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Combining corn N recommendation tools for an improved economical optimal nitrogen rate estimation

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Abstract

Improving corn (*Zea mays* L.) nitrogen (N) rate fertilizer recommendation tools can improve farmers' profits and mitigate N pollution. Numerous approaches have been tested to improve these tools, but to date improvements for predicting economically optimum N rate (EONR) have been modest. This work's objective was to use ensemble learning to improve our estimation of EONR (for a single at-planting and split N application timing) by combining multiple corn N recommendation tools. The evaluation was conducted using 49 corn N response trials from eight states in the US Corn Belt and three growing seasons (2014–2016). Elastic net and decision tree approaches regressed EONR against three unique tools for each N application timing. Tools used in various combinations included a yield goal method, two soil nitrate tests (pre-plant and late season), a computer simulation crop model (Maize-N), and canopy reflectance sensing. Any combination of two or three N recommendation tools improved or maintained performance metrics (R^2, root-mean square error , and number of sites close to EONR). The best results for a single at-planting recommendation occurred when combining the three at-planting N recommendation tools (including interactions) with an elastic net regression model. This combined recommendation tool had a significant linear relationship with EONR ($R^2 = 0.46$), an increase of 0.27 over the best tool evaluated alone. Combining multiple tools increased the implementation cost, but it did not reduce profitability and, sometimes, improved profitability. These results show tools can be combined to better match EONR, and thus could aid farmers in improving N management.

Abbreviations: cEONR, reasonably close to the economical optimal N rate; EONR, economical optimal N rate; LSNT, late-spring soil nitrate test; MRTN, maximum return to N; PPNT, pre-plant soil nitrate test; RMSE, root mean square error; YG, yield goal.

1 | INTRODUCTION

Maximizing corn grain production and profitability requires applying nitrogen (N) fertilizer at the economically optimum N rate (EONR). Applying fertilizer below EONR decreases grain yield while overfertilization increases the risk of environmental degradation. Determining what the EONR will be for a field is difficult as plant N uptake is affected by many variables based on genetic (G), environment (E), management (M), and the interactions between these factors (G × E × M) (Kablan et al., 2017; Scharf et al., 2005; Tremblay et al., 2012). Understanding how these factors impact plant N requirements (within and across fields, and from year to year) has been the focus of significant public resources over the last six decades, resulting in the development of many publicly available corn N rate recommendation tools (e.g., yield goal, soil nitrate tests, Maximum Return to Nitrogen (MRTN), computer simulation models, and canopy reflectance sensors) (Bean et al., 2018a; Nafziger et al., 2004; Setiyono et al., 2011; Stanford, 1973). A comprehensive review by Morris et al. (2018) of many of the publicly available tools outlined well the strengths and weakness of each and are summarized in Table S1.

This same review highlighted some of these tools' performance, which showed inconsistency when measured against EONR (R^2 values of 0.00 to 0.68) across a broad geographical area that included multiple US Midwest states. They and others (Bean et al., 2018b; Clark et al., 2020a; Ransom et al., 2020) have attributed this inconsistency to weather factors. Another reasonable explanation for unreliable N fertilizer recommendations is that they only account for one or two components of the soil–plant system known to affect EONR (Morris et al., 2018; Scharf et al., 2005). For example, most pre-plant and pre-sidedness soil nitrate tests are based on measured inorganic nitrate and a soybean [*Glycine max* (L.) Merr.] credit, but they do not consider precipitation, mineralization potential, or soil hydrological properties. Therefore, incorporating more site-specific weather and soil information allows them to be more adaptive to differences in growing conditions. Previous investigations have shown tools can be improved by incorporating additional soil and weather information (coefficient of determination [R^2] ≤ 0.57 and root mean square error [RMSE] ≥ 47 kg N ha^{-1}) (Bean et al., 2018b; Ransom et al., 2021). To date, these investigations have focused on individual tools and evaluated their performance in a side-by-side manner. Additional effort is needed to further improve the adaptability of these well-established tools.

This investigation explores the novel idea of combining some of these same tools. In other words, multiple tools are integrated to better inform the decision of how much N fertilizer to apply. The concept of combining two or more of tools (i.e., tool fusion) deserves consideration, particularly when considering the decades worth of field studies establishing the science of crop and soil N dynamics (Morris et al., 2018). Strategically combining multiple tools that focus on measuring different factors affecting soil N supply and crop N need within the G × E × M framework might be successful at producing tools that function well across larger regions.

Core Ideas

- Individual corn N recommendation tools poorly estimated EONR (R^2 ≤ 0.24) across many US Midwest states.
- Combining or "ensembling" two or more corn N recommendation tools improved EONR estimation (R^2 ≤ 0.46).
- Both ensembling techniques evaluated proved effective at combining tools.

The idea of combining different tools is not unique and has been implemented successfully across many scientific fields using statistical or machine learning ensemble learning techniques. Ensemble learning works by aggregating the outcome of multiple weak learners (i.e., individual models of low prediction accuracy) into strong learners. Some common examples include boosting (modeling using sequential steps where each attempt learns from the previous step, e.g., Adaboost), bagging (an average of multiple models that are created simultaneously where each model is developed using a random bootstrapped subset of the data, e.g., random forests), and stacking (a weighted average of multiple weak learners, e.g., regression models). Ensemble learning has been used to produce more accurate predictive models than the best weak learner used alone (Hansen & Salamon, 1990; Mendes-Moreira et al., 2012; Rosenzweig et al., 2013; Unger et al., 2009; Wallach et al., 2016). Within agriculture, these techniques have been implemented with crop simulation models for improved accuracy and reduced uncertainty—as demonstrated by the Agricultural Model Inter-Comparison and Improvement Project when they ensembled 15 wheat models (Maiorano et al., 2017). Similar findings have been reported when ensembling spectral data from different remote sensing platforms for estimating plant and soil parameters (Dobarco et al., 2017; Fei et al., 2021; Feng et al., 2020; Shahhosseini et al., 2020; Wang et al., 2021). This technique has also been used successfully to improve weather predictions (Aleksovska et al., 2021; Brown et al., 2018; Gu et al., 2021). However, using these machine learning techniques to integrate multiple publicly available N recommendation tools has not been tested. The objective of this investigation was to use ensemble learning techniques for combining N recommendation tools for improved corn EONR estimation.

2 | MATERIALS AND METHODS

2.1 | Experimental design

This research was conducted as a part of a public–private collaborative project between Corteva Agriscience, USDA Agricultural Research Service, and eight US 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). A total of 49 site-year field trials were conducted from 2014 to 2016, with each state conducting research on two sites each year with a third site in Missouri (MO) in 2016. About half the sites were on farmers' fields and the remaining sites were on university research stations. A common protocol for plot research established at the onset of the project was followed across all site-years, which included site selection, weather data collection, soil, plant sample timing and collection methodology, N application timing, N source, and N rates. Specific protocol details have been described in Kitchen et al. (2017), and the data and meta-data have been published in Ransom et al. (2021). Treatments included ammonium nitrate applied at rates between 0 and 315 kg N ha^{-1} either in a single application at-planting (referred to as "single N application") or a split application where 45 kg N ha^{-1} was applied at-planting with the remaining N fertilizer broadcast at the V9 ± 1 corn developmental stage (referred to as "split N application") (Abendroth et al., 2011). This investigation was applied to each of these fertilizer application timings.

2.2 | Calculating the economic optimal nitrogen rate

To calculate EONR for each site and N application timing, grain yield was modeled as a function of N fertilizer rate, across all four replicates. Four different models were evaluated (linear, quadratic, linear-plateau, and quadratic-plateau) and the best model was selected based on the R^2, RMSE, and significance of model probability values (Cerrato & Blackmer, 1990; Scharf et al., 2005). Using the best fit model, EONR values were calculated using a price for N at US\$0.88 kg N^{-1}, and the price of corn at US\$0.158 kg grain^{-1} (equivalent to US\$0.40 lb N^{-1} and US\$4.00 bu^{-1}). The EONR was set to not exceed the maximum N rate applied (315 kg N ha^{-1}) and EONR was set to equal 0 kg N ha^{-1} if the models were insignificant ($p \leq 0.10$). Five of the seven irrigated sites had N applied through irrigation >12 kg N ha^{-1}, and this was included in determining the EONR of these sites. The EONR results were used as the standard for evaluating all N recommendation tools and combinations of tools. Additional details about which models were used at each site and N application timing can be found in Table 4 of Kitchen et al. (2017).

2.3 | Recommendation tools considered

There are many publicly available N recommendation tools currently available for farmers to use, as outlined by Morris et al. (2018), and many of them have been evaluated using this same dataset by Ransom et al. (2020). For this investigation, a subset of the tools was selected. From a practical standpoint, the total number of tools a farmer would be willing to invest in for a single N rate decision would be limited by costs and logistics (i.e., labor, analysis costs, equipment). Ideally, the best candidates for a combination would occur when N recommendation inputs are diverse (i.e., each tool measured a different aspect of the soil–plant N dynamic) and accurate—similar to requirements for "ensembling" in machine learning (Hansen & Salamon, 1990). Following these accuracy (Ransom et al., 2020) and diversity guidelines, three tools for each application timing were selected. For the single N application, a yield goal (YG), Wisconsin pre-plant nitrate test (WI PPNT), and the Maize-N computer simulation model were used. Whereas for the split N application, a YG, Iowa late spring soil nitrate test (LSNT), and a canopy reflectance sensor were used.

2.3.1 | Yield goal

Numerous versions of corn YG have been developed starting with the foundational work by Stanford (1973) decades ago. All of them work on estimating the total N need by multiplying an expected yield by an internal N use efficiency. Here, the YG was determined by multiplying the expected yield by an internal N use efficacy factor of 0.021 kg N (kg grain)$^{-1}$, or 1.2 lb N bu^{-1}. A 45 kg N ha^{-1} credit was subtracted from sites that followed a soybean crop. The expected yield for each site was determined using the average of the previous 5-year county corn yields for the respective county the site was within. This 5-year average was adjusted based on the soil productivity of the predominantly mapped soil of each site, similar to that done previously (Laboski & Peters, 2012). This procedure classifies soil productivity as either low, medium, or high using soil texture, irrigation, depth to bedrock, drainage class, temperature regime, and plant available water content information. The expected yield of a site was then calculated by increasing the 5-year average yield for low, medium, and high soil productivity by 10%, 20%, or 30%, respectively.

2.3.2 | WI PPNT

The WI PPNT was calculated based on guidelines outlined by Laboski and Peters (2012) using soil NO_3–N samples taken to a depth of 90 cm. For this investigation, details of the sampling and NO_3–N analysis protocols were previously documented in a project overview article (Kitchen et al., 2017). The measured NO_3–N (converted to mass by using an assumed bulk density of 1.3 g cm^{-3}) was subtracted from N recommendations developed using the MRTN. The MRTN recommended application rates for all years were based on the reported 2016 values. The MRTN application rates for Iowa, Illinois, Indiana, Minnesota, and Wisconsin were from the online Iowa State Extension N Rate Calculator (cnrc.agron.iastate.edu). The MRTN rates for North Dakota were 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. Since neither Missouri nor Nebraska currently have a compiled database and online tool for an MRTN recommendation, sites from these states (n = 13) used their respective YG-based recommendations (Buchholz et al., 2004; Shapiro et al., 2008):

$$\text{Missouri}\,\text{YG} = 1.12 \times (0.9 \times \text{YG} + 4 \times \text{Pop} - N_{\text{OM-credit}} - N_{\text{Credit}}) \quad (1)$$

$$\text{Nebraska}\,\text{YG} = 1.12 \times [35 + (1.2 \times \text{YG}) - 0.14 \times \text{YG} \times \text{OM} - N_{\text{Credit}}] \times \text{Price}_{\text{adj}} \quad (2)$$

where Missouri or Nebraska's YG is the expected yield calculated using the same protocol described previously, "Pop" is the plant population, "$N_{\text{OM-credit}}$" is a measure of the soil N supplying capacity based on organic matter and cation exchange capacity, "N_{credit}" is a soybean credit of either 34, 39, or 50 kg N ha^{-1} for Missouri, Nebraska sandy, or Nebraska non-sandy soils, respectively. The Nebraska YG used "OM" for organic matter and "$\text{Price}_{\text{adj}}$" is the adjustment factor for the price of corn and N fertilizer.

Two of the 49 sites (2016 Nebraska sites) did not complete PPNT sampling, therefore, the PPNT was estimated using data from the previous years' Nebraska research sites. This was justified as one of the 2016 Nebraska sites that was missing data was on the same research station as the 2014 and 2015 sites. The other 2016 Nebraska site was conducted on sandy soil and was expected to have minimal measurable NO_3–N which is consistent with the 2014 and 2015 Nebraska sandy locations. The WI PPNT is not recommended for sandy soils. However, to keep all observations in the analysis, the four sandy locations (three from Nebraska and one from Minnesota) were still included.

2.3.3 | Maize-N

The Maize-N crop model version 2016.6.0 (Setiyono et al., 2011) was used to generate an N fertilizer recommendation for all sites for a single N application. A total of 30 years of historical data for each site was obtained from Corteva Agriscience using a proprietary method for interpolating between multiple weather stations around each site. These weather data mostly came from public National Service Storms Lab (NOAA) weather stations, supplemented with data observed by Corteva's internal weather network. The weather data were collected within the acceptable range of 50 to 100 km radius, as listed in the Maize-N user guide. Explicit information required by the Maize-N crop growth model by each site included management records (i.e., date of planting, plant population, average historical yield, tillage operations, and previous crop) and soil information (i.e., bulk density, % organic matter, rooting zone depth, soil pH, and soil NO_3–N).

2.3.4 | LSNT

The LSNT was calculated using soil sample NO_3–N taken to a depth of 30 cm at the V5 ± 1 corn development stage. Soil samples were taken from plots that received 0 kg N ha^{-1} and averaged together to obtain a site-level NO_3–N concentration. The site-level NO_3–N concentration was used to determine the amount of N to apply as an in-season N application. Values above the 25 mg kg^{-1} critical limit received no additional N. To determine the N recommendation when NO_3–N was below the critical limit, the difference between the critical limit and the measured NO_3–N concentration was multiplied by 8. The critical limit was reduced by 3 mg kg^{-1} when spring rainfall (April 1 to soil sampling) was 20% above average (Sawyer & Mallarino, 2017).

2.3.5 | Canopy reflectance sensing

Canopy reflectance measurements were obtained using the RapidSCAN CS-45 (Holland Scientific, Lincoln, NE) the same day or just before the split N application. For the majority of sites, this was done 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 an N fertilizer recommendation derived from these reflectance measurements.

This algorithm was 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:

$$SI = \frac{VI_{Target}}{VI_{N-rich}} \quad (3)$$

where SI was the sufficiency index; "VI_{Target}" was the vegetative index obtained from averaging measurements from all plots that received 0 kg N ha^{-1} at-planting, and "$VI_{N\text{-}Rich}$" was 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:

$$NDRE = \frac{NIR - RE}{NIR + RE} \quad (4)$$

Fertilizer N recommendations were calculated using the equation described in Holland and Schepers (2010):

$$N_{Rec} = \left(MZ_i \times N_{Opt} - N_{PreFert} - N_{CRD} + N_{Comp}\right) \times \sqrt{\frac{(1 - SI)}{\Delta SI}} \quad (5)$$

where N_{Rec} was the calculated N fertilizer recommendation; "MZ_i" was a scaling value ($0 \geq MZ_i \leq 2$) used to adjust the N recommendation based on areas of high or low yield performance; "N_{Opt}" was the base N rate, which was determined by the farmer; "$N_{PreFert}$" was the amount of N already applied before sensing; "N_{CRD}" were N credits associated with the previous crop, NO_3–N in irrigation water, manure, or residual NO_3–N; "N_{Comp}" was an optional compensation factor for growth-limiting conditions; SI was the sufficiency index; ΔSI was 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's N 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. 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.

2.4 | Ensemble model development

For this investigation, we focused on using the stacking ensemble approach—as this approach is much easier to interpret than other ensemble techniques. We evaluated two algorithms: elastic net and a recursive partitioning decision tree, computed for both application timings. For each ensemble scenario, EONR was modeled as a function of up to three N recommendation tools. We judged three tools as the upper limit of what would be practical for a farmer to implement (more details below).

The elastic net regression models were evaluated in two ways: (1) using a combination of each of the three tools as the main effects and (2) using the same combination of main effects plus all two- and three-way interactions. This resulted in a total of 16 modeling scenarios (i.e., 8 modeling scenarios × 2 application timings). This was accomplished using the {caret} and {glmnet} packages with R Statistical Software (R Core Team, 2020; Friedman et al., 2010; Kuhn, 2017). For each elastic net model, the alpha and lambda tuning parameters (parameters within the model that determine how the model learns) were optimized using a 10-fold cross-validation repeated five times, where the data were split randomly into 10 equal folds or subsets. Nine of the folds were selected as a training dataset to fit models with all combinations of alpha (i.e., five values: 0.10, 0.25, 0.55, 0.75, and 1) and lambda (i.e., 100 values ranging from 0.001–50 in increments of 0.505). All models were tested using the 10th fold, previously not used in the training dataset, and the RMSE was calculated using the model's predicted and actual EONR values. This was repeated until every fold was used as the testing dataset. This process was then further repeated another four times—so new random folds were created—to where 50 RMSE values were calculated for each combination of alpha and lambda values. The optimal tuning parameter values were determined as those that produced the lowest average RMSE across all 50 cross-validation testing sets.

For the decision tree models, only the main effects (i.e., the three tools for the single and split application) were evaluated using the {caret} and {rpart} package in R (Therneau & Atkinson, 2019). Each tree was developed by selecting variables at each node of the tree which explained the greatest homogeneity of the data (Questier et al., 2005). The homogeneity was measured as the absolute deviation from the mean. The decision trees' performance was optimized by tuning the complexity parameter, a parameter that determines if additional splits should be done. Tuning occurred using the same cross-validation methods as the elastic net regression models (see Supporting Information for example code).

2.5 | Evaluating tool improvement

Four different metrics were used to evaluate the performance of each new combined tool. All metrics were based on the measured EONR and the predicted values from the combined tools which included: (1) the coefficient of determination, (2) RMSE, (3) the average difference, and (4) the percentage of sites where the tool's N recommendation came within ± 30 kg N ha^{-1} of EONR—this value was considered reasonably close to EONR (cEONR) based on practicality of generating an

N recommendation and the modeling error associated with EONR (Laboski et al., 2014; Sawyer, 2013; Sela et al., 2017).

2.6 | Foregone profit

To determine the amount of profit lost when using each tool or combination of tools relative to EONR, a "foregone profit" was calculated. This was done by calculating a partial profit (i.e., revenue from grain yield minus the cost of N) for each tool and EONR using \$0.158 kg grain^{-1} and \$0.88 kg N^{-1}. The N rate used in the calculation was the tools' recommended N rate and EONR, and the grain yield was based on each site's N response curve associated with that N rate. The foregone profit (in \$ ha^{-1}) was calculated by subtracting from the partial profit of each tool the partial profit at EONR and an additional tool implementation cost. The tools' implantation cost varied based on the N fertilizer application timing and the labor and costs for obtaining the information required to produce an N recommendation (e.g., labor for collecting soil samples, cost of soil analyses, and equipment acquisition). These costs were based on the Iowa Farm Custom Rate Survey (Plastina et al., 2021) and the cost of soil analysis—calculated as the average of six Midwest soil testing laboratories (University of Minnesota, Midwest Laboratories, North Dakota State University, University of Missouri, University of Wisconsin–Madison, and Ward Laboratory). To determine if combining tools minimized forgone profits (i.e., a cost-effective approach), an analysis of variance (ANOVA) model was used to model forgone profits as a function of each tool and a combination of tools (across both single and split N application). Significant means were separated using a Tukey's honest significance test ($p \leq 0.05$).

3 | RESULTS

Results for combinations of corn N rate recommendation tools using ensemble learning modeling are provided in Table 1, with the resultant recommendation algorithm outcomes provided in Table S2. Best performance of combined tools is judged as those with the greatest coefficient of determination, lowest RMSE, least average difference, and highest cEONR. These metrics generally track each other when examining tool combinations. Model outcomes are presented in Table 1 and are graphically presented in Figures 1–6.

3.1 | Elastic net-based combinations for single and split N applications

The tool with the best performance before combining was the WI PPNT with an R^2 = 0.20, RMSE = 76 kg N ha^{-1}, and cEONR = 35% (Table 1). The best improvement using the elastic net for the single N application occurred when all three N recommendations were combined using all three- and two-way interaction terms and the main effects resulting in an R^2 = 0.46, RMSE = 60 kg N ha^{-1}, and cEONR = 41% (Figures 1 and 2; Table 1). The best combination of two tools occurred with the Maize-N crop growth model and YG. By themselves, the YG and Maize-N model had only 14% and 18% of their sites cEONR, respectively. But the cEONR increased to 41% when combined. In general, the majority of these improvements occurred by correcting the YG N recommendation when it overestimated (low EONR values) or underestimated (high EONR values) a site's N response.

For the split N application timing, the best tool used alone was the LSNT with R^2 = 0.24, RMSE = 68 kg N ha^{-1}, and cEONR = 41% (Table 1). The best improvement occurred when all three split N recommendation tools were combined by using all three- and two-way interaction terms and the main effects resulting in a R^2 = 0.42, RMSE = 55 kg N ha^{-1}, and cEONR = 47% (Figure 3; Table 1). The best combination of two tools was the canopy reflectance sensor and the YG (Table 1). Alone, the YG overestimated many of the site's EONR values when recommendations were ≤200 kg N ha^{-1} (Figure 4a). Alone, the canopy reflectance sensor underestimated many of the site's EONR values when N recommendations were ≥175 kg N ha^{-1} (Figures 3 and 4c). The combination of these tools helped to reduce the error observed for both tools (Figures 3 and 4c,e,i).

There were some combinations of tools, specifically when only two tools were used, that showed minimal improvement. This occurred when the two tool's performance was not distinct enough (i.e., similar linear relationship with EONR) to warrant a combination. For example, the WI PPNT, on average, came cEONR and had a positive linear relationship with EONR (Figure 2b), whereas the Maize-N model underestimated EONR on average and had no relationship with EONR (Figure 2c). The resulting ensemble (Figure 2f) therefore looked similar to the WI PPNT (Figure 2b). In contrast, when the YG, which overestimated EONR and had a negative linear relationship, was combined with the Maize-N model, which underestimated EONR, greater improvement resulted (Figure 2a,c,e). Even though some pairs of tools did not significantly improve the performance of predicting EONR, the combinations caused the average difference between N recommendations and EONR to be close to 0 kg N ha^{-1} and a decrease in RMSE (Table 1). Of note, there was no observed performance loss by combining tools.

3.2 | Decision tree-based combination for single and split N applications

The decision tree-based combination for a single N application resulted in a R^2 = 0.37, which for this performance

TABLE 1 Elastic net and decision tree combined tools used to predict the economical optimal N rate (EONR) for a single or split N application. The coefficient of determination calculated by regressing EONR

Tools	Main effects only					Main and interaction effects				
	p	R^2	Average	RMSE	cEONR	p	R^2	Average	RMSE	cEONR
			kg N ha^{-1}		%			kg N ha^{-1}		%
Single										
YG	1	0.10	58	117	14	–	–	–	–	–
WI PPNT	1	0.20	−7	76	35	–	–	–	–	–
Maize-N	1	0.00	−44	116	18	–	–	–	–	–
YG + WI PPNT	2	0.29	0	68	35	3	0.37	0	64	33
YG + Maize-N	2	0.33	0	67	41	3	0.37	0	64	41
WI PPNT + Maize-N	2	0.20	0	73	31	3	0.20	0	73	31
YG + WI PPNT + Maize-N	3	0.39	0	64	41	7	0.46	0	60	41
Decision Tree (Figure 5)	2	0.37	0	53	43	–	–	–	–	–
Split										
YG	1	0.13	65	113	18	–	–	–	–	–
LSNT	1	0.24	−25	68	41	–	–	–	–	–
Canopy Ref.[a]	1	0.19	−23	73	29	–	–	–	–	–
YG + LSNT	2	0.29	0	61	45	3	0.29	0	61	45
YG + Canopy Ref.	2	0.25	0	63	37	3	0.33	0	59	43
LSNT + Canopy Ref.	2	0.26	0	63	41	3	0.26	0	62	43
YG + LSNT + Canopy Ref.	2	0.31	0	61	41	7	0.42	0	55	47
Decision Tree (Figure 6)	3	0.45	0	53	45	–	–	–	–	–

Note: The coefficient of determination calculated by regressing EONR ($n = 49$) as a function of each tool or combined tool's N 784 recommendation. The precision and accuracy of each N recommendation tool were evaluated using the average difference (N 785 recommendation tool – EONR), root mean square error (RMSE) of the difference, and the percentage of sites within ±30 kg N ha^{-1} of EONR (cEONR, 786 "relatively close to EONR"). "p" is the number of tools and interaction effects used in each regression or decision tree model. Tools 787 include the yield goal (YG), Wisconsin (WI) pre-plant nitrate test (PPNT), Iowa late-spring soil nitrate test (LSNT) with 0 kg N ha^{-1} applied at788 planting, Maize-N crop growth model, and canopy reflectance sensing using the Holland and Schepers (2010) algorithm. Dashes 789 indicate the test was not applicable.

[a]Canopy Ref. refers to canopy reflectance sensing.

metric was not as good as the best elastic net combined tool. However, this method had the lowest RMSE and the highest percentage of sites cEONR (Figure 1; Table 1). A product of the decision tree method is a set of discrete N recommendations, not continuous rates, where it bins N recommendations based on the number of end nodes in the tree. For the single N application decision tree combination, there were five different end nodes and therefore five different N rate recommendations (Figure 5). For each N recommendation, many of the sites either under- or overestimated EONR, but on average came cEONR (Figures 1 and 3). For these tool combinations, only two of the three N recommendation tools (YG and WI PPNT) were used. The WI PPNT was used to make splits throughout the decision tree, with increasing N recommendation with increasing WI PPNT rates, which follows the positive linear relationship between WI PPNT and EONR. On the other hand, as the YG recommendations increased the resulting N recommendations decreased—a result of the negative linear relationship YG has with EONR.

The split N application decision tree resulted in an $R^2 = 0.45$ (Figure 4l), which was the best performance of any split ensemble tool. Also, this method had the lowest RMSE and the second highest percentage of sites cEONR (Table 1). This method used all three N recommendation tools in the combined model (Figure 6). For the LSNT and canopy reflectance sensor, as their N recommendations increased the resulting decision tree's recommendations increased. The YG effect was in the opposite manner.

3.3 | Foregone profits

Mean foregone profit of tools and combination of tools ranged from \$73 to \$228 ha^{-1} (mean of \$99 ha^{-1}) for the single application and from \$91 to \$132 ha^{-1} (mean of \$110 ha^{-1}) for the split application (Table 2). A comparison between using a tool or combination of tools and not using any tools (i.e., an average state N rate). Generally,

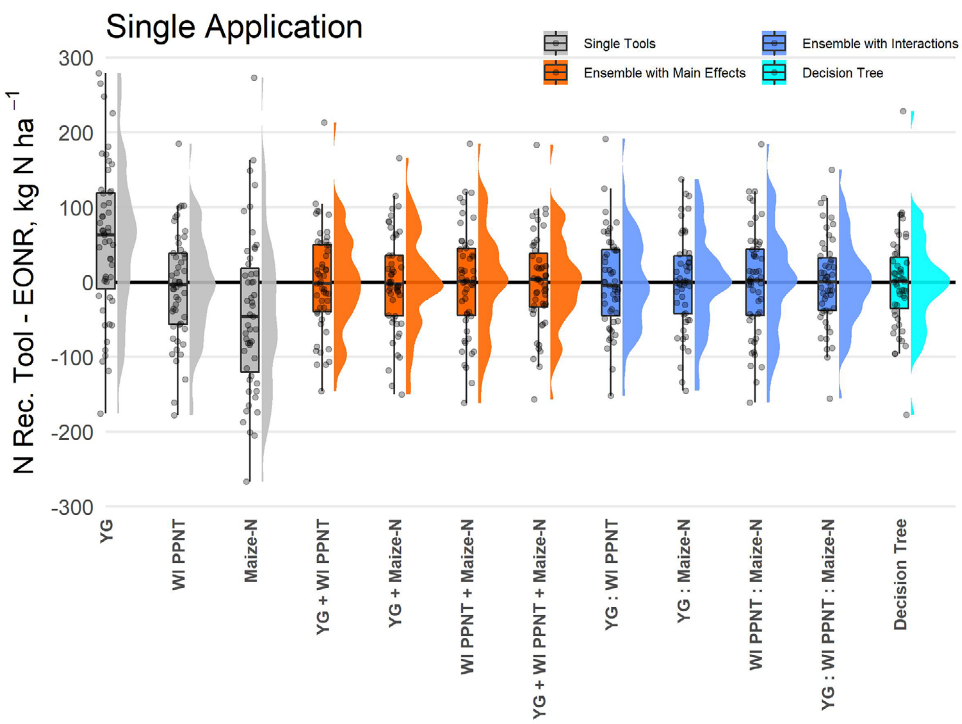

FIGURE 1 Boxplot and distribution plots showing the difference between N recommendation tools used for a single N application at-planting and the economically optimal N rate (EONR). Tools included the yield goal (YG), Wisconsin pre-plant soil nitrate test (WI PPNT), and the Maize-N crop growth model. Tools were combined with either an elastic net regression model or a decision tree. Elastic net combinations were done with and without interactions. All combinations of main effects and interaction terms are marked with ":". The boxplots show the median (center line), 25th and 75th percentiles (lower and upper box limits), and 1.5 × the inter-quartile range (lower and upper whiskers) of the data.

combinations of tools reduced forgone profit over individual tools. The greatest forgone profit (i.e., highest profitability loss) for single application was with Maize-N and least was the decision tree. However, the mean foregone profit was the same for most tool/combinations. Whereas for the split application there was no significant difference between the tools' forgone profit. The difference between the single and split application timing was minimal; even though the tools' implementation cost was much lower for the single application (mean of \$35 ha^{-1}) compared to the split application (\$55 ha^{-1}).

4 | DISCUSSION

We found that combining N recommendation tools using both ensemble learning techniques improved the prediction of EONR compared with N recommendation tools used alone. We observed this with both ensemble learning methods tested (i.e., elastic net and decision tree)—which provides validity to this approach. These results also show we can take individual tools that were developed in smaller geographical regions—which tend to underperform across large variations in soils and growing conditions—and combine them to broaden their usability across larger geographical regions without a decrease in model accuracy or profitability from the N application.

4.1 | Comparing ensemble-based tools

When compared to other investigations using this dataset, the ensemble-based method ($R^2 \leq 0.46$ an increase in $R^2 = 0.26$; and RMSE $\geq$ 53 kg N ha^{-1}) performed better than anyone tool evaluated alone ($R^2 \leq 0.20$ and RMSE $\geq$ 70 kg N ha^{-1}) (Ransom et al., 2020). In addition, this method outperformed some attempts to better predict EONR but not all. For example, when incorporating soil and weather information into the same tools used in this study for a single (i.e., YG and PPNT) or split (i.e., YG, LSNT, and canopy reflectance sensor) application respectively, results for adjusted tools had an $R^2 \leq 0.37$ and RMSE $\geq$ 57 kg N ha^{-1} (an increase in $R^2 = 0.33$ and a decrease in RMSE = 20 kg N ha^{-1}) and $R^2 \leq 0.57$ and RMSE $\geq$ 47 kg N ha^{-1} (an increase in $R^2 = 0.44$ and a decrease in RMSE = 38 kg N ha^{-1}) (Bean et al., 2018b; Ransom et al., 2021). When incorporating potentially mineralizable N with soil nitrate tests (i.e., PPNT or pre-side dress nitrate tests), results were promising in coarse-textured soils with an $R^2 \leq$ 0.63 (an increase in $R^2 = 0.35$) but showed minimal improvement across all soil types (an increase in $R^2 \leq 0.11$) (Clark

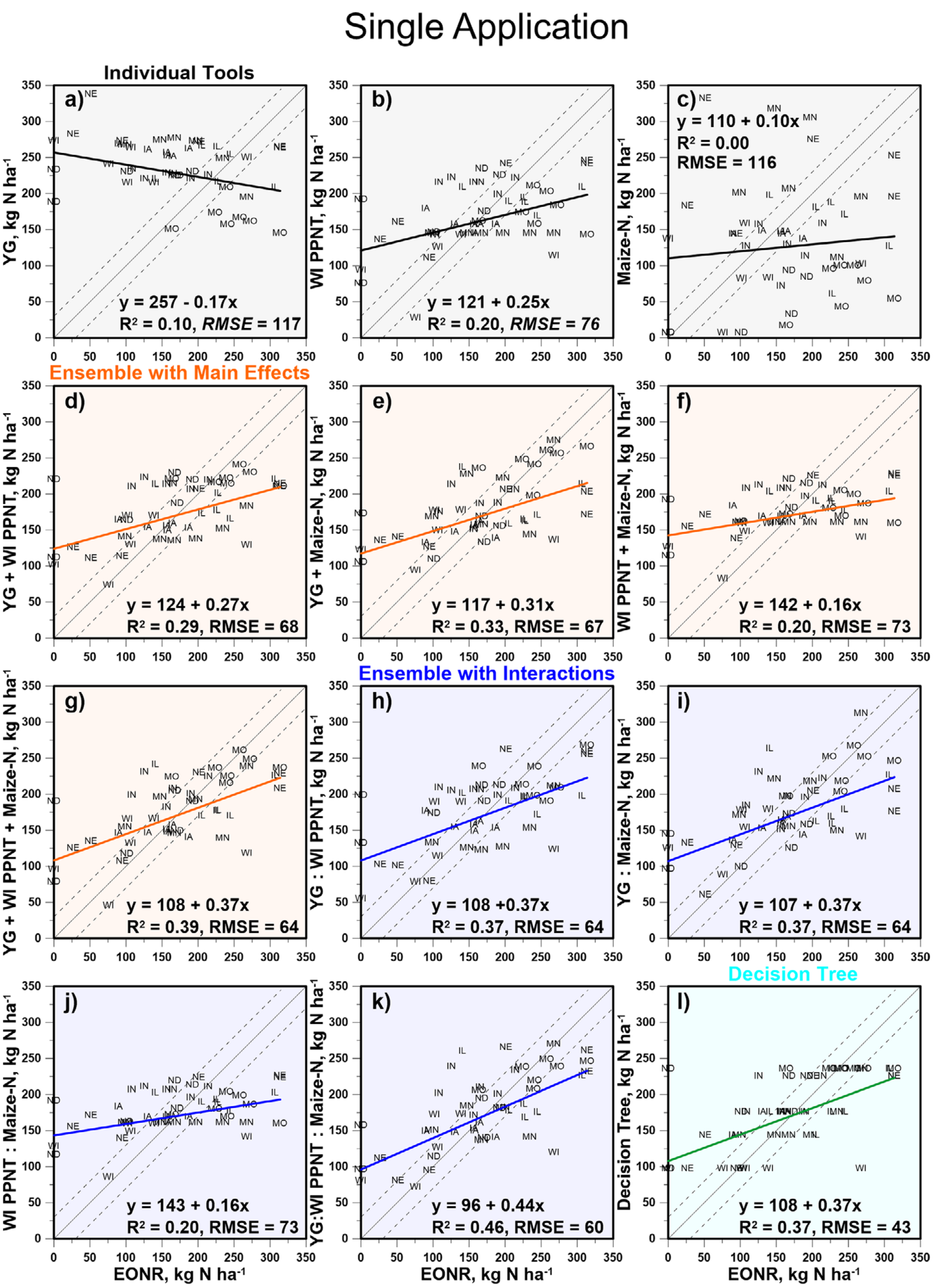

FIGURE 2 Nitrogen recommendation tools used for a single N application at planting evaluated relative to the economically optimal N rate (EONR). Tools included the yield goal (YG), Wisconsin pre-plant soil nitrate test (WI PPNT), and the Maize-N crop growth model. Tools' performances are shown with the tools by themselves (a–c), combined using only main effects (d–g), combined using both main effects and interaction terms (h–k), and combined using a decision tree (l). The 1:1 line is an indicator of a perfect predictor of EONR. The dashed lines show the area in which tools are within ± 30 kg N ha^{-1} of EONR or relatively close to EONR and root mean square error units are in kg N ha^{-1}.

et al., 2020b). Using various machine learning algorithms to develop a new N recommendation tool resulted in an $R^2 \leq 0.60$ and RMSE $\geq$ 27.8 kg N ha^{-1} (Qin et al., 2018). However, the best attempt to date included using a hierarchical approach based on hydrologic soil groups and drainage classifications to adjust N recommendation tools with soil and weather information, which resulted in an $R^2 \leq 0.78$ (Bean et al., 2021).

Compared to the performance of many of the same tools reported in the literature across the Midwest, either in a single state or across multiple states, this ensemble approach outperformed most tools used by themselves. These included yield goal-based recommendations (R^2 between 0.06 and 0.38 reported by Blackmer et al., 1992; Fox & Piekielek, 1995; Schmidt et al., 2009; Vanotti & Bundy, 1994), PPNT (R^2 between 0.20 and 0.38 reported by Scharf, 2001; Schmidt

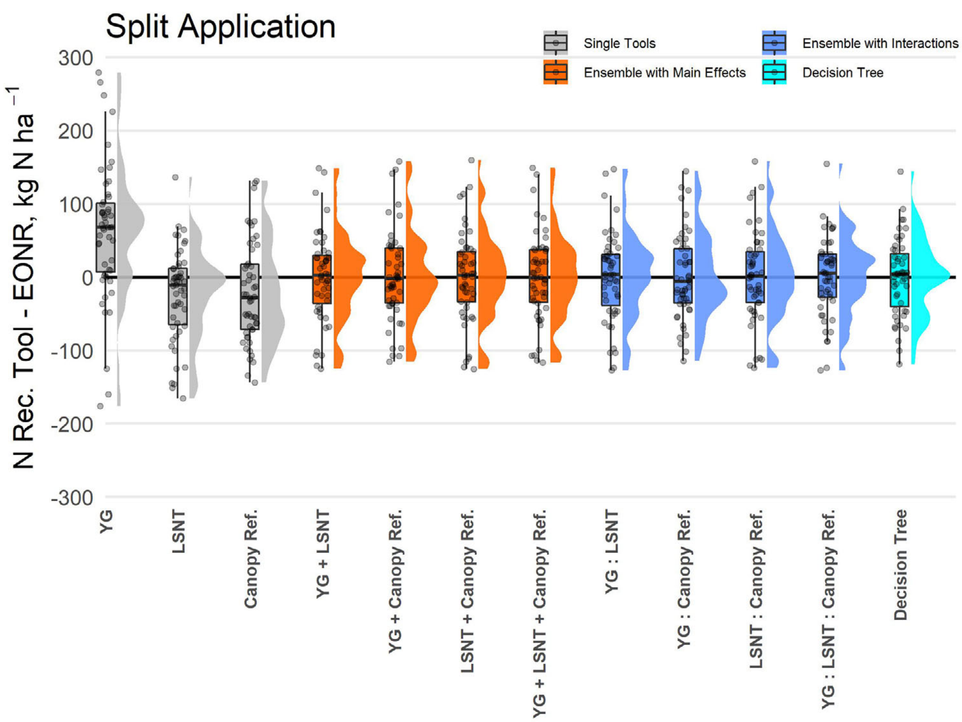

FIGURE 3 Boxplot and distribution plots showing the difference between N recommendation tools used for a split N application (at-planting + sidedress) and the economically optimal N rate (EONR). Tools included the yield goal (YG), Iowa late-spring nitrate test with 0 kg N ha^{-1} applied at-planting (LSNT), and canopy reflectance sensing. Tools were combined with either an elastic net regression model or a decision tree. Elastic net combinations were done with and without interactions. All combinations of main effects and interaction terms are marked with ":". The boxplots show the median (center line), 25th and 75th percentiles (lower and upper box limits), and 1.5 × the inter-quartile range (lower and upper whiskers) of the data.

et al., 2009), pre-sidedress N tests (R^2 between 0.04 and 0.48 reported by Scharf, 2001; Scharf et al., 2006; Schmidt et al., 2009). Others have reported single tools which had better performance than these ensemble-based methods, such as crop growth models (R^2 between 0.09 and 0.85 reported by Puntel et al., 2016; Sela et al., 2018; Setiyono et al., 2011; Thompson et al., 2015), canopy reflectance sensors (R^2 between 0.02 and 0.72 reported by Bean et al., 2018a; Roberts et al., 2010; Sripada et al., 2008; Thompson et al., 2015), and chlorophyll meters (R^2 between 0.27 and 0.84 reported by Dellinger et al., 2008; Scharf, 2001; Scharf et al., 2006; Schmidt et al., 2009). While many of these high R^2 values were from research conducted in a single state; individual tool performance generally decreased when evaluated across a wider range of growing conditions (Ransom et al., 2020; Scharf et al., 2006). This highlights one of the two things. Either tools need to be developed/tested to be more robust across growing conditions, or it must be accepted that N fertilizer management is too complex across diverse environmental conditions—such as represented by the US Midwest Corn Belt—and that local–regional specialized tools are the most practical and suitable approach.

4.2 | Strengths and limitations of tools

Current N recommendation tools poorly predict when sites will be non/low N-responsive (i.e., low EONR values) or highly N responsive (i.e., high EONR values) to N fertilization (Ransom et al., 2020). This is often because of uncertainty about seasonal weather. To account for this uncertainty, and the knowledge that underfertilization rapidly decreases yield and profitability, farmers tend to over apply N to maximize yield. This practice will not change unless farmers are confident that N recommendation tools are more reliable. The current tools being recommended by university extension agencies in the US Midwest (e.g., YG approach and the "MRTN") do not account for seasonal site-specific conditions which influence when EONR values will be high or low (Morris et al., 2018; Ransom et al., 2020). There are only a few tools that recommend low N rates (i.e., PPNT and LSNT, crop growth models, and canopy reflectance sensors [based on user inputs]) and even fewer that will recommend high N rates (e.g., crop growth models). Thus, the potential value of using an ensemble method, as it could optimize the strengths of each tool to improve recommendations and confidence in

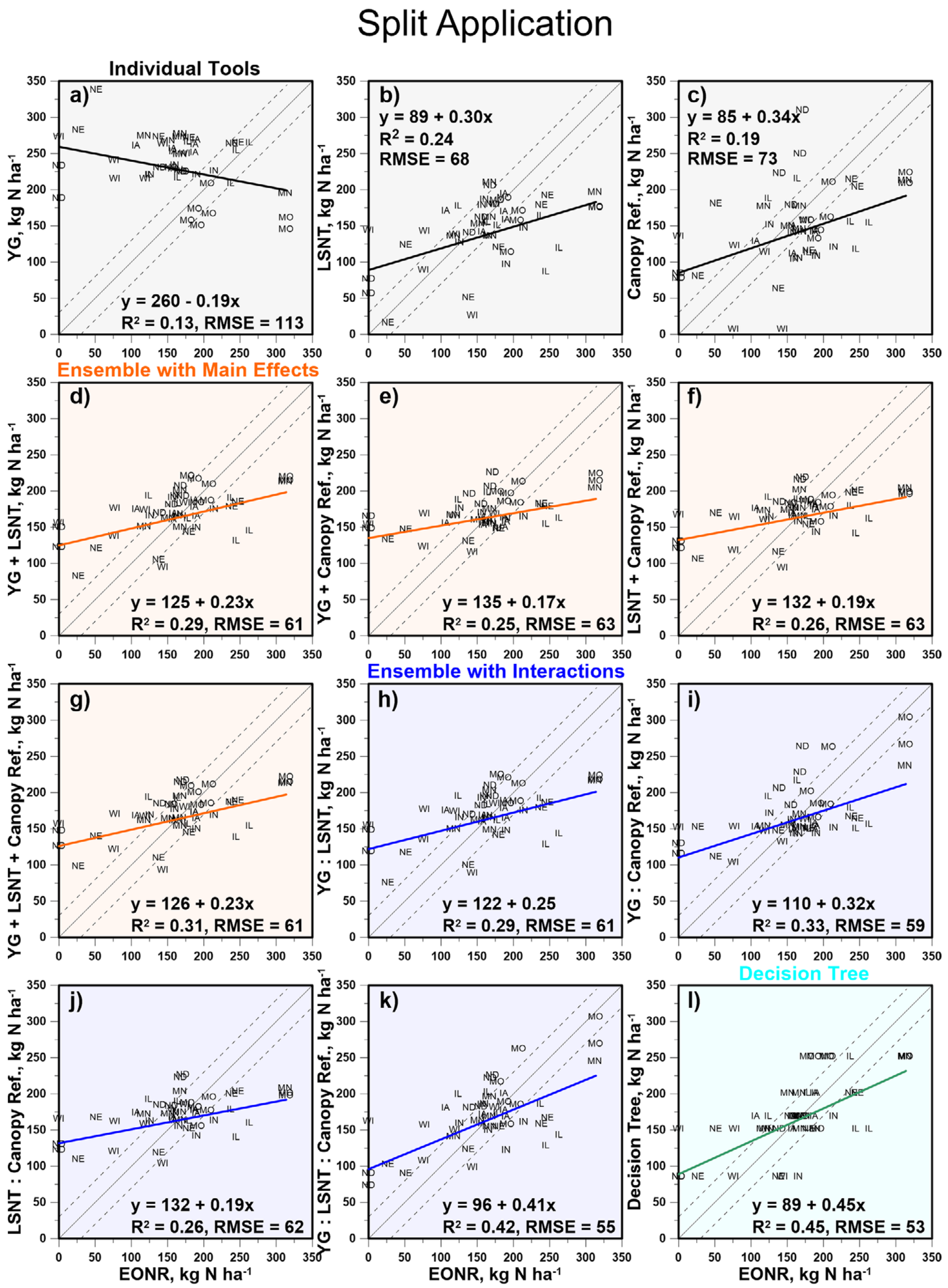

FIGURE 4 Nitrogen recommendation tools used for a split N application (at-planting + sidedress) evaluated relative to the economically optimal N rate (EONR). Tools included the yield goal (YG), Iowa late spring nitrate test with 0 kg N ha^{-1} applied at-planting (LSNT), and canopy reflectance sensing. Tools performances are shown with the tools by themselves (a-c), combined using only main effects (d-g), combined using both main effects and interaction terms (h-k), and combined using a decision tree (l). The 1:1 line is an indicator of a perfect predictor of EONR. The dashed lines show the area in which tools are within ± 30 kg N ha^{-1} of EONR or relatively close to EONR and root mean square error units are in kg N ha^{-1}.

minimizing errors. This is made evident in how ensembling helps overcome the weakness of other tools. For example, the YG approach tends to overestimate EONR as it is based on an expected yield estimation and does not consider N mineralization or soil nitrate (Morris et al., 2018). When ensembled with other tools that do account for these and other aspects soil and plant N dynamics (e.g., WI PPNT, LSNT, and canopy reflectance sensors) this overestimation is reduced especially when EONR is low. These same tools underestimate corn N need when EONR is high. Coupling them with the YG helps to compensate for this underestimation. This results in much better relationships with EONR—as shown by the decrease in regressed intercept terms and an increase in slope terms (Figures 2 and 4).

TABLE 2 The implementation costs used to calculate foregone profits and the corresponding range of foregone profits (relative to EONR) associated with each tool and combination of tools.

Tools	Implementation cost[a]	Main effects foregone profit			Main and interaction effects foregone profit		
		Max	Min	Mean	Max	Min	Mean
	US$ ha^{-1}				US$ ha^{-1}		
Single N application							
YG	13.70	342	14	103ab	–	–	–
WI PPNT[b]	31.70	367	32	92ab	–	–	–
Maize-N[c]	34.27	933	34	228c	–	–	–
YG + WI PPNT	31.00	256	32	81ab	201	32	77ab
YG + Maize-N	32.30	350	34	84ab	337	32	82ab
WI PPNT + Maize-N	52.27	318	32	86ab	316	32	87ab
YG + WI PPNT + Maize-N	52.27	290	52	98ab	247	52	94ab
Decision Tree	31.00	233	32	73a	–	–	–
Split N application							
YG	42.85	449	43	130ab	–	–	–
LSNT[d]	60.15	495	60	131b	–	–	–
Canopy Ref.[e]	44.31	331	44	132b	–	–	–
YG + LSNT	60.15	357	60	106ab	367	60	106ab
YG + Canopy Ref.	44.31	312	44	91ab	291	44	88ab
LSNT + Canopy Ref.	61.61	377	62	110ab	372	62	110ab
YG + LSNT + Canopy Ref.	61.61	328	62	107ab	369	62	102ab
Decision Tree	61.61	329	62	102ab	–	–	–

Note: Tools include the yield goal (YG), Wisconsin (WI) pre-plant nitrate test (PPNT), Iowa 795 late-spring soil nitrate test (LSNT) with 0 kg N ha^{-1} applied at-planting, Maize-N crop growth model, and canopy reflectance sensing 796 using the Holland and Schepers (2010) algorithm. All significant mean differences (using Tukey's honest significant difference test across both N application 797 timings; $p \leq 0.05$) are shown with unique lower-case letters.

[a]The implementation cost was calculated as the sum of the cost for the N application and using the tool(s). The costs for the single ($13.70 ha^{-1}) and split ($13.70 ha^{-1} + 29.15 ha^{-1}) applications were based on the Iowa Farm Custom Rate Survey using the average cost of applying dry bulk fertilizer (at-planting) and sidedressing liquid fertilizer (split) (Plastina et al., 2021).

[b]The WI PPNT tool cost ($18.00) was based on GPS grid soil sampling ($16.67 ha^{-1}; Plastina et al., 2021) and the cost of analyzing two depths (0–30 and 30–60 cm) for soil nitrate ($5.30/sample or $1.31 ha^{-1}; based on the average cost from six Midwest soil testing laboratories [University of Minnesota, Midwest Laboratories, North Dakota State University, University of Missouri, University of Wisconsin–Madison, and Ward Laboratory]) for an 8-ha area (Laboski & Peters, 2012).

[c]The Maize-N tool cost ($20.57 ha^{-1}) was based on GPS grid soil sampling ($16.67 ha^{-1}; Plastina et al., 2021), cost of analyzing soil for organic matter, bulk density, pH, and nitrate ($31.58/sample or $3.90 ha^{-1}; based on the average costs reported from the six Midwest soil testing laboratories) for an 8-ha area.

[d]The LSNT tool cost ($17.30 ha^{-1}) was based on GPS grid soil sampling ($16.67 ha^{-1}; Plastina et al., 2021) and the cost of analyzing one depth of soil (0–30 cm) for soil nitrate ($5.30/sample; based on the average costs reported from six Midwest soil testing laboratories) for an 8-ha area.

[e]The canopy reflectance sensing tool cost ($1.46 ha^{-1}) was estimated as an additional cost to the application cost ($29.15 ha^{-1}) using the reported average sidedress liquid fertilizer application rate from the Iowa Farm Rate Survey (Plastina et al., 2021). It was assumed that 50% of the sidedress application cost comes from machinery upkeep and acquisition, and 50% from labor and fuel (R. Massey, personal communication, 2017). The additional cost of using canopy reflectance sensors and a variable rate application was calculated as 10% of the base machinery upkeep and acquisition costs ($1.46 ha^{-1}).

The ensemble methods evaluated here are based on a simple principle of weighted averaging, with the weights being optimized by the different machine learning processes. We perceive that additional improvement could be observed by using other techniques such as boosting (i.e., continually fitting models by using the previous' models residuals) or bagging (i.e., using bootstrapping methods to minimize bias in the models). These methods would also work by combining site-specific soil, weather, or management information to better account for situations where no additional N is required (e.g., from mineralization) or where additional fertilizer is needed (e.g., excessive rainfall events). That said, most of those methods do not represent growth and yield potential determined during the late vegetative and reproductive phases of the growing season. Thus, to expect these tools to be perfect predictors of seasonal crop N need before or early in the season is unrealistic.

As many of the tool ensembles combinations the performance over any one tool used alone, ensemble evaluation would allow farmers the flexibility of using the N management information they have on hand. For example, if they typically rely on LSNT results for their N rate management decisions, then they could evaluate how N recommendations may change based on incorporating a YG recommendation.

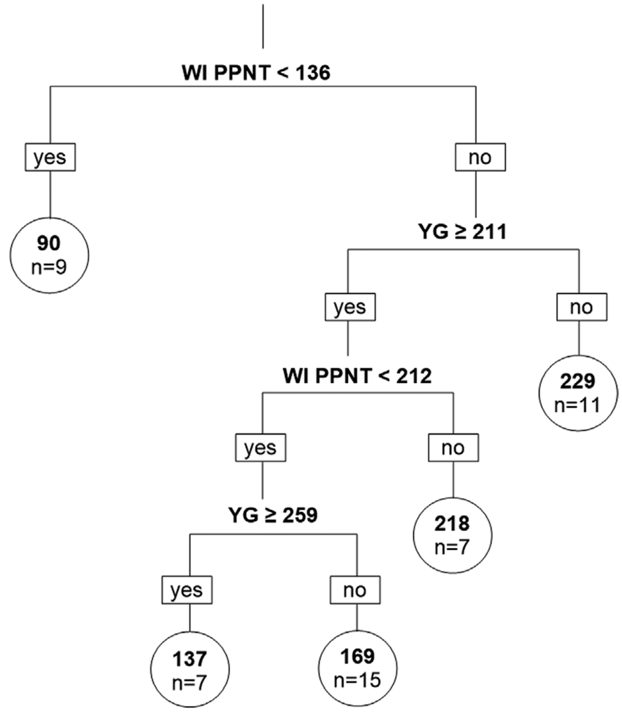

FIGURE 5 The decision tree model used to predict the economically optimal N rate (EONR) for a single N application at-planting using the yield goal (YG) and the Wisconsin pre-plant soil nitrate test (WI PPNT). Values at each split represent each tool's N recommendation in kg N ha^{-1}. Values at each terminal node show the resulting N recommendation (kg N ha^{-1}) and number of sites (n).

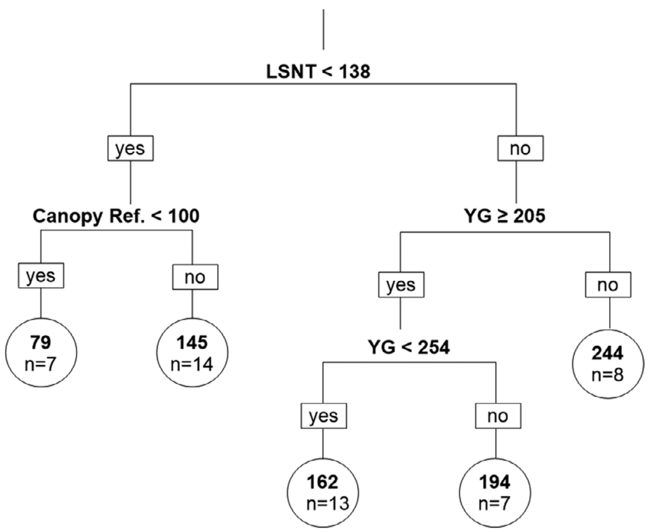

FIGURE 6 The resulting decision tree model used to predict the economically optimal N rate (EONR) for a split N application (at-planting + sidedress) using the yield goal (YG), Iowa late spring soil nitrate test with 0 kg N ha^{-1} applied at-planting (LSNT), and canopy reflectance sensing. Values at each split represent each tool's N recommendation in kg N ha^{-1}. Values at each terminal node show the resulting N recommendation (kg N ha^{-1}) and number of sites (n).

From a practical standpoint, this would best be accomplished with an online interface, where users could input the tools' information, select one or more ensembling techniques, and observe N recommendation changes.

A concern with combining multiple tools is the implementation cost increases with each additional tool added to the ensemble. Ideally, the increase in accuracy of combining multiple tools would increase the revenue from higher yields and lower fertilizer costs, which would offset the implementation costs. While this was true to an extent, there never was a point where the ensemble-based method significantly improved profitability. However, the ensemble-based method never significantly decreased profitability either. This is encouraging, as the implementation cost for many of these tools could become more economical with the advancement of low-price information technologies. For example, using a more accurate crop growth model that relies on publicly available data could reduce this particular tool's usage costs down to \$0 as compared to the \$20.57 required to have soil samples collected and analyzed for the inputs necessary to run Maize-N. Until acquisition and implementation costs are reduced it is unlikely that farmers and advisors will collect multiple types of measurements. However, there are times where farmers will have multiple sources of information (e.g., routine soil fertility samples, aerial imagery) and therefore this approach could be used to adjust or validate their current N fertilization management.

5 | CONCLUSION

Determining the optimal rate of N fertilizer to apply to optimize corn grain yields while minimizing environmental degradation is a difficult task. Solving similarly complex problems by using ensemble learning have shown promise in multiple scientific fields. A similar approach was used in this investigation to combine or "fuse" multiple N recommendation tools. Combining two or more tools together lead to an increased ability to estimate EONR (R^2 = 0.46, an increase of 0.27 over the best tool evaluated alone) will decrease error (RMSE = 43 kg N ha^{-1}, a decrease of 33 kg N ha^{-1}) without decreasing profitability across a wide range of soils and growing conditions. Combining tools worked with both ensemble learning methods and for both a single at-planting and split N application. Using this ensembling approach, farmers could be more confident they are applying close to the right N rate. But additional work is needed to make this approach more practical for farmers and advisors. Future efforts will need to evaluate which additional N recommendation tools could be included, developing an online tool for users to interactively select which tools to combine based on the information they have, determine if auxiliary information (e.g., weather, soil characteristics, management, drainage classification) could be used to further improve ensemble models, and provide further validation with more on-farm N response data and at a more local scale.

It is not possible to explain all the variability around EONR especially when recommendations are made before planting or early in the growing season and without knowing if the subsequent growing conditions would optimize or limit plant growth. However, finding ways to utilize multiple sources of data will be paramount for decreasing the uncertainty around nutrient management decisions and thereby improving our ability to produce corn adaptively and sustainably.

AUTHOR CONTRIBUTIONS

Curtis J. Ransom: Conceptualization; data curation; formal analysis; investigation; methodology; project administration; validation; visualization; writing—original draft. **Newell R. Kitchen**: Conceptualization; data curation; funding acquisition; investigation; methodology; project administration; resources; supervision; writing—review and editing. **James J. Camberato**: Data curation; investigation; methodology; resources; writing—review and editing. **Paul R. Carter**: Data curation; funding acquisition; investigation; methodology; project administration; resources; writing—review and editing. **Richard B. Ferguson**: Data curation; investigation; methodology; resources. **Fabián G. Fernández**: Data curation; investigation; methodology; resources; writing–review and editing. **David W. Franzen**: Data curation; investigation; methodology; resources; writing——and editing. **Carrie A. M. Laboski**: Data curation; investigation; methodology; resources; writing—review and editing. **David Brenton Myers**: Methodology; validation; writing—review and editing. **Emerson D. Nafziger**: Data curation; investigation; methodology; resources. **John E. Sawyer**: Data curation; investigation; methodology; resources; writing—review and editing. **John F. Shanahan**: Funding acquisition; investigation; methodology; project administration; resources; supervision; writing—review and editing.

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