Remote Sensing

An Active Sensor Algorithm for Corn Nitrogen Recommendations Based on a Chlorophyll Meter Algorithm

Fernando Solari, John F. Shanahan,* Richard B. Ferguson, and Viacheslav I. Adamchuk

ABSTRACT

In previous research we found active canopy sensor reflectance assessments of corn (*Zea mays* L.) N status have potential for directing in-season N applications, but emphasized an algorithm was needed to translate sensor readings into appropriate N application (N_{app}) rates. The objectives of this work were to: (i) develop an active canopy sensor algorithm based on a SPAD chlorophyll meter algorithm and (ii) validate the active canopy sensor algorithm using data collected from a companion study. We derived the sensor algorithm using a linear relationship between sensor sufficiency index (SI_{sensor}) and SI_{SPAD} values established in the previous research and a published SPAD algorithm employing a quadratic equation to calculate N_{app} as a function of SI_{SPAD}. The resulting equation: $N_{app} = 317\sqrt{0.97 - SI_{sensor}}$ represents the function for translating SI_{sensor} to N_{app}. To validate the algorithm, SI_{sensor} values collected from small plots receiving varying N amounts were converted into N_{app} using the algorithm. Then N_{app} was converted into crop N balance ($N_{balance}$) estimates, where $N_{balance}$ = applied N-N_{app}. Negative $N_{balance}$ values indicate N deficiency while positive values indicate excess N. The $N_{balance}$ values were compared with relative yields and a quadratic-plateau model fit to the data set for both growth stages (V11 and V15), producing an R^2 of 0.66. Relative yields plateaued at an $N_{balance}$ near zero (–11 kg N ha^{-1}), indicating the algorithm provided reasonable estimates of N_{app} for maximizing yields. The equation provides a basis for the use of active crop canopy sensors for in-season N management of irrigated corn

The development of alternative N management strategies is crucial for sustaining future corn production in the United States and around the world, because current N management approaches have led to low nitrogen use efficiency (NUE), economic losses, and environmental contamination issues (Shanahan et al., 2008). In previous work (Solari et al., 2008), use of active sensor reflectance measurements of the corn canopy to guide spatially variable in-season N applications was proposed as a means to improve corn NUE and decrease environmental contamination. The active canopy sensor used in this work was the Crop Circle model ACS-210 (Holland Scientific, Inc., Lincoln, NE), which measures canopy reflectance at two wavebands in the visible (VIS) and near infrared (NIR), centered at 590 ± 5.5 nm (VIS_{590}) and 880 ± 10 nm (NIR_{880}), respectively. We found that sensor readings, expressed as either normalized difference vegetation index ($NDVI_{590}$) or chlorophyll index (CI_{590}) values, and standardized to measurements obtained in well-fertilized N reference plots (sufficiency index, SI_{sensor}), were most highly correlated with normalized SPAD chlorophyll meter (SI_{SPAD}) values and relative grain yields when acquired during vegetative growth (V11 through V15) than reproductive growth. Thus, it was concluded that sensor readings obtained during vegetative growth have potential for directing spatially variable in-season N applications. Despite demonstrating the potential for using active sensors to guide N applications in the previous work, it was nevertheless noted that it would first be necessary to develop an algorithm for converting active sensor measurements into appropriate N fertilizer application rates.

In this paper, an algorithm for converting active canopy sensor measurements into site-specific N applications is proposed. The sensor algorithm is based on a SPAD algorithm published by Varvel et al. (2007) that outlines procedures for translating SPAD readings into corn N rate recommendations and incorporates results from Solari et al. (2008) showing a linear relationship between normalized active canopy sensor (SI_{sensor}) and SI_{SPAD} readings. Studies were conducted under sprinkler irrigation (using irrigation water with no N contamination) at the Management Systems Evaluation Area (MSEA), a relatively uniform site in the central Platte Valley located near Shelton, NE, on a Hord silt loam (fine-silty, mixed, superactive, mesic Cumulic Haplustoll) soil (see Fig. 1).

The SPAD algorithm work by Varvel et al. (2007) originated from a long-term study initiated at the MSEA 1 site in 1991 (Fig. 1), and involved treatments consisting of a factorial combination of two crop rotations [monoculture corn and corn–soybean [*Glycine max* (L.) Merr.], four corn

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Abbreviations: CI, chlorophyll index; MSEA, Management Systems Evaluation Area; NDVI, normalized difference vegetation index; NIR, near infrared reflectance; NUE, nitrogen use efficiency; SI, sufficiency index; SPAD, SPAD chlorophyll meter.

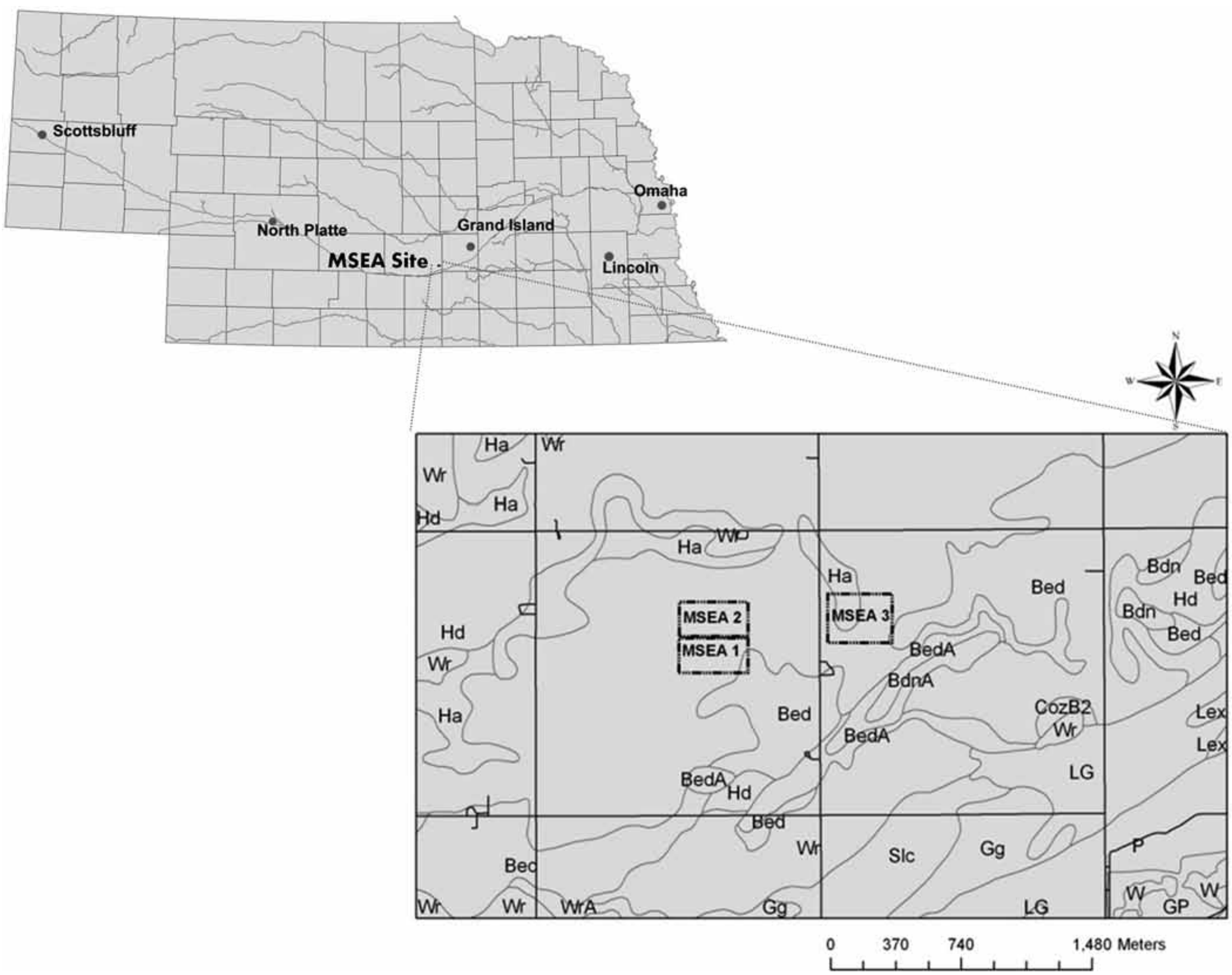

Fig. 1. Map of the state of Nebraska and localized soils map of management systems evaluation area (MSEA) and location of MSEA 1, MSEA 2, and MSEA 3 sites where various studies were conducted to develop the active sensor algorithm.

hybrids and five N rates applied at planting (0, 50, 100, 150, and 200 kg N ha^{-1}). All phases of the monoculture corn and soybean– corn systems appeared each year, and N treatments were imposed on the same plots each year of the study. Data collected for this work included SPAD readings taken at weekly intervals during the growing season, usually starting at the V6 growth stage for approximately 6 to 9 wk. Besides SPAD measurements, grain yield was also determined for each treatment area. Data used for this research covered a 10-yr period (1995–2004). Results showed that there were significant linear correlations between SI_{SPAD} and normalized grain yields across growth stages and years, indicating both response variables responded similarly to N fertilizer application. Regression analyses of normalized yield response to increasing N best fit a quadratic model, and indicated maximum yield occurred at around 179 kg N ha^{-1} when averaged over the 10-yr period of the study. Furthermore, maximum yields occurred within 10 to 20 kg N ha^{-1} of this value across years, indicating yield-maximizing N application rates deviated only slightly from year to year. Likewise, normalized SPAD readings exhibited a quadratic response to increasing N for SPAD data acquired from V8 to V12 growth stages and over years (R^2 = 0.70). From these results, Varvel et al. (2007) concluded that SI_{SPAD} measurements collected during vegetative growth could be used to assess corn N status across a range of environmental conditions and growth stages.

Based on their results, Varvel et al. (2007) proposed an algorithm (Fig. 2) for converting SI_{SPAD} values into in-season N application rates that could be used to correct in-season N deficiencies at V8 through V12 growth stages and potentially maximize grain yields. An example of how this SPAD algorithm could be used in prescribing N applications is illustrated in Fig. 2 by substituting a hypothetical SI_{SPAD} value of 0.89 into their equation shown and solved for N rate. This N rate is the amount of fertilizer N required to obtain the hypothetical SI value. This calculated N rate can then be subtracted from the maximum N rate (i.e., 179 – 50 = 129 kg N ha^{-1}) to determine amount of fertilizer N to be applied at or very near the time of SPAD data collection to achieve maximum yields obtainable within the constraints of location and season (Fig. 2). Varvel et al. (2007) suggested this general approach should be valid regardless of the instruments used to acquire data for SI, with the only requirements being that the instrument readings respond to N rate and they are related to yield. These limitations are reasonable and should allow the SPAD approach to be used with noncontact active

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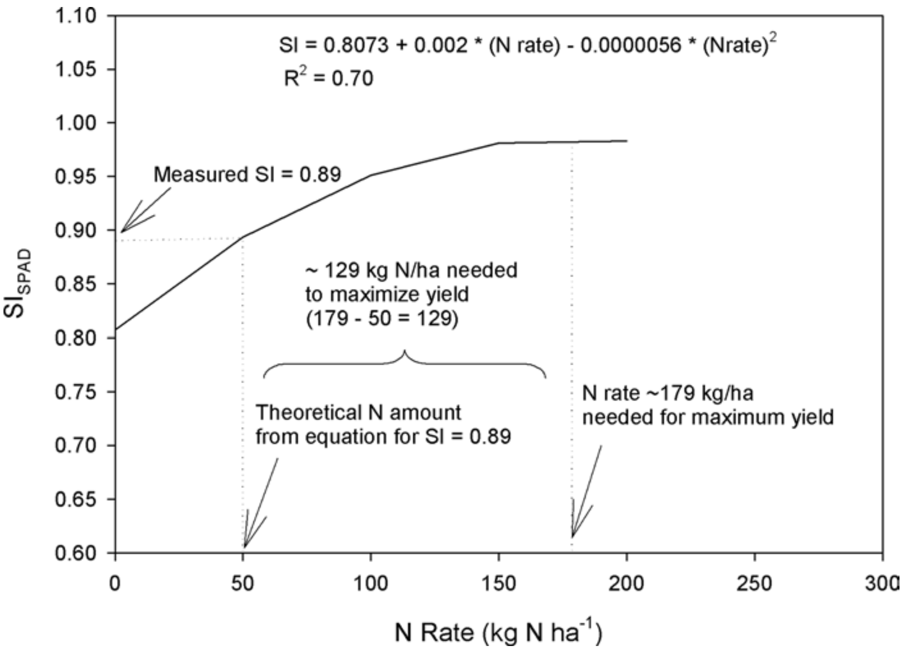

Fig. 2. Quadratic response model from regression analyses of relative chlorophyll meter readings (SI_{SPAD}) and N fertilizer rates at all growth stages (V8, V10, and V12) combined for monoculture corn data (1995–2004) at Shelton, NE, and an example of N application calculation (from Varvel et al., 2007).

canopy sensors as well. Results from Solari et al. (2008) with the active canopy sensor showed that normalized active sensor canopy reflectance measurements were in fact responsive to N rate and were highly correlated with SPAD and grain yield data. Collectively, these results provide strong support for the concept that active canopy sensor readings can be used in lieu of SPAD readings for prescribing N applications. Hence, the objectives of this work were to: (i) develop an active canopy sensor algorithm based on a SPAD chlorophyll meter algorithm and (ii) validate the active canopy sensor algorithm using data collected from a companion study.

MATERIALS AND METHODS

Development of Sensor Algorithm

The procedures for development of a sensor algorithm for translating active canopy sensor readings into variable N applications are outlined as follows. First, equations used for converting active sensor reflectance bands in the VIS_{590} and NIR_{880} into the normalized difference vegetative index ($NDVI_{590}$) or chlorophyll index (CI_{590}) are shown as per Solari et al. (2008):

$$\mathrm{NDVI}_{590} = \frac{\mathrm{NIR}_{880} - \mathrm{VIS}_{590}}{\mathrm{NIR}_{880} + \mathrm{VIS}_{590}} \qquad [1]$$

$$\mathrm{CI}_{590} = \frac{\mathrm{NIR}_{880}}{\mathrm{VIS}_{590}} - 1 \qquad [2]$$

Then the SI concept (Biggs et al., 2002) was used to convert sensor output expressed as NDVI or CI into sensor-based SI (SI_{sensor}) using:

$$\mathrm{SI}_{\mathrm{sensor\ NDVI}} = \frac{\mathrm{NDVI}}{\mathrm{NDVI}_{\mathrm{N\ reference}}} \qquad [3]$$

$$\mathrm{SI}_{\mathrm{sensor\ CI}} = \frac{\mathrm{CI}}{\mathrm{CI}_{\mathrm{N\ reference}}}$$

where, the numerator represents sensor readings ($NDVI_{590}$ or CI_{590}) of a targeted crop area (potentially N deficient) and the denominator is sensor output from a well-fertilized area. Normalizing sensor data to a well-fertilized reference plot allows the estimation of the crop's ability to respond to applied N and serves to normalize data to a particular environment. This eliminates the need to develop a calibration function for each set of specific variables and local conditions (Samborski et al., 2009).

Since this algorithm was to be developed on the SPAD-based framework (Varvel et al., 2007), the generalized (Eq. [4]) and specific (Eq. [5]) forms of the quadratic (second-order polynomial) response function are:

$$\mathrm{SI}_{\mathrm{SPAD}} = a_0 + a_1 \times \mathrm{N}_{\mathrm{rate}} + a_2 \times (\mathrm{N}_{\mathrm{rate}})^2 \qquad [4]$$

$$\mathrm{SI}_{\mathrm{SPAD}} = 0.8073 + 0.002 \times \mathrm{N}_{\mathrm{rate}} - 0.0000056 \times (\mathrm{N}_{\mathrm{rate}})^2 \qquad [5]$$

For Eq. [4], the a_0, a_1, a_2 coefficients represent the – intercept, linear, and quadratic terms, respectively, and the response portion of the equation can be solved for N rate as follows:

$$\mathrm{N}_{\mathrm{rate}}(\mathrm{SI}_{\mathrm{SPAD}}) = \frac{-a_1 - \sqrt{a_1^2 - 4a_2(a_0 - \mathrm{SI}_{\mathrm{SPAD}})}}{2a_2} \qquad [6]$$

In this case, yield-maximizing N_{rate} can be found as:

$$\mathrm{N}_{\mathrm{rate}}(\max \mathrm{SI}_{\mathrm{SPAD}}) = \frac{-a_1}{2a_2} \qquad [7]$$

For Eq. [5], the N_{rate} that corresponded to the maximum SI_{SPAD} measurement is 179 kg ha^{-1} (see Fig. 2). An appropriate nitrogen application rate (N_{app}) for any SI_{SPAD} measurement below maximum (max SI_{SPAD}) can then be found as follows:

$$\mathrm{N}_{\mathrm{app}} = \mathrm{N}_{\mathrm{rate}}(\max\mathrm{SI}_{\mathrm{SPAD}}) - \mathrm{N}_{\mathrm{rate}}(\mathrm{SI}_{\mathrm{SPAD}}) \qquad [8]$$

Next, the method for converting sufficiency indices that are based on active canopy sensor measurements ($SI_{sensor\ NDVI}$ or $SI_{sensor\ CI}$) into SI_{SPAD} measurements for input into the SPAD algorithm is illustrated. Solari et al. (2008) demonstrated a linear association between SI_{SPAD} and SI_{sensor} illustrated its general form as:

$$\mathrm{SI}_{\mathrm{SPAD}} = b_0 + b_1 \times \mathrm{SI}_{\mathrm{sensor}} \qquad [9]$$

For Eq. [9], b_0, b_1 coefficients represent the y intercept and linear terms, respectively. Using the same data set, the following

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specific equations (Fig. 3) were determined for SI_{NDVI} (Eq. [10]) or SI_{CI} (Eq. [11]):

$$SI_{SPAD} = -0.146 + 1.117 \times SI_{sensor\ NDVI} \quad [10]$$

$$SI_{SPAD} = 0.421 + 0.564 \times SI_{sensor\ CI} \quad [11]$$

Since Solari et al. (2008) had previously found $SI_{sensor\ CI}$ to be more sensitive in assessing crop canopy status than SI_{NDVI} and the standardized prediction error for measuring SI_{SPAD} was 33% larger for $SI_{sensor\ NDVI}$ than for $SI_{sensor\ CI}$ (Fig. 3), only the $SI_{sensor\ CI}$ (Eq. [11]) equation was used in development of the sensor algorithm, which we hereafter refer to as SI_{sensor}. After substituting Eq. [6], [7], and [9] into Eq. [8], the following generalized parametric function can be derived as:

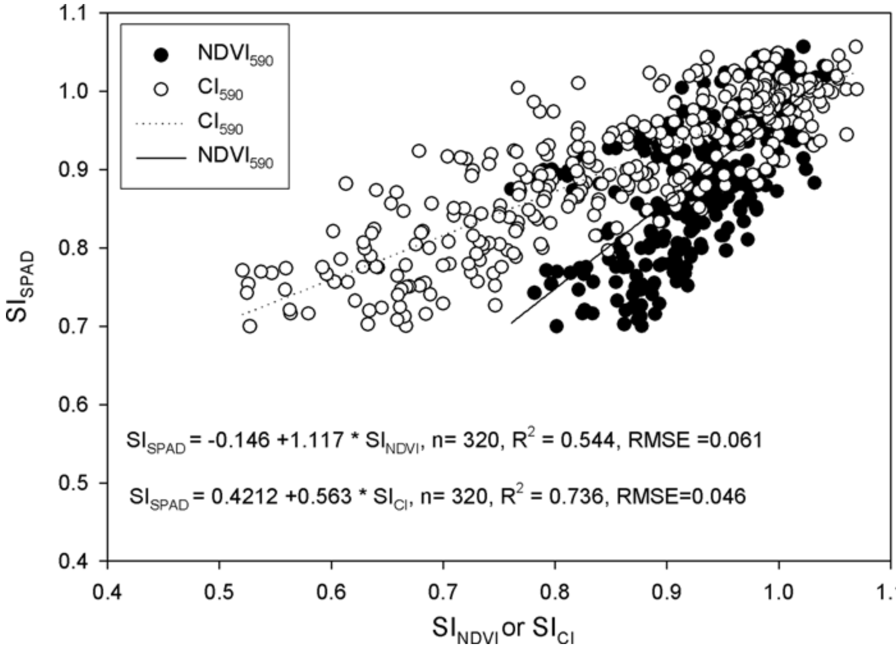

Fig. 3. Relationships between relative variation in two sensor-determined vegetation indices (SI_{NDVI}, normalized difference vegetation index; SI_{CI}, chlorophyll index) and variation in relative chlorophyll meter (SI_{SPAD}) readings for data collected on two vegetative growth stages (V11 and V15) during the 2005 growing season at two sites near Shelton, NE, for corn receiving varying amounts of applied N at planting (Solari et al., 2008). Other parameters provided include linear regression equation, sample number (*n*), coefficient of determination (R^2), root mean square error (RMSE).

$$N_{app} = R\sqrt{SI_R - SI_{sensor}} \quad [12]$$

where, R represents the rate of N in kg ha^{-1} to be applied times the square root of the difference between a reference SI_{sensor} values (SI_R) and target SI_{sensor}. The SI_R term represents a SI_{sensor} value that corresponds to the yield maximizing SI_{SPAD} measurement. The R and SI_R terms can be solved for using the following equations:

$$R = \sqrt{\frac{-b_1}{a_2}} \quad [13]$$

$$SI_R = \frac{4a_2a_0 - a_1^2 - 4a_2b_0}{4a_2b_1} \quad [14]$$

Substitution of coefficients from Eq. [5] and [11] into the general algorithm (Eq. [12]) results in the sensor algorithm taking the following specific form (Eq. [15]):

$$N_{app} = 317\sqrt{0.97 - SI_{sensor}} \quad [15]$$

N_{app} (N application) rate is determined by input of SI_{sensor} values into this simplified equation, which represents the algorithm for translating active sensor readings into site-specific N application rates based on crop N sufficiency.

Experimental Treatments to Validate Algorithm

To validate the active canopy sensor algorithm, we used sensor and yield data collected in 2005 from the companion study conducted at the Nebraska MSEA 3 site (Fig. 1) near Shelton, NE (40°45'01" N, 98°46'01" W; elevation 620 m above sea level). Details related to cultural practices and experimental procedures are reported by Solari et al. (2008). Briefly, the experimental design was a randomized complete block (three replications) with treatments arranged as split-split plots. Treatment factors were at-planting N application rates (0, 45, 90, or 270 kg ha^{-1}), time of in-season N application (V11 or V15), and in-season N rates (0, 45, 90, 135, or 180 kg ha^{-1}). Time of in-season N application was assigned to whole-plots, at-planting N application rates to subplots, and in-season N application rates to subsubplots. In-season applications rates were superimposed on all main plots except those receiving 270 kg N ha^{-1} at planting (Table 1), which was considered the N reference. The N treatments were applied at the appropriate times as 28% N urea ammonium nitrate (UAN) solution. Pioneer brand hybrid "P34N42" was planted at the MSEA 3 site. Daily climatological data (Fig. 1 in Solari et al., 2008) were recorded throughout the growing season using an automated weather station (High Plains Climate Center Network, University of Nebraska) located on the research site. Phenology data according to Ritchie et al. (1997) were recorded weekly from the first of June through mid-August.

Acquisition of Sensor Reflectance Data and Conversion to Vegetation Indices

Canopy sensor readings were collected just before the two vegetative growth stages (V11 and V15) that in-season N applications were made. The canopy sensor was mounted on an adjustable height boom on a high clearance vehicle to maintain the sensor at a specified height above the canopy at each growth stage. The sensor was positioned directly over a row in the center of the plot in the nadir view, at a distance of approximately 0.8 m above the crop canopy for plots receiving the highest N rate, producing a sensor *footprint* of approximately 0.1 by 0.5 m. The long dimension of this footprint was oriented perpendicular to the row direction. This sensor position was determined to be the most optimal, of several positions evaluated, for sensing corn canopy greenness in previous research by Solari (2006). The sensor and a DGPS receiver (model 16A, Garmin International, Inc., Olathe, KS) were interfaced to a computer via a serial hub and data were logged (sensor and spatial coordinates) as the vehicle traveled through the plots at 6 to 7 km

Table 1. Treatments used at the management system evaluation area (MSEA) site, involving four N rates applied at planting and five N rates applied at the V11 and V15 growth stages, to generate corn canopies varying N status. Plots receiving the 270 kg ha^{-1} N rate preplanting and no N in-season were considered as non-N limiting and were used as reference plots.

V11			V15		
At planting rate	In-season rate	Total N applied	At-planting rate	In-season rate	Total N applied
kg N ha^{-1}					
0	0	0	0	0	0
	45	45		45	45
	90	90		90	90
	135	135		135	135
	180	180		180	180
45	0	45	45	0	45
	45	90		45	90
	90	135		90	135
	135	180		135	180
	180	225		180	225
90	0	90	90	0	90
	45	135		45	135
	90	180		90	180
	135	225		135	225
	180	270		180	270
270	0	270	270	0	270
	0	270		0	270
	0	270		0	270
	0	270		0	270
	0	270		0	270

h^{-1}, acquiring approximately 200 readings per plot. Sensor data were imported into a geographical information system (GIS) for analysis using ArcGIS 9.2 (ESRI, Redland, CA). Analysis consisted of creating an area of interest for each plot that corresponded to the plot boundary minus a 1.0-m buffer area adjacent to plot alleyways. Active canopy sensor measurements were extracted from the area of interest to avoid border effects in each plot. The VIS_{590} and NIR_{880} bands from individual sensor readings were converted into CI_{590} values (using Eq. [2]) and averaged to produce one value per plot. The CI_{590} values for individual small plots were normalized within each replication to a reference using Eq. [3] and active canopy sensor readings from the N reference plot (N rate of 270 kg ha^{-1}) according to Biggs et al. (2002).

Grain Yield and Data Analysis

At maturity, three of the center eight rows were machine-harvested to determine grain yield. Grain yields were adjusted to a constant moisture basis of 155 g kg^{-1} water. As with active canopy sensor measurements, grain yields were normalized within each replication using the N reference plot. Grain yield and sensor data were analyzed via ANOVA with a mixed model, using the PROC MIXED procedure (Littel et al., 1996) available in the SAS statistical software package version 9.2 (Cary, NC). For yield data, hybrids and N treatments were considered fixed effects and blocks random effects. For the vegetation indices and SPAD data, the analysis was the same except sensor collection dates for the two different growth stages were included in the model and considered as repeated observations. Plots of relative yield vs. SI_{sensor} were used to establish critical SI_{sensor} values. The critical level was determined using the Cate–Nelson procedure (Cate and Nelson, 1971). This procedure is a discontinuous statistical model that identifies a critical level of some crop nutrient (X_c), in this case crop N as indicated by SI_{sensor}, with the goal of separating SI_{sensor} values into high and low probability of crop N response. The statistical model can be written as:

$$Y = \alpha + \beta\, d + \varepsilon$$

where Y is the dependent variable (relative yield), α and β are parameters of the model and d is a binary variable, being d = 0 if $X < X_c$, and d = 1 when $X >= X_c$; ε is the error term. Note that $Y = \alpha + \beta$ when $X < Xc$, and that $Y = \alpha + \beta + \varepsilon$ when $X >$ Xc. The iterative process to estimate X_c consists of assigning an initial value to X_c and calculating the R^2 and the process continues until a maximum R^2 is found.

Finally, to validate the sensor algorithm, SI_{sensor} readings collected at V11 and V15 growth stages from plots receiving varying N amounts were converted into N_{app} values using the algorithm. Then N_{app} was converted into crop N balance ($N_{balance}$) estimates, where $N_{balance}$ = actual applied N-N_{app}. Negative values of $N_{balance}$ indicate a sensor-estimated N deficiency while positive values indicate excess N, in which case no yield response is expected. The $N_{balance}$ values were compared with relative yields and a quadratic-plateau model was fit to the data set for the two in-season growth stages (V11 and V15) using the NLIN procedure available in SAS. The quadratic plateau model used in this work is as follows:

$$E[Y\,|\,x] = \begin{cases} \alpha + \beta x + \gamma x^2 & \text{if } x < x_0 \\ c & \text{if } x \geq x_0 \end{cases}$$

where, for values of x less than $x_{0,}$ the mean of Y is a quadratic function of x and for values of x greater than $x_{0,}$ the mean of

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Y is constant., The α, β, and γ parameters represent coefficients of the quadratic segment, and c is the plateau of the mean function. The rationale for using the NLIN procedure is that it allows fitting a continuous model consisting of two separate segments, and can fit such a segmented model even when the join point (x_0) is unknown.

RESULTS AND DISCUSSION

Active Canopy Sensor Algorithm

To illustrate the performance of the proposed sensor algorithm in translating active canopy sensor readings into potential variable N application (N_{app}) rates, N_{app} was calculated using Eq. [15] for SI_{sensor} values ranging from 0.65 to 0.97 (Fig. 4). The sensor algorithm was evaluated across this range of SI_{sensor} values because maximum N_{app} for the SPAD algorithm was 179 kg ha^{-1} (Fig. 2), which corresponds to a SI_{sensor} value of ~0.65 using Eq. [15] (Fig. 4). This figure illustrates that the critical SI_{sensor} threshold for triggering the initiation of N application is 0.97 and N_{app} reaches its maximum value at another critical SI_{sensor} threshold of 0.65. Because the canopy sensor algorithm was constructed using the SPAD algorithm it is not surprising that the critical SI_{sensor} value for triggering N application was 0.97. Varvel et al. (1997) showed that the critical SI_{SPAD} threshold value denoting an N deficiency for corn was 0.95, which corresponds to SI_{sensor} threshold of 0.97 for the sensor algorithm (Eq. [15]). It is worth noting that the range in critical SI values for translating the full range of potential N_{app} is much wider for the active canopy sensor algorithm (~0.65–0.97, Fig. 4) than the SPAD algorithm (~0.8–0.95, Fig. 2), indicating the former is more sensitive than the latter in translating SI values into N_{app}. These results are due to the slope of the SI_{SPAD} vs. SI_{sensor} relationship (Fig. 4) being significantly less than one (slope = 0.563 for SI_{SPAD} vs. SI_{sensor}). Thus, for each unit change in a SI_{sensor} reading there is a correspondingly smaller rate of change in SI_{SPAD} value, which implies greater sensitivity in SI_{sensor} than SI_{SPAD} in measuring and diagnosing crop N status. Since the active sensor algorithm incorporates the SI_{SPAD} vs. SI_{sensor} relationship, it is not unexpected that it would be more sensitive than the SPAD algorithm in translating the full range of N_{app} values. According to Samborski et al. (2009), increased sensitivity in diagnosis of crop N status along with improved sensor algorithms are keys to the more widespread use of plant sensor-based diagnostic information for making N recommendations.

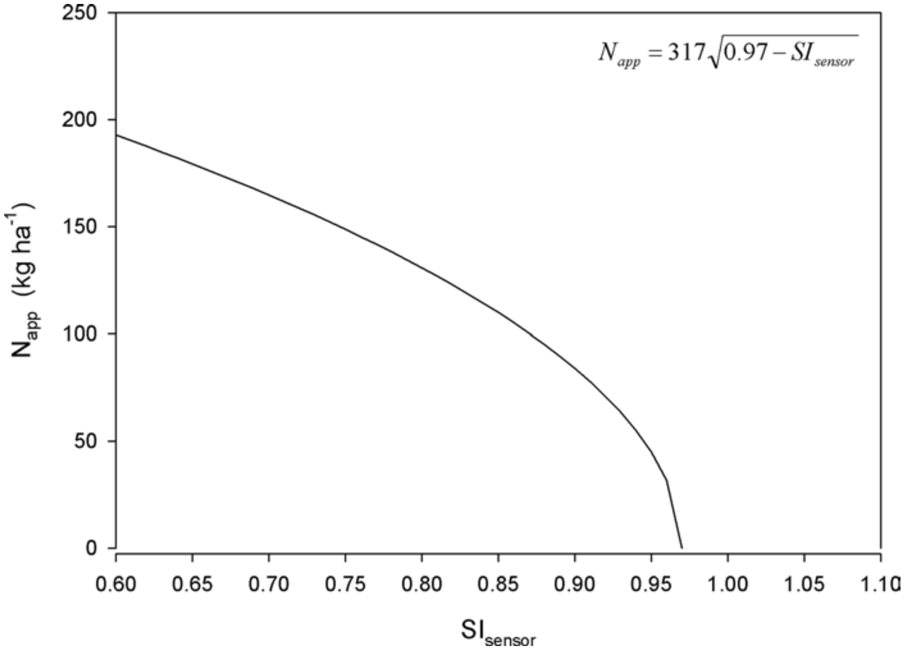

Fig. 4. Prescribed N application (N_{app}) rate as a function of sensor sufficiency index (SI_{sensor}) values using the Crop Circle algorithm shown in Eq. [15].

Validation of Sensor Algorithm

Having developed and illustrated the use of the SPAD-based sensor algorithm, our next goal was to validate the active canopy sensor algorithm and demonstrate its ability to make N recommendations. To accomplish this, the SI_{sensor} values and yields collected from the MSEA site in the previous work (Solari et al., 2008) were used. As was noted in the preceding work, the low residual soil N levels at this site (15 kg N ha^{-1} in the 0.9-m profile) and low N in the irrigation water created favorable conditions for crop responses to N. The treatments implemented at this site (Table 1) resulted in significant differences in sensor-determined SI_{sensor} values collected at both growth stages (V11 and V15) as well as a range of grain yields.

These treatment combinations enabled the evaluation of the response of crop N stress (via SI_{sensor} readings) to varying times and amounts of N application and the resultant impact on crop yield. To gain a general understanding of these relationships, relative yields were plotted vs. SI_{sensor} readings collected on both N application dates for all treatment combinations (V11 and V15, Fig. 5, respectively). The correlation coefficients for the linear regression of relative yield vs. SI_{sensor} at the V11 and V15 growth stages (shown in Fig. 5) were 0.61 ($P < 0.0001$) and 0.81($P < 0.0001$), respectively. Thus, there was a general positive association between active canopy sensor assessments of crop N stress (expressed as SI_{sensor}) and final grain yield, with a stronger association as the crop matured and reached the V15 growth stage. None of the treatments receiving 0 N at planting produced relative yields >0.90, regardless of the amount of N applied in-season, but treatments receiving 45 or 90 kg N ha^{-1} at planting were able to produce maximum yields if enough N was applied in a timely manner. Collectively, these results suggest that N applications should be timed to minimize early season crop N stress and avoid N stress as the crop nears V15 to maximize crop yields. Scharf et al. (2002) also found that irreversible yield losses were less likely to occur when N applications occurred by V11 compared to applying N at later growth stages. This is likely due to the fact that V15 is within the critical period of 2 wk before and 3 wk after silking when ear kernel numbers and crop yield potential are very sensitive to crop assimilate supply (Tollenaar, 1977; Tollenaar et al., 1992; Uhart and Andrade, 1995). Nitrogen stress affects assimilate supply to the ear because it reduces leaf area index, leaf area duration, and photosynthetic rate (Novoa and Loomis, 1981; Lemcoff and Loomis, 1986; Sinclair and Horie, 1989; Connor

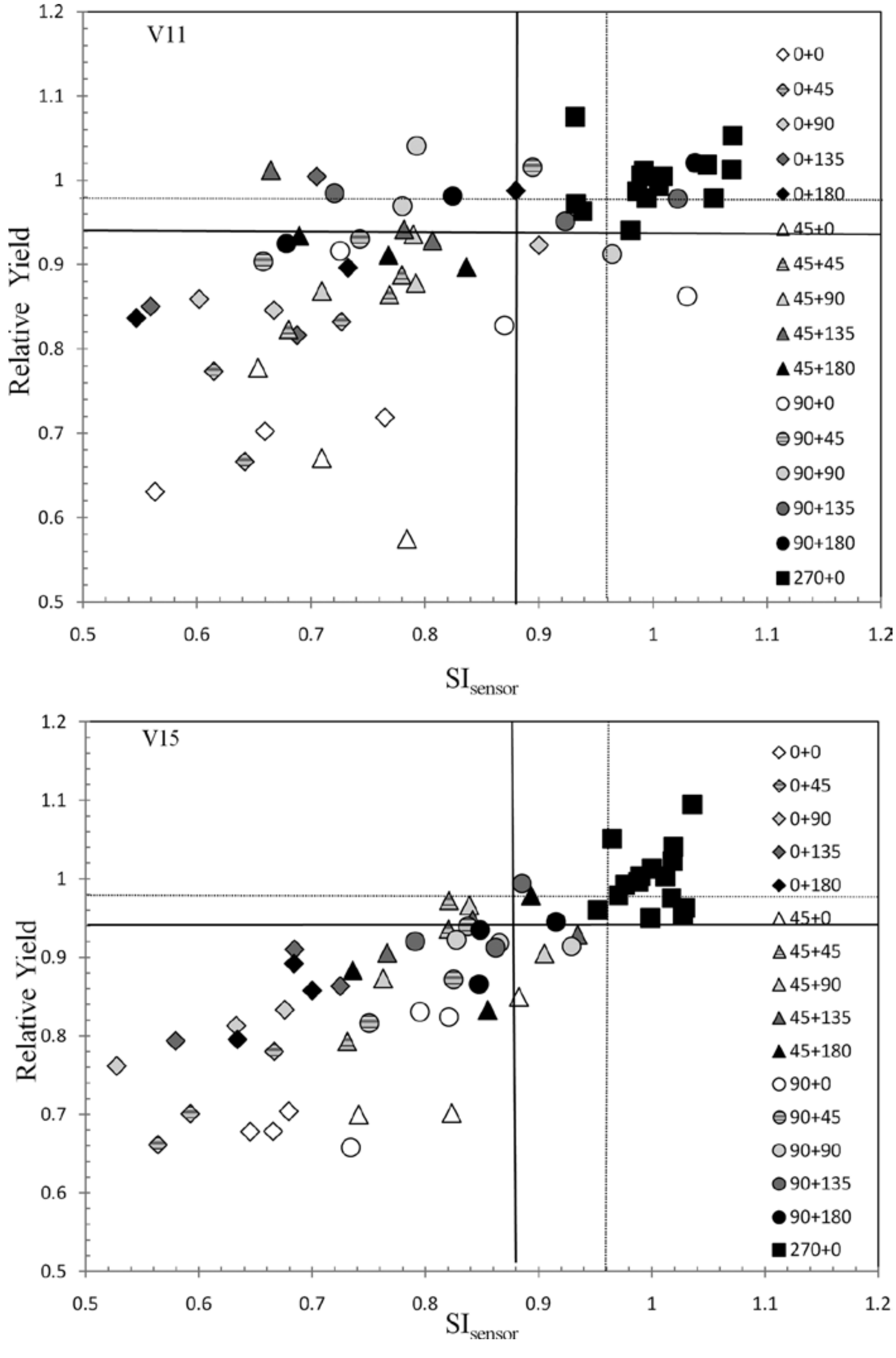

Fig. 5. Association between relative grain yields vs. sensor based sufficiency index (SI_{sensor}) values obtained at the V11 and V15 growth stages for small plot treatments receiving various amounts of N applied at either V11 or V15 growth stage (legend shows at planting and in-season N application rates in kg ha^{-1}). The vertical lines show the corresponding critical threshold SI values for relative yield values (horizontal lines) of 0.94 (solid) and 0.98 (dashed), using a Cate–Nelson analysis.

et al., 1993), which in turn reduces radiation interception and radiation use efficiency (Uhart and Andrade, 1995).

To further understand the relationship between timing of crop N stress and yield loss, a Cate–Nelson analysis of relative yields vs. SI_{sensor} values (Fig. 5) was conducted to establish a critical threshold for SI_{sensor} values. This analysis indicated that a SI_{sensor} value of 0.88 was the critical threshold for maintaining relative yields of at least 0.94, independent of the growth stage at sensing (Fig. 5). A relative yield value of 0.94 was chosen, because it minimized the number of outliers in the upper left and lower right quadrants and it corresponded to the lower relative yield of the N reference plots. Using this threshold value, 18 points were classified as outliers. Situations like those in the lower right quadrant are what farmers want to avoid. In this experiment, they are explained by relatively high N availability at sensing and a shortage of N afterward. All the points but one in the lower right quadrant had either 45 or 90 kg of N ha^{-1} applied at planting, which may explain the relatively high SI_{sensor} value at sensing. However, five out of seven plots had a total N applied <135 kg ha^{-1}, which explains the low yield. One of the treatments received a total of 180 kg N ha^{-1} (two applications of 90 kg N ha^{-1}). Of the observations in the upper left quadrant, 10 out of 11 had at least 135 kg ha^{-1} total N applied. An interesting observation was that 6 of these 11 observations correspond to the V11 fertilization event (Fig. 5), suggesting that the ability of using active canopy sensors to detect N stress and maintain yield with in-season fertilization increases if sensing closer to V11 rather than the V15 growth stage.

While the preliminary Cate–Nelson analysis used a relative yield value of 0.94 to establish the critical SI_{sensor} threshold of 0.88, it is not likely that farmers would be willing to accept this level of yield loss as it would result in reduced economic returns for the producer. Hence, another analysis was conducted using a relative yield level of 0.98, which is more likely to be accepted by growers. The corresponding critical SI_{sensor} value of 0.96 was obtained for both growth stages (Fig. 5). This value coincides closely with the critical SI_{sensor} threshold value of 0.97 triggering the initiation of N application by the sensor algorithm provided. Ten out of the 17 observations in the upper left quadrant received some in-season fertilization at V11, which again supports the concept of applying N closer to V11 rather than at a later growth stages. These results suggest an active canopy sensor can be used to assess crop N status, and N stress can be treated without yield loss, depending on the degree of this stress.

To validate the sensor algorithm, relative yields for each treatment were plotted vs. sensor based estimates of $N_{balance}$ determined for both V11 and V15 growth stages (Fig. 6). A quadratic-plateau model was fit to the data for both growth stages, though the model parameters did not differ statistically between the two growth stages (data not shown). The lack of difference between the two growth stages is difficult to explain, but indicates the algorithm should be applicable across this window of growth stages. Therefore, a single model was fit to the pooled data relating relative yield to $N_{balance}$, producing the coefficient of determination of 0.66. The relationship in Fig. 6 shows that relative yields increased in a curvilinear fashion with increasing levels of sensor-estimated crop N sufficiency (from negative to positive $N_{balance}$), reaching a plateau at –11 kg N ha^{-1} and yields did not increase with more positive estimates of crop N status. That $N_{balance}$ reached a plateau value near 0 kg N ha^{-1} suggests the algorithm provided reasonable sensor-based estimates of the appropriate amount of in-season N to maximize grain yield.

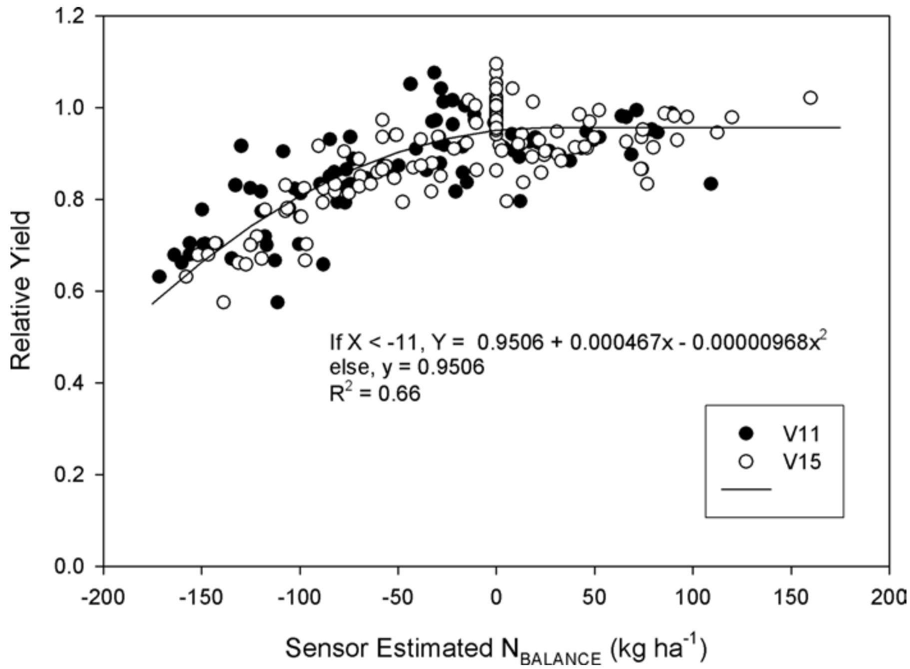

Fig. 6. Relative grain yield vs. sensor estimated crop N balance ($N_{balance}$) for small plots receiving varying amounts of N applied at two in-season growth stages (V11 and V15) at the MSEA3 site in 2005. $N_{balance}$ was estimated by first converting SI_{sensor} into Napp values using the algorithm. Then Napp was converted into $N_{balance}$, where $N_{balance}$ = actual applied N-N_{app}. Negative values of sensor-estimated $N_{balance}$ indicate N deficiency while positive values indicate excess N.

There has been substantial research on the development of N recommendation algorithms for other active canopy sensors such as the GreenSeeker (NTech Industries, Ukiah, CA) for wheat (Raun et al., 2002; Li et al., 2009) or the Yara N sensor system (Yara UK Limited, Lincolnshire, UK) for cereals (Schröder et al., 2000; Olfs et al., 2005; Berntsen et al., 2006; Tremblay and Belec, 2006; Zillmann et al., 2006), all showing potential benefit in using these sensors to improve N management vs. traditional approaches. Less research has been published to date on the development of algorithms for use with the Crop Circle active sensor for making N applications to corn. However, recent research in Pennsylvania with this sensor (same model used in this work) evaluating various sensor-determined vegetative indices for estimating corn N requirement (Sripada et al., 2008) led to the development of N recommendations procedures for corn (Dellinger et al., 2008), and these procedures showed potential for improving N management decisions for corn production over other approaches (Schmidt et al., 2009). Similarly, results by Kitchen et al. (2010) in Missouri showed canopy reflectance measurements using the same sensor have potential for improving N management over conventional single-rate applications. Hence, results shown in this paper combined with the work conducted in Missouri and Pennsylvania suggest Crop Circle active canopy sensor measurements can be used to guide spatially variable in-season N applications as an alternative means for improving corn NUE and decreasing environmental contamination.

The methodology outlined here is a more reactive approach than current strategies involving large preplant doses of uniformly applied N, and should improve NUE, because it addresses factors contributing to low NUE; poor synchrony of N supply with crop N demand, uniform N applications to spatially variable landscapes, and failure to account for temporal influences on N needs (Shanahan et al., 2008). Because our model was developed and validated with data from a specific location, the algorithm may be limited in its application to locations with similar soils and climate (i.e., irrigated conditions). Limited availability of algorithms that are reliable in a wide variety of soil and weather conditions has in fact been suggested as a reason for lack of widespread use of crop canopy sensors for directing N applications (Samborski et al., 2009). However, the SPAD algorithm (Varvel et al., 2007) used in developing the active canopy sensor algorithm was constructed using chlorophyll meter and yield data collected over a 10-yr period, where yields ranged from 3.50 to 13.63 Mg ha^{-1} during the course of the study. Additionally, the SPAD algorithm was found to be valid for both monoculture corn and corn–soybean systems at this site. Thus, the framework of the active canopy sensor algorithm was developed under diverse climatic conditions and multiple cropping systems, suggesting the potential applicability of the algorithm for similar soils and climate. Nonetheless, we recognize the proposed algorithm was developed under irrigated conditions and may require additional modification to accommodate more diverse conditions than those experienced in the present study.

SUMMARY AND CONCLUSIONS

- Results presented in this paper indicate that using in-season canopy reflectance measurements obtained via an active canopy sensor can be used to assess the amount of N needed to maximize corn yield.
- This method requires areas where N is not limiting (N reference) to determine SI_{sensor} values. Once the N reference area has been established, the model developed indicates that sensor data collected anytime during the vegetative growth period from V11 through V15 can be used to determine SI_{sensor} values, which can in turn be put into the generalized algorithm shown in Fig. 4 and solved for N rate. This N rate is the amount of N fertilizer recommended to maximize yield.

- For this method to be successful, a nominal amount (45–90 kg ha^{-1}) of preplant N application may be required, particularly when residual soil N levels are low, to avoid crop N stress before the time of sensor directed N applications.
- Since the proposed active canopy sensor algorithm was developed under the climate and soils of one particular study site, we recognize its applicability to broader situations will require further evaluation. Our future research plans include additional testing of the model on a wider range of producer fields to evaluate if the concept can be used in other areas with more diverse soils and climatic conditions.

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