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Developing a machine learning and proximal sensing-based in-season site-specific nitrogen management strategy for corn in the US Midwest

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Abstract

Effective in-season site-specific nitrogen (N) management or precision N management (PNM) strategies are urgently needed to ensure both food security and sustainable agricultural development. One promising method is the use of active canopy reflectance sensor-based PNM strategies, which have been developed and evaluated in different parts of the world. However, recent studies have shown that sensor-based N recommendation algorithms developed in localized regions of the US rarely performed well when used broadly across the US Midwest. While efforts have been made to improve these algorithms using soil, weather, and management information, they could still be improved upon. The objective of this research was to develop a machine learning-based in-season and site-specific N recommendation strategy by incorporating active canopy sensor data with soil, weather, and management information. Data consisted of 2333 observations from 36 site-year N rate trials conducted over three years (2014-2016) in eight US Midwest states. At each site-year, there were 16 N rate treatments with different pre-plant and side-dress combinations. A portable active canopy reflectance sensor, RapidSCAN CS-45, was used to collect canopy reflectance at V6-V10 stages before a side-dress N application. Four machine learning algorithms [ridge regression (RR), random forest regression (RFR), extreme Gradient Boost regression (XGBR), and support vector regression (SVR)] were used to develop the corn yield estimation model. Models were trained, tested, and validated on a subset of the data containing 64, 20, and 6% of the data, respectively. The input variables included normalized difference vegetation index, normalized difference red-edge index, Maccioni index, Canopy chlorophyll content index, corn heat units, growing degree days, abundant and well-distributed rainfall, Shannon Diversity Index, precipitation, irrigation, pre-plant N rate, side-dressed N rate, seeding rate, previous crops, tillage practice and soil texture (clay, silt, and sand percentage). The R^2 for validation results of the four machine learning models ranged from 0.53 to 0.76 with the relative root-mean-square error (RRMSE) ranging from 15.62 to 11.07. Among the machine learning models, the XGBR model outperformed the other models with an R^2 of 0.76 and an RRMSE of 11.07. Using the XGBR model, the economic optimum N rate (EONR) was also estimated based on in-season simulated yield response to side-dress N application rates, with the predicted EONRs at 69% of site-years being within 45 kg ha^{-1} of the EONRs based on measured yield. These results show that a regional dataset can be used to derive a robust canopy reflectance sensor-based recommendation that works well across the region. More studies are needed to further improve this in-season N recommendation strategy and evaluate it under on-farm conditions.

Keywords*: Precision nitrogen management, Machine learning, Proximal sensing, Economic optimum nitrogen rate*

Abbreviations.

EONR, economically optimum N rate; N, nitrogen; PNM, plant nitrogen management; RR, ridge regression; RFR, random forest regression; XGBR, extreme gradient boost regression; SVR, support vector regression; NDVI, normalized difference vegetation index; NDRE, normalized difference red-edge index; MACC, Maccioni Index; CCCI, Canopy chlorophyll content index; CHU, corn heat units; GDD, growing degree days; AWDR, abundant and well-distributed rainfall; SDI, Shannon Diversity Index; PPT, precipitation; R^2, the determination coefficient; RMSE, root mean square error; RRMSE, relative root mean square error; ML, machine learning; R^2c, the determination coefficient of calibration dataset; RMSEc, the root mean square error of calibration dataset;

RRMSEc, the relative root mean square error of calibration dataset; R^2t, the determination coefficient of test dataset; RMSEt, the root mean square error of test dataset; RRMSEt, the relative root mean square error of test dataset; R^2v, the determination coefficient of validation dataset; RMSEv, the root mean square error of validation dataset; RRMSEv, the relative root mean square error of validation dataset.

Introduction

Optimizing nitrogen (N) management is crucial to optimize corn grain yield and improve N use efficiency while minimizing fertilizer input costs and environmental impact (Chlingaryan et al. 2018). Insufficient N fertilizer application will cause a dramatic decrease in protein content and grain yield. Excessive fertilization can cause diseases and lodging problems, reduce economic returns, and attributes to multiple environmental problems (Miao et al., 2011; Cao et al., 2017). Nitrogen recommendation and reliable estimation of the economic optimum N rate (EONR) aim to narrow the gap between the N supply and the requirements of the plant (Qin et al. 2018).

The EONR varies annually, and N recommendation tools do not consistently recommend rates close to the EONR (Ransom et al., 2020; 2021). Predicting EONR values at the time of an N application is difficult as EONR can differ within the field and years as well as changes in crop and N prices (Jin et al. 2019a; Puntel et al. 2018), especially over a wide range of environments (Morell et al. 2016). The EONR variability within fields, across fields, and from year to year can be due to the interactions among genotype, environment, and management practices (Ransom et al. 2020; Wang et al., 2021).

Active canopy sensor based N recommendations have been developed to estimate EONR and improve N use efficiency (Franzen et al., 2016; Evangelou et al. 2020; Wang et al., 2019). Studies evaluating active sensor-based N recommendation algorithms found that they performed well in the regions where they were developed, but the application of these methods outside the regions of development was challenging and would need local calibration (Bean et al. 2018a; Puntel et al. 2019). Machine learning (ML) models have been used to predict EONR directly. However, EONR is also influenced by changing crop and N fertilizer prices, which may limit the applications of models predicting EONR using fixed prices. More research is needed to develop machine learning-based in-season N recommendation algorithms to incorporate the genetic, soil, weather, and management information as well as up-to-date crop and fertilizer price information for applications across diverse environmental conditions as well as changing grain and fertilizer prices.

The overall goal of this study was to develop a new machine learning-based in-season N recommendation strategy based on in-season prediction of corn yield responses to side-dress N application rates. The specific objectives of this study were to (i) compare the performances of four ML algorithms for predicting corn grain yield using various types of inputs, and (ii) evaluate the best performing ML algorithm as a N recommendation tool for in-season N management.

Materials and Methods

Study Design

A total of 49 N rate response trials were conducted across an array of soil, weather, and management conditions of the US Corn Belt from 2014 to 2016 through a research collaboration between Corteva Agrisciences and eight US Midwest universities (Kitchen et al. 2017). For this research we only looked at 36 site-years that had the active canopy sensor data around V9 stage. A randomized complete block design with four replications were used at each site-year including sixteen N fertilizer treatments. Eight treatments applied all N fertilizer applied at planting ranging from 0 to 315 kg N ha^{-1} on 45 kg ha^{-1} increments). There were six split-application treatments, with 45 kg N ha^{-1} being applied at planting and side-dress N application at V9 ± one corn development stage with N rates of 45-270 kg N ha^{-1} on 45 kg ha^{-1} increments. There were two other split treatments 90 kg N ha^{-1} being applied at plant and two side-dress rates of 90 and 180 kg N ha^{-1} (Kitchen et al., 2017).

The corn canopy reflectance was collected using a handheld active optical sensor RapidSCAN CS-45 (Holland Scientific, Lincoln, NE) with wavelengths at 670, 730, and 780 nm. Hobo U 30 automatic weather stations (Onset Computer Corporation, Bourne, MA) were set up adjacent to each experimental site (Kitchen et al. 2017). Four vegetation indices were derived from RapidSCAN sensor data (Table 1). The corn heat unit (CHU), precipitation (PPT), growing degree days (GDD), Shannon diversity index (SDI), and abundant and well-distributed rainfall (AWDR) were generated from the daily precipitation and temperature data collected with weather stations at each site as well as planting and sampling dates, using weather data from planting up to sending (Table 1). Grain yield was collected after physiological maturity, by harvesting each plot, measuring the weight and moisture, and adjusting grain yield to 15.5 % moisture.

Table 1 The variables used in the complete dataset with calculations, methods, and citations

Indicator	Definition	Description	Reference
NDVI	Normalized Difference vegetation index	$(R_{NIR} - R_{RED})/(R_{NIR} + R_{RED})$	(Rouse et al. 1974)
Macc	Maccioni	$(R_{NIR} - R_{RedEdge})/(R_{NIR} - R_{RED})$	(Maccioni et al. 2001)
NDRE	Normalized Difference RED Edge Index	$(R_{NIR} - R_{RedEdge})/(R_{NIR} + R_{RedEdge})$	(Fitzgerald et al. 2010)
CCCI	Canopy chlorophyll content index	$(NDRE - NDRE_{min})/(NDRE_{max} - NDRE_{min})$	
CHU	Corn heat Units	$\sum \frac{(Y_{max} + Y_{min})}{2}$	(Tremblay et al. 2012)
PPT	Cumulative precipitation	$\sum Rain$	
GDD	Growing degree days	$\frac{T_{max} + T_{min}}{2} - T_{Base}$	(Tremblay et al., 2012)
AWDR	Abundant and well-distributed rainfall	$\mathrm{PPT} \times \mathrm{SDI}$	(Tremblay et al. 2012)
SDI	Shannon diversity index	$-\sum pi \frac{\ln pi}{\ln n}$	(Tremblay et al., 2012)
Clay	Soil clay content	0-60 cm, (%), Pipette	
Sand	Soil sand content	0-60 cm, (%), Pipette	(Bean et al. 2018b)
Silt	Soil silt content (%)	0-60 cm, (%), Pipette	
SeedRate	Planting population	Seeds ha^{-1}	
Tillage	Tillage description before planting	Yes ('1')/No('0')	
Irrigation	Irrigation	Yes ('1')/No('0')	
P_Crop	Crop grown 1 year before the trial	Legumes, Yes ('1')/No('0')	
Tiled	Tiled	Yes ('1')/No('0')	Kitchen et al. (2017)
Yield	Grain Yield	Kg ha^{-1}	
Preplant N	The amount of N fertilizer application at planting	With 45 Kg N ha^{-1} increment	
Sidedress N	The amount of N fertilizer at sidedress	With 45 kg N ha^{-1} increment	
EONR	Economically optimal nitrogen rate	Quadratic plus plateau model	

Development and Evaluation of the Regression Models

Four machine-learning algorithms were used to predict grain yield, including ridge regression (RR), random forest regression (RFR), support vector regression (SVR) and extreme gradient boost regression (XGBR). The complete research data (n = 2333) was split into a calibration (n =1492 or 64% of the data), a testing (n = 467 or 20% of the data), and a validation dataset (n = 374 or 16% of the data). Three statistical indicators were used to evaluate the performance of corn yield estimation models: the determination coefficient of the model (R^2), the root-mean-square error (RMSE) and the relative root-mean-square error (RRMSE).

Using Models to Predict EONR

The best performing ML algorithm was used to predict the EONR at each site. This was accomplished by using the model to simulate the grain yield with 45 kg N ha^{-1} applied at planting and an additional amount applied in-season. The additional amount ranged from 0 to 315 kg N ha^{-1} at an increment of 15 kg N ha^{-1}. The measured EONR for each site-year was calculated using a quadratic plus plateau model using a corn price of US \$0.16 kg^{-1} and a N fertilizer price of US \$0.88 kg^{-1} (Kitchen et al., 2017). For the simulated grain yield, a similar procedure was used to fit a quadratic plus plateau model using 'python-eonr 0.2.1' (Nigon et al., 2019) for each site.

Results

Comparison of four machine learning models for corn yield estimation

The performances of the ML models are given in Table 2 and scatter plots showing the difference between the predicted versus the actual grain yield in Fig. 1. The results showed a difference in model performances with XGBR ≥ RFR > SCR >> RR across all three calibration, test, and validation datasets.

Table 2 The performance of the machine learning models

Methods	Calibration			Test			Validation		
	R^2c	RRMSE%	RMSEc	R^2t	RRMSEt%	RMSEt	R^2v	RRMSEv%	RMSEv
RR	0.52	15.1	1885.8	0.55	15.7	1965.2	0.53	15.6	1918.2
RFR	0.97	3.7	458.3	0.80	10.4	1302.8	0.75	11.3	1382.9
XGBR	0.98	3.0	370.9	0.82	9.9	1241.7	0.76	11.1	1359.3
SVR	0.92	6.1	766.6	0.70	12.9	1614.1	0.73	11.8	1454.2

Note: RR: ridge regression; RFR: random forest regression; XGBR: extreme gradient boost regression; SVR: support vector regression.

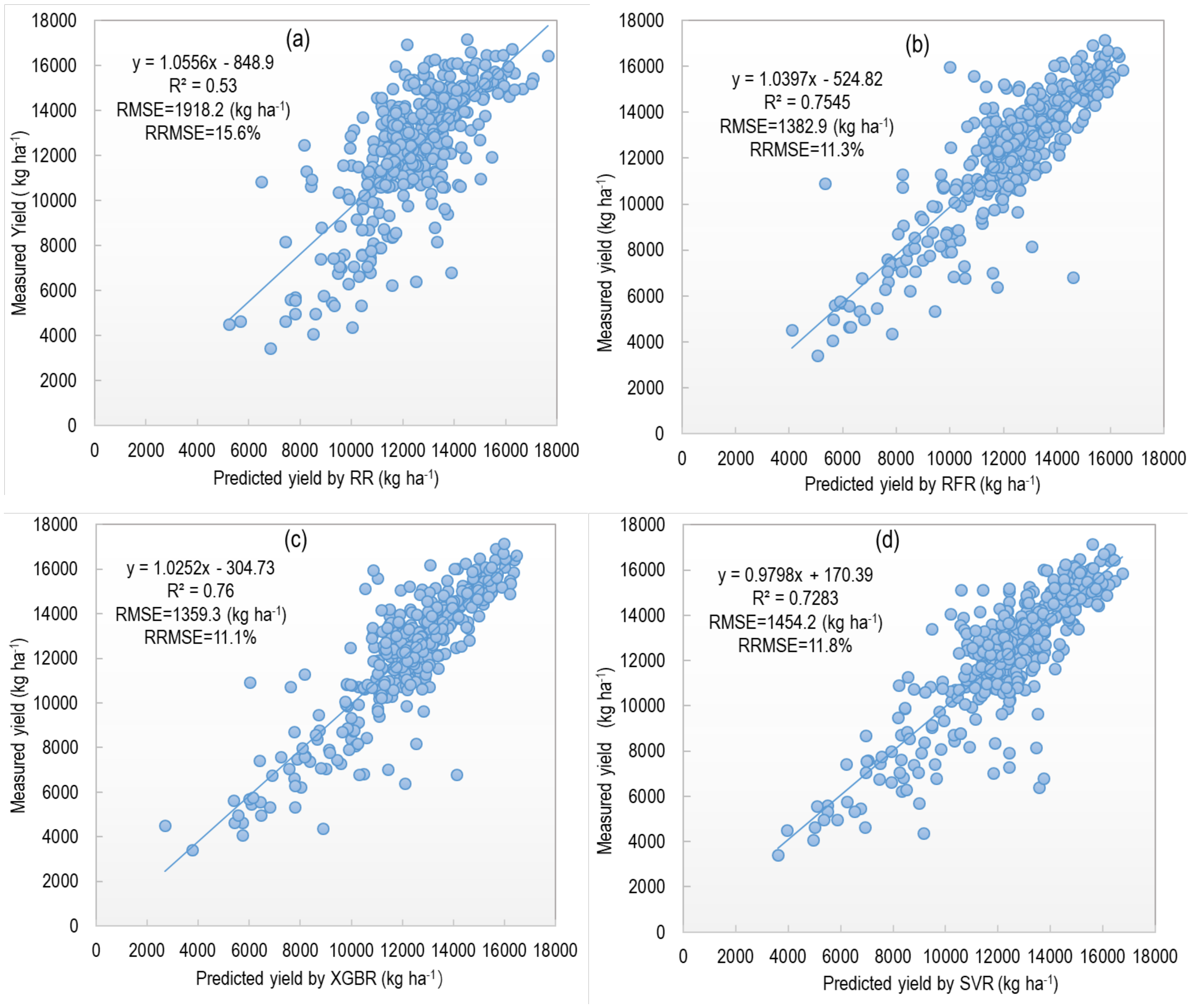

Fig. 1 The scatterplots of measured yield and predicted yield by four machine-learning methods.

Simulation of EONR by XGBR corn yield prediction model

Based on the results discussed above, the XGBR model was used to predict corn yield at different side-dress N rates ranging from 0 to 315 kg N ha^{-1} in 15 kg N ha^{-1} increments for the simulated dataset with 45 Kg N ha^{-1} applied at planting time. The simulated yield response to different side-dress N rates at the IA_Boone_2015 site is shown in Fig. 2 as an example, as compared with the measured yield response to applied side-dress N rates. The average simulated EONR was close to the measured EONR (Fig. 3). There were a few instances where the model's predictions overestimated the measured EONR (Fig. 3 and Fig. 4). For the majority of sites this method of predicting EONR did well.

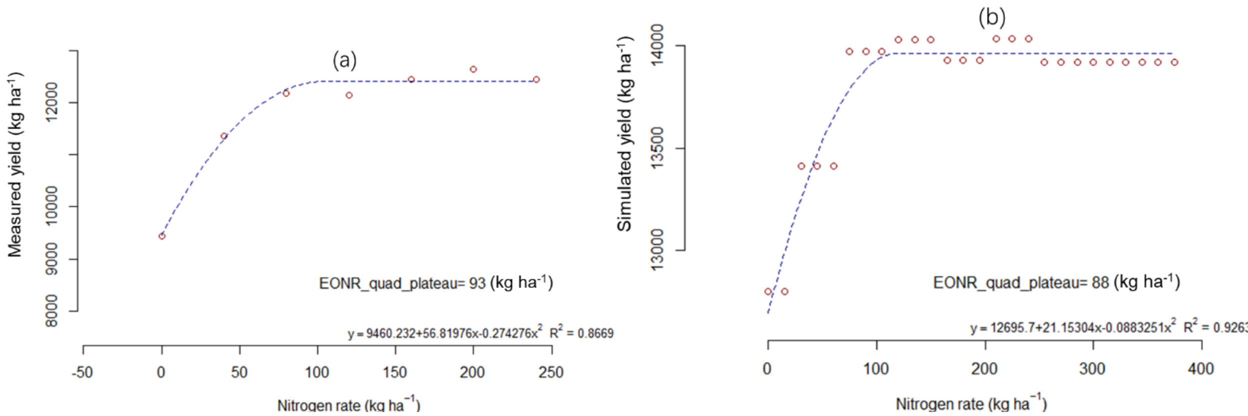

Fig. 2 The measured (a) and simulated (b) yield response at different side-dress N rates for the Boone site in Iowa, 2015.

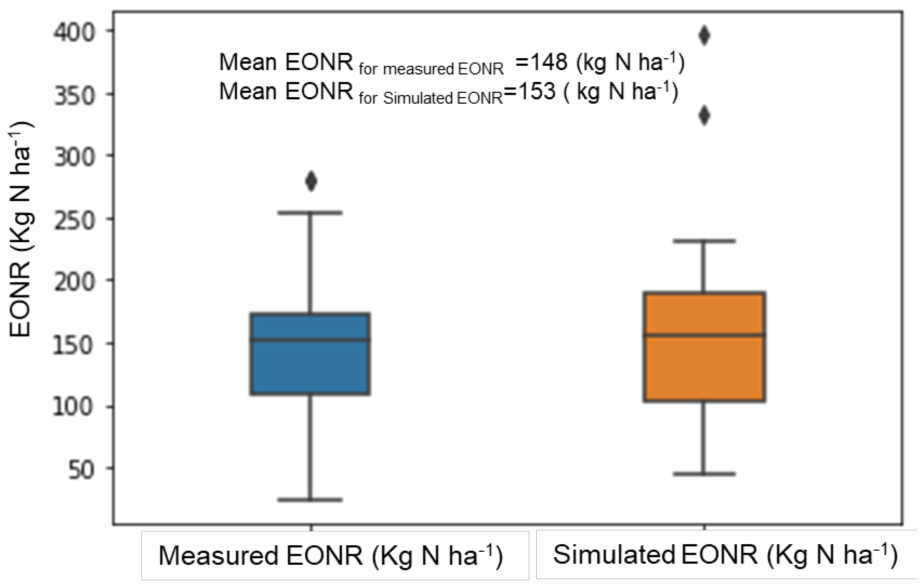

Fig 3. The box-whisker plot of measured EONR and simulated EONR with 45 kg N ha^{-1} applied at planting and an additional amount applied at V9 corn developmental stage.

The variation of measured EONRs and predicted EONRs are given in Fig 4. The predicted EONRs matched the measured EONRs well for most site-years with two major exceptions. There were 25 site-years (69%) with differences between predicted and measured EONR ≤ 45 kg N ha^{-1}.

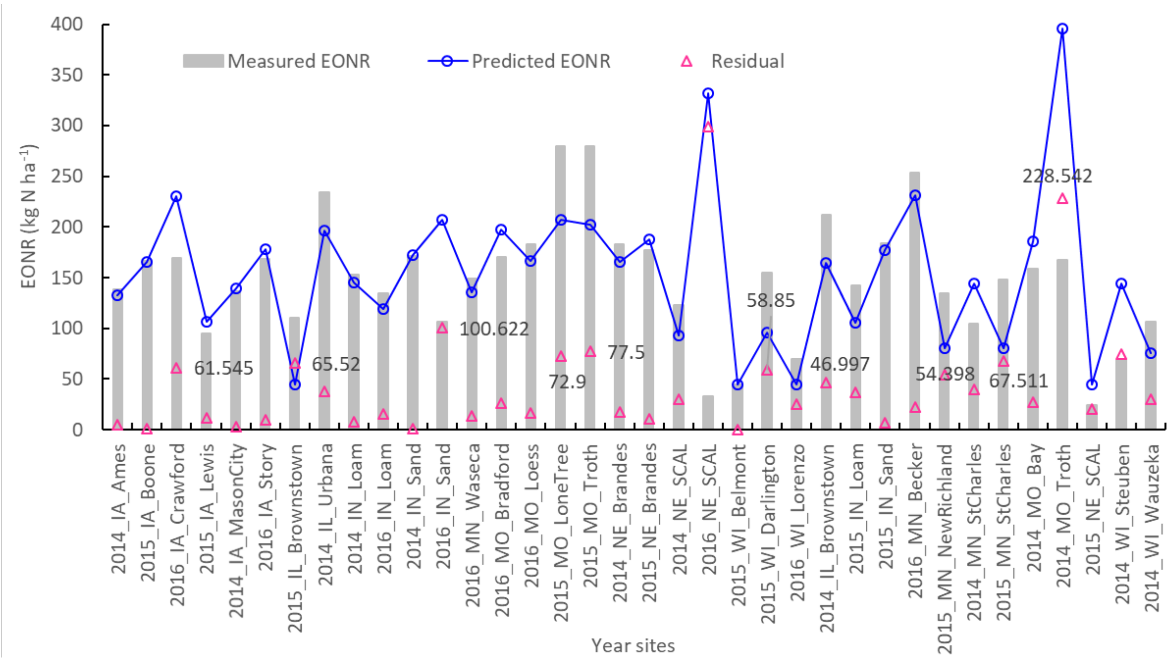

Fig 4 The variations of measured EONR and predicted EONR at different site-years with 45 kg N ha^{-1} being applied at planting time. Triangles indicate the difference between predicted and measured EONR. For differences larger than 45 kg ha^{-1}, the specific values are shown on the graph.

Discussion

We found that the XGBR and RFR models performed the best at predicting grain yield using VIs, soil, weather(from planting to sensing), and management variables. Additionally, the XGBR performed well as an in-season N management tool as the predicted EONR at 69% site-years matched the measured EONR well. These findings are similar to what others have observed (Nasielski et al. 2020; Puntel et al. 2019; Qin et al., 2018; Ransom et al. 2019). This ML method of combining multiple sources of data also outperformed N recommendation models evaluated using a single source of data like the active optical reflectance sensor data, climate indices, or other related data (Balboa et al. 2019; Jiang et al. 2020; Puntel et al. 2019). Random et al. (2020) compared 31 methods for determining corn N rate and concluded that for the US mid-west corn belt database only 10 (mainly soil nitrate tests) recommended N rates weakly correlated with measured EONR ($p<0.10$, $R^2<0.20$).

Our findings show that ML can be used to combine activate sensor data, soil, weather, and management information to improve our estimation of EONR. Other efforts have reported similar findings for predicting EONR values for a few different grain crops (Wen et al., 2021; Wang et al., 2021). However, their findings focused on a single ML algorithm (i.e., random forest), and additional improvement could occur by using other ML algorithms as shown here and by Ransom et al. (2019). Additionally, these models could be improved by including additional soil properties (e.g., soil water table) as was done by Qin et al., (2018). They used the models to predict EONR directly. Since EONR is influenced by corn and N prices, which change significantly in recent years, the application of such approaches may be limited. The approach proposed in this study uses a yield prediction model to predict corn yield at different side-dress N rates and then determines the EONR form the estimated yield response curve and using current corn and N prices. This approach can easily incorporate the most up-to-date corn and N price information to better reflect the current market information when making in-season N management decisions. More studies including on-farm trials are needed to further improve and evaluate this N recommendation strategy.

Conclusion

In this study, corn yield prediction models using four ML algorithms (RR, RFR, SVR, and XGBR) incorporating easily available soil, weather, and management data with active crop sensor data were established and evaluated. The XGBR model developed by four VIs together with soil texture data, weather indicators, and management information performed the best for corn yield estimation, with R^2 of 0.76 and RRMSE of 11.07 in validation dataset. The RR model had the lowest performance, while the RFR model performed similarly to XGBR. The XGBR yield estimation model was used to predict corn yield at different side-dress N rates, with 45 kg N ha^{-1} applied at planting and EONR could be determined using current corn and N prices. In general, the predicted EONR matched the measured EONR well, with a few site-years having large differences. More studies are needed to further improve this strategy for in-season N recommendation and evaluate it under on-farm conditions.

Acknowledgments

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