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Active-Optical Reflectance Sensing Corn Algorithms Evaluated over the United States Midwest Corn Belt

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ABSTRACT

Uncertainty exists with corn (*Zea mays* L.) N management due to year-to-year variation in crop N need, soil N supply, and N loss from leaching, volatilization, and denitrification. Active-optical reflectance sensing (AORS) has proven effective in some fields for generating N fertilizer recommendations that improve N use efficiency, but locally derived (e.g., within a US state) AORS algorithms have not been tested simultaneously across a broad region. The objective of this research was to evaluate locally developed AORS algorithms across the US Midwest Corn Belt region for making in-season corn N recommendations. Forty-nine N response trials were conducted across eight states and three growing seasons. Reflectance measurements were collected and sidedress N rates (45–270 kg N ha^{-1} on 45 kg ha^{-1} increments) applied at approximately V9 corn development stage. Nitrogen recommendation rates from AORS algorithms were compared with the end-of-season calculated economic optimal N rate (EONR). No algorithm was within 34 kg N ha^{-1} of EONR > 50% of the time. Average recommendations differed from EONR 81 to 147 kg N ha^{-1} with no N applied at planting and 74 to 118 kg N ha^{-1} with 45 kg of N ha^{-1} at planting, indicating algorithms performed worse with no N applied at planting. With some algorithms, utilizing red edge instead of the red reflectance improved N recommendations. Results demonstrate AORS algorithms developed under a particular set of conditions may not, at least without modification, perform very well in regions outside those within which they were developed.

Core Ideas

- Active-optical reflectance sensor algorithms perform poorly outside the area for which they were originally developed.
- The red edge waveband is more sensitive to N stress than the red waveband.
- Some active-optical reflectance algorithms are dependent on the sensor for which they were developed.

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Nitrogen fertilizer applications early in the growing season that match end-of-season measured economic optimal N rate (EONR) can reduce early season N loss while protecting grower profits and the environment (Scharf and Lory, 2002; Scharf et al., 2011; Roberts et al., 2012). However, within-field spatial variability of soil characteristics, year-to-year variations in weather factors, and other variables make it difficult to predict EONR early in the season (Schmidt et al., 2002; Scharf et al., 2005; Tremblay et al., 2012; Dhital and Raun, 2016).

Active-optical reflectance sensors emit visible and near infrared wavebands of modulated light onto the corn (*Zea mays* L.) canopy and measure the intensity of light reflected back (Shanahan et al., 2003). Active-optical reflectance sensors capture plant condition information in small areas within fields and have the ability to assess spatially variable crop N requirements (Solari et al., 2008). Such a diagnostic tool can aid in recommending the correct amount of N fertilizer needed to reach optimal N (Scharf and Lory, 2002; Barker and Sawyer, 2010; Kitchen et al., 2010; Scharf et al., 2011). Unlike soil- or tissue-test based in-season N fertilizer rate recommendations, AORS can be directly mounted to a fertilizer applicator, making it possible to collect reflectance data and apply variable N fertilizer rates in an on-the-go one-pass operation.

Gathering reflectance data with AORS is generally not limited by time of day or cloud cover; however, it has been shown in some situations, including under water stress and with some

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Abbreviations: AORS, active-optical reflectance sensor; ALG_{HS}, Holland-Schepers algorithm; ALG_{MU}, University of Missouri algorithm; ALG_{OSU}, Oklahoma State University algorithm; CC-210, Crop Circle 210; EONR, economic optimal nitrogen rate; GS, GreenSeeker; ISR, inverse simple ratio; NDRE, normalized difference red edge index; NDVI, normalized difference vegetative index; NIR, near-infrared waveband; R, red waveband; RE, red edge waveband; RS, RapidScan sensor; SI, sufficiency index.

sensor types, that AORS can be affected by cloud cover or time of day (Schepers et al., 1996; Barker and Sawyer, 2013). Generally, the chlorophyll content or photosynthetic health of a corn plant can be determined by measuring the relative reflectance of visible light in the 440 to 690 nm spectral range, while the plant's structural size is primarily captured using reflectance in the near infrared wavebands (760–900 nm). Typically, reflected light in both spectral regions is measured by AORS and used to calculate a vegetative index that is an indicator of the N status of the plant (Kitchen et al., 2010). Compared with chlorotic and N deficient plants, healthy corn plants absorb more (reflect less) visible light and as the plant increases in size near infrared light reflectance increases. Thus, the application of AORS for N management often is based on the relative reflectance readings between adequately N fertilized corn and unfertilized or deficiently N fertilized corn (Biggs et al., 2002; Teal et al., 2006; Solari et al., 2008; Kitchen et al., 2010). Reflectance measurements are first gathered from a strip or area in the field that is not N-limited. This is referred to as an N reference or N-rich strip and is usually established at planting by applying enough fertilizer to ensure the corn is not N limited. An alternative approach has been called a *virtual N reference*, where no extra N fertilizer is applied (Holland and Schepers, 2013). In this approach, a distribution of reflectance measurements (i.e., histogram) is obtained from which the 95 percentile value is extracted to represent the N reference equivalent value. Once an N reference is defined, AORS measurements are then obtained from plants intended for fertilization. This is sometimes referred to as the *target* corn. A ratio of sensor readings from target to N reference plants provides a response or sufficiency index (RI or SI), that when used with an AORS algorithm provides an N fertilizer recommendation. Active-optical reflectance sensor algorithms are the mathematical formulas used to transform reflectance readings into in-season N fertilizer recommendations. These AORS algorithms are considered to be at the core of successful AORS based N fertilizer management (Scharf, 2010).

Using an AORS to synchronize the application of N fertilizer with the time of maximum corn N uptake has resulted in increased profit for farmers. In 55 on-farm trials in Missouri, AORS increased partial grower profits (value of corn grain – cost of N fertilizer applied) by an average of \$42 ha^{-1} when compared with historical producer rates (Scharf et al., 2011). In another assessment in Missouri conducted across three differing soil types, AORS-based N fertilizer application rates performed better than producer chosen rates on about half of 16 field-scale experiments and on average generated a \$38 ha^{-1} additional profit (Kitchen et al., 2010).

Despite documented economic and environmental benefits found in some situations, AORS for corn N management can have shortcomings. For example, N stress must be detectable by the sensors when comparing reflectance readings between the N reference and target corn (Barker and Sawyer, 2010; Solie et al., 2012; Franzen et al., 2016). If no measured difference exists between target and reference corn, then the RI or SI is unity and uncertainty exists for how much additional N should be applied, if any. Generally, a point of saturation is reached where added N no longer increases yield when either the RI or SI is near unity (Gitelson and Merzlyak, 1996; Holland and Schepers, 2010). Also, previous research has shown AORS measurements are significantly related to relative yield (Holland and Schepers, 2010; Solari et al., 2010; Tagarakis and Ketterings, 2017). As reflectance saturation is reached, relative yield approaches one, indicating no measured yield response with additional N.

Since plant N uptake is minimal early in the growing season and N stress does not typically show until after the V6 development stage, producers are inclined to delay AORS-based applications (Barker and Sawyer, 2010). If producers wait, the corn may get too tall for their application equipment to pass over the crop without damaging plants. However, specialized high-clearance equipment has become more available in recent years, reducing this concern. Regardless of equipment type, extended wet periods also may prohibit timely field operations, reducing the time available for AORS-based N fertilizer applications. In rainfed corn cropping systems, inadequate rainfall following AORS-based applications limits the amount of plant N uptake and the effectiveness of AORS N management (Sawyer et al., 2007). Also, the time and effort required to establish N reference areas or strips may be cumbersome (Franzen et al., 2016). Lastly, potential risk of reduced yield is increased if N is not applied in a timely manner relative to crop N need.

The unique growing conditions and environments under which these various AORS algorithms were developed may limit their utility over larger geographic areas. Some developers have even qualified algorthims require region-specific or local information (Franzen et al., 2016). Further, many algorithms are developed dependent on the make and model of the AORS used, making it questionable how well the algorithm will perform when used with different sensors. These circumstances create challenges when determining which AORS and algorithm will work best.

Three locally derived (e.g., within a US state) AORS algorithms have been developed for corn utilizing different approaches, and are the basis of this evaluation. These published corn algorithms are the University of Missouri algorithm (ALG_{MU}; Scharf et al., 2011), the Holland-Schepers algorithm (ALG_{HS}; Holland and Schepers, 2010), and the Oklahoma State University algorithm (ALG_{OSU}; Oklahoma State University, 2018). The ALG_{MU} is a linear-based model requiring only gathered AORS measurements to determine an N fertilizer rate. The algorithm is modified to accommodate early, mid, and late vegetative growth stages. The ALG_{HS} is a generalized quadratic-based model that includes several user and producer inputs along with the AORS data. The ALG_{OSU} comes from a family of algorithms employing an approach where each individual algorthim requires specific crop and region information (Raun et al., 2005, 2010; Arnall et al., 2013). To accomplish this, the yield potential with no N added is related to AORS measurements and growing degree days (GDD). Because of this stated need for yield response relative to specific soil and weather conditions, many different ALG_{OSU} algorithms have been developed, each with geographic dependency (Oklahoma State University, 2018). Additionally, the ALG_{OSU} approach uses several other input variables, such as N use efficiency and maximum yield. The development of all three of these algorithms just described (ALG_{MU}, ALG_{HS}, and ALG_{OSU}) are explained with justification in Franzen et al. (2016).

Research to simultaneously compare AORS algorithm performance is undocumented. Since users have questioned how

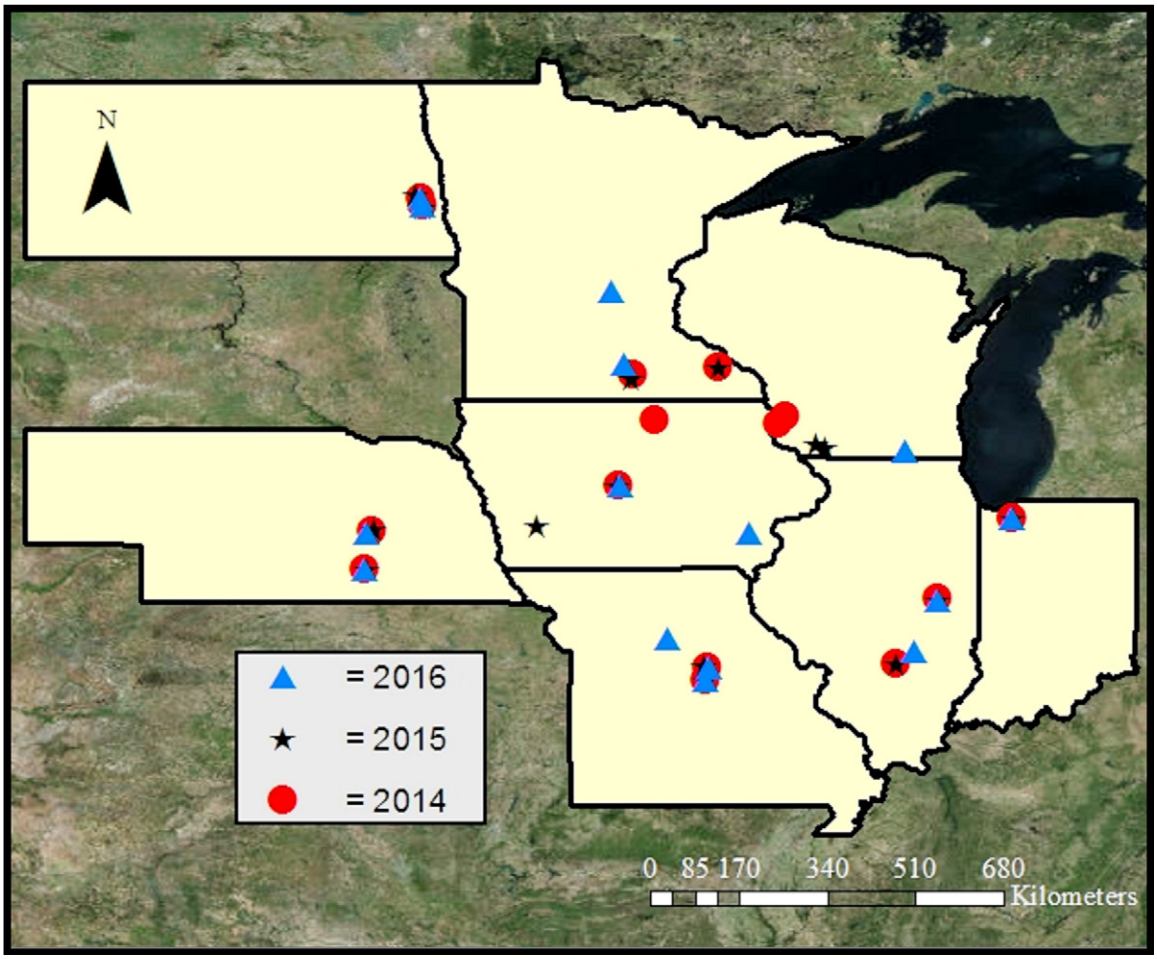

Fig. 1. Field research sites were located within eight US Midwest Corn Belt states (Iowa, Illinois, Indiana, Minnesota, Missouri, Nebraska, North Dakota, and Wisconsin). Each state contained two sites for three growing seasons (2014–2016), totaling 49 sites (Missouri had three sites in 2016). The 2014, 2015, and 2016 sites are represented by red circles, black stars, and blue triangles, respectively.

published locally developed algorthims perform for making N fertilizer recommendations, regardless of where these algorithms were developed, research is needed to compare AORS algorithm performance. An investigation to compare AORS algorithm performance across a large geographical area that represents a range of soil and weather scenarios (for which these algorithms were not originally developed) would help ensure the utility of an optical canopy sensing strategy for corn N management and provide insights into limitations. Such algorithm comparison could additionally lead to a better understanding of how AORS algorithms may be altered for making improved in-season N fertilizer recommendations. The objective of this research was to evaluate across the US Midwest Corn Belt region the performance of locally derived algorithms for making in-season corn N fertilizer recommendations. Inclusive within this objective were two sub-objectives: (i) to assess reflectance readings and algorithm recommendations with corn receiving no N fertilizer as well as minor N fertilization at planting, and (ii) to determine the impact of sensor model and reflectance waveband on algorithm performance.

MATERIALS AND METHODS

Research Sites and Locations

Research was conducted as part of public-industry partnership between eight land-grant universities within the US Corn Belt (Iowa State University, University of Illinois, Purdue University, University of Minnesota, University of Missouri and USDA-ARS, North Dakota State University, University of Nebraska, and the University of Wisconsin) and DuPont Pioneer (Johnston, IA). For this investigation, N fertilizer application response field-plot studies were conducted with standardized protocols and methods across a wide range of soil and weather conditions, and have been previously documented (Kitchen et al., 2017). Yield and soil measurements from these field studies provided both the measurements needed to generate N recommendations with the AORS algorithms, as well as N response functions for obtaining measurements of corn N fertilization need (and EONR).

Forty-nine corn N response trials were conducted from 2014 to 2016 in eight Midwest Corn Belt states. In each state, two sites contrasting in soil productivity were selected for each growing season, one located on a highly productive soil and the other on a relatively less productive soil (Missouri had three sites for 2016; Fig. 1). Productivity was determined by historical yield and general soil productivity. Research sites were planted at a population of 86,450 plants ha^{-1} using Pioneer hybrids (planted on 76 cm row spacing) suitable for the selected sites within the region. Most sites followed soybean [*Glycine max* (L.) Merr.], with the exception of five sites following corn and one site following sunflower (*Helianthus annuus* L.). Tile drainage was present at eight sites, and eight sites were irrigated (irrigation

water was analyzed for N content and included in the final EONR amount). All but three sites received at least some form of tillage. Planting occurred in a timely fashion. Planting dates ranged from 6 April to 23 May and AORS dates ranged from 3 June to 10 July and were targeted for the V9 development stage. Additional site descriptions, site characterization protocols, and management details can be found in Kitchen et al. (2017).

Plot and Treatments

Plot dimensions were state and site dependent and were determined by the planting and harvesting equipment available, but all plot harvest areas were ≥18.6 m^2. Nitrogen fertilizer application treatments were replicated four times in a randomized complete block design. Dry-prilled NH_4NO_3 fertilizer was used for all N treatments and was broadcast by hand. Eight treatments (0–315 kg N ha^{-1} in 45 kg ha^{-1} increments) constituted the "at planting" application treatments and were applied within 48 h of planting. Six treatments defined a "split" application with 45 kg ha^{-1} N at planting and the remainder (45–270 kg N ha^{-1} in 45 kg ha^{-1} increments) as a sidedress targeted at V9 ± one growth stage (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 the RapidSCAN CS-45 (RS) Handheld Crop Sensor (Holland Scientific, Lincoln, NE). The RS sensor provides reflectance information for three different wavebands of light: red (670 nm, R), red edge (720 nm, RE), and near-infrared (780 nm, NIR). All three wavebands were utilized in calculating vegetative indices associated with the N rate algorithms tested. Manufacturer recommendations were followed for calibration and operation. The sensor was held approximately 60 cm directly above the top of the corn row as the operator steadily walked approximately 4 km h^{-1} alongside the row. Only plot rows used for yield measurements (2–3 rows per plot depending on plot layout) were sensed individually and then averaged to obtain plot level readings.

Reflectance Measurements and Algorithms Evaluated

The algorithms evaluated required AORS values from adequately N-fertilized corn used as an N reference (reference), and unfertilized or deficiently fertilized corn targeted for in-season fertilization (target). Corn plots that received 225 and 270 kg N ha^{-1} at planting were used as the N reference. The exception was the 2015 Missouri LoneTree (less productive) 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 reference. Nitrogen recommendations were calculated using two scenarios to represent the target corn to be fertilized at approximately the V9 development stage. The first was the average of all experimental units fertilized at planting with 45 kg N ha^{-1} (n = 28 plots averaged by site), and the second from unfertilized experimental units (0 kg N ha^{-1}; n = 4 plots averaged by site). Active-optical reflectance sensor data from both the target plots and reference plots were used to calculate the vegetative indices specific to AORS algorithms.

Three published AORS algorithms for making corn N fertilizer recommendations were evaluated: ALG_{MU} (Scharf et al., 2011), ALG_{HS} (Holland and Schepers, 2010), and ALG_{OSU} (Oklahoma State University, 2018). Further, to evaluate algorithm recommendation sensitivity to varying wavebands, vegetative indices associated with these algorithms were calculated using a combination of the R and NIR wavebands as well as the RE and NIR wavebands. In addition to examining how AORS algorithms are affected by sensor model, both ALG_{MU} and ALG_{OSU} (developed using different sensors) were examined using RS measurements and reflectance measurements transformed to values more similar to the sensor from which the algorithm was developed.

University of Missouri Algorithm

The form of the ALG_{MU} used for this evaluation was developed for corn at the V8 to V10 growth stage (Scharf et al., 2011). The vegetative index used is the inverse simple ratio (ISR), defined as:

$$\mathrm{ISR} = \frac{\mathrm{R}}{\mathrm{NIR}} \quad [1]$$

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 (Scharf et al., 2011):

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

where $NRec_{MU}$ is the N fertilizer recommendation in kg N ha^{-1} for the ALG_{MU}. The coefficients 280 and 224 kg N ha^{-1} represent the slope and intercept of the model for corn at the V8 to V10 growth development stage. This empirical relationship between EONR and active-optical reflectance measurements was detailed in Scharf et al. (2011).

A second N recommendation was also obtained for evaluation by substituting RE for R in Eq. [1] above.

The ALG_{MU} was originally developed using Holland-Scientific's Crop Circle 210 (CC-210), an earlier sensor model than the RS used in this study. Therefore, the AORS measurements of this study were converted to equivalent CC-210 readings based on an equation that was derived from simultaneous readings of these two sensors from other studies (R^2 = 0.86; previously unpublished data) for V8 to V10 development stage corn. The sensors were related in the following way:

$$\mathrm{ISR}_{\mathrm{CC\text{-}210}} = 0.454 + \ln\left(\mathrm{ISR}_{\mathrm{RS}}\right) \times 0.125 \quad [3]$$

where $ISR_{CC\text{-}210}$ is ISR needed for ALG_{MU} (in equivalent CC-210 readings), and ISR_{RS} is ISR of the RS. Once RS values were transformed, the N fertilizer recommendation could be determined using Eq. [2].

Holland-Schepers Algorithm

The ALG_{HS} for corn N fertilization is not specific to any one vegetative index (Holland and Schepers, 2010). For this analysis the normalized difference vegetative index (NDVI) and the normalized difference red edge index (NDRE) were used, and are calculated as:

$$\mathrm{NDVI} = \frac{(\mathrm{NIR} - \mathrm{R})}{(\mathrm{NIR} + \mathrm{R})} \quad [4]$$

$$\mathrm{NDRE} = \frac{(\mathrm{NIR} - \mathrm{RE})}{(\mathrm{NIR} + \mathrm{RE})} \quad [5]$$

The NDVI and NDRE were calculated for both the reference and target corn.

A SI for NDVI was calculated as:

$$\mathrm{SI} = \frac{\mathrm{NDVI}_{\mathrm{target}}}{\mathrm{NDVI}_{\mathrm{reference}}} \quad [6]$$

Nitrogen fertilizer recommendations were then derived using either SI or $\mathrm{SI}_{\mathrm{RE}}$ (NDRE substituted for NDVI in Eq. [6]) as follows:

$$\mathrm{NRec}_{\mathrm{HS}} = \left[\mathrm{MZ}_{\mathrm{i}} \times \left(\mathrm{N}_{\mathrm{OPT}} - \sum \mathrm{N}_{\mathrm{CRD}} + \mathrm{N}_{\mathrm{COMP}}\right)\right] \times \sqrt{\left(\frac{1 - \mathrm{SI}}{\Delta \mathrm{SI}}\right)} \quad [7]$$

where $\mathrm{NRec}_{\mathrm{HS}}$ is the N fertilizer recommendation in kg N ha^{-1} for $\mathrm{ALG}_{\mathrm{HS}}$; MZ_{i} is management or soil sample scalar/adjustment; $\mathrm{N}_{\mathrm{OPT}}$ is maximum amount of N fertilizer applied by the producer or anticipated EONR; $\mathrm{N}_{\mathrm{CRD}}$ is N credits including pre-plant or split fertilizer applied before sensing, manure N, nitrate found in the soil and irrigation water, or previous leguminous crops, all in kg N ha^{-1}; $\mathrm{N}_{\mathrm{COMP}}$ is amount in excess of $\mathrm{N}_{\mathrm{OPT}}$ needed to satisfy soil limited conditions (kg N ha^{-1}); and ΔSI is the difference between where SI is equal to 1 and the point at which the response curve intersects the *y* axis. For all years and sites a ΔSI of 0.3 was used. The information needed to calculate $\mathrm{N}_{\mathrm{OPT}}$ and $\mathrm{N}_{\mathrm{CRD}}$ was obtained for all sites from the research station's or producer's site history records. For this assessment $\mathrm{MZ}_{\mathrm{i}} = 1$ and the $\mathrm{N}_{\mathrm{COMP}}$ adjustment was excluded.

A second N recommendation was determined using NDRE where $\mathrm{SI}_{\mathrm{RE}}$ was calculated as follows:

$$\mathrm{SI}_{\mathrm{RE}} = \frac{\mathrm{NDRE}_{\mathrm{target}}}{\mathrm{NDRE}_{\mathrm{reference}}} \quad [8]$$

and substituted for SI along with an appropriate $\Delta\mathrm{SI}_{\mathrm{RE}}$ into Eq. [7] to generate an N fertilizer recommendation.

Oklahoma State University Algorithm

From the family of OSU corn N algorithms available (Oklahoma State University, 2018), the "Irrigated/Rainfed-Corn USA, Cummulative GDD" algorithm (in units of bu ac^{-1}) was used in this analysis. The $\mathrm{ALG}_{\mathrm{OSU}}$ was developed using NDVI (Oklahoma State University, 2018) and is calculated by first computing the following:

$$\mathrm{RI} = \left(\frac{\mathrm{NDVI}_{\mathrm{reference}}}{\mathrm{NDVI}_{\mathrm{target}}}\right) \times 1.64 - 0.53 \quad [9]$$

where RI is response index.

$$\mathrm{GDD} = \frac{T_{\mathrm{Max}} + T_{\mathrm{Min}}}{2} - T_{\mathrm{Base}} \quad [10]$$

where GDD is growing degree days from the time of planting to the time AORS measurements were taken; T_{Max} is the maximum air temperature, T_{Min} is the minimum air temperature, and T_{Base} is 10°C.

Then an in-season estimated yield (INSEY) is determined for the target corn as:

$$\mathrm{INSEY} = \frac{\mathrm{NDVI}}{\sum \mathrm{GDD}} \quad [11]$$

and is used to calculate a yield potential without N fertilizer added (YP_{O}) and a yield potential with N fertilizer added (YP_{N}) for the target corn as follows:

$$\mathrm{YP}_{O} = 1.291^{(\mathrm{INSEY} \times 2649.9)} \quad [12]$$

$$\mathrm{YP}_{\mathrm{N}} = \mathrm{YP}_{O} \times \mathrm{RI} \quad [13]$$

The N fertilizer recommendation was then calculated as:

$$\mathrm{NRec}_{\mathrm{OSU}} = \frac{(\mathrm{YP}_{\mathrm{N}} - \mathrm{YP}_{\mathrm{O}}) \times 56 \times \mathrm{grainN}}{\mathrm{Expected\ NUE}} \quad [14]$$

where $\mathrm{NRec}_{\mathrm{OSU}}$ is the N fertilizer recommendation in lbs N ac^{-1}; 56 is the value needed to convert to lbs grain ac^{-1}; expected NUE is the expected N fertilizer use efficiency (value set to 0.5); and grain N is fractional grain N concentration for corn (value set to 0.0125). For publication here, the final recommendation was then converted to kg N ha^{-1}. Temperature needed to calculate GDD was collected using a weather station at each site (Kitchen et al., 2017). The above process was also used to calculate an N fertilizer recommendation by substituting NDRE in place of NDVI in Eq. [9]. The rest of the calculations were the same.

The $\mathrm{ALG}_{\mathrm{OSU}}$ was developed using the GreenSeeker (GS; model 506) canopy reflectance sensor currently manufactured by Trimble (Trimble Navigation, Ltd., Sunnyvale, CA), a completely different make and model from the RS. The first step was transforming the RS values to equivalent $\mathrm{ISR}_{\mathrm{CC\text{-}210}}$ values using Eq. [3]. Second, the $\mathrm{ISR}_{\mathrm{CC\text{-}210}}$ values were converted to equivalent $\mathrm{ISR}_{\mathrm{GS}}$ values using relationships developed from other studies where simultaneous readings were taken using the CC-210 and GS on corn stands throughout several growing seasons ($R^2 = 0.82$; unpublished). This relationship was as follows:

$$\mathrm{ISR}_{\mathrm{GS}} = 1.24 \times \mathrm{ISR}_{\mathrm{CC\text{-}210}} - 0.0903 \quad [15]$$

where $\mathrm{ISR}_{\mathrm{GS}}$ reflectance values and $\mathrm{ISR}_{\mathrm{CC\text{-}210}}$ are reflectance gathered by the RS that was transformed to be $\mathrm{ISR}_{\mathrm{CC\text{-}210}}$ equivalent using Eq. [3]. This algorithm used NDVI, making the final step the conversion between ISR and NDVI.

$$\mathrm{NDVI} = \frac{1 - \mathrm{ISR}}{1 + \mathrm{ISR}} \quad [16]$$

Following these transformations, the recommendation could be calculated using Eq. [14].

Performance Evaluation and Statistics

Results were first examined to help establish AORS measurements were sensitive to soil and crop N status. This was accomplished three different ways. First, AORS SI (ISR using RE) was examined as a function of at-planting N rates (mean of four replications). This relationship was fit using a quadratic model.

Second, relative yield by plot was examined as a function of the AORS SI (ISR using both R and RE), and fit using linear models by year. Relative yield was calculated as follows:

$$\mathrm{RY} = \frac{\mathrm{Yield}_{\mathrm{Plot}}}{\mathrm{Yield}_{\mathrm{Opt}}} \qquad [17]$$

where RY is relative yield, $\mathrm{Yield}_{\mathrm{Plot}}$ is the yield of each individual plot, and $\mathrm{Yield}_{\mathrm{Opt}}$ is the site-level optimal yield (i.e., plateau of Q-P model), which is the point at which added N no longer increased yield (Kitchen et al., 2017).

Lastly, AORS SI (ISR using both R and RE) was examined by plot as a function of V5 development stage soil nitrate N, and fitted using linear-plateau models by year. For treatments receiving N at planting, six 0- to 30-cm depth soil cores were combined and analyzed for soil nitrate N as described in Kitchen et al. (2017).

For AORS algorithm performance, results were analyzed using SAS version 9.2 (SAS Institute Inc., Cary, NC). An EONR (corn grain price, \$ 0.158 kg^{-1} [\$4.00 bu^{-1}], N fertilizer cost, \$0.88 kg N^{-1} [\$0.40 lb^{-1}]) was calculated for N split applied with 45 kg N ha^{-1} at planting and the remainder applied at the V9 development stage as a sidedress (Kitchen et al., 2017). The quadratic-plateau function was found most appropriate for all but one site where a quadratic function was a better fit (Kitchen et al., 2017). The EONR split applications were calculated as:

$$\mathrm{EONR} = \frac{-b - (\mathrm{N{:}\ corn\ price})}{2c} \qquad [18]$$

where b and c are linear and quadratic response coefficients from optimized quadratic function. The EONR was the season total fertilizer N applied (planting + split). For evaluating AORS algorithms for the target corn scenario that did not receive N at planting, this EONR value was used directly and is represented as $\mathrm{EONR}_{\mathrm{Tot}}$ for this analysis. For evaluating AORS for the target corn scenario that received 45 kg N ha^{-1} at planting, the EONR value was reduced by this same amount so that it represents the N fertilizer that was applied as sidedress. This is represented in this analysis as $\mathrm{EONR}_{\mathrm{SD}}$. Throughout the rest of this analysis a non-subscripted EONR is used in the general sense to represent both situations.

Box and whisker plots were made using Grapher 11 (Golden Software, Golden, CO) to graphically represent the median, upper, and lower quartiles, and the range of the difference between an algorithm's recommendation and EONR. This was done for AORS measurements of target corn receiving 0 and 45 kg N ha^{-1} at planting.

The RMSE across sites was calculated for each algorithm as follows:

$$\mathrm{RMSE} = \sqrt{\frac{\Sigma\left(\mathrm{N}_{\mathrm{Alg}} - \mathrm{N}_{\mathrm{EONR}}\right)^2}{n}} \qquad [19]$$

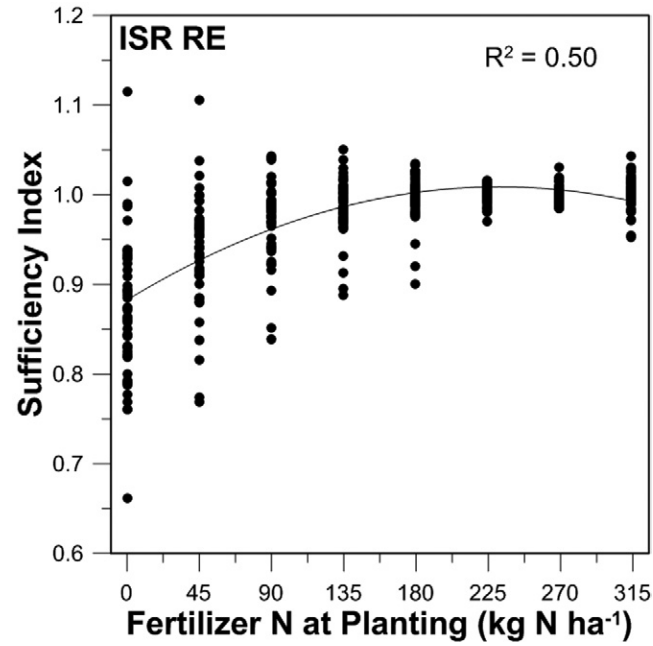

Fig. 2. Active-optical reflectance sensing sufficiency index (SI) for approximately V9 corn as a function of N fertilizer rates applied at planting over 49 sites and three growing seasons (2014–2016). Reflectance SI (target by N rate and reference the mean of 225 and 270 kg N ha^{-1} rates) were calculated with the inverse simple ratio vegetative index employing red edge and near infrared wavebands (ISR RE). Data was fit using both a quadratic and quadratic-plateau model. Results were similar; the simpler quadratic model is shown here.

where $\mathrm{N}_{\mathrm{Alg}}$ is the algorithm N rate recommendation, $\mathrm{N}_{\mathrm{EONR}}$ is the measured EONR, and n is the total number of site years.

Algorithm performance was also assessed by examining what percentage of the 49 sites resulted in an N rate recommendation within 34 kg N ha^{-1} of EONR. This value is similar to what others have used as an acceptable performance recommendation (Sawyer, 2013; Laboski et al., 2014), and is also comparable to the economic–environmenatal threshold of 30 kg N ha^{-1} determined from this same reseach project (Bandura, 2017).

RESULTS AND DISCUSSION

Relating Reflectance Sensing to Soil Nitrogen and Yield

With no N fertilizer applied at planting, AORS SI (inverse simple ratio using RE; ISR RE) was less than 0.95 for most sites (Fig. 2; Table 1). With the majority of sites, a visual N deficiency at the time of sensing was observed with no N applied at planting. With increasing N at planting, plant N stress, as indicated by the SI, diminished. However, a few sites showed N stress even with >90 kg N ha^{-1} applied at planting. These sites generally experienced excessive early season rainfall on either coarse- or fine-textured soils.

The SI was related to variation in relative yield, with r^2 values ranging from 0.29 to 0.58 for different years and wavebands (Fig. 3; Table 1). The relationship was better with RE than with the R reflectance. As relative yield approached 1, SI also approached unity. This comparison additionally verifies the sensitivity of the AORS data used to determine corn N status for these sites.

The SI of sensor measurements taken at V9 development stage were related to V5 development stage soil nitrate N in the upper

Table 1. Quadratic, linear, or linear-plateau regression models associated with Fig. 2–4 are presented with coefficients of determination. All models were significant ($P < 0.001$). The sufficiency index (SI) used for each figure was the inverse simple ratio (ISR) of either red (R) or red edge (RE) reflectance for V9 growth stage corn. For Fig. 2, N fertilizer applied at planting in kg N ha^{-1} units. For Fig. 3, relative yield (RY) was calculated by dividing each plot yield by the modeled site-level optimal yield. For Fig. 4, soil nitrate N was analyzed from samples obtained by combining six 0- to 30-cm depth soil cores taken at the V5 growth stage.

Figure	Dependent variable	Independent variable	Model type	Waveband	Year	Equation	r^2/R^2
2	SI	N at planting	Quadratic	RE	All	$y = 0.883 + 0.0011x - 2.341x^2$	0.50
3	RY	SI	Linear	R	2014	$y = 0.832x + 0.076$	0.41
					2015	$y = 0.763x + 0.128$	0.29
					2016	$y = 0.700x + 0.208$	0.31
				RE	2014	$y = 2.186x + 1.246$	0.58
					2015	$y = 2.271x + 1.333$	0.53
					2016	$y = 1.721x + 0.796$	0.42
4	SI	Soil nitrate N	Linear-plateau	R	2014	$y = 0.0311x + 0.5454; y = 1.0049$ ($x \geq 14.8$)	0.42
					2015	$y = 0.0211x + 0.6537; y = 1.0072$ ($x \geq 16.7$)	0.30
					2016	$y = 0.0178x + 0.6965; y = 1.0157$ ($x \geq 17.9$)	0.26
				RE	2014	$y = 0.0171x + 0.7458; y = 0.9952$ ($x \geq 14.6$)	0.60
					2015	$y = 0.0109x + 0.7982; y = 0.9950$ ($x \geq 18.0$)	0.49
					2016	$y = 0.0099x + 0.8154; y = 1.0072$ ($x \geq 19.3$)	0.48

30-cm (from plots that received 0–315 kg N ha^{-1} at planting in 45 kg ha^{-1} increments) and found to best fit a linear plateau relationship (Fig. 4; Table 1). As with relative yield, the relationship using RE reflectance was better than the R reflectance. Sufficiency index values increased as soil nitrate N increased up to approximately 15 to 19 mg kg^{-1}, where SI values plateaued. Thus, target corn at the V5 development stage with over 20 mg kg^{-1} of soil nitrate N will likely have similar V9 AORS measurements as reference corn. Interestingly, 20 mg kg^{-1} of soil nitrate N present in the soil at sidedress is normally accepted as N sufficiency (Blackmer et al., 1989).

Algorithm Performance using the Red Waveband

Using the R waveband (ISR for the ALG_{MU} and NDVI for both ALG_{HS} and ALG_{OSU}), N fertilizer recommendations for the 49 sites are shown graphically relative to $EONR_{Tot}$ for 0 target corn (Fig. 5, left side) and $EONR_{SD}$ for 45 kg N ha^{-1} target corn (Fig. 5, right side). Performance is summarized using box and whisker plots (Fig. 6). Data points on or near the 1:1 diagonal line in Fig. 5 show sites that an algorithm performed reasonably well for making an N fertilizer recommendation. Points below and above the 1:1 line represent recommendations that under- and overestimated N need, respectively. Sites within the yellow shaded region were within 34 kg N ha^{-1} of EONR. Dashed linear fit lines show the relationship of AORS algorithms to EONR values, with linear equations reported in Table 2. A paired t test ($\alpha = 0.05$) showed recommendations performed better when target corn received 45 kg N ha^{-1} at planting (Table 2 and Fig. 5 and 6). Generally, all algorithms underestimated EONR and were not sensitive to the wide range of EONR values (median values using R of −43, −88, and −96 kg N ha^{-1} for ALG_{MU}, ALG_{HS}, and ALG_{OSU}, respectively; Table 2, Fig. 6). Of the three, the ALG_{MU} was the most accurate. The percentage of sites within 34 kg N ha^{-1} of EONR using the R waveband and with 45 kg N ha^{-1} applied at planting were 29, 16, and 14% for ALG_{MU}, ALG_{HS}, and ALG_{OSU}, respectively.

Algorithm Performance Using the Red Edge Waveband

For the ALG_{MU}, using the RE (ISR_{RE}) as opposed to the R (ISR) waveband did not appreciably change the performance of the algorithm (compare Fig. 7 with Fig. 5; Fig. 6). This includes the comparison of target corn with no N at planting and corn receiving 45 kg N ha^{-1} at planting. Although no significant performance enhancement was seen with ALG_{MU} using the ISR_{RE}, it should be noted the ISR_{RE} reflectance was not transformed before being used with the algorithm. The conclusion is that using ISR_{RE} from the RS sensor with the ALG_{MU} would generate recommendations equivalent to the same algorithm using ISR from a CC-210 sensor.

Compared to using R (NDVI) reflectance, overall performance of the ALG_{HS} was improved using RE (NDRE) for both target corn N rates. This is seen with all performance metrics. For example, median values improved from −98 to −54 kg N ha^{-1} for target corn that received no N at planting and from −88 to −64 for target corn that received 45 kg N ha^{-1} at planting. Linear fit slope values are closer to unity, demonstrating better sensitivity to varying EONR. Interestingly, the ALG_{HS} performance when utilizing the RE waveband was close to equal that of the ALG_{MU} when using the R waveband. Although the ALG_{HS} has been described as independent of the vegetative index used (Holland and Schepers, 2010), it is clear from this analysis the RE waveband used within a vegetative index does affect the resulting N fertilizer recommendation. The reason NDVI is so sensitive until canopy closure is that raw R and NIR reflectance values move in opposite directions (i.e., one goes up and the other goes down with variation in crop biomass). After canopy closure, both RE and R values remain nearly constant. Following canopy closer, subtracting and adding a very small R waveband value to the NIR value (Eq. [4]) results in an insensitive vegetative index. Doing the same for a larger RE waveband value (Eq. [5]) results in a vegetative index that has a wider range in values. Thus, it is not that RE reflectance is more sensitive to chlorophyll status, but rather that NDRE mathematically "sensitizes" the vegetative index.

For $ALG_{OSU,}$ performance diminished when using the RE (NDRE) waveband compared with the R (NDVI) waveband

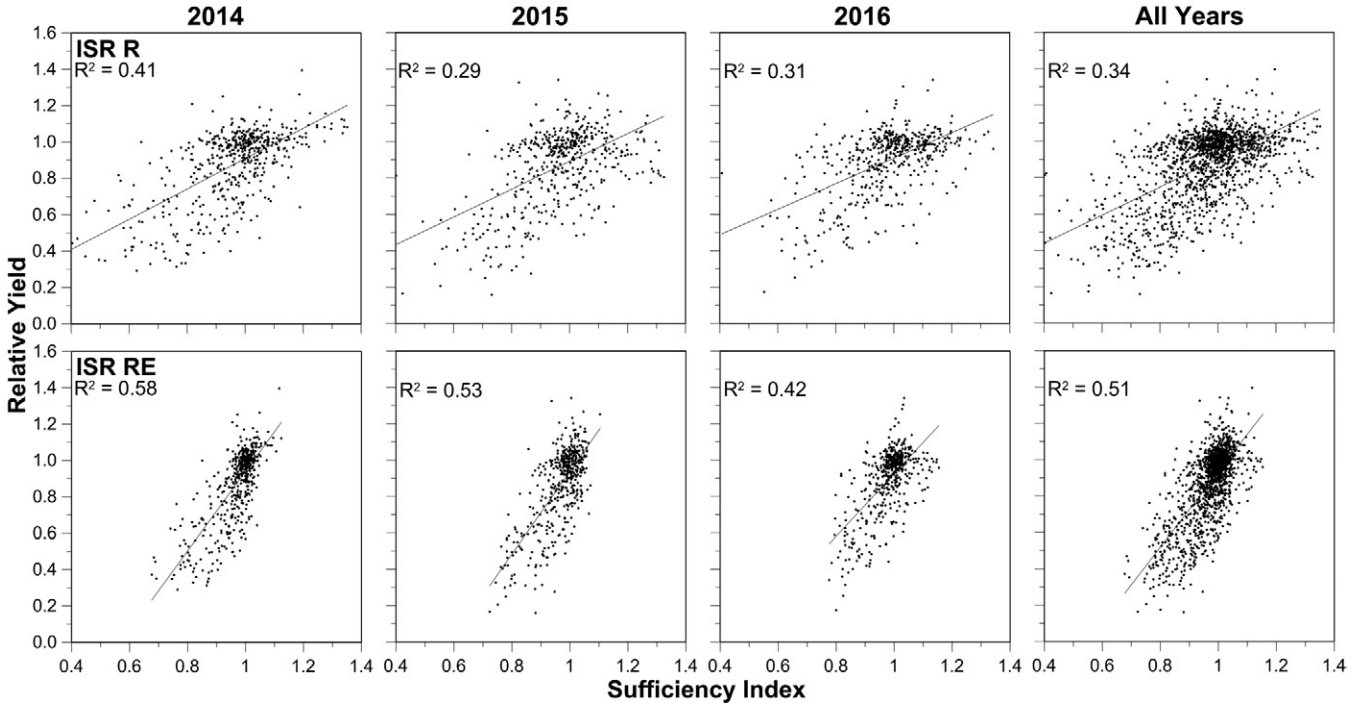

Fig. 3. Sufficiency index (SI) shown in relation to the relative yield calculated by dividing each plot yield by the site-level optimal yield for plots receiving N fertilizer at planting (32 plots per site), over three growing seasons (2014–2016). Reflectance SI (target by N rate and reference the mean of 225 and 270 kg N ha^{-1} rates) were used with the inverse simple ratio vegetative index employing red edge and near infrared wavebands (ISR RE).

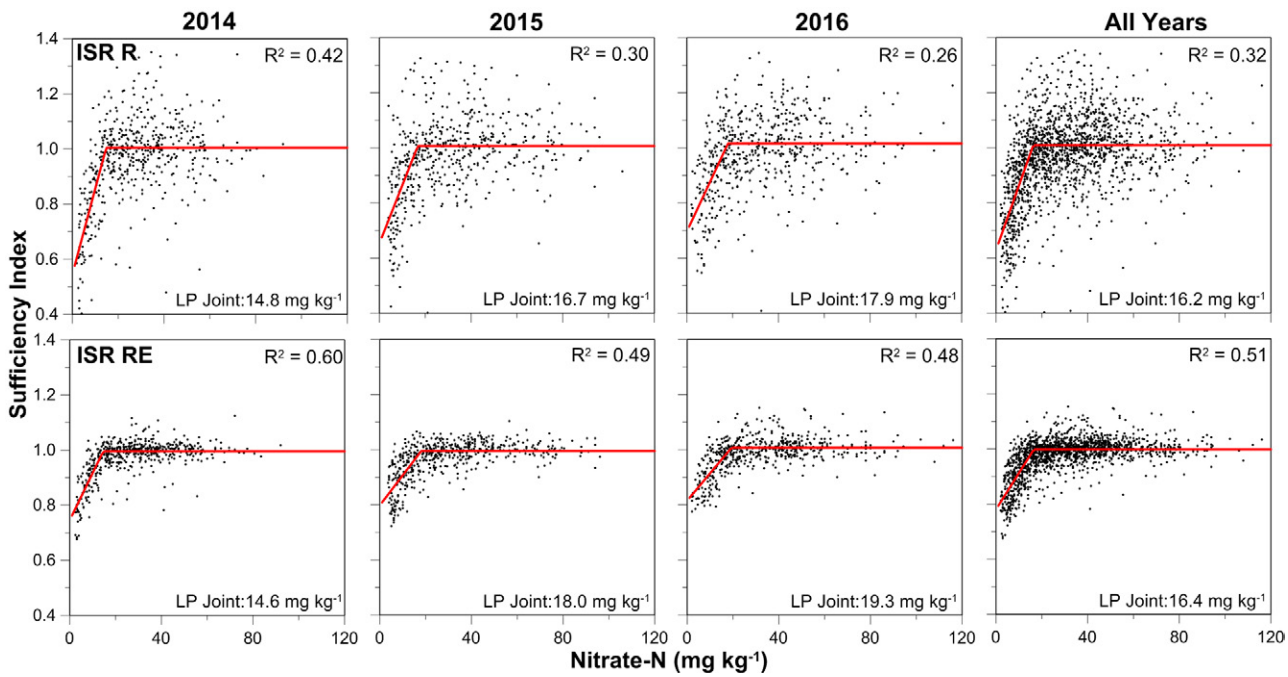

Fig. 4. Sufficiency index (SI) shown in relation to V5 development stage soil nitrate N (0- to 30-cm depth), fitted with a linear-plateau model. Results are for plots N fertilized at planting (32 plots per site; 0–315 kg N ha^{-1} in 45 kg N ha^{-1} increments), over three growing seasons (2014–2016). Reflectance SI (target by N rate and reference the mean of 225 and 270 kg N ha^{-1} rates) were used with the inverse simple ratio vegetative index employing red edge and near infrared wavebands.

(compare Fig. 7 with Fig. 5; Fig. 6). The percentage of sites within 34 kg N ha^{-1} was similar, but the median difference values increased by approximately 20 kg N ha^{-1} and linear slope values decreased. This is due to the calculation of INSEY (Eq. [11]). The INSEY variable is calculated by dividing the target corn reflectance measurement by the GDD (GDD ranged from 315 to 650 for this analysis). Target and N reference corn reflectance NDVI values ranged from approximately 0.48 to 0.86 and 0.50 to 0.88, respectively. Target and reference reflectance NDRE values ranged from approximately 0.15 to 0.45 and 0.17 to 0.45, respectively. Therefore, when using the NDRE, a significantly smaller INSEY value resulted. This diminished value was then used to calculate YP_O. When using NDVI, the average YP_O value was 6100 kg ha^{-1}, whereas YP_O values using NDRE were up to an

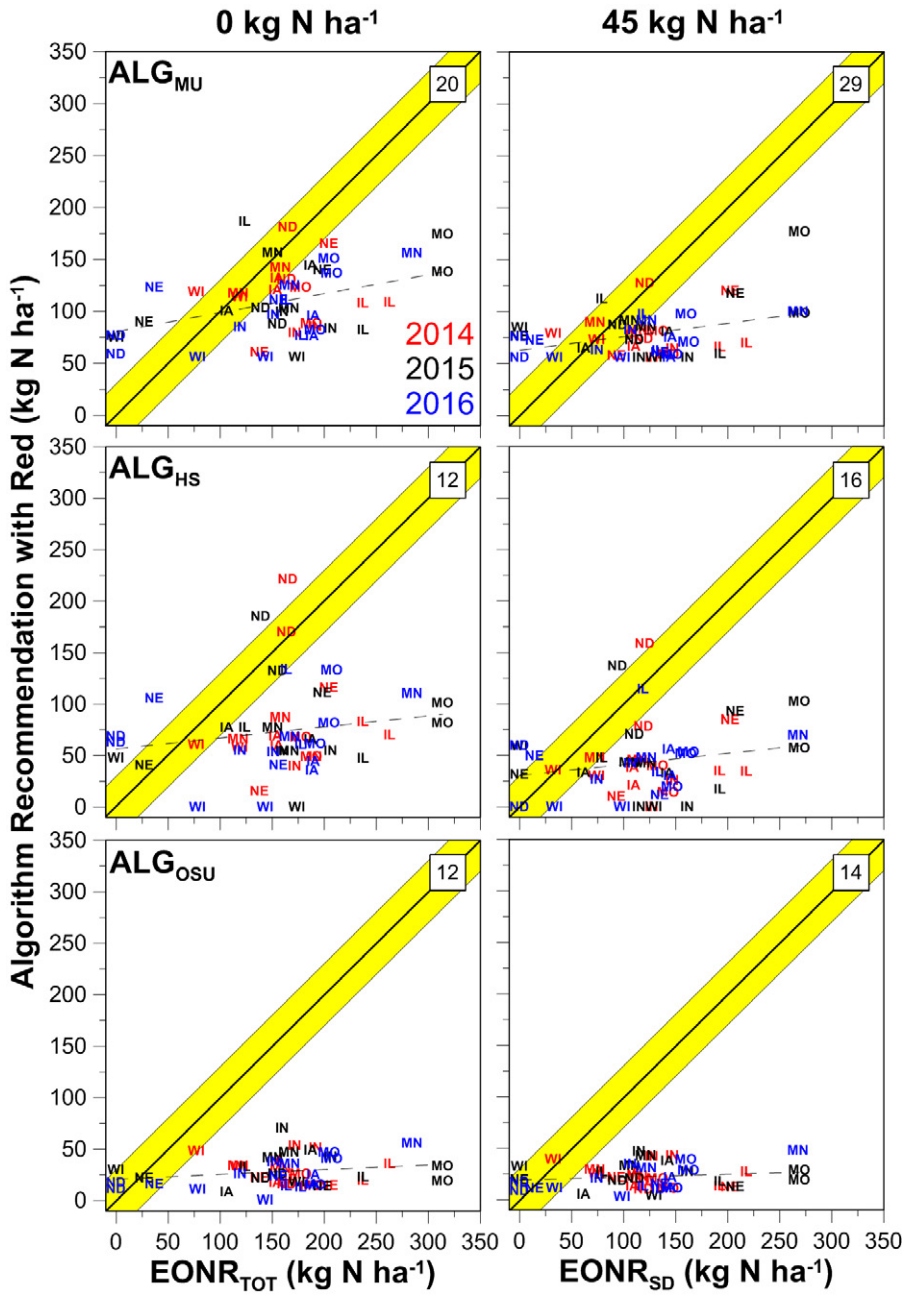

Fig. 5. Performance of three active-optical reflectance sensor algorithms (University of Missouri, ALG_{MU}; Holland-Schepers, ALG_{HS}; Oklahoma State University, ALG_{OSU}) shown by comparing the algorithm recommendation relative to economic optimal N rate (EONR), where $EONR_{Tot}$ is the total EONR N amount and $EONR_{SD}$ is the sidedress EONR (difference between $EONR_{Tot}$ and N applied at planting). Results are for two different target corn at-planting N fertilizer rates (0 and 45 kg N ha^{-1}) including the red (R) and near infrared (RE) wavebands. Sites near the 1:1 line dissecting the graphs suggest sensor algorithms were accurate in recommending EONR. Sites that fell within the yellow shaded region are those within 34 kg N ha^{-1} of EONR, and this is shown as a percentage of sites in the top right corner of each graph. Dashed lines represent a linear fit between algorithm recommendation and EONR.

order of magnitude less (average 552 kg ha^{-1}). When these smaller values were used to calculate other variables of the ALG_{OSU}, the N recommendation collapsed to less than 25 kg N ha^{-1}. Thus, when using this ALG_{OSU} algorithm, the RE waveband should be avoided.

Algorithm Performance Differences

Although the objective of this analysis was to test the AORS algorithms as they have been published, and not the approaches used to develop them, an understanding of the unique construction of each algorithm helps explain the observed performance differences. The ALG_{MU} was sensitive to corn reflectance values since that input variable alone drives N recommendations. No matter the at-planting N fertilizer rate, greater differences between the target and reference corn resulted in more N fertilizer being recommended. When reflectance values are equivalent between the target and reference corn, the ALG_{MU} recommends a base rate of 56 kg N ha^{-1} (Eq. [2]), but this is still for many sites an under-recommendation compared with EONR.

The ALG_{HS} also was somewhat sensitive to changes in reflectance between reference and target corn. However, the effect of the N_{COMP}, an input variable not included in this analysis,

Table 2. Root mean square error (RMSE) values, percentages of sites within 34 kg N ha^{-1} of the economical optimal N rate, and linear fit lines for each algorithm (University of Missouri, ALG_{MU}; Holland-Schepers, ALG_{HS}; Oklahoma State University, ALG_{OSU}). Lower RMSE values suggest greater algorithm accuracy. Greater percent values of sites within 34 kg N ha^{-1} of EONR also suggest better algorithm performance. Both the red (R) and red edge (RE) are represented. Across all three algorithms, performance was better when target corn received 45 kg N ha^{-1} at planting. The performance of the ALG_{MU} without reflectance transformation (No Trans) is also shown below. The reflectance transformation is described by Eq. [2].

Algorithm	Target corn N rate	Waveband	RMSE	Sites within 34 kg N ha^{-1}	Linear fit equation	r^2
	kg N ha^{-1}		kg N ha^{-1}	%		
ALG_{MU}	0	R	81	20	$y = 0.1826x + 80.52$	0.14
		RE	86	20	$y = 0.1435x + 78.69$	0.12
	45	R	74	29	$y = 0.1299x + 63.02$	0.13
		RE	75	33	$y = 0.1145x + 62.24$	0.14
ALG_{HS}	0	R	114	12	$y = 0.1073x + 56.48$	0.03
		RE	81	22	$y = 0.2589x + 69.93$	0.16
	45	R	103	16	$y = 0.1075x + 30.53$	0.04
		RE	81	29	$y = 0.2431x + 41.09$	0.14
ALG_{OSU}	0	R	147	12	$y = 0.0456x + 20.95$	0.05
		RE	169	10	$y = 0.0101x + 3.198$	0.15
	45	R	118	14	$y = 0.0271x + 19.27$	0.02
		RE	134	14	$y = 0.0076x + 1.976$	0.16
ALG_{MU} (No Trans)	0	R	77	29	$y = 0.2919x + 100.2$	0.11
	45	R	73	37	$y = 0.2267x + 62.41$	0.11

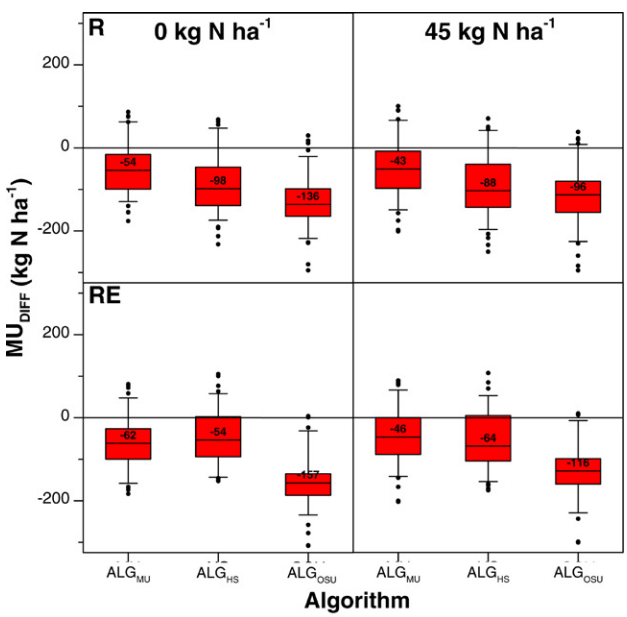

Fig. 6. The performance of three active-optical reflectance sensor algorithms (University of Missouri, ALG_{MU}; Holland-Schepers, ALG_{HS}; Oklahoma State University, ALG_{OSU}) summarized in box and whisker plots of the difference between the algorithm recommendation and the economic optimal N rate (EONR). Results are for both at-planting N fertilizer rates (0 and 45 kg N ha^{-1}) and including both red (R) and red edge (RE) wavebands. Whisker length represents the 90th percentile and black dots represent the N recommendations that fall outside the 90th percentile. Median values of these differences ~0 indicate better accuracy. Negative values represent algorithm underestimating the N recommendation and positive values represent overestimating the N recommendation. Box size and whisker length is a measure of precision with smaller boxes and whiskers indicating greater precision.

may have greatly altered the final N recommendation for many sites. The N_{COMP} variable considers historical, personal, and field-specific information provided by the producer. For example, sites from this investigation with high clay content and known to be vulnerable to denitrification (Missouri and Illinois claypan sites; see site details in Kitchen et al., 2017) could have included an N fertilizer rate increase using the N_{COMP} adjustment. Other sites were sandy and prone to leaching (some Nebraska, Minnesota, and Indiana sites). Likewise, an adjustment with additional N fertilizer could have been applied to compensate for possible N loss. Sites with a history of limited response to N fertilizer (one Wisconsin site in 2015) could have had this included as a decrease in N fertilizer recommendation (i.e., $-N_{COMP}$). All these considerations for modifying N_{COMP} require prior experience regarding the optimal N rate for that specific site to make an N application decision at the time of sensing. Producers using AORS N fertilizer management who have past knowledge of optimal N rates during varying weather conditions could use this feature to fit specific field needs. As such, the N_{COMP} algorithm component is subjective requiring user experience, and consequently would be difficult to objectively include in an unbiased way with this analysis. Even so, a decision to include the example adjustments to N_{COMP} likely would have improved the ALG_{HS} N fertilizer recommendations in this study for a number of sites. Another subjective variable is N_{OPT}, crucial for successful AORS N management (Franzen et al., 2016). This variable also accounts for producer's experience, including site specific knowledge of productivity capacity. More accurate estimates of N_{OPT} may have also improved algorithm performance.

For the ALG_{OSU}, an analysis of the RI and YP_O variables, components of the algorthim that require localized information, helps explain why it did not perform well when tested across a large region, a point of caution made by its developers (Raun et al., 2005, 2010). An estimated RI (Eq. [9]) using the comparison of NDVI from the target and N-reference corn was used to predict the N responsiveness of each location. Using this equation the average RI across sites was 1.2. However, the actual RI as calculated by dividing the EONR yield by yield with no N applied was 2.0. These two different RI values were weakly

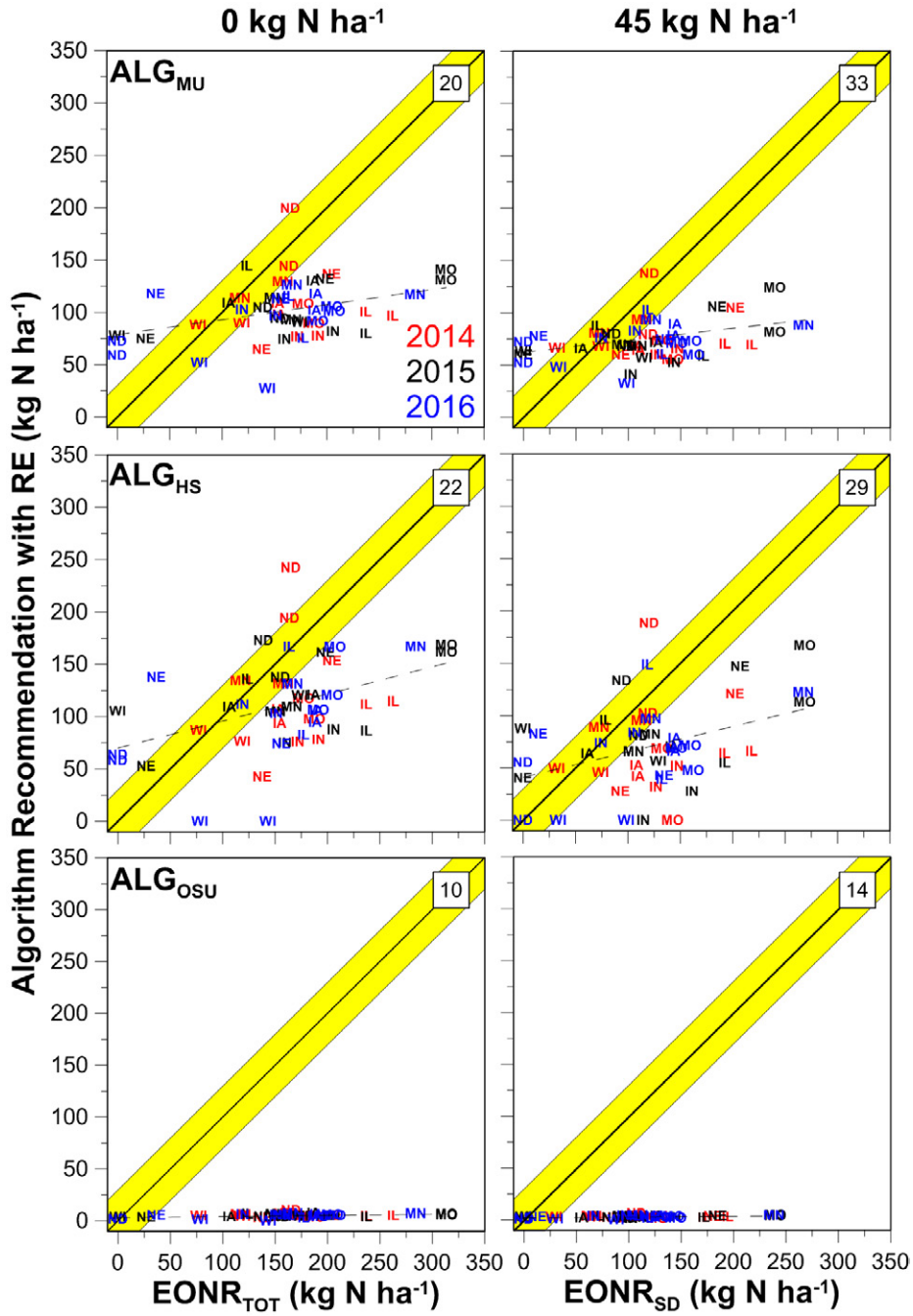

Fig. 7. Performance of three active-optical reflectance sensor algorithms (University of Missouri, ALG_{MU}; Holland-Schepers, ALG_{HS}; Oklahoma State University, ALG_{OSU}) shown by comparing the algorithm recommendation relative to calculated end-of-season economic optimal N rate (EONR), where $EONR_{Tot}$ is the total EONR N amount and $EONR_{SD}$ is the sidedress EONR (difference between $EONR_{Tot}$ and N applied at planting). Results are for two different target corn at-planting N fertilizer rates (0 and 45 kg N ha^{-1}) using the red edge (RE) waveband. Sites near the 1:1 line dissecting the graphs suggest sensor algorithms were accurate in recommending EONR. Sites that fell within the yellow shaded region are those within 34 kg N ha^{-1} of EONR, and this is shown as a percentage of sites in the top right corner of each graph. Dashed lines represent a linear fit between algorithm recommendation and EONR.

related using linear regression ($r^2 = 0.20$). This underestimation of the RI using ALG_{OSU} partly explains the low recommendations of N fertilizer.

Additionally, a significant calculation when generating an N fertilizer recommendation using ALG_{OSU} is YP_O. Multiplied by the estimated RI, YP_O is used to determine the YP_N (Eq. [13]). Ultimately, the algorithm derived crop N fertilizer need is the difference in grain N uptake as calculated by a defined grain N concentration and yield response (i.e., RI) between YP_O and YP_N (Franzen et al., 2016). Because this algorthim's focus is on grain response and grain N only, it does not seem to account for the extra N that may be required for the vegetative growth needed to support the yield increase. Further, NUE is used to determine the final N fertilizer recommendation. The average ALG_{OSU} estimated YP_O across all sites was 6100 kg ha^{-1} while actual YP_O (yield with no N applied) was 7510 kg ha^{-1}; simple linear regression showed no relationship between these two ($r^2 < 0.001$). On average, the algorithm YP_O was 19% below the measured YP_O for this study. Although the YP_O equation used in this analysis

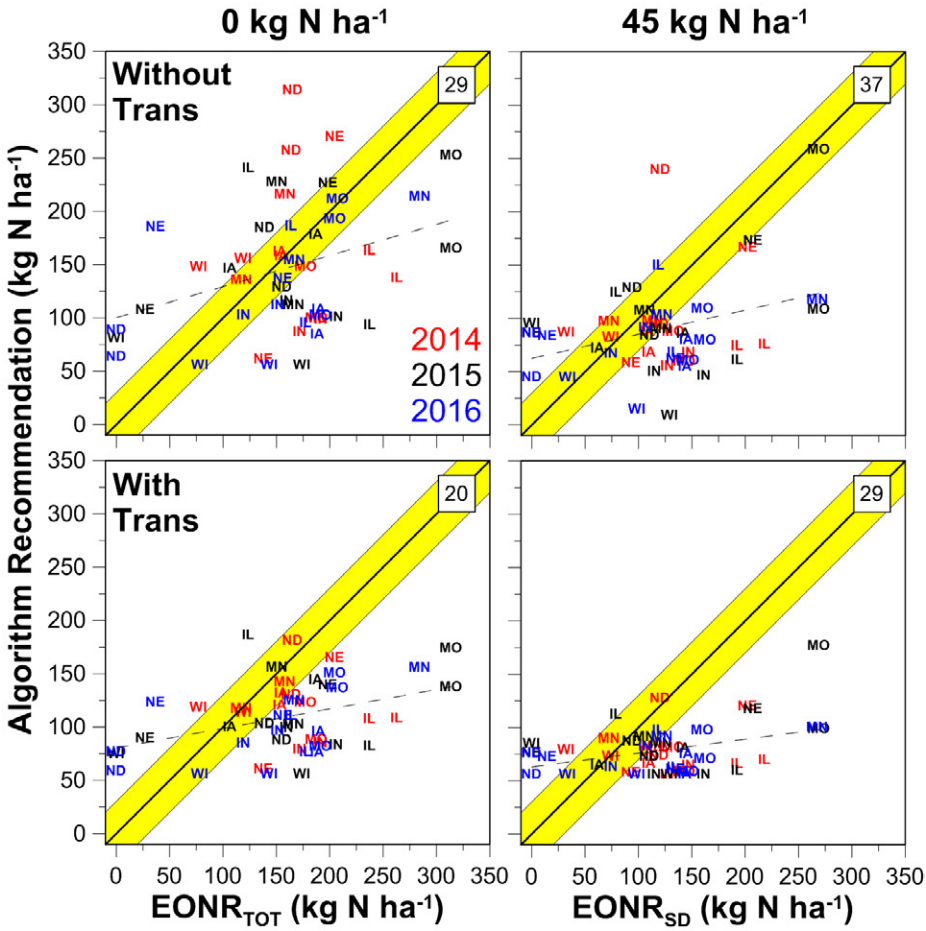

Fig. 8. Performance of the University of Missouri algorithm (ALG_{MU}) with and without the reflectance transformation described by Eq. [3]. Sites near the 1:1 line dissecting the graphs suggest sensor algorithms were accurate in recommending the calculated end-of-season economic optimal N rate (EONR). Sites that fell within the yellow shaded region are those within 34 kg N ha^{-1} of EONR, and this is shown as a percentage of sites in the top right corner of each graph, where $EONR_{Tot}$ is the total EONR N amount and $EONR_{SD}$ is the sidedress EONR (difference between $EONR_{Tot}$ and N applied at planting). When the target corn received no N fertilizer at planting, the algorithm recommendation without reflectance transformation performed worse than the algorithm recommendation with reflectance transformation. Dashed lines represent a linear fit between algorithm recommendation and EONR.

(Eq. [12]) was labeled for US irrigated or rainfed corn production (Oklahoma State University, 2018), it was developed for corn grown in hot and dry conditions in Oklahoma, and was not necessarily intended to be used in the US Corn Belt region represented by this study. Because of the poor performance of the ALG_{OSU} when tested over the large geographic region in this study, it is clear site- or region-specific YP_O equations should be considered. Others have similarly stated localized information is needed to calibrate both ALG_{OSU} RI and YP_O equations (Raun et al., 2005, 2010; Arnall et al., 2013; Franzen et al., 2016). The NUE and grain N concentrations associated with the ALG_{OSU} used in this analysis are also input variables that could have been adjusted based on corn hybrid and site- or region-specific conditions. Additionally, research performed on 21 existing field trials throughout the state of Oklahoma found corn growth development stage greatly influenced the prediction of YPo (Teal et al., 2006) and that AORS N management before V7 or after V9 was poor at predicting YPo. Therefore, ALG_{OSU} performance may have improved had sensing occurred earlier in the growing season.

Algorithm Sensitivity to Reflectance Transformation

For target corn that received no N at planting, improvements in ALG_{MU} performance were observed between using transformed and not transformed reflectance measurements (Eq. [3]; Table 2). The percentage of sites within 34 kg N ha^{-1} of EONR was 29% without transformation and 20% with transformation (Fig. 8), whereas RMSE values were within 4 kg N ha^{-1}. Likewise, when target corn received 45 kg N ha^{-1} at planting, reflectance without transformation performed better than with transformation. Percentage of sites within 34 kg N ha^{-1} of EONR was 37% without transformation and 29% with transformation. At the same time RMSE values with and without transformation were within 1 kg N ha^{-1}. There is no clear explanation for these mixed results on the effect of reflectance transformation.

For $ALG_{OSU,}$ reflectance transformation (Eq. [15]) on both 0 and 45 kg N ha^{-1} target corn performed similarly (analysis not shown). The results indicated the ALG_{OSU} is much less sensitive to reflectance transformation than ALG_{MU}. This is not surprising because the construction of the two algorithms is unique. The ALG_{MU} is solely reliant on gathered reflectance

data (Eq. [2]), but the ALG_{OSU} relies on a number of additional inputs, such as NUE, GDD, and grain N content (Eq. [9]–Eq. [14]).

Impact of Soil and Weather Conditions

At several sites, precipitation before and following sensing was excessive and frequent. For example, the 2015 Missouri LoneTree (claypan soil) site received more than twice as much precipitation as the 2014 Missouri Bay (claypan soil) site. Excessive precipitation on claypan soil creates an environment for significant surface runoff and denitrification because of surface soil saturation (Blevins et al., 1996). Nitrogen loss before sensing may be captured and corrected by canopy sensing, but post-sensing N loss cannot be accounted for unless another sensing is made later in the season. Extreme conditions of this type undoubtedly will result in insufficient N fertilizer recommendations when using mid-vegetative AORS (see 2015 Missouri sites in Fig. 5).

Unless expressed by the reflectance properties of the crop, the algorithms assessed do not account for weather factors and how they affect crop N need (exception is GDD with ALG_{OSU}). Others (Tremblay et al., 2012; Xie et al., 2013) have shown weather conditions and soil properties had profound effects on corn yield response to applied N. Including such information could potentially help improve using AORS for making N recommendations.

CONCLUSIONS

The goal of this research was to apply AORS data gathered at a regional scale (US Midwest Corn Belt) to three algorithms developed from differing geographic areas and evaluate their utility over a larger region than from which they were initially developed. Under these conditions, all three algorthims performed poorly. Generally, ALG_{MU} and ALG_{HS} underestimated EONR less (median range −43 to −98 kg N ha^{-1}) than the ALG_{OSU} (median range −96 to −136 kg N ha^{-1}). The algorithms performed best when the difference between target corn reflectance was detectable. This reinforces the principle that for AORS to work well as a tool for determining how much in-season N fertilizer to apply, crop N deficiency needs to be detectable and reflect season-long plant N requirement. However, it should be noted if N stress becomes too extreme, yield may not be recoverable. If plant N need is not detected when comparing reference and target corn (either as differences in color, biomass, or both) then using AORS alone is insufficient to determine adequacy or N fertilization need. Even so, expressed deficiency may or may not be found over a whole field. Others have shown that crop N status at the time of sensing and sidedressing is often spatially variable within the same field, ranging from insufficient to sufficient (Scharf et al., 2005; Kitchen et al., 2010). Use of AORS within fields showing spatially variable N need is particularly effective (Scharf et al., 2011).

This research demonstrated that AORS algorithms developed locally (i.e., within a US state) often will not perform well when its use is scaled to reach a greater region than the data used to develop the algorithm originally included. This outcome demonstrates that for an algorithm to be utilized over a broad region, development would be best if done employing datasets that give context representing the range of soil and weather conditions. For example, if the dataset used in this analysis was employed to derive new YPo and RI relationhsips specific to the area in this study, ALG_{OSU} performance may have improved. Likewise, if the N_{COMP} and MZ_i were implemented, the ALG_{HS} may have performed better. The ALG_{MU} has no like variables, and therefore performance was fixed. Findings here also demonstrated that the AORS type (make and model) and waveband used does impact algorithm N fertilizer recommendations. As such, algorithms developed using a specific sensor and waveband need to communicate that dependency to those users of the technology.

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