Utilizing Weather, Soil, and Plant Condition for Predicting Corn Yield and Nitrogen Fertilizer Response

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Abstract. *Improving corn (Zea mays L.) nitrogen (N) fertilizer rate recommendation tools should increase farmer's profits and help mitigate N pollution. Weather and soil properties have repeatedly been shown to influence crop N need. The objective of this research was to improve publicly-available N recommendation tools by adjusting them with additional soil and weather information. Four N recommendation tools were evaluated across 49 N response trials conducted in eight U.S. states over three growing seasons. Tools were evaluated for split (planting+side-dress) fertilizer applications. Using an elastic net algorithm the difference between each tool's N recommendation and the economically optimum N rate (EONR) was regressed against soil and weather information, then the elastic net regression coefficients were used to adjust the tool's N recommendation. The evenness of rainfall calculated from planting to the date of sidedness and soil pH (0-0.30 m) were the most frequently identified parameters for adjusting tools. All tools showed improvement with adjustment (+$r^2 \geq 0.09$). The greatest improvement in tool performance was with including soil and weather information with the Late-Spring Soil Nitrate Test (LSNT), canopy reflectance sensing, and MRTN. This analysis demonstrated that incorporating soil and weather information can help improve N recommendations.*

Keywords. *Canopy Reflectance Sensing, Nitrogen Recommendation Tools, MRTN, Yield Goal*

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Introduction

To maximize profits and minimize environmental issues associated with corn N management, N fertilizer at rates close to the EONR are needed (Hong et al. 2007; Kyveryga et al. 2009; Bandura 2017). However, crop N need for any given growing season is not well known at the time of N application. Moreover, EONR has been shown to vary considerably within a field and from year-to-year making EONR challenging to estimate (Kyveryga et al. 2009; Scharf et al. 2005; Shanahan et al. 2008). Both the spatial and temporal variability of EONR are driven by environmental, genetic, and management factors. More specifically rainfall distribution, soil texture, soil water-holding capacity, plant genetics, management practices, and grain and fertilizer prices have been shown to influence EONR (Dinnes et al. 2002; Kay et al. 2006; Morris et al. 2018; Schmidt et al. 2009; Tremblay et al. 2012; Zhu et al. 2009). Many of the current methods used to determine how much N fertilizer to apply do not account for many of these factors.

Some publically-available N recommendation tools have been developed that incorporate aspects of management, soil, and weather factors. A few examples include the yield goal (YG) method which when adjusted with a soybean (*Glycine max*) credit if the previous crop was soybean (Stanford 1973). Other YG based methods have also included an estimate of N mineralized by organic matter or a measure of soil nitrate (NO_3–N) before N fertilizer application (Brown et al. 2004; Shapiro et al. 2008). The Pre-Sidedress Nitrate Test or LSNT indirectly measures in-season mineralization and a sufficient N threshold is adjusted based on spring precipitation (Blackmer et al. 1997). The MRTN incorporates multiple yield response studies grouped on geographical boundaries, soil texture, and climatic conditions to better account for spatial and temporal variability (Sawyer et al. 2006). Canopy reflectance sensing assesses the color and biomass of corn plants at a very short spatial scale to integrate the plant and soil N status into an N recommendation (Kitchen et al. 2010). Even though these tools indirectly or directly incorporate some aspect of management, soil, and weather into their N recommendation process, these tools have often been found to be poorly related with EONR when examined across the U.S. Corn Belt (Ransom 2018), and therefore may not be reliable for making N fertilizer recommendations over the whole region.

Incorporating additional soil and weather factors could improve N recommendation tools. Previously the incorporation of various weather and soil variables and their interactions improved the relationship of a canopy reflectance sensing derived N recommendation to EONR from an r^2 of 0.14 to 0.43 (Bean et al. 2018). Others showed that including soil-specific information with a pre-plant soil test significantly improved the predictability of optimal N rate (r^2 = 0.92; Vanotti and Bundy 1999).

The objective of this research was to determine if site-specific soil and weather information could improve N recommendation tools.

Materials and Methods

Experimental Design

This research was conducted as a part of a public-private collaboration between DuPont Pioneer and eight U.S. Midwest universities (Iowa State University, University of Illinois Urbana-Champaign, University of Minnesota, University of Missouri, North Dakota State University, Purdue University, University of Nebraska-Lincoln, and University of Wisconsin-Madison). Each state conducted research at two sites each year during 2014 to 2016, with a third site in Missouri in 2016, totaling 49 site-years. About half the sites were on farmers' fields and the other half on University research stations. All states followed a similar protocol for plot research implementation including site selection, weather data collection, soil sample timing and collection methodology, N application timing, N source, and N rates. Specific details are described in Kitchen et al. (2017). Treatments included N fertilizer rates between 0 and 315 kg N ha^{-1} applied either all at-planting or split where 45 kg N ha^{-1} was applied at-planting with the remaining fertilizer N applied at the

V9 corn developmental stage.

Determining the Economically Optimal Nitrogen Rate

Grain yield in response to N fertilizer rate was used to calculate the EONR on a site-year basis as described in Kitchen et al. (2017), using proven quadratic or quadratic-plateau modeling methods (Cerrato and Blackmer 1990; Scharf et al. 2005). For this paper, EONR values were used for N fertilizer split applied between planting and a single side-dress application. The cost of N was \$0.88 kg $N^{-1,}$ and the price of corn was \$0.158 kg $grain^{-1}$ (equivalent to \$0.40 lb N^{-1} and \$4.00 bu^{-1}). The EONR was set to not exceed the maximum N rate (315 kg N ha^{-1}). The EONR results were used as the standard for evaluating all N recommendation tools and adjustments to the tools.

Nitrogen Recommendation Tools Evaluated

State-Specific Yield Goal

Though currently most states in this study now discourage using yield-goal based N fertilizer recommendations, however such was considered here using each state's guidelines from several decades ago. A State-Specific YG tool was evaluated where sites within each state only used their respective state's YG method, but the overall performance of each YG recommendation was evaluated as a single tool. All states except Wisconsin (WI) at one point in time utilized a YG, as such all but the WI sites are included in the State-Specific YG analysis (n =43). All YG methods followed a similar mass balance approach established by Stanford (1973), but each has been uniquely modified by adjusting coefficients within the calculation and incorporating additional soil and management information. For example, the Nebraska YG was changed by incorporating pre-plant soil nitrate to a depth of 1.20 m.

Each state-specific YG required an expected yield. The previous five-year corn yield average of the county for each site was used to determine expected yield for individual sites. The five-yr average was then adjusted based on the soil productivity of the predominantly-mapped soil of each site, similar to that done by Laboski et al. (2012). This procedure classifies soil productivity as either low, medium, or high using soil texture, irrigation, depth to bedrock, drainage class, temperature regime, and available water content information. The yield of a site was then calculated by increasing the five-yr average yield for low, medium, and high soil productivity by 10, 20, or 30%, respectively. This estimated yield value was used to calculate the State-Specific YG (Table 1).

MRTN

The MRTN recommendation values for all sites were determined by using N rate obtained in 2016, as only a few states had updated the MRTN database during the three years of this project. The MRTN values for IA, IL, IN, MN, and WI were obtained from the online Iowa State Extension N rate calculator (cnrc.agron.iastate.edu). The MRTN values for North Dakota were obtained from the North Dakota Corn Nitrogen Calculator (www.ndsu.edu/pubweb/soils/corn). The price of corn to N fertilizer ratio used was 10:1 (using \$/bu and \$/lb N). Since neither Missouri nor Nebraska currently have the compiled database and online tool for an MRTN recommendation, sites from these states were excluded from this tool's evaluation (n=36).

Late-Spring Nitrate Test

The LSNT was developed out of IA and evaluated under conditions where no or minimal N was applied at-planting. For this calculation a site average of measured NO_3–N from plots that received 0 kg N ha^{-1} at-planting was used. Soil samples were taken at the V5 ± 1 corn development stage and to a depth of 0.30 m. The measured concentration of NO_3–N was then used as described in Table 1 for determining an N recommendation.

Canopy Reflectance Sensing

Canopy reflectance measurements were obtained using the RapidSCAN CS-45 (Holland

Scientific, Lincoln NE, USA) the same day or just prior to the split N application. For the majority of sites, this was done at the V9 ±1 corn development stage. Measurement details are described in Kitchen et al. (2017). The Holland and Schepers algorithm [HS; Holland and Schepers (2010)] was used to calculate an N fertilizer recommendation derived from these reflectance measurements. This algorithm is based on a sufficiency index calculated using measurements from both well-fertilized corn ("N-Rich") and minimally-fertilized corn that was referred to here as the "target" corn:

$$SI = \frac{VI_{Target}}{VI_{N-Rich}} \qquad [1]$$

where SI is the sufficiency index; VI_{Target} is the NDRE vegetative index obtained from averaging measurements from all plots that received 45 kg N ha^{-1} at-planting and where a top-dress fertilizer was to be applied, and $VI_{N\text{-}Rich}$ is the vegetative index obtained by averaging all plots for two of the high N treatments (225 and 270 kg N ha^{-1} applied all at-planting). The NDRE vegetative index was calculated using the red-edge (730 nm; RE) and near-infrared (780 nm; NIR) wavelengths as shown:

$$NDRE = \frac{NIR-RE}{NIR+RE} \qquad [2]$$

Fertilizer N recommendations were then calculated as described in Holland and Schepers (2010).

Table 1. Methods associated with corn N recommendation tools included in this investigation. Variables used in calculations are Pop as plant population, OM as organic matter, and CEC as cation exchange capacity.

Tools	Approach & Calculation	Reference
Iowa YG	Calculation using an expected yield and a soybean credit equal to the previous year yield up to 56 kg N ha^{-1}. *IA YG = 1.12 × [1.22 × YG] or 1.12*† *× [0.9 × YG] for fine-silty Hapludolls – up to 56 kg N* ha^{-1} *soybean credit*	Voss and Killorn 1998
Illinois YG	Calculation using an expected yield and a soybean credit of 45 kg N ha^{-1}. $N_{rec} = 1.12^{\dagger} \times [1.2 \times YG - N_{credit}]$	Hoeft and Peck 1999
Indiana YG	Calculation using an expected yield and a soybean credit of 34 kg N ha^{-1}. $N_{rec} = 1.12^{\dagger} \times [-27 + 1.36 \times YG - N_{credit}]$	Vitosh et al. 1995
Minnesota YG	Calculation using an expected yield, organic matter content, and soybean credit of 22 to 45 kg N ha^{-1}. Soils are grouped into either low or high organic matter content with 30 g OM kg^{-1} soil being the threshold *(Table 1 of publication)*.	Schmitt et al. 2002
Minnesota YG	Calculation using an expected yield, plant population, and N supplying power of the soil based on organic matter and cation exchange capacity, and a soybean credit of 34 kg N ha^{-1}. $N_{rec} = 1.12^{\dagger} \times [0.9 \times YG + 4 \times Pop - N_{OM\text{-}credit} - N_{credit}]$	Brown et al. 2004
Nebraska YG	Calculation using an expected yield, measured or estimated inorganic soil $NO_3–N_{(0–1.20\ m)}$, measured or estimated N supplied from organic matter, and a soybean credit of 39 or 50 kg N ha^{-1}, for sandy and non-sandy soils, respectively. An estimated amount of N applied through irrigation is also credited. The N recommendation rate is adjusted for soil texture classification and time of N fertilizer application. $N_{rec} = 1.12^{\dagger} \times [35 + (1.2 \times YG) - (8 \times NO_3–N_{(0–1.20\ m)}) - 0.14 \times YG \times OM - N_{Credit}] \times Time_{adj} \times Price_{adj}$	Shapiro et al. 2008

North Dakota YG	The calculation is the measured soil NO_3–$N_{(0–0.60\ m)}$ concentration (converted to mass) subtracted from the ND YG calculation and using a soybean credit of 45 kg N ha^{-1}. $N_{rec} = 1.12^{\dagger} \times [1.2 \times YG - NO_3\text{–}N_{(0-0.60\ m)} - N_{credit}]$	Franzen 2010
LSNT	Calculated using measured soil NO_3–$N_{(0-0.30\ m)}$ concentration and a critical limit of 25 mg kg^{-}. To determine the N recommendation when NO_3–$N_{(0-0.30\ m)}$ is below the critical threshold, the difference between the critical threshold and the measured NO_3–$N_{(0–0.30\ m)}$ concentration is multiplied by 8. The critical limit is reduced by 3 to 5 mg kg^{-1} when spring precipitation is 20% above normal amounts. $N_{rec} = 1.12^{\dagger} \times [(25\ mg\ kg^{-1} - NO_3\text{–}N_{(0-0.30\ m)}\ mg\ kg^{-1}) \times 8]$	Blackmer et al. 1997; Sawyer and Mallarino 2017
MRTN	Nitrogen rate response trials spanning multiple years. From each trial, yield response is modeled as a function of N fertilizer rate and the N recommendation is determined by grouping trials and adjusting the price of corn and N. Nitrogen recommendations are specific for geographical locations or soil property.	Sawyer et al. 2006
Canopy Reflectance Sensing	Nitrogen recommendations are based on reflectance wavelengths measured with proximal sensors.	Holland and Schepers 2010

Incorporating Soil and Weather Information

First, linear regression was used to find significant ($p < 0.05$) one-way relationships between soil and weather properties and delta yield (yield at EONR - yield with no N) and relative yield or response index (yield at EONR/yield with no N) were examined using the PROC REG function in SAS 9.2. The top four most significant variables were then used in a stepwise PROC GLMSELECT model ($p < 0.05$). This modeling approach is a "leave one out" method to minimize model bias when a site is dissimilar from the rest. Final model results for both the delta yield and relative yield analyses were then used for the remainder of this paper.

Second, to determine what soil and weather information was to be incorporated for tool adjustment, an elastic net regression (Zou and Hastie 2005) was used with soil and weather variables as the explanatory variables. The response variable of this regression was the difference between each tool's N recommendation and the EONR for each site as follows:

$$Tool_{Diff} = Tool_{N\ Rec} - EONR \qquad [3]$$

where EONR was calculated using split N treatments. The EONR values calculated from split N treatments were compared to MRTN, State-Specific YG, LSNT, and canopy reflectance sensing. Explanatory variables included measured physical and chemical soil properties and measured weather information. Soil properties were collected by sampling 1.20 m-depth soil cores from each of the sites and analyzing by pedological soil horizon for texture, bulk density, pH salt, pH water, CEC, total N, total carbon, inorganic carbon, organic carbon, and organic matter as described in Kitchen et al. (2017). Soil properties were then depth weighted to obtain values for 0-0.30, 0-0.60, and 0-0.90 m depth increments. Weather data were collected using on-site weather stations (HOBO U30 Automatic Weather Station; Onset Computer Corporation, Bourne, MA). Daily values were calculated for the maximum and minimum temperature and precipitation. These values were then used to calculate a cumulative precipitation, growing degree days, corn heat units, Shanon's diversity index of precipitation (evenness of rainfall), and abundantly and well-distributed rainfall as described by Tremblay et al. (2012), for two time periods, 30 days before planting up to planting and from planting to the time of sidedress (Table 2).

Many of these variables were highly correlated ($|r| > 0.85$). To minimize multicollinearity, the explanatory variables with the highest mean absolute pair-wise correlation value were removed from the model (remaining variables used in models are shown in Table 2). This procedure was automated by using the findCorrelation function from the R 'caret' package (Kuhn 2017). Using the reduced number of variables, two models were created with and without two-way interaction terms for each N recommendation tool. All explanatory variables were normalized before running the model by subtracting the mean and dividing by the standard deviation.

The elastic net was fit with the 'caret' package using R Statistical Software (R Core Team 2016). The elastic net was optimized by tuning the alpha and lambda parameters using a tenfold cross-validation repeated five times, where for each fold of the cross-validation the data was split randomly into ten folds. Nine of the folds were selected as a training dataset to fit a model for each combination of alpha and lambda tuning parameters and the 10th fold was used as the testing dataset to calculate the accuracy of the predicted model. This was repeated a total of 50 times and the accuracy for each combination of tuning parameters was determined using the average root-mean-square error (RMSE) across these 50 folds.

Table 2. Variables inputs used in the elastic net algorithm modeling.

Parameter	Calculation
Weather	
PPT (Side-dress†)	Sum of daily rainfall, mm.
Corn Heat Units (Side-dress)	Σ(Ymax + Ymin)/2; Ymax and Ymin are the daily maximum and minimum temperatures, °C.
GDD (Planting‡)	Σ((Ymax + Ymin)/2)-T_{base}; Ymax, Ymin, T_{base} are the daily maximum, minimum, and base temperatures, respectively. T_{base} = 10°C.
SDI (Planting)	[-Σpi ln(pi)]/ln(n); where pi = Rain/PPT (daily rainfall relative to total rainfall in a given time; n = total number of days.
SDI (Side-dress)	
AWDR (Planting)	Side-dress SDI × PPT
Soil	
Clay	Clay depth weighted between 0 and 0.90 m
Silt	Silt depth weighted between 0 and 0.60 m
Total carbon (TC)	Total C depth weighted between 0 and 0.60 m
Total inorganic C (TIC)	Inorganic C depth weighted between 0 and 0.30 m
Organic matter (OM)	Organic matter depth weighted between 0 and 0.90 m
pH (Water)	Soil pH depth weighted between 0 and 0.30 m
Bulk Density (BD)	Bulk density depth weighted between 0 and 0.30 m

† SIDE-DRESS indicates data used from the date of planting up to the date of sidedress
‡Planting indicates data used 30 days prior to planting up to the date of planting

Statistics Analysis

Final models with all the essential variables and corresponding coefficients were used to adjust each N recommendation tool as follows:

$$Tool_{adj} = Tool - \text{Model } Parameters \quad [5]$$

Each adjusted tool was then compared to EONR as described in Eq. 5 to determine if performance of the tools was improved. This was accomplished by calculating 1) a coefficient of determination, 2) an RMSE for each adjusted tool using the difference between each tool's adjusted N recommendation and EONR, and 3) the percentage of sites within ± 30 kg N ha^{-1} of EONR, or reasonably close to EONR (RC-EONR).

Results

Which Soil and Weather Variables Were Found to be Important?

Yield increase with N (Fig. 1) and a yield response index to N (Fig. 2) were examined as a function of soil properties and weather. While a number of soil and weather parameters helped explain corn response to N (not shown), those included in these two graphs were some of the most meaningful. Yield increase with N was greatest as canopy reflectance SI (Eq. 1) decreased, with soils with less clay in the top 0-0.60 m, and with soils with lower PMN (Fig. 1). As a yield response index to added N (Fig. 2), response was greatest with lower red-edge canopy reflectance SI, when the ratio of shallow to deep Veris 3100 apparent soil electrical conductivity (EC_a) readings were lower, and when rainfall from planting to side-dress SDI was more even. The trends in these figures follow well-known agronomic science: 1) relative to well N fertilized plants, plants with less biomass and/or greenness are more N deficient and require more N and produce a greater yield response (SI); 2) less clay means sandier soils and a greater propensity for N leaching or natively have less OM and therefore less N is mineralized, resulting in a greater need for N; 3) soils that provide more N through mineralization need less N fertilizer; 4) layered soils with lighter textured horizons over heavier textured horizons (soil EC_a shallow:deep < 1.0) respond less to N; and 5) more evenly distributed rainfall (higher SDI) results in greater response to N fertilizer. These results demonstrate how soil properties, weather, and plant condition (as measured with canopy reflectance) collectively help describe corn N response over a wide range of environmental conditions. As such, N recommendation tools that don't include these factors will more likely fail.

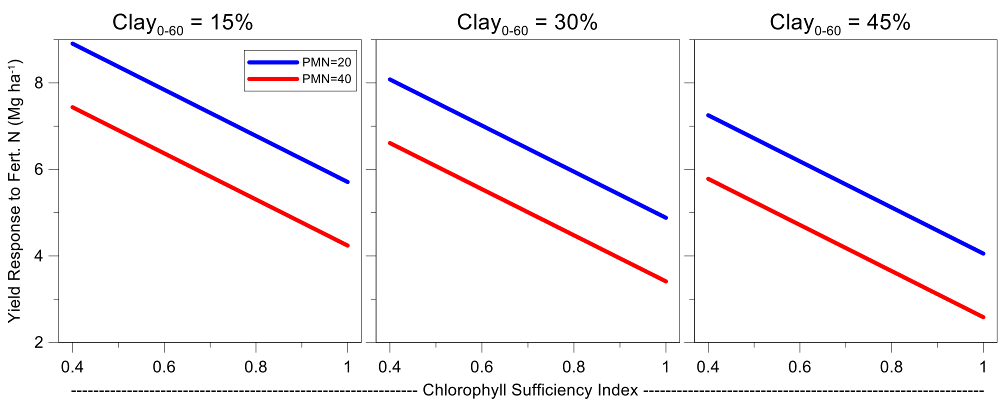

Figure 1: Yield increase to N fertilizer was impacted by canopy reflectance chlorophyll sufficiency index (red band), clay content, and potential mineralizable N (PMN) (model R^2=0.31).

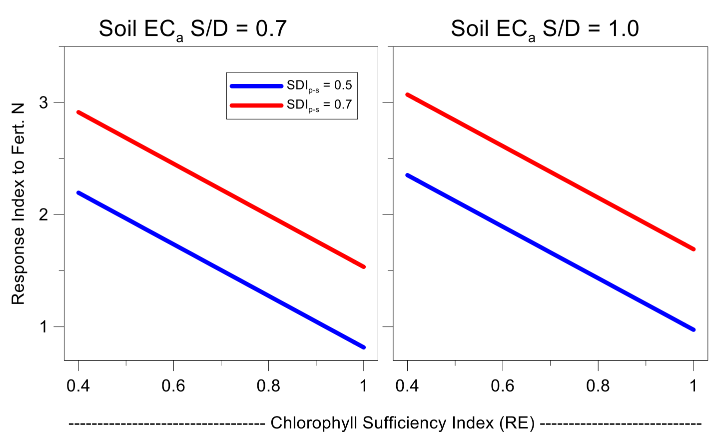

Figure 2: Yield response index to N fertilizer was impacted by canopy reflectance chlorophyll sufficiency index (red-edge band), the ratio of Veris 3100 apparent soil electrical conductivity (ECa) shallow readings to deep readings, and rainfall SDA (planting to side-dress) (model R^2=0.43).

Integrating Weather and Soil into N recommendation Tools

Using elastic net regression, the variables found to be important for explaining the difference between each N recommendation tool and EONR varied by tool (Table 3). Of the weather variables, the SDI was found to be an essential variable for adjusting all four tools.

Table 3. Coefficients of weather and soil parameters used to adjust N recommendation tools that were determined important using the elastic net regression. (See Table 2 for explanation of variable names.)

Tool	Parameter Adjustments
$MRTN_{adj}$=	**MRTN** + 90.7 + 162.9 *Side-dress SDI* - 31.6 *pH30*
State-Specific YG_{adj} =	**State-Specific YG** - 203.5 + 287.5 *Side-dress SDI*
$LSNT_{adj}$ =	**LSNT** - 5.2 + 22.7 *Planting SDI* + 157.5 *Side-dress SDI* - 2.0 *OM30* - 12.1 *pH30* + 19.8 *BD30* - 0.2 *Silt60* - 11.2 *TC90*
Canopy $Reflectance_{adj}$ =	**Canopy Reflectance** - 58.0 + 70.0 *Planting SDI* + 144.9 *Side-dress SDI* - 20.9 *TIC30* - 10.9 *pH30* + 57.8 *BD30* - 0.1 *Silt60* - 0.8 *Clay90* - 5.8 *TC90*

Not surprisingly, SDI was one of the most important variables as precipitation-based measurements often have a bigger impact on N fertilizer response and EONR calculations than soil parameters (Sogbedji et al. 2001; Tremblay et al. 2012; Sela et al. 2017). Precipitation is a major driving factor for soil organic matter mineralization, yield potential, NO_3–N leaching losses, and N uptake (Cassman and Munns 1980; Schröder et al. 2000; Wilhelm and Wortmann 2004; Melkonian et al. 2007). The SDI helped explain 22% of the variation ($P < 0.001$) in the observed EONR values. This is similar to what Xie et al. (2013) reported, that SDI of precipitation and not precipitation alone better-explained corn response to sidedressed N fertilizer. This relationship could be explained by an increased N loss, decreased plant N uptake, or a reduced soil N supply. With increased SDI, the soil moisture would be maintained at a higher level over an extended period leading to possible soil surface runoff, N leaching, or denitrification (Maag and Vinther 1996). The general trend observed among the sites of this study showed the smallest SDI values were from the northwestern locations (North Dakota) and generally increased to the southeast, similar to the long-term rainfall trend seen for the U.S. Midwest.

Of all the soil parameters that were used in the final model, pH (0-0.30 m) was the most frequently identified as important (Table 3). The pH across all sites ranged from 5.5 to 7.8. As pH increased, the difference between a tool's N recommendation and EONR increased. Soil pH affects soil fertility and drives many factors of the N cycle. The pH of a field was found to commonly be related to corn yield and protein factors across multiple growing conditions and hybrids (Miao et al. 2006). However, directly relating pH to EONR showed no significant relationship ($P = 0.13$). For this investigation, the pH was found to be greater for the northern sites, where soils were formed under drier and colder conditions, and therefore are less weathered soils with free calcium carbonates. Adjusting for pH was necessary for many of the northern sites such, as North Dakota and Wisconsin, where pH > 7.0. A few of these sites were non-responsive to added N fertilizer, suggesting the possible positive impact these pH values had on N mineralization when adequate organic matter was present. However, it is unlikely there is a direct causal relationship between EONR and pH, as the weather most likely drove the majority of N mineralization. This was observed with the 2016 ND sites that were both non-responsive to added N fertilizer. However, the ND sites in 2014 and 2015, conducted on the same or nearby fields with very similar soil pH, had EONR values that ranged between 100 and 180 kg N ha^{-1}.

Improving Performance of N Recommendation Tools

Incorporating soil and weather information into the N recommendation tools helped improve the tools. For all tools, the average difference between each tool's N recommendation and EONR all came closer to 0 (Fig. 3), and most RMSE values were decreased (mean overall tools of 75 vs. 56 for unadjusted vs. adjusted, respectively). Additionally, MRTN when unadjusted was not significant and positively related to EONR but after adjusting with soil and weather information has a significant and positive linear relationship with EONR.

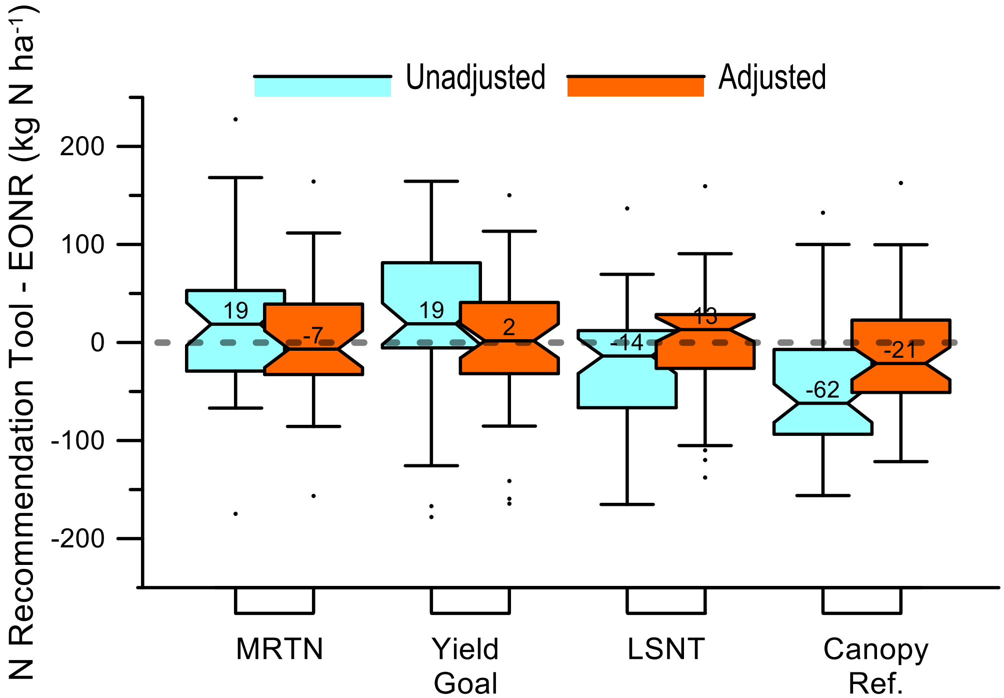

Fig. 3. Box and whisker plots showing the difference between each of the tools' N recommendation and the economically optimal N rate (EONR) after adjusting with soil and weather information. The median is reported by the value in the middle of the box. Notches on the side of each the box indicate the 95% confidence interval around the median. Limits of the box indicate the first and third quartile, whiskers indicate 1.5 × IQR, and small circles indicate outliers. Improvement is assessed by the decrease in the box and whisker length, and the box is centered on the zero line (dashed line).

The most critical metric for improvement was to have an increased linear relationship (r^2) with EONR (mean for all tools from r^2=0.12 to 0.29, unadjusted and adjusted respectively), followed by an increase in the percentage of sites RC-EONR (mean for all tools from 36 to 44% for unadjusted and adjusted, respectively; Table 4).

Of the four tools evaluated, MRTN had the most notable improvement based on the adjusted tools improved linear relationship with (r^2 increased 0.21; Table 4). When averaging across all sites, MRTN alone came close to EONR. However, because this tool unadjusted was unable to account for sites that were less responsive to N or sites which required high N rates (i.e., sites with excessive N loss), there was no significant linear relationship with EONR. Using weather and soil information helped to adjust for these extreme sites. Nitrogen recommendations for the MRTN where it overestimated EONR were decreased based on sites characterized by a higher pH and a lower side-dress SDI. Whereas sites where MRTN underestimated EONR, the recommendation increased. Sites where the adjustment increased the MRTN recommendation had lower soil pH and a higher side-dress SDI (Table 3). After adjusting for soil and weather information, MRTN showed a greater range of N rate recommendations of 80 to 240 kg N ha^{-1}.

Utilizing a yield goal approach often results in overestimating the amount of N required, one of the limitations of this method is farmers can often be over-optimistic (Vanotti and Bundy 1994). This was observed with the State-Specific YG tool, which was the only tool where the majority of sites overestimated EONR. After adjusting with side-dress SDI, 41 of the 43 sites resulted in a decreased N recommendation. Side-dress SDI values ≥ 0.71 increased in the N recommendation, but with 41 of the 43 sites having side-dress SDI value ≤ 0.71 the majority of sites were reduced.

Of these tools, the best-adjusted tool was the LSNT, where the adjusted tool's r^2 was 0.39, and the percentage of sites RC-EONR was 55% (Table 4). Unadjusted the LSNT had an r^2 of 0.24, the highest of all the tools. Unlike MRTN, the LSNT was successful at identifying when some sites would be less responsive and thus were more successful without adjustment. With adjustment, the most improvement occurred with sites where the LSNT underestimated EONR, which after incorporating side-dress SDI into the recommendation increased N closer to EONR.

Adjusting the Holland and Schepers canopy reflectance sensing algorithm with soil and weather information helped to improve the predictability of EONR, from an r^2 of 0.13 up to 0.36 (Table 4). This method for determining an N recommendation is unique in that it quantifies the plant's color and biomass using specific reflectance wavelengths to estimate a plant's N status. The conclusion here is that soil and weather information provided an estimate of N that was lost, but that this loss was not evident in the reflectance properties of the crop at the time of sensing. The soil and weather adjustment resulted in a general increase in the recommendation over all EONR values. As such, sites with low EONR values without adjustment had even greater over-recommendation with adjustment.

Table 4. The performance of each N recommendation tool unadjusted and adjusted with soil and weather information as presented in Table 3. The precision and accuracy were evaluated using the coefficient of determination measured from a simple linear relationship between each tool and the economically optimal N rate (EONR), RMSE of the difference between a tool's N recommendation and EONR, and the percentage of sites with ±30 kg N ha^{-1} of EONR or "reasonably close to EONR" (RC-EONR). The number of sites (n) included in the evaluation differed for each tool based on the availability of information to test the tool. Tools used for a split N application recommendation included MRTN, State-Specific yield goal (YG), Late-Spring Soil Nitrate Test (LSNT), and canopy reflectance sensing using the Holland and Schepers algorithm.

N Recommendation Tool	n	*P*-Value	r^2	RMSE	RC-EONR
Unadjusted Tools				-kg N ha^{-1}-	--- % ---
MRTN	36	0.45	0.02	72	42
State-Specific YG	43	0.04	0.10	74	37
LSNT	49	<0.001	0.24	68	41
Canopy Reflectance	49	0.01	0.13	85	22
Adjusted Tools					
MRTN	36	<0.01	0.23	58	47
State-Specific YG	43	<0.01	0.19	64	37
LSNT	49	<0.001	0.39	56	55
Canopy Reflectance	49	<0.001	0.36	58	35

How Much Tool Improvement Is Possible?

Improvement using soil and weather information was observed for many tools, but tested over this 8-state, 3-season dataset improvements did not match what others have reported for some N recommendation tools. The Pennsylvania PSNT tested against EONR was found to have an $r^2 = 0.48$ (Schmidt et al. 2009). Utilizing a dataset from New York, Sela et al. (2017) showed that the Adapt-N crop growth model had an $r^2 = 0.56$. While Scharf et al. (2006) and Schmidt et al. (2009) in two separate investigations showed that chlorophyll meter derived N recommendations resulted in a strong linear relationship with EONR with r^2 values that ranged between 0.53 to 0.76. Using the same dataset as the current investigation, Bean et al. (2018) showed slightly better results when improving the University of Missouri canopy reflectance sensing algorithm using soil and weather information ($r^2 = 0.43$). One of the likely reasons for the more mediocre results in this analysis is that the tools and their adjustments were tested using a dataset that represented a large range in weather conditions unlike what the previous studies had (Kitchen et al. 2017). Most of these tools tested were developed or tailored from field research within a given U.S. state. It is perhaps unreasonable to expect tools developed in specific states to perform well across a broad region. However, to do so shows whether existing tools are robust enough to fit a wide array of environmental extremes for growing corn. These results would suggest they are not. Additional improvements may be needed with different types, and intensity of information in order produce better performing corn N recommendations that could be used more universally.

Conclusions

Efforts to improve N recommendation tools utilizing soil and weather information was successful. Many of the improvements occurred at locations that overestimated EONR as any adjustment was based on soil information, while sites that underestimated EONR were improved with weather information. Tools overestimated EONR when they did not take into account the potential soil N supply of a site. Tools underestimated EONR when conditions lead to excessive N loss or greater N mineralization; accounting for this with an evenness of rainfall was shown to be an effective adjustment. Both of these N dynamics were better accounted for by incorporating soil and weather information into the N recommendation tools' calculations.

The best adjustments occurred with tools that prior to being adjusted were able to identify non-responsive sites. This included the LSNT and the Holland and Schepers canopy reflectance sensing algorithm. After adjusting these tools, they had the highest linear relationship with EONR. In addition to these two tools, MRTN was greatly improved.

With all of these adjustments, however, many of these tools still had a weak linear relationship with EONR. This means the majority of the variability in EONR was not captured with N recommendation tools. Additional improvements could occur by incorporating other soil, weather, or management variables not included in this analysis that might better delineate N response. However, even with all the information one might collect up to the point of a sidedress application, it would only account for about 1/3 of the growing season. Therefore, N recommendations will only be useful as "predictions" or "forecasts" that can be used to estimate corn N needs for the rest of the growing season.

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