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Improving publicly available corn nitrogen rate recommendation tools with soil and weather measurements

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Abstract

Improving corn (*Zea mays* L.) N fertilizer rate recommendation tools is necessary for improving farmers' profits and minimizing N pollution. Research has repeatedly shown that weather and soil factors influence available N and crop N need. Adjusting available corn N recommendation tools with soil and weather measurements could improve farmers' ability to manage N. The aim of this research was to improve publicly available N recommendation tools with site-specific soil and weather measurements. Information from 49 site-years of N response trials in the U.S. Midwest was used to evaluate 21 rate recommendation tools for a single (at-planting) and split (at-planting + sidedress) N application. Using elastic net and decision tree algorithms, the difference between each tool's N recommendation and the economically optimum nitrogen rate (EONR) was modeled against soil and weather measurements. The model's predicted values were used to adjust the tools. Unadjusted the best performing tool had r^2 = .24; after adjustment, the best performing tool had r^2 = .57. Overall tool improvement was modest and sometimes required many

Abbreviations: AWDR, abundant and well-distributed rainfall; BD, bulk density; cEONR, reasonably close to economically optimal nitrogen rate; CHU, corn heat units; EONR, economically optimal nitrogen rate; GDD, growing degree days; LSNT, late-spring soil nitrate test; MRTN, maximum return to nitrogen; OM, organic matter; PPNT, pre-plant soil nitrate test; PPT, total precipitation; PSNT, pre-sidedress soil nitrate test; SDI, Shannon diversity index; SI, sufficiency index; TC, total carbon; TIC, total inorganic carbon; YG, yield goal

additional inputs. Using weather measurements (e.g., evenness of rainfall or abundant and well-distributed rainfall) helped increase N recommendations by accounting for N loss while soil measurements (e.g., pH and total C) helped decrease N recommendations when there was sufficient available soil N. This investigation showed that incorporating soil and weather measurements is a viable approach for improving corn N recommendation tools regionally; but even with adjustments, tools still have room for additional improvement.

1 | INTRODUCTION

Nitrogen management in cereal crop production seeks to maximize profits and minimize the risk of N losses that contribute to environmental issues. One key performance goal is to apply N fertilizer at rates close to the economically optimal nitrogen rate (EONR) (Bandura, 2017; Hong et al., 2007; Kyveryga et al., 2009). Yet EONR varies annually, and N recommendation tools do not consistently recommend rates close to the EONR (Ransom et al., 2020; Schmidt et al., 2009; Tao et al., 2018). Predicting EONR values at the time of an N application is difficult as EONR can differ within a field and from year to year (Kyveryga et al., 2009; Scharf et al., 2005; Shanahan et al., 2008). Both the spatial and temporal variability of EONR are driven by environmental (e.g., soil texture, soil water-holding capacity, and rainfall distribution), genetic (e.g., hybrid and stress tolerance traits), management practicies (e.g., N form, placement, timing, rate, previous crop, manure history), and their interactions (Dinnes et al., 2002; Kay et al., 2006; Moebius-Clune et al., 2013; Schmidt et al., 2009; Zhu et al., 2009).

Of all the N recommendation tools available, only the crop growth model approach integrates many of the genetic, environment, management factors, and their interactions (G x E x M) to make a site-specific N recommendation (Morris et al., 2018). But most crop growth model-based tools available to farmers require extensive parameter inputs, training (Puntel et al., 2018), or are commercially based (e.g., Adapt-N and Granular's Encirca Services) and require a service fee limiting their widespread adoption by farmers (Melkonian et al., 2008; Morris et al., 2018). Also, many of the publicly available recommendation tools consider only a few of the G x E x M factors. For example, canopy reflectance sensing uses visible and near-infrared wavelengths to estimate the N status of plants as a function of the plant's color and biomass (Kitchen et al., 2010). While canopy sensing works by integrating all abiotic and biotic factors that affect N status in the plant, it does not account for the potential soil N supply or conditions leading to N loss and plant N stress after the time of sensing. Other N recommendation tools were derived from empirical data across years, N rates, hybrids, and cropping systems but ignore the seasonal differential or complexity of G x E x M. These include soil nitrate tests (e.g., pre-plant nitrate test [PPNT], pre-sidedress nitrate test [PSNT], and late-spring nitrate test [LSNT]), and empirical-based models (e.g., yield goal-based recommendations [YG] and maximum return to nitrogen [MRTN]) (Morris et al., 2018).

A recent evaluation of 31 publicly available N recommendation tools showed that across eight states of the U.S. Midwest, no one tool performed exceptionally well across a wide range of growing conditions (Ransom et al., 2020). To improve these tools, additional G x E x M factors should be considered. One approach for improvement is to modify current N recommendation tools using site-specific soil and weather measurements. Soil and weather measurements correlate well with corn (*Zea mays* L.) response to N fertilizer (Tremblay et al., 2012) as they drive seasonal N mineralization and N losses. Using proven ensemble learning methods, multiple weak predictors (i.e., tools, soil, weather) could be combined for a more accurate prediction of EONR. One example of ensemble learning that was successful at improving a few N recommendation tools was boosting (Bean et al., 2018; McDaniel et al., 2020; Ransom et al., 2019). Boosting works as a forward adaptative model, where an initial model is improved by fitting a new function to the residuals of the prediction (e.g., difference between tool's recommendations and EONR). Using this method more publicly available N recommendation tools could be improved.

The primary objective of this investigation was to improve publicly available corn N rate recommendation tools by integrating soil and weather information. An expected outcome of this evaluation is identifying soil and weather measurements most helpful in improving recommendations. We expect that N recommendation tools will more accurately estimate EONR across the U.S. Midwest after accounting for site-specific soil and weather measurements.

2 | MATERIALS AND METHODS

2.1 | Experimental design

This research was conducted as a part of a public-private collaboration between Corteva Agriscience 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 on two sites each year from 2014 to 2016, with a third site in Missouri in 2016, totaling 49 site-years (Figure 1). 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 and plant sample timing and collection methods, plot dimensions, N application timing, N source, and N rates with specific details described in Kitchen et al. (2017). Treatments included four replications of ammonium nitrate fertilizer rates between 0 and 315 kg N ha^{-1} in 45 kg N ha^{-1} increments applied either in a single (at-planting) application or a split application to where 45 kg N ha^{-1} was surface broadcast at-planting and the remaining fertilizer N was broadcast at the V9 corn developmental stage (Abendroth et al., 2011).

2.2 | Determining the economically optimal nitrogen rate

Grain yield response to N fertilizer rates was used to calculate the EONR at each site by fitting a quadratic or quadratic-plateau to all four replicates (Cerrato & Blackmer, 1990; Scharf et al., 2005). Economically optimal N rate values were calculated for all N fertilizer applied in a single at-planting application (hereafter referred to as "single N application"), and N split applied between planting and a sidedress application (hereafter referred to as "split N application"). The cost of N was US\$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 capped at the maximum N rate (315 kg N ha^{-1}). For additional details refer to Kitchen et al. (2017). Five of the seven irrigated sites had N applied through irrigation between 1 and 53 kg N ha^{-1}, which was included in determining the EONR of those sites. For 19 of the 49 sites, the single and split EONR values were similar because the difference in return to N at EONR between N timings was within \$2.50 ha^{-1} (Bandura, 2017). Thus, for these sites the EONR used was the average of the two timings. The EONR results were used as the standard for evaluating the N rate recommendation tools used or developed in this study.

2.3 | Nitrogen recommendation tools evaluated

Publicly available corn N recommendation tools evaluated for improvement included only those that previously did not have a negative linear relationship with EONR (Ransom et al., 2020). The reason for this focus was because other research showed tools with a negative linear relationship with EONR were not substantially improved when modified with soil and weather information (Ransom et al., 2019). As such, tools included in this analysis (i.e., no or a positive linear relationship with EONR) are listed in Table 1. Tools were evaluated for a single (at-planting) and a split (at-planting + sidedress), when applicable, N application.

For a brief description of N recommendation tools' methodology see Table 1. Any additional steps or calculations used to determine a tool's N recommendation are found below.

Core Ideas

- Tested two methods for improving 21 different corn N recommendation tools.
- Majority of tools improved by incorporating weather and soil measurements.
- Best unadjusted tool had an r^2 = .24, with adjustments best tool had r^2 = .57.

2.4 | Yield goal

All yield goal (YG) tools required an expected yield. The expected yield for each site was determined using the average of the previous 5-yr county corn yields for the county where the site was located. The expected yield was then increased by 10, 20, or 30% for low, medium, and high productive soils, respectively. The soil productivity was determined using the site's predominantly mapped soil, similar to that done by Laboski and Peters (2012). This procedure classifies soil productivity as either low, medium, or high using soil texture, drainage class, depth to bedrock, available water capacity in the upper 1.50 m of soil, average growing degree days, irrigation, and artificial tile drainage.

2.5 | Soil nitrogen tests

For pre-plant soil nitrate test (PPNT) tools, soil samples were obtained in the spring before any N fertilizer applications. Ten cores were taken with a hand-probe and combined to represent each block to a depth of 0.90 m, separated in 0.30 m increments. Samples were air or oven-dried (≤32 ˚C) depending on the state within 12 h of sampling. If samples could not be immediately dried, they were frozen or refrigerated until samples could be dried and processed. Dried samples were crushed with a flail-type grinder, passed through a 2-mm

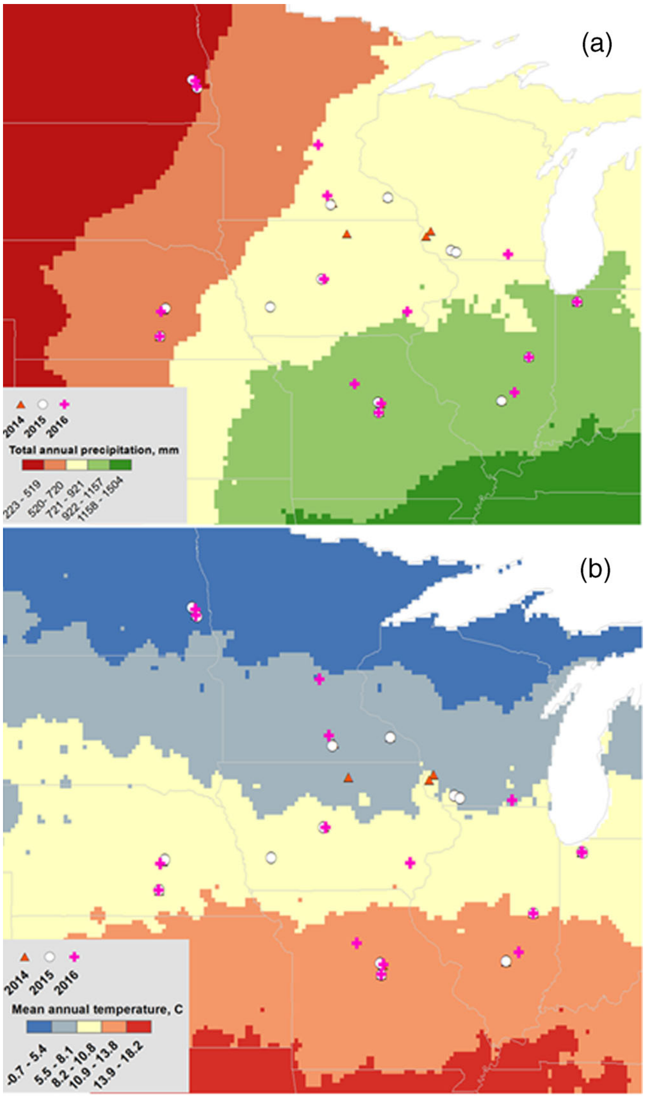

FIGURE 1 U.S. maps depicting the spatial distribution of (a) mean annual rainfall from the National Severe Storms Lab (NOAA), and (b) mean annual temperature. The location of the 49 study sites from 2014 to 2016 within the eight states Iowa, Illinois, Indiana, Minnesota, Missouri, Nebraska, North Dakota, and Wisconsin are also overlaid on each map. This figure was adapted from Kitchen et al. (2017)

sieve, and homogenized before sending to Agvise Laboratories for soil nitrate-N analysis. A 7.65-g soil sample was mixed with 19.13 ml of 0.2 M KCl, shaken for >5 min, filtered, and soil nitrate-N determined using the Cadmium Reduction method (Gelderman & Beegle, 1998) with a modified Technicon AutoAnalyzer (SEAL Analytical, Inc.). A site's soil nitrate-N was used in the PPNT tools' recommendations by averaging soil nitrate-N values of all four blocks. Two of the 49 sites lacked PPNT data, so this tool was tested using 47 of the 49 sites.

For pre-sidedress soil nitrate test (PSNT) tools, soil samples were obtained at the V5 ± 1 corn development stage (Abendroth et al., 2011) from plots that received either 0 or 45 kg N ha^{-1}. Each plot's soil sample was a composite of six cores taken with a hand-probe down to a depth of 0.60 m, separated in 0.30-m increments. The same sample preparation and analysis protocols were followed as described for the PPNT samples. Each PSNT/late-spring soil nitrate test (LSNT) tool was evaluated using a site average of measured nitrate-N from plots that received either 0 or 45 kg N ha^{-1} at planting. These are noted as PSNT/LSNT 0 and PSNT/LSNT 45, respectively.

2.6 | Maximum return to nitrogen

The maximum return to nitrogen (MRTN) recommendations for all site-years were determined by using values obtained in 2016, as only a few states had updated the MRTN database during the 3 yr of this project. The MRTN values for Iowa, Illinois, Indiana, Minnesota, and Wisconsin were obtained from the online Corn N Rate Calculator (cnrc.agron.iastate.edu; verified 5 Mar. 2017). The MRTN values for North Dakota were obtained from the North Dakota Corn Nitrogen Calculator (www.ndsu.edu/pubweb/soils/corn; verified 5 Mar. 2017). The price of corn/N fertilizer ratio used was 5.6:1 (US$ per kg grain and US$ per kg N) (or 10:1 using US$ and bushel or lb units). Since neither Missouri nor Nebraska had a compiled database supporting the MRTN approach, sites from these states were excluded ($n = 13$) from this tool's evaluation.

2.7 | Canopy reflectance sensing

Canopy reflectance sensing measurements using the RapidSCAN CS-45 (Holland Scientific) were collected concurrently with split N applications (i.e., ± 2 d of split N application). For most sites, this occurred at the ~V8–V10 corn development stage. Measurement details are described in Kitchen et al. (2017). The Holland and Schepers algorithm (HS) (Holland & Schepers, 2010) was used to calculate a N fertilizer recommendation derived from these reflectance measurements. This algorithm used a sufficiency index (SI) calculated with measurements from both well-fertilized corn ("N-rich") and minimally fertilized corn ("Target"):

$$SI = \frac{VI_{Target}}{VI_{N-rich}} \tag{1}$$

where SI is the sufficiency index; VI_{Target} is the vegetative index obtained by averaging measurements from all plots that received 45 kg N ha^{-1} at planting and where split fertilizer was to be applied, and $VI_{N\text{-}Rich}$ is the vegetative index obtained by averaging all plots of two high N treatments (225 and 270 kg N ha^{-1} applied all at planting). The NDRE

TABLE 1 Methods associated with corn N recommendation tools included in this investigation. The tools include the farmer's nitrogen rate (NR), yield goal (YG), pre-plant nitrate test (PPNT), late spring nitrate test (LSNT 0/45), and pre-sidedress nitrate test (PSNT 0/45) with 0 or 45 kg N ha^{-1} applied at-planting. Variables used in calculations include plant population (Pop), organic matter (OM), and cation exchange capacity (CEC)

Tools	Approach and calculation	Reference
Farmer's N rate	For sites on farmer's fields ($n = 25$), the farmers' historically applied N rate under normal corn-growing conditions were used. For sites at research stations ($n = 24$), the rate was identified by research station managers and was similar to that found on nearby production fields.	
State-specific YG	Sites within each state only used their respective state's YG method (shown below). The Wisconsin sites were excluded as no YG tool was available for Wisconsin.	
-IA YG	IA YG = 1.12[a] × [1.22 × YG] or 1.12 × [0.9 × YG] for fine-silty Hapludolls – up to 56 kg N ha^{-1} (50 lb N $acre^{-1}$) soybean credit	Voss and Killorn, 1988
-IL YG	IL YG = 1.12[a] × [1.2 × YG – N_{credit}] using a 40 lb N $acre^{-1}$ soybean credit	Hoeft and Peck, 1999
-IN YG	IN YG = 1.12[a] × [–27 + 1.36 × YG – N_{credit}] using a 30 lb N $acre^{-1}$ soybean credit	Vitosh et al., 1995
-MN YG	Calculation using an expected yield, organic matter content, and soybean credit of 22–45 kg N ha^{-1}. Soils are grouped into either low or high OM content with 30 g OM kg^{-1} soil being the threshold (Table 1 of Schmitt et al., 2002).	Schmitt et al., 2002
-MO YG	Calculation using an expected yield, plant population (plants $acre^{-1}$), and N supplying power of the soil based on OM and CEC. MO YG = 1.12[a] × [0.9 × YG + 4 × Pop – $N_{OM\text{-}credit}$ – N_{credit}] using a 30 lb N $acre^{-1}$ soybean credit	Buchholz et al., 2004
-NE 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 35 or 45 lb N $acre^{-1}$, 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.NE YG = 1.12[a] × [35 + (1.2 × YG) – (8 × NO_3–$N_{(0–1.20\ m)}$) – 0.14 × YG × OM – N_{credit}] × $Time_{adj}$ × $Price_{adj}$	Shapiro et al., 2008
-ND YG	ND YG = 1.12[a] × [1.2 × YG – NO_3–$N_{(0–\ 0.60\ m)}$ – N_{credit}] using a 40 kg N ha^{-1} soybean credit	Franzen, 2010
General PPNT	The calculation is the measured soil NO_3–$N_{(0–0.60\ m)}$ concentration (converted to mass) subtracted from MRTN[b].General PPNT = 1.12[a] × [MRTN[b] – NO_3–$N_{(0–0.60\ m)}$]	Bundy et al., 1999
MN PPNT	The calculation is 60% of the measured soil NO_3–$N_{(0–0.60\ m)}$ concentration (converted to mass) subtracted from MRTN[b].MN PPNT = 1.12[a] × [MRTN [b] – (0.60 × NO_3–$N_{(0–0.60\ m)}$)]	Kaiser et al., 2016
ND PPNT	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 40 lb N $acre^{-1}$.ND PPNT = 1.12[a] × [1.2 × YG – NO_3–$N_{(0–0.60\ m)}$ – N_{credit}]	Franzen, 2010
WI PPNT	Calculation using the measured soil NO_3–N concentration (converted to mass) in the top 0.90 m (sample taken down to 0.60 m and last 0.30 m is estimated) subtracted from MRTN[b]. To account for background soil NO_3–N 56 kg N ha^{-1} is subtracted from the total profile NO_3–N value.WI PPNT = 1.12[a] × [MRTN[b] – (ΣNO_3–$N_{(0–0.90\ m)}$ – 50)], no adjustments made if the sum of NO_3–N is below 56 kg N ha^{-1}.	Laboski et al., 2012

(Continues)

TABLE 1 (Continued)

Tools	Approach and calculation	Reference
General PSNT	MRTN or YG recommendation is adjusted proportionally based on if soil NO_3–$N_{(0–0.30\ m)}$ concentration is below 25 mg kg^{-1} and above 10 mg kg^{-1}. The full recommended rate is applied if the soil NO_3–$N_{(0–0.30\ m)}$ concentration is below 10 mg kg^{-1} and no additional N is applied if above 25 mg kg^{-1}.	Fernández et al., 2009
LSNT	Calculated using measured soil NO_3–$N_{(0–0.30\ m)}$ concentration and a critical limit of 25 mg kg^{-1}. 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.LSNT = 1.12[a] × [(25 mg kg^{-1} – NO_3–$N_{(0–0.30\ m)}$ mg kg^{-1}) × 8]	Sawyer and Mallarino, 2017
IN PSNT	Calculation using yield goal and soil NO_3–$N_{(0–0.30\ m)}$ concentration (Table 2 of Brouder and Mengel, 2003).	Brouder and Mengel, 2003
WI PSNT	A soil N credit is calculated based on soil NO_3–$N_{(0–0.30\ m)}$ concentration and on the yield potential of the soil. No N application is recommended if the measured soil NO_3–$N_{(0–0.30\ m)}$ concentration is above 21 mg kg^{-1}. No N credits are applied if the soil NO_3–$N_{(0–0.30\ m)}$ concentration is below 10 mg kg^{-1}. (Table 6.6 of Laboski et al., 2012)	Laboski et al., 2012
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 for the price of corn and N. Nitrogen recommendations are specific for a geographical location 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

[a]1.12 was used to convert N recommendations from lb N $acre^{-1}$ to kg N ha^{-1}.
[b]MRTN values were used unless states did not recommend MRTN, in which case that state's yield goal calculation was used.

vegetative index was calculated using the red-edge (730 nm; RE) and near-infrared (780 nm; NIR) wavelengths as shown:

$$\mathrm{NDRE} = \frac{\mathrm{NIR} - \mathrm{RE}}{\mathrm{NIR} + \mathrm{RE}} \tag{2}$$

Fertilizer N recommendations were then calculated:

$$N_{Rec} = \left(MZ_i \times N_{Opt} - N_{PreFert} - N_{CRD} + N_{Comp}\right) \times \sqrt{\frac{(1 - SI)}{\Delta SI}} \tag{3}$$

where N_{Rec} is the calculated nitrogen fertilizer recommendation; MZ_i is a scaling value ($0 \geq MZ_i \leq 2$) used to adjust the nitrogen recommendation based on areas of high or low yield performance; N_{Opt} the base nitrogen rate, which is determined by the farmer or researcher; $N_{PreFert}$ is the amount of nitrogen already applied before sensing; N_{CRD} is nitrogen credits associated with the previous crop, NO_3–N in irrigation water, manure, or residual NO_3–N; N_{Comp} is an optional compensation factor for growth-limiting conditions; SI is the sufficiency index, and ΔSI is a value to define the response range. For this analysis, MZ_i was left as the default value of 1.0, N_{opt} was set as the recorded farmer or researcher's nitrogen rate for each site, and $N_{PreFert}$ = 45 kg N ha^{-1}. With no supportive information relative to N_{CRD} and N_{Comp}, these two parameters were set to zero for all sites. The recommended value of 0.30 was used for ΔSI, which provides a response range between the measured vegetative index value between 0.70 and 1.00.

2.8 | Incorporating soil and weather information into tools

We used an ensemble learning method to incorporate soil and weather information into N recommendation tools as shown in Equations 4–6.

$$\sigma = \mathrm{EONR}_{Tool} - \mathrm{EONR}_{measured} \tag{4}$$

$$\sigma = f\,(\mathrm{soil},\ \mathrm{weather}) \tag{5}$$

$$\text{EONR}_{\text{ensemble}} = \text{EONR}_{\text{Tool}} - \hat{\sigma} \tag{6}$$

The first step is to calculate the N recommendation tool's residual error (σ) using Equation 4. The second step is to model σ as a function of soil and weather measurements (Equation 5). The last step is to sum the tool's N recommendation and $\hat{\sigma}$ (Equation 6). For the second step, two algorithms were used. These included the elastic net regression (Zou & Hastie, 2005) and a recursive partitioning decision tree (Loh, 2014). Using two algorithms allows for greater confidence in conclusions and provides unique methods for interpreting results.

Soil properties used in the models included measured physical and chemical soil properties. These were obtained from four soil cores collected down to 1.20 m from each of the sites (one from each block of treatments) and analyzing by pedological soil horizon for texture, bulk density, pH salt, pH water, cation exchange capacity (CEC), total N, total C, inorganic C, organic C, and organic matter as described in Table 2. Soil properties were then depth weighted to obtain values for 0-to-0.30-, 0-to-0.60-, and 0-to-0.90-m depth increments and then averaged across all four profile samples.

Weather data were collected using on-site weather stations (HOBO U30 Automatic Weather Station; Onset Computer Corporation). Daily values were calculated for the maximum and minimum temperature and precipitation. These values were then used to engineer new features: total precipitation (PPT), growing degree days (GDD), corn heat units (CHU), Shanon diversity index (SDI) of precipitation (i.e., evenness of rainfall), and abundant and well-distributed rainfall (AWDR) (Tremblay et al., 2012). Weather measurement calculations were done for two time periods, 30 d before planting up to planting and from planting to the time of the split application (Table 2).

When two measurements were highly correlated (|r| > .85), the measurement with the largest mean absolute pair-wise correlation value was removed from the model (Table 3). This feature selection procedure was automated by using the findCorrelation function from the R 'caret' package (Kuhn, 2017). For the elastic net models, all features were normalized before running the model by subtracting the mean and dividing by the standard deviation for each explanatory variable. Normalization was necessary to minimize any bias the elastic net regression had with variables that comprised of different units or ranges of values (e.g., cumulative precipitation vs. bulk density). After finding the optimal hyperparameters (a parameter in the model that controls the learning process) all elastic net variable coefficients were "non-normalized" to their original scale to provide equations in relevant soil and weather units. For the decision tree modeling, normalizing features was not required.

The elastic net regressions and decision trees were fit with the 'caret', 'glmnet', and 'rpart' packages using R Statistical Software (R Core Team, 2016; Friedman et al., 2010; Therneau & Atkinson, 2019). The elastic net and decision tree models were optimized by tuning their hyperparameters (i.e., alpha and lambda parameters for elastic net regressions and a complexity parameter for decision trees) using a 10-fold cross-validation repeated five times. Where each fold of the cross-validation the data was split randomly into 10-folds. Nine of the folds were selected as a training dataset to fit a model for each set of 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 hyperparameters was determined using the average root mean square error (RMSE) across these 50-folds. The optimal model was selected based on the hyperparameters that produced the lowest RMSE value.

2.9 | Metrics for evaluating performance improvement

To adjust the N recommendation tools, the optimal models' predicted N rate values were subtracted from the original tool's N rate recommendation. Each adjusted tool's performance was tested based on the accuracy of predicting EONR. Models were ranked using a coefficient of determination (r^2), RMSE, and the percentage of sites within ± 30 kg N ha^{-1} of EONR [labeled as "reasonably close to EONR" (cEONR)]. The r^2 was calculated using a simple linear regression model based on the observed (measured EONR) and predicted (tool's unadjusted or adjusted N recommendations) values as:

$$r^2 = 1 - \frac{\sum_i \left(y_i - \hat{y}_i\right)^2}{\sum_i \left(y_i - \bar{y}\right)^2} \tag{7}$$

where y_i was the observed economically optimal nitrogen rate, $\hat{y}_i$ was the tool's unadjusted or adjusted nitrogen recommendation rates, and $\bar{y}$ was the mean of economically optimal nitrogen rate. The RMSE was calculated based on the difference between the adjusted tool's recommendation rates and EONR values as:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \tag{8}$$

To scrutinize which algorithm provided the greatest overall tool improvement, linear slope coefficients from the unadjusted and adjusted tools were tested for differences. Slopes were determined using a linear regression model with EONR as a function of the unadjusted and adjusted tools based on the least-squares estimates and tested for significant differences using a pair-wise comparison from the 'emmeans' package in

TABLE 2 Weather and soil measurements used in the complete dataset with calculations, methods, and associated citations

Measurements	Units	Complete dataset Calculations and sample depths	Method	References
Weather				
Precipitation (PPT)	mm	Sum of daily rainfall, mm	Tipping bucket[a]	
Corn heat units (CHU)	°C	$\Sigma(Y_{max} + Y_{min})/2$; $Y_{max} = 3.33(T_{max} - 10) - 0.084(T_{max} - 10)2$, if $T_{max} < 10.0$, $Y_{max} = 0.0$; $Y_{min} = 1.8(T_{min} - 4.44)$, if $T_{min} < 4.44$, $Y_{min} = 0.0$. T_{max} and T_{min} are the maximum (up to 30 °C) and minimum daily air temperatures (°C), respectively.	Temperature sensor	(Bootsma et al., 2005)
Growing degree day (GDD)	°C	$\Sigma((T_{max} + T_{min})/2) - T_{base}$; T_{max}, T_{min}, T_{base} are the daily maximum, minimum, and base temperatures (°C), respectively. If $T_{max} > 30$ °C, $T_{max} = 30$ °C; If $T_{min} < 10$ °C, $T_{min} = 10$ °C; $T_{base} = 10$ °C.	Temperature sensor	
Shannon diversity index (SDI)		$[-\Sigma pi \ln(pi)]/\ln(n)$; where pi = Rain/PPT (daily rainfall relative to total rainfall in a given time); n = total number of days.	Tipping bucket	(Tremblay et al., 2012)
Abundant and well-distributed rainfall (AWDR)	mm	SDI × PPT	Tipping bucket	(Tremblay et al., 2012)
Soil				
Clay	%	0–0.30, 0–0.60, 0–0.90 m	Pipette	3A1[b]
Sand	%	0–0.30, 0–0.60, 0–0.90 m	Pipette	3A1[b]
Silt	%	0–0.30, 0–0.60, 0–0.90 m	Pipette	3A1[b]
Cation exchange capacity	cmol kg^{-1}	0–0.30, 0–0.60, 0–0.90 m	Ammonium acetate	4B1a1a1a1a-b1[b]
Total N	%	0–0.30, 0–0.60, 0–0.90 m	Dry combustion	4H2a1[b]
Total carbon	%	0–0.30, 0–0.60, 0–0.90 m	Dry combustion	4H2a1[b]
Total organic carbon	%	0–0.30, 0–0.60, 0–0.90 m	Dry combustion	Nelson & Sommers (1996)
Total inorganic carbon	%	0–0.30, 0–0.60, 0–0.90 m	Difference between total C and total organic C	
Organic matter	%	0–0.30, 0–0.60, 0–0.90 m	Loss-on-ignition	5A[b]
pH (Salt)		0–0.30, 0–0.60, 0–0.90 m	pH meter	4C1a1a2[b]
pH (Water)		0–0.30, 0–0.60, 0–0.90 m	pH meter	4C1a1a2[b]
Bulk density	g cm^{-3}	0–0.30, 0–0.60, 0–0.90 m	Core	3B6a[b]

[a]Daily temperature and precipitation measured using HOBO weather station instrumentation (Onset Computer Corporation, Bourne, MA).
[b]Indicates the method code associated with the Kellogg Soil Survey Laboratory Methods Manual (Soil Survey Staff, 2014).

R (Lenth, 2018). The Tukey's Honest Significant Difference test was used to delineate significant differences between the slope coefficients ($\alpha = .05$).

3 | RESULTS AND DISCUSSION

Using two unique algorithms (elastic net and decision tree) to modify N recommendation tools using soil and weather information helped improve most tools (Table 4, Figures 2 and 3). Across both algorithms, improvements ranged from no improvement to great improvement. The best improvements resulted in r^2 increases $\leq .48$ with the highest $r^2 = .57$, RMSE decreases ≤ 38 kg N ha^{-1} with the lowest RMSE = 47 kg N ha^{-1}, and percentage of sites cEONR increases $\leq 29\%$ with the highest value = 55%. The input measurements identified to improve the prediction of EONR differed for each tool and algorithm. Findings for which soil and

TABLE 3 Weather and soil measurement inputs and associated range of values across all sites used as model inputs for the elastic net and decision tree algorithms after removing multicollinearity. Within the table, ✓ indicates features selected to be used for ensemble learning and NA indicates not applicable

Measurement	Abbreviation	Planting tools	Split tools	Min.	Max.	Mean
Weather						
30 d Before planting up to the date of planting						
Growing degree days, ˚C	$GDD_{30–P}$		✓	67	178	117
Shannon diversity index	$SDI_{30–P}$	✓	✓	0.30	0.73	0.59
Abundant and well distributed rainfall, mm	$AWDR_{30–P}$	✓	✓	5.5	171.7	52.3
Planting to split N application						
Total precipitation, mm	$PPT_{P–S}$	NA	✓	61	438	207
Corn heat units, ˚C	$CHU_{P–S}$	NA	✓	899	2,395	1,624
Growing degree days, ˚C	$GDD_{P–S}$	NA		258	688	479
Shannon diversity index	$SDI_{P–S}$	NA	✓	0.48	0.75	0.63
Soil						
Total inorganic carbon (0–0.30 m), %	TIC 90	✓	✓	0.0	0.4	0.05
Total carbon (0–0.90 m), %	TC 90	✓	✓	0.3	2.6	1.1
Organic matter (0–0.30), %	OM 30	✓		0.8	5.2	2.7
Organic matter (0–0.90 m), %	OM 90		✓	0.5	4.3	1.8
Clay (0–0.90 m), %	Clay 90	✓	✓	2	67	27
Sand (0–0.90 m), %	Sand 90	✓		2	91	26
Silt (0–0.60 m), %	Silt 60		✓	6	73	48
pH (Water) (0–0.30 m)	pH 30	✓	✓	5.5	7.8	6.7
Bulk density (0–0.30 m), g cm^{-3}	BD 30	✓	✓	1.07	1.76	1.39

weather measurements were included for elastic net regression are in Table 5 (with normalized coefficients) and Table 6 (converted back to non-normalized coefficients after modeling). Findings for the decision tree method are summarized in Figures 4 and 5.

3.1 | Elastic net outcomes

For seven of the eight single N application tools, the elastic net identified several soil and weather measurements that helped improve the tools as identified by the performance metrics (i.e., r^2, RMSE, and cEONR). The improvement varied across tools and performance metrics. Compared to unadjusted, when averaging across these seven tools the r^2 values increased from .05 to .17, the RMSE values decreased from 83 to 73 kg N ha^{-1}, and the cEONR values increased from 30 to 37% (Table 4). For these seven tools, the adjusted tools' median and the average difference between the tool's N recommendation and EONR came closer to 0 and the box-and-whisker's 95% confidence intervals decreased (Figure 2). For General PPNT, the elastic net identified no soil and weather measurements to modify this tool. However, the intercept of the model showed improvement (i.e., RMSE and cEONR), with an increase of ∼40 kg N ha^{-1} (Table 6). Five of these eight tools (i.e., Farmer NR, MRTN, Nebraska YG, State-specific YG, and North Dakota PPNT) when unadjusted were not significant and not positively related to EONR ($\alpha = .05$). After adjustment, all but the Nebraska YG became significant and positively related to EONR.

For 11 of the 13 split N application tools, the elastic net using soil and weather information helped improve tools' performance metrics. Compared to unadjusted, when averaging across these 11 tools, the r^2 values increased from .08 to .23, the RMSE values decreased from 80 to 65 kg N ha^{-1}, and the cEONR values increased from 34 to 45% (Table 4). Adjusting these 11 tools with soil and weather information also showed improvements based on the median and average difference between each tool's N recommendation, EONR came closer to 0, and the box-and-whisker's 95% confidence interval decreased (Figure 3). Unadjusted tools that were not significant and positively related to EONR (Farmer NR, MRTN, Nebraska YG, Indiana PSNT 0, General PSNT 45, and Wisconsin PSNT 45) became significant and positively related to EONR after adjustment.

The number of measurements used to adjust each tool ranged between 1 and 11 (Table 5). The most important and frequently used measurements to adjust single N application

TABLE 4 The performance of each N recommendation tool unadjusted and adjusted by soil and weather information as presented in Tables 5 and 6 (elastic net) and Figures 4 and 5 (decision tree). The precision and accuracy were evaluated using the coefficient of determination measured from a simple linear relationship between each tool and the economically optimal nitrogen rate (EONR), RMSE of the difference between a tool's N recommendation and EONR, and the percentage of sites within ±30 kg N ha^{-1} of EONR or "reasonably close to economically optimal nitrogen rate" (cEONR). The number of sites (*n*) included in the evaluation differed for each tool based on the availability of information to test the tool. Tools include the State-specific yield goal (YG), pre-plant nitrate test (PPNT), pre-sidedress nitrate test (PSNT), and late-spring nitrate test (LSNT) with 0 and 45 kg N ha^{-1} applied at-planting, maximum return to nitrogen (MRTN), and canopy reflectance sensing using the Holland and Schepers algorithm

		Unadjusted tools			Elastic net adjusted tools			Decision tree adjusted tools		
	n	r^2	RMSE	cEONR	r^2	RMSE	cEONR	r^2	RMSE	cEONR
N Fertilizer recommendation tool			kg N ha^{-1}	%		kg N ha^{-1}	%		kg N ha^{-1}	%
Single										
Farmer NR	49	.01	88	31	.20	73	41	.49	58	47
MRTN	36	.01	77	39	.23	63	50	.37	57	36
NE YG	49	.01	86	35	.07	81	35	.43	63	33
State-specific YG	43	.04	84	23	.09	77	33	.37	64	37
General PPNT	47	.15	85	21	.15	75	30	.28	69	34
MN PPNT	47	.13	80	32	.20	73	40	.27	69	40
ND PPNT	47	.00	93	13	.09	80	23	.27	71	40
WI PPNT	44	.16	71	34	.29	64	36	.31	64	36
Split										
Farmer NR	49	.00	84	29	.19	65	49	.45	53	37
MRTN	36	.02	72	42	.23	58	44	.31	55	44
NE YG	49	.00	81	37	.15	67	49	.16	68	45
State-specific YG	43	.07	74	37	.22	63	40	.21	64	35
General PSNT 0	49	.13	70	43	.13	70	41	.24	64	39
LSNT 0	49	.24	68	37	.39	56	55	.36	58	47
IN PSNT 0	49	.03	83	24	.21	64	47	.18	67	45
WI PSNT 0	49	.11	73	41	.11	73	39	.21	66	37
General PSNT 45	49	.07	92	29	.15	74	43	.38	60	47
LSNT 45	49	.14	79	43	.27	65	35	.14	72	31
IN PSNT 45	49	.12	75	41	.18	70	49	.32	64	35
WI PSNT 45	49	.05	90	35	.17	71	39	.17	70	35
Canopy reflectance	49	.13	85	22	.36	58	41	.57	47	51

tools were the $GDD_{30–P}$, $AWDR_{30–P}$, soil organic matter (OM) (0–0.30 m), and total carbon (TC) (0–0.90 m). Whereas the most important and frequently used measurements for split tools were the $SDI_{P–S}$, soil pH (0–0.30 m), and TC (0–0.90 m). When looking across both single and split N application tools, the $SDI_{30–P}$ and bulk density (0–0.30 m) were influential about 50% of the time.

For weather measurements, $GDD_{30–P}$ was sometimes helpful (for both single and split tools), but it is not surprising that the most influential information used to adjust tools were precipitation-based measurements (Table 5). Precipitation drives soil organic matter mineralization, yield potential, NO_3–N leaching losses, and N uptake (Cassman & Munns, 1980; Melkonian et al., 2007; Schröder et al., 2000; Wilhelm & Wortmann, 2004). Precipitation-based measurements often have a bigger impact on N fertilizer response and EONR predictions than soil parameters (Sela et al., 2017; Sogbedji et al., 2001; Tremblay et al., 2012). For all the precipitation based-measurements in this analysis, we found only the $SDI_{P–S}$ to have a significant and positive linear relationship with EONR (r^2 = .22 for split application EONR). In all cases, increasing $SDI_{P–S}$ values increased the adjusted tools' N rate recommendations (Table 6). The magnitude of the $SDI_{P–S}$ adjustment differed by tool, ranging from +59 to +241 kg N ha^{-1}. For reference, an SDI value of 1.0 indicates equal precipitation amounts that were evenly spaced among the measurement timeframes. An SDI of 0 indicates all precipitation occurred on a single day.

TABLE 5 Elastic net regression normalized coefficients of influential soil and weather measurements selected for adjusting N recommendation tools. Includes weather measurements calculated from 30 d before planting up to planting ($_{30\text{-P}}$) and from planting to the date of the split N fertilizer application ($_{\text{P-S}}$). Weather measurements include the growing degree days (GDD), Shannon diversity index of rainfall (SDI), abundant and well-distributed rainfall (AWDR), cumulative precipitation (PPT), and corn heat units (CHU). Soil measurements include total inorganic carbon (TIC), total carbon (TC), organic matter (OM), silt, clay and sand percentage, pH, and bulk density (BD). Soil measurements were taken in depth increments of 0–0.30, 0–0.60, or 0–0.90 m. Measurements not in the final model have no value. The direction of the relationship is shown by the + or – sign. Nitrogen recommendation tools included the farmer's N rate, maximum return to nitrogen (MRTN), Nebraska yield goal (NE YG), State-Specific YG, pre-plant nitrate test (PPNT), pre-sidedress nitrate tests (PSNT) with 0 and 45 kg N ha^{-1} applied at-planting, and canopy reflectance sensing using the Holland and Schepers algorithm

Tool	Intercept	$GDD_{30\text{–}P}$	$SDI_{30\text{–}P}$	$AWDR_{30\text{–}P}$	$PPT_{P\text{–}S}$	$SDI_{P\text{–}S}$	$CHU_{P\text{–}S}$	TIC 30	TC 90	OM 30/90	Silt 60	Clay 90	Sand 90	pH 30	BD 30
				——mm——					——g kg^{-1}——						g cm^{-3}
Single															
Farmer NR	+23.7	–7.6	+1.2	–7.2	NA[b]	NA	NA	+2.8	+7.1	+2.4		+6.9	–5.6	+8.8	–6.5
MRTN	+15.8[a]			–5.3	NA	NA	NA							+26.1	
NE YG	–12.5	–6.3		–0.1	NA	NA	NA		+3.3	+6.3					–3.6
State-specific YG	+21.3[a]				NA	NA	NA			+13.2					
General PPNT	–40.3				NA	NA	NA								
MN PPNT	–25.7				NA	NA	NA		+11.9						
ND PPNT	+7.1[a]	–7.8			NA	NA	NA			+33.0					
WI PPNT	–4.8[a]	–7.9	–2.5	–8.9	NA	NA	NA	+0.6	+1.2			–0.6	+8.5	+3.8	
Split															
Farmer NR	+31.1	–5.1		–5.9		–12.2	–4.2	+4.7	+2.4		+6.4	+5.6		+7.7	–4.8
MRTN	+19.2[a]					–10.4								+18.9	
NE YG	–26.7	–5.3	–6.2		+4.7	–19.5			+2.0	+0.7	+0.9				–4.2
State-specific YG	+23.4					–18.9				+4.0					
General PSNT 0	–4.2														
LSNT 0	–25.4[a]		–2.1			–10.1			+7.2	+1.7	+4.3			+7.6	–2.9
IN PSNT 0	+39.6	–6.5	–1.0		+1.5	–12.1			+3.5	+6.8	+5.0			+1.3	–1.3
WI PSNT 0	–4.6														
General PSNT 45	–44.1		–7.9			–7.4			+5.3					+10.6	
LSNT 45	–33.5[a]	+0.6	–5.0			–8.7			+6.1		+2.8			+8.3	–4.2
IN PSNT 45	+2.2		–0.2			–8.1			+1.3					+3.4	–5.4
WI PSNT 45	–38.5		–6.2	–4.4		–10.3			+8.2		+2.5			+14.4	+1.2
Canopy reflectance	–49.5[a]		–6.1			–8.9		+2.2	+3.1	+1.3	+1.3	+9.5		+6.7	–7.1
Variable occurrences (%)		38	48	29	15	85	8	19	62	43	33	19	10	57	48
Total variable occurrences		8	10	6	2	11	1	4	13	9	7	4	2	12	10
Mean of absolute coefficients		5.9	3.8	5.3	3.1	11.5	4.2	2.6	4.8	7.7	3.3	5.7	7.1	9.8	4.1

[a]Indicates that the sign of the intercept does not change when data is normalized (scaled and centered). See Table 6 for non-normalized coefficients.
[b]NA indicates measurements that are not available for use in the model because these measurements were collected after the single N application time.

TABLE 6 Elastic net regression non-normalized coefficients of weather and soil parameters used to adjust N recommendation tools. Tools include the farmer's N rate, maximum return to nitrogen (MRTN), yield goal (YG), pre-plant nitrate test (PPNT), pre-sidedress nitrate test (PSNT) and late spring nitrate test (LSNT) with 0 and 45 kg N ha^{-1} applied at-planting, and canopy reflectance sensing using the Holland and Schepers algorithm. Includes weather measurements calculated from 30 d before planting up to planting ($_{30\text{-P}}$) and from planting to the date of the split N fertilizer application ($_{\text{P-S}}$). Weather measurements include the growing degree days (GDD; ˚C), Shannon diversity index of rainfall (SDI), and abundant and well-distributed rainfall (AWDR; mm), cumulative precipitation (PPT; mm), and corn heat units (CHU; ˚C). Soil measurements include sand, silt, and clay (%), total carbon (TC; %), total inorganic carbon (TIC; %), organic matter (OM; %), pH, and bulk density (BD; g cm^{-3})

Tool	Parameter adjustments
Single	
	Farmer NR – 4.3 + 0.3 $GDD_{30–P}$ – 13.8 $SDI_{30–P}$ + 0.2 $AWDR_{30–P}$ – 28.3 TIC30 – 11.3 TC90 – 2.6 OM30 – 0.6 Clay90 + 0.2 Sand90 – 14.6 pH30 + 53.1 BD30
	MRTN + 265.9 + 0.2 $AWDR_{30–P}$ – 43.7 pH30
	NE YG – 29.8 + 0.2 $GDD_{30–P}$ + 0.004 $AWDR_{30–P}$ – 5.3 TC90 – 6.8 OM30 + 29.4 BD30
	State-specific YG + 15.7 – 14.3 OM30
	General PPNT + 40.3
	MN PPNT + 45.6 – 18.7 TC90
	MN PPNT + 55.6 + 0.3 $GDD_{30–P}$ – 34.9 OM30
	WI PPNT – 12.3 + 0.3 $GDD_{30–P}$ + 34.3 $SDI_{30–P}$ + 0.3 $AWDR_{30–P}$ – 6.2 TIC30 – 1.9 TC90 + 0.05 Clay90 – 0.4 Sand90 – 6.1 pH30
Split	
	Farmer NR – 145.8 + 0.2 $GDD_{30–P}$ + 0.2 $AWDR_{30–P}$ + 200.1 $SDI_{P–S}$ + 0.02 $CHU_{P–S}$ – 48.0 TIC30 – 3.9 *TC90*– 0.4 Silt60 – 0.5 Clay90 – 12.7 pH + 39 BD30
	MRTN + 90.7 + 162.9 $SDI_{P–S}$ – 31.6 pH30
	NE YG – 265.4 + 0.2 $GDD_{30–P}$ + 73.1 $SDI_{30–P}$ – 0.1 $PPT_{P–S}$ + 319.7 $SDI_{P–S}$ – 3.2 TC90 – 1.1 OM90 – 0.1 Silt60 + 34.1 BD30
	State-specific YG – 200.7 + 303.6 $SDI_{P–S}$ –*7.7* OM90
	General PSNT 0 + 4.2
	LSNT 0 – 13.8 + 25.1 $SDI_{30–P}$ + 166.3 $SDI_{P–S}$ – 11.2 TC90 – 2.7 OM90 – 0.2 Silt60 – 12.5 pH30 + 23.3 BD30
	IN PSNT 0 – 155.3 + 0.2 $GDD_{30–P}$ + 12.1 $SDI_{30–P}$ – 0.02 $PPT_{P–S}$ + 198.1 $SDI_{P–S}$ – 5.5 TC90 – 10.4 OM90 – 0.3 Silt60 – 2.1 pH30 + 10.4 BD30
	WI PSNT 0 – 4.6
	General PSNT 45 + 38.7 + 93.5 $SDI_{30–P}$ + 121.5 $SDI_{P–S}$ – 8.5 TC90 – 17.5 pH30
	LSNT 45 – 26.0 – 0.02 $GDD_{30–P}$ + 58.8 $SDI_{30–P}$ + 142.0 $SDI_{P–S}$ – 9.7 TC90 – 0.2 Silt60 – 13.7 pH30 + 34.4 BD30
	IN PSNT 45 – 107.8 + 2.9 $SDI_{30–P}$ + 132.3 $SDI_{P–S}$ – 2.1 TC90 – 5.7 pH30 + 44.2 BD30
	WI PSNT 45 +75.5 + 73.0 $SDI_{30–P}$ + 0.1 $AWDR_{30–P}$ + 168.2 $SDI_{P–S}$ – 13.2 TC90 – 0.1 Silt60 – 23.8 pH30 – 9.4 BD30
	Canopy reflectance – 57.7 + 71.8 $SDI_{30–P}$ + 145.5 $SDI_{P–S}$ – 22.2 TIC30 – 5.8 TC90 – 2.0 OM90 – 0.07 Silt60 – 0.8 Clay90 – 11.0 pH30 + 58.1 BD30

We postulate $SDI_{P–S}$ helped increase N recommendations because this measurement could be a good predictor of increased N loss at high $SDI_{P–S}$ values. Nitrogen loss (i.e., soil surface runoff, N leaching, or denitrification) increases when soil moisture content is high, and thus more N would be required to compensate for the loss (Maag & Vinther, 1996). Maintained high soil moisture is more likely to occur when precipitation events are evenly spaced (high SDI) and total precipitation is high. On the other hand, infrequent precipitation (Low $SDI_{P–S}$ values) corresponded with lower EONR values. The lower fertilizer N need could have resulted from deeper rooting systems that are often promoted when soils are dry during early vegetative growth stages (Nielsen, 2013). A deep rooting system would increase a plant's access to profile nitrate resulting in less fertilizer need. It is difficult to surmise how SDI values affects N response, as SDI values can be calculated equifinality (i.e., 10 mm of precipitation everyday results in the same SDI value as 1 mm of precipitation everyday) and therefore masks the magnitudinal effect of precipitation. But compared to $SDI_{P–S}$, including the magnitude effect (i.e., AWDR) showed no improved predictability of EONR or the difference between tools' N recommendation and EONR.

The most frequently appearing soil measurement in the elastic net models were pH (0–0.30 m) and TC (0–0.90 m) (Table 5). As pH or TC increased the adjusted tools' N recommendations decreased (Table 6). Soil pH resulted in

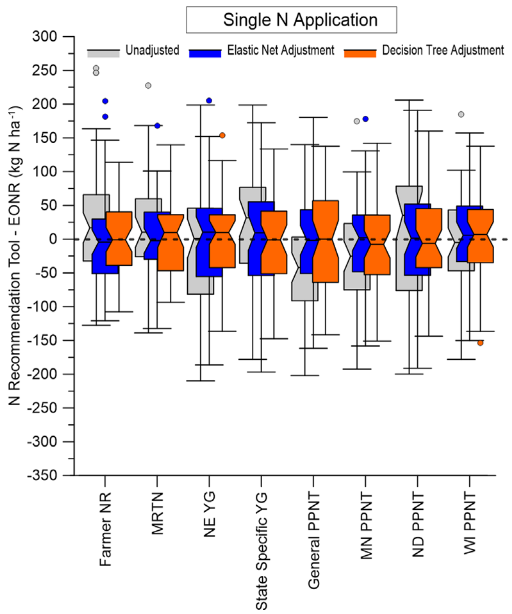

FIGURE 2 Box-and-whisker plots showing the difference between each of the single application (at-planting) tools' N recommendation and the economically optimal nitrogen rate (EONR) for tools before and after adjusting with soil and weather information. The median is reported by the value in the middle of the box. Notches on the side of each box represent the 95% confidence interval around the median. Limits of the box indicate the first and third quartile, whiskers represent 1.5 × interquartile range, and small circles are outliers. Improvement is assessed by the decrease in the box-and-whisker length, and the box is centered on the zero line (dashed line)

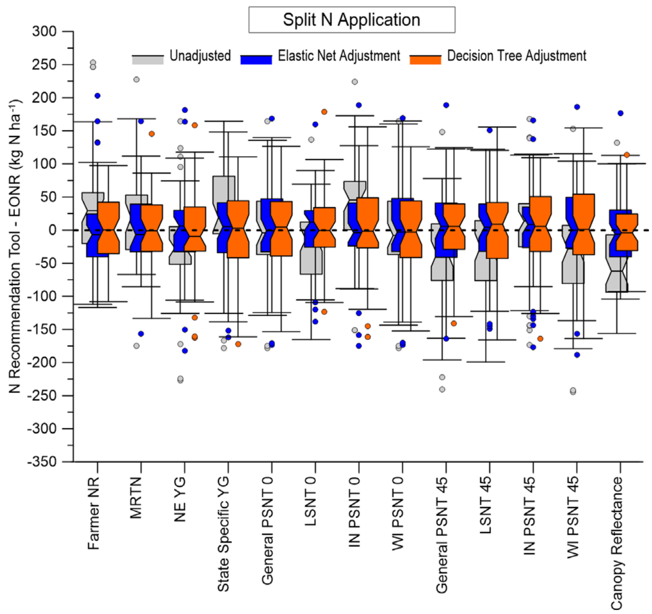

FIGURE 3 Box-and-whisker plots showing the difference between each of the split application (at-planting + sidedress) tools' N recommendation and the economically optimal nitrogen rate (EONR) for tools before and after adjusting with soil and weather information. The median is reported by the value in the middle of the box. Notches on the side of each box represent the 95% confidence interval around the median. Limits of the box indicate the first and third quartile, whiskers represent 1.5 × interquartile range, and small circles are outliers. Improvement is assessed by the decrease in the box-and-whisker length, and the box is centered on the zero line (dashed line)

tools being adjusted between −11 and−343 kg N ha^{-1}. The TC 90 resulted in tools being adjusted between −1 and −49 kg N ha^{-1} (Table 6).

Soil pH affects soil fertility and drives many factors of the N cycle. For example, the microbial-driven conversion of ammonium to nitrate is optimized at pH values above 7.5 (Kyveryga et al., 2004) and denitrification rates are greatest at pH values <7 (Šimek & Cooper, 2002). Soil pH was shown to be an important factor influencing corn yield and protein levels in two Illinois corn fields (Miao et al., 2006). However, directly relating pH to EONR in our study showed no significant relationship (P values of .18 and .14 for single and split EONR, respectively). Northern sites tended to have higher pH values because these soils were formed under drier and colder conditions (Figure 1b; e.g., North Dakota), and therefore were less weathered with free calcium carbonate or a recent lime application was used to raise the pH (measured total inorganic carbon (TIC) in the top 0.30 m only occurred in Illinois, Missouri, North Dakota, Minnesota, and Wisconsin sites and ranged from 0.01 to 0.42%; with North Dakota and Minnesota having the highest values). Decreasing any of the tools' recommendations based on higher soil pH was helpful for many of the northern sites such as North Dakota (pH ranged between 6.7 and 7.8) and Wisconsin (pH ranged between 6.1 and 7.5), where a few of these sites were non-responsive to N fertilizer.

Total C (0–0.90 m) was meaningful for adjusting 13 of the 21 tools (Table 5). The TC 90 accounted for 16% (P value = .004) and 13% (P value = .01) of the variability around the single and split EONRs, respectively. The TC values were related to organic C–when averaged across all sites, organic C accounted for 88% of the TC 90. The northern sites contained the highest TC 90 content (and highest organic C content) and were co-located with sites with high pH values. Adjusting for organic C could account for mineralization rates, as positive linear and quadratic responses (r^2 > .24) were observed using this data with a 28 d anaerobic potentially mineralizable N soil test (Clark et al., 2019). Higher mineralization rates would help explain the lack of fertilizer N response for many of the northern locations. In colder climates and with shorter growing seasons these soils accumulated more organic matter than soils in warmer wetter regions, and thus a potentially greater soil N supply exists in these soils today (Figure 1b). Accounting for mineralization indirectly through TC allows tools to account for N supplied by the soil. The inability for tools to account for

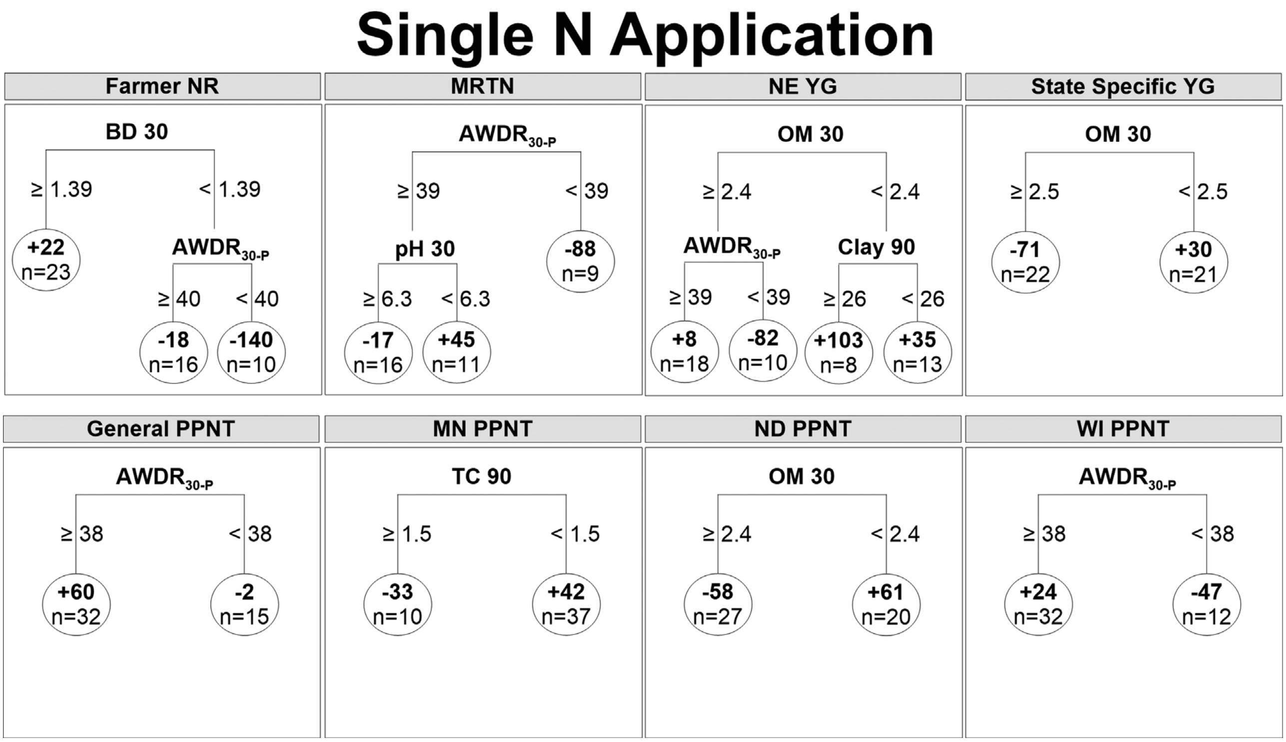

FIGURE 4 Decision trees models used to adjust single application (at-planting) N recommendation tools with soil and weather measurements. The weather measurement used was the abundant and well-distributed rainfall calculated from 30 d before planting up to planting ($AWDR_{30–P}$; mm). Soil measurements were taken in depth increments of 0–0.30, 0–0.60, or 0–0.90 m. Soil measurements and their respective depth include total carbon (TC 90; g kg^{-1}), organic matter (OM 30; g kg^{-1}), clay (Clay 90; g kg^{-1}), pH (pH 30), and bulk density (BD 30; g cm^{-3}). Nitrogen recommendation tools include the farmer's N rate, maximum return to nitrogen (MRTN), Nebraska yield goal (NE YG), State-specific YG, and four different pre-plant nitrate tests (PPNT). The adjustment recommended for each tool in kg N ha^{-1} and the number of observations used in each split are circled at the end of each terminal node

N mineralization rates is one reason that they performed poorly across a wide geographical region, as shown in Ransom et al. (2020).

3.2 | Decision tree outcomes

For all eight single N application tools, decision trees identified at least one measurement that helped improve these tools. Going from unadjusted to adjusted, and averaging across these eight tools, the r^2 values increased from .05 to .35, the RMSE values decreased from 83 to 64 kg N ha^{-1}, and the cEONR values increased from 30 to 38% (Table 4). However, the adjustments to the MRTN and Nebraska YG recommendations negatively affected the cEONR values as a few sites were moved further away from EONR than those that were adjusted cEONR. Overall, the modifications resulted in the average and median difference between each tool's N recommendation and EONR coming closer to 0, and all box-and-whisker's 95% confidence intervals decreasing (Figure 2). These adjustments resulted in all tools being significant and positively related to EONR.

For 12 of the 13 split tools, decision trees identified at least one measurement that helped improve these tools (with no improvement to LSNT 45). Compared to the unadjusted, when averaging across these 12 tools, the r^2 values increased from .08 to .30, the RMSE values decreased from 79 to 61 kg N ha^{-1}, and the cEONR values increased from 35 to 41% (Table 4). As with the other adjusted tools, the average difference between each tool's N recommendation and EONR was nearer to 0 and the box-and-whisker's 95% confidence interval decreased (Figure 3). Across all 12 tools, six were not significant and positively related to EONR when unadjusted (Farmer NR, MRTN, Nebraska YG, Indiana PSNT 0, General PSNT 45, and Wisconsin PSNT 45), but they all became significant and positively related to EONR after adjustment.

The decision tree models resulted in one, two, or three splits as shown in Figures 4 and 5. For each of the important soil and weather measurements, the values used to create a split were similar across all tools. The most frequently used measurements to adjust single N application tools included the $AWDR_{30–P}$ (Figure 4), while for split tools it was the $AWDR_{30–P}$ and bulk density (0–0.30 m) measurements (Figure 5). The $AWDR_{30–P}$ was important for 10 of the 21

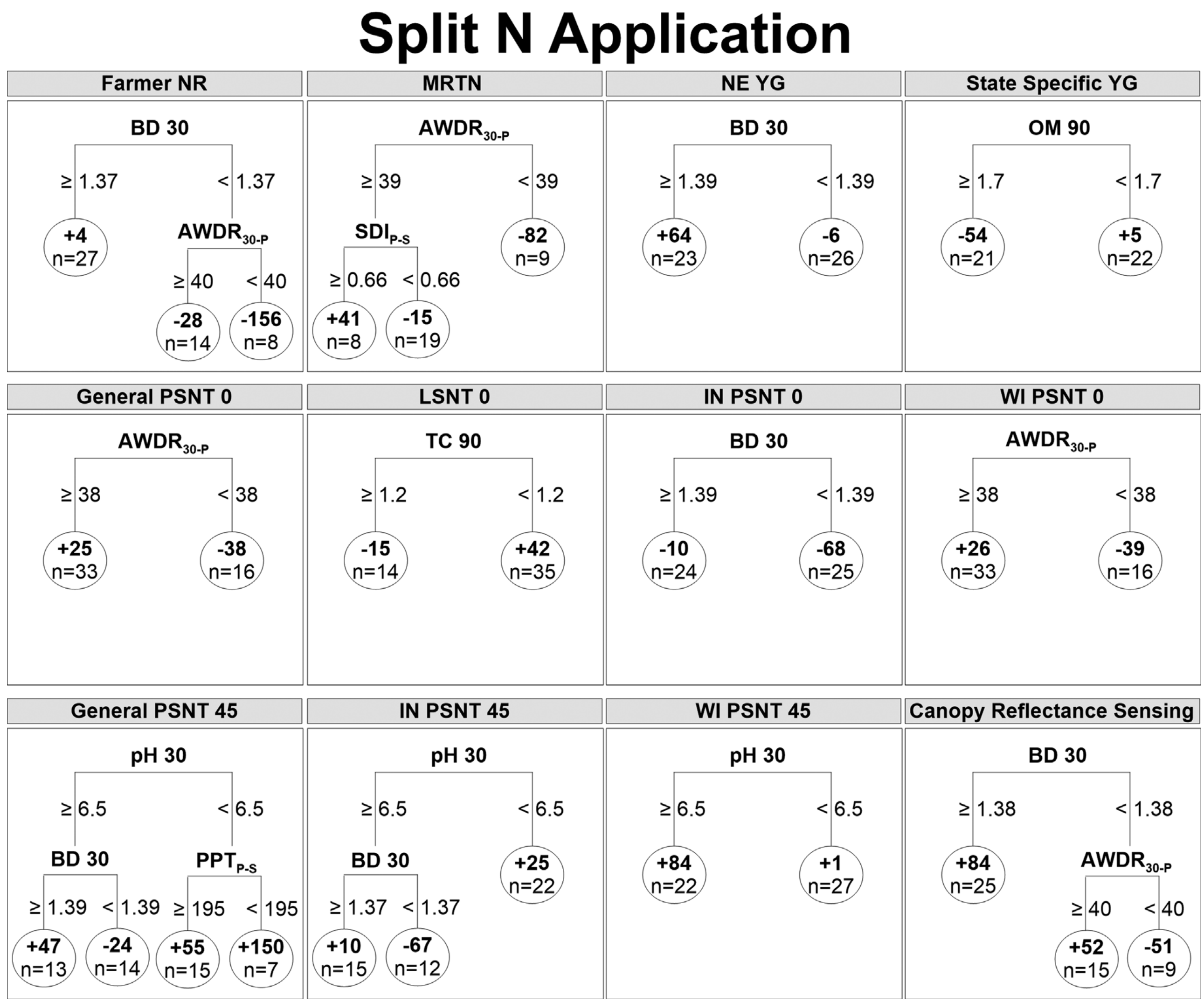

FIGURE 5 Decision trees models used to adjust split application (at-planting + sidedress) N recommendation tools with soil and weather measurements. Weather measurements were calculated from 30 d before planting up to planting ($_{30–P}$) and from planting to the date of the split N fertilizer application ($_{P–S}$). Weather measurements include the cumulative precipitation ($PPT_{P–S}$; mm), Shannon diversity index of rainfall ($SDI_{P–S;}$ unitless), and abundant and well-distributed rainfall ($AWDR_{30–P}$; mm). Soil measurements were taken in depth increments of 0–0.30, 0–0.60, or 0–0.90 m. Soil measurements and their respective depth include total carbon (TC 90; g kg^{-1}), organic matter (OM 90; g kg^{-1}), pH (pH 30), and bulk density (BD 30; g cm^{-3}). Nitrogen recommendation tools included the farmer's N rate, maximum return to nitrogen (MRTN), Nebraska yield goal (NE YG), State-specific YG, pre-sidedress nitrate tests (PSNT) with 0 and 45 kg N ha^{-1} applied at-planting, and canopy reflectance sensing using the Holland and Schepers algorithm. The late spring nitrate test with 45 kg N ha^{-1} applied at-planting (LSNT 45) was not included because the decision tree found no splits. The adjustment recommended for each tool in kg N ha^{-1} and the number of observations used in each split are circled at the end of each terminal node

decision tree adjustments. Across all decision trees adjustments, the $AWDR_{30–P}$ splits occurred between 38 and 40 mm. For reference, all sites with $AWDR_{30–P}$ <40 mm received ≤66 mm of precipitation and had $SDI_{30–P}$ values between 0.30 (i.e., most precipitation occurring close together) and 0.65 (i.e., adequately distributed precipitation). Agronomically it is unclear why $AWDR_{30–P}$ (a measurement of abundant and well-distributed precipitation) would be so influential at adjusting a wide variety of single and split N application tools. Precipitation before planting could affect planting conditions, seed germination, and impact soil profile water content which subsequently could affect leaching or denitrification losses. But presumably pre-plant precipitation would have little impact on season-long N dynamics or grain production since no N fertilizer was applied during this period. Regardless of the agronomic reasons, for this set of 49 site-years, this measurement helped in many tool adjustments by identifying N need based on low and high $AWDR_{30–P}$ values. For example, tool recommendations tended to overestimate EONR for sites with low $AWDR_{30–P}$ values but adjusting tools for $AWDR_{30–P}$ helped correct for this.

Also, bulk density (BD) (0–0.30 m) was an important measurement for adjusting tools. This measurement helped adjust 7 of the 21 tools. Across all tools, the BD split occurred at values between 1.37 and 1.39. For BD values < 1.37 recommendations were generally adjusted down, and for values ≥1.37 recommendation were adjusted up. High BDs reduce root elongation and inhibit water and nutrient uptake (Passioura, 1991). Often soil compaction contributes to higher BD, and can limit water movement which can cause higher denitrification rates (Gregorich et al., 2014). Bulk density was found to have a negative relationship with potentially mineralizable N–indicating that sites with high BDs had reduced soil N supply (Clark et al., 2019). This relates well with observations of higher N needed at sites with high BD.

3.3 | Which tools were best adjusted?

To facilitate a discussion about which tools were best adjusted, we grouped tools into three categories of tool improvement ("most improved", "moderately improved", and "least improved"). The classification was based on how well the average of both algorithms improved the tools across all three metrics of performance. A threshold for each metric was chosen to separate the 21 tools into the three groups. The thresholds were an increased r^2 value of .15, a decreased RMSE of 13 kg N ha^{-1}, and an increased percentage of site cEONR of 10%. For "most improved" tools, the average of the elastic net and decision tree's metrics all had to be greater than these values. For "least improved" tools, the average metrics all had to equal or be less than these values. Tools that did not fit in either of these categories–because at least one of the average metrics was above the thresholds, while the other metric(s) were below the thresholds–were classified as "moderately improved".

Most improved tools are presented in Figure 6. Unadjusted, these tools had poor performance metrics and therefore had the most room for improvement. For example, all unadjusted tools in the "most improved" category had r^2 between .00 and .13, RMSE between 83 and 93 kg N ha^{-1}, cEONR between 13 and 31%, and five of the seven unadjusted tools were not significantly related to EONR. For "most improved" tools, incorporating soil and weather information improved the tools' performance by decreasing N recommendations when EONR values were low, while also increasing N recommendations when EONR values were high. These adjustments helped N recommendations to better align with EONR as seen by points aligning closer to the 1:1 line in Figure 6.

Moderately improved tools are shown in Figure 7. For these tools, using soil and weather information improved the tools but not for all performance metrics. The reason for this was that the unadjusted "moderately improved" tools were already performing better than unadjusted "most improved" tools. The unadjusted "moderately improved" tools had a r^2 between .00 and .24, RMSE between 68 and 90 kg N ha^{-1}, cEONR between 21 and 42%, and four of the seven unadjusted tools were not significantly related to EONR. Like the "most improved" performing tools, the "moderately improved" tools were adjusted in similar ways. Tools that could not account for sites with low or high EONR values were shifted.

Least improved tools are illustrated in Figure 8. There was minimal improvement for some of these tools as they were some of the better performing tools without adjustment. Before adjustment they had r^2 between .07 and .16, RMSE between 70 and 80 kg N ha^{-1}, cEONR between 32 and 43%, and all were significantly related to EONR. Of these seven tools, four showed minimal improvement (Minnesota PPNT, Wisconsin PPNT, State-specific YG, and Indiana PSNT 45), showing that soil and weather information was helpful for adjusting a few sites but did not provide meaningful improvement for all sites. For the other three tools, no soil or weather adjustments helped. Therefore, only a constant value was used to adjust these tools, which resulted in a minimal improvement (Table 4).

3.4 | Comparing model methods

The elastic net algorithm performs well when the number of observations is high and modeling includes interactions and nonlinearities when interactions and nonlinearities are present (Grömping, 2009). For this analysis the number of observations was relatively low and modeling excluded interactions or second order polynomials because previous research showed minimal improvements with such an analysis (Ransom et al., 2019). Decision trees can work well with minimal observations and can model data where interactions and nonlinearities are present (Grömping, 2009). With this analysis, decision tree modeling gave the greatest improvement. The decision tree outperformed the elastic net with increased r^2 values of .18 and .07 and decreased RMSE values of 9 and 4 kg N ha^{-1} for single and split N application tools, respectively (Table 4). The decision tree best adjusted sites with extremely low and high N responses (i.e., EONR values <50 kg N ha^{-1} and EONR values >200 kg N ha^{-1}) and therefore improved the r^2 values. The elastic net did well at adjusting recommendations for sites with moderate N responses (i.e., EONR values that ranged between 50 and 200 kg N ha^{-1}). This resulted in only a minor improvement to r^2 values but, for many tools, increased the cEONR values compared to the decision tree (Table 4).

Contrasting the two modeling approaches by examining linear regression slopes of tools' recommendations to EONR (Figures 6–8) statistically showed 8 of the 21 decision tree

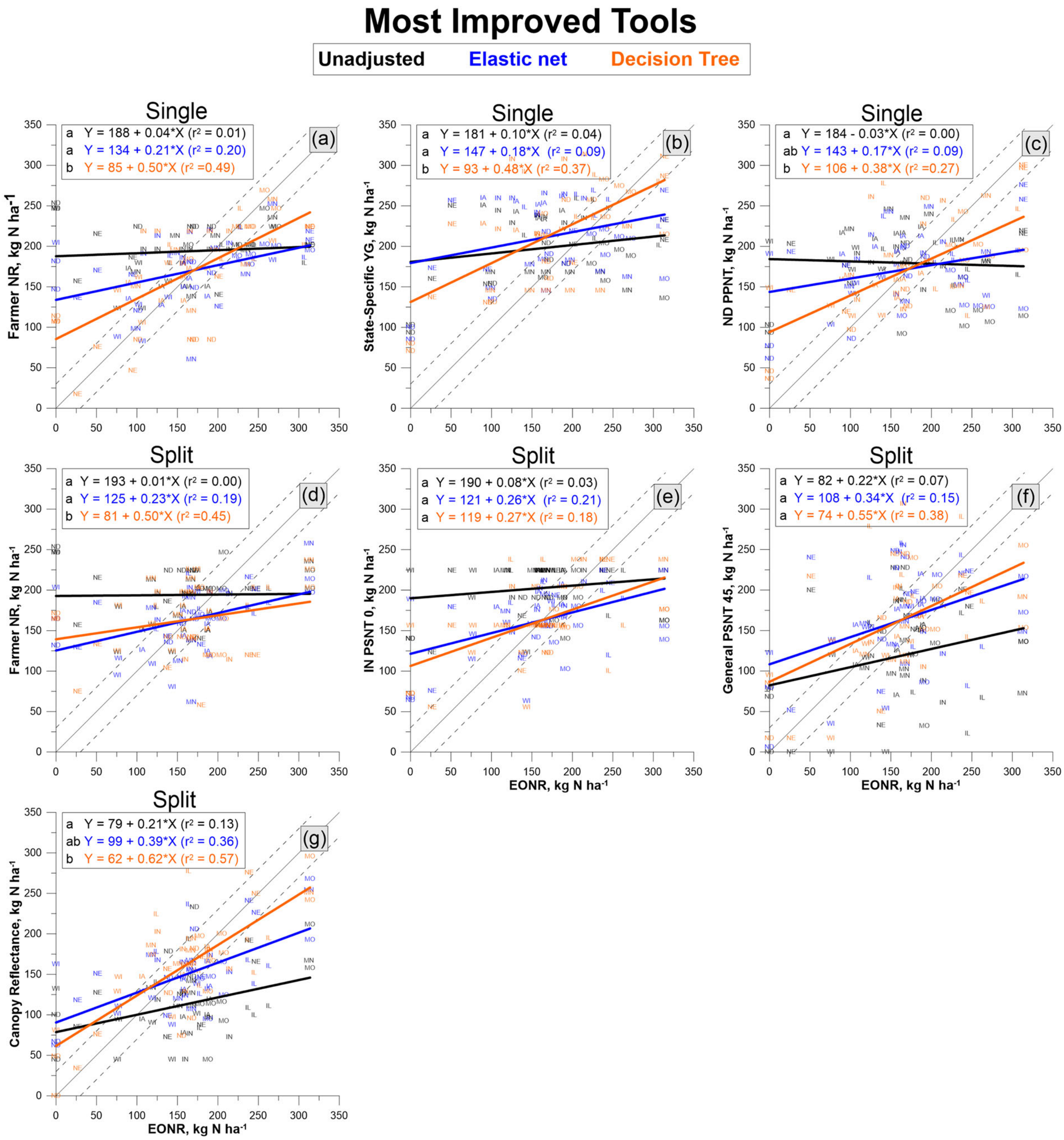

FIGURE 6 "Most improved" N recommendation tool improvement (i.e., best improvement of performance metrics across elastic net and decision tree models) for predicting the economically optimal N rate (EONR) after adjusting with soil and weather measurements. Comparison of before (black labels and lines) and after adjusting for soil and weather information using an elastic net regression (blue labels and lines) or recursive partitioning decision trees (orange labels and lines). Linear regression equations and their coefficient of variance are shown with significant differences between slopes identified with letters at the beginning of each equation. The 1:1 line is an indicator of a perfect predictor of EONR. The dashed lines represent the area in which tools were within ± 30 kg N ha^{-1} of EONR or relatively close to EONR. Tools were used for a "single" (at-planting) or a "split" (at-planting + sidedress) N application

tools improved (*P* values ≤ .05), giving a relationship closer to the 1:1 line. Six of these eight decision tree adjustments were significantly improved over the elastic net adjustments (Figure 6A–E; Figure 7A, 7B, and 7E). Whereas no elastic net improvement was significant compared to the unadjusted tools.

Both algorithms pointed to similar soil and weather measurements when adjusting N recommendations tools, reinforcing the legitimacy of these modeling tools. The most common measurements used by both algorithms were $AWDR_{30\text{–}P}$, soil pH (0–0.30 m), and BD (0–0.30 m) (Table 5 and Figures 4 and 5). Only in three cases did the decision tree

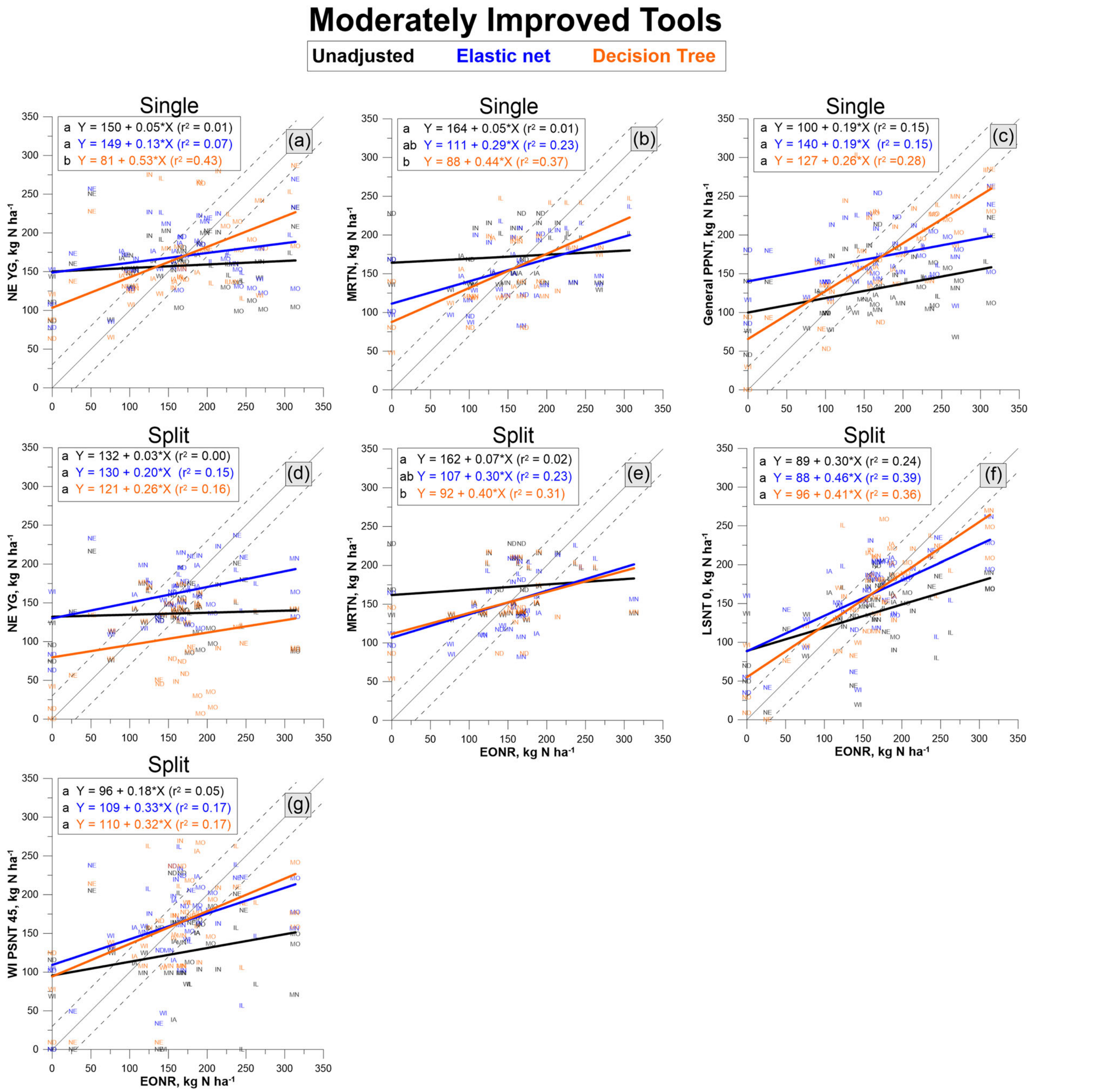

FIGURE 7 "Moderately improved" N recommendation tool improvement (i.e., good but inconsistent improvement of performance metrics across elastic net and decision tree models) for predicting the economically optimal nitrogen rate (EONR) after adjusting with soil and weather measurements. Comparison of before (black labels and lines) and after adjusting for soil and weather information using an elastic net regression (blue labels and lines) or recursive partitioning decision trees (orange labels and lines). Linear regression equations and their coefficient of variance are shown with significant differences between slopes identified with letters at the beginning of each equation. The 1:1 line is an indicator of a perfect predictor of EONR. The dashed lines represent the area in which tools were within ± 30 kg N ha^{-1} of EONR or relatively close to EONR. Tools were used for a "single" (at-planting) or a "split" (at-planting + sidedress) N application

identify a measurement that was not used by the elastic net [single NebraSKA YG (percent clay) and split General PSNT 45 (PPT_{P-S} and BD)]. All other measurements identified as important in the decision tree were also used in the elastic net (Table 5 and Figures 4 and 5).

From a practical standpoint, decision tree adjustment outcomes were the most helpful as they used ≤3 measurements in their adjustments, compared to up to 10 measurements with elastic net outcomes. Requiring more than one soil measurement to adjust tools will increase the cost (time and money) of using that tool. For example, the canopy reflectance sensor improved when using total inorganic C, organic matter, pH, bulk density, silt, and total C. The cost of soil sampling (at multiple soil depths) and laboratory analyzes for

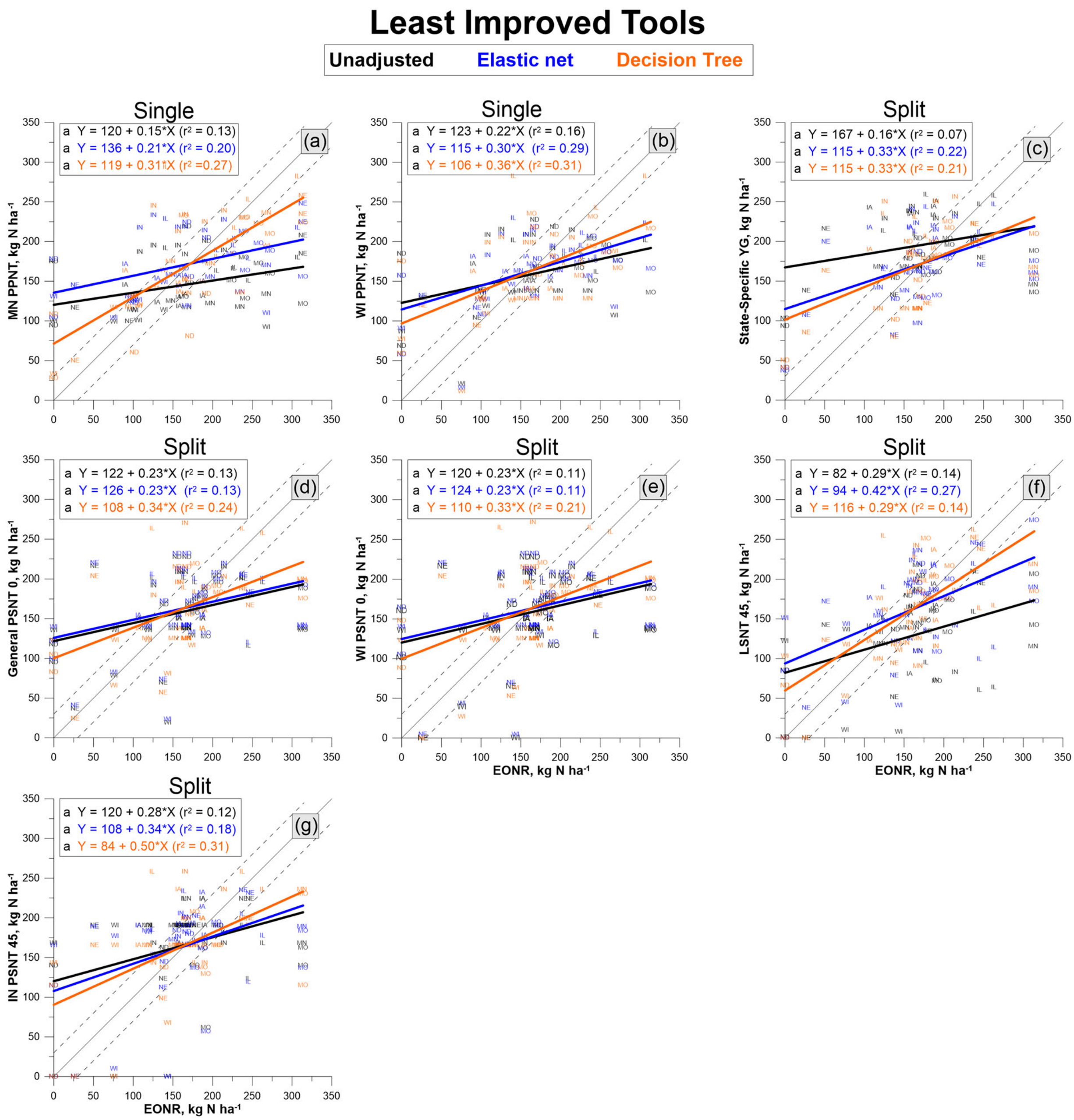

FIGURE 8 "Least improved" N recommendation tool improvement (i.e., poorest improvement to performance metrics across elastic net and decision tree models) for predicting the economically optimal nitrogen rate (EONR) after adjusting with soil and weather measurements. Comparison of before (black labels and lines) and after adjusting for soil and weather information using an elastic net regression (blue labels and lines) or recursive partitioning decision trees (orange labels and lines). Linear regression equations and their coefficient of variance are shown with significant differences between slopes identified with letters at the beginning of each equation. The 1:1 line is an indicator of a perfect predictor of EONR. The dashed lines represent the area in which tools were within ± 30 kg N ha^{-1} of EONR or relatively close to EONR. Tools were used for a "single" (at-planting) or a "split" (at-planting + sidedress) N application

multiple places across a field is impractical and cost prohibitive. Comparably, the decision tree adjustment for the canopy reflectance sensor only required BD and resulted in a remarkably better improvement over the elastic net adjustment. Bulk density is an inexpensive measurement and has become easier and more cost effective to get at a high spatial resolution with advancing precision agriculture technology (Brune et al., 2018). Furthermore, the decision tree approach did better at identifying sites with low N need and correctly decreasing N recommendations. This is critical for reducing overapplication of N and negative environmental outcomes.

3.5 | Tools improved enough?

Improvement using soil and weather information was observed for many tools, but final performance metrics were inferior compared to what others have reported for some N recommendation tools. Tested against EONR values in Pennsylvania, the Pennsylvania PSNT was found to have a $r^2 = .48$ (Schmidt et al., 2009). Using a dataset from New York, the Adapt-N crop growth model had a r^2 of .56 (Sela et al., 2017). Across multiple site-years within the U.S. Midwest, chlorophyll meter-derived N recommendations resulted in a strong linear relationship with EONR, with r^2 values that ranged between .53 and .76 (Scharf et al., 2006; Schmidt et al., 2009) A likely reason for our more modest results is that the sites represent a vast geographic area, and therefore represent extreme diversity in soil and weather environments (Kitchen et al., 2017). Most of these tools tested were developed or tailored from field research within a given U.S. state or subregion of the U.S. Midwest. Thus, testing the tool more extensively would be considered an "extrapolation". Since these tools were generally grounded in biophysical principles and agronomy, testing their utility throughout the region is warranted. But we conclude these tools are not very robust over broad environmental conditions, even with the soil and weather adjustments we considered, and that additional development of N fertilizer recommendations are needed.

4 | CONCLUSIONS

Two unique adjustment methods were used to show that N recommendation tools could be improved by incorporating measured soil and weather information. Results showed that incorporating soil and weather information was successful for most of the tools, but the tools improved to varying degrees. When tool recommendations overestimated EONR, improvements were generally made by adjusting with soil information, while recommendations that underestimated EONR were improved with weather information. When tools overestimated EONR (potentially not considering soil N supply) using soil measurements like TC and soil pH decrease recommendations closer to EONR. When tools underestimated EONR (excessive N loss) using weather information like SDI or AWDR helped increase recommendations closer to EONR. Using these improved tools at a regional level shows encouraging results and could improve farmers' profits and reduce N lost to the environment.

Even with the adjustments, however, these tools could still be further improved as the best linear relationship with EONR resulted in r^2 values $\leq .57$. This means most of the variability in EONR was not captured with N recommendation tools or with the studied adjustments. Additional improvements might occur by incorporating other soil, weather, or management measurements not used in our analysis that might better delineate N response. Therefore, predicting N need for a mature plant when the plant is not yet germinated or is only at about ∼20% of total dry matter of a mature plant will always be challenging when using a single, split, or sidedress application. Nitrogen rate recommendation tools will always have some uncertainty, and enhancements should be viewed as offering "suggestions" or "forecasts" of estimated corn N needs for the growing season. This research was not intended to introduce new tools for public use but showcase that tools could be improved by incorporating additional soil and weather information. These methods show promise but require validation using multi-year N response trials from the same locations to make certain recommendation adjustment can fully account for temporal variation.

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