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Modifying the University of Missouri Corn Canopy Sensor Algorithm Using Soil and Weather Information

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Abstract. Corn production across the U.S. Corn belt can be often limited by the loss of nitrogen (N) due to leaching, volatilization and denitrification. The use of canopy sensors for making in-season N fertilizer applications has been proven effective in matching plant N requirements with periods of rapid N uptake (V7-V11), reducing the amount of N lost to these processes. However, N recommendation algorithms used in conjunction with canopy sensor measurements have not proven accurate in making N recommendations for many fields of the U.S. Corn Belt. The objective of this research was to determine if soil and weather information could be used to make the University of Missouri canopy reflectance sensing algorithm more accurate. Nitrogen response trials were conducted across eight states over two growing seasons, totaling 32 sites (four per state) with soils ranging in productivity. Reflectance measurements at ±V9 were used with the University of Missouri canopy sensor algorithm to calculate an in-season N fertilizer recommendation. This recommendation was related to the economic optimal N rate (EONR). The University of Missouri algorithm was only mediocre in predicting EONR, averaging within 74 kg N ha^{-1} of EONR when target corn received 45 kg N ha^{-1} at-planting. However, when this algorithm was adjusted using weather and either measured or USDA SSURGO soil properties the suggested N fertilizer recommendation improved. The error as determined by the root mean square error (RMSE), for corn receiving 45 kg N ha^{-1} at-planting the RMSE was 74 kg N ha^{-1} without soil and weather and 52 kg N ha^{-1} with the soil and weather adjustment. This suggests the incorporation of soil and weather information into other canopy sensor algorithms may enhance their accuracy at predicting site-specific EONR.

Keywords. *Missouri, Canopy Sensor, Corn, Nitrogen, Algorithm, Adjustment.*

Introduction

Efficient nitrogen (N) management in corn (*Zea mays* L.) is critical for increasing grower profits and preventing environmental pollution. Fertilizer applications that match end-of-season measured economic optimum N fertilizer rate (EONR) can reduce N loss while protecting grower profits and the environment (Scharf et al., 2002; Roberts et al., 2010; Scharf et al., 2011). However, between- and within-field spatial variability of soil characteristics and variation in year-to-year weather factors make it difficult to determine the right amount of N fertilizer needed early in the season to match EONR.

Crop canopy reflectance sensors capture plant condition information (greenness and biomass) from small areas within fields and therefore can assess spatially-variable N requirements. Such a diagnostic tool therefore can aid in recommending the correct amount of N fertilizer applied to reach optimal yields (Scharf et al., 2002; Kitchen et al., 2010; Barker and Sawyer, 2010; Scharf et al., 2011). Unlike soil- or tissue-test based in-season N fertilizer recommendations, canopy sensors are directly mounted to a fertilizer applicator making it possible to collect reflectance data and apply variable N fertilizer in an on-the-go operation.

Canopy sensor algorithms are the mathematical expressions used to transform reflectance readings into an in-season N fertilizer recommendation. The unique growing conditions and environments these algorithms were developed for may limit their universal adoption.

Financial benefits have been documented by using the MU algorithm to synchronize the application of N fertilizer with corn N uptake. Fifty-five on-farm trials during 2004 to 2008 were conducted in Missouri where canopy sensing was used to inform topdress N fertilizer application rates (Scharf et al., 2011). Sensing N applications were then compared to a fixed rate that producers' used on these same fields. Across all fields, canopy sensors increased partial grower profits by an average of \$42 ha^{-1} over producer rates. However, the MU algorithm's performance on a regional scale across the U.S. Cornbelt was mediocre. The question considered here is, could the performance of the algorithm be improved by incorporating into the algorithm soil or weather information.

Weather factors such as precipitation and temperature generally drive plant growth and influence soil conditions (Tremblay and Bélec, 2006), which ultimately influence corn yield. Monthly rainfall has been proven to effect corn yield variability (Teigen and Thompson, 1995). Nitrogen response across North America was found to be most affected by precipitation during June and July, as well as by temperatures during July and August (Jeutong et al., 2000). Some have identified the distribution or evenness of rainfall as being significant in describing responsiveness to N fertilizer, thus affecting yield (Shaw, 1964; Reeves et al., 1993; Tremblay et al., 2012). For example, frequent rainfall events were observed in 51 studies from 2006 to 2009 in several North American locations and were explained to have high soil moisture early in the growing season that promoted N loss through denitrification and leaching, as well as increased responsiveness to N fertilizer (Tremblay et al., 2012). Rainfall and temperature are generally accepted as metrics directly impacting yield-limiting soil factors of oxygen levels, biological activity, decomposition of organic matter to soil mineral N, nutrient availability, plant available water (PAWC), and ultimately crop yield (Power et al., 2001; Tremblay, 2004; Tremblay and Bélec, 2006; Kyveryga et al., 2007; Shanahan et al., 2008; Tremblay et al., 2012).

Spatially-diverse soil properties at sub-field to regional scales are key to understanding crop N needs. Soil texture, soil organic matter (SOM), and PAWC combined with varying total rainfall, the evenness of rainfall, and temperature, contribute to the complexities of N fate in crops and the environment (Power et al., 2001; Tremblay et al., 2004). Multiple N loss processes and pathways can exist in any given field. Significant denitrification (the conversion of NO_3^- to N0x and N_2 gases) most often occurs in clayey textured soils experiencing anaerobic soil conditions from excessive rainfall and with warm soil temperatures (Blevins et al., 1996). In contrast, NO_3^- leaching below the rooting depth results when high amounts of rainfall occur and is more pronounced on soils with low water holding capacity or coarse textured soils (Power et al., 2001). Volatilization, (the loss of N through ammonia-NH_3 gas), may also occur if certain N fertilizers, such as urea, are not incorporated into the soil (Ma et al., 2010). These weather-soil interactions result in varying field conditions, suggesting the need for targeting of N management to match these variations. Research is needed to decide if and how these soil and weather variables can improve N fertilizer recommendations to help match EONR.

Soil information can be obtained from different sources. Through the USDA-NRCS Soil Survey Geographical database (SSURGO), the most used conventional soils database in the United States (Yang et al., 2011), most of the previously mentioned soil variables can be obtained. The accuracy and precision of SSURGO information is affected by mapping techniques, the level of spatial detail, and the exactitude of soil attributes (Zhu, 1997; Zhu et al., 2001). Efforts to verify SSURGO reports with actual soil measurements have given contradictory results. Field-truthing of SSURGO reports on the Hunewell ranch in Erath County, Texas showed poor relationships between SSURGO estimated soil texture and pH to actual samples (Zylman et al., 2015). Variation between SSURGO and the collected samples was greatest in erosional areas and transitional areas between SSURGO mapping units.

The objective of this research was to determine if soil and weather information could be used to inform the MU canopy sensor algorithm in making a better-performing in-season N fertilizer recommendation. Sub-objectives of this research were to compare algorithm performance with weather and soil information for 1) two different target N fertilizer rates; and 2) when employing SSURGO soil information versus actual within-field soil measurements.

Materials and Methods

Research Sites and Locations

This research was conducted as part of public-private collaboration between eight major land-grant universities (University of Iowa, University of Illinois, University of Indiana, University of Minnesota, University of Missouri, North Dakota State University, University of Nebraska, and the University of Wisconsin) within the US Corn Belt and DuPont Pioneer. This project is commonly referred to as the, "Performance and Refinement of Nitrogen Fertilization Tools" project. The approach for this research was fundamental N fertilizer response field-plot studies conducted with standardized protocols and methods across a wide range of soil and weather conditions. Yield and soil measurements from these plot studies provided both the measurements needed as well as N response functions.

Thirty-two corn N response trials were conducted during 2014 to 2015 in eight Midwestern Corn Belt States. In each state, two sites ranging in productivity were selected for each growing season, giving four sites per state (Figure 1.1). Productivity was determined by historical yield and general soil productivity. Research sites were planted at a target population of 86,450 plants ha^{-1} using Pioneer hybrids (DuPont Pioneer, Johnstown, IA) best suited for the selected sites within the region. Most research sites followed soybean, however four sites followed corn. The MN New site and the IA Mason site were tiled drained. NE sites were irrigated. All but three sites received at least some form of tillage. Planting dates ranged from April 19 – May 23 and topdress/sensing dates ranged from June 7 – July 10. Descriptions of management for all sites are presented in Tables 1.1 and 1.2.

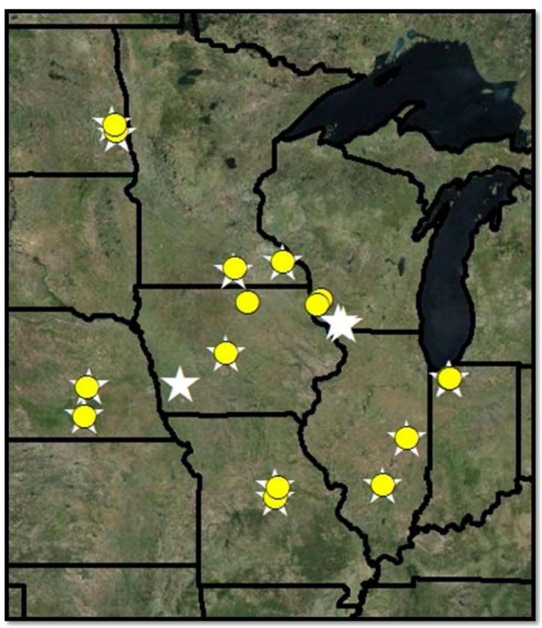

Figure 1.1. Field research sites were located within eight U.S. Corn Belt states (Iowa, Illinois, Indiana, Minnesota, Missouri, Nebraska, North Dakota, and Wisconsin). Each state contained two sites for two growing seasons (2014 - 2015), totaling 32 sites. The 2014 sites are represented by yellow circles while the 2015 sites are represented by white stars.

Table 1.1. Management description for the 16 sites for the 2014 growing-season. Each of the eight participating states chose two sites that contrasted in productivity within the state.

State	Site	Productivity	Previous Crop	Tiled	Irrigated	Tillage†	Hybrid	Seed Rate	Row Space	Planting Date	Sensing Date	Sensing Growth Stage
								seeds/ha	cm			
IA	Ames	Low	SB	No	No	FC	P0987AMX	87,685	76	7 May	26 Jun	V9
IA	Mason	High	SB	Yes	No	No-till	P0636AMX	86,450	76	9 May	9 Jul	V9
IL	Brown1	Low	SB	No	No	FC	P1498AM	79,040	76	24 Apr	13 Jun	V8
IL	Urbana1	High	SB	No	No	FC	P1498AM	86,450	76	25 Apr	15 Jun	V8.5
IN	Loam1	High	SB	No	No	F chis/SP FC	P0987AMX	81,510	76	19 May	27 Jun	V9
IN	Sand1	Low	SB	No	No	F chis/SP FC	P0987AMX	81,510	76	19 May	27 Jun	V9
MN	New1	High	SB	Yes	No	-	P9917AMX	85,215	76	21 May	7 Jul	V9
MN	Charles1	Low	SB	No	No	Vertical-till	P9917AMX	85,215	76	16 May	8 Jul	V10
MO	Bay	Low	SB	No	No	FC	P1498AM	86,450	76	2 May	20 Jun	V10
MO	Troth1	High	SB	No	No	No-till	P1498AM	86,450	76	2 May	21 Jun	V10.5
ND	Amenia1	High	Corn	No	No	F chisel/ FC	P8954AM1	79,040	56	23 May	10 Jul	V8.5
ND	Durbin1	Low	Corn	No	No	F chisel/FC	P8954AM1	79,040	56	23 May	10 Jul	V8.5
NE	Brandes1	Low	SB	Yes	Yes	No-till	P1151HR	86,450	76	19 Apr	26 Jun	V9
NE	SCAL1	High	SB	No	Yes	No-till	P1151HR	79,040	76	7 May	24 Jun	V8.5
WI	Steuben	High	SB	No	No	No-till	P0636AMX	86,450	76	7 May	25 Jun	V9
WI	Wauzeka	Low	SB	No	No	No-till	P0636AMX	79,781	76	6 May	25 Jun	V9

†FC, field cultivated; F, fall; Chis, Chisel; SP, spring.

Table 1.2. Management description for the 16 sites for the 2015 growing season. As done previously, each of the eight participating states chose two sites ranging in productivity of the 2015 growing season.

State	Site	Productivity	Previous Crop	Tiled	Irrigated	Tillage†	Hybrid	Seed Rate	Row Space	Plant Date	Sensing Date	Sensing Growth Stage
								seeds/ha	cm			
IA	Boone	Low	SB	No	No	FC	P0987AMX	86,450	76	18 May	7 Jul	V10
IA	Lewis	High	SB	No	No	FC	P1498AM	85,215	76	29 Apr	7 Jul	V10
IL	Brown2	Low	SB	No	No	SP FC/ F deep ripped	P1498AM	86,450	76	28 Apr	16 Jun	V9
IL	Urbana2	High	SB	No	No	FC / F deep ripped	P0987AMX	86,450	76	23 Apr	15 Jun	V9
IN	Loam2	High	SB	No	No	FC	P0987AMX	80,275	76	29 Apr	17 Jun	V10
IN	Sand2	Low	SB	No	No	No-till	P0987AMX	80,275	76	29 Apr	17 Jun	V10
MN	New2	High	SB	No	No	F FC/ SP FC	P0157AMX	87,685	76	18 Apr	26 Jun	V8
MN	Charles2	Low	SB	No	No	Vertical-till	P0157AMX	85,215	76	1 May	1 Jul	V9
MO	Lonetree	Low	SB	No	No	FC	P1498AM	86,450	76	17 Apr	19 Jun	V9
MO	Troth2	High	SB	No	No	FC	P1498AM	86,450	76	14 Apr	10 Jun	V9
ND	Amenia2	High	Corn	Yes	No	No-till	P9188AMX	83,980	56	24 Apr	14 Jun	V5
ND	Durbin2	Low	Corn	No	No	No-till	P9188AMX	83,980	56	24 Apr	18 Jun	V6
NE	Brandes2	Low	SB	No	Yes	F chisel/ SP FC	P1151HR	86,450	76	19 Apr	29 Jun	V9
NE	SCAL2	High	SB	No	Yes	F chisel/ SP FC	P1151HR	83,980	76	24 Apr	24 Jun	V8
WI	Belmont	Low	SB	No	No	No-till	P0987AMX	90,155	76	4 May	1 Jul	V9
WI	Darling	High	SB	No	No	No-till	P0987AMX	93,119	76	4 May	1 Jul	V9

†FC, field cultivated; F, fall; Chis, Chisel; SP, spring.

Plots and Treatments

Plot dimensions were state and site dependent and were determined by the planting (planter width) and harvesting (combine width) equipment available, but minimal plot harvest area was 18.6 m^2. Average research area size per site was 0.4 ha. Sixteen different N rate treatments replicated four times (totaling 64 plots per site) were used in a randomized complete block design (Table 1.3). Nitrogen treatments were obtained using dry-prilled NH_4NO_3-N fertilizer broadcast applied. The "at-planting" fertilizer was applied within 48 hours of initial planting while the topdress fertilizer was applied between the eighth and tenth leaf. Treatment one was the non-fertilized control. Treatments 2 to 8 received all N at-planting in 45 kg N ha^{-1} increments from 45 to 315 kg N ha^{-1}, while treatments 9 to 14 received 45 kg N ha^{-1} at-planting and the rest at topdress in 45 kg N ha^{-1} increments from 45 to 270 kg N ha^{-1}. Treatments 15 and 16 received 90 kg N ha^{-1} at-planting with the remaining N at topdress.

Table 1.3. Sixteen different N fertilizer rates split over two times were replicated four times at each site.

Trt #	Planting N	Topdress N	Total N
	kg ha^{-1}		
1	0	0	0
2	45	0	45
3	90	0	90
4	135	0	135
5	180	0	180
6	225	0	225
7	270	0	270
8	315	0	315
9	45	45	90
10	45	90	135
11	45	135	180
12	45	180	225
13	45	225	270
14	45	270	315
15	90	90	180
16	90	180	270

Canopy Sensing

Reflectance measurements were collected using the RapidSCAN CS-45 (RS) Handheld Crop Sensor (Holland Scientific, Lincoln, NE) just prior to topdress application (growth stage V8-V10 leaf stage). Manufacturer recommendations were followed during initial canopy sensor setup. The sensor was held approximately 60 cm above the row as the operator steadily walked approximately 4 kph alongside the row. Only plot rows used for yield measurements were sensed. While the RS uses three different wavelengths of light, red (670 nm, VIS), red edge (730 nm, RE), and near-infrared (780 nm, NIR), only VIS and NIR were utilized in calculating vegetative indices for the N recommendation algorithms tested in this study.

Algorithm

The MU algorithm tested was an equation developed for the V8-V10 growth stage (Scharf et al., 2011). The vegetative index used in this algorithm is the Inverse Simple Ratio (ISR) and is defined as:

$$ISR = \frac{VIS}{NIR} \qquad [1]$$

where VIS = reflectance of the visible wavelength, and NIR= reflectance of the near infrared wavelength. Measurements were taken to obtain ISR values from both N reference corn ($ISR_{reference}$) and target corn (ISR_{target}). The N recommendation was then calculated as follows:

$$NRec_{MU} = \left(280\ kg\ N\ ha^{-1} \times \frac{ISR_{target}}{ISR_{reference}}\right) - 224\ kg\ ha^{-1} \qquad [2]$$

where $NRec_{MU}$= the recommendation in kg ha^{-1}.

One complication was this recommendation algorithm was developed with the Holland Scientific's Crop Circle 210 (CC-210), an earlier sensor model than the RS used in this study. The CC-210 sensor employed slightly different reflectance wavelengths than the RS. Thus in order to test this algorithm, reflectance measurements gathered with the RS had to be converted to equivalent CC-210 measurements. Simultaneous measurements from these two sensors were taken on V8-V10 corn stands over several growing seasons (unpublished data) and found related in the following way:

$$ISR = 0.454 + \ln(ISR_{RS}) \times 0.125 \qquad [3]$$

where ISR= Inverse Simple Ratio needed for the MU algorithm, and ISR_{RS} = Inverse Simple Ratio of the RS. Once RS values were transformed into equivalent CC-210 values, the recommendation could be determined using Eq. [2].

Reflectance Measurements for Recommendations

Nitrogen application treatments used to calculate an average site level N-rich reference were those that received 135, 180, and 225 kg N ha^{-1} at-planting (Treatments 4, 5, and 6 in Table 1.3; n=12). The exception was the Lonetree site where because of extreme early-season N loss, noted with a visual N deficiency the plots that received 315 kg N ha^{-1} at-planting were used as the N-rich reference. Nitrogen recommendations were calculated using two scenarios to represent the target corn to be fertilized at ~V9. One was the average of all experimental units fertilized at planting with 45 kg N ha^{-1} (n=28), and the other from unfertilized experimental units (0 kg N ha^{-1}; n=4). Canopy sensor reflectance data from both the target plots and N-rich reference plots were used to calculate the vegetative index specific to the MU algorithm.

Soil and Weather

Both within-field soil measurements and SSURGO data were gathered for all sites and years. Soil EC_a surveys were performed one to four weeks prior to planting using a Veris 3100 (Veris Technologies, Salina, KS). Sensing was performed on 4.5 m spacing travelling 5 kph across the plot area. Perpendicular passes were made through the plot area to aid in the creation of an interpolated map.

Soil Characterization was done by sampling two 1.2 m soil cores with a diameter of 4.76 cm from each of the four replications at each site using a Giddings Model #5-UV / MGSRPSUV (Giddings Machine Company, Windsor, CO). The location of both soil cores in each replication was determined using the soil EC_a survey map performed just prior to sampling, such that core sites represented the range of soil differences within a site as observed by soil EC_a. Both drilled cores were laid side-by-side and characterized and separated by horizon. One core was used to calculate bulk density (BD) and soil moisture while the other was processed and sent to the University of Missouri Soil Health Assessment Center for additional soil property analyses. Analyses included the following properties: particle size determination through the pipette method, cation exchange capacity (CEC), total carbon, total organic carbon, total inorganic carbon, SOM, pH (salt and water), and BD. Amount of clay (i.e. %clay) was calculated by using the particle size determination (R. Burt and Soil Survey Staff, 2014; Nelson and Sommers, 1996). Plant Available Water Content was determined using the Saxton and Rawls formula (Saxton and Rawls, 2006). This equation uses measured sand and clay textural information along with SOM and BD to determine soil moisture at both the permanent wilting point and field capacity. The difference between the soil moisture at field capacity and permanent wilting point results in PAWC. Following this analysis, the four cores from each site were averaged together to obtain site-level data.

Soil organic matter, PAWC and clay content values collected from SSURGO and the University of Missouri's Soil Health Assessment Center were depth-weighted to three intervals; 0-30cm, 0-61cm, and 0-91cm.

Each site's weather data were collected using a HOBO U30 Automatic Weather Station (Onset Computer Corporation, Bourne, MA). Daily temperatures were used to calculate growing degree days (GDD) while daily precipitation (and irrigation), in conjunction with the Shannon Diversity Index (a measure of evenness; SDI) was used to calculate a measurement called abundant and well-distributed rainfall (AWDR; Tremblay et al., 2012). These variables were calculated using the equations below:

$$GDD = \frac{T_{Max} + T_{Min}}{2} - T_{Base} \qquad [4]$$

where T_{Max} = maximum daily temperature, T_{Min} = minimum daily temperature and T_{Base} = 10^0 C. All temperature values were measured in degrees Celsius (^{0} C).

$$SDI = \left[-\sum pi \frac{\ln(pi)}{\ln(n)} \right] \qquad [5]$$

where pi = daily rainfall/total precipitation, n = number of days in the specified time period being used.

$$AWDR = SDI \times Total\ Precipitation \qquad [6]$$

where precipitation and AWDR are measured in cm. Weather data used in the analysis were collected between the date of planting to the date of canopy sensing and topdress.

Evaluation and Statistics

Data were analyzed by site using SAS version 9.2 (SAS Institute Inc., Cary, NC). The EONR was calculated using a quadratic-plateau function since it has generally been found to be the best model in describing corn yield response to N (Scharf et al., 2005; Cerrato and Blackmer, 1990). Proc NLIN in SAS 9.2 was used to fit the data to the quadratic-plateau function. The EONR (kg N ha^{-1}) was calculated for all 32 site years using treatments 1, 2, and 9-14 (Table 1.3) as shown:

$$EONR = \frac{(-b-(ratio)}{(2c)} \quad [7]$$

where *b* and *c* = linear and quadratic response coefficients from the optimized quadratic function, and ratio = \$0.88 kg^{-1} N/\$0.03 kg^{-1} grain (i.e., N price/corn price). The EONR was set to not exceed the maximum N rate (315 kg N ha^{-1}).

Differences between the MU algorithm recommendations and EONR (MU_{Diff}) were calculated as follows:

$$MU_{Diff} = NRec_{MU} - EONR \quad [8]$$

where the MU_{Diff} is in kg N ha^{-1}.

Linear regression, was performed for all soil (at all three depth intervals) and weather variables, at one N rate (45 kg N ha^{-1}), using the Proc REG function in SAS 9.2, to determine which were significant ($p < 0.10$) and related to the MU_{Diff} . The interactions between these variables were also modeled using linear regression ($p < 0.10$). University of Missouri Algorithm Adjustment

A total of three adjusted MU algorithms were created. One algorithm was adjusted with significant weather variables, another with significant SSURGO variables combined with weather, and the last with significant measured soil measurements combined with weather variables. Adjustments were made to each algorithm based on the intercept correction and coefficients produced by the Proc GLMSELECT ($p < 0.05$). This model is a “leave one out” approach to minimize model bias when a site is dissimilar from the rest.

Results and Discussion

Using the procedures described above the following are the determined models used to adjust the MU algorithm.

$$MU45_{Weather} = NRec_{MU} - 262 + 483 \times SDI \quad [9]$$

$$MU45_{SRGO} = NRec_{MU} - 156 + 336 \times SDI - 6 \times 10^{-7} \times (Clay_{30} \times PPT) \quad [10]$$

$$MU45_{Meas} = NRec_{MU} - 126 + 329 \times SDI - 0.007 \times (PPT \times PAWC_{60}) \quad [11]$$

where all adjusted algorithm N recommendations are in kg N ha^{-1}. The SDI = the evenness of rainfall from the time of planting to the time or sensing, and $Clay_{30}$ = SSURGO surface clay (0-30 cm) and PPT = precipitation from planting to sensing. $PAWC_{60}$ = measured plant available water (0-60 cm).

Impact of Soil and Weather Information on the Algorithm

The MU algorithm was mediocre in matching N fertilizer recommendations with EONR across a regional landscape. However, after adjusting the MU algorithm with gathered soil and weather information, N fertilizer recommendations improved (Figures 1.2, 1.3, and 1.4). Algorithm N fertilizer rate recommendations for 32 sites are shown relative to EONR in Table 4.6 and scatter plots (Figure 1.2). Points on or near the 1:1 diagonal line indicate the algorithm performed well for making an N rate recommendation. Points below the line represent an underestimated N recommendation and sites above the line represent an over-estimated N recommendation.

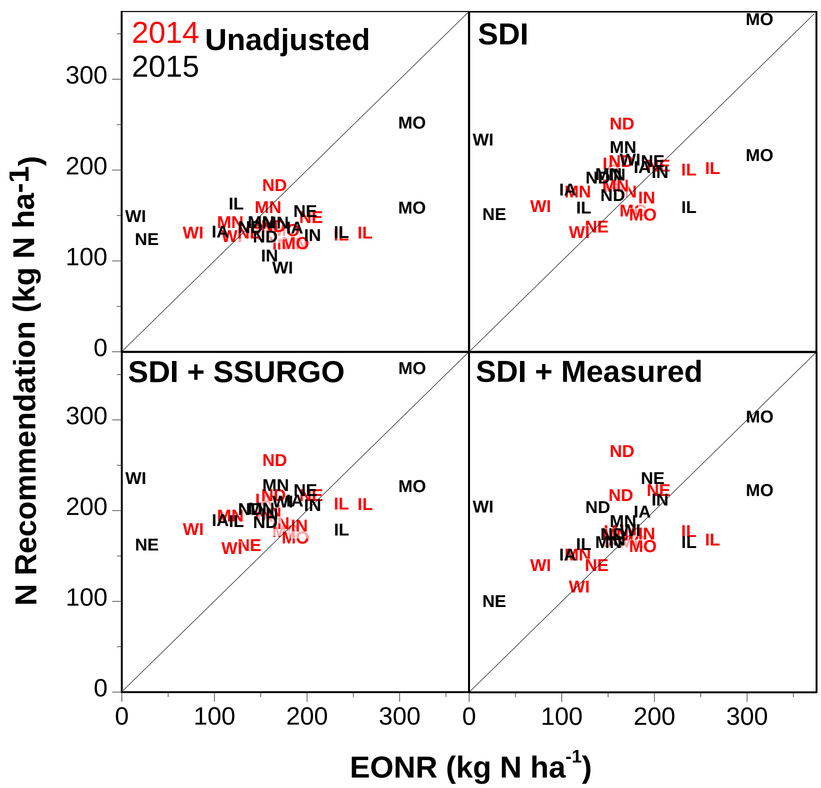

Figure 1.2. The unadjusted MU algorithm compared to the MU adjusted algorithms, for all 32 site locations across the 2014 and 2015 growing seasons. The diagonal line on each graph represents a 1:1 relationship between the economic optimum N rate (EONR) and the algorithms' recommendation. Ideally all sites would be on or close to this line suggesting the algorithm matched EONR. Sites below the line represent an underestimated N recommendation and sites above the line represent an over-estimated N recommendation. Generally across growing seasons, soil or weather information used to modify the original MU algorithm improved performance. The 2014 sites are closer to the 1:1 line than 2015 sites which may be due to more variable weather experienced during the 2015 growing season.

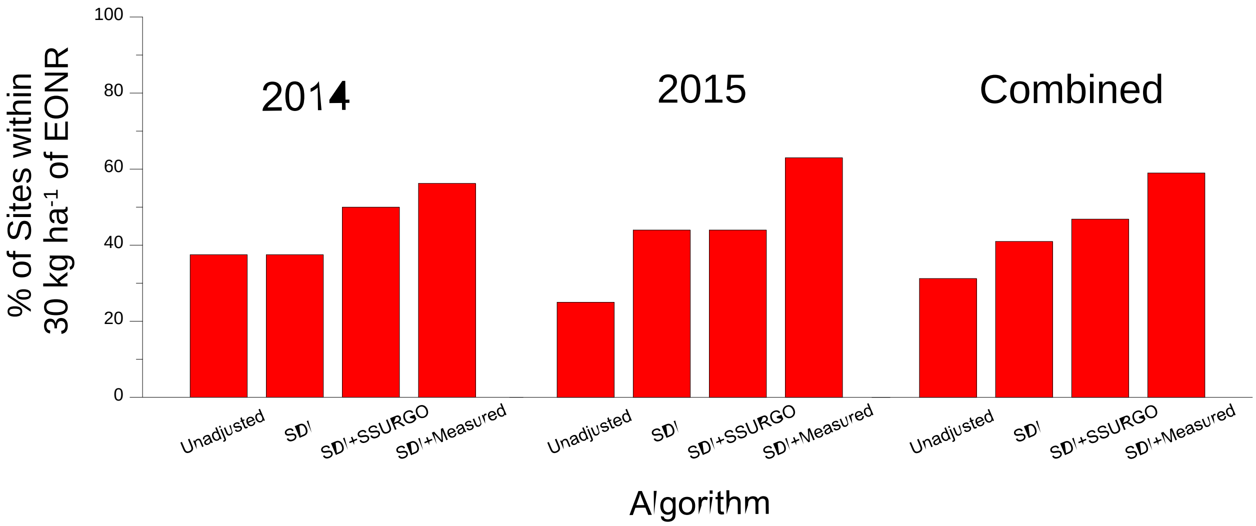

Figure 1.3. The percentage of 2014 and 2015 sites within 30 kg N ha^{-1} of the economic optimum N rate (EONR), contrasting four algorithms. Algorithm performance is evaluated based on the height of the bar. Taller bars suggest a larger percentage of sites were within 30 kg N ha^{-1} of EONR. As soil information was used to adjust the MU algorithm, more sites fell within 30 kg N ha^{-1} of EONR. Weather information alone did not improve the MU algorithm for 2014.

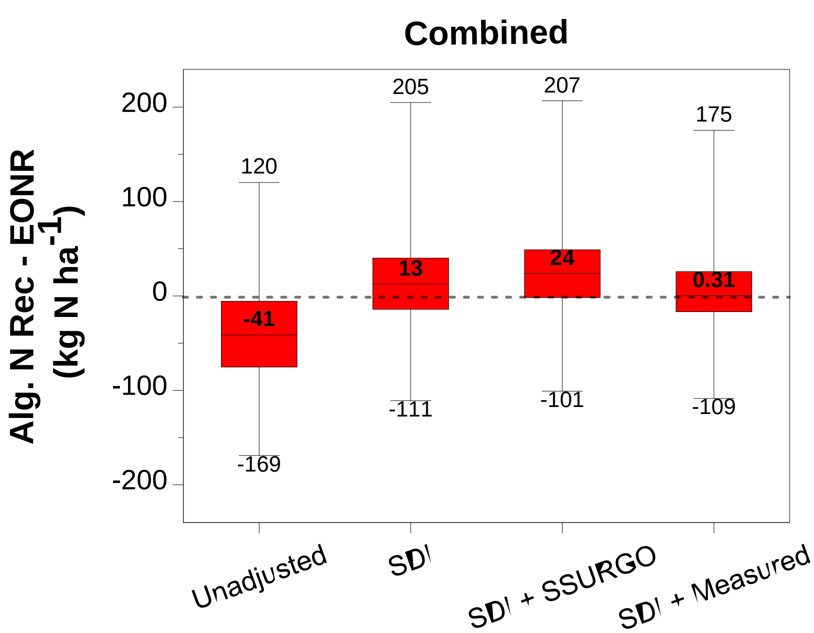

Figure 1.4. Difference between EONR and the N recommendations for 32 sites during the 2014 and 2015 growing seasons, contrasting four algorithms. Accuracy is represented by alignment of the box median line to a difference = 0. Precision is represented by box size and whisker length. The adjusted University of Missouri (MU) algorithm performed the best when soil or weather information was added.

The distribution of rainfall (SDI) from the time of planting to the time of sensing was the only weather variable, which exhibited no interaction with soil measurements, that was found to be significantly related to the difference between the MU algorithm recommendations and EONR. This is likely because precipitation and the distribution of precipitation largely influence the availability of N and/or N losses early in the growing season. Too much precipitation can deprive microbial bacteria of oxygen forcing them to respire anaerobically, using NO_3^- as an oxygen source (denitrification). This process ultimately decreases the amount of N available for plant uptake, possibly leading to decreased corn yield (Blevins et al., 1996). An example of this was the Lonetree site. This site experienced large amounts of rainfall (33 cm) that was distributed evenly (SDI = 0.75). Therefore, as the MU algorithm was adjusted for the SDI, the N recommendation increased from 238 to 353 kg N ha^{-1}. This modification resulted in an N fertilizer recommendation within 38 kg N ha^{-1} of EONR for target corn that received 45 kg N ha^{-1}.

The interaction between SSURGO surface clay (0-30 cm) and precipitation was also related to the differences between the algorithms recommendations and EONR. Soil texture, to some extent, determines the diffusivity, tortuosity, and permeability of water in the soil. Clayey soils have more surface area than medium or coarse textured soils, are mostly negatively charged, and are highly attracted to water (Schaetzl and Anderson, 2014), creating conditions that decrease PAWC and promote the loss of N through denitrification, which can shrink corn yield (Blevins et al., 1996). Also, soils with large clay percentages close to the surface of the soil are prone to large amounts of surface runoff due to slow infiltration rates (Schaetzl and Anderson, 2005). Nitrogen loss can also occur in the absence of clay through leaching, as seen on the Brandes and Brandes2 sites. These sites have <10% clay but received substantial amounts of water, likely resulting in leached NO_3^-. Following the addition of SSURGO collected surface clay and it's interaction with precipitation, the MU algorithm recommendations improved for these sites. Recommendations, for both growing seasons, increased by as much as 69 kg N ha^{-1} resulting in an N fertilizer recommendation within 11 kg N ha^{-1} of EONR.

The interaction between precipitation and measured PAWC (0-60 cm) was also found significant in describing the difference between the MU algorithms and EONR. Explanations for this are numerous. Water, as mentioned above, drives both soil and plant processes that are crucial for plant development and yield. These processes include and are not limited to photosynthesis, evapotranspiration, the movement of N to plant roots, N loss through leaching and denitrification, bacterial N fixation, and microbial respiration, all of which contribute to the fate of N and corn yield. All interactions found significant had a temporal component supporting observations from previous research that temporal variability driven by weather may be as or more important than spatial soil variability (Kitchen et al., 2005). Examples of improved site N fertilizer recommendations after incorporating the interaction between precipitation and measured PAWC into the MU algorithm are seen in the Mason, Sand2, and Darling sites. The Mason site recommendation increased by 26 kg N ha^{-1} to match EONR. The Sand2 site N fertilizer recommendation increased by 85 kg N ha^{-1} to be within 7 kg N ha^{-1} of EONR. An 87 kg N ha^{-1} increase for the Darling site resulted in an N application recommendation within 11 kg N ha^{-1} of EONR.

Weather versus Soil

When comparing the weather adjusted MU algorithm with the SSURGO and measured adjusted MU algorithms, considering both growing seasons, the MU algorithm adjusted with measured soil information performed best (Figure 1.4; Table 1.4). When adjusted with measured soil information, the median value decreased from -41 kg N ha^{-1} to 0.31 kg N ha^{-1} (Figure 1.4). This produced an improvement in algorithm accuracy. The RMSE improved from 76 kg N ha^{-1} to 53 kg N ha^{-1} suggesting a meaningful improvement in precision. To a lesser extent, N recommendation accuracy and precision also improved with the weather adjusted MU algorithm and the SSURGO adjusted algorithm. These improvements are illustrated in Figure 1.3 showing that a larger percentage of the 32 sites were within 30 kg N ha^{-1} of EONR than the unadjusted MU algorithm. The percentage of sites within 30 kg N ha^{-1} of EONR improved from 31 to 56% when the algorithm was adjusted with weather and measured soil variables. However, some differences between EONR and the MU algorithm recommendation were simply not explained by the weather and soil variables used here. Both the Belmont and Troth2 sites were largely unaffected by the modified MU algorithm. The Troth2 site had large amounts of standing water on the field caused by groundwater seep partially due to its proximity to the Missouri river and heavy rainfall events that occurred upriver. The Belmont site is historically known for being unresponsive to N (personal communication) for reasons unknown. Exploring other soil or weather factors may, in the future, help explain these responses.

Table 1.4. The mean and RMSE for the difference between the algorithm N recommendation and EONR are presented. Results are presented by growing season and combined over growing seasons. Negative and positive mean values indicate an under- and over-estimation, respectively, in the N rate recommendation. Lower RMSE values indicate greater precision.

Target N Treatment	**Year**	**Algorithm**	**Mean**	**RMSE**
kg N ha^{-1}			—kg N ha^{-1}—	
45	2014	MU	-45	66
		$MU_{weather}$	0	42
		MU_{SSURGO}	14	45
		$MU_{Measured}$	13	45
	2015	MU	-39	84
		$MU_{weather}$	23	74
		MU_{SSURGO}	32	75
		$MU_{Measured}$	9	60
	Combined	MU	-42	76
		$MU_{weather}$	12	60
		MU_{SSURGO}	23	61
		$MU_{Measured}$	1.2	53

Differences between Growing Seasons

The decline in accuracy seen in the unadjusted MU algorithm for the 2015 growing season (Figures 1.2 and 1.3) may be attributed to abnormal excessive precipitation, particularly for the southernmost sites. At several sites, precipitation before and following sensing was excessive and frequent. The 2015 Troth2 site received 28 cm of rain between sensing to plant maturity which is three times as much as the 2014 Troth site. Similarly, the 2015 Lonetree site, located on a claypan soil, received twice as much precipitation as the claypan soil 2014 Bay site. Excessive precipitation on claypan soil creates an environment for both significant surface runoff and denitrification (Blevins et al., 1996). Nitrogen loss prior-to-sensing may be captured and corrected by the canopy sensor, but post-sensing N loss cannot be corrected without additional late season N applications. These excessive rainfall scenarios generally resulted in inaccurate N fertilizer recommendations. Also, the N recommendations given by the algorithms were highly sensitive to the difference in reflectance readings between the target and N-reference corn. Larger differences generally resulted in N fertilizer recommendations closer to EONR.

Following the adjustments for the 2015 growing season, median values were similar to those from the 2014 growing season, and the percentage of sites that adjusted to within 30 kg N ha^{-1}, in some instances, surpassed those from 2014 (Figures 1.3). However, while the accuracy may have increased, higher mean and RMSE values (Table 1.4) showed a decrease in precision compared to 2014. Definite improvements in both accuracy and precision were seen when soil and weather information was used to inform the MU algorithm for both growing seasons.

Conclusion

Singly and when combining growing seasons, all adjusted algorithms outperformed the original MU algorithm. Thus, even though canopy sensing uses the corn plant as a bioassay to generally capture the N health of the crop, health that is impacted by early-season soil and weather interactions, it was shown that additional direct soil and weather measurements could be used to improve the MU algorithm for sensor-based corn N recommendations.

Differences in algorithm performances between growing seasons are attributed to the amount of precipitation from the time of sensing to the time of plant maturity. Most recommendations by the MU algorithm adjusted with measured soil data out performed those by the SSURGO adjusted algorithm; however SSURGO soil variables are easier and less expensive to collect. The increased performance by the measured soil variables may not be worth the added time and money it takes to collect samples.

Other soil and weather variables not mentioned or explored with this research may also be considered for modifying the MU algorithm for improved N fertilizer recommendations. Further, this same approach should be tried with other corn canopy sensor algorithms. Significantly, this work demonstrated that using soil and weather information improved the MU algorithm recommendation. The application of this work ultimately could lead to increased grower profit and lower negative environmental impacts.

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