N/acre
Tillage		

Type of tillage	No-till	
Date of tillage operation	4/16/2017	
Soil properties		
Top-soil organic matter content	3.3	%
Top-soil bulk density	1.3	g/cm3
Average soil texture of root zone	Silt Loam	
Soil pH	Neutral	
Soil root zone depth	48	inch
Manuring		
N/A		
Measured Soil Nitrate		
Amount	34	lb N/acre
Date of soil sampling	4/5/2017	

Table A.11. Maize-N model output for sensor + model-II treatment for SCAL17 site year at the V12 stage.

SCAL17		
N rate recommendation for maize		
Date: 07/02/2017		
Overall economically optimal N rate (EONR)	24	(±19) lb N/acre
N doses:		
Total N already applied	6	lb N/acre
N to be applied	18	lb N/acre
Total fertilizer cost	10	/acre
Recovery Efficiency (RE) of fertilizer	0.6 0	N-uptake/N-applied
Physiological efficiency of N-uptake from fertilize (PE)	0	lb maize/lb N-uptake
Agronomic Efficiency of fertilizer-N (AE)	0	lb maize/lb fertilizer-N
Yield potential (Yp)	241	(±24) bu/acre
Yield at EONR (Y_EONR)	205	bu/acre
Yield without N fertilizer (Y0)	209	bu/acre
Total N uptake demand:	179	lb/acre
N uptake from indigenous sources, total:	186	lb/acre
From N-leftover	0	lb N/acre
From SOM mineralization	98	lb N/acre
From crop residues mineralization	14	lb N/acre
From manure	0	lb N/acre
From slow-release fertilizer	68	lb N/acre
From irrigation water	6	lb N/acre
This season up-to-date N leaching	2	lb N/acre
Long-term average N leaching loss of the same period	4	lb N/acre

Table A.12. User input Maize-N model settings for sensor + model-I and model treatments for WCREC17 site year at the V8 stage.

WCREC17		
USER INPUT SETTINGS (setting file: 20170626-WCREC-MaizeN_v2017_InputSettings Trts 6 and 8.stg)		
Weather data	20170626-WCREC-MaizeN_Weather_All_Trts.wth	
The Maize Crop		
Hybrid relative maturity (days)	107	
Date of planting	05/08/17	
Plant population	34	x1000/acre
Price of maize	3.46	/bu
An average yield of last 5 years	N/A	
Last Crop		
Type of crop	Soybean	
Economic yield	60	bu/acre
Total N applied	0	lb/acre
User-set last crop fertilizer recover rate, %	N/A	
Date of maturity	10/03/16	
Amount of residues left in the field	All	
Soil moisture of entire rooting depth at maturity as % of field capacity	50%	
Nitrogen Fertilizer Management		
N already applied		
Dates	05/04/17, 05/08/17	
Amount	70, 6	lb N/acre
N to be applied		
Type of fertilizer for in-season applications	Urea ammonium nitrate (UAN 32%)	
N content of the fertilizer	32	%
Price of the fertilizer	288	/ton
User-set overall fertilizer recover rate, %	N/A	
N from irrigation water	1	lb N/acre
Applied slow-release N fertilizer		
N/A		
Tillage		
Type of tillage	No-till	

Date of tillage operation	11/30/16	
Soil properties		
Top-soil organic matter content	2	%
Top-soil bulk density	1.3	g/cm3
Average soil texture of root zone	Silt Loam	
Soil pH	Alkaline	
Soil root zone depth	48	inch
Manuring		
N/A		
Measured Soil Nitrate		
Amount	67	lb N/acre
Date of soil sampling	04/14/17	

Table A.13. Maize-N model output for sensor + model-I and model treatments for WCREC17 site year at the V8 stage.

WCREC17		
N rate recommendation for maize		
Date: 06/28/17		
Overall economically optimal N rate (EONR)	114	(±47) lb N/acre
N doses:		
Total N already applied	76	lb N/acre
N to be applied	41, 38	lb N/acre
Total fertilizer cost	51	/acre
Recovery Efficiency (RE) of fertilizer	0.54	N-uptake/N-applied
Physiological efficiency of N-uptake from fertilize (PE)	52	lb maize/lb N-uptake
Agronomic Efficiency of fertilizer-N (AE)	28	lb maize/lb fertilizer-N
Yield potential (Yp)	247	(±34) bu/acre
Attainable yield at EONR (Ya)	210	bu/acre
Yield without N fertilizer (Y0)	153	bu/acre
Total N uptake demand:	184	lb/acre
N uptake from indigenous sources, total:	122	lb/acre
From N-leftover	19	lb N/acre
From SOM mineralization	85	lb N/acre
From crop residues mineralization	18	lb N/acre
From manure	0	lb N/acre
From slow-release fertilizer	0	lb N/acre
From irrigation water	1	lb N/acre
This season up-to-date N leaching	0	lb N/acre
Long-term average N leaching loss of the same period	0	lb N/acre

Table A.14. User input Maize-N model settings for sensor + model-II treatment for WCREC17 site year at the V8 stage.

WCREC17		
USER INPUT SETTINGS (setting file: 20170626-WCREC-MaizeN_v2017_InputSettings_Trts_7.stg)		
Weather data	20170626-WCREC-MaizeN_Weather_All_Trts.wth	
The Maize Crop		
Hybrid relative maturity (days)	107	
Date of planting	05/08/17	
Plant population	34	x1000/acre
Price of maize	3.46	/bu
An average yield of last 5 years	N/A	
Last Crop		
Type of crop	Soybean	
Economic yield	60	bu/acre
Total N applied	0	lb/acre
User-set last crop fertilizer recover rate, %	N/A	
Date of maturity	10/03/16	
Amount of residues left in the field	All	
Soil moisture of entire rooting depth at maturity as % of field capacity	50%	
Nitrogen Fertilizer Management		
N already applied		
Dates	05/08/17	
Amount	6	lb N/acre
N to be applied		
Type of fertilizer for in-season applications	Urea ammonium nitrate (UAN 32%)	
N content of the fertilizer	32	%
Price of the fertilizer	288	/ton
User-set overall fertilizer recover rate, %	N/A	
N from irrigation water	1	lb N/acre
Applied slow-release N fertilizer		
Date applied	05/03/17	
Amount	57	lb N/acre
Tillage		

Type of tillage	No-till	
Date of tillage operation	11/30/16	
Soil properties		
Top-soil organic matter content	2	%
Top-soil bulk density	1.3	g/cm3
Average soil texture of root zone	Silt Loam	
Soil pH	Alkaline	
Soil root zone depth	48	inch
Manuring		
N/A		
Measured Soil Nitrate		
Amount	67	lb N/acre
Date of soil sampling	04/14/17	

Table A.15. Maize-N model output for sensor + model-II treatment for WCREC17 site year at the V8 stage.

WCREC17		
N rate recommendation for maize		
Date: 06/28/17		
Overall economically optimal N rate (EONR)	35	(±47) lb N/acre
N doses:		
Total N already applied	6	lb N/acre
N to be applied	29	lb N/acre
Total fertilizer cost	13	/acre
Recovery Efficiency (RE) of fertilizer	0.5 4	N-uptake/N-applied
Physiological efficiency of N-uptake from fertilize (PE)	45	lb maize/lb N-uptake
Agronomic Efficiency of fertilizer-N (AE)	24	lb maize/lb fertilizer-N
Yield potential (Yp)	247	(±34) bu/acre
Attainable yield at EONR (Ya)	210	bu/acre
Yield without N fertilizer (Y0)	197	bu/acre
Total N uptake demand:	184	lb/acre
N uptake from indigenous sources, total:	168	lb/acre
From N-leftover	19	lb N/acre
From SOM mineralization	85	lb N/acre
From crop residues mineralization	18	lb N/acre
From manure	0	lb N/acre
From slow-release fertilizer	46	lb N/acre
From irrigation water	1	lb N/acre
This season up-to-date N leaching	0	lb N/acre
Long-term average N leaching loss of the same period	0	lb N/acre

Table A.16. User input Maize-N model settings for model treatment for SCAL18 site year at planting.

SCAL18		
USER INPUT SETTINGS		
Weather data	2018 05 02-SCAL-MaizeN_Weather_Trts_All.wth	
The Maize Crop		
Hybrid relative maturity (days)	107	
Date of planting	5/2/2018	
Plant population	34.0	x1000/acre
Price of maize	3.72	/bu
Average yield of last 5 years	N/A	
Last Crop		
Type of crop	Corn	
Economic yield	236	bu/acre
Total N applied	123	lb/acre
User-set last crop fertilizer recovery rate, %	N/A	
Date of maturity	9/28/2017	
Amount of residues left in the field	All	
Soil moisture of entire rooting depth at maturity as % of field capacity	50%	
Nitrogen Fertilizer Management		
N already applied		
Dates	5/2/2018	
Amount	5	lb N/acre
N to be applied		
Type of fertilizer for in-season applications	Urea ammonium nitrate (UAN 32%)	
N content of the fertilizer	32	%
Price of the fertilizer	260	/ton
User-set overall fertilizer recovery rate, %	N/A	
N from irrigation water	8	lb N/acre
Applied slow release N fertilizer		
N/A		
Tillage		
Type of tillage	No-till	

Date of tillage operation	5/2/2018	
Soil properties		
Top-soil organic matter content	3.3	%
Top-soil bulk density	1.3	g/cm3
Average soil texture of root zone	Silt loam	
Soil pH	Neutral	
Soil root zone depth	48	inch
Manuring		
N/A		
Measured Soil Nitrate		
Amount	56	lb N/acre
Date of soil sampling	4/19/2018	

Table A.17. Maize-N model output for model treatment for SCAL18 site year at planting.

SCAL18		
N rate recommendation for maize		
Date: 05/02/2018		
Overall economically optimal N rate (EONR)	130	(±29) lb N/acre
N doses:		
Total N already applied	5	lb N/acre
N to be applied	125	lb N/acre
Total fertilizer cost	53	/acre
Recovery Efficiency (RE) of fertilizer	0.6 0	N-uptake/N-applied
Physiological efficiency of N-uptake from fertilize (PE)	54	lb maize/lb N-uptake
Agronomic Efficiency of fertilizer-N (AE)	32	lb maize/lb fertilizer- N
Yield potential (Yp)	245	(±24) bu/acre
Yield at EONR (Y_EONR)	209	bu/acre
Yield without N fertilizer (Y0)	133	bu/acre
Total N uptake demand:	183	lb/acre
N uptake from indigenous sources, total:	105	lb/acre
From N-leftover	13	lb N/acre
From SOM mineralization	89	lb N/acre
From crop residues mineralization	-4	lb N/acre
From manure	0	lb N/acre
From slow release fertilizer	0	lb N/acre
From irrigation water	6	lb N/acre
This season up-to-date N leaching	0	lb N/acre
Long-term average N leaching loss of the same period	2	lb N/acre

Table A.18. User input Maize-N model settings for model treatment for WCREC18 site year at planting.

WCREC18		
USER INPUT SETTINGS		
Weather data	20180508-WCREC-weather-input.wth	
The Maize Crop		
Hybrid relative maturity (days)	107	
Date of planting	5/8/2018	
Plant population	34.0	x1000/acre
Price of maize	3.72	/bu
Average yield of last 5 years	N/A	
Last Crop		
Type of crop	Soybean	
Economic yield	60	bu/acre
Total N applied	0	lb/acre
User-set last crop fertilizer recovery rate, %	N/A	
Date of maturity	10/3/2017	
Amount of residues left in the field	All	
Soil moisture of entire rooting depth at maturity as % of field capacity	50%	
Nitrogen Fertilizer Management		
N already applied		
Dates	5/8/2018	
Amount	5	lb N/acre
N to be applied		
Type of fertilizer for in-season applications	Urea ammonium nitrate (UAN 32%)	
N content of the fertilizer	32	%
Price of the fertilizer	260	/ton
User-set overall fertilizer recovery rate, %	N/A	
N from irrigation water	1	lb N/acre
Applied slow release N fertilizer		
N/A		
Tillage		
Type of tillage	No-till	
Date of tillage operation	5/8/2018	
Soil properties		

Top-soil organic matter content	2.1	%
Top-soil bulk density	1.3	g/cm3
Average soil texture of root zone	Silt loam	
Soil pH	Alkaline	
Soil root zone depth	48	inch
Manuring		
N/A		
Measured Soil Nitrate		
Amount	49	lb N/acre
Date of soil sampling	5/7/2018	

Table A.19. Maize-N model output for model treatment for WCREC18 site year at planting.

WCREC18		
N rate recommendation for maize		
Date: 5/8/2018		
Overall economically optimal N rate (EONR)	151	(±47) lb N/acre
N doses:		
Total N already applied	5	lb N/acre
N to be applied	146	lb N/acre
Total fertilizer cost	61	/acre
Recovery Efficiency (RE) of fertilizer	0.5 4	N-uptake/N-applied
Physiological efficiency of N-uptake from fertilize (PE)	54	lb maize/lb N-uptake
Agronomic Efficiency of fertilizer-N (AE)	29	lb maize/lb fertilizer-N
Yield potential (Yp)	247	(±34) bu/acre
Yield at EONR (Y_EONR)	210	bu/acre
Yield without N fertilizer (Y0)	131	bu/acre
Total N uptake demand:	184	lb/acre
N uptake from indigenous sources, total:	103	lb/acre
From N-leftover	11	lb N/acre
From SOM mineralization	75	lb N/acre
From crop residues mineralization	16	lb N/acre
From manure	0	lb N/acre
From slow release fertilizer	0	lb N/acre
From irrigation water	1	lb N/acre
This season up-to-date N leaching	0	lb N/acre
Long-term average N leaching loss of the same period	0	lb N/acre

Table A.20. User input Maize-N model settings for model treatment for SCAL18 site year at the VT stage.

SCAL18		
USER INPUT SETTINGS		
Weather data	2018 07 09-SCAL-MaizeN_Weather_Trts_8.wth	
The Maize Crop		
Hybrid relative maturity (days)	107	
Date of planting	5/2/2018	
Plant population	34	x1000/acre
Price of maize	3.72	/bu
An average yield of last 5 years	N/A	
Last Crop		
Type of crop	Corn	
Economic yield	236	bu/acre
Total N applied	123	lb/acre
User-set last crop fertilizer recovery rate, %	N/A	
Date of maturity	9/28/2017	
Amount of residues left in the field	All	
Soil moisture of entire rooting depth at maturity as % of field capacity	50%	
Nitrogen Fertilizer Management		
N already applied		
Dates	5/2/2018, 5/11/2018	
Amount	5, 70	lb N/acre
N to be applied		
Type of fertilizer for in-season applications	Urea ammonium nitrate (UAN 32%)	
N content of the fertilizer	32	%
Price of the fertilizer	260	/ton
User-set overall fertilizer recovery rate, %	N/A	
N from irrigation water	8	lb N/acre
Applied slow-release N fertilizer		
N/A		
Tillage		
Type of tillage	No-till	
Date of tillage operation	5/2/2018	

Soil properties		
Top-soil organic matter content	3.3	%
Top-soil bulk density	1.3	g/cm3
Average soil texture of root zone	Silt Loam	
Soil pH	Neutral	
Soil root zone depth	48	inch
Manuring		
N/A		
Measured Soil Nitrate		
Amount	56	lb N/acre
Date of soil sampling	4/19/2018	

Table A.21. Maize-N model output for model treatment for SCAL18 site year at the VT stage.

SCAL18		
N rate recommendation for maize		
Date: 7/9/2018		
Overall economically optimal N rate (EONR)	102	(±29) lb N/acre
N doses:		
Total N already applied	75	lb N/acre
N to be applied	27	lb N/acre
Total fertilizer cost	41	/acre
Recovery Efficiency (RE) of fertilizer	0.6 0	N-uptake/N-applied
Physiological efficiency of N-uptake from fertilize (PE)	52	lb maize/lb N-uptake
Agronomic Efficiency of fertilizer-N (AE)	31	lb maize/lb fertilizer-N
Yield potential (Yp)	245	(±24) bu/acre
Yield at EONR (Y_EONR)	209	bu/acre
Yield without N fertilizer (Y0)	152	bu/acre
Total N uptake demand:	183	lb/acre
N uptake from indigenous sources, total:	121	lb/acre
From N-leftover	14	lb N/acre
From SOM mineralization	105	lb N/acre
From crop residues mineralization	-4	lb N/acre
From manure	0	lb N/acre
From slow-release fertilizer	0	lb N/acre
From irrigation water	6	lb N/acre
This season up-to-date N leaching	0	lb N/acre
Long-term average N leaching loss of the same period	17	lb N/acre

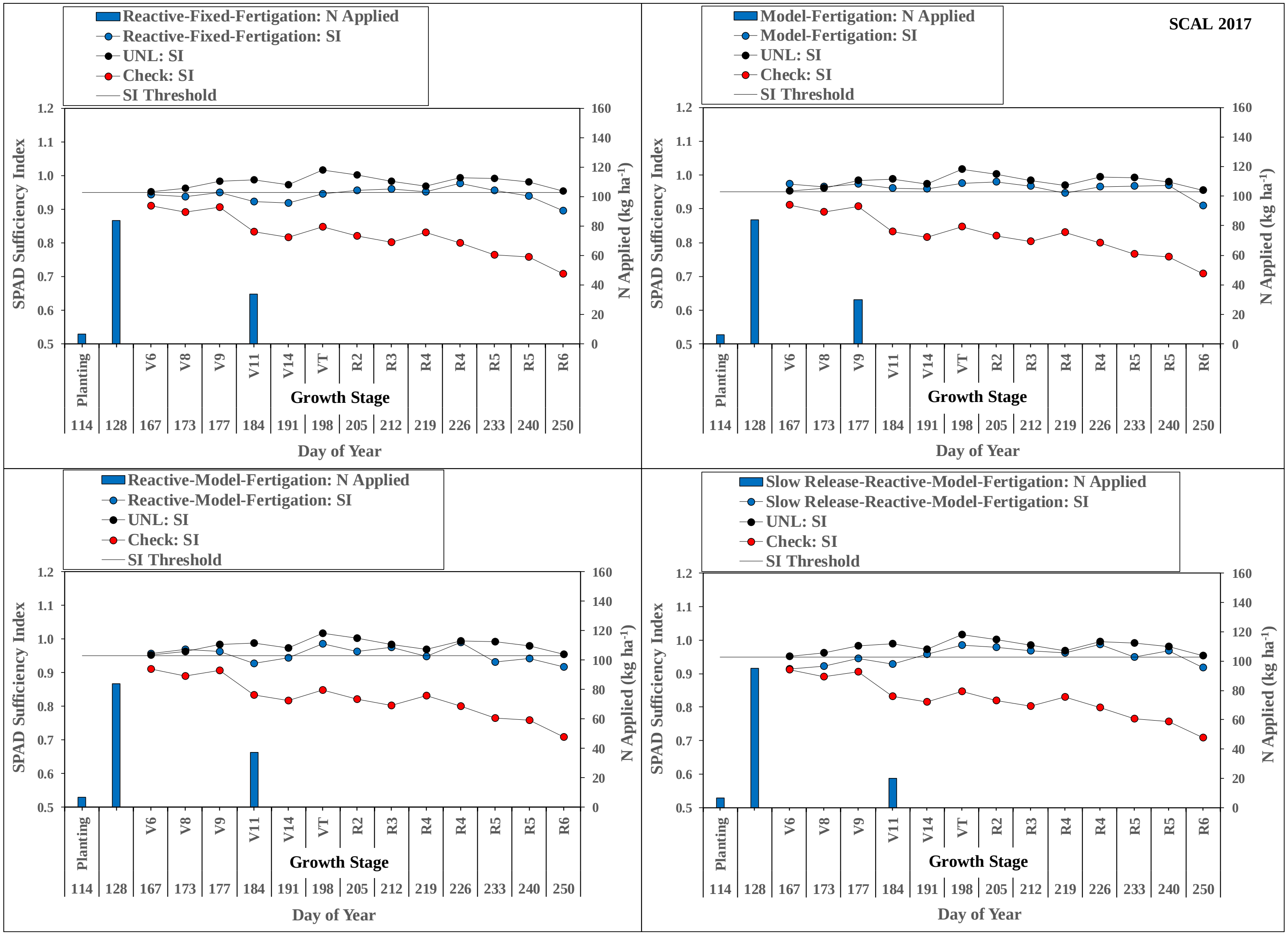

Figure A.1. A timeline view of average SI values and N applied for the reactive-fixed fertigation (top left), model fertigation (top right), reactive-model fertigation (bottom left), and slow-release reactive-model fertigation (bottom right) treatments with the check and UNL treatments used as comparisons for the SCAL site in 2017

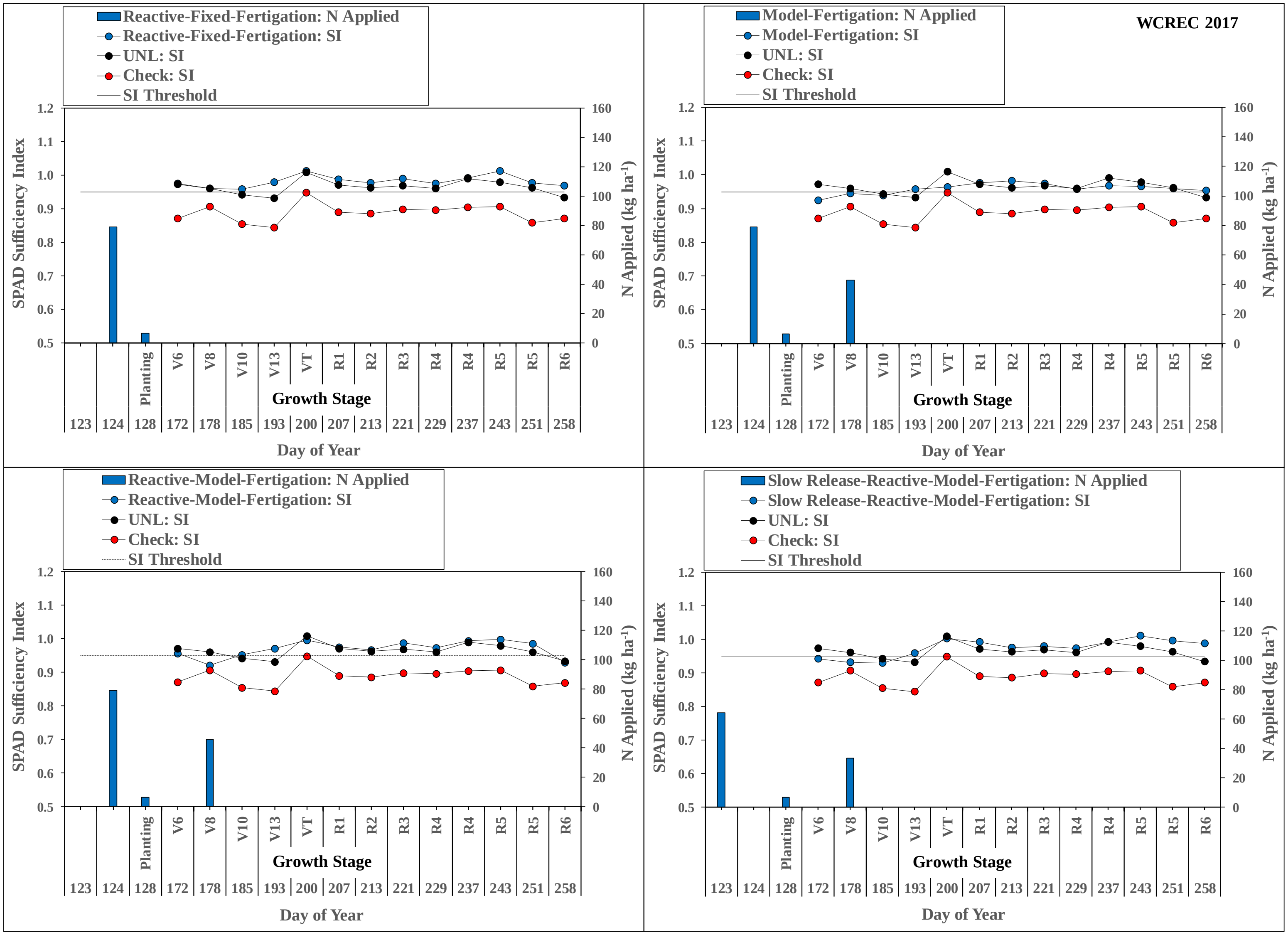

Figure A.2. A timeline view of average SI values and N applied for the reactive-fixed fertigation (top left), model fertigation (top right), reactive-model fertigation (bottom left), and slow-release reactive-model fertigation (bottom right) treatments with the check and UNL treatments used as comparisons for the WCREC site in 2017.

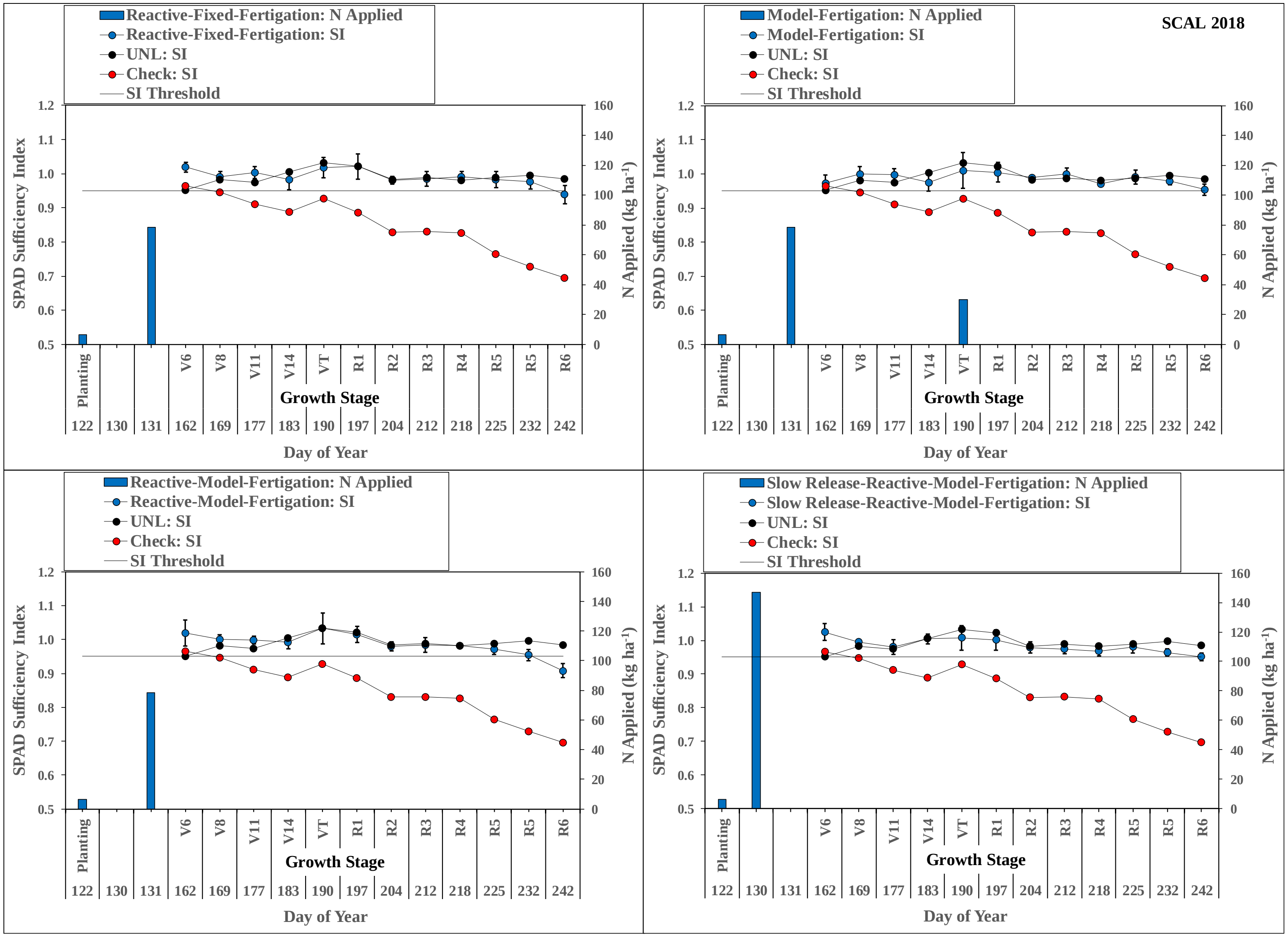

Figure A.3. A timeline view of average SI values and N applied for the reactive-fixed fertigation (top left), model fertigation (top right), reactive-model fertigation (bottom left), and slow-release reactive-model fertigation (bottom right) treatments with the check and UNL treatments used as comparisons for the SCAL site in 2018. Error bar is the standard error for four replications.

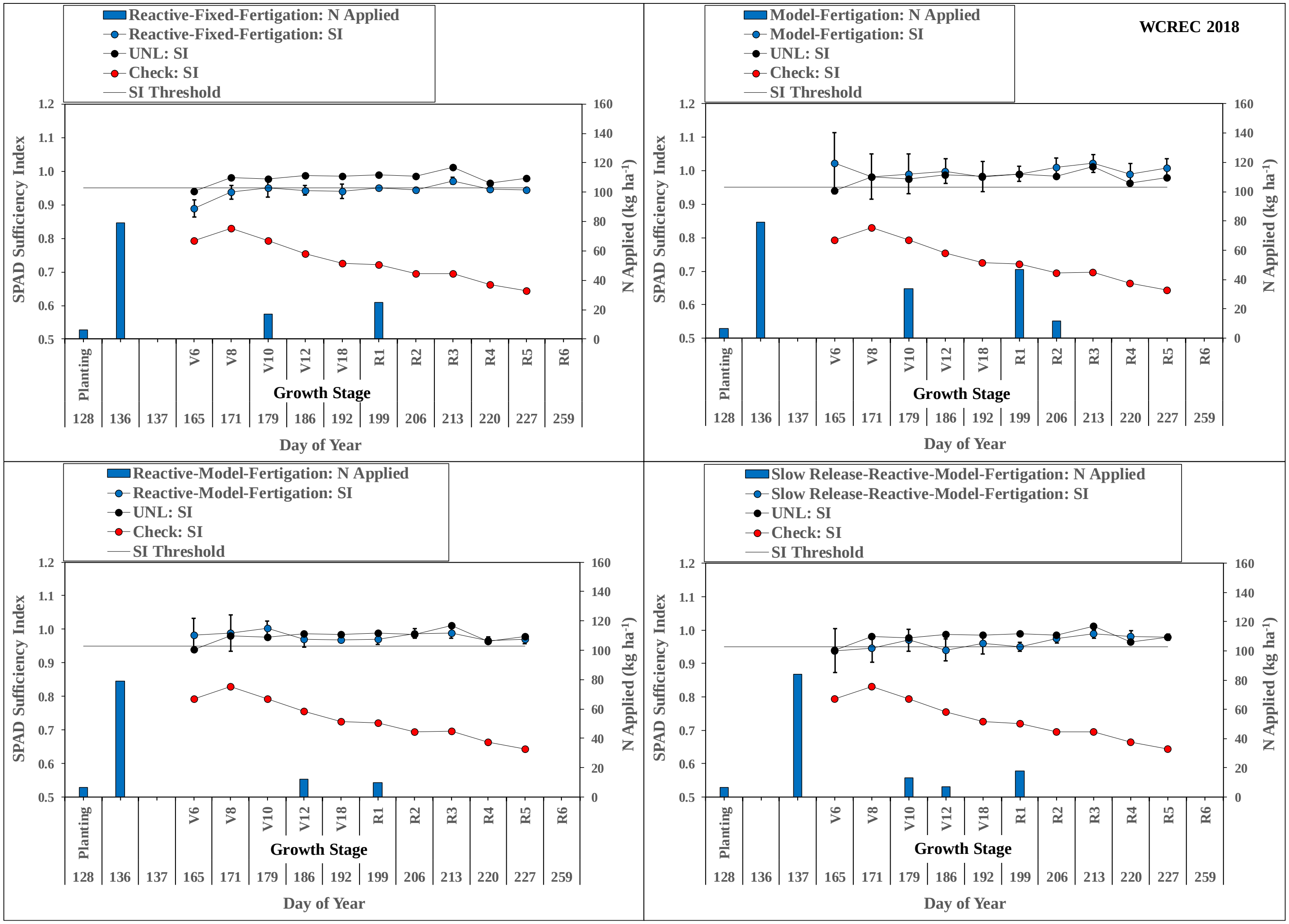

Figure A.4. A timeline view of average SI values and N applied for the reactive-fixed fertigation (top left), model fertigation (top right), reactive-model fertigation (bottom left), and slow-release reactive-model fertigation (bottom right) treatments with the check and UNL treatments used as comparisons for the WCREC site in 2018. Error bar is the standard error for four replications.

Appendix B

Table. B.1 User input Maize-N model settings for model treatment for SCAL18 site year at planting.

SCAL18		
USER INPUT SETTINGS		
Weather data	2018 05 10-SCAL-MaizeN_Weather_All_Trt.wth†	
The Maize Crop		
Hybrid relative maturity (days)	107	
Date of planting	05/02/2018	
Plant population	34	x1000/acre
Price of maize	3.72	/bu
An average yield of last 5 years	N/A	
Last Crop		
Type of crop	Corn	
Economic yield	237	bu/acre
Total N applied	107	lb/acre
User-set last crop fertilizer recover rate, %	N/A	
Date of maturity	9/28/2017	
Amount of residues left in the field	All	
Soil moisture of entire rooting depth at maturity as % of field capacity	50%	
Nitrogen Fertilizer Management		
N already applied		
Dates	05/02/2018	
Amount	5	lb N/acre
N to be applied		
Type of fertilizer for in-season applications	Urea ammonium nitrate (UAN32%)	
N content of the fertilizer	32	%
Price of the fertilizer	260	/ton
User-set overall fertilizer recover rate, %	N/A	
N from irrigation water	8	lb N/acre
Applied slow-release N fertilizer		
N/A		

Tillage		
Type of tillage	No-till	
Date of tillage operation	05/02/2018	
Soil properties		
Top-soil organic matter content	3.3	%
Top-soil bulk density	1.3	g/cm3
Average soil texture of root zone	Silt Loam	
Soil pH	Neutral	
Soil root zone depth	48	inch
Manuring		
N/A		
Measured Soil Nitrate to 1.2 m Depth		
Amount	56	lb N/acre
Date of soil sampling	04/19/2018	

† Long term weather data was used to predict the amount of N mineralization for the remainder of the season.

Table. B.2 Maize-N model output for model treatment for SCAL18 site year at planting.

SCAL17		
N rate recommendation for maize		
Date: 05/10/18		
Overall economically optimal N rate (EONR)	125	(±29) lb N/acre
N doses:		
Total N already applied	5	lb N/acre
N to be applied	120	lb N/acre
Total fertilizer cost	51	/acre
Recovery Efficiency (RE) of fertilizer	0.6 0	N-uptake/N-applied
Physiological efficiency of N-uptake from fertilize (PE)	54	lb maize/lb N-uptake
Agronomic Efficiency of fertilizer-N (AE)	32	lb maize/lb fertilizer-N
Yield potential (Yp)	245	(±24) bu/acre
Attainable yield at EONR (Ya)	209	bu/acre
Yield without N fertilizer (Y0)	136	bu/acre
Total N uptake demand:	183	lb/acre
N uptake from indigenous sources, total:	107	lb/acre
From N-leftover	13	lb N/acre
From SOM mineralization	92	lb N/acre
From crop residues mineralization	-4	lb N/acre
From manure	0	lb N/acre
From slow-release fertilizer	0	lb N/acre
From irrigation water	6	lb N/acre
This season up-to-date N leaching	0	lb N/acre
Long-term average N leaching loss of the same period	2	lb N/acre

Table. B.3 User input Maize-N model settings for model treatment for SCAL19 site year at planting.

SCAL18		
USER INPUT SETTINGS		
Weather data	2019 05 22-SCAL-MaizeN_Weather_All_Trt.wth	
The Maize Crop		
Hybrid relative maturity (days)	109	
Date of planting	05/14/2019	
Plant population	34	x1000/acre
Price of maize	3.81	/bu
An average yield of last 5 years	N/A	
Last Crop		
Type of crop	Corn	
Economic yield	221	bu/acre
Total N applied	125	lb/acre
User-set last crop fertilizer recover rate, %	N/A	
Date of maturity	10/03/2018	
Amount of residues left in the field	All	
Soil moisture of entire rooting depth at maturity as % of field capacity	50%	
Nitrogen Fertilizer Management		
N already applied		
Dates	05/14/2019	
Amount	5	lb N/acre
N to be applied		
Type of fertilizer for in-season applications	Urea ammonium nitrate (UAN32%)	
N content of the fertilizer	32	%
Price of the fertilizer	255	/ton
User-set overall fertilizer recover rate, %	N/A	
N from irrigation water	8	lb N/acre
Applied slow-release N fertilizer		
N/A		
Tillage		
Type of tillage	No-till	

Date of tillage operation	05/14/2019	
Soil properties		
Top-soil organic matter content	3.3	%
Top-soil bulk density	1.3	g/cm3
Average soil texture of root zone	Silt Loam	
Soil pH	Neutral	
Soil root zone depth	48	inch
Manuring		
N/A		
Measured Soil Nitrate to 1.2 m Depth		
Amount	38	lb N/acre
Date of soil sampling	04/17/2019	

Table. B.4 Maize-N model output for model treatment for SCAL19 site year at planting.

SCAL17		
N rate recommendation for maize		
Date: 05/22/19		
Overall economically optimal N rate (EONR)	154	(±29) lb N/acre
N doses:		
Total N already applied	5	lb N/acre
N to be applied	148	lb N/acre
Total fertilizer cost	61	/acre
Recovery Efficiency (RE) of fertilizer	0.60	N-uptake/N-applied
Physiological efficiency of N-uptake from fertilize (PE)	56	lb maize/lb N-uptake
Agronomic Efficiency of fertilizer-N (AE)	33	lb maize/lb fertilizer-N
Yield potential (Yp)	249	(±24) bu/acre
Attainable yield at EONR (Ya)	212	bu/acre
Yield without N fertilizer (Y0)	120	bu/acre
Total N uptake demand:	185	lb/acre
N uptake from indigenous sources, total:	93	lb/acre
From N-leftover	8	lb N/acre
From SOM mineralization	82	lb N/acre
From crop residues mineralization	-3	lb N/acre
From manure	0	lb N/acre
From slow-release fertilizer	0	lb N/acre
From irrigation water	6	lb N/acre
This season up-to-date N leaching	2	lb N/acre
Long-term average N leaching loss of the same period	3	lb N/acre

Table B.5. Site year, sampling date, growth stage, predicted N uptake, and observed N uptake for Maize-N model treatment for SCAL18 and SCAL19.

Site Year ID	Sampling Date	Growth Stage	Predicted N Uptake (kg ha^{-1})	Observed N Uptake (kg ha^{-1})
SCAL18	**2018/06/19**	V8	59.7	62.0
	2018/07/02	V12	97.1	115.3
	2018/07/16	R1	135.1	166.2
	2018/08/01	R3	166.9	201.0
	2018/08/13	R5	184.4	225.3
	2018/09/08	R6	190.5	234.8
SCAL19	**2019/07/02**	V8	83.4	54.4
	2019/07/16	V12	124.4	130.5
	2019/07/29	R1	155.0	144.5
	2019/08/20	R3	188.5	165.3
	2019/09/15	R6	193.8	194.8

Table B.6. Site year, sampling date, growth stage, predicted soil nitrate-N, and observed soil nitrate-N for Maize-N model treatment for SCAL18 and SCAL19.

Site Year ID	Sampling Date	Growth Stage	Predicted Soil Nitrate-N (kg ha^{-1})	Observed Soil Nitrate-N (kg ha^{-1})
SCAL18	**2018/06/18**	V8	178.9	113.0
	2018/07/03	V12	148.8	95.9
	2018/07/17	R1	124.6	36.1
	2018/07/31	R3	107.8	21.8
	2018/08/17	R5	98.6	21.2
SCAL19	**2019/07/01**	V8	122.1	77.7
	2019/07/15	V12	94	37.8
	2019/07/29	R1	73.9	41.5
	2019/08/19	R3	59.8	17.4

Table B.7. Site year, sampling date, growth stage, and observed soil nitrate-N by depth for Maize-N model treatment for SCAL18 and SCAL19.

Site Year ID	Sampling Date	Growth Stage	Observed Soil Nitrate-N (kg ha^{-1}) Depth (cm)			
			30	**60**	**90**	**120**
SCAL18	**2018/06/18**	V8	45.6	29.5	18.7	19.3
	2018/07/03	V12	51.7	12.8	15.1	16.4
	2018/07/17	R1	13.5	6.7	7.7	8.2
	2018/07/31	R3	9.6	3.5	4.1	4.7
	2018/08/17	R5	13.2	3.1	2.2	2.7
SCAL19	**2019/07/01**	V8	27.5	15.8	19.5	14.8
	2019/07/15	V12	10.6	6.2	9.4	11.6
	2019/07/29	R1	13.0	9.0	8.6	11.0
	2019/08/19	R3	9.5	3.5	1.8	2.6

Appendix C

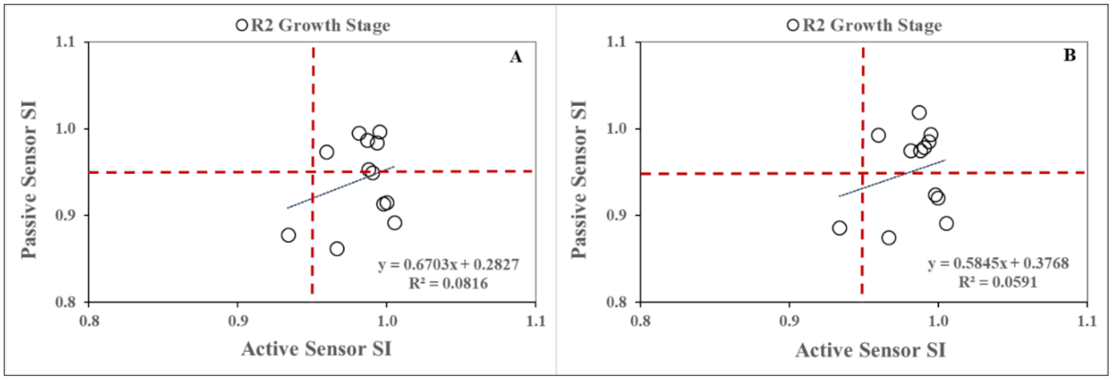

Figure C.1. Correlation between active sensor sufficiency index (based on average NDRE values) and passive sensor sufficiency index (based on average NDRE values) values (A) active sensor sufficiency index and passive sensor sufficiency index (based 90 percentile NDRE value) values (B) for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments (n=12) at R2 growth stage for SCAL 2017.

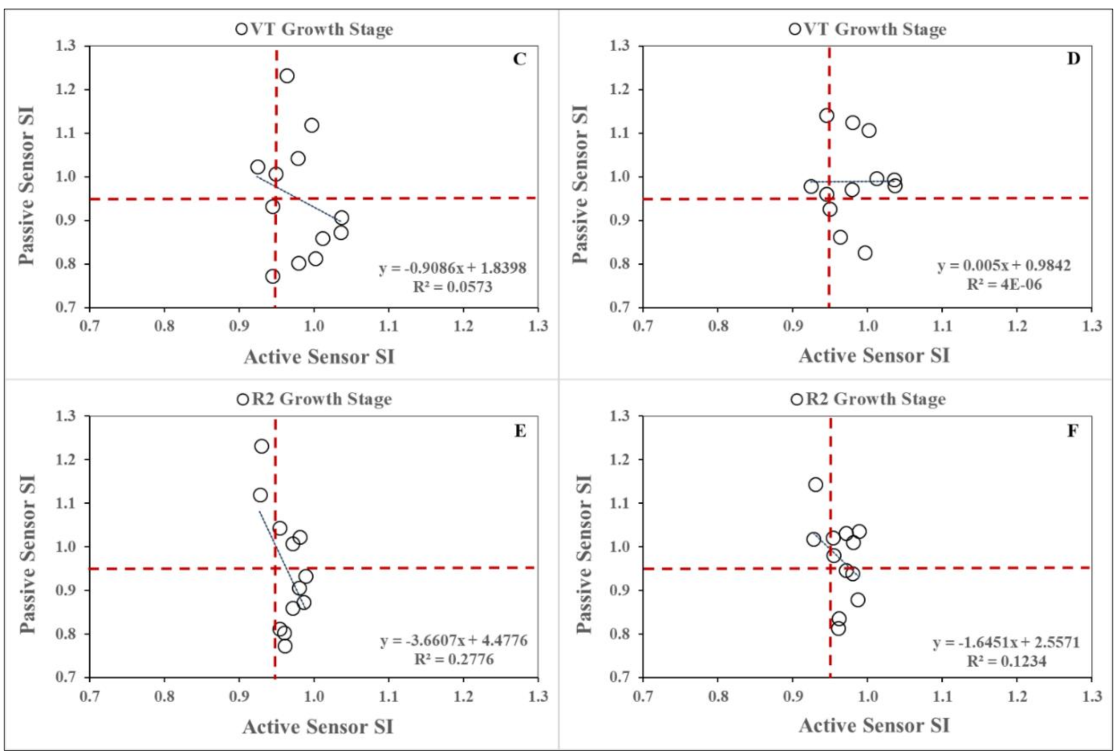

Figure C.2. Correlation between active sensor sufficiency index (based on average NDRE values) and passive sensor sufficiency index (based on average NDRE values) values (C and E) active sensor sufficiency index and passive sensor sufficiency index (based 95 and 90 percentile NDRE values) values (D and F) for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments (n=12) at VT and R2 growth stages for SCAL 2018.

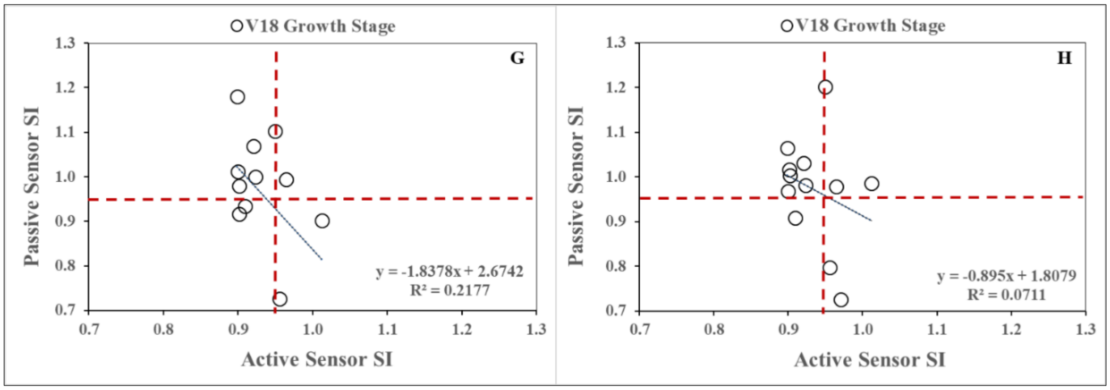

Figure C.3. Correlation between active sensor sufficiency index (based on average NDRE values) and passive sensor sufficiency index (based on average NDRE values) values (G) active sensor sufficiency index and passive sensor sufficiency index (based 90 percentile NDRE value) values (H) for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments (n=12) at V18 growth stage for WCREC 2018.

Table C.1. Relationship between active sensor sufficiency index (based on average NDRE values) and passive sensor sufficiency index (based on average NDRE values) fertigation decisions for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments at R2, VT, R2, and V18 growth stages for SCAL2017, SCAL 2018, and WCREC 2018, respectively.

		Treatment			
Site Year	Growth Stage	R-F-Fixed	R-F-Model	R-F-Model-SR	
		Matching Fertigation Decisions			Overall
SCAL 2017	**R2**	0.75	0.50	0.50	0.58
SCAL 2018	**VT**	0.25	0.75	0.75	0.58
SCAL 2018	**R2**	0.25	0.00	0.50	0.25
WCREC 2018	**V18**	0.50	0.00	0.25	0.25

Table C.2. Relationship between active sensor sufficiency index (based on average NDRE values) and passive sensor sufficiency index (based on 90 and 95 percentile NDRE values) fertigation decisions for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments at R2, VT, R2, and V18 growth stages for SCAL2017, SCAL 2018, and WCREC 2018, respectively.

		Treatment			
Site Year	Growth Stage	R-F-Fixed	R-F-Model	R-F-Model-SR	
		Matching Fertigation Decisions			Overall
SCAL 2017†	R2	0.75	0.75	0.50	0.67
SCAL 2018δ	VT	0.25	0.50	1.00	0.58
SCAL 2018†	R2	0.25	0.50	0.50	0.42
WCREC 2018†	V18	0.50	0.00	0.25	0.25

† Passive SI value-based on 90 percentile NDRE value
δ Passive SI value-based on 95 percentile NDRE value

Table C.3. SPAD SI values for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments with plot number and replications at V6 through R2 growth stage for SCAL17.

			Growth Stage						
			V6	V8	V9	V11	V14	VT	R2
Plot	Trt	Rep	SPAD SI	SPAD SI	SPAD SI	SPAD SI	SPAD SI	SPAD SI	SPAD SI
106	R-F-Fixed	1	0.97	0.91	1.00	0.93	0.91	0.97	0.98
104	R-F-Model	1	0.99	0.96	0.96	0.91	0.92	0.99	0.99
105	R-F-Model-SR	1	0.91	0.93	1.01	0.91	0.95	0.96	0.98
207	R-F-Fixed	2	0.90	0.93	0.92	0.89	0.90	0.93	0.96
203	R-F-Model	2	0.99	0.98	0.95	0.96	0.99	0.99	0.99
202	R-F-Model-SR	2	0.92	0.92	0.93	1.00	0.96	0.99	0.99
308	R-F-Fixed	3	1.01	0.96	0.97	0.93	0.89	0.88	0.96
301	R-F-Model	3	0.96	0.99		0.91	0.92	0.92	0.92
304	R-F-Model-SR	3	0.97	0.93	0.93	0.89	0.96	0.94	0.99
407	R-F-Fixed	4	0.90	0.94	0.92	0.94	0.96	1.01	0.93
405	R-F-Model	4	0.89	0.95	0.96	0.93	0.94	1.05	0.96
406	R-F-Model-SR	4	0.86	0.92	0.92	0.92	0.96	1.05	0.96

The red color of SI values indicates SI values were equal to or less than the 0.95 thresholds.

Table C.4. Active sensor SI values for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments with plot number and replications at V6 through R2 growth stage for SCAL17.

			Growth Stage						
			V6	V8	V9	V11	V14	VT	R2
Plot	Trt	Rep	Active sensor SI	Active sensor SI	Active sensor SI	Active sensor SI	Active sensor SI	Active sensor SI	Active sensor SI
106	R-F-Fixed	1	0.95	0.99	0.98	0.95	1.01	1.00	1.01
104	R-F-Model	1	0.90	0.95	0.95	0.94	1.00	0.98	0.98
105	R-F-Model-SR	1	0.89	0.94	0.94	0.93	0.97	1.02	1.00
207	R-F-Fixed	2	0.89	0.90	0.91	0.92	0.95	0.98	0.96
203	R-F-Model	2	0.99	0.98	0.97	0.96	0.95	1.02	0.99
202	R-F-Model-SR	2	0.90	0.94	0.94	0.95	0.97	1.04	0.99
308	R-F-Fixed	3	0.90	0.96	0.94	0.93	0.96	0.93	0.93
301	R-F-Model	3	0.87	0.95	0.93	0.93	1.04	0.96	0.97
304	R-F-Model-SR	3	0.83	0.93	0.90	0.93	1.01	0.97	1.00
407	R-F-Fixed	4	0.86	0.94	0.93	0.94	1.03	0.99	0.99
405	R-F-Model	4	0.88	0.93	0.92	0.94	1.06	0.99	0.99
406	R-F-Model-SR	4	0.83	0.93	0.92	0.93	0.99	1.00	0.99

Table C.5. SPAD SI values for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments with plot number and replications at V6 through R2 growth stage for SCAL18.

			Growth Stage						
			V6	V8	V10	V14	VT	R1	R2
Plot	Trt	Rep	SPAD SI	SPAD SI	SPAD SI	SPAD SI	SPAD SI	SPAD SI	SPAD SI
103	R-F-Fixed	1	1.02	1.00	1.00	0.94	0.97	1.02	0.99
106	R-F-Model	1	1.02	1.02	1.02	1.00	1.00	1.01	0.99
107	R-F-Model-SR	1	1.02	0.99	1.00	1.03	0.99	1.00	1.02
204	R-F-Fixed	2	0.98	0.96	0.96	0.92	1.09	0.97	0.95
205	R-F-Model	2	0.91	0.97	0.97	0.94	1.12	0.99	0.98
202	R-F-Model-SR	2	0.97	1.00	0.96	0.98	1.11	0.96	0.95
301	R-F-Fixed	3	1.05	0.98	1.00	1.02	0.97	0.97	0.99
302	R-F-Model	3	1.06	1.01	1.01	1.01	0.92	0.98	1.01
306	R-F-Model-SR	3	1.01	0.98	0.93	0.98	0.94	0.95	0.98
405	R-F-Fixed	4	1.03	1.03	1.05	1.05	1.04	1.13	1.00
408	R-F-Model	4	1.09	1.01	0.98	1.02	1.09	1.08	0.94
404	R-F-Model-SR	4	1.09	1.01	1.03	1.03	0.99	1.09	0.96

Table C.6. Active sensor SI values for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments with plot number and replications at V6 through R2 growth stage for SCAL18.

			Growth Stage						
			V6	V8	V10	V14	VT	R1	R2
Plot	Trt	Rep	Active sensor SI	Active sensor SI	Active sensor SI	Active sensor SI	Active sensor SI	Active sensor SI	Active sensor SI
103	**R-F-Fixed**	**1**	0.97	0.95	1.00	1.00	1.04	0.98	0.98
106	**R-F-Model**	**1**	1.04	0.99	1.03	1.02	1.01	0.97	0.97
107	**R-F-Model-SR**	**1**	1.05	1.01	1.03	1.02	1.04	1.00	0.99
204	**R-F-Fixed**	**2**	0.99	0.94	0.95	0.95	1.00	0.94	0.93
205	**R-F-Model**	**2**	0.96	0.97	0.95	0.95	0.96	0.95	0.93
202	**R-F-Model-SR**	**2**	1.00	0.96	0.98	0.98	0.95	0.95	0.97
301	**R-F-Fixed**	**3**	1.09	1.05	1.03	1.05	0.94	1.00	0.96
302	**R-F-Model**	**3**	1.05	1.03	1.05	1.02	0.98	0.98	0.96
306	**R-F-Model-SR**	**3**	1.02	1.00	1.00	1.00	1.00	0.96	0.95
405	**R-F-Fixed**	**4**	1.07	1.06	1.05	1.00	0.92	1.03	0.98
408	**R-F-Model**	**4**	1.02	1.01	1.03	0.95	0.94	1.00	0.99
404	**R-F-Model-SR**	**4**	1.02	1.01	1.03	1.00	0.98	1.03	0.95

Table C.7. SPAD SI values for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments with plot number and replications at V6 through R2 growth stage for WCREC17.

			Growth Stage						
			V6	V8	V10	V13	VT	R1	R2
Plot	**Trt**	**Rep**	**SPAD SI**	**SPAD SI**	**SPAD SI**	**SPAD SI**	**SPAD SI**	**SPAD SI**	**SPAD SI**
107	**R-F-Fixed**	**1**	0.91	0.87	0.93	0.94	0.99	0.97	0.96
105	**R-F-Model**	**1**	0.90	0.94	0.93	0.94	0.94	0.96	0.96
106	**R-F-Model-SR**	**1**	0.88	0.93	0.93	0.95	0.98	1.00	0.98
208	**R-F-Fixed**	**2**	1.00	1.03	0.96	0.98	1.02	0.97	0.98
204	**R-F-Model**	**2**	1.04	0.93	0.93	0.97	1.02	0.96	0.97
202	**R-F-Model-SR**	**2**	0.95	0.92	0.92	0.94	1.00	0.97	0.96
309	**R-F-Fixed**	**3**	1.03	0.98	0.96	0.98	1.01	1.03	0.97
301	**R-F-Model**	**3**	0.98	0.85	0.99	0.98	1.00	0.99	0.97
304	**R-F-Model-SR**	**3**	1.01	0.92	0.93	0.97	1.02	1.01	1.00
408	**R-F-Fixed**	**4**	0.97	0.96	0.99	1.02	1.03	0.98	1.00
405	**R-F-Model**	**4**	0.91	0.96	0.96	0.99	1.03	0.99	0.97
407	**R-F-Model-SR**	**4**	0.92	0.95	0.94	0.97	1.02	0.99	0.95

Table C.8. Active sensor SI values for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments with plot number and replications at V6 through R2 growth stage for WCREC17.

			Growth Stage						
			V6	V8	V10	V13	VT	R1	R2
Plot	Trt	Rep	Active sensor SI	Active sensor SI	Active sensor SI	Active sensor SI	Active sensor SI	Active sensor SI	Active sensor SI
107	R-F-Fixed	1	0.97	0.94	0.97	0.97	0.96	0.98	0.99
105	R-F-Model	1	0.98	0.93	0.97	1.00	0.98	1.02	1.00
106	R-F-Model-SR	1	0.89	0.86	0.89	0.99	0.97	1.00	0.97
208	R-F-Fixed	2	1.05	1.03	1.03	1.00	0.96	0.97	0.98
204	R-F-Model	2	0.99	1.00	1.02	0.99	0.99	0.99	1.03
202	R-F-Model-SR	2	0.92	0.90	0.99	0.98	0.95	0.99	1.03
309	R-F-Fixed	3	1.05	1.06	1.02	0.99	0.97	1.02	0.98
301	R-F-Model	3	1.02	1.03	0.98	0.98	0.99	1.02	1.00
304	R-F-Model-SR	3	0.96	0.97	0.97	0.98	1.00	1.00	0.98
408	R-F-Fixed	4	0.92	0.99	1.00	1.00	1.01	0.99	0.99
405	R-F-Model	4	0.85	0.92	0.95	0.95	1.00	0.98	0.97
407	R-F-Model-SR	4	0.84	0.90	0.90	0.93	0.96	0.98	0.96

Table C.9. SPAD SI values for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments with plot number and replications at V6 through R2 growth stage for WCREC18.

			Growth Stage						
			V6	V8	V10	V13	V18	R1	R2
Plot	Trt	Rep	SPAD SI	SPAD SI	SPAD SI	SPAD SI	SPAD SI	SPAD SI	SPAD SI
108	R-F-Fixed	1	0.81	0.88	0.88	0.92	0.92	0.94	0.94
103	R-F-Model	1	0.92	0.98	0.97	0.91	0.95	0.99	1.02
106	R-F-Model-SR	1	0.81	0.86	0.90	0.91	0.93	0.95	0.97
206	R-F-Fixed	2	0.92	0.97	1.00	0.97	0.99	0.96	0.96
202	R-F-Model	2	0.90	0.85	0.96	0.96	0.96	0.92	0.95
203	R-F-Model-SR	2	1.07	1.03	1.06	1.04	1.05	0.99	1.01
301	R-F-Fixed	3	0.92	0.96	0.93	0.92	0.89	0.94	0.92
308	R-F-Model	3	1.12	1.12	1.05	1.02	0.98	0.98	0.99
305	R-F-Model-SR	3	1.03	1.00	0.97	0.90	0.92	0.94	0.94
407	R-F-Fixed	4	0.91	0.95	0.98	0.96	0.96	0.95	0.95
405	R-F-Model	4	1.00	1.00	1.03	1.00	0.98	0.97	0.98
406	R-F-Model-SR	4	0.84	0.89	0.95	0.92	0.94	0.94	0.97

Table C.10. Active sensor SI values for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments with plot number and replications at V6 through R2 growth stage for WCREC18.

			Growth Stage						
			V6	V8	V10	V13	V18	R1	R2
Plot	Trt	Rep	Active sensor SI	Active sensor SI	Active sensor SI	Active sensor SI	Active sensor SI	Active sensor SI	Active sensor SI
108	R-F-Fixed	1	0.77	0.85	0.89	0.88	0.90	0.92	0.91
103	R-F-Model	1	0.98	1.02	1.00	0.98	0.92	0.98	0.99
106	R-F-Model-SR	1	0.87	0.85	0.91	0.92	0.95	0.96	0.94
206	R-F-Fixed	2	0.94	0.94	1.00	0.99	1.01	0.95	0.94
202	R-F-Model	2	0.86	0.85	0.93	0.94	0.96	0.93	0.94
203	R-F-Model-SR	2	1.10	1.02	1.06	1.03	0.97	0.99	1.04
301	R-F-Fixed	3	0.94	0.92	0.92	0.92	0.90	0.98	0.97
308	R-F-Model	3	1.26	1.19	1.09	1.01	0.90	1.00	0.99
305	R-F-Model-SR	3	1.09	1.00	0.96	0.95	0.90	0.96	1.00
407	R-F-Fixed	4	0.91	0.95	0.93	0.95	0.91	0.94	0.95
405	R-F-Model	4	1.05	1.02	1.00	0.98	0.92	0.96	0.93
406	R-F-Model-SR	4	0.89	0.87	0.91	0.91	0.96	0.92	0.94

Table C.11. Passive sensor SI values for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments with plot number and replications at V6 through R2 growth stage for SCAL17.

			Growth Stage	
			R2	R2
Plot	Trt	Rep	Passive sensor SI†	Passive sensor SI^δ
106	R-F-Fixed	1	0.89	0.89
104	R-F-Model	1	0.99	0.97
105	R-F-Model-SR	1	0.92	0.92
207	R-F-Fixed	2	0.97	0.99
203	R-F-Model	2	0.95	0.98
202	R-F-Model-SR	2	0.95	0.98
308	R-F-Fixed	3	0.88	0.89
301	R-F-Model	3	0.86	0.88
304	R-F-Model-SR	3	0.91	0.92
407	R-F-Fixed	4	0.98	0.99
405	R-F-Model	4	1.00	0.99
406	R-F-Model-SR	4	0.99	1.02

† Passive SI value-based on average NDRE values.
δ Passive SI value-based on 90 percentile NDRE value.

Table C.12. Passive sensor SI values for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments with plot number and replications at V6 through R2 growth stage for SCAL18.

			Growth Stage			
			VT	VT	R2	R2
Plot	Trt	Rep	Passive sensor SI†	Passive sensor SI*	Passive sensor SI†	Passive sensor SI δ
103	R-F-Fixed	1	0.94	0.98	0.91	0.94
106	R-F-Model	1	0.98	1.00	0.86	1.03
107	R-F-Model-SR	1	0.99	0.99	0.87	0.88
204	R-F-Fixed	2	0.78	0.83	1.12	1.02
205	R-F-Model	2	0.82	0.86	1.23	1.14
202	R-F-Model-SR	2	0.84	0.93	1.01	0.95
301	R-F-Fixed	3	1.06	1.14	0.77	0.84
302	R-F-Model	3	1.03	1.12	0.80	0.81
306	R-F-Model-SR	3	1.01	1.11	0.81	0.98
405	R-F-Fixed	4	0.93	0.98	1.02	1.01
408	R-F-Model	4	0.93	0.96	0.93	1.04
404	R-F-Model-SR	4	0.86	0.97	1.04	1.02

† Passive SI value-based on average NDRE values.
*** Passive SI value-based on 95 percentile NDRE value.**
δ Passive SI value-based on 90 percentile NDRE value.

Table C.13. Passive sensor SI values for R-F-Fixed, R-F-Model, and R-F-Model-SR treatments with plot number and replications at V6 through R2 growth stage for WCREC18.

			Growth Stage	
			V18	V18
Plot	TRT	Rep	Passive sensor SI †	Passive sensor SI δ
108	R-F-Fixed	1	0.92	1.02
103	R-F-Model	1	1.07	1.03
106	R-F-Model-SR	1	1.10	1.20
206	R-F-Fixed	2	0.90	0.99
202	R-F-Model	2	0.73	0.80
203	R-F-Model-SR	2	0.68	0.73
301	R-F-Fixed	3	0.98	1.00
308	R-F-Model	3	1.18	1.06
305	R-F-Model-SR	3	1.01	0.97
407	R-F-Fixed	4	0.93	0.91
405	R-F-Model	4	1.00	0.98
406	R-F-Model-SR	4	0.99	0.98

† Passive SI value-based on average NDRE values.
δ Passive SI value-based on 90 percentile NDRE value.