IMPROVING CORN NITROGEN RATE RECOMMENDATIONS THROUGH TOOL FUSION

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Abstract. Improving corn (*Zea mays* L,) nitrogen (N) fertilizer rate recommendation tools can improve farmer's profits and help mitigate N pollution. One way to improve N recommendation methods is to not rely on a single tool, but to employ two or more tools. This could be thought of as "tool fusion". The objective of this analysis was to improve N management by combining N recommendation tools used for guiding rates for an in-season N application. This evaluation was conducted on 49 N response trials that spanned eight states and three growing seasons. An economical optimal N rate (EONR) was calculated for N treatments receiving 45 kg N ha^{-1} applied at-planting and the remaining fertilizer N applied at the V9 corn developmental stage. A yield goal approach, the Iowa Late-Spring Nitrate Test (IA LSNT) , and canopy reflectance sensing were the three recommendation tools used to evaluate the tool fusion concept. Tools were fused using either an elastic net or decision tree approach. Using the elastic net approach tools, were fused with all combinations of main and two- or three-way interaction terms regressed against EONR. The decision tree was developed using only the main effects compared against EONR. Regardless of the method used to combine tools, any combination of two or three N recommendation tools together improved performance compared to using any one tool alone. The best elastic net based tool fusion occurred when all three recommendation tools and all possible interactions were included in the model which helped explain 42% of the variation around EONR, a 75% increase over the best tool alone. Additionally, the root-mean-square error (RMSE) improved from 68 kg N ha^{-1} (best tool used alone) to 55 kg N ha^{-1}. However, the best combination occurred when using the three N recommendation tools in a decision tree. The decision tree method explained 45% of the variation in EONR and had a RMSE value equal to 53 kg N ha^{-1}. This analysis demonstrated that combining tools is a valid way to improve N recommendations, and thus could aid farmers in better managing N than using a single tool by itself.

Keywords. *Nitrogen recommendation tools, Nitrogen fertilizer, Elastic Net, Decision Tree, Canopy reflectance sensing, EONR, corn, LSNT, PSNT, and Tool fusion*

Introduction

Over the last six decades, significant public resources have been spent on developing corn N rate recommendation tools (Nafziger et al., 2004; Morris et al., 2018). The goal for each of these tools has been to instruct farmers as to the optimal fertilizer N rate necessary for optimizing production and minimizing water quality effects. However, developing a site-specific N recommendation is very complicated due spatial and temporal differences in crop N need as a result of interactions of genetics, management practices, and growing conditions driven by weather and soil factors (Scharf et al. 2005; Tremblay et al. 2012). A variety of N recommendation tools have been developed by focusing on different aspects of the soil-plant N dynamics. For example, soil samples used in-season allow for measurements of residual soil nitrate (NO_3–N) as well as an estimate of the N supplying capacity for that soil to determine if sufficient N is available in the soil. Canopy reflectance sensing is another tool that measures the soil-plant N dynamic indirectly by assessing the plant's biomass and color. A thorough review of these and other N recommendation tools can be found in Morris et al. (2018).

Many of these publicly-available tools' performance have been assessed and found to be inaccurate for use across the U.S. Midwest (Ransom, 2018). Ransom, (2018) and Bean et al., 2018) found that the effectiveness of these tools can be improved when soil and weather information is incorporated, but that research also found that no more than 40% of the variability could be explained when compared to EONR. Hence, improvements are still needed to maximize profits and minimize water impairment associated with N loss to surface runoff, subsurface drainage, or to the atmosphere (Hong et al. 2007; Tremblay et al. 2012; Zhang et al. 2004). Instead of spending additional time and resources developing new methods for determining corn N fertilizer rates, utilizing two or more tools already developed might aid in improving the predictability of crop N need. No one tool has been able to capture every aspect of the soil-plant N dynamic, with some being limited by soil or plant sampling constraints or others fail to incorporate the spatial and temporal variability of weather and soil (Morris et al. 2018). Combining N recommendation tools together ("tool fusion") that vary in methodology may allow for an N recommendation approach to account for multiple aspects of the soil-plant N dynamic not previously accounted for when only using a single tool.

Nitrogen recommendation tool fusion could be accomplished by following similar procedures used in other scientific fields for creating an ensemble of separate algorithms (Hansen and Salamon 1990). An ensemble is merely the average of multiple predictive models, done to obtain one prediction which is more accurate than the best predictive model used alone. There are multiple ways to create an ensemble which include: averaging predictions, taking a weighted average of predictions, or using other algorithms to determine which predictive models to include or exclude in the ensemble (Mendes-Moreira et al. 2012; Unger et al. 2009; Zheng et al. 2014). This strategy has been found useful with crop, climate, and economic models to improve their predictability by using vastly different models developed by many different researchers (Rosenzweig et al. 2013; Wallach et al. 2016). The objective of this research was to improve N recommendations by combining multiple N recommendation tools used for making an in-season recommendation.

MATERIALS AND METHODS

Experimental Design

This research was conducted as a part of a public-private collaboration between DuPont Pioneer and eight U.S. Midwest universities (Iowa State University, University of Illinois Urbana-Champaign, University of Minnesota, University of Missouri, North Dakota State University, Purdue University, University of Nebraska-Lincoln, and University of Wisconsin-Madison). Each state conducted research at two sites each year during 2014 to 2016, with a third site in Missouri in 2016, totaling 49 site-years. About half the sites were on farmers' fields and the other half on

University research stations. All states followed a similar protocol for plot research implementation including site selection, weather data collection, soil, and plant sample timing and collection methodology, N application timing, N source, and N rates. Specific details are described in Kitchen et al. (2017). Treatments included N fertilizer rates between 0 and 315 kg N ha^{-1} split applied where 45 kg N ha^{-1} was applied at-planting with the remaining fertilizer N applied at the V9 corn developmental stage.

Determining the Economic Optimal Nitrogen Rate

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

Nitrogen Recommendation Tools Considered for Combinations

General Yield Goal

The General yield goal (YG) approach used in this work represents the approach established by Stanford (1973) where the expected yield was multiplied by a constant factor 0.021 kg N (kg grain)$^{-1}$, or 1.2 lbs N bu^{-1}. An additional soybean (*Glycine max*) credit of 45 kg N ha^{-1} was subtracted from the final N recommendation for sites that followed a soybean crop. The expected yield for each site was determined using the average of the previous five-yr county corn yields for the respective county the site was within. The five-yr average was then adjusted based on the soil productivity of the predominantly mapped soil of each site, similar to that done by Laboski et al. (2012). This procedure classifies soil productivity as either low, medium, or high using soil texture, irrigation, depth to bedrock, drainage class, temperature regime, and available water content information. The yield of a site was then calculated by increasing the five-yr average yield for low, medium, and high soil productivity by 10, 20, or 30%, respectively.

IA LSNT

The IA LSNT was calculated using soil NO_3–N, sampled to a depth of 0.30 m 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 is below the critical limit, the difference between the critical limit and the measured NO_3–N concentration is multiplied by 8. The critical limit is reduced by 3 mg kg^{-1} when spring precipitation (April to June) is 20% above normal amounts (Sawyer and Mallarino 2017).

Canopy Reflectance Sensing

Canopy reflectance measurements were obtained using the RapidSCAN CS-45 (Holland Scientific, Lincoln NE, USA) the same day or just prior to the in-season 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 and Schepers (2010)] was used to calculate an N fertilizer recommendation derived from the reflectance measurements. This algorithm is based on a sufficiency index calculated using measurements from both well-fertilized corn ("N-Rich") and minimally-fertilized corn that is referred to here as the "target" corn:

$$SI = \frac{VI_{Target}}{VI_{N-Rich}} \quad [3]$$

where SI is the sufficiency index; VI_{Target} is the NDRE vegetative index obtained from averaging measurements from all plots that received 0 kg N ha^{-1} at-planting, and $VI_{N\text{-}Rich}$ is the vegetative index obtained by averaging additional plots where 225 and 270 kg N ha^{-1} were 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 then calculated as described in Holland and Schepers (2010) as follows:

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

where N_{Rec} is the calculated N fertilizer recommendation; MZ_i is 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 is determined by the farmer; $N_{PreFert}$ is the amount of N already applied prior to sensing; N_{CRD} are N 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's N rate for each site, and $N_{PreFert}$ = 0 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.

Tool Fusion

Tool fusion was accomplished using either elastic net regression (Zou and Hastie, 2005) or decision tree regression models (Questier et al. 2005). For the elastic net based tool fusion, a series of ensemble models were created with three N recommendation tools. This analysis was limited to only three tools, to ensure that these methods would still be practical for a farmer to utilize without having to acquire excessive information. The fusion tools were created using two and three tool combinations of the General YG, IA LSNT calculated with 0 kg N ha^{-1} applied at planting, and canopy reflectance sensing based on the Holland and Schepers algorithm. Ideally, the best tool fusion would occur when N recommendations are diverse and accurate—similar to requirements for ensembling in machine learning (Hansen and Salamon, 1990). Following these guidelines, each of the tools was selected because their methods for determining an N rate had unique properties and inputs, with the majority of these tools also identified as some of the more accurate tools for predicting EONR as described in Ransom (2018).

The elastic net regression based fused tools were developed with the EONR regressed as a function of the N recommendation tools. For the fused tool, the N recommendation tools were evaluated under two scenarios. The first was with using only the main effects, and the second was using the main effects and all possible three-way and two-way interactions when applicable. Additional fused tools were created where the interaction terms were added to each of these ensembles.

The elastic net used for tool fusion was fit with the 'caret' package using R Statistical Software (Kuhn, 2017; R Core Team 2016). The elastic net was optimized by tuning the alpha and lambda parameters using a tenfold cross-validation repeated five times, where for each fold of the cross-validation the data were split randomly into ten folds. Nine of the folds were selected as a training dataset to fit a model, and the 10th fold was used as the testing dataset to calculate the accuracy of the predicted model. The test statistic used to determine accuracy was the root-mean-square error (RMSE) between the predicted values and actual values of the 10th fold. Fifty RMSE values were calculated for each combination of alpha and lambda values. The best combination of these tuning parameters was determined as the one producing the lowest average RMSE, which was then used to determine the coefficients necessary for creating each fused tool.

A decision tree modeling approach for tool fusion was also utilized. Regression tree models were created using the 'caret' and 'rpart' package in R (Therneau and Atkinson 2018). The EONR was fit as a function of the three in N recommendation tools. Variables were selected at each node of the tree to where the greatest homogeneity of the data would be explained (Questier et al. 2005). The homogeneity was measured as the absolute deviation from the mean.

Determining Tool Improvement

Three different metrics were used to evaluate the performance of each elastic net and decision tree based fused N recommendation tool across all sites. First, the elastic net or decision tree fused tools were compared to the EONR across all sites using a simple linear regression model and the performance was based on the coefficient of determination. Secondly, the average and the RMSE of the difference between a fused tool's N recommendation and EONR were used to evaluate accuracy. Lastly, the performance of each fused tool was examined by determining the percentage of sites where the tool's N recommendation came within ±30 kg N ha^{-1} of EONR. Sites within this range of EONR were considered reasonably close to EONR (RC-EONR). This value around EONR was chosen based on this value to be found reasonable and practicable for evaluating a tool's successful performance for generating an N fertilizer recommendation (Laboski et al. 2014; Sawyer 2013; Sela et al. 2017).

RESULTS AND DISCUSSION

Combining Nitrogen Recommendation Tools

In almost every case, the combination of use of two or three tools together vs. individual tools showed marked improvement using the performance metric of comparing to EONR (Table 1). The combinations did cause the average difference between N recommendations and EONR to be close to 0 kg N ha^{-1} and a decrease in RMSE (Table 1; Fig. 1). For most combinations, the improvement was evidenced by an increased r^2 (≥ 0.05) and decreased RMSE values (≥ 7 kg N ha^{-1}). There was no observed performance loss by combining tools.

Table 1. Elastic net and decision tree fused tools used to predict the economical optimal N rate (EONR). The coefficient of determination calculated by regressing EONR as a function of each tool or fused tool N recommendation. The precision and accuracy of each N recommendation tool were evaluated using the average difference (N recommendation tool – EONR), RMSE of the difference between a tools' N recommendation and EONR, and the percentage of sites ±30 kg N ha^{-1} of EONR or "relatively close to EONR" (RC-EONR). The number of sites (n) included in the evaluation†. The number of tools (p) used in each regression or decision tree model. Tools include the General yield goal (YG), IA Late-Spring Nitrate Test (IA LSNT), and canopy reflectance sensing using the Holland and Schepers algorithm. Dashes indicate not applicable.

Tools	n	p	r^2	Average	RMSE	RC-EONR
				----- kg N ha^{-1} -----		%
Main Effects Only						
General YG	49	1	0.13	65	113	18
IA LSNT	49	1	0.24	–25	68	41
Canopy Ref.†	49	1	0.19	–23	73	29
General YG + IA LSNT	49	2	0.29	0	61	45
General YG + Canopy Ref.	49	2	0.25	0	63	37
IA LSNT + Canopy Ref.	49	2	0.26	0	63	41
General YG + IA LSNT + Canopy Ref.	49	2	0.31	0	61	41
Decision Tree (Fig. 3)	49	3	0.45	0	53	45
Main and Interaction Effects‡						
General YG : IA LSNT	49	3	0.29	0	61	45
General YG : Canopy Ref.	49	3	0.33	0	59	43
IA LSNT : Canopy Ref.	49	3	0.26	0	62	43
General YG : IA LSNT : Canopy Ref.	49	7	0.42	0	55	47

†Canopy reflectance sensing was calculated using plots that received 0 kg N ha^{-1} at-planting.

‡ Elastic net based fused N recommendation tools are marked with " : " indicates all combinations of main effects and interaction terms.

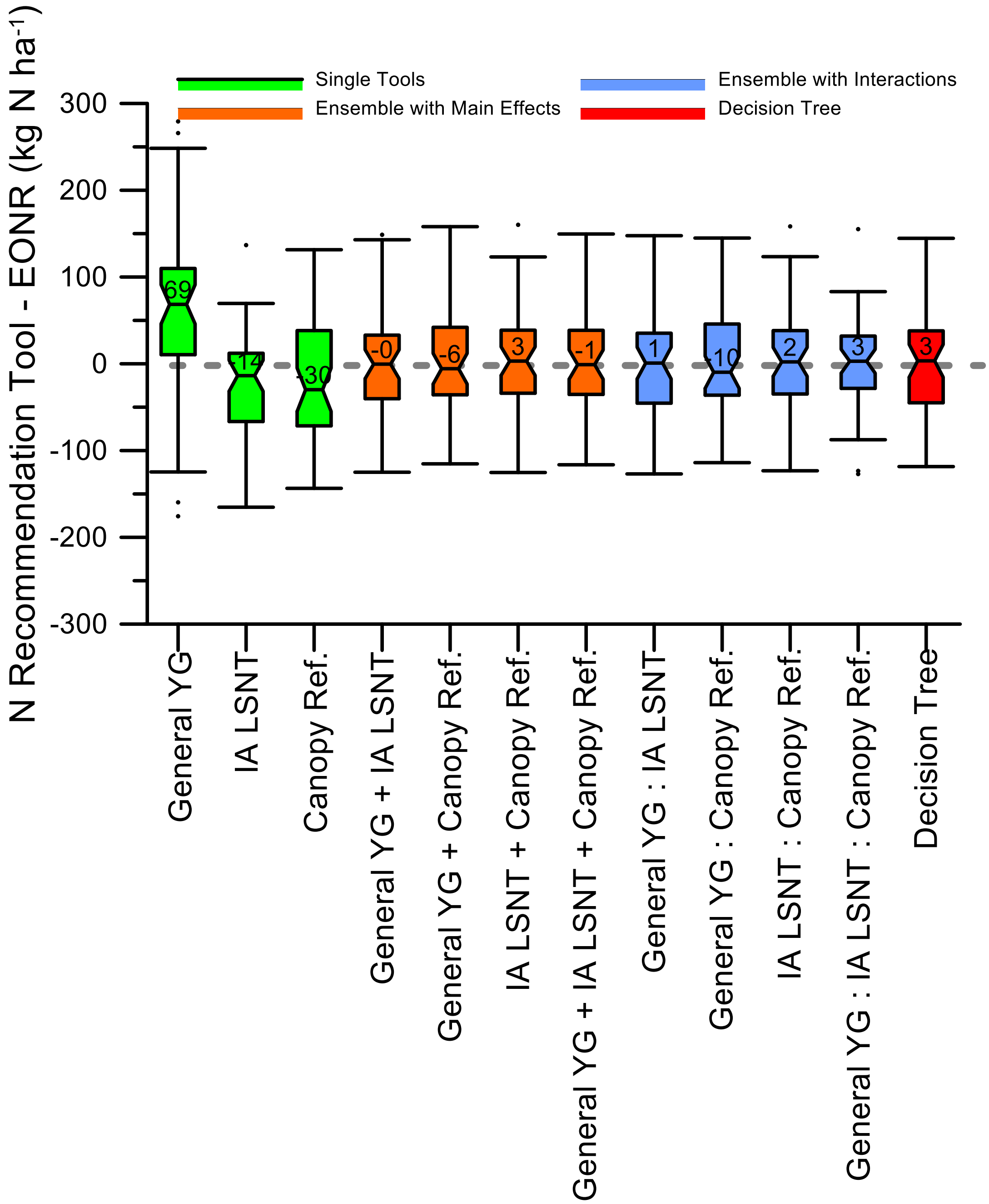

Fig. 1. Box and whisker plots showing the difference between the tools used at sidedress and the economically optimal N rate (EONR). General yield goal (YG), Iowa Late-Spring Nitrate Test (IA LSNT), and canopy reflectance sensing N recommendation tools were used to create eight combinations of elastic net models, with and without interaction terms and a decision tree. Elastic net based fused N recommendation tools are marked with " : " indicates models with all combinations of main effects and interaction terms. The median is reported by the value in the middle of the box. Notches on the side of each box indicate the 95% confidence interval around the median. Limits of the box indicate the first and third quartile, whiskers indicate 1.5 × IQR, and small circles indicate outliers.

Performance of Elastic Net Based Tool Fusion

The elastic net performed well at adjusting each tool in order to improve the accuracy and precision of N recommendation tools (Table 2). As shown in Fig. 1, the length of the interquartile range decreases when tools are combined compared to when they are used alone. The best improvement occurred when all three N recommendation tools were combined by using all three- and two-way interaction terms and the main effects (Fig. 1). This resulted in an r^2 = 0.42 and RC-EONR at 47% (Table 1; Fig. 2h). Compared to previous efforts of improving tools by incorporating soil and weather information, the best improvement was the IA LSNT which had an r^2 = 0.39, and 55% of sites RC-EONR (Ransom, 2018). In contrast, the best-fused tool only had 47% of sites RC-EONR. Hypothetically, an additional improvement to the fused tool might be obtained by adjusting the fused tool with soil and weather information, as was done in Ransom (2018).

Table 2. The elastic net model coefficients for predicting EONR using fused N recommendation tools with and without interactions. The " : " between tools indicates when interactions and main effects were included in the model.

Tool	Parameter Adjustments
General YG + IA LSNT	171 - 0.36 **General YG** + 0.55 **IA LSNT**
General YG + Canopy Ref.	193 - 0.32 **General YG** + 0.32 **Canopy Ref.**
IA LSNT + Canopy Ref.	80 + 0.38 **IA LSNT** + 0.22 **Canopy Ref.**
General YG + IA LSNT + Canopy Ref.	153 - 0.29 **General YG** + 0.35 **IA LSNT** + 0.19 **Canopy Ref.**
General YG **:** IA LSNT	172 - 0.39 **General YG** + 0.59 **IA LSNT**
General YG **:** Canopy Ref.	-194 + 1.24 **General YG** + 2.99 **Canopy Ref.** - 0.01 **General YG x Canopy Ref.**
IA LSNT **:** Canopy Ref.	92 + 0.27 **IA LSNT** + 0.11 **Canopy Ref.**+ 0.00094 **IA LSNT x Canopy Ref.**
General YG **:** IA LSNT **:** Canopy Ref.	0 + 1.9 **General YG** + 0.96 **IA LSNT** + 3.79 **Canopy Ref.** - 0.0005 **General YG x IA LSNT** - 0.015 **General YG x Canopy Ref.** - 2.53 **IA LSNT x Canopy Ref.** + 0.000003 **General YG x IA LSNT x Canopy Ref.**

The use of canopy reflectance sensing as a part of the tool combination would help farmers to better account for spatial variability between and among fields. Alone this tool does a mediocre job of predicting EONR (Table 1; Fig. 2c). When combined with other N recommendation tools, this tool more than doubles the % of explained variability around EONR (Table 1; Fig. 2k).

Performance of Decision Tree Based Tool Fusion

The decision tree fused tool resulted in an r^2 = 0.45 (Fig. 2), which was the best performance of any fused tool (Table 1). Also, this method had the lowest RMSE and the second highest percentage of sites RC-EONR (Table 1). This method used all three N recommendation tools in the model (Fig. 3). The downside to using this particular decision tree method is that interaction terms could not be used in the model, which was shown to be very helpful for many of the elastic net models.

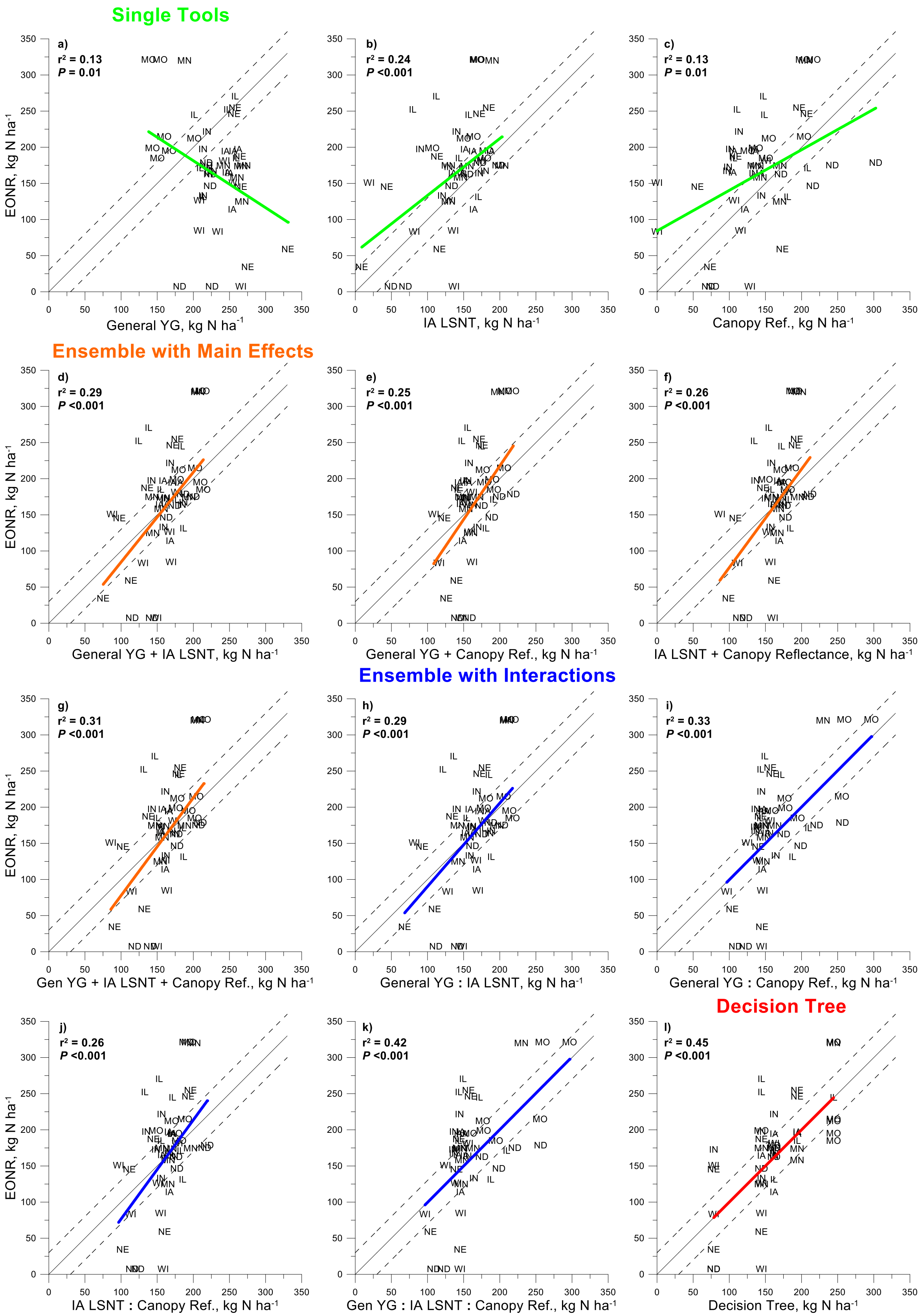

Fig. 2. Sidedress N recommendation tools evaluated relative to the economic optimal N rate (EONR). Tools included General yield goal (YG), Iowa Late-Spring Nitrate Test (IA LSNT), and canopy reflectance sensing. Graphs a-c) are tools evaluated alone (green), d-g) are combined using only main effects (orange), h-k) are combined using both main effects and interaction terms (blue) , and l) decision tree (red). Elastic net based fused N recommendation tools are marked with " : " indicates all combinations of main effects and interaction terms. The 1:1 line is an indicator of a perfect predictor of EONR, the dashed lines indicated the area in which tools ± 30 kg N ha^{-1} of EONR or relatively close to EONR.

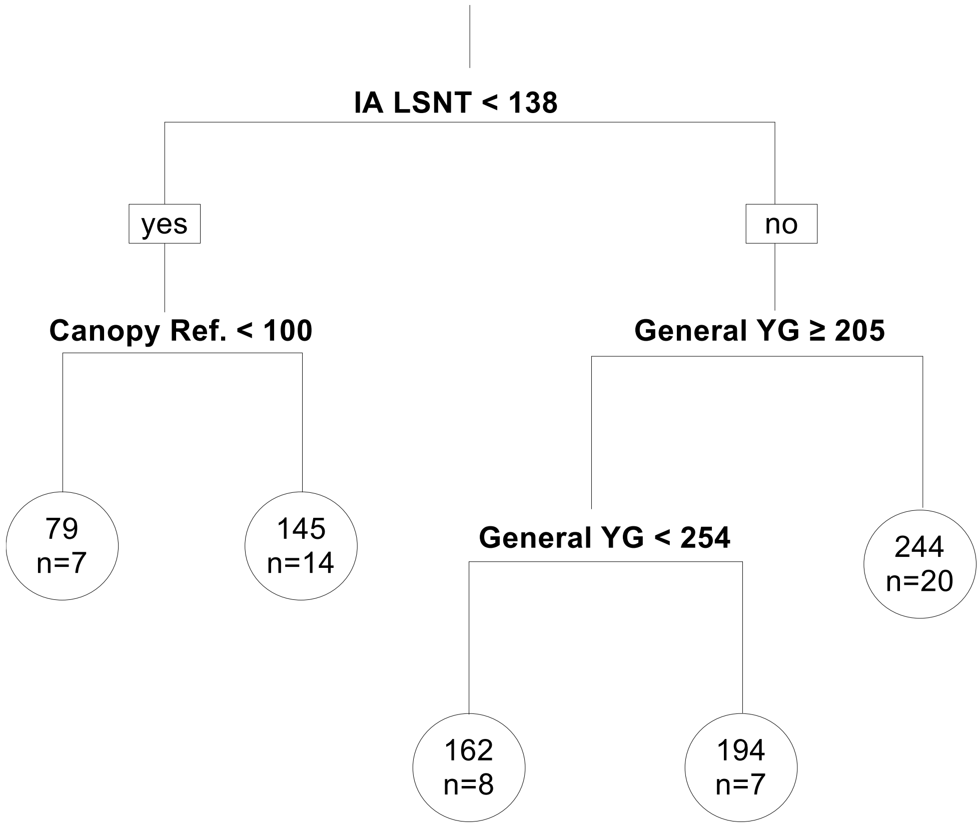

Fig. 3. The resulting decision tree model used to predict the economically optimal N rate (EONR) for an in-season N application using the General yield goal (YG), Iowa Late-Spring Nitrate Test (IA LSNT), and canopy reflectance sensing using the Holland and Schepers algorithm. The number of sites (n) that were used to make up each final node of the tree.

Was this Improvement Enough?

The best improvement observed from this analysis (r^2 = 0.45) was much better than the previous analysis used to adjust recommendations with soil and weather information (r^2 = 0.39; Ransom, 2018). The best improvement observed with tool fusion was similar to what was reported for the relationship between the Pennsylvania PSNT and EONR (r^2 = 0.48; Schmidt et al., 2009). However, further improvement is necessary to match the performance reported for other N recommendation tools. Sela et al. (2017) showed that the Adapt-N crop growth model had an r^2 = 0.56. While Scharf et al. (2006) and Schmidt et al. (2009) in two separate studies showed that chlorophyll meter derived N recommendations were more strongly related with EONR (r^2 between 0.53 and 0.76).

Conclusion

Efforts to improve N recommendations by combining two or three unique N recommendations were successful when using both the elastic net and decision tree approach. The best elastic net approach was when all three tools and all two- and three-way interaction terms were included in the model. This approach explained 42% of the variability around EONR, an improvement of 75% over the best tool used alone. The best improvements occurred when three tools were combined using the decision tree approach, which explained 45% of the variability around EONR. This method also had the lowest RMSE value of 53 kg N ha^{-1} and one of the highest percentages of sites RC-EONR (45%).

Combining two N recommendation tools could improve the performance of N recommendations tools. There was no observed decrease in performance by combining these tools; however, while this theory has been proven effective additional validation is necessary to determine if these combinations work on independent data sets. Including more than three N recommendation tools in the model could also improve the performance of both the decision trees and elastic net fused tools. However, deploying too many recommendation tools could result in farmers ignoring the approach because too much information would be required.

Another feasible method for improving the elastic net and decision tree fused tools would be to adjust them using site-specific soil and weather information. A previous analysis showed that the evenness of rainfall between planting and the time of sidedress was able to explain 22% of the variation around EONR (Ransom, 2018). Using this weather parameter could help to further adjust the fused tools as they explained ≤ 45% of the variability around EONR. It is not possible to explain all of the variability around EONR especially when recommendations are made early in the growing season without knowing if the subsequent growing conditions would optimize or limit plant growth. However, the process of combining multiple tools provides an improved method of estimating EONR compared to using a single N recommendation tool.

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