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Improving an Active-Optical Reflectance Sensor Algorithm Using Soil and Weather Information

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ABSTRACT

Active-optical reflectance sensors (AORS) use light reflectance characteristics from a crop canopy as an indicator of the plant's N health. However, studies have shown AORS algorithms used in conjunction with measured reflectance characteristics for corn (*Zea mays* L.) N fertilizer rate recommendations are not consistently accurate. Our objective was to determine if soil and weather information could be utilized with an AORS algorithm developed at the University of Missouri (ALG_{MU}) to improve in-season (~V9 corn development stage) N fertilizer recommendations. Nitrogen response trials were conducted across eight states over three growing seasons, totaling 49 sites with soils ranging in productivity. Nitrogen fertilizer rates according to the ALG_{MU} were compared to economic optimal nitrogen rate (EONR). Without soil and weather information included, the root mean square error (RMSE) of the difference between ALG_{MU} and EONR (MU_{DIFF}) was 81 and 74 kg N ha^{-1} for treatments receiving 0 and 45 kg N ha^{-1} applied at planting, respectively. When ALG_{MU} was adjusted using weather (seasonal precipitation and distribution prior to sidedress) and soil clay content, the RMSE was reduced by 24 to 26 kg N ha^{-1}. Without adjustment, 20 and 29% of sites were within 34 kg N ha^{-1} of EONR with 0 and 45 kg N ha^{-1} at planting, respectively. But with adjustment for soil and weather data, 45 and 51% of sites were within 34 kg N ha^{-1} of EONR. These results show that weather and soil information could be used to improve ALG_{MU} N recommendation performance.

Core Ideas

- Canopy sensor performance improved using site-specific information.
- Evenness of early-season rainfall is crucial for adjusting N recommendations.
- Adjusting N recommendations using measured vs. USDA mapped soil data performed alike

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Nitrogen fertilizer recommendations for corn generated by AORS algorithms have proven to be inaccurate across a broad geographical region (Bean et al., 2018). Accounting for site-specific spatial and temporal variability may enhance AORS algorithm performance. Weather factors such as precipitation and temperature greatly influence crop N response and growth directly as well as affect soil conditions (Tremblay and Bélec, 2006), which ultimately impact plant available N supply and yield. Many evaluations have demonstrated how corn yield as well as within-field yield variability fluctuate in response to N management and rainfall (Teigen and Thompson, 1995; Tremblay, 2004; Kyveryga et al., 2007; Shanahan et al., 2008). Corn generally responds more to applied N fertilizer during years of above-average rainfall than years of below-average rainfall (Yamoah et al., 1998; Tremblay et al., 2012). Additionally, across North America N fertilizer response is most affected by precipitation during June and July and 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 (Shaw, 1964; Reeves et al., 1993; Tremblay et al., 2012). As an example, increased responsiveness to N fertilizer observed at North American sites was attributed to early- and frequent rainfall events resulting in high soil moisture early in the growing season that promoted N loss through denitrification and

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Abbreviations: $ALG_{MU,}$ University of Missouri algorithm; AORS, active-optical reflectance sensor(s); BD, bulk density; EONR, economic optimal nitrogen rate; $EONR_{SD}$, sidedress economic optimal nitrogen rate; $EONR_{Tot}$, total economic optimal nitrogen rate; MU_{DIFF}, difference between the University of Missouri algorithm recommendation and economic optimal nitrogen rate; NIR, near-infrared waveband; PAWC, plant available water content; R, red waveband; RE, red-edge waveband; RS, RapidScan sensor; SDI, Shannon diversity index; SOM, soil organic matter; SSURGO, USDA-NRCS Soil Survey Geographical database.

leaching (Tremblay et al., 2012). Rainfall amount and distribution, and temperature have been found to directly affect yield-limiting soil factors of soil oxygen levels, biological activity, decomposition of organic matter to soil mineral N, nutrient availability, N loss, plant available water content (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).

Understanding and quantifying how varied soil properties at the subfield to regional scales impact soil N and crop growth is crucial. Soil texture affects soil water flow, thus also affecting available N, PAWC, the transportation and availability of ions (Schaetzl and Anderson, 2014), and crop yield (Zhu et al., 2009; Armstrong et al., 2009; Tremblay et al., 2012). While conflicting results exist, corn yield is generally greater on medium- and coarse-textured soils in wet years than dry years. Also, corn yields tend to be greater on fine-textured soils in dry years than wet years (Tremblay et al., 2011). Soil organic matter (SOM) has also proven to be related to corn yield (Kravchenko and Bullock, 2000). Although SOM typically makes up a small percentage of the total soil volume (<5%) it has a large effect on many soil properties (Sylvia et al., 2005). As SOM increases, cation exchange capacity increases, soil aggregation improves, water infiltration rates rise, water holding capacity and aeration increase. Collectively, these effects ultimately improve growing conditions.

Soil properties (e.g., texture, SOM, and PAWC) interact with weather factors (e.g., total rainfall, distribution of rainfall, and temperature) in complex ways that alter plant N availability in crop production and loss to the surrounding environment (Power et al., 2001; Tremblay, 2004). When significant within-field soil and landscape variability exists, multiple N loss processes and pathways also exist, leading to short-range differences in available soil N (Scharf et al., 2005). Significant denitrification (the conversion of NO_3^- to NOx and N_2 gases) most often occurs in fine-textured soils experiencing anaerobic soil conditions from excessive rainfall and with warm soil temperatures (Blevins et al., 1996). In contrast, nitrate-N leaching below the rooting depth also occurs with high amounts of rainfall but is more pronounced on soils with low water holding capacity or coarse-textured soils (Power et al., 2001). Fifty-seven studies on smallholder farms in sub-Saharan Africa demonstrated that N fertilizer response was greater on soils with high clay content compared to loamy or sandy soils (Chivenge et al., 2011). Similarly, in North America, finer-textured soils were found to respond more to N fertilizer, but response was greatest with above average precipitation (Tremblay et al., 2012).

Soil property characteristics can be obtained from actual soil sample measurements or through soil map databases (Yang et al., 2011), such as the USDA-NRCS Soil Survey Geographical database (SSURGO) for the United States. Soil sampling and measurement are expensive and time intensive, generally requiring sample preparation and laboratory analyses. Information from SSURGO is available to producers without financial fee and can be accessed at any time. However, SSURGO soil information can be inaccurate or outdated (Zylman et al., 2005). Hence, research is needed that compares the ability of SSURGO descriptions of agricultural soils with actual field-measured soil properties (Drohan et al., 2003) to better explain corn N responses.

Because weather and soil interactions result in varying field conditions for both N availability and crop N need, adaptive N management strategies are needed that can refine fertilizer applications. Active-optical reflectance sensors developed for in-season N applications help account for uncertainties in N availability caused by weather and soil variation. With AORS, canopy reflectance from different wavebands of light are used to determine the photosynthetic health, structural size, and overall N status of the plant (Raun et al., 2002; Kitchen et al., 2010; Franzen et al., 2016). Others have made efforts, with varying success, to improve the accuracy of canopy reflectance data. These include, reflectance measurement adjustments using soil electrical conductivity maps (Bausch and Brodahl, 2011), replacing the high-N reference area with virtual N reference strips (Holland and Schepers, 2013), and comparing specific wavebands used in competing sensor models (Barker and Sawyer, 2013). An algorithm transforms the reflectance information into an in-season N fertilizer recommendation. However, studies have shown AORS algorithms used for making N fertilizer recommendations are not consistently accurate when tested over large geographic regions (Bean et al., 2018).

Research is needed to explore the opportunity for using site-specific soil and weather information to improve AORS algorithms. Our objective was to determine if soil and weather measurements could be utilized with an AORS algorithm to improve in-season N fertilizer recommendations.

MATERIALS AND METHODS

Research Sites and Treatments

This research was conducted as part of a public-industry partnership between eight land-grant universities as detailed in Kitchen et al. (2017). Forty-nine corn N rate response trials were conducted from 2014 to 2016 in eight Midwestern Corn Belt States. Nitrogen fertilizer treatments were replicated four times in a randomized complete block design. Eight N fertilizer rates (0– 315 kg N ha^{-1} in 45 kg N ha^{-1} increments) applied as hand-broadcast ammonium nitrate within 48 h of initial planting are designated "at planting" fertilizer rates. Six N fertilizer treatments referred to as "split" applications received 45 kg N ha^{-1} at planting and the remaining N during the V8 to V10 development stages (45– 270 kg N ha^{-1} in 45 kg N ha^{-1} increments). Additional details about the trial sites, treatments, and measurements have been previously documented (Kitchen et al., 2017).

Active-Optical Reflectance Sensing

Active-optical reflectance sensing measurements were collected the same day or immediately preceding the split N application using a RapidSCAN CS-45 (RS) Handheld Crop Sensor (Holland Scientific, Lincoln, NE). The RS provides reflectance information for three different wavebands of light: red (670 nm, R), red edge (720 nm, RE), and near-infrared (780 nm, NIR). Only the R and the NIR wavebands were utilized in this analysis. Further AORS setup information is detailed in Bean et al. (2018).

Reflectance Measurements and Algorithm Evaluated

The ALG_{MU} tested is an equation developed for the V8–V10 development stage and requires AORS values from both adequately N fertilized corn used as an N reference (reference), and un-fertilized or deficiently fertilized corn (target) for in-season N fertilization (Scharf et al., 2011). The vegetation index used in this algorithm is the inverse simple ratio (ISR) and is defined as:

$$\mathrm{ISR} = \mathrm{R/NIR} \qquad [1]$$

where R= the red waveband and NIR = the near-infrared waveband.

Measurements were taken to obtain ISR values from both reference corn ($ISR_{reference}$) and target corn (ISR_{target}). The N recommendation was then calculated as follows:

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

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

The N applications used to calculate an average site level reference were those that received 225 and 270 kg N ha^{-1} at planting. The exception was the 2015 Missouri claypan site where because of high early-season precipitation and visibly decreased availability of N to the plants, the plots that received 315 kg N ha^{-1} at planting were used as the reference. Nitrogen recommendations were calculated using two scenarios to represent the target corn to be fertilized at ~V9 development stage. One was the average of all experimental units fertilized at planting with 45 kg N ha^{-1} (n = 28 per site), and the other from unfertilized experimental units (0 kg N ha^{-1}; n = 4 per site).

The ALG_{MU} was developed with the Holland Scientific Crop Circle 210, an earlier sensor model than the RS used in this study. Thus, the AORS readings of this dataset were converted to equivalent Crop Circle 210 measurements as previously described in Bean et al. (2018).

Soil and Weather

Both within-field soil measurements and SSURGO soil data were gathered for all sites and years (Kitchen et al., 2017). Soil apparent electrical conductivity (EC_a) surveys, at two depths (0.3 and 0.9 m), were performed 1 to 4 wk before planting using a Veris 3100 electrical conductivity sensor (Veris Technologies, Salina, KS). Soil EC_a survey data was collected on transects at approximately 5 m spacing on 1-s intervals, traveling 2 m s^{-1} across the plot area, which corresponded to a measurement about every 2 m along the transects. Perpendicular passes were made through the plot area to aid in the creation of an interpolated map. This map was used for selecting representative locations within the site's replication blocks for deep core sampling.

Soil for characterization was collected 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 no. 5-UV/MGSRPSUV (Giddings Machine Company, Windsor, CO). Both cores were laid side by side, characterized and segments separated by pedogenic horizon. Soil from one core was used to determine bulk density (BD) and soil moisture while the other core was processed and sent to the University of Missouri Soil Health Assessment Center for additional soil property analyses. Analyses included: particle size determination by the pipette method (Soil Survey Staff, 2014; Nelson and Sommers, 1996), SOM (loss on ignition; Nelson and Sommers, 1996), and BD (Soil Survey Staff, 2014). Plant available water content was determined according to Saxton and Rawls (2006). This equation uses sand and clay content 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. Soil properties from the four cores per site were averaged together for a site-level assessment.

Soil organic matter, PAWC, and clay content values collected from both SSURGO and the University of Missouri's Soil Health Assessment Center were depth weighted to two intervals (0–30 and 0–60 cm).

Weather data, for the entire growing season, were collected using instrumented weather stations located at each site, with details described in Kitchen et al. (2017). However, only weather data from planting to the time of sidedress was used in this analysis. Daily temperatures were used to calculate growing degree days (GDD). Daily precipitation (including irrigation when applied) was used to calculate a precipitation evenness index using the Shannon diversity index (SDI; Tremblay et al., 2012) and an index that is the product of SDI and total precipitation, called abundant and well-distributed rainfall (AWDR; Tremblay et al., 2012). These were calculated as:

$$GDD = \frac{T_{Max} + T_{Min}}{2} - T_{Base} \qquad [3]$$

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

$$\mathrm{SDI} = \left[-\sum \mathrm{pi}\frac{\ln(\mathrm{pi})}{\ln(n)}\right] \qquad [4]$$

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

$$\mathrm{AWDR} = \mathrm{SDI}\ '\ \text{total precipitation} \qquad [5]$$

where total precipitation and AWDR were measured in centimeters. Weather data used in these calculations were between the date of planting to the date of collected AORS measurements.

Performance Evaluation and Statistics

Data were analyzed using SAS version 9.2 (SAS Institute Inc., Cary, NC). First, EONR values were determined for each site using a corn grain price of \$ 0.158 kg^{-1} (US\$4.00 bu^{-1}) and N fertilizer cost of \$0.88 kg N^{-1} (\$0.40 lb^{-1}) as detailed in Kitchen et al. (2017). For this analysis, values for EONR were calculated using the split applied N rates, with 45 kg N ha^{-1} at planting and the remainder applied at the V9 development stage as a sidedress. This EONR is a season total amount of N fertilizer applied. For evaluating AORS for the target corn scenario that did not receive N at planting, the EONR value was used directly and is represented as $EONR_{Tot}$. For evaluating AORS for the target corn scenario that received 45 kg N ha^{-1} at planting, the EONR value was reduced by 45 kg N ha^{-1} so that the EONR represented the N fertilizer that was applied as sidedress. This is represented as $EONR_{SD}$. Throughout the rest of this paper a non-subscripted "EONR" is used in the general sense to represent both situations.

Table 1. Soil and weather variables and potential two-way interactions that were examined using linear regression for explaining the difference between economic optimal nitrogen rate (EONR) and the University of Missouri active-optical reflectance sensor algorithm (ALG_{MU}). For soil variables, all were considered for both the 0 to 30- and 0- to 60-cm depths.

Weather/Soil	Variable†
Weather	SDI
	GDD
	PPT
	AWDR
Measured	Clay
	PAWC
	SOM
SSURGO	Clay
	PAWC
	SOM
Weather × SSURGO	SDI × Clay
	SDI × PAWC
	SDI × SOM
	GDD × Clay
	GDD × PAWC
	GDD × SOM
	PPT × Clay
	PPT × PAWC
	PPT × SOM
	AWDR × Clay
	AWDR × PAWC
	AWDR × SOM
Weather × measured	SDI × Clay
	SDI × PAWC
	SDI × SOM
	GDD × Clay
	GDD × PAWC
	GDD × SOM
	PPT × Clay
	PPT × PAWC
	PPT × SOM
	AWDR × Clay
	AWDR × PAWC
	AWDR × SOM

† SDI, Shannon diversity index; GDD, growing degree days; PPT, total precipitation from time of planting to time of sensing (mm); AWDR, abundant and well distributed rainfall; Clay, % clay; PAWC, plant available water content (cm 30 cm^{-1}); SOM, percent soil organic matter.

A difference between the $NRec_{MU}$ and EONR was calculated as follows:

$$MU_{DIFF} = NRec_{MU} - EONR \quad [6]$$

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

Using linear regression, significant ($p < 0.05$) single (one-way) and two-way interaction relationships between MU_{DIFF} and soil properties (at both 0–30-cm and 0–60-cm depth intervals) and weather variables (Table 1) were examined using the PROC REG function in SAS 9.2. This was done independently for the two different at-planting (0 and 45 kg N ha^{-1}) N fertilizer rates. Only the most significant single variable or two-way interaction was included for adjusting the ALG_{MU} N fertilizer rate.

Table 2. Using linear regression, significant ($p < 0.05$) soil and weather variables found related to the difference between economic optimum nitrogen rate (EONR) and the University of Missouri algorithm. Results shown are for both target corn at-planting N rates (0 and 45 kg N ha^{-1}). Weather variables were calculated using data from the time of planting to the time of sensing (approximately development stage V9).

N Rate	Weather/Soil	Variable†	r^2	p value
kg N ha^{-1}				
0	Weather	SDI	0.19	0.001
	Measured soil	$Clay_{30}$	0.08	0.033
		$Clay_{60}$	0.10	0.018
		SOM_{30}	0.07	0.035
		SOM_{60}	0.09	0.020
	SSURGO Soil	$Clay_{30}$	0.09	0.023
	Weather × Measured soil	$Clay_{30}$ × PPT	0.06	0.050
		$Clay_{60}$ × PPT	0.07	0.034
		SOM_{60} × PPT	0.07	0.043
		$Clay_{60}$ × GDD	0.07	0.043
	Weather × SSURGO soil	$Clay_{30}$ × PPT	0.08	0.029
		$Clay_{30}$ × GDD	0.06	0.050
45	Weather	SDI	0.18	0.002
	Measured soil	$Clay_{30}$	0.08	0.023
		$Clay_{60}$	0.11	0.012
		SOM_{30}	0.08	0.031
		SOM_{60}	0.09	0.023
		$PAWC_{60}$	0.07	0.043
	SSURGO Soil	$Clay_{30}$	0.11	0.013
		$Clay_{60}$	0.07	0.034
	Weather × measured soil	$Clay_{60}$ × GDD	0.07	0.041
	Weather × SSURGO soil	$Clay_{30}$ × PPT	0.06	0.050
		$Clay_{30}$ × GDD	0.07	0.043

† SDI, Shannon diversity index; PPT, total precipitation from time of planting to time of sensing (mm); $Clay_{30}$, % clay in the upper 30 cm of soil; $Clay_{60}$, % clay in the upper 60 cm of soil; SOM_{60}, soil organic matter in the upper 60 cm of soil; GDD, growing degree days; $PAWC_{60}$, plant available water content in the upper 60 cm of soil (cm 30 cm^{-1}).

University of Missouri Algorithm Adjustment

Adjustments were made based on the output coefficients produced by the PROC GLMSELECT ($p < 0.05$). This modeling approach is a "leave one out" method to minimize model bias when a site is dissimilar from the rest. A total of five scenarios were explored for adjusting the ALG_{MU} N fertilizer rate. The five adjustment scenarios included the following sets of soil and/or weather information: (i) Weather, (ii) SSURGO soil properties, (iii) measured soil properties, (iv) Weather + SSURGO soil properties, and (v) Weather + measured soil properties. Final model results for each of these scenarios were used directly to modify the ALG_{MU} N fertilizer rate. The previously mentioned adjustment process was also performed on two other AORS algorithms, namely the Holland Schepers and Oklahoma State University algorithms as defined in Bean et al. (2018).

Performance measurements were calculated for unadjusted and adjusted algorithms. These included: (i) median and range of the MU_{DIFF} values (values closer to zero and smaller ranges indicate better performance); (ii) linear regression between the end-of-season EONR and the adjusted and unadjusted $NRec_{MU}$ (coefficient of determination and slope); (iii) root mean square error (RMSE) of MU_{DIFF}; and (iv) percentage of

Table 3. University of Missouri (ALG_{MU}) performance for both at-planting target corn N rates (0 and 45 kg N ha^{-1}) with and without soil and weather adjustments made to the ALG_{MU} nitrogen fertilizer recommendation (Nrec). The root mean square error (RMSE), median of the differences between economic optimal nitrogen (EONR) rate and ALG_{MU}, and the percentage of sites within 34 kg N ha^{-1} of EONR were all used to compare algorithm performances.

Target corn N rate	Adjustment†	Model equation	r^2	p value	RMSE	Median	Sites within 34 kg N ha^{-1} of EONR
kg N ha^{-1}					—— kg N ha^{-1}	——	%
0	None	y = Nrec	0.14	0.004	81	–10	20
	W	y = Nrec– 231 + 444 × SDI	0.33	<0.001	58	–11	41
	S_{SRGO}	y = Nrec + 97– 2 × $Clay_{30}$	0.25	0.001	62	2	39
	S_{MEAS}	y = Nrec + 94– 1.7 × $Clay_{60}$	0.26	0.001	62	3	43
	W + S_{SRGO}	y = Nrec– 219 + 492 × SDI– 0.009 × (PPT × $Clay_{30}$)	0.43	<0.001	55	–1	45
	W + S_{MEAS}	y = Nrec– 167 + 400 × SDI– 1.5 × ($Clay_{60}$)	0.40	<0.001	57	–1	43
45	None	y = Nrec	0.12	0.009	73	–43	29
	W	y = Nrec– 211 + 395 × SDI	0.29	<0.001	55	–2	43
	S_{SRGO}	y = Nrec + 85– 2 × $Clay_{30}$	0.23	0.003	57	–8	53
	S_{MEAS}	y = Nrec + 82– 1.7 × $Clay_{60}$	0.23	0.003	57	–2	55
	W + S_{SRGO}	y = Nrec– 200 + 435 × SDI– 0.008 × (PPT × $Clay_{30}$)	0.39	<0.001	50	–3	47
	W + S_{MEAS}	y = Nrec– 201 + 430 × SDI– 0.006 × (PPT × $Clay_{60}$)	0.38	<0.001	51	–2	51

† W, weather; S_{SRGO}, SSURGO soil; S_{MEAS}, measured soil; W + S_{SRGO}, weather + SSURGO; W + S_{MEAS}, weather + measured soil; SDI, Shannon diversity index; PPT, total precipitation from time of planting to time of sensing (mm); $Clay_{30}$, % clay in the upper 30 cm of soil; $Clay_{60}$, % clay in the upper 60 cm of soil.

sites at which the recommended N fertilizer rate was within 34 kg N ha^{-1} of EONR (Bean et al., 2018).

RESULTS AND DISCUSSION

Impact of Soil and Weather Information on the University of Missouri Algorithm

Regression analysis relating the MU_{DIFF} to soil and weather variables produced several significant simple and two-way interaction effects between variables (Table 2). Though significant, coefficients of determination were <0.20. However, coefficient of determination values were also low for the unadjusted ALG_{MU} (Table 3). For the two at-planting N rates, the single most significant simple or two-way weather/soil variables from Table 2 were used to adjust the ALG_{MU} N fertilizer rate recommendation (Table 3).

Unadjusted and adjusted ALG_{MU} N fertilizer recommendations for all 49 sites were related to EONR for both corn receiving no N at planting (Fig. 1) and corn receiving 45 kg N ha^{-1} at planting (Fig. 2). Overall performance compared to EONR was summarized using box and whisker plots (Fig. 3). Points on or near the 1:1 diagonal lines in Fig. 1 and 2 represent sites that an algorithm performed reasonably well for making an N fertilizer recommendation. Whereas, points markedly below and above the 1:1 lines represent recommendations that under- and overestimated N need, respectively. Sites within the yellow shaded region were within 34 kg N ha^{-1} of EONR. As found with linear fit regressions between AORS algorithms and EONR (Table 4), modified algorithms resulted in higher coefficients of determination and improved fit to the 1:1 regression lines compared to the non-adjusted ALG_{MU}. Slope values increased from 0.18 to approximately 0.47 for target corn with no N applied at planting and from 0.13 to approximately 0.43 for target corn that received 45 kg N ha^{-1} at planting (Table 4). Generally better algorithm performance was observed when both soil and weather variables were used to adjust the ALG_{MU} recommendation. This was expected since it has been previously noted that early-season precipitation and soil properties greatly affect corn N response over large geographical regions (Tremblay et al., 2012). Additionally, once adjusted with soil and weather variables, differences in algorithm performance between the two at-planting N rates were similar, demonstrating the importance of using soil and weather variables to adjust the ALG_{MU} N fertilizer recommendation.

Distribution of rainfall using SDI was the only weather variable that as a simple linear factor was significantly related to the MU_{DIFF} (Table 2). These results support the importance of early-season precipitation distribution relative to soil N (Xie et al., 2013; Kaur et al., 2017) and N fertilizer response (Tremblay et al., 2012). Precipitation and its distribution can have a large influence on the availability of N early in the growing season. Too much precipitation can deprive facultative anaerobes of oxygen forcing them to use nitrate N as an oxygen source resulting in denitrification, decreasing the amount of plant available N and ultimately corn yield (Blevins et al., 1996; Power et al., 2001; Kaur et al., 2017). An example of extensive denitrification was attributed to the 2015 MO LoneTree site (Kitchen et al., 2017). This site experienced large amounts of rainfall (33 cm) from the time of planting to the time of AORS measurements with rainfall evenly distributed over the early part of the growing season (SDI = 0.75 with 1.0 being exactly even). Because of this extended period of soil wetness, it was assessed to have little N mineralization and extensive denitrification of existing mineral N. Therefore, as the ALG_{MU} was adjusted for the SDI (Table 3), the N fertilizer recommendation for this site increased from 174 to 290 kg N ha^{-1} (target corn = 0 N at planting) and from 176 to 276 kg N ha^{-1} (target corn = 45 kg N ha^{-1} at planting). This single weather modification to the algorithm resulted in an N fertilizer recommendation for this site within 23 kg N ha^{-1} of EONR for target corn that received no N at planting and within 7 kg N ha^{-1} of EONR for target corn that received 45 kg N ha^{-1}.

The amount of clay in the upper 30 and 60 cm of soil (SSURGO $Clay_{30}$, measured $Clay_{60}$, and SSURGO $Clay_{30}$ × PPT interaction) for both target corn N rates was also significantly related to MU_{DIFF} (Table 2). Soil texture has a major role in the diffusivity, tortuosity, and permeability of water in the soil. Clayey soils have smaller pore sizes and more surface area than medium- or coarse-textured soils, are mostly negatively

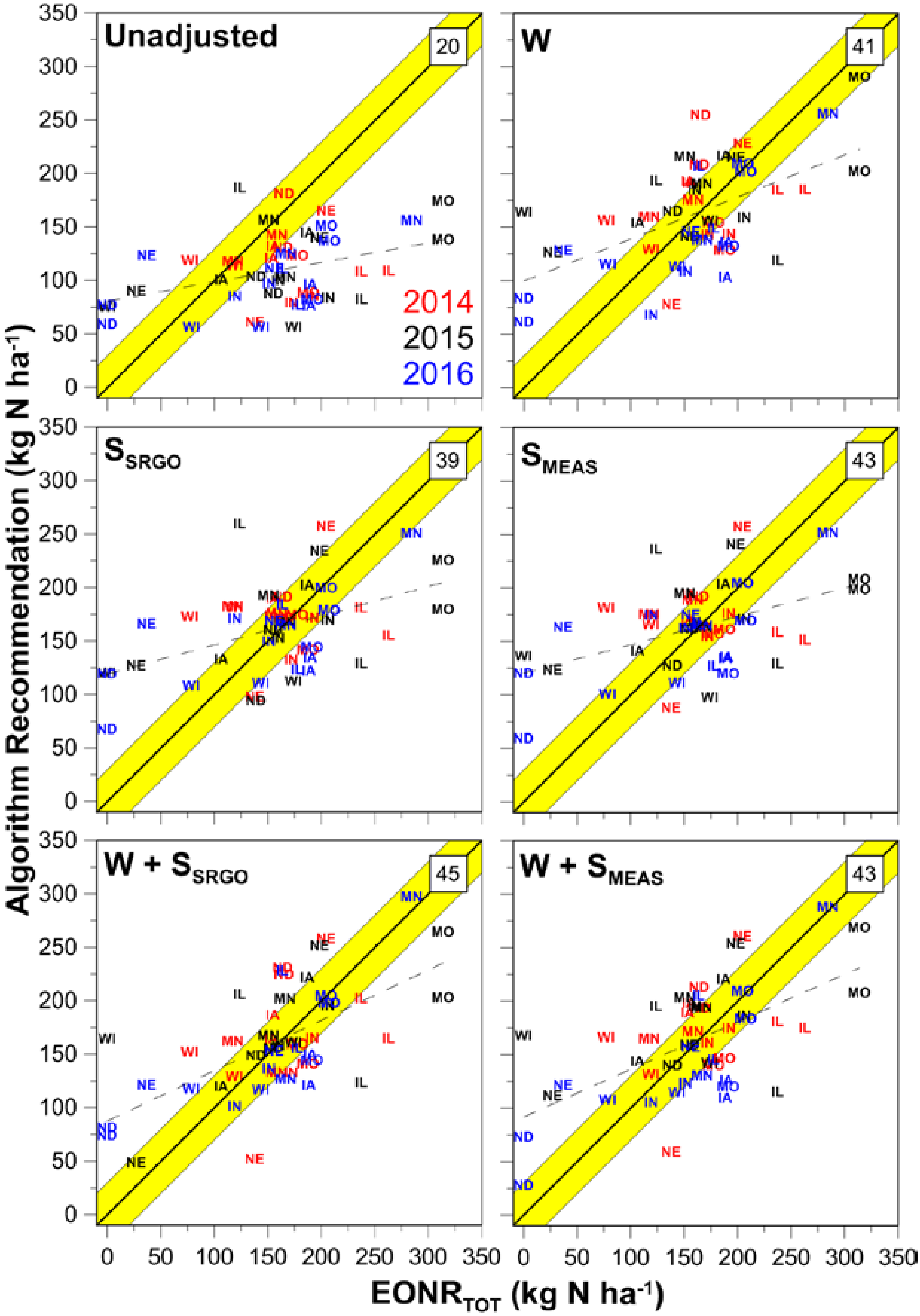

Fig. 1. For corn receiving no N at planting, performance of the University of Missouri active-optical reflectance sensor algorithm (ALG_{MU}) for making N fertilizer recommendations, with and without weather (W) and soil (USDA SSURGO [S_{SRGO}]; Measured [S_{MEAS}]) adjustments, by comparing the recommendation to economic optimal nitrogen rate ($EONR_{TOT}$). Points near the 1:1 line dissecting the graph indicate sites where the AORS algorithm was relatively accurate in recommending an N rate approximate to $EONR_{TOT}$. Sites that fell within the yellow shaded region are those within 34 kg N ha^{-1} of $EONR_{TOT}$, with the percentage of the 49 sites within this region indicated in the top right corner of each graph. The dashed line represents the linear fit regressions between ALG_{MU} and $EONR_{TOT}$.

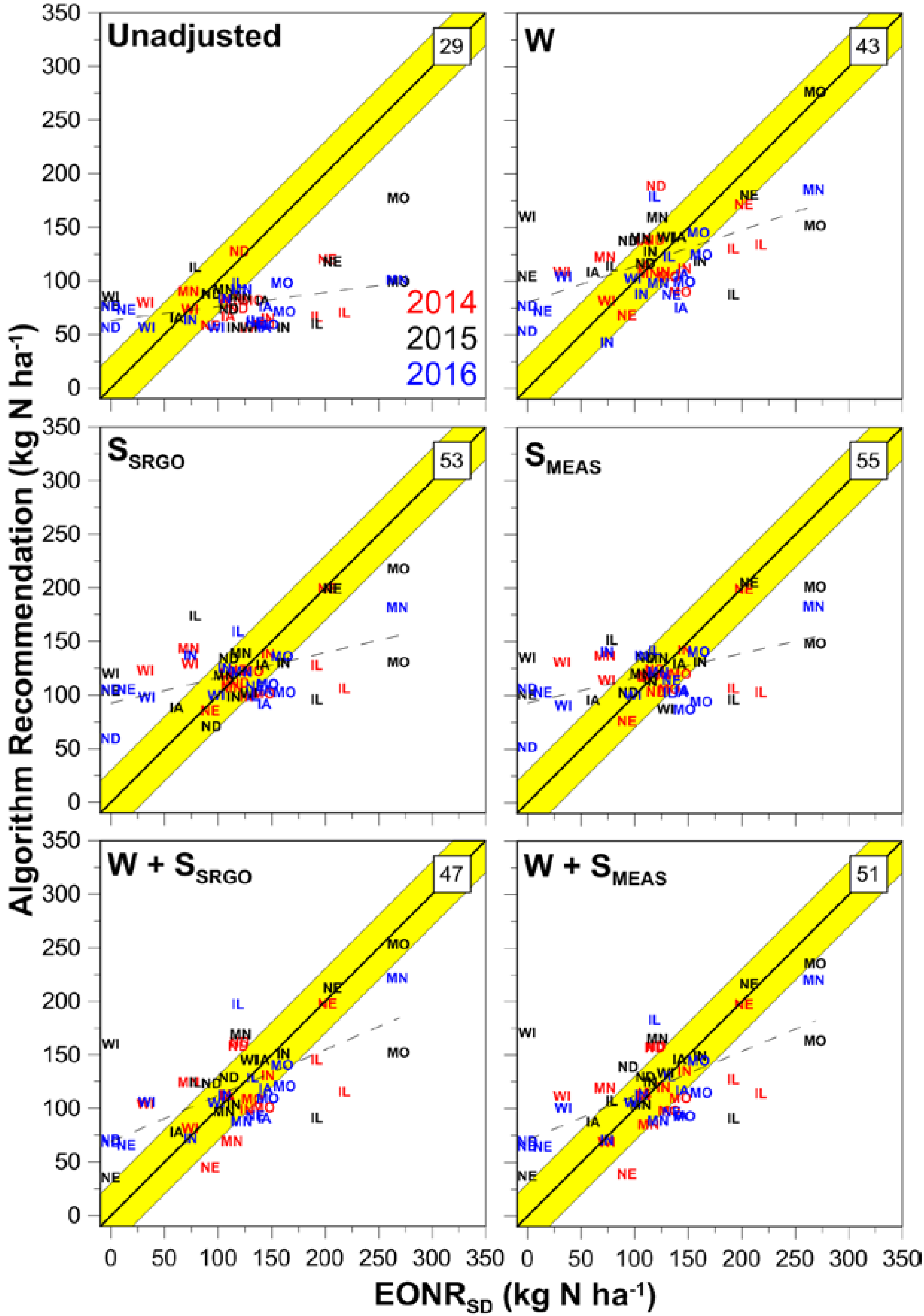

Fig. 2. For corn receiving 45 kg N ha^{-1} at planting, performance of the University of Missouri active-optical reflectance sensor algorithm (ALG_{MU}) for making N fertilizer recommendations, with and without weather (W) and soil (USDA SSURGO [S_{SRGO}]; Measured [S_{MEAS}]) adjustments, by comparing the recommendation to economic optimal N rate ($EONR_{SD}$). Points near the 1:1 line dissecting the graph indicate sites where the AORS algorithm was relatively accurate in recommending an N rate approximate to $EONR_{SD}$. Sites that fell within the yellow shaded region are those within 34 kg N ha^{-1} of $EONR_{SD}$, with the percentage of the 49 sites within this region indicated in the top right corner of each graph.

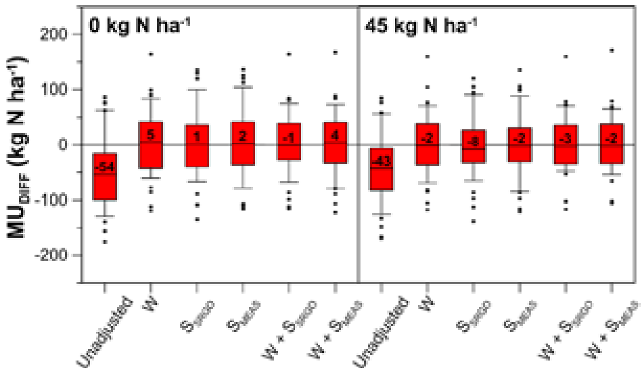

Fig. 3. For corn receiving 0 and 45 kg N ha^{-1} at planting, performance of the University of Missouri active-optical reflectance sensor algorithm (ALG$_{MU}$) for making N fertilizer recommendations, with and without weather (W) and soil [USDA SSURGO (S$_{SRGO}$); Measured (S$_{MEAS}$)] (USDA SSURGO [S$_{SRGO}$]; Measured [S$_{MEAS}$]) adjustments, by comparing the recommendation to economic optimal nitrogen rate (EONR) summarized by box and whisker plots of the difference (MU$_{DIFF}$) between the ALG$_{MU}$ recommendation and economic optimal nitrogen rate (EONR). Whisker length represents the 90th percentile while black dots represent N recommendations that fall outside of the 90th percentile. Median values close to zero indicate better accuracy. Negative values represent an underestimation of EONR while positive values represent and overestimation of EONR. Box size and whisker length is a measure of precision with smaller box size and whisker length indicating greater precision. The dashed line represents linear fit regressions between ALG$_{MU}$ and EONR$_{SD}$.

charged, and strongly attract water by adhesion (Schaetzl and Anderson, 2014), creating conditions that decrease PAWC and promote denitrification losses, which can decrease corn yield (Blevins et al., 1996; Power et al., 2001; Kaur et al., 2017). Also, soils with large clay percentages close to the soil surface are prone to surface sealing, which promotes surface runoff due to slow infiltration rates (Schaetzl and Anderson, 2014; Conway et al., 2017). Nitrogen loss can also occur in soils with small clay percentages through leaching. We attribute significant N loss to leaching for both the 2014 and 2015 NE Brandes coarse-textured sites. These sites have <10% clay and received substantial amounts of early-season precipitation and or irrigation. For target corn with 45 kg N ha^{-1} at planting, using measured Clay$_{60}$ to modify the ALG$_{MU}$ improved N recommendations at these two sites. The MU$_{DIFF}$ decreased by as much as 88 kg N ha^{-1}, resulting in N recommendations that were all within 3 kg N ha^{-1} of EONR. Additionally, the MU$_{DIFF}$ decreased by as much as 121 kg N ha^{-1} for the 2016 MN Becker coarse-textured site when adjusted using soil and weather information, resulting in improved algorithm performance.

Considering pre-sidedress weather conditions was imperative to improving the ALG$_{MU}$ N fertilizer recommendation, and as others have found, is a critical period of the corn growing season that impacts soil N availability and N loss (Sogbedji et al., 2001; Kahabka et al., 2004). However, weather conditions after sidedress undoubtedly will also greatly influence N availability and crop N needs. At the time AORS measurements are taken and sidedress fertilizer rates applied, only 15 to 20% of total aboveground biomass has been accumulated and 25% of the total seasonal plant N absorbed (Hanway, 1962; Abendroth et al., 2011). Generally as post-sidedress precipitation increases,

Table 4. Linear fit lines for each University of Missouri algorithm (ALG$_{MU}$; x variable), unadjusted and adjusted compare to economic optimal N fertilizer rate (y variable), with accompanying correlation coefficient values.

Target corn N rate	Adjustment†	Linear fit equation	r^2
kg N ha^{-1}			
0	None	$y = 0.183x + 80.52$	0.14
	W	$y = 0.393x + 99.94$	0.31
	S$_{SRGO}$	$y = 0.273x + 120$	0.21
	S$_{MEAS}$	$y = 0.301x + 84.55$	0.24
	W + S$_{SRGO}$	$y = 0.471x + 87.60$	0.39
	W + S$_{MEAS}$	$y = 0.444x + 91.77$	0.36
45	None	$y = 0.130x + 63.02$	0.13
	W	$y = 0.337x + 80.16$	0.30
	S$_{SRGO}$	$y = 0.235x + 92.60$	0.24
	S$_{MEAS}$	$y = 0.230x + 93.10$	0.25
	W + S$_{SRGO}$	$y = 0.429x + 69.04$	0.40
	W + S$_{MEAS}$	$y = 0.414x + 70.85$	0.40

† W, weather; S$_{SRGO}$, SSURGO soil; S$_{MEAS}$, measured soil; W + S$_{SRGO}$, weather + SSURGO; W + S$_{MEAS}$, weather + measured soil.

corn N response increases (Fox and Piekielek, 1998; Tremblay et al., 2012). Such post-sidedress information could also be used to adjust an AORS algorithm, but only if a reliable and accurate forecast of weather was available (Tremblay et al., 2012).

Comparison of Weather and Soil Adjustments

Soil and weather variables used to adjust the ALG$_{MU}$ enhanced overall algorithm performance. However, objectively determining which adjusted algorithm was best proved difficult. When comparing adjusted algorithms using either weather (SDI), soil (SSURGO or measured) or both and considering the two at-planting N rates, the relative improvement varied slightly depending on which performance metric was considered (Tables 3 and 4). Therefore, adjusting for either weather or soil variables alone cannot be placed above one another, but both variables should be considered. Even though the ALG$_{MU}$ adjusted with both weather and soil information did not always outperform the other adjusted algorithms in terms of the percentage of sites within 34 kg N ha^{-1} of EONR, it produced the lowest median and RMSE values while having the highest r^2 and linear fit slope values (Tables 3 and 4). Even with adjustment, the best resulting slope value of 0.47 (Table 4) gives a general overestimation for sites with low EONR and an underestimation for sites with high EONR.

The MU$_{DIFF}$ for some sites were simply not compensated for by the weather and soil variables used here. The 2015 MO Troth site (EONR = 270 kg N ha^{-1}) was largely unaffected by the modified ALG$_{MU}$ (Fig. 1 and 2). There were extreme conditions in this field because the water table was near surface as a result of high Missouri River levels for 4 to 5 wk of the growing season as a consequence of exceptionally high rainfall. With some sites, weather and soil adjustments to ALG$_{MU}$ resulted in a poorer N recommendation. The 2015 Belmont site (EONR = 0) is an example where the adjusted N recommendation was less accurate than the unadjusted algorithm (Fig. 1 and 2). Interestingly, in 2014, an adjacent and similarly managed field on this farm (not part of this analysis) did not respond to added N for reasons unknown and yielded 14.7 Mg ha^{-1} (C.A.M. Laboski, personal communication, 2015). Exploring other soil, crop, and weather factors may be needed to help explain these responses.

Table 5. Holland–Schepers (ALG_{HS}) and Oklahoma State University (ALG_{OSU}) algorithm performances for at-planting target corn N rates (0 and 45 kg N ha^{-1}) with and without soil and weather adjustments made to the ALG_{HS} and ALG_{OSU} nitrogen fertilizer recommendation (Nrec). The root mean square error (RMSE), median of the differences between economic optimal N rate (*y* variable) and algorithm N fertilizer recommendation (*x* variable), and the percentage of sites within 34 kg N ha^{-1} of economic optimal nitrogen rate (EONR) were all used to compare algorithm performances.

N	Algorithm	Adjustment†	Equation	R^2	*p* value	RMSE	Median	Sites within 34 kg N ha^{-1} of EONR
kg N ha^{-1}						—— kg N ha^{-1} ——		%
0	ALG_{HS}	None	y = Nrec	0.16	0.002	62	−16	29
		S_{SRGO}	y = Nrec + 57– 2 × ($Clay_{30}$)	0.27	<0.001	57	−1	43
		S_{Meas}	y = Nrec + 51– 1.7 × ($Clay_{60}$)	0.26	0.001	58	−8	39
	ALG_{OSU}	None	y = Nrec	0.01	0.206	113	−93	14
		W	y = Nrec– 211 + 467 × SDI	0.25	0.002	55	−2	45
		W + S_{Meas}	y = Nrec– 155 + 456 × SDI– 161 × ($PAWC_{60}$)	0.33	<0.001	53	−6	49
45	ALG_{HS}	None	y = Nrec	0.12	0.008	81	−64	29
		W	y = Nrec– 156 + 320 × SDI	0.24	0.002	59	−16	37
		W + S_{SRGO}	y = Nrec– 79 + 273 × SDI– 2 × ($Clay_{30}$)	0.33	<0.001	56	−13	43
		W + S_{Meas}	y = Nrec– 83 + 275 × SDI– 1.7 × ($Clay_{60}$)	0.33	<0.001	56	−4	37
	ALG_{OSU}	None	y = Nrec	0.002	0.297	118	−96	14
		W	y = Nrec– 213 + 479 × SDI	0.24	0.002	55	−1	45
		W + S_{SRGO}	y = Nrec– 155 + 467 × SDI– 168 × ($PAWC_{60}$)	0.33	<0.001	53	−3	49

† W, weather; S_{SRGO}, SSURGO soil; S_{MEAS}, measured soil; W + S_{SRGO}, weather + SSURGO; W + S_{MEAS}, weather + measured soil; SDI, Shannon diversity index; $Clay_{30}$, % clay in the upper 30 cm of soil; $Clay_{60}$, % clay in the upper 60 cm of soil; $PAWC_{60}$, plant available water in the upper 60 cm of soil (cm 60 cm^{-1}).

Modification to Other Active-Optical Reflectance Sensor Algorithms

The same procedure used here to make soil and weather adjustments to the ALG_{MU} was also performed using the Holland–Schepers and Oklahoma State University algorithms described in Bean et al. (2018). Using soil and weather information also improved performance of these two algorithms (Tables 5 and 6). Relative improvement for each of the soil and weather scenarios was similar to that of the ALG_{MU}. When considering both at planting target corn N fertilizer rates, the Holland–Schepers had 43 and the Oklahoma State University algorithm had 49% of the sites within 34 kg N ha^{-1} of EONR when adjusted with soil and weather information. However, it is important to stress that the specific soil and weather variables found significant and used for making the adjustments were not always the same as those used for the ALG_{MU} (Table 3). The overall findings support the hypothesis that AORS N fertilizer management can be improved by including site-specific soil and weather information and adjustments, but soil and weather information may be specific for each algorithm.

Table 6. Linear fit lines for Holland–Schepers (ALG_{HS}) and Oklahoma State University (ALG_{OSU}) algorithm N fertilizer recommendation (*x* variable) compared to economic optimum N fertilizer rate (*y* variable), with accompanying correlation coefficient values.

Target corn N rate	Algorithm	Adjustment†	Linear fit equation	r^2
kg N ha^{-1}				
0	ALG_{HS}	None	$y = 0.294x + 75.78$	0.18
		S_{SRGO}	$y = 0.398x + 70.53$	0.27
		S_{MEAS}	$y = 0.387x + 71.75$	0.26
	ALG_{OSU}	None	$y = 0.041x + 23.26$	0.03
		W	$y = 0.292x + 85.10$	0.27
		W + S_{MEAS}	$y = 0.359x + 77.03$	0.33
45	ALG_{HS}	None	$y = 0.243x + 41.09$	0.14
		W	$y = 0.364x + 64.25$	0.25
		W + S_{SRGO}	$y = 0.430x + 56.27$	0.32
		W + S_{MEAS}	$y = 0.480x + 63.35$	0.33
	ALG_{OSU}	None	$y = 0.027x + 19.27$	0.02
		W	$y = 0.283x + 86.15$	0.27
		W + S_{SRGO}	$y = 0.353x + 77.72$	0.33

† W, weather; S_{SRGO}, SSURGO soil; S_{MEAS}, measured soil; W + S_{SRGO}, weather + SSURGO; W + S_{MEAS}, weather + measured soil.

CONCLUSIONS

We found that adjusting AORS algorithm recommendations with site-specific weather and soil information usually resulted in improved N fertilizer recommendations compared to the unadjusted ALG_{MU}. Even though this subregionally developed (i.e., within the state of Missouri) ALG_{MU} uses the corn plant as a bioassay to generally capture crop N status, additional direct and site-specific soil and weather measurements can be used to improve the algorithm's performance regionally. Likewise following similar adjustments, two other AORS algorithm recommendations (Holland–Schepers and Oklahoma State University) enhanced their N rate predictability for the region. These indicate that a similar process may be applied to improve other AORS algorithm recommendations with site-specific soil and weather information.

Recommendations adjusted with either measured soil data or SSURGO soil data performed similarly. Because SSURGO soil variables are easier and less expensive to collect, using these data may be more advantageous compared to physically measured soil variables. Additional soil and weather variables not considered in this study such as field N tests (e.g., pre-plant and pre-sidedress soil nitrate, potentially mineralizable N), may also be explored for modifying the ALG_{MU} for improved N fertilizer recommendations. Additionally, other management practice information (e.g., crop rotation, tillage, manure history, tile drainage) are known to impact N fertilizer response and are factors that need consideration into AORS algorithm modification or development.

Active-optical reflectance sensor algorithms for corn have primarily been developed using subregion or smaller datasets. Before this study, there was no dataset available for regional assessment of AORS algorithms. Further, this dataset could be used for the development of a regional AORS algorithm. Since the dataset includes numerous crop and soil measurements along with AORS data, additional testing could include how other N management decision tools (e.g., Maximum Return to Nitrogen, Pre-plant Soil Nitrate Test, crop growth models, soil health tests) might be used to adjust current AORS algorithms or inform the development of a new algorithm. The application of this work ultimately could lead to increased fertilizer N use efficiency and grower profit, and decreased negative environmental impacts.

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