Ground-Based Canopy Reflectance Sensing for Variable-Rate Nitrogen Corn Fertilization

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ABSTRACT

Nitrogen available to support corn (*Zea mays* L.) production can be highly variable within fields. Canopy reflectance sensing for assessing crop N health has been proposed as a technology to base side-dress variable-rate N application. Objectives of this research were to evaluate the use of active-light crop-canopy reflectance sensors for assessing corn N need, and derive the N fertilizer rate that would return the maximum profit relative to a single producer-selected N application rate. A total of 16 field-scale experiments were conducted over four seasons (2004–2007) in three major soil areas. Multiple blocks of randomized N rate response plots traversed the length of the field. Each block consisted of eight treatments from 0 to 235 kg N ha^{-1} on 34 kg N ha^{-1} increments, side-dressed between the V7–V11 vegetative growth stages. Canopy sensor measurements were obtained from these blocks and adjacent N-rich reference strips at the time of side-dressing. Within fields, the range of optimal N rate varied by >100 kg N ha^{-1} in 13 of 16 fields. A sufficiency index (SI) calculated from the sensor readings correlated with optimal N rate, but only in 50% of the fields. As fertilizer cost increased relative to grain price, so did the value of using canopy sensors. While soil type, fertilizer cost, and corn price all affected our analysis, a modest (\$25 to \$50 ha^{-1}) profit using canopy sensing was found. These results affirm that, for many fields, crop-canopy reflectance sensing has potential for improving N management over conventional single-rate applications.

The quest for precision in N management, both by improved prediction of crop N needs (i.e., fertilizer rate) and by synchronizing fertilizer application with plant N uptake, has prompted numerous recent investigations exploring the potential of active-light, crop-canopy reflectance sensors (Raun et al., 2002; Mullen et al., 2003; Raun et al., 2005; Freeman et al., 2007; Teal et al., 2006; Dellinger et al., 2008; Shanahan et al., 2008). These sensor systems contain light emitting diodes (LEDs) that emit modulated light onto the canopy (thus, the term *active*) and detect reflectance of the modulated light from the canopy with photodiodes (Stone et al., 1996). Both visible (VIS) and near-infrared (NIR) wavelengths are typically included, so that reflectance can be interpreted in terms of commonly used vegetative indices, like the normalized difference vegetative index (NDVI), useful in assessing crop growth (Myneni et al., 1995; Moran et al., 1997; Pinter et al., 2003) and crop N status (Freeman et al., 2007; Solari et al., 2008; Sripada et al., 2008). With their own light sources, these sensors are less sensitive to diurnal variations than sensors that rely on ambient sunlight. Operationally, these sensors can be mounted on N fertilizer applicators equipped with computer processing and variable rate controllers, so that sensing and fertilization is accomplished in one pass over the crop.

Calculations combining VIS light reflectance (a measure of the plant's color and thus its photosynthetic health) with NIR reflectance (a measure of the plant's structure and capacity to assimilate carbon) have been used successfully in evaluating crop N health and making N fertilizer additions. Stone et al. (1996) were able to reduce N fertilizer input and increase N use efficiency for wheat by variably applying N using a plant-N spectral index derived from red and NIR reflectance values. Transformation of reflectance into a biomass indicator (like NDVI) puts the information into potential yield terms, allowing for N requirements to be calculated on a mass balance basis (Raun et al., 2002; Mullen et al., 2003). Corn canopy NIR and green reflectance have also been used to develop a N reflectance index correlated to chlorophyll meter readings (Shanahan et al., 2003; Solari et al., 2008), plant N content (Bausch and Duke., 1996) and within season soil N (Diker and Bausch, 1999).

Algorithms using crop-canopy reflectance sensing to make N recommendations for wheat have been identified (Raun et al., 2002), with ongoing studies being conducted in the U.S. and elsewhere assessing this technology for corn (Teal et al., 2006; Dellinger et al., 2008; Solari et al., 2008) and other crops (see Oklahoma State University, 2009). Typically the best evaluations have been obtained by comparing the crop in an area known to be nonlimiting in N to the crop in areas inadequately fertilized. Measurements from the two areas are used to

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Abbreviations: FGR, nitrogen fertilizer cost to grain price ratio (using international system of units); ISR, inverse of the simple ratio, calculated as the ratio of the visible to near-infrared reflectance readings; NDVI, normalized difference vegetative index; NIR, near-infrared reflectance; RMSE, root mean square error; SI, nitrogen sufficiency index; UAN, urea ammonium nitrate; VIS, visible reflectance.

calculate a relative reflectance to represent the potential need for additional N fertilizer. This relative reflectance approach has been accomplished with spectral radiometer measurements (Chappelle et al., 1992; Blackmer et al., 1996b; Shanahan et al., 2003), photography (Blackmer et al., 1996a; Flowers et. al., 2001; Scharf and Lory, 2002), and active-light crop reflectance sensors (Teal et al., 2006; Dellinger et al., 2008; Solari et al., 2008). This approach somewhat normalizes the confounding effects of numerous management (e.g., hybrid) and environmental (e.g., soil and precipitation) factors will have on understanding the specific N need for the crop and field in question.

Methods for varying N both within and among fields are justified by the spatially variable nature of mineralization and N loss potential over nonuniform agricultural landscapes. Previous field studies have indicated both economic and environmental benefit for spatially-variable N applications across a variety of agricultural landscapes (Malzer et al., 1996; Mamo et al., 2003; Koch et al., 2004; Scharf et al., 2005; Shahandeh et al., 2005; Lambert et al., 2006; Hong et al., 2007). Uniform applications within fields discount the fact that N supply from the soil, crop N uptake, and response to N are not spatially uniform (Inman et al., 2005). Without tools to address spatially variable crop N need, farmers tend to apply N at a uniform rate to meet crop needs in the more N-demanding areas of the field, resulting in greater risk of N loss from field areas needing less N (Hong et al., 2007).

Research is needed to test active-light crop-canopy reflectance sensing on corn production fields showing spatially variable need for N fertilizer. Such investigations provide the relevant information to develop algorithms for making N fertilizer rate decisions. The first objective of this research was to evaluate the use of active-light crop-canopy reflectance sensors for assessing corn N need on a variety of Missouri soils. From these results, a second objective was to empirically derive the sensor-based N fertilizer rate that would return the maximum profit (i.e., from corn yield and N fertilizer amount), relative to a single-rate producer-selected N application.

MATERIALS AND METHODS

Fields and General Management

A total of 22 field-scale (400–800 m in length) experiments were conducted over four growing seasons (2004–2007) in three major soil areas of Missouri: river alluvium, deep loess, and claypan. However, five experiments (three in 2005, one in 2006, and one in 2007) experienced severe season-long drought, minimizing N rate as a factor for crop growth, and therefore were not included in this analysis. A sixth experiment from 2007 was excluded because extreme heat and deficient soil-water conditions at the time of canopy sensing resulted in leaf curling that produced erratic sensor measurements. A summary of the 16 remaining fields, soil characteristics, and management practices are provided in Tables 1 and 2. In general, these fields were representative of other cropped fields in their locale, with some within-field variability evident in landscape and soil. With many of these experimental fields, historical yield maps provided by farmers confirmed within-field variability in production. Cooperating producers selected the planting date, hybrid, planting population, and prepared and planted each field with their own equipment. Most fields were rainfed only. Three center pivot irrigated fields were exceptions and are noted in Table 2. Temperatures and rainfall amounts and distribution in 2004 were highly favorable for corn production. The 2005 growing season was very droughty for much of the state and was the reason only two fields were included from that year. Rainfall amounts and distribution were generally favorable for corn production in 2006 and 2007. Precipitation amounts recorded from gauges either at or near (within 15 km) the research fields are provided (Table 2).

Experimental Design for Nitrogen Treatments

Multiple blocks of randomized N rate response plots were arranged end-to-end so that blocks traversed the length of each field. Each block consisted of 8 N treatments from 0 to 235 kg N ha^{-1} on 34 kg N ha^{-1} increments, side-dressed sometime between vegetative growth stages V7 and V11 (Ritchie et al., 1997) (Table 2). Farmers in the area we work are willing to apply N in-season from the V7 to V11 growth stage, especially

Table 1. Characteristics of research fields and cropping information.

Year	Field	Soil	Predominant soil subgroup	Previous crop	Tillage†	Planting date	Planting rate	Hybrid
							seeds ha^{-1}	
2004	Ben	claypan	Vertic Albaqualf	soybean	no-till	27 April	74,100	Pion_33P67
2004	Cop	river alluvium	Aquic Udifluvent	soybean	no-till	15 April	74,100	Pion_33D31
2004	Die	river alluvium	Fluvaquentic Hapludoll	soybean	tilled	16 April	69,100	AG_RX752YG
2004	Hay	claypan	Vertic Albaqualf	soybean	no-till	29 April	70,100	Pio_34B23
2004	Pet	deep loess	Aquic Argiudoll	soybean	mulch tilled	7 April	74,100	DKC60-215
2004	Sch	claypan	Vertic Epiaqualf	soybean	mulch tilled	9 April	61,700	Pion_33G28
2004	Wil	claypan	Vertic Albaqualf	soybean	no-till	14 April	66,700	Pion_34M95
2005	Geb1	deep loess	Aquic Argiudoll	soybean	mulch tilled	8 April	71,600	AG_RX715RR2
2005	Lic	deep loess	Fluvaquentic Endoaquoll	soybean	mulch tilled	9 April	70,400	NK_N67T4
2006	Ben	claypan	Vertic Albaqualf	soybean	mulch tilled	20 April	71,600	Pion_33P62
2006	Cop	river alluvium	Aquic Udifluvent	soybean	no-till	13 April	74,100	Wyffel_7260
2006	Geb2	deep loess	Aquic Argiudoll	soybean	mulch tilled	7 April	71,600	AG_RX715RR/YG
2006	Rie	claypan	Vertic Albaqualf	soybean	no-till	7 April	64,200	FC_8510P
2007	Geb1	deep loess	Aquic Argiudoll	soybean	mulch tilled	20 April	74,100	AG_RX785RR/YG
2007	Hac	river alluvium	Typic Udipsamment	corn	tilled	17 April	75,100	Pion_33K42
2007	San	river alluvium	Fluvaquentic Hapludoll	corn	tilled	5 April	73,100	Pion_34P89

† Tilled = multiple tillage operations with little or no crop residue remaining at planting; mulch tilled = minimum tillage with ~30% or more of soil covered with crop residue at planting.

Table 2. Nitrogen management and seasonal precipitation information for research fields.

Year	Field	Producer N rate	Preplant N rate	N rate at emergence for 2nd set of response plots	Date of side-dress and sensing	Days from planting to side-dress	Growth stage at side-dress	Seasonal precipitation (1 Apr.–31 Aug.)	Mid-season precipitation (15 June–15 Aug.)	Sprinkler irrigation (June–Aug.)
		kg N ha^{-1}						cm		
2004	Ben	179	32		16 June	50	9.5	59	18	7
2004	Cop	157	0		3 June	49	7	67	27	na
2004	Die	202	0		4 June	49	8	54	19	na
2004	Hay	168	30		21 June	53	10.5	47	13	na
2004	Pet	202	0		4 June	58	9	67	24	na
2004	Sch	168	34		7 June	59	8	59	18	na
2004	Wil	134	45		8 June	55	8	59	18	na
2005	Geb1	202	0		17 June	70	11	71	22	na
2005	Lic	202	0		17 June	69	11	61	18	na
2006	Ben	179	39	34	19 June	60	11	62	16	11
2006	Cop	157	28	34	9 June	57	9.5	54	17	na
2006	Geb2	202	12	67	8 June	62	10	48	17	na
2006	Rie	157	30	34	6 June	60	9.5	63	16	na
2007	Geb1	202	12	67	8 June	49	10	45	13	na
2007	Hac	258	0	67	4 June	48	9	38	16	13
2007	San	196	0	67	5 June	61	9	35	11	na

if N with a starter or other early N fertilization is included. Extremely wet spring and early summers in recent years, resulting in loss of fall and early spring applied N, have promoted this willingness. Because of differences in harvesting procedures (explained later) and other logistical constraints, experimental plot dimensions differed over the 4-yr period. For 2004 experiments, each plot within each block was six rows wide (4.5 m with 76-cm corn row spacing) by 15.2 m long. Treatment blocks were two plots wide by four plots long. In 2005, research plots were larger, 12 rows wide (9.1 m on 76-cm corn row spacing) by 30.5 m long, with blocks four plots wide by two plots long. The larger width in 2005 was needed to accommodate a separate investigation requiring aerial imagery of the plots. For 2006 and 2007 experiments, plots were six rows wide (4.5 m on 76 cm row spacing) by 36.6 m long, with treatment blocks eight plots wide. For these later 2 yr, a complete second field-length set of blocks was also established where either 34 or 67 kg N ha^{-1} was uniformly applied over the second set of blocks shortly after corn emergence. The 34 kg N ha^{-1} rate was used when the producer had applied ~30 kg N ha^{-1} rate during preplant operations, as shown in Table 2. This second set of treatments was added in response to farmers expressing concern over a N management system where little or no N fertilizer was provided to the crop during emergence and early growth. Therefore, this second set tested the sensitivity of the reflectance sensors for assessing N fertilizer need when the crop was generally not as N stressed.

The number of treatment blocks varied from 3 to 28 per field, depending on the plot length, length of the field, and whether the study included the second set of blocks with early N fertilization. In all, 223 sets of response plots were obtained from the 16 field experiments.

Adjacent to and on both sides of the response blocks, N-rich (235 kg N ha^{-1}) reference strips were also established. These ran the full length of the field and were treated shortly after corn emergence or as soon thereafter as field conditions allowed (Table 2).

Nitrogen Fertilizer Treatments

An AGCO Spra-Coupe (AGCO Corp., Duluth, GA)[1] high-clearance applicator equipped with an AGCO FieldStar Controller was used to side-dress urea ammonium nitrate (UAN) solution (28 or 32% N) fertilizer between corn rows for the N rate treatments. Fertilizer was not incorporated. A label-prescribed amount of urease inhibitor (Agrotain) was mixed with the UAN for all fields except three blocks of the 2004 Cop field. To achieve the different N rates, the Spra-Coupe was outfitted with a set of three drop nozzles per fertilized row, each nozzle with a different-sized orifice plate to achieve 1×, 2×, and 4× (1× = 34 kg N ha^{-1}) application rates. Combinations of these three nozzles being turned on accomplished the different rates. In 2004, drop nozzles were installed between rows 1 and 2, 3 and 4, and 5 and 6. In subsequent years, nozzles were in each row middle. Activation of the nozzle booms was controlled by in-house software running on a tablet PC, while the Field Star controller compensated for variations in ground speed. Tests of the system indicated actual rates were within ±3% of targeted rates. This same equipment was used to establish the N-rich reference strips.

Application of N rates was automated as the Spra-Coupe traveled through the field. Before side-dress application, maps of randomized sets of N rate treatments were established for each field in a GIS. Map files were imported into application software on the tablet PC. The software used a differential GPS (1.5 m or better accuracy) signal to synchronize the prescribed rate with the respective map location and automatically change rates as the operator drove through the field.

Canopy Sensing and Yield Measurements

Crop canopy reflectance sensor (Model ACS-210, Holland Scientific, Inc., Lincoln, NE) measurements were obtained from the corn canopy of the N response blocks at the same time

[1] Mention of trade name or commercial products is solely for the purpose of providing specific information and does not imply recommendation or endorsement by the U.S. Department of Agriculture or the University of Missouri.

the Spra-Coupe was used to apply N rate treatments (Table 2). These sensors emitted and measured light at ~590 (VIS) and ~880 (NIR) nm. Two sensors were mounted on the front of the applicator at ~60 cm above Rows 2 and 5 of the six-row corn strip. On the same day N rate treatments were applied to the N response plots, reflectance sensor measurements were also obtained from the N-rich reference strips. As the Spra-Coupe drove through the field, reflectance data and GPS coordinates were recorded on the tablet PC in the Spra-Coupe cab.

In 2004, 6 m of the middle two rows of each plot were hand-harvested, with ears transferred for shelling by stationary equipment and weighing. In 2005, the middle eight rows were harvested with a four-row Gleaner R42 combine (AGCO Corp., Duluth, GA) equipped with an Ag Leader Yield Monitor 2000 (Ag Leader Technology, Ames, IA). Eighteen meters of row length centered within each plot was kept to calculate yield. In 2006 and 2007, the four middle rows of each plot were harvested with the same combine and 20 m of row length was retained. Yield data were cleaned using Yield Editor 1.02 (Sudduth and Drummond, 2007), removing questionable yield-data points for reasons such as GPS positional error, abrupt combine speed changes, significant ramping of grain flow (due to significant yield differences of consecutive plots) during entering or leaving the crop, and other outlying values. Yield on a small number of plots (<4%) were assigned as *missing* because of errors during treatment implementation or harvesting operations.

Chlorophyll Meter and Canopy Reflectance Measurements Compared

For better understanding of the larger field studies, a separate small plot study was conducted in 2007 near Centralia, MO, to contrast reflectance sensor and chlorophyll meter measurements at different corn vegetative growth stages. Each experimental unit was 9 m long and 3 m wide (4 rows on 76 cm row spacing). Plants from three at-planting N fertilizer treatments (0, 45, and 246 kg ha^{-1}) with three replicates in a RCB design were assessed at various growth stages between V4 and V15. Leaf chlorophyll from the most recently collared leaf at each growth stage was measured on 20 randomly chosen plants from the two middle rows with a Chlorophyll Meter SPAD-502 (Konica Minolta, Osaka, Japan). At the same time, canopy reflectance sensor measurements were obtained from the same two rows (model ACS-210, Holland Scientific, Inc., Lincoln, NE). For illustrative purposes, these two measurements from this small plot study were compared for their relative ability to delineate corn N health.

Data Analysis

Data analysis of the 16 field studies included four major steps: (1) determining optimal N with quadratic-plateau modeling; (2) processing of canopy reflectance sensor data from response plots and the N-rich reference areas; (3) relating modeled optimal N from Step 1 with sensor measurements from Step 2; and (4) empirically derive the N fertilizer rate that, when using these sensors, returned the maximum profit relative to a single-rate producer-selected N application.

Step 1: Determining Optimal Nitrogen

Yield response to N rate was modeled using a quadratic-plateau function, previously found appropriate for this type of dataset (Cerrato and Blackmer, 1990; Scharf et al., 2005). Using Proc NLIN in SAS (SAS Institute, 2000), the quadratic-plateau regression model was fit to data for each block of N treatments. From the model parameters, optimal yield (model plateau), optimal N rate (N rate where optimal yield is first achieved), and delta yield (yield increase between no N and optimal N rate) were calculated. Additionally, a functional coefficient of determination (R^2) for the quadratic plateau model was calculated as

$$R^2 = 1 - \mathrm{ESS}/\mathrm{TSS} \qquad [1]$$

where ESS = the model error sum of squares and TSS = the total sum of squares for each block. A root mean square error (RMSE) between observations and the quadratic plateau model was calculated as:

$$\mathrm{RMSE} = \sqrt{\mathrm{ESS}/(n-2)} \qquad [2]$$

where n = the number of observations used for each developed model.

For each block of N fertilizer response plots, the observed yield and regression function were graphed together and visually inspected to verify the NLIN procedure produced reasonable results. A systematic approach was taken to remove all blocks with questionable outcomes. We felt this was necessary for this experimental design without replicated N treatments. First, blocks with model RMSE greater than 1.5 Mg ha^{-1} were judged to have excessive experimental error and were excluded from further analysis. Second, the remaining quadratic-plateau models were evaluated relative to missing data. Since with nonreplicated treatments the quadratic-plateau fitting procedure can be very sensitive to missing data, blocks with two or more missing yield points were also discarded. Blocks with one missing yield point were tested for potential exclusion. This test compared the quadratic-plateau model produced with the missing yield measurement to quadratic-plateau models produced with replacement values for the missing yield measurement. Replacement values examined were the initial model predicted yield ± 2 × RMSE. Blocks were discarded if either of these two replacement values produced model outcomes where the optimal N rate exceeded the initial model optimal N rate by >28 kg ha^{-1} (i.e., models were especially sensitive to the particular missing data). With this procedure, most retained blocks gave outcomes that varied by <15 kg N ha^{-1}. These two procedures described removed a total of 41 blocks of response plots over the 16 site-years, giving a final set of 182 blocks (76, 71, and 35 for alluvial, claypan, and loess soils, respectively). Although 18% of the total response blocks were discarded, this systematic procedure gave us confidence that the final set was reliable for further interpretation when relating to sensor measurements.

Step 2: Processing Canopy Reflectance Measurements

Canopy sensor data from response plots and the N-rich reference areas were used to calculate the inverse of the simple ratio (ISR) (Gong et al., 2003), or the ratio of the VIS/NIR. This ratio is directly related to the commonly used NDVI index as follows:

$$ISR = (1 - NDVI)/(1 + NDVI) \quad [4]$$

With the ISR, greener healthier corn has a lower value than corn showing an N deficiency. Any ISR values from the response plots or the N-rich reference area exceeding 0.40 were removed. This was done based on our previous experience, which showed that for V7 or older corn, ISR readings exceeding 0.40 were from areas with few or no corn plants (i.e., predominantly soil readings).

Fundamental in the use of sensors for N applications is the need to examine the relative differences between healthy corn, known to not be N deficient, and corn that is suspected to need N. Obtaining good ISR values from both the N-rich corn and target areas is crucial. The ISR of the target corn was obtained by averaging all readings within a block of response plots, since this whole area was used to determine yield response to N. For an ISR of N healthy corn, average readings from the sections of N-rich strips adjacent on each side of the block of response plots were examined and the strip with the lowest value selected. In a few situations, we found the ISR value of the N-rich strip greater (i.e., seemingly less healthy) than the value for the block of target corn. This particular situation was notably found in a few locations in 2006 and 2007 for the second set of response plots where ~67 kg N ha^{-1} was applied at planting. To ensure that the healthiest corn was chosen for each block of response plots, the lowest ISR value from either of the adjacent N-rich reference strips or the average of the single best plot within the block of response plots was selected. As a final precaution for the rare case where all of these plots appeared to either be N deficient or stunted because of other environmental factors, we set a ceiling of 0.23 for the N-rich ISR. Empirically, we found healthy corn at the growth stages of this study never exceeded this value.

An SI was calculated by dividing the ISR of the N-rich reference area by the ISR of the response plot area. Index values ranged between 0 and 1. Preliminary evaluation of several different indices showed SI developed from ISR values gave results comparable with the chlorophyll index (Roberts, 2006), an index found to be better at delineating N health differences in corn than NDVI (Solari et al., 2008).

Step 3: Relating Optimal Nitrogen to Reflectance Measurements

Optimal yield derived from Step 1 modeling was related to the SI calculated from Step 2 using scatter graphs and linear regression analysis. Relationships were examined for all fields combined and by each individual field.

Step 4: Deriving Nitrogen Rate from Sensors that Achieved Maximum Profit

The final step was to empirically derive, using data from Steps 1 and 2, N fertilizer rates that resulted in maximized economic return (i.e., from corn yield and N fertilizer amount) relative to producer blanket application rates. Marginal profit using the canopy reflectance technology was defined here as the difference in the N fertilizer cost and the yield gain or loss relative to the producer N rate and simulated yield as determined from the quadratic-plateau model results. This analysis balances returns on grain yield in response to N additions with the costs of the fertilizer N. Technology costs were not included.

To enable this analysis, a computer program was written to evaluate the most profitable N rate at different SI levels. To accomplish this, the response block data were placed into five bins of approximately equal size, based on their sorted SI values. For each of these bins, the program iteratively determined the N rate that optimized marginal profit relative to the uniform application rate the producers had historically used for these same fields (see Table 2). The N rates that optimized marginal profit for the five bins were graphed relative to average SI for each bin and connected with a dashed line. Five bins were chosen so that, for any set of conditions evaluated, a reasonable number of response blocks (≥12) were available for generating an optimal N rate. An exception was when examining the loess soil alone. Because data were limited for this soil type, only three bins were used.

The program included the following inputs: (i) values and quadratic response curves from optimal N rate modeling (Step 1 above); (ii) field-measured SI values for each response block (Step 2 above); (iii) set price of corn grain and N fertilizer; and (iv) producer prescribed N rate for each site-year. The analysis was repeated on subsets of data, based on combinations of the following two variables: (i) N applied at planting (0 kg N ha^{-1}, 67 kg N ha^{-1}, both combined), with no distinction as to soil type, and (ii) three major soil types and all soils combined (alluvial, claypan, loess, all soils), with no distinction as to N applied at planting.

Optimized for each bin during the iterative phase was the marginal profit from sensors vs. uniform N applications rates. Profit at different N rates (iterated from 0 to 235 kg N ha^{-1} by 5 kg N ha^{-1} increments) was examined relative to the application rates the producers had historically used for these same fields.

The program to determine N rate for maximum marginal profit was run with a number of different ratios of N fertilizer cost to grain price (FGR), to investigate profitability across a range of potential economic conditions. Corn price and N costs historically have gone up and down in a somewhat parallel fashion so that the FGR typically has ranged between 3 and 9 (using metrics from the international system of units). However, market perturbations in recent years have caused significant fluctuations in grain and fertilizer prices, resulting in greater uncertainty in future ratios. As an example, if N costs became especially high because of fertilizer shortages and grain prices were relatively low because of high supplies, then FGR might exceed 15. Therefore, a wider range of ratios were assessed here. Table 3 provides a matrix of FGR using SI units. Equivalent prices in non-SI units are also provided. Additionally, a single FGR value generated from different grain prices will produce different profits. Therefore, optimal profit from Step 4 is graphically presented relative to FGR for corn priced at \$0.08 and \$0.24 kg^{-1} (\$2.00 and \$6.00 bu^{-1}).

RESULTS AND DISCUSSION

Variation in Corn Nitrogen Need Verified

A summary of the R^2 and RMSE values of the modeling for optimal yield with N fertilization is graphically shown in Fig. 1. Models including a quadratic response

Table 3. Fertilizer to grain ratio (FGR), using the international system of units (SI), for various combinations of N fertilizer and corn grain prices. Equivalent prices in non-SI units are also shown in the shaded areas.

N fertilizer cost	Corn grain price, \$ kg^{-1} 0.079	0.118	0.158	0.197	0.236	0.276	0.315	N fertilizer cost
\$ kg^{-1}				FGR				\$ lb^{-1}
0.44	5.6	3.7	2.8	2.2	1.9	1.6	1.4	0.20
0.66	8.4	5.6	4.2	3.4	2.8	2.4	2.1	0.30
0.88	11.2	7.5	5.6	4.5	3.7	3.2	2.8	0.40
1.10	14.0	9.3	7.0	5.6	4.7	4.0	3.5	0.50
1.32	16.8	11.2	8.4	6.7	5.6	4.8	4.2	0.60
1.54	19.6	13.1	9.8	7.8	6.5	5.6	4.9	0.70
1.76	22.4	14.9	11.2	9.0	7.5	6.4	5.6	0.80
1.98	25.2	16.8	12.6	10.1	8.4	7.2	6.3	0.90
2.21	28.0	18.7	14.0	11.2	9.3	8.0	7.0	1.00
Corn grain price, \$ bushel^{-1}	2.00	3.00	4.00	5.00	6.00	7.00	8.00	

were significant ($P \leq 0.05$). Four examples of modeled yield response to N are included in Fig. 1 to illustrate the goodness of fit of this analysis. The R^2 and RMSE values of these four are referenced on the cumulative fraction lines. Approximately 75% of the 182 sets had an R^2 value > 0.6. Only about 20% gave RMSE values > 0.8 Mg ha^{-1} (12.7 bu ac^{-1}). Blocks with low R^2 values were generally those that were not responsive to N fertilization, as displayed in Fig. 2 (top). Yield was poorly related to optimal N rate with a linear regression $R^2 = 0.14$ (data not shown). Delta yield was much better related to optimal N rate, as Lory and Scharf (2003) demonstrated, with a linear regression $R^2 = 0.53$ (Fig. 2, bottom). Still, for any typical delta yield value, optimal N rate varied by >100 kg ha^{-1}.

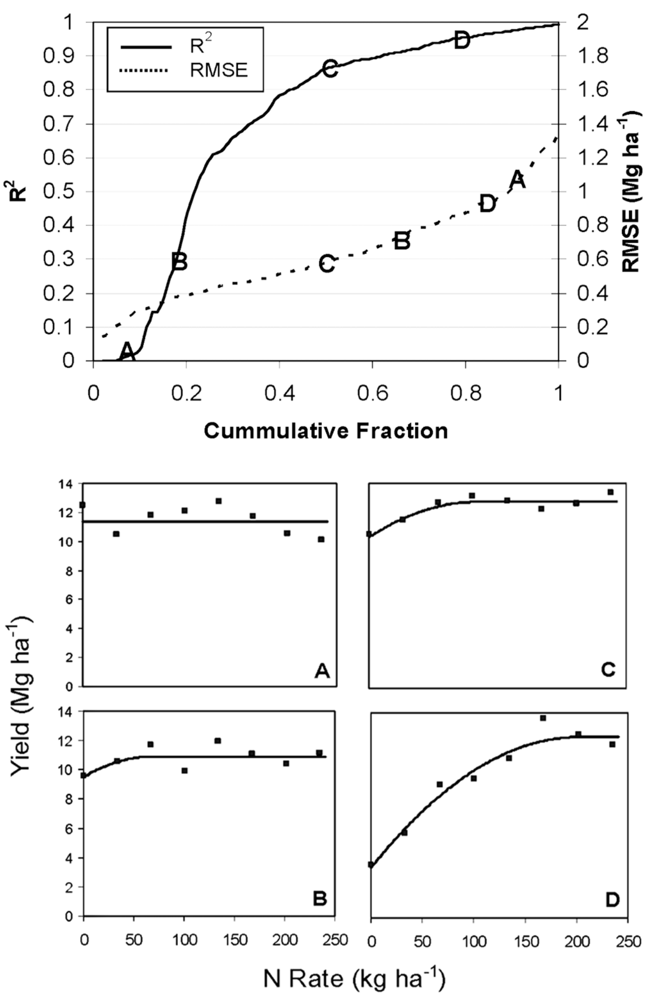

Fig. 1. Top: Cumulative fraction of the coefficient of determination and root mean square error (RMSE) of yield response models for the 182 yield response blocks. Bottom: Four examples of modeled yield response to N, included to illustrate the goodness of fit. The R^2 and RMSE values of these four are referenced on the cumulative fraction lines.

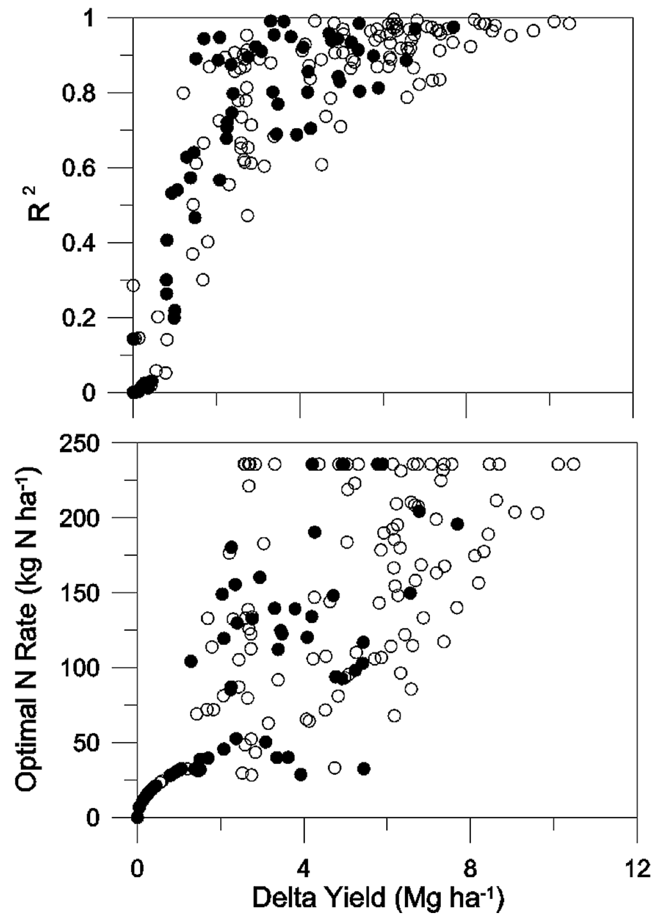

Fig. 2. Coefficient of determination for yield response models (top) and optimal N rate (bottom) related to yield increase with N fertilization. Open symbols represent sets of response plots where no early N was applied, other than what the producer applied (see Table 2). Filled symbols represent sets of response plots where total early N was ~67 kg ha^{-1}. Low coefficients of determination were found when yield response was small. The cluster of points near the origin of the bottom graph is an artifact created by Proc NLIN in SAS (SAS Institute, 2000) where the plateau of the quadratic-plateau modeling is reached between 0 and the first N rate.

Table 4. Summary of optimal yield and side-dress optimal N rate calculated from the quadratic-plateau models.

Year	Field	Number of response blocks	Mean optimal yield	Mean optimal N rate	Min. optimal N rate	Max. optimal N rate	Range in optimal N rate
			Mg ha^{-1}	kg N ha^{-1}			
2004	Ben	10	14.7	192	140	235	95
2004	Cop	8	13.3	222	189	235	46
2004	Die	5	15.7	222	192	235	43
2004	Hay	4	13.6	192	133	231	98
2004	Pet	3	15.8	94	32	133	101
2004	Sch	5	12.2	188	133	235	102
2004	Wil	5	13.1	187	156	231	75
2005	Geb1	2	12.6	144	72	235	163
2005	Lic	2	12.6	173	110	235	125
2006	Ben	28	11.9	124	50	204	154
2006	Cop	15	9.8	128	0	235	235
2006	Geb2	17	11.9	64	0	235	235
2006	Rie	19	10.7	90	0	235	235
2007	Geb1	11	11.7	95	32	222	190
2007	Hac	20	11.5	156	31	235	204
2007	San	28	10.3	62	0	235	235

Optimal yield over the 16 sites averaged 12.6 Mg ha^{-1}, ranging from 9.8 to 15.8 Mg ha^{-1} (Table 4). Thus, this analysis only included fields and N response blocks that were relatively high-yielding for Missouri conditions. Mean optimal N rate by field ranged from a low of 62 kg N ha^{-1} to a high of 222 kg N ha^{-1}. Within fields, the range of optimal N rate varied by >100 kg N ha^{-1} in 13 of the 16 fields. This within-field variation is similar to a previous corn N rate analysis where the conclusion was that variable-rate N may be warranted for many Missouri fields (Scharf et al., 2005). Range in optimal N for 2006 and 2007 was generally greater than for 2004. We attribute this difference to particularly well-suited growing conditions during the 2004 growing season, both in precipitation and temperature, that resulted in high yields regardless of soil differences within fields. Because of droughty conditions in 2005, only a few response blocks remained in the analysis.

While no strong trend can be drawn from this dataset, the average optimal N by soil type was 144, 163, and 113 kg N ha^{-1} for alluvial, claypan, and loess soils, respectively. At the same time, the average range in optimal N by soil type was 153, 119, and 172 kg N ha^{-1} for alluvial, claypan, and loess soils, respectively.

Relating Optimal Nitrogen to Canopy Reflectance

Optimal N was examined relative to SI, similar to what others have done with the chlorophyll meter (Varvel et al., 1997; Scharf et al., 2006; Varvel et al., 2007). Conceptually, canopy sensing could be used to successfully determine N rate if optimal N rate increased as the sensor-based SI decreased. Combined across all 16 fields, a poor relationship was found between optimal N rate and SI ($R^2 = 0.04$; $P < 0.04$). However, by individual field (Fig. 3; Table 5), a significant linear relationship between these two was found for some cases (five fields at $P < 0.10$ and seven fields at $P < 0.15$). For about half the fields, there appeared to be little relationship between optimal N and SI (e.g., 2004 Cop, 2004 Die, 2006 Rie). A few fields had too few blocks to make this assessment. A greater range in optimal N (as noted for 2006 and 2007) did not necessarily help establish a relationship. When assessed by soil type, claypan and loess fields indicated significance at $P < 0.10$ (Table 5). One field to note was 2004 Pet. This field averaged the highest yield (15.8 Mg ha^{-1}) of the 16 fields, yet for 2004, had generally the lowest optimal N along with relatively high SI values. This field had been a well-fertilized pasture for >30 yr before being put into soybean production in 2003 and then corn in 2004. Average optimal N for this field was at least 90 kg N ha^{-1} less than the average optimal N of the other 2004 fields (Table 4).

An observation supporting the assertion that the canopy sensors recognized crop N status comes from comparing the 2006 and 2007 response blocks where early N was not added at planting with those that received ~67 kg N ha^{-1} (producer preplant + emergence applied N) (Fig. 3). Of these seven fields, four show a general decrease in optimal N and an increase in SI when comparing the set of response blocks receiving N at emergence with those receiving no additional N (see 2006 Geb2, 2007 Geb1, 2007 Hac, and 2007 San). This shift of lower optimal N and higher SI verifies the corn receiving the N at emergence needed less side-dressed N and reflectance

Table 5. Summary of linear regression analysis by field and combination of fields, examining optimal N relative to canopy sensor sufficiency index. Only fields with more than three observations were examined.

Year	Field or soil	Intercept	Slope	Model R^2	$P > F$
2004	Ben	460	–349	0.28	0.11
2004	Cop	187	52	0.03	0.68
2004	Die	107	150	0.33	0.31
2004	Hay	69	146	0.01	0.90
2004	Pet	na†	na	na	na
2004	Sch	382	–238	0.21	0.44
2004	Wil	746	–808	0.71	0.07
2005	Geb1	na	na	na	na
2005	Lic	na	na	na	na
2006	Ben	360	–282	0.31	<0.01
2006	Cop	681	–772	0.52	<0.01
2006	Geb2	441	–440	0.19	0.08
2006	Rie	238	–165	0.03	0.48
2007	Geb1	583	–628	0.22	0.14
2007	Hac	222	–216	0.06	0.30
2007	San	332	–399	0.28	<0.01
2004–2007	alluvial fields	201	–133	0.02	0.24
2004–2007	claypan fields	462	–393	0.30	<0.01
2004–2007	loess fields	363	–332	0.10	0.07
2004–2007	all fields	202	–110	0.02	0.04

† na, not analyzed because of limited number of observations.

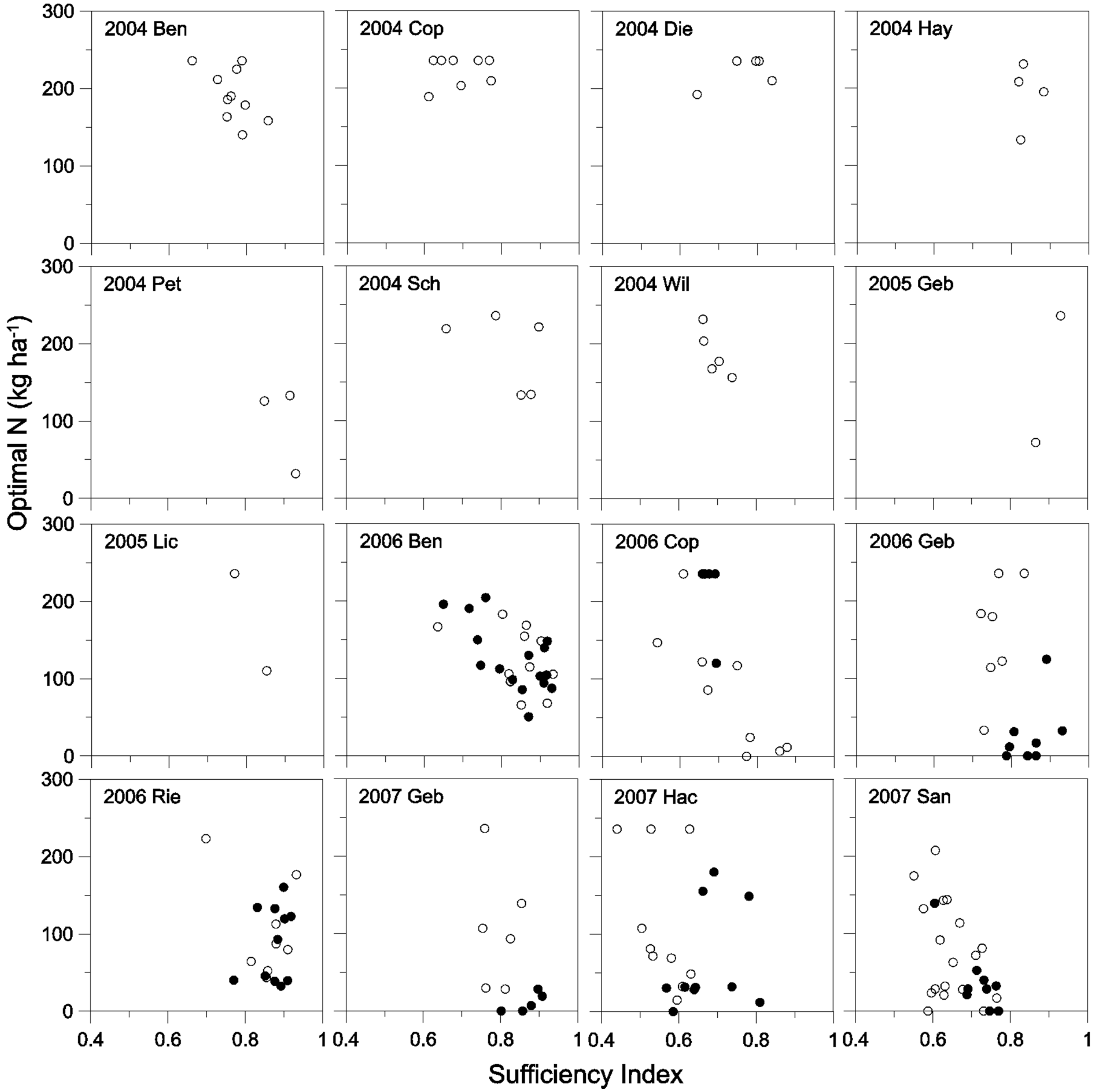

Fig. 3. Optimal N rate relative to canopy-based N sufficiency index for 16 production field studies. Open symbols represent sets of response plots where no early N was applied, other than what the producer applied (see Table 2). Filled symbols represent sets of response plots where total early N was ~67 kg ha^{-1}.

measurements delineated this difference. The three fields that didn't show this trend were fields where the producer had applied ~30 kg ha^{-1} in association with preplant phosphorus fertilization (Table 2). For these fields we credited the producer-applied N, even though it was applied weeks to months before planting, and cut the amount applied at emergence for the second set of response plots to 34 kg ha^{-1}. Our rationale was that if too much N was applied before sensing, there would be little or no difference observed between the corn from the N reference and corn in the response blocks. Because of this N credit for these three fields, the actual difference between the two sets of response plots relative to N application at planting was only 34 kg ha^{-1}. So, differences could be seen for fields where the response blocks differed by ~67 kg N ha^{-1} but not on fields that only differed by ~34 kg N ha^{-1}.

Using Optimal Profit to Determine Nitrogen Rates

Although the linear relationship between optimal yield and SI was weak with all fields combined, we surmised that the trend in the dataset could be used to empirically derive the N rates that would be most profitable relative to N rates historically used on these same fields. The panels in Fig. 4 graphically provide a summary of those N fertilizer rates determined to give the highest marginal profit using the reflectance sensors. The broken lines on each panel represent different

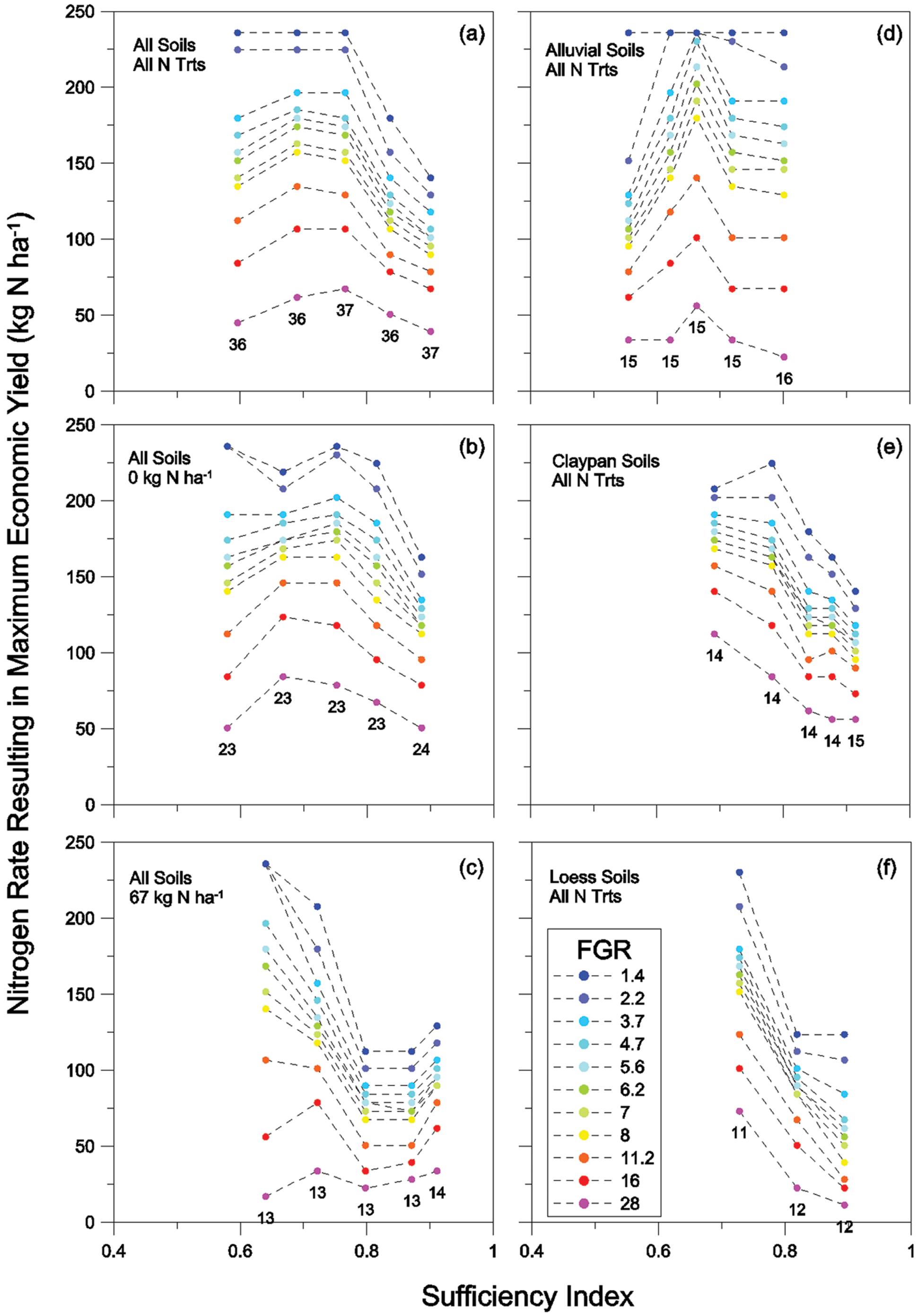

Fig. 4. From the results shown in Fig. 3, N fertilizer rates that gave the maximum economic return, compared with producer practice on these same fields, were determined and are shown relative to canopy sensor sufficiency index. For this analysis, results were compiled for (a) all data; (b, c) N applied at planting; and (d, e, f) soil types. To obtain the most profitable N rate, observations were first sorted by SI and assigned to one of five bins (three bins for loess soil alone). The number of observations per bin is shown below the bottom line within each panel. Then, for each bin the N rate that gave the highest marginal profit (defined as the difference in the N fertilizer cost and the value of yield gain or loss) was calculated. The N rate for highest marginal profit was determined with a number of different N fertilizer cost to grain price ratios (FGR; see Table 4), as shown with dashed lines.

FGR values. Figure 4a represents all 182 observations of this study. In this panel, the amount of N for optimal profit increased as SI decreased from 0.9 to 0.75. Below 0.75, the most profitable N rate stayed approximately the same or decreased slightly at the low SI reading. Agronomically, the downward turn in the most profitable N rate seen for the lowest SI values of Fig. 4a suggests that yields of corn with greater N deficiency cannot be profitably increased with higher rates of N fertilizer. The exception would be when fertilizer N is very inexpensive relative to grain prices (i.e., low FGR); then the most profitable N rate is the maximum allowed in this analysis.

When SI values were around 0.9 for all soils combined (i.e., sensor readings from the N reference area and the target area are nearly the same), the analysis shows 50 to 125 kg N ha^{-1} is still generally needed for maximum profit. The interpretation of this outcome is that corn appearing N-healthy at the growth stage corn was sensed in this study (~V8–V11) does not necessarily indicate sufficient N to meet the full-season crop N need. This is not surprising, since only about 30% of total N needed for the whole crop is taken up by V12 (Ritchie et al., 1997).

The most profitable N rates increase as FGR decreases. This is seen as an upward shift in lines with decreasing FGR values for all panels in Fig. 4. When the cost of fertilizer relative to grain price increases (high FGR values), the highest profit is achieved by applying less N fertilizer. In other words, N costs become a more important factor in the marginal profit. This factor is not insignificant, and has the potential to be even more important as grain and fertilizer prices widely and independently fluctuate.

When all observations of this study (as shown in Fig. 4a) are split-out by early N management, the most profitable N rates generally increase when N was not applied at planting (Fig. 4b), and decrease when a base of N was applied at planting (Fig. 4c). Sufficiency index values when N was applied at planting are slightly higher than those when N was not applied at planting. For similar SI and FGR values between the scenarios represented by Fig. 4b and 4c, the most profitable side-dress N when N was also applied at planting was about 25 to 60 kg N ha^{-1} less than when N was not applied at planting. The results help verify the premise that canopy reflectance and optimal N are related.

When N is not applied at planting (Fig. 4b), the most profitable N rates are similar to those for the analysis of all observations combined. The similarity arises from the fact that treatments without N at planting contributed a higher number of observations to the total (64%). The situation of not applying any N at planting may not be realistic for most fields because many participating farmers we interacted with were apprehensive about waiting until side-dressing before applying any N fertilizer. Exceptions might include fields that receive manure for meeting a significant portion of the crop's N needs (Jokela, 1992). Generally, fields will be managed with some N applied before or at planting.

When a portion of the crop N is supplied at planting (Fig. 4c), the most profitable N rate remains generally flat for SI values between 1.0 and 0.8. [No reasonable explanation could be offered for the slight decrease in N between the highest (SI ≈ 0.92) and next highest (SI ≈ 0.87) bins.] In effect, significant N applied at planting, resulting in corn that looks similar to N-rich corn, may make it difficult to assess N needs for the rest of the growing season. This leads us to conclude that when N reference corn and corn to be side-dressed look visually similar over most of a field, sensors for variable-rate N application may not be needed and a flat rate over the field may be the best option. Our experiences suggest that when standing on the edge of the field, the human eye can usually detect differences associated with SI values < ~0.90. If above the corn canopy such as in a tractor cab, one can begin to see subtle differences in biomass and/or color when SI values are < ~0.95. Corn plots with SI values < 0.80 are very noticeable. Thus, when noticeable differences in color and biomass can be visually seen within a field, large differences in SI exist, and using sensors to detect and variably apply N may be especially warranted.

Additional analysis indicated soil type was an important consideration and produced unique interpretations (Fig. 4d–f). For claypan soils, the change in the most profitable N rates over the five SI bins was fairly consistent (Fig. 4e). These rates generally increased with decreasing SI values. Regardless of FGR, the variation in N rate over SI values was <90 kg N ha^{-1}.

Most profitable N rates for the other two soils were much more variable over the range of conditions tested, but likely for different reasons. River alluvial soils (Fig. 4d) are commonly highly variable within each field. All the river alluvium soil fields of this study were in the Missouri River flood plain, within 2 km of the main river channel. Many of these fields have soil textures that range from loamy sand to clay. Noticeably, SI values for this soil were somewhat lower than the other two soils. Further, the relationship of increasing N rate with decreasing SI was not nearly as evident for this soil. In fact, the sharp and distinctive decline in N rate observed for the two lowest SI bins of this soil was not seen with the other two soils. By deduction, we can conclude this soil is the cause of the downturn in N rates with low SI values observed in Fig. 4a,b. Excess precipitation early in the growing season creates conditions on this soil conducive for leaching (sandy soils) and denitrification (clay soils) losses. Thus, areas on these fields can be especially vulnerable to insufficient N early in the growing season. It seems plausible to conclude that when either N was not applied at planting or when early planting N was lost on these soils, the canopy sensors gave low SI values and early-season crop N health was compromised and yield potential lost. Under such conditions, greater side-dress N applications could not compensate, and therefore the most profitable N rate was less than at a higher SI value (Fig. 4d). Again, the exception is when N costs are especially low compared with grain price.

With the limited dataset for loess soils (Fig. 4f), our results show the most profitable N rate increases as SI decreases. For high SI values, the most profitable N rates were generally less than with the other two soils. Loess soils are typically deep, well-drained mollisols and commonly have higher subsoil organic matter content than the other two soil types. Therefore when N-rich corn and unfertilized corn looked similar over a loess field (e.g., SI ≈ 0.9), a modest single-rate application would most likely suffice. If visual variation is evident, using the canopy reflectance sensors to direct N applications would likely be beneficial.

Marginal Profit Potential

The highest marginal profit associated with each FGR value was summed and graphed for all soils combined and by individual soil type (Fig. 5). Profit using the sensors increased in an exponential fashion as the FGR increased. Conversely, as fertilizer cost decreased relative to grain price, the value of using canopy sensors for N management diminished. The exception here appears to be with alluvial soils, where extremely inexpensive N can also increase profit slightly. With all soils combined and with FGR values typical of what producers have seen in the past decade, profit using the sensors will be modest (<\$25 ha^{-1}). However, the price paid for corn grain can have

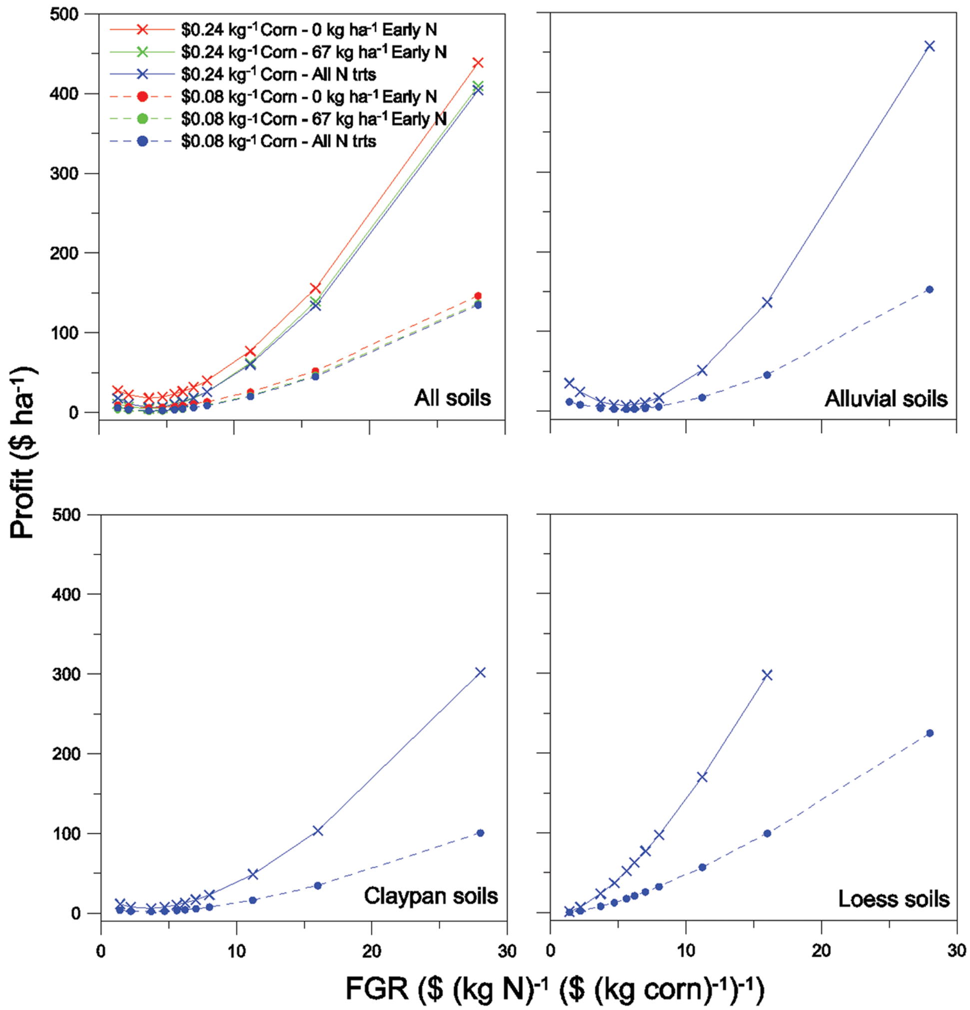

Fig. 5. Marginal profit associated with the N rates displayed in Fig. 4 in relation to N fertilizer cost to corn price ratio (FGR). Data for all soils combined and separated by soil type are presented for two different corn prices.

a significant effect. With corn priced at \$0.08 kg^{-1} (\$2 bu^{-1}), profit ≥ \$24.70 ha^{-1} (\$10 ac^{-1}) could only be accomplished when the FGR was ~13 or greater. At this FGR value, N fertilizer would cost \$1.04 kg^{-1} (\$0.47 lb^{-1}). However, with corn priced at \$0.24 kg^{-1} (\$6 bu^{-1}), that same profit or more could be achieved when the FGR was ~7. At this FGR value, fertilizer would cost \$1.68 kg^{-1} (\$0.76 lb^{-1}). In this scenario, corn price tripled while N price only increased by a factor of 1.6. Therefore, equivalent profit was achieved with the higher grain price and lower FGR. Thus, as illustrated in Fig. 5, both the FGR and the absolute grain price will determine the profit potential.

Similar to Fig. 4, a different story emerges for profit when examined by soil type. For alluvial soils, profit was found to be similar to that for all soils combined (Fig. 5). For claypan soils, profit potential was more modest. For these two soil types, and with corn priced at \$0.08 kg^{-1} (\$2 bu^{-1}), profit was <\$5 ha^{-1} or there was a slight loss with FGR values < 6. From a FGR of 5 to 10, one would rarely expect profit to exceed \$15 ha^{-1}. Our findings suggest canopy sensing for N applications may be well suited for loess soils that historically have had high N applications. For these soils, profit of between \$10 and \$50 ha^{-1} was projected with FGR values between 5 and 10. With higher-priced corn at \$0.24 kg^{-1}, profit increased rapidly when FGR > 5. The profit is mostly generated by adding only modest amounts of N at side-dress when SI values are high (Fig. 4f). Loess soils are typically deep, well-drained mollisols and commonly have higher subsoil organic matter content than the other two soil types. So, from the limited number of loess fields evaluated, very little additional N was needed at the time of canopy sensing, particularly when N was applied at planting (see 2006 Geb2 and 2007 Geb1 of Fig. 3). Additional studies on similar loess fields are needed to confirm this result.

Further Discussion of Findings

Although these results were helpful in generating N rates that would optimize profit using canopy sensors, we expected the relationship between optimal N and SI to be more consistent than was found. Several explanations are possible. One, canopy reflectance sensors may be less sensitive to crop N health than other in-season diagnostic tools, such as chlorophyll meters. Chlorophyll meters measure transmittance of chlorophyll-absorbing light through the leaf, with the sensor device clamped directly onto a plant leaf and the sensing components within 1 cm of the leaf surface. Typically, the most recently-collared corn leaf in the midsection of the plant is measured. Readings are sensitive to leaf greenness, and have

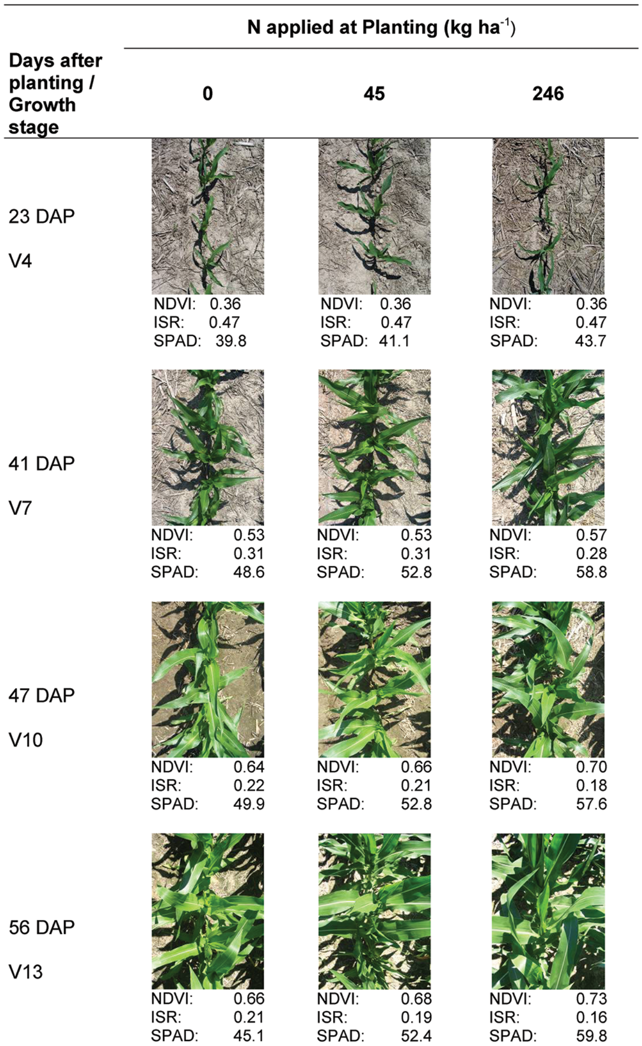

Fig. 6. Photographs along with chlorophyll meter (SPAD) and active-light crop-canopy reflectance sensor readings [NDVI and inverse simple ratio (ISR)] taken at various growth stages for corn fertilized differently at planting. The photograph perspective is similar to perspective of the canopy reflectance sensor when mounted nadir over a row.

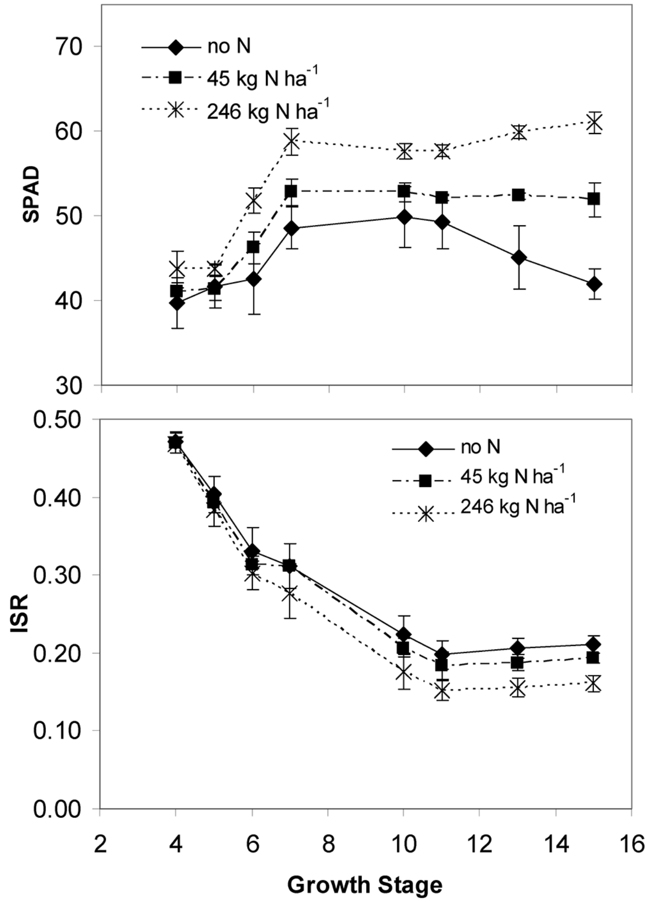

Fig. 7. A comparison of chlorophyll meter (SPAD) and active-light crop-canopy reflectance sensor [inverse simple ratio (ISR)] readings at different corn growth stages and at three levels of N fertilization at planting.

been found to be quite reliable for assessing corn N health (Schepers et al., 1992) and fertilizer need (Scharf et al., 2006; Varvel et al., 2007). With canopy reflectance sensing, plant biomass and color are delineated by relative soil-plant reflectance as assessed usually from above the crop, from a nadir view. While significant correlation between chlorophyll meter and canopy reflectance measurements have been shown (Shanahan et al., 2008; Solari et al., 2008), subtle differences in crop N health may be more easily delineated with the chlorophyll meter than the canopy sensors. Figure 6 shows photos from the viewpoint of the canopy sensor of three levels of corn N health through a series of growth stages. Accompanying NDVI, ISR, and SPAD readings are provided with each snapshot of Fig. 6, and a range of ISR and SPAD readings at these and additional growth stages are graphed in Fig. 7. Though the photos in Fig. 6 represent only a small segment of the row length that was measured by the sensors, one is only able to visually see slight differences in N treatments looking down onto the canopy from the typical position of canopy sensors. The differences are more apparent in the later growth stages. However, chlorophyll meter readings discriminate differences in corn N health much earlier than canopy reflectance readings. A major factor contributing to this difference is which leaves are being sensed. For canopy reflectance sensors, leaves emerging out of the whorl have the most influence on the reading (Fig. 6). For the chlorophyll meter, measurements come from the uppermost fully-expanded leaf (Scharf et al., 2006), which is underneath the whorl leaves. As a mobile nutrient within plants, N deficiency will show sooner here than in the upper leaves. In Fig. 7 the chlorophyll meter detected differences between no N and 45 kg N ha^{-1} at V6 and later, but with the canopy sensor, differences were almost nondistinguishable until V10, and even then the differences were subtle. Also, greater differences in chlorophyll readings were seen as the plants matured through the later vegetative growth stages of V11–V15, changes that were not detected with the canopy sensors. In short, on-the-go canopy sensing can detect N status of corn, but methods and sensors employed with this research may not have sensitivity to crop N-health equivalent to a chlorophyll meter. Additional research may be needed to evaluate oblique-pointing sensors that minimize soil and target the plants from the side (and therefore multiple rows) as has been done with the Kiel system (Heege et al., 2008).

A second point is the difficulty in diagnosing season-long crop N need from plants that have only taken up approximately one third of their total N (Ritchie et al., 1997). This, along with the fact that many weather factors affect yield between the time of in-season fertilization and harvest, make predicting exact N fertilizer needed impossible. This is especially the case for a humid region that primarily relies on natural precipitation for crop production,

A third point to help explain our findings relates to the experimental design. These response plot blocks, with the full range of N rates needed for modeling crop response to N, required significantly large areas. Also, to consider variations in N response across a field, N application, canopy sensing, and yield measurements needed to be automated, which required these larger experimental units. The size of these blocks varied by year but typically was from 0.1 to 0.2 ha. Ideally, crop response to N rates should be evaluated on much smaller areas. Because of the size needed for the response plot study, uncontrollable error associated with spatial differences and measurement averaging may have compromised the ability to find stronger relationships. We noted this to especially be a challenge on the Missouri River alluvial soils.

CONCLUSIONS

Central to this research is the premise that, within many crop production fields, the optimal amount of N to apply is highly variable. From such, the challenge is to find technologies and procedures that are responsive to spatially variable N need, as well as those that are practical, automated, and convenient for producers to use. The use of crop canopy sensors mounted to in-season fertilization equipment has the potential to respond to this challenge. Yet, with all new technologies, the steps producers make from consideration, to experimentation, to adoption will fail if economic value is not obvious to producers (Lamb et al., 2008). Thus, for the development of new N management procedures, and ultimately decision algorithms, economic scrutiny is required. This research was conducted to assess the relationship between crop canopy sensor data and corn response to side-dress N fertilization. Additionally, these findings were used to examine the potential profit that could be achieved (i.e., from increasing corn yield and on decreasing N fertilizer amount) by using this sensing technology to control variable-rate N fertilizer.

Crop canopy sensor information was related to in-season N fertilizer need about 50% of the time, over a wide range of Missouri soil conditions. Uncontrollable factors related to field-scale research may be partly to blame. Understanding N source and fate within fields containing variable soils and for a humid, rainfed environment is complex. While we offered a few specific explanations for why these results were not more consistent, no solid case could be made for why the pattern was seen on some fields and not on others. Yet, even with these mixed results, N rates more profitable than blanket applications were derived which followed established agronomic principles relative to N management. While soil type, fertilizer cost, and corn price affected our findings, we generally found the potential for a modest profit increase using canopy sensing for N applications. The advantage of using crop canopy sensors increased as FGR increased. Profit also appeared to improve on loess soils, but with this limited dataset, we feel additional evaluation is needed.

We have noted from these research fields and other producer demonstration trials that use of the canopy sensors for N management is generally more applicable when certain field conditions are present, such as extreme within-field variability in soil type; following recent animal manure applications; and when cropland was recently converted from pasture, hay, or CRP management. We surmise that any time conditions are present where uncertainty is high about how much N the soil will provide a crop, canopy sensors may be an appropriate strategy for in-season N applications. This is especially true when conditions driving N availability vary across the field landscape. Other examples of such situations include corn grown following a leguminous cover crop, applying rescue N fertilizer because excessive spring and early summer rainfall have caused loss of preplant N, and for a crop grown following a droughty growing season where N carryover is likely.

We suspect that, as sensors are modified or newly designed and/or agronomic understanding of the relationships between sensor information and nutrient management is improved, many more studies of this type will be needed. Including specific weather, soil (e.g., soil electrical conductivity, organic matter), and landscape attributes in the evaluation may be needed to better understand N fertilizer requirements in relation to reflectance sensing. In the meantime, as fertilizer costs soar in response to increased energy prices, many farmers are anxious to learn and apply what is known about these new technologies today. Just as plant breeding for hybrids has been a process of incremental improvements spanning decades, so might we find the development of crop sensing technologies and methods for improved economic and environmental nutrient management.

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