



# Developing an innovative stacking ensemble machine learning and multi-source data fusion-based precision nitrogen management strategy for corn

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## Abstract

**Purpose** The primary goal of this research was to develop an innovative in-season nitrogen (N) recommendation strategy for corn (*Zea mays* L.) using stacking ensemble machine learning (ML) and multi-source data fusion.

**Methods** Forty-nine site-years of N rate experiments conducted across the U.S. Corn Belt were used to evaluate the performance of five individual ML algorithms (Random Forest Regressor (RFR), Support Vector Regressor (SVR), Extreme Gradient Boosting Regressor (XGBR), CatBoost Regressor (CBR), and Multi-Layer Perceptron (MLP)) and stacking regression (STR) for in-season corn yield prediction under different preplant and split N application conditions using the active canopy sensor data along with genetics, environmental and management information. These models were further evaluated for their prediction of yield responses to sidedress N application rates and in-season estimation of site-specific economic optimal N rate (EONR) across the U.S. Corn Belt.

**Results** The results indicated that the stacking model performed consistently well across all datasets for corn yield prediction, demonstrating robustness ( $R^2 > 0.85$  for validation dataset). Preplant N rate, Sidedress N rate and normalized difference red edge (NDRE) were identified as key variables for predicting corn yield. For EONR estimation, the stacking regression 2 model (STR2) using RFR, SVR, XGBR, CBR, and MLP as base estimators and linear regression as the meta estimator performed the best for the full dataset ( $R^2 = 0.82$  and root mean square of error (RMSE) =  $27.50 \text{ kg N ha}^{-1}$ ).

**Conclusion** It is concluded that the stacking regression and multi-source data fusion framework is a promising strategy for in-season site-specific corn yield prediction and sidedress N recommendation.

**Keywords** Corn yield · Ensemble machine learning · Economic optimum nitrogen rate · Precision nitrogen management

## Introduction

Optimizing nitrogen (N) management is crucially important for improving crop yield and N use efficiency, while reducing operation costs and negative environmental impact (Elrys et al., 2023; Miao, 2023; Dong et al., 2024). Insufficient N fertilizer application will reduce crop yield and grain protein content (Ren et al., 2022). Over-application not only wastes fertilizers but also causes a series of environmental problems (Miao et al., 2011; Fernández et al., 2016). Precision N management (PNM) aims to match N supply with crop N requirement in amount, space and time to increase N use efficiency (NUE), economic returns and environmental sustainability (Miao, 2023). The increasing concerns for environmental degradation and shrinking profit margins in crop management call for the development and adoption of effective PNM strategies and technologies (Xiao et al., 2024; Yin & Cui, 2024; van Ittersum et al., 2025).

Different N management strategies have been developed to improve NUE (Morris et al., 2018; Ransom et al., 2020). Early N recommendation strategies were based on soil and plant sampling and testing, leading to improved efficiency of chemical fertilizers (Micha et al. 2023; Liu et al. 2024a, b). However, soil and plant testing is time-consuming and labor-intensive, making them impractical for guiding PNM across large fields. It could only provide a snapshot on time and cannot reflect dynamic changes in weather conditions (Cai et al., 2025; Sela et al., 2018; Schut & Giller, 2020). The maximum return to N (MRTN) approach makes N rate recommendations based on N response curves from N rate studies conducted in each state or region within a state (Clark et al., 2020). It has advantages in guiding regional N management (Ransom et al., 2023) and is commonly used in several states of the U.S. Midwest (Moriss et al., 2018). However, MTRN falls short in addressing climate variability for specific years and site-specific conditions (Morris et al., 2018). The optimal N rates have been found to vary significantly across different fields, within a large field, or in different years due to the variability of genotypes, environmental factors, management practices and their interactions (Baum et al., 2023; Krause et al., 2020; Thompson et al., 2024).

For in-season site-specific PNM, non-destructive proximal and remote sensing technologies have been identified as valuable tools (Cao et al. 2017a; Dehghan-Shoar et al. 2023). Active canopy sensors are especially promising, which are not affected by environmental lighting conditions (Morris et al., 2018). Many active sensor-based PNM strategies have been developed for different crops (Franzen et al. 2016; Cao et al. 2017b; Bean et al., 2018a). However, an evaluation of different sensor-based N recommendation algorithms across the U.S. Midwest indicated that the algorithms developed locally would not perform well when they were used outside of their regions of development (Bean et al., 2018a). These algorithms should be adjusted with site-specific weather and soil information, because they mainly use crop sensor data alone or with simple variables like growing degree days (GDD) or days after planting (Bean et al. 2018b). Many static and dynamic (change rapidly over time) factors can influence EONR and yield prediction (Puntel et al., 2019), making it very difficult to incorporate these factors into such sensor-based N recommendation algorithms using traditional statistical methods.

Machine learning (ML) models have been increasingly used for predicting crop yield, plant growth parameters and EONR in precision agriculture, due to their capabilities to handle different types of data and big data (Chlingaryan et al., 2018; Li et al., 2022). Qin et

al. (2018) used four ML models incorporating soil and weather data with crop sensor data to predict corn (*Zea mays* L.) EONR directly ( $R^2=0.46$ , mean absolute error (MAE)=33.6 kg N ha<sup>-1</sup> for the best performing model). Ransom et al. (2019) evaluated the performance of eight statistical and ML algorithms to incorporate soil and weather variables into farmer's N recommendation, yield goal-based N recommendation and proximal active canopy sensor-based N recommendation tools to predict EONR, achieving  $R^2$  of 0.72 to 0.84 and root mean square error (RMSE) of 41 to 94 kg N ha<sup>-1</sup>. These approaches mainly considered soil and weather variables and did not include corn hybrid information and management practices in the ML models for EONR prediction. A crop growth model simulation analysis indicated that genetics, environmental conditions and management practices could explain 27%, 41% and 31% of EONR variability, respectively (Baum et al., 2023). Therefore, ML model performance can potentially be further improved by incorporating genetics, environmental and management information than only using soil and weather variables (Li et al., 2022). Another limitation is that those approaches used ML models to predict EONR calculated with fixed corn grain and N fertilizers prices that can have large fluctuations from year to year. New approaches need to be developed that can use current corn grain and N fertilizer prices as well as genetic, environmental and management information to estimate the in-season site-specific EONRs to further improve N management.

A promising strategy to address the limitations of previous ML-based EONR prediction approaches is to develop ML models by incorporating crop genetics, environment and management factors including N application information to predict corn yield. Then the ML models can be used to simulate corn yield response to different N rates under different conditions. Current corn and N price information can be used together with the N responses to determine the EONR. This approach has been tested to predict EONR for corn in North-east China based on 12 site-years of N experiments involving two soil types, four planting densities and several N rates, with very promising results (RMSE=17 kg N ha<sup>-1</sup> and relative error (RE) of 14–15%) (Wang et al., 2021). However, this study only involved one corn hybrid and two sites located very close to each other using LASSO and Random Forest (RF) regression models. More studies are needed to further evaluate this approach under diverse environmental conditions across large regions like the U.S. Midwest Corn Belt using more ML models.

Many different ML models have been applied in precision agriculture research, with different performances (Wakahara et al., 2025; Wang et al., 2024; Xu et al., 2024; Zhang et al., 2025). Extreme Gradient Boosting Regressor (XGBR) and CatBoost Regressor (CBR) are gradient-boosting frameworks known for their high accuracy, with CBR offering efficient handling of categorical variables. Support Vector Regression (SVR), while not a boosting method, is a strong kernel-based model often used for nonlinear regression. The Multi-layer Perceptron (MLP) is a feed-forward neural network trained using backpropagation and capable of modeling nonlinear relationships (Bishop, 2006). In addition to individual ML models, ensemble modelling can improve model training and performance by integrating different ML algorithms to mitigate the overfitting problem and provide more stable and accurate predictions (Liu et al. 2024a, b; Xu et al. 2024; Li et al. 2025). Stacking regression (STR) is a type of ensemble ML model that can combine different types of ML methods into a hierarchical framework, with diverse models being used as base models and their outcomes being used as inputs for meta model training (Liu et al. 2024a, b). Such ensemble modeling approach has been shown to outperform individual models in crop growth param-

eter and yield prediction tasks (Wang et al., 2024; Li et al., 2025). However, stacking regression has not been used for predicting crop yield responses to N and site-specific EONR.

Up to date, no studies have been reported to develop an in-season site-specific N recommendation strategy based on stacking ensemble regression fusing genetic, environmental, management practice, remote sensing data as well as crop and fertilizer price information under diverse conditions across a large region like the US Midwest. To address this research gap, this research aimed to develop an innovative PNM strategy for corn across the U.S. Midwest based on stacking ensemble ML along with multi-source data fusion and update to date corn yield and N fertilizer price information. The specific objectives were to (1) evaluate the performance of different ML algorithms and stacking ensemble regression models using active canopy sensor data and multi-source data fusion for in-season corn yield prediction; and (2) simulate yield responses to sidedress N application rates and estimate EONR across the U.S. Midwest.

## Materials and methods

### Study design

From 2014 to 2016, through research collaboration between Corteva Agrisciences and eight universities in the Midwest of the United States, a total of 49 site-year N rate experiments were conducted in the corn belt. More detailed information can be found in Kitchen et al. (2017); Ransom et al. (2021a, b). The raw data for this experiment can be downloaded directly from this website (<https://dataadryad.org/dataset/doi:https://doi.org/10.5061/dryad.66t1g1k2g>). The treatments included four replications of N fertilizer application rates ranging from 0 to 315 kg N ha<sup>-1</sup>, all applied at planting or in splits, with 45 kg N ha<sup>-1</sup> applied at planting and the remaining N fertilizer applied at the V9 ± 1 corn developmental stage (Bean et al. 2018a, b; Kitchen et al. 2017; Ransom et al. 2021a). A total of 3094 experimental data points (plots) were used in this study. The statistical information of each variable was given in Table S1.

### Data collection

The handheld active canopy sensor RapidSCAN CS-45 (Holland Scientific, Lincoln, NE) was used to collect corn canopy reflectance at three wavelengths with centers of 670, 730, and 780 nm. Fourteen vegetation indices (VIs) were calculated from the collected reflectance data (Table 1). A total of 42 variables related to the genetic, environmental and management information were included as potential predictors of corn yield in the analysis.

Regarding genetic information, hybrid related variables were obtained from Pioneer company (<https://www.pioneer.com/us/products/corn/corn-seed-finder.html>), including comparative relative maturity (CRM), CRM to silk (SCRM), growth degree units (GDUs) to silk (GDUs-S), and GDUs to physiological maturity (GDUs-PM).

Environmental data included weather and soil data. For weather data, Hobo U 30 automatic weather stations (Onset Computer Corporation, Bourne, MA) were established near each experimental site to collect weather data (Kitchen et al., 2017) for calculating corn heat units (CHU), cumulative precipitation (PPT), growing degree days (GDDs), abundant

**Table 1** The variables used in the study

| Indicators | Definitions                              | Descriptions                                                                                                | References                    |
|------------|------------------------------------------|-------------------------------------------------------------------------------------------------------------|-------------------------------|
| NDVI       | Normalized difference vegetation index   | $(R_{NIR} - R_{RED}) / (R_{NIR} + R_{RED})$                                                                 | (Rouse et al., 1973)          |
| DVI        | Difference vegetation index              | $(R_{NIR} - R_{RED})$                                                                                       | (Richardsons & Wiegand, 1977) |
| NDRE       | Normalized difference red edge Index     | $(R_{NIR} - R_{REDEEDGE}) / (R_{NIR} + R_{REDEEDGE})$                                                       | (Fitzgerald et al., 2010)     |
| CCCI       | Canopy chlorophyll content index         | $(NDRE - NDRE_{min}) / (NDRE_{max} - NDRE_{min})$                                                           |                               |
| RVI_re     | Ratio vegetation index                   | $\frac{R_{NIR}}{R_{REDEEDGE}}$                                                                              | (Fitzgerald et al., 2010)     |
| NLI        | Non-Linear index                         | $(R_{NIR}^2 - R_{RED}^2) / (R_{NIR}^2 + R_{RED}^2)$                                                         | (Goel & Qin, 1994)            |
| RDVI       | Re-difference vegetation index           | $\frac{(R_{NIR} - R_{RED})}{\sqrt{(R_{NIR} + R_{RED})}}$                                                    | (Roujean & Breon 1995)        |
| MTCI       | MERIS terrestrial chlorophyll index      | $(R_{NIR} - R_{REDEEDGE}) / (R_{REDEEDGE} - R_{RED})$                                                       | (Dash & Curran 2004)          |
| PVI        | Perpendicular vegetation index           | $\frac{R_{NIR} - 10R_{RED} - 6.604}{\sqrt{1 + 10.489 * 10.489}}$                                            | (Richardsons & Wiegand 1977)  |
| SAVI       | Soil adjusted vegetation index           | $\frac{1.5(R_{NIR} - R_{RED})}{R_{NIR} + R_{RED} + 0.5}$                                                    | (Huete, 1988)                 |
| OSAVI      | Optimized soil adjusted vegetation index | $\frac{(R_{NIR} - R_{RED})}{R_{NIR} + R_{RED} + 0.16}$                                                      | (Rondeaux et al., 1996)       |
| ReCI       | Red edge chlorophyll index               | $\frac{R_{NIR}}{R_{REDEEDGE}} - 1$                                                                          | (Gitelson et al., 2005)       |
| NIRv       | Near infrared reflectance of vegetation  | $(R_{NIR} \bullet NDVI)$                                                                                    | (Badgley et al., 2017)        |
| DCNI       | Double-peak canopy nitrogen index        | $\frac{(R_{NIR} - R_{REDEEDGE})}{R_{REDEEDGE} - R_{RED}} \bullet \frac{1}{(R_{NIR} - R_{REDEEDGE} + 0.03)}$ | (Chen et al., 2010)           |
| 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   | $PPT \times SDI$                                                                                            |                               |
| SDI        | Shannon diversity index                  | $-\sum p_i \frac{\ln p_i}{\ln n}$ , $p_i$ =precipitation/PPT                                                |                               |

and well-distributed rainfall (AWDR) and Shannon diversity index (SDI), based on daily precipitation and temperature data from planting date to crop sensing date before sidedress N application (Bean et al. 2018b; Tremblay et al. 2012) (Table 1).

Soil variables used in the ML models included cation exchange capacity (CEC, ), total carbon (TC), soil N content (N), soil bulk density (BD\_Saxton) estimated using the Saxton-Rawls pedotransfer equation based on soil texture and organic matter (Saxton & Rawls, 2006), pH measured in water (pH\_water) and in salt (pH\_salt), soil water content (WC), soil clay content (Clay), silt content (Silt) and sand content (Sand).

Management-related variables included N rate (planting and sidedress N rates at  $V9 \pm 1$ ), irrigation (as a logical variable, with 1 indicating the presence of irrigation and 0 indicating the absence of irrigation), seeding rate (SeedRate). And rotation with leguminous plants (Crop1back, 1 indicates rotation with leguminous plants, and 0 indicates rotation with non-leguminous plants).

The dataset containing all the above-mentioned variables (i.e., 42 genetic, environmental, and management variables) was recorded as All\_in dataset. Fourteen variables were selected to form Simplified dataset, including normalized difference red edge (NDRE), CRM, clay content, silt content, sand content, slope, CHU, PPT, GDDs, SDI, AWDR, seeding rate, preplant N rate and sidedress N rate. These variables were selected based on the accessibility and expert knowledge. The selected variables can be easily obtained through publicly available database, from the farmer or through a service in a cheap and time-efficient way. For example, most farmers in US have or have access to planters and fertilizer applicator machines that record the as-planted (seeding rate) and as-applied (N application rate) data. The dry grain yield was calculated based on grain moisture data and used as the dependent variable (Table S1).

The experimental EONR values were calculated using N application rates and the measured yield data for each site-year using quadratic-plateau model and quadratic model (for only 1 site-year) based on a corn grain price of \$ 0.158 kg<sup>-1</sup> and N fertilizer cost of \$0.88 kg N<sup>-1</sup> (Kitchen et al., 2017 to facilitate the comparison with previous studies using the same dataset.

## Selection of machine learning models

Five commonly used ML models were selected in this study, including RFR as a tree-based ensemble learning method that utilizes multiple decision trees to improve prediction accuracy, MLP as a type of artificial neural network capturing complex relationships in data, XGBR as a gradient-boosting framework that can process structured data, CBR that can optimize the handling of categorical features and SVR that uses support vector machines to perform regression tasks. These models have been demonstrated to perform well in crop yield estimation (van Klompenburg et al., 2020) and were selected in this study to be further evaluated for their performances in predicting corn yield, yield response to different sidedress N rates and EONR under diverse conditions across the US Midwest.

Two Stacking Regression models (STR1 and STR2) combining predictions from multiple fundamental models were evaluated. For STR1, the base models were RFR, XGBoost, CatBoost, and MLP, and the meta-model was the linear regression model. Additionally, the stacking model STR2 incorporating SVR into the base models of STR1 was also evaluated in this study (Table 2). The hyper-parameter settings for different ML models are presented in Table 2. The hyper-parameter tuning was performed with grid-search. The 5-fold cross-validation was used to evaluate the candidate parameter set (Table 2). The grid that covered all listed hyper-parameter ranges was exhaustively searched, with the combination yielding the lowest root-mean-square error (RMSE) being retained as the final setting.

**Table 2** Overview of hyperparameter settings for different machine learning models

| Methods | Hyperparameters                                                                                                                                                                                                                                      |
|---------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| MLP     | Hidden_layer_sizes: [(20,16), (30,20), (40,30)];<br>Activation: ['relu', 'tanh', 'logistic']<br>Solver: ['adam', 'sgd', 'lbfgs']; Learning_rate_init: [[0.001, 0.01, 0.1]]<br>Max_iter: [1000, 2000, 3000, 4000, 5000]; Alpha: [0.0001, 0.001, 0.01] |
| SVR     | Kernel: rbf; Gamma: np.logspace(-2,2,20) ; C: [1e0, 1e1, 1e2, 1e3, 1e4]                                                                                                                                                                              |
| STR1    | Base estimator: [RFR', 'XGBR', 'CBR', 'MLP'];<br>Meta estimator: linear regression (copy_x: True; fit_intercept=True; n_jobs=None, positive: False)                                                                                                  |
| STR2    | Base estimator: [RFR', 'XGBR', 'CBR', 'MLP', 'SVR']; Meta estimator: linear regression (copy_x: True; fit_intercept=True; n_jobs=None, positive: False)                                                                                              |
| RFR     | n_estimators: (10, 1000); min_samples_split: (2,20); max_features: (1,20); max_depth: (3,10); min_samples_leaf: (1, 30); max_leaf_nodes: (10,40)                                                                                                     |
| XGBR    | N_estimators: (10, 1000); max_depth: (2, 10); num_leaves: (5, 20); min_child_samples: (3, 100); reg_alpha: (0.1, 1); reg_lambda: (0.001, 1); subsample: (0.8, 1); colsample_bytree: (0.8, 1)                                                         |
| CBR     | depth: (1, 10); iterations: (250, 1000); learning_rate: (0.02; 0.3); l2_leaf_reg: (1, 100); border_count: (5, 200); ctr_target_border_count: (5, 200); loss_function=MAE, RMSE; n_calls=50; random_state=0                                           |

## Dataset splitting and model interpretation

The dataset was split using a two-step process to ensure proper stratification and presentation. The dataset was initially divided into training (80%) and testing (20%) sets, with stratification based on the 'site-year' number column to maintain proportional representation of this variable across subsets. A fixed random state (1) was used. The training set was further split into training (80%) and validation (20%) subsets without stratification, using a random state of 100. For All\_in dataset, the calibration set contained 1980 data records. The testing set contained 619 data records. The validation set contained 495 data records. For each record, over 40 independent variables were included. For the Simplified dataset, each record was derived by removing some variables as described in Supplementary Table 1, resulting in a dataset with 14 independent variables per record. The data was scaled by StandardScaler, fitting on the training set and applying it to the validation, testing and simulation sets to avoid data leakage. Missing data was handled prior to scaling.

Shapley Additive Explanations (SHAP) was used for interpreting ML models. The Shapley value provides a unified approach to interpret the output of ML models. The algorithms used in this study were implemented in the Python 3.8 environment. The scikit-learn version was 1.5.1. The xg-boost version was 2.1.3. The cat-boost version was 1.2.3. The mlxtend version was 0.23.4. The shap version was 0.46.0.

## Evaluation of model performance for corn yield and eonr predictions

A simulated dataset was created by averaging the four replications for each treatment at each site-year receiving 45 kg N ha<sup>-1</sup> at planting, consisting of seven split N rate treatments (0, 45, 90, 135, 180, 225, 270 kg N ha<sup>-1</sup>). This dataset represents the environmental conditions of different site-years but was not directly used in the training of the models. They were used to further access the performance of the yield prediction models for estimating EONR.

The quadratic plus plateau and quadratic models were able to capture the non-linear relationship between corn yield and nitrogen rates, enabling the calculation of EONR. These models are simple, easy to interpret, and widely used in agricultural research and practice, making them reliable tools for optimizing fertilizer management decisions (Baum et al., 2023). The site-year-specific EONR was calculated using the ‘eonr’ python package published by Nigon et al. (2019) (<https://eonr.readthedocs.io/en/latest/index.html>). The corn price was \$0.158 per kg and the cost of N fertilizer was \$0.88 per kg following Kitchen et al. (2017) to facilitate the comparison with previous research results. Different prices were used to evaluate how EONR was affected by different price ratios at selected site-years to demonstrate the advantage of the proposed strategy.

The prediction performance of different ML models for corn yield and EONR was evaluated by comparing the predicted values of yield or EONR by the ML model with the observed yield or EONR using four statistical indicators: coefficient of determination (R<sup>2</sup>), RMSE, MAE and mean absolute percentage error (MAPE). The definition of MAPE is shown in Eq. (1).

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (1)$$

where  $n$  is the samples size.  $y_i$  is the observed EONR.  $\hat{y}_i$  is the predicted EONR by ML methods.

The metrics (R<sup>2</sup>, MAE, RMSE, and MAPE) were calculated for the training, validation and testing datasets, as explicitly implemented in the code. In this process, no specific random seed was used. The analysis was conducted on a Windows system using Python 3.8. Key libraries included scikit-learn, pandas, numpy, and matplotlib.

The overall research framework of this study is presented in Fig. 1.

## Results

### In-season prediction of corn grain yield based on different ML algorithms

In both the All\_in dataset and the Simplified dataset, XGBR, RFR, and CBR generally had high R<sup>2</sup> values (close to 1) across the calibration, test, and validation sets, demonstrating strong fitting capabilities (Fig. 2). Among them, XGBR showed the lowest errors (MAE, RMSE, and MAPE) in the calibration set, but larger errors in the testing and validation sets, indicating a potential overfitting issue. In contrast, RFR and CBR exhibited stable performance on the testing and validation sets, especially CBR, which achieved the lowest MAE

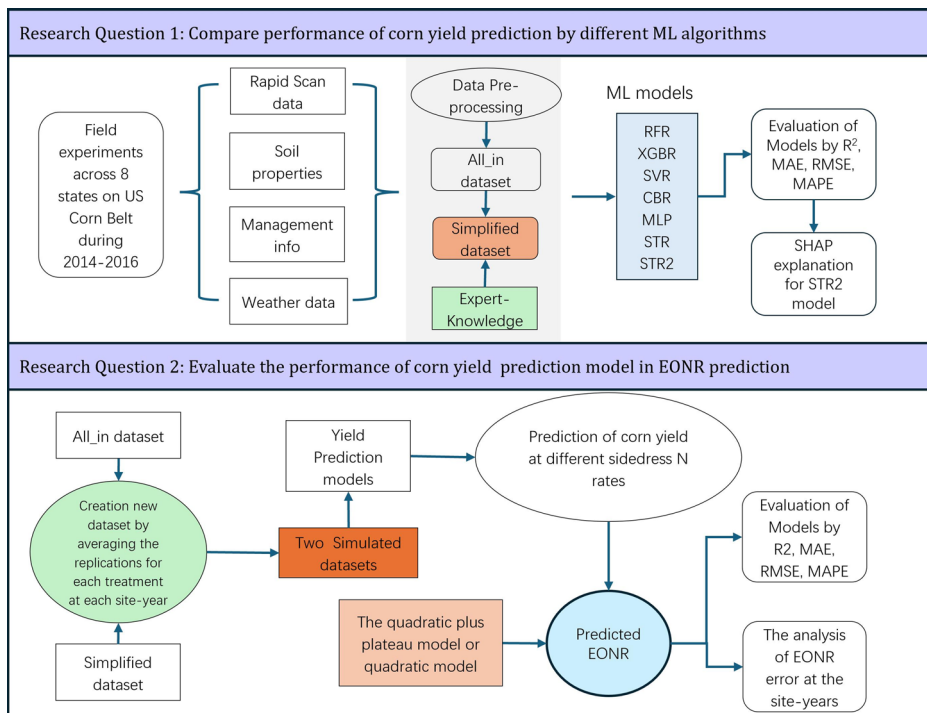


**Fig. 1** The research flowchart used in this study to predict corn grain yield and economic optimal nitrogen rate (EONR) using different machine learning (ML) algorithms and multi-source data fusion

and RMSE in the Simplified dataset, demonstrating better generalization ability. The CBR, MLP, STR1 and STR2 models performed consistently well across calibration, test and validation datasets and better than the other tested models.

For corn grain yield estimation, using a more comprehensive dataset led to a better model performance. Simplified models generally had lower  $R^2$  and higher MAE and RMSE values, showing reduced accuracy compared to the models based on the All\_in dataset. MLP, STR1 and STR2 generally achieved higher  $R^2$  values and lower MAE and RMSE values. However, the models based on the simplified dataset still achieved good performance in corn yield estimation with the  $R^2$  values larger than 0.85 in validation dataset. Removing some less important variables such as irrigation and previous crops did not significantly reduce the ML model's accuracy for yield estimation.

## Simulating yield response to N rates for EONR estimation

The corn yield at each N rate in the separate evaluation dataset was predicted by the above-mentioned corn yield estimation models. The quadratic-plateau and quadratic models were applied to fit the simulated corn yield response curves to N rates. The EONR values were then calculated. The scatter plots between measured and predicted EONR values are pre-

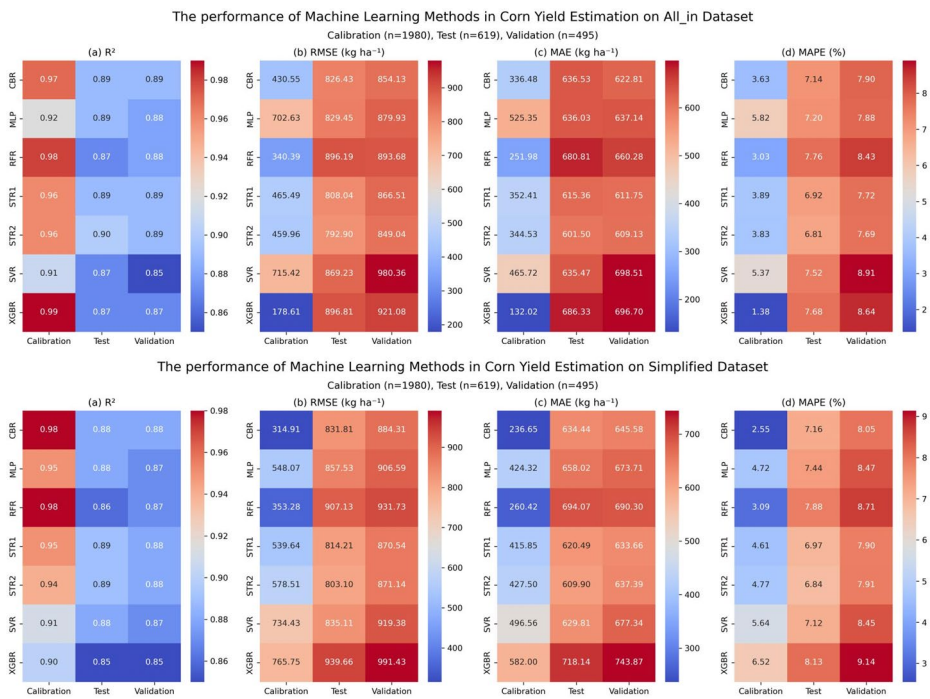


**Fig. 2** The heatmaps indicating the performance of different machine learning models for corn yield prediction in terms of coefficient of determination ( $R^2$ ), root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE). RFR: Random Forest Regression; SVR: Support Vector Regression; XGBR: Extreme Gradient Boosting Regression; CBR: CatBoost Regression; MLP: Multi-Layer Perceptron regression; STR1: Stacking Regression 1; STR2: Stacking Regression 2

sented in Figs. 3 and 4 for models based on the All\_in and Simplified datasets, respectively. The points out of 95% CIs were identified (Figs. 3 and 4).

For the All\_in dataset, the MLP, STR1 and STR2 had  $R^2$  values larger than 0.80 for EONR estimation, with STR2 having the highest  $R^2$  of 0.83. These models also had relatively low MAE, RMSE and MAPE values. For the Simplified dataset, the  $R^2$  values of CBR, MLP, STR1 and STR2 were greater than 0.70. It can be observed that the STR2 model had the lowest number of points out of 95% CI (Figs. 3g and 4g).

Figure 5 illustrated the simulated corn yield responses to N rates using the STR2 models for two selected site-years (2014\_WI\_Steuben and 2014\_MN\_StCharles) based on All\_in and Simplified datasets. The gross return to N represents the total economic return based on corn yield without considering the cost of N fertilizers. The gross return minus the cost of N fertilizer was the net return to N. The cost of N fertilizer increased linearly with the amount of N applied. The gray shaded area represents the uncertainty of the predicted output response to N (Confidence Interval). The maximum value of the Net Return to N curve is the MRTN (Nigon et al., 2019). It can be observed that the simulated EONRs showed little difference between the All-in and Simplified models.

Figure 6 illustrated the variations in EONR predicted using the All\_in and Simplified STR2 models along with the measured values for each site-year. The Tukey Honestly Significant Difference (HSD) test results and Cohen's d results are given in Fig. 6 (a). It is clear

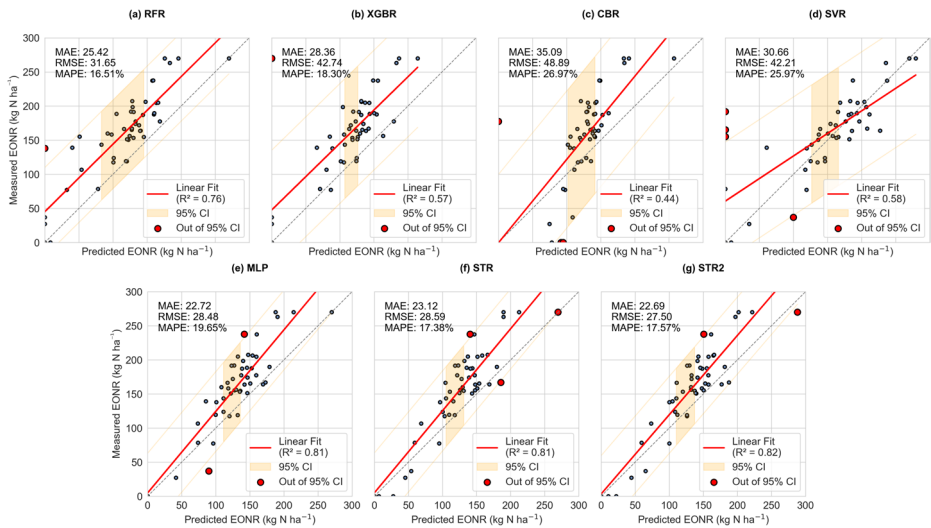


**Fig. 3** Comparison of predicted and measured economic optimum nitrogen rate (EONR) (kg N ha<sup>-1</sup>) for different full (All-in) machine learning models based on the simulated separate test dataset ( $n=49$ ). RFR: Random Forest Regression; SVR: Support Vector Regression; XGBR: Extreme Gradient Boosting Regression; CBR: CatBoost Regression; MLP: Multi-Layer Perceptron regression; STR: Stacking Regression; STR2: Stacking Regression 2

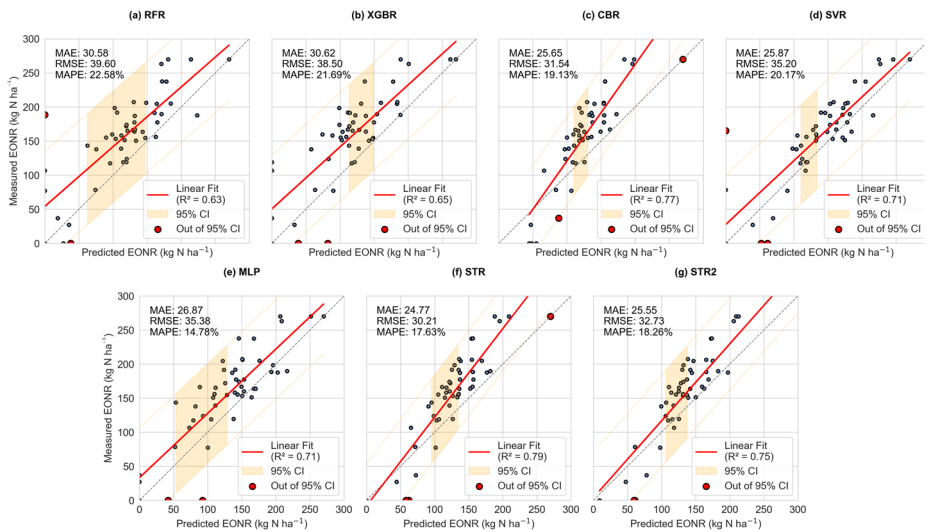


**Fig. 4** Comparison of predicted and measured economic optimum nitrogen rate (EONR) (kg N ha<sup>-1</sup>) for different simplified machine learning models with reduced input variables based on the simulated separate test dataset ( $n=49$ ). RFR: Random Forest Regression; SVR: Support Vector Regression; XGBR: Extreme Gradient Boosting Regression; CBR: CatBoost Regression; MLP: Multi-Layer Perceptron regression; STR: Stacking Regression; STR2: Stacking Regression 2

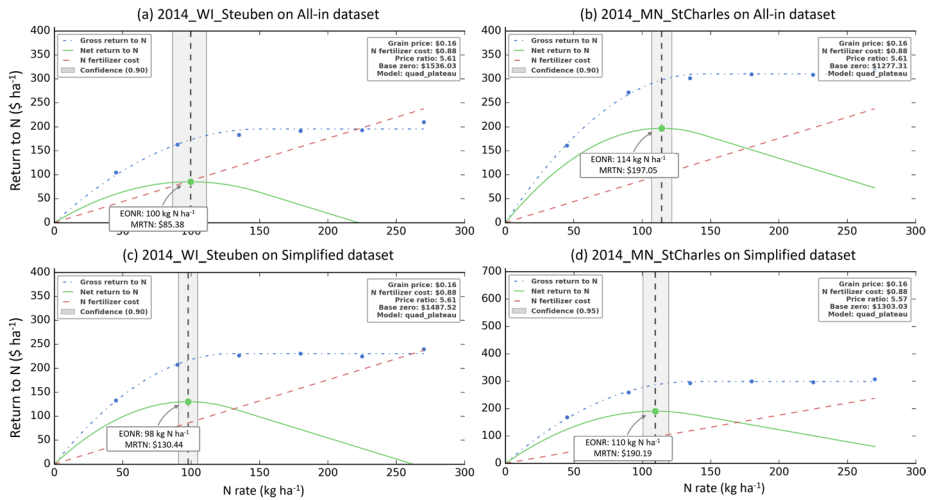


**Fig. 5** Examples of simulated economic optimum nitrogen rate (EONR) ( $\text{kg N ha}^{-1}$ ) and maximum return to nitrogen (MRTN) ( $\text{kg N ha}^{-1}$ ) using the STR2 model based on the All\_in dataset (a, b) and Simplified dataset (c, d) for the 2014\_WI\_Steuben and 2014\_MN\_StCharles site-years

that the predicted EONR values by the models were not significantly different from the measured values. The effect sizes for “Measured vs. STR2-All” and “Measured vs. STR2-simplified” are small to moderate. There was no significant difference between the measured EONR and predictions from both the full model (STR2-All\_in) and the simplified model (STR2-Simplified).

In most site-years, the predicted EONRs using both models aligned closely with the measured EONR, indicating relatively accurate estimations. Larger differences were reported by the two STR2 models at the Brownstown site in 2014, Urbana site in 2015, Sand site in 2014, Urbana site in 2015, LoneTree site in 2015, Bradford site in 2016, and Loess site in 2016 (Fig. 6 (b)).

### Contribution of different variables for corn grain yield estimation

The SHAP values based on test set for the All\_in dataset and Simplified dataset were presented in Fig. 7. For All\_in dataset, according to the SHAP summary graph (Fig. 7a) and feature importance graph (Fig. 7b), five main predictors were identified: Side\_N, Preplant\_N, NDRE, Silt and pH\_salt. The mean absolute SHAP values were about 800, 750, 600, 500 and 400, respectively (Fig. 6a). The ranges of SHAP values were  $-2000$  to  $500$  for Side\_N and  $-2000$  to  $1500$  for Preplant\_N (Fig. 7b). The SHAP value distributions for five ML models across the All\_in dataset were also presented in Fig. 7c. CatBoost and MLP had wider SHAP ranges. For Simplified dataset, NDRE, Side\_N, Preplant\_N, silt and Clay made high contributions on yield (Fig. 6d-e), which was consistent with results from the All\_in dataset. The SHAP value distributions for five ML models based on the Simplified dataset were presented in Fig. 7f.

For All\_in dataset, the SHAP dependence plots were given in Fig. S3. Higher NDRE values contributed positively to the model’s predictions. At lower NDRE values, SHAP values

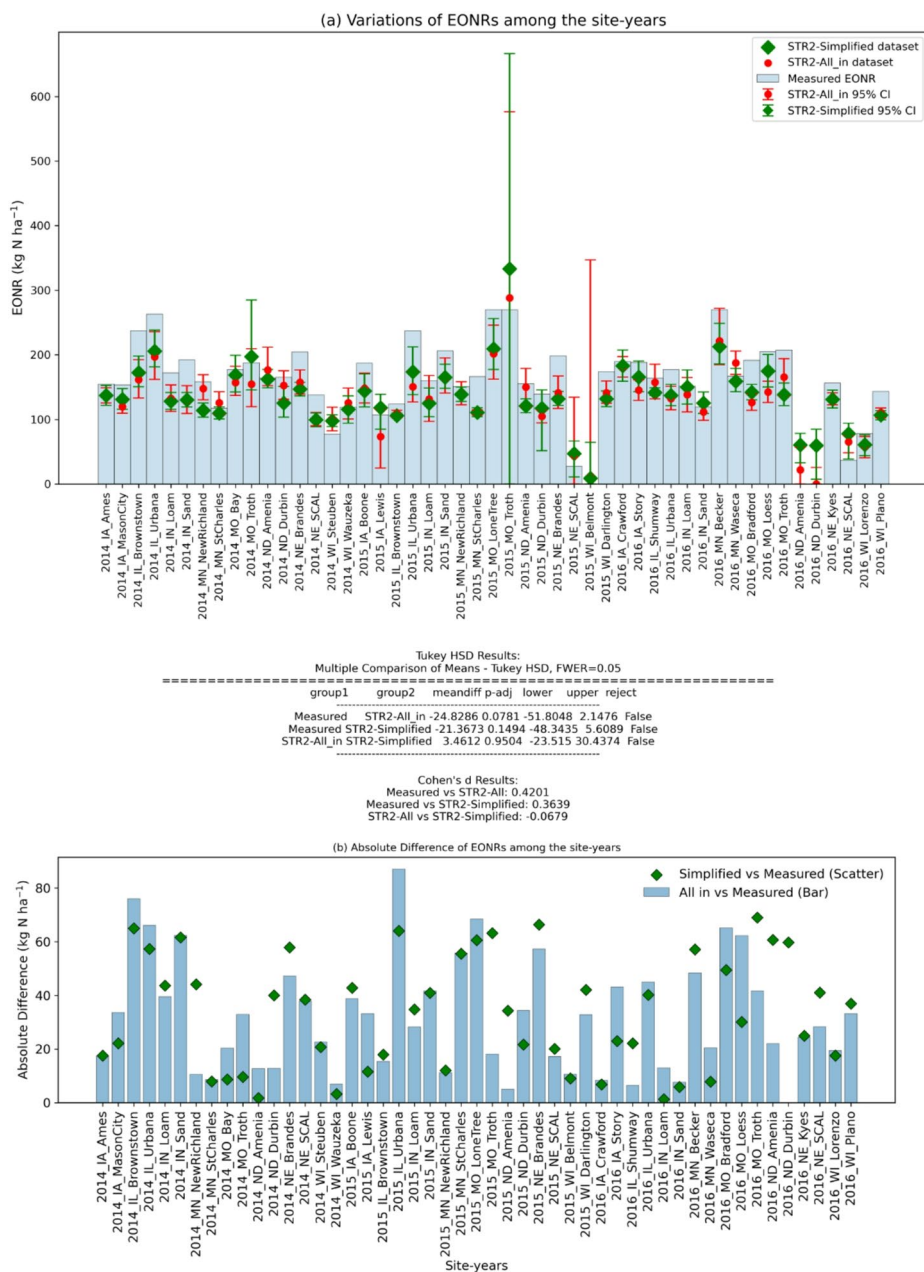


**Fig. 6** Comparison of the economically optimal nitrogen rates (EONR) predicted using the STR2 model based on the All\_in dataset and Simplified dataset vs. measured EONR values (a) and their absolute differences (b) for each site-year

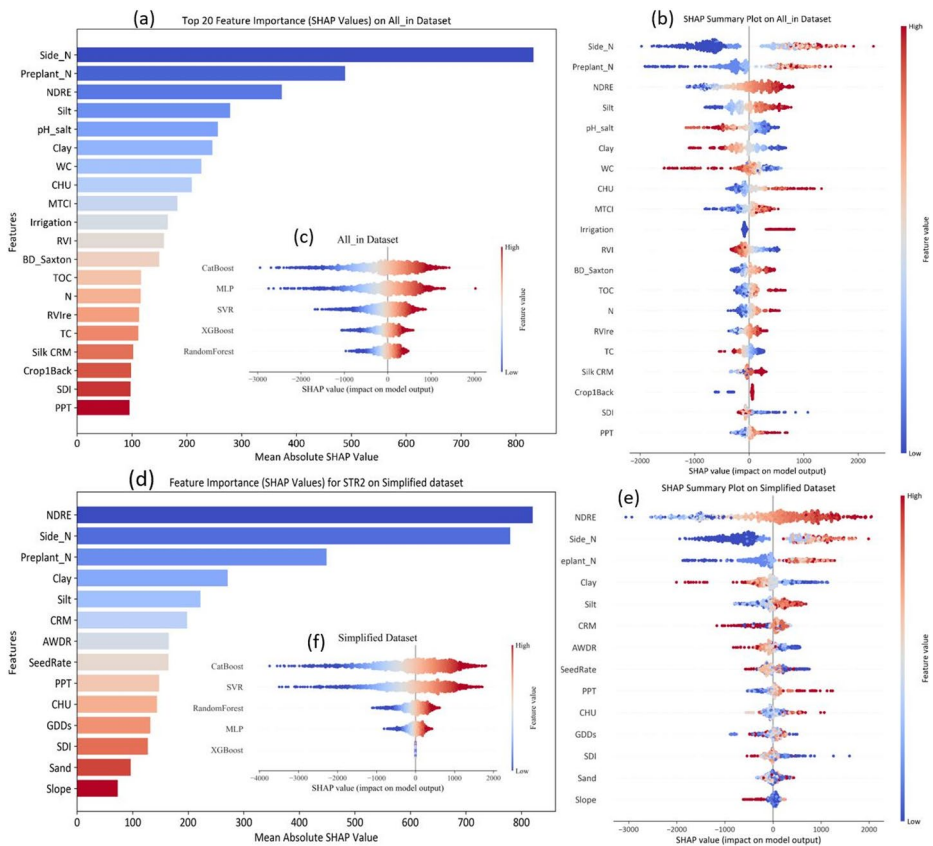


**Fig. 7** Feature importance and impact analysis results based on SHAP values of full (All-in, **a** and **b**) simplified (with reduced input variables, **d** and **e**) STR2 models as well as the SHAP values of the five individual full (All-in, **c**) and simplified (**f**) machine learning models based on the test dataset. Correlated predictors were included in the models

were more concentrated and mostly negative. The SHAP values shifted from being predominantly negative to a mix of negative and positive when NDRE was around 0.30 (Fig. S 3a).

As Side\_N increased from 0 to 270 kg ha<sup>-1</sup>, the SHAP values generally increased. This indicated that higher Side\_N values contributed positively to the model's predictions of yield. At lower Side\_N values (e.g., 0–50 kg ha<sup>-1</sup>), SHAP values were more concentrated and mostly negative. At higher Side\_N values (e.g., 200–270 kg ha<sup>-1</sup>), SHAP values were more dispersed and mostly positive. Around 100 kg ha<sup>-1</sup>, SHAP values transitioned from being predominantly negative to a mix of positive and negative. Above 150 kg ha<sup>-1</sup>, SHAP values were mostly positive, indicating a stronger positive contribution to yield predictions (Fig. S 3b).

As Preplant\_N increased from 0 to 300 kg ha<sup>-1</sup>, the SHAP values generally changed from −2000 to +1500, showing a positive correlation. For preplant N in the range of 0 to 50 kg ha<sup>-1</sup>, SHAP values are mostly negative, ranging from −2000 to 0 and were closely clustered. At higher values (e.g., 200–300 kg ha<sup>-1</sup>), SHAP values were more dispersed and mostly positive (Fig. S 3c).

For Clay and WC, increased values negatively impacted yield predictions. SHAP values dropped dramatically at higher Clay values ( $>25\%$ ). For WC larger than  $0.20 \text{ g g}^{-1}$ , SHAP values were mostly negative. For Silt and BD\_Saxton, higher values positively impacted yield predictions. The SHAP value of BD\_Saxton ranged from  $-300$  to  $+400$ . As BD\_Saxton increased, SHAP values transitioned to being positive. For BD\_Saxton ranging from  $1.4$  to  $1.5 \text{ g cm}^{-3}$ , SHAP values positively influenced the predictions (Fig. S3 d-i).

The interaction effects of important features to yield were also investigated by SHAP interaction plots (Fig. S4). Both Side\_N and Preplant\_N had the positive contribution of NDRE. At higher NDRE values, the impact of silt and PPT became more pronounced. As pH\_salt increased, the SHAP values generally decreased. At higher pH\_salt values (e.g.,  $7.0\text{--}7.5$ ), the SHAP values were mainly negative. Higher WC mitigated the negative impact of pH\_salt on corn yield, while lower WC amplified it. The SHAP values also increased with the seeding rate (SeedRate). The relationship was more pronounced at higher SeedRate values (e.g.,  $90,000\text{--}94,000$  seeds  $\text{ha}^{-1}$ ).

The 4D scatterplots visualized the relationships among four variables (Fig. S5). At lower NDRE values (e.g.,  $0.10\text{--}0.20$ ), increasing Side\_N did not increase the yield unless Preplant\_N was high. At high NDRE values (e.g.,  $0.30\text{--}0.45$ ), the yield improved significantly when Side\_N and Preplant\_N were both high (Fig. S 5a). High yield values were observed when Clay, Silt and Sand were within moderate ranges. Low yield values were found when Clay or Silt levels was either too high or too low (Fig. S 5b). High yield values were presented with higher NDRE values, pH\_salt ranging from  $5.5$  to  $6.5$  and WC being less than  $0.20 \text{ g g}^{-1}$  (Fig. S 5c). Low CHU ( $300\text{--}400 \text{ }^{\circ}\text{C}\cdot\text{d}$ ), extreme precipitation (either too much or too little), and low AWDR (blue dots mean severe water deficit) resulted in low corn yield (Fig. S 5d).

## Discussion

### An innovative in-season site-specific nitrogen recommendation strategy

The most significant contribution of this research is the development of an innovative active canopy sensor-based in-season site-specific N management strategy for corn across the Midwest US using stacking ensemble ML and multi-source data fusion. This strategy has several advantages compared with previous PNM strategies.

The first advantage is that this strategy developed an in-season yield prediction ML model using active canopy sensor data collected around V9 growth stage before sidedress N application together with genetic, soil, weather and management information (including preplant and sidedress N rates). Then this ML model can be used to predict corn yield responses to different sidedress N rates under a specific genetic  $\times$  environment  $\times$  management condition. In addition to predicting the agronomic optimum sidedress N rate that will optimize corn yield, current corn and N fertilizer price information can be used to determine the EONR or MRTN for sidedress application that will optimize economic returns. The ability to allow farmers to incorporate up-to-date corn and N price information into the sidedress N decision making is especially important because their prices can vary substantially from year to year in responses to changes in environmental conditions, energy costs, global supply-demand conditions and policy shifts (Yang et al., 2022). This improvement distinguishes this strat-

egy from most of the previous proximal and remote sensing-based in-season site-specific N recommendation strategies that either don't consider profitability or uses fixed corn and N prices (Dong et al., 2024; Morris et al., 2018; Qin et al., 2018; Ransom et al., 2020).

The second advantage is that this strategy uses stacking ensemble ML model rather than a single ML model for corn yield prediction and in-season site-specific N recommendations. Different MLs have been applied in precision agriculture and there was no consensus with the best performing model(s) (Chlingaryan et al., 2018; Qin et al., 2018; Ransom et al., 2019; van Klompenburg et al., 2020; Raza et al., 2025). These ML algorithms differ in their ability to handle nonlinear and categorical data, as well as in their predictive performance, model complexity, interpretability, robustness, data requirements and computational efficiency. These differences largely stem from variations in algorithmic structure and the characteristics of the dataset being used (Chlingaryan et al., 2018; Ransom et al., 2019; Mohammed & Kora, 2023). The ensemble ML approach can combine the strengths of multiple ML models, reduce the limitations of a single model and improve prediction accuracy and robustness. The stacking ensemble ML models performed consistently well among all the ML models for yield prediction tested across the datasets in this study. The MLP, STR and STR2 models outperformed RFR, XGBR, CBR, and SVR models for yield predictions. Although MLP models had relatively good accuracy, their performances were still inferior to STR and STR2 for yield predictions (Figs. 2 and 3). Some models (e.g., XGBR) demonstrated strong calibration performance but weaker validation performance.

Although these ML models performed well in corn grain yield estimation, their performances differed significantly when simulating yield responses to sidedress N application. The XGBR, CBR, and SVR models performed well in yield prediction, but their performance significantly declined when predicting EONR. The crop response to N fertilizer is generally nonlinear and influenced by multiple factors (e.g., soil properties, climate conditions) and management practices. The stacking ensemble models could combine predictions from multiple base models, leveraging the strengths of each model (Garouani et al., 2025). In the scatter plots of most models (Figs. 3 and 4), there was an accumulation of sample points at the position where predicted EONR was 0 kg N ha<sup>-1</sup>. Some of these sample points represented cases where the algorithm failed to successfully capture the yield response to N variation. A similar conclusion was also reported by Barbosa et al. (2020), who predicted corn yield responses to management and environmental variables by convolutional neural network. In this study, four different types of base estimators (RFR, CBR, XGBR and MLP) were used in the STR model and five base estimators (RFR, CBR, XGBR, MLP and SVR) were used in the STR2 model. By introducing SVR model, the base estimators of the STR2 model became more diverse and the model generalized better, producing consistently good performances across the All-in and Simplified databases for EONR prediction ( $R^2=0.75-0.82$ , Figs. 3 and 4). From the scatter plots of Figs. 3 and 4, it can be observed that the accumulation of sample points at zero kg ha<sup>-1</sup> was decreased. This indicated that the ensemble ML approach could improve generalization and robustness compared with single ML models.

The third advantage is the adoption of multi-source data fusion. In addition to crop sensor data, soil and weather data, hybrid related variables (e.g., CRM, SCRM, GDUs-S, and GDUs-PM) and management practices (e.g., previous crop, Seed Rate, Irrigation, Preplant N rate and sidedress N rate) were incorporated in the modeling. Most of the previous studies mainly included soil and weather data (Qin et al., 2018; Ransom et al., 2019; Raza et

al., 2025). In addition to improving model performance for corn N status, yield or EONR prediction, incorporating the full set of genotype  $\times$  environment  $\times$  management factors can further enhance the generalization and robustness of the ML models (Li et al., 2022). Such models will also allow predictions of hybrid-, soil-, weather and management-specific EONRs rather than predictions for general conditions.

To balance the advantage of multi-source data fusion and practical applications, we also developed a simplified dataset reducing the full set of 42 variables to 14 based on the agronomic knowledge and accessibility. Only easily available or obtainable variables were kept. Models based on the simplified dataset performed comparatively well while requiring fewer inputs. This make the ML models more practical for farmers, crop consultants and extension specialists.

The fourth advantage is the use of SHAP for model interpretability, as it bridges the gap between black-box ML models and agronomic decision-making. Each feature's contribution to yield predictions can be quantified using SHAP, enabling agronomists and researchers to understand why the model predicts certain yield levels or recommends certain EONR. This transparency not only increases trust in the models but also helps identify which genotypic, environmental, and management factors drive crop yield responses under different conditions. Furthermore, SHAP interaction values allow the exploration of complex genotype  $\times$  environment  $\times$  management interactions, revealing nonlinear relationships that traditional statistical models often miss. Such insights can guide more informed N management strategies, support hypothesis generation for field research, and ultimately improve the adoption and usability of ML-based decision tools in precision agriculture (Mohan et al., 2025).

The SHAP analysis indicated that Side\_N, Preplant\_N and NDRE were the most important factors for corn yield prediction. There was a strong positive correlation between NDRE and yield. The models relied on this correlation, especially when Side\_N and Preplant\_N increased. Specifically, NDRE and Side\_N showed significant positive contributions at higher ranges (NDRE  $> 0.30$ , Side\_N  $> 150 \text{ kg ha}^{-1}$ ). Additionally, optimal pH levels (6–7) and higher silt content enhanced the positive contribution of NDRE. Adequate soil water content and precipitation may amplify NDRE's positive impact on yield. In this study, the critical point of NDRE around 0.30 at V9  $\pm 1$  growth stage might correspond to the level at which corn N demand was met. Crema et al. (2020) found that NDRE close to 0.32 corresponded to an N nutrition index close to 0.1.

Both Side\_N and Preplant\_N showed a nonlinear effect on yield, rather than a simple linear increase or decrease. At low application levels, the model associated Side\_N and Preplant\_N with lower predicted yields (a negative relationship). The insufficient N application failed to meet the corn growth demands. At moderate levels, the models showed Side\_N and Preplant\_N contributed positively to yield. At this level, N application met the corn growth requirements, optimizing growth conditions. Beyond these optimal levels (Side\_N  $> 200 \text{ kg ha}^{-1}$  or Preplant\_N  $> 250 \text{ kg ha}^{-1}$ ), their marginal contributions to yield began to diminish. Excessive N applications can lead to the saturation of corn N uptake.

Coarse-textured soils with high sand content ( $> 4\%$ – $10\%$ ) and even rainfall (SDI  $> 0.56$ – $0.59$ ) were more suitable for split N application (Clark et al., 2020; Spackman et al., 2019). In this study, soils with high silt content ( $> 40\%$ ) and moderate clay content ( $10\%$ – $20\%$ ) produced high yield. These soils typically have good aeration and drainage while retaining an adequate amount of water and nutrients. Tremblay et al. (2012) found that the precipitation

in the early growth stage and soil properties had significant effect on corn yield response to N rate.

The fifth advantage is that the ML models were developed based on a collaborative dataset spanning 49 site-years of N rate and timing experiments across eight U.S. Midwest states through a public-industry partnership (Kitchen et al., 2017). In addition to the framework of ML algorithms, the simulation of yield response to crop management can be highly affected by the spatial structure and quality of the data (Barbosa et al., 2020; Kakimoto et al., 2022). This large dataset covers diverse genetic, environmental and management conditions, ensuring the study's rigor and real-world grounding, as compared with many previous studies only based on a few site-years of experimental data.

### Limitations, implications for practical applications and research needs

The first limitation is that although it is very valuable to include 49 site-years of N experiments covering eight US-Midwest states in this study, the N experiments were concentrated in certain regions between 2014 and 2016 and cannot fully capture the full spatial and temporal variability of the U.S. Corn Belt. Therefore, the research mainly demonstrated the concept and the potential of the multi-source data fusion and stacked ensemble ML-based N recommendation strategy, and the models developed in this study are still not ready to be implemented. More site-years of N experimental data conducted under diverse environmental conditions should be added to the database for model development and this database should be constantly updated as new experimental data become available to make sure the models will be trained using data fully representing the diverse and complex environmental conditions in the U.S. Corn Belt.

The second limitation is that even though the simplified models performed well in general, they did not perform well for some site-years, showing significant deviations from measured EONR. Therefore, the risks of applying simplified models under diverse conditions should not be ignored. The STR2 ensemble model using the All\_in dataset more accurately captured yield responses at several low-EONR sites (e.g., Belmont\_2015; Durbin\_2016; Amenia\_2016), where models based on the simplified dataset failed. These sites were characterized by favorable initial soil N levels, prior legume crops, or limited early-season rainfall-condition that reduced or delayed crop response to sidedress N (Clark et al., 2020). Variable selection for the simplified dataset was based on expert knowledge and data accessibility, which may have excluded other critical variables. Some studies also confirmed that simplified methods performed well in certain situations but might fail to adequately capture the influence of key variables under more complex conditions (Qin et al., 2018; Ransom et al., 2019). Complex or atypical environmental conditions challenge simplified models and highlight the benefit of integrating multi-source datasets for more robust EONR estimation across diverse growing conditions. This is consistent with the findings of many studies, indicating that the effectiveness of N fertilizer recommendation is closely related to genetic, environmental and management factors (Tremblay et al., 2012; Sawyer et al., 2017; Huang et al., 2024). Therefore, a balance needs to be achieved by including all key factors influencing corn responses to N application but also considering practical applications and data accessibility, which deserves more research.

The third limitation is that neither the simplified nor the full models performed satisfactorily at certain sites like Urbana 2015, Brownstown 2014, and Lonetree 2015. These loca-

tions experienced factors such as waterlogging, high denitrification potential (Bean et al., 2018a), or misalignment between N uptake timing and soil supply (e.g., high CEC or early crop maturity). For SCAL 2015, observed N response could be influenced by the residual effects of hail damage to soybean plants of the previous season. For Amenia 2016, incorrect application of urea and ammonium fertilizers in June resulted in invalid yield response data for EONR calculation (Ransom et al., 2019 a). Qin et al. (2018) achieved  $R^2$  of 0.46 for corn EONR prediction by removing the data at the SCAL site in 2015 and Amenia site in 2016. In this study, an  $EONR=0 \text{ kg ha}^{-1}$  may indicate sufficient soil N or no crop response to N fertilizer due to other stress factors and the models did not include such inputs. Such predictions should be critically evaluated within the context of farm management practices and local conditions. Additionally, extreme environmental conditions (e.g., waterlogging, or high denitrification potential) introduced prediction errors at some site-years. These results indicate that further refinement is needed to handle atypical or stress-prone sites. Another consideration is that the ML models should be used as a decision support tool. For normal conditions, we can rely on them. But for atypical conditions, local knowledge and expertise should be used to adjust the model predictions. At the same time, we can continue to explore ways to improve the ML models, for example, by adding a new input variable representing atypical stress conditions or adding certain rules to make sure the N recommendations will be reliable even under unusual climate conditions or in atypical environments. Additionally, possible biases may arise due to unequal representation of soil types, climatic conditions or management regimes in the dataset. A balanced representative training dataset needs to be developed to ensure robust model generalization and performance.

The fourth limitation is that although the use of SHAP improved the interpretation of how different factors contributed to the corn yield prediction and helped us identify the key factors, it does not guarantee causal inference. SHAP feature importance reflects correlations and associations of different variables with corn yield, but not necessarily agronomic causality, because SHAP applies the cooperative game theory to model outputs for feature attribution and does not account for underlying causal mechanisms or confounders (Huang & Marques-Silva, 2024). For example, soil pH was identified as an important factor with higher pH genitively contributing to corn yield and lower pH positively contributing to corn yield (Fig. 7), yet this does not prove it causally drove yield variations without additional causal analysis. To address this gap, extensions like Causal SHAP have been proposed, which integrate causal graphs to move beyond standard SHAP's limitations (Heskes et al., 2020). Future research should also explore more intuitive and robust interpretability methods. For example, rule-based models through 'if-then' logic (Berhane et al., 2018), causal inference approaches by answering 'why' and 'what-if' questions (Guo et al., 2024; Jiao et al., 2024) may offer new insight into variable contributions in yield and EONR prediction. This also aligns with the requirements for white-box models and model interpretability in agricultural applications (Rudin, 2019; Paudel et al., 2023; Hu et al., 2023).

The fifth limitation is the development of stacking regression models. The integration of multi-source data can improve agricultural management and decision-making processes (Cao et al., 2021; Zhou et al., 2020; Mena et al., 2025). In our study, the ML models exhibit significant differences in performance when predicting yield responses to N rates and EONRs. Among these models, the stacking regression algorithm demonstrated its superiority in EONR prediction compared to CBR and SVR models, which failed to capture marginal N effects under specific conditions (e.g., the Bay site in 2014). In stacking regres-

sion models, the inclusion of multiple ML models with different structures into the base estimators can leverage their individual strengths. However, in this study, we only included four-five ML models as base models. How to optimize the combination of base models and meta-models has not been thoroughly explored yet. Novel algorithms and diverse data structures should be explored for modeling corn yield responses to N rates in future studies. For example, Graph Neural Networks (GNNs) (Corso et al., 2024; Khemani et al., 2024; Jia et al., 2020) or Transformer-based regression models (Aleissae et al., 2023; Niu et al., 2024) need to be explored for their effectiveness in EONR modelling.

The sixth limitation is that the ML-based N recommendation strategy was based on small plot N experiments, not under real on-farm conditions. As a result, these experimental areas are relatively small and flat without much variability in topographic and terrain attributes, which have been identified as key factors influencing within-field yield and N response variabilities (Miao et al., 2006; Li et al., 2025; Rabia et al., 2022). Therefore, the developed ML models may perform well for field-specific or zone-specific N recommendations or for flat fields but may not perform satisfactorily for site-specific sidedress N recommendations in fields with rolling topography.

The seventh limitation is that although NDRE played a significant role in the ML models, it was based on a portable active canopy sensor with only spectral data. There is a potential to further improve the performance of the models by incorporating the spatial, temporal, and spectral richness of high spatial resolution unmanned aerial vehicle (UAV) or satellite remote sensing images (Lapaz, et al., 2023). The increasing availability of high-resolution datasets (e.g. PlanetScope satellite remote sensing) and products (such as soil organic content, solar-induced chlorophyll fluorescence, meteorological reanalysis data) may provide new opportunities for large scale in-season predictions of crop yield and EONR to improve crop N management.

In addition, the uncertainty propagation from yield prediction to EONR has not been fully quantified in our study. How prediction errors propagate through the modeling process is critical for improving model robustness.

Finally, the developed strategy was demonstrated for corn yield prediction and in-season sidedress EONR recommendation in this study, however, this framework has the potential to be adapted for different crops, regions and dynamic price environments. This should be further explored in future studies. To further expand the impact of this research, web-based decision support tools or applications with user-friendly interfaces should be developed to support researchers, extension educators, crop consultants and farmers to adopt the developed technologies, which is needed to bridge the gap between advanced ML models and practical agricultural decision-making and adoptions (Mossinger et al., 2022; Karunathilake et al., 2023).

## Conclusion

This study developed an innovative multi-source data fusion and stacking ensemble ML model-based strategy for corn yield prediction and in-season site-specific sidedress EONR recommendation. This strategy incorporates genetic, environmental and management factors as well as active canopy sensor data to improve corn yield and EONR predictions under different conditions. Up-to-date corn yield and N fertilizer price information can also be

used for in-season N recommendation to optimize economic returns. The results indicated that this strategy could effectively estimate corn yield, with the models'  $R^2$  being above 0.85 in the calibration, prediction, and validation datasets. The ML models were further evaluated for simulating corn yield responses to sidedress N rates and estimating EONR. The sidedress EONR calculated by the STR2 matched the measured EONR, with an  $R^2$  of 0.82 and an RMSE of 27.50 kg N ha<sup>-1</sup>. The stacking regression models performed more consistently for both corn yield prediction and EONR estimation compared with individual ML models. SHAP analysis was used to improve the interpretability of the ML models and identified sidedress N rate, preplant N rate and NDRE as the most important factors for corn yield prediction. It is concluded that the stacking regression and multi-source data fusion framework is a promising strategy for in-season site-specific corn yield prediction and sidedress N recommendation. The study is limited by the relatively small number (49) of site-years of small plot N experiments, which is not large enough to represent the diverse U.S. Midwest Corn Belt and will affect the robustness of the developed ML models for regional applications. However, the presented framework can be improved by adding more plot and on-farm N experimental data collected across diverse environmental conditions to guide in-season site-specific N management in the U.S. Midwest. It can also be adapted and improved for different crops, regions and dynamic price environments using UAV and satellite remote sensing and more advanced ML models with user-friendly interfaces to make greater contributions to the improvement of N use efficiency, farm profitability and agricultural sustainability.

**Supplementary Information** The online version contains supplementary material available at <https://doi.org/10.1007/s11119-026-10344-7>.

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**Data availability** TThe raw data for this experiment can be downloaded directly from this website (<https://data.dryad.org/dataset/doi:10.5061/dryad.66t1g1k2g>). The datasets specifically used in this study are available upon request.

## Declarations

**Competing interests** The authors declare no competing interests.

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## References

- Aleissae, A. A., Kumar, A., Anwer, R. M., Khan, S., Cholakkal, H., Xia, G. S., & Khan, F. S. (2023). Transformers in remote sensing: a survey. *Remote Sensing*, 15(7), 1860.
- Ang, Y., Shafri, H. Z. M., Lee, Y. P., Mansor, S., & Shariff, A. R. M. (2022). Oil palm yield prediction across blocks from multi-source data using machine learning and deep learning. *Earth Science Informatics*, 15(3), 2349–2367.
- Badgley, G., Field, C. B., & Berry, J. A. (2017). Canopy near-infrared reflectance and terrestrial photosynthesis. *Science Advances* 3(3), e1602244.
- Barbosa, A., Trevisan, R., Hovakimyan, N., & Martin, N. F. (2020). Modeling yield response to crop management using convolutional neural networks. *Computers and Electronics in Agriculture*, 170, 105197.
- Baum, M. E., Sawyer, J. E., Castellano, M. J., & Archontoulis, S. V. (2023). Ranking genotype, environment, and management effects on the optimum nitrogen rate for maize: A cropping system modeling analysis. *Agronomy Journal*, 116, 1775–1791.
- Bean, G. M., Kitchen, N. R., Camberato, J. J., Ferguson, R. B., Fernández, F. G., Franzen, D. W., Laboski, C. A. M., Nafziger, E. D., Sawyer, J. E., Scharf, P. C., Schepers, J. S., & Shanahan, J. F. (2018b). Improving an active-optical reflectance sensor algorithm using soil and weather information. *Agronomy Journal*, 110(6), 2541–2551.
- Bean, G. M., Kitchen, N. R., Camberato, J. J., Ferguson, R. B., Fernández, F. G., Franzen, D. W., Laboski, C. A. M., Nafziger, E. D., Sawyer, J. E., Scharf, P. C., Schepers, J. S., & Shanahan, J. F. (2018a). Active-optical reflectance sensing corn algorithms evaluated over the United States Midwest Corn Belt. *Agronomy Journal*, 110(6), 2552–2565.
- Berhane, T. M., Lane, C. R., Wu, Q., Autrey, B. C., Anenkhonov, O. A., Chepinoga, V. V., & Liu, H. (2018). Decision-tree, rule-based, and random forest classification of high-resolution multispectral imagery for wetland mapping and inventory. *Remote Sensing*, 10(4), 580.
- Bishop, C. M. (2006). *Pattern Recognition and Machine Learning*. Springer.
- Cai, S., Zhao, X., & Yan, X. (2025). Towards precise nitrogen fertilizer management for sustainable agriculture. *Earth Critical Zone*, 2, 100026.
- Cao, Q., Miao, Y., Feng, G., Gao, X., Liu, B., Liu, Y., Li, F., Khosla, R., Mulla, D. J., & Zhang, F. (2017a). Improving nitrogen use efficiency with minimal environmental risks using an active canopy sensor in a wheat-maize cropping system. *Field Crops Research*, 214, 365–372.
- Cao, Q., Miao, Y., Li, F., Gao, X., Liu, B., Lu, D., & Chen, X. (2017b). Developing a new Crop Circle active canopy sensor-based precision nitrogen management strategy for winter wheat in North China Plain. *Precision Agriculture*, 18(1), 2–18.
- Cao, Q., Miao, Y., Shen, J., Yuan, F., Cheng, S., & Cui, Z. (2018). Evaluating two Crop Circle active canopy sensors for in-season diagnosis of winter wheat nitrogen status. *Agronomy*, 8(10), 201.
- Cao, J., Zhang, Z., Tao, F., Zhang, L., Luo, Y., Zhang, J., Han, J., & Xie, J. (2021). Integrating multi-source data for rice yield prediction across China using machine learning and deep learning approaches. *Agricultural and Forest Meteorology*, 297, 108275.
- Chen, P., Haboudane, D., Tremblay, N., Wang, J., Vigneault, P., & Li, B. (2010). New spectral indicator assessing the efficiency of crop nitrogen treatment in corn and wheat. *Remote Sensing of Environment*, 114(9), 1987–1997.
- Chlingaryan, A., Sukkarieh, S., & Whelan, B. (2018). Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: a review. *Computers and Electronics in Agriculture*, 151, 61–69.
- Clark, J. D., Bean, G. M., Kitchen, N. R., Scharf, P. C., Camberato, J. J., Ferguson, R. B., Fernández, F. G., Franzen, D. W., Laboski, C. A. M., Nafziger, E. D., Sawyer, J. E., & Shanahan, J. F. (2020). Corn nitrogen nutrition index prediction improved by integrating genetic, environmental, and management factors with active canopy sensing using machine learning. *Remote Sensing*, 12(3), 394.
- Corso, G., Stark, H., Jegelka, S., Jaakkola, T., & Barzilay, R. (2024). Graph neural networks. *Nature Reviews Methods Primers*, 4, 17.
- Crema, A., Boschetti, M., Nutini, F., Cillis, D., & Casa, R. (2020). Influence of soil properties on maize and wheat nitrogen status assessment from Sentinel-2 data. *Remote Sensing*, 12(13), 2175.
- Dash, J., & Curran, P. J. (2004). The MERIS terrestrial chlorophyll index. *International Journal of Remote Sensing*, 25(23), 5403–5413.
- Dehghan-Shoar, M. H., Orsi, A. A., Pullanagari, R. R., & Yule, I. J. (2023). A hybrid model to predict nitrogen concentration in heterogeneous grassland using field spectroscopy. *Remote Sensing of Environment*, 285, 113360.

- Dong, R., Miao, Y., Wang, X., & Kusnierek, K. (2024). An active canopy sensor-based in-season nitrogen recommendation strategy for maize to balance grain yield and lodging risk. *European Journal of Agronomy*, 155, 127120.
- Elrys, A. S., Wang, J., Meng, L., Zhu, Q., El-Sawy, M. M., Chen, Z., Tu, X., El-Saadony, M. T., Zhang, Y., Zhang, J., Cai, Z., Müller, C., & Cheng, Y. (2023). Integrative knowledge-based nitrogen management practices can provide positive effects on ecosystem nitrogen retention. *Nature Food*, 4(12), 1075–1089.
- Fernández, F. G., Venterea, R. T., & Fabrizzi, K. P. (2016). Corn nitrogen management influences nitrous oxide emissions in drained and undrained soils. *Journal of Environmental Quality*, 45, 1847–1855.
- Fitzgerald, G. J., Rodríguez, D., & O’Leary, G. J. (2010). Measuring and predicting canopy nitrogen nutrition in wheat using a spectral index—the canopy chlorophyll content index (CCCI). *Field Crops Research*, 116(3), 318–324.
- Franzen, D. W., Kitchen, N. R., Camberato, J. J., Ferguson, R. B., Fernández, F. G., Nafziger, E. D., Sawyer, J. E., Scharf, P. C., Schepers, J. S., Shanahan, J. F., Bean, G. M., & Laboski, C. A. M. (2016). Advances in active optical sensor technology for nitrogen management in corn. *Agronomy Journal*, 108(1), 1–11.
- Garouani, M., Barhrhouj, A., & Teste, O. (2025). XStacking: An effective and inherently explainable framework for stacked ensemble learning. *Information Fusion*, 124, 103358.
- Gitelson, A. A., Viña, A., Ciganda, V., Rundquist, D. C., & Arkebauer, T. J. (2005). Remote estimation of canopy chlorophyll content in crops. *Geophysical Research Letters*, 32(8), L08403. <https://doi.org/10.1029/2005GL022688>
- Goel, N. S., & Qin, W. (1994). Influences of canopy architecture on relationships between various vegetation indices and LAI and Fpar: a computer simulation. *Remote Sensing Reviews*, 10(4), 309–347.
- Guo, J., Zhang, Y., Xu, Q., Jiang, L., Liu, X., Lv, S., & Zhu, J. (2024). A robust N-gram causal inference approach based on multi-model fusion. *Physical Communication*, 64, 102293.
- Heskes, T., Sijben, E., Bucur, I. G., & Claassen, T. (2020). Causal Shapley values: Exploiting causal knowledge to explain individual predictions of complex models. *Advances in Neural Information Processing Systems (NeurIPS)*, 33, 4778–4789.
- Hu, T., Zhang, X., Bohrer, G., Liu, Y., Zhou, Y., Martin, J., Li, Y., & Zhao, K. (2023). Crop yield prediction via explainable AI and interpretable machine learning: dangers of black box models for evaluating climate change impacts on crop yield. *Agricultural and Forest Meteorology*, 336, 109458. <https://doi.org/10.1016/j.agrformet.2023.109458>
- Huang, X., & Marques-Silva, J. (2024). On the failings of Shapley values for explainability. *International Journal of Approximate Reasoning*, 171, 109112. <https://doi.org/10.1016/j.ijar.2023.109112>
- Huang, X., Xu, X., Zhu, Q., & Zhang, Y. (2024). Optimizing water and nitrogen inputs for sustainable wheat yields and minimal environmental impacts. *Agricultural Systems*, 220, 104061.
- Huete, A. R. (1988). A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment*, 25(3), 295–309. [https://doi.org/10.1016/0034-4257\(88\)90106-X](https://doi.org/10.1016/0034-4257(88)90106-X)
- Jia, J. T., & Benson, A. R. (2020). Residual correlation in graph neural network regression. In: Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining (KDD ‘20). ACM, New York, NY, USA, pp. 588–598. <https://doi.org/10.1145/3394486.3403092>
- Jiao, L., Wang, Y., Liu, X., Li, L., Liu, F., Ma, W., Guo, Y., Chen, P., Yang, S., & Hou, B. (2024). Causal inference meets deep learning: a comprehensive survey. *Research*, 7, 0467. <https://doi.org/10.34133/research.0467>
- Kakimoto, S., Mieno, T., Tanaka, T. S. T., & Bullock, D. S. (2022). Causal forest approach for site-specific input management via on-farm precision experimentation. *Computers and Electronics in Agriculture*, 198, 107095. <https://doi.org/10.1016/j.compag.2022.107095>
- Karunathilake, E. M. B. M., Le, A. T., Heo, S., Chung, Y. S., & Mansoor, S. (2023). The path to smart farming: innovations and opportunities in precision agriculture. *Agriculture*, 13(8), 1593. <https://doi.org/10.3390/agriculture13081593>
- Khemani, B., Patil, S., Kotecha, K., & Tanwar, S. (2024). A review of graph neural networks: concepts, architectures, techniques, challenges, datasets, applications, and future directions. *Journal of Big Data*, 11, 18. <https://doi.org/10.1186/s40537-024-00742-1>
- Kitchen, N. R., Shanahan, J. F., Ransom, C. J., Bandura, C. J., Bean, G. M., Camberato, J. J., Carter, P. R., Clark, J. D., Ferguson, R. B., Fernández, F. G., Franzen, D. W., Laboski, C. A. M., Nafziger, E. D., Qing, Z., Sawyer, J. E., & Shafer, M. (2017). A public–industry partnership for enhancing corn nitrogen research and datasets: project description, methodology, and outcomes. *Agronomy Journal*, 109(6), 2371–2389. <https://doi.org/10.2134/agronj2017.03.0139>
- Krause, M. R., Crossman, S., DuMond, T., Lott, R., Swede, J., Arliss, S., Robbins, R., Ochs, D., & Gore, M. A. (2020). Random forest regression for optimizing variable planting rates for corn and soybean using topographical and soil data. *Agronomy Journal*, 112(6), 5045–5066. <https://doi.org/10.1002/agj2.20433>

- Lapaz Oliveira, A. M., Castro-Franco, M., Rozas, S., Carciochi, H. R., Balzarini, W. D., Avila, M., Ciampitti, O., & Calvo, I. R., N.I (2023). Monitoring corn nitrogen nutrition index from optical and synthetic aperture radar satellite data and soil available nitrogen. *Precision Agriculture*, 24(5), 2592–2606. <https://doi.org/10.1007/s11119-023-10030-6>
- Li, D., Miao, Y., Ransom, C. J., Bean, G. M., Kitchen, N. R., Fernández, F. G., Sawyer, J. E., Camberato, J. J., Carter, P. R., Ferguson, R. B., Scharf, P. C., & Shanahan, J. F. (2022). Integrating genetic, environmental, and management factors with active canopy sensing for corn nitrogen status diagnosis using machine learning. *Remote Sensing*, 14(2), 394. <https://doi.org/10.3390/rs14020394>
- Li, Y., Miao, Y., Rawat, A., Stueve, K., & Cao, W. (2025). Identifying key soil and landscape factors influencing yield spatial patterns for management zone delineation using ensemble machine learning. *Computers and Electronics in Agriculture*, 237, 110487. <https://doi.org/10.1016/j.compag.2025.110487>
- Liu, H., Chen, J., Xiang, Y., Geng, H., Yang, X., Yang, N., Du, R., Wang, Y., Zhang, Z., Shi, L., Wang, G., Wang, P., & Gong, W. (2024a). Improving UAV hyperspectral monitoring accuracy of summer maize soil moisture content with an ensemble learning model fusing crop physiological spectral responses. *European Journal of Agronomy*, 160, 127299.
- Liu, Y., Zhuang, M., Liang, X., Lam, S. K., Chen, D., Malik, A., Li, M., Lenzen, M., Zhang, L., Zhang, R., Zhang, L., & Hao, Y. (2024b). Localized nitrogen management strategies can halve fertilizer use in Chinese staple crop production. *Nature Food*, 5, 825–835.
- Mena, F., Pathak, D., Najjar, H., Sanchez, C., Helber, P., Bischke, B., Habelitz, P., Miranda, M., Siddamsetty, J., Nuske, M., Charfuelan, M., Arenas, D., Vollmer, M., & Dengel, A. (2025). Adaptive fusion of multimodal remote sensing data for optimal sub-field crop yield prediction. *Remote Sensing of Environment*, 318, 114547.
- Miao, Y. (2023). Precision nutrient management. In Q. Zhang (Ed.), *Encyclopedia of Digital Agricultural Technologies* (pp. 1054–1061). Springer Nature. [https://doi.org/10.1007/978-3-031-24861-0\\_152](https://doi.org/10.1007/978-3-031-24861-0_152)
- Miao, Y., Mulla, D. J., & Robert, P. C. (2006). Identifying important factors influencing corn yield and grain quality variability using artificial neural networks. *Precision Agriculture*, 7(2), 117–135.
- Miao, Y., Stewart, B. A., & Zhang, F. (2011). Long-term experiments for sustainable nutrient management in China: A review. *Agronomy for Sustainable Development*, 31(2), 397–414. <https://doi.org/10.1051/agro/2010033>
- Micha, E., Tsakiridis, A., Ragkos, A., & Buckley, C. (2023). Assessing the effect of soil testing on chemical fertilizer use intensity: An empirical analysis of phosphorus fertilizer demand by Irish dairy farmers. *Journal of Rural Studies*, 97, 186–191.
- Mohammed, A., & Kora, R. (2023). A comprehensive review on ensemble deep learning: Opportunities and challenges. *Remote Sensing of Environment*, 35, 757–774.
- Mohan, R. N. V. J., Rayanoothala, P. S., & Sree, R. P. (2025). Next-gen agriculture: integrating AI and XAI for precision crop yield predictions. *Frontiers in Plant Sciences*, 15, 1451607.
- Morris, T. F., Murrell, T. S., Beegle, D. B., Camberato, J. J., Ferguson, R. B., Grove, J., Ketterings, Q., Kyvergya, P. M., Laboski, C. A. M., McGrath, J. M., Meisinger, J. J., Melkonian, J., Moebius-Clune, B. N., Nafziger, E. D., Osmond, D., Sawyer, J. E., Scharf, P. C., Smith, W., Spargo, J. T., van Es, H. M., & Yang, H. (2018). Strengths and limitations of nitrogen rate recommendations for corn and opportunities for improvement. *Agronomy Journal*, 110(1), 1–37.
- Mössinger, J., Troost, C., & Berger, T. (2022). Bridging the gap between models and users: A lightweight mobile interface for optimized farming decisions in interactive modeling sessions. *Agricultural Systems*, 195, 103315. <https://doi.org/10.1016/j.agsy.2021.103315>
- Nigon, T. J., Yang, C., Mulla, D. J., & Kaiser, D. E. (2019). Computing uncertainty in the optimum nitrogen rate using a generalized cost function. *Computers and Electronics in Agriculture*, 167, 105030.
- Niu, X., Liu, Y. N., & Ma, M. (2024). A transformer-based model for time series prediction of remote sensing data. In D. S. Huang, C. Zhang, & Y. Pan (Eds.), *Advanced Intelligent Computing Technology and Applications. ICIC 2024* (Vol. 14876, pp. 188–200). Springer. Lecture Notes in Computer Science. [https://doi.org/10.1007/978-981-97-5666-7\\_16](https://doi.org/10.1007/978-981-97-5666-7_16)
- Paudel, D., de Wit, A., Boogaard, H., Marcos, D., Osinga, S., & Athanasiadis, I. N. (2023). Interpretability of deep learning models for crop yield forecasting. *Computers and Electronics in Agriculture*, 206, 107663. <https://doi.org/10.1016/j.compag.2023.107663>
- Puntel, L. A., Pagani, A., & Archontoulis, S. V. (2019). Development of a nitrogen recommendation tool for corn considering static and dynamic variables. *European Journal of Agronomy*, 105, 189–199.
- Qin, Z., Myers, D. B., Ransom, C. J., Kitchen, N. R., Liang, S., Camberato, J. J., Zhang, H., & Shanahan, J. F. (2018). Application of machine learning methodologies for predicting corn economic optimal nitrogen rate. *Agronomy Journal*, 110(6), 2596–2607.
- Rabia, A. H., Neupane, J., Lin, Z., Lewis, K., Cao, G., & Guo, W. (2022). Principles and applications of topography in precision agriculture. *Advances in Agronomy*, 171, 143–189.

- Ransom, C. J., Kitchen, N. R., Camberato, J. J., Carter, P. R., Ferguson, R. B., Fernández, F. G., Nafziger, E. D., Sawyer, J. E., & Shanahan, J. F. (2019). Statistical and machine learning methods evaluated for incorporating soil and weather into corn nitrogen recommendations. *Computers and Electronics in Agriculture*, 164, 104906.
- Ransom, C. J., Kitchen, N. R., Camberato, J. J., Carter, P. R., Ferguson, R. B., Fernández, F. G., Franzen, D. W., Laboski, C. A. M., Nafziger, E. D., Sawyer, J. E., & Shanahan, J. F. (2020). Corn nitrogen rate recommendation tools' performance across eight U.S. Midwest Corn Belt states. *Agronomy Journal*, 112(1), 470–492.
- Ransom, C. J., Clark, J., Bean, G. M., Bandura, C., Shafer, M. E., Kitchen, N. R., & Shanahan, J. (2021a). Data from a public–industry partnership for enhancing corn nitrogen research. *Agronomy Journal*, 113(6), 4429–4436.
- Ransom, C. J., Kitchen, N. R., Sawyer, J. E., Camberato, J. J., Carter, P. R., Ferguson, R. B., Fernández, F. G., Franzen, D. W., Laboski, C. A. M., Myers, D. B., Nafziger, E. D., & Shanahan, J. F. (2021b). Improving publicly available corn nitrogen rate recommendation tools with soil and weather measurements. *Agronomy Journal*, 113(4), 2068–2090.
- Ransom, C. J., Kitchen, N. R., Camberato, J. J., Carter, P. R., Ferguson, R. B., Fernández, F. G., Franzen, D. W., Laboski, C. A. M., Myers, D. B., Nafziger, E., Sawyer, J. E., & Shanahan, J. F. (2023). Combining corn N recommendation tools for an improved economical optimal nitrogen rate estimation. *Soil Science Society of America Journal*, 87(4), 902–917.
- Raza, A., Miao, Y., Huang, Y., Stueve, K., Lu, J., Yang, Z., & Bindlish, R. (2025). Optimizing on-farm corn yield prediction by a multi-source data fusion approach using remote sensing and machine learning. *Smart Agricultural Technology*, 12, 101630.
- Ren, K., Xu, M., Li, R., Zheng, L., Liu, S., Reis, S., Wang, H., Lu, C., Zhang, W., Gao, H., Duan, Y., & Gu, B. (2022). Optimizing nitrogen fertilizer use for more grain and less pollution. *Journal of Cleaner Production*, 360, 132180.
- Richardson, A. J., & Wiegand, C. L. (1977). Distinguishing vegetation from soil background information. *Remote Sensing of Environment*, 6(3), 209–224.
- Rondeaux, G., Steven, M., & Baret, F. (1996). Optimization of soil-adjusted vegetation indices. *Remote Sensing of Environment*, 55(2), 95–107.
- Roujean, J. L., & Bréon, F. M. (1995). Estimating PAR absorbed by vegetation from bidirectional reflectance measurements. *Remote Sensing of Environment*, 51(3), 375–384.
- Rouse, J. W., Haas, R. H., Schell, J. A., & Deering, D. W. (1973). Monitoring vegetation systems in the Great Plains with ERTS. In: Third Earth Resources Technology Satellite-1 Symposium. Volume 1: Technical Presentations. NASA SP-351, Washington, DC, pp. 309–317.
- Rudin, C. (2019). Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nature Machine Intelligence*, 1(5), 206–215. <https://doi.org/10.1038/s42256-019-0048-x>
- Sawyer, J. E., Nafziger, E. D., Randall, G. W., Camberato, J. J., Joern, B. C., & Mallarino, A. P. (2017). Concepts and rationale for regional nitrogen rate guidelines for corn. Iowa State University Extension and Outreach Publication PM 2015, Ames, IA.
- Saxton, K. E., & Rawls, W. J. (2006). Soil water characteristic estimates by texture and organic matter for hydrologic solutions. *Soil science society of America Journal*, 70(5), 1569–1578.
- Schut, A. G. T., & Giller, K. E. (2020). Soil-based, field-specific fertilizer recommendations are a pipe-dream. *Geoderma*, 380, 114680.
- Sela, S., van Es, H. M., Moebius-Clune, B. N., Marjerison, R., & Kneubuhler, G. (2018). Dynamic model-based recommendations increase the precision and sustainability of N fertilization in midwestern US maize production. *Computers and Electronics in Agriculture*, 153, 256–265.
- Spackman, J. A., Fernández, F. G., Coulter, J. A., Kaiser, D. E., & Paiao, G. D. (2019). Soil texture and precipitation influence optimal time of nitrogen fertilization for corn. *Agronomy Journal*, 111, 2018–2030. <https://doi.org/10.2134/agronj2018.09.0605>
- Thompson, L. J., Archontoulis, S. V., & Puntel, L. A. (2024). Simulating within-field spatial and temporal corn yield response to nitrogen with APSIM model. *Precision Agriculture*, 25, 2421–2446.
- Tremblay, N., Bouroubi, Y. M., Bélec, C., Mullen, R. W., Kitchen, N. R., Thomason, W. E., Ebelhar, S., Mengel, D. B., Raun, W. R., Francis, D. D., Vories, E. D., & Ortiz-Monasterio, I. (2012). Corn response to nitrogen is influenced by soil texture and weather. *Agronomy Journal*, 104, 1658–1671.
- van Ittersum, M. K., Silva, J. V., Bommarco, R., Hijbeek, R., Lundin, O., Nandillon, R., Bergkvist, G., Menegat, A., Öborn, I., Söderholm-Emas, A., Stoddard, F. L., Vico, G., Vonk, W. J., Watson, C. A., & Maclaren, C. (2025). Narrowing the ecological yield gap to sustain crop yields with less inputs. *Global Food Security*, 45, 100857.
- van Klompenburg, T., Kassahun, A., & Catal, C. (2020). Crop yield prediction using machine learning: a systematic literature review. *Computers and Electronics in Agriculture*, 177, 105709.

- Wakahara, S., Miao, Y., McNearney, M., & Rosen, C. J. (2025). Non-destructive potato petiole nitrate-nitrogen prediction using chlorophyll meter and multi-source data fusion with machine learning. *European Journal of Agronomy*, 164, 127483.
- Wang, X., Miao, Y., Dong, R., Zha, H., Xia, T., Chen, Z., Kusnierek, K., Mi, G., Sun, H., & Li, M. (2021). Machine learning-based in-season nitrogen status diagnosis and side-dress nitrogen recommendation for corn. *European Journal of Agronomy*, 123, 126204.
- Wang, J., Wang, Y., Li, G., & Qi, Z. (2024). Integration of remote sensing and machine learning for precision agriculture: a comprehensive perspective on applications. *Agronomy*, 14(9), 1975.
- Xiao, L., Wang, G., Wang, E., Liu, S., Chang, J., Zhang, P., Zhou, H., Wei, Y., Zhang, H., Zhu, Y., Shi, Z., & Luo, Z. (2024). Spatiotemporal co-optimization of agricultural management practices towards climate-smart crop production. *Nature Food*, 5, 59–71.
- Xu, X., Chen, F., Wang, B., Harrison, M. T., Chen, Y., Liu, K., Zhang, C., Zhang, M., Zhang, X., Feng, P., & Hu, K. (2024). Unleashing the power of machine learning and remote sensing for robust seasonal drought monitoring: a stacking ensemble approach. *Journal of Hydrology*, 634, 131102.
- Yang, Z., Du, X., Lu, L., & Tejeda, H. (2022). Price and volatility transmissions among natural gas, fertilizer, and corn markets: A revisit. *Journal of Risk and Financial Management*, 15(2), 91.
- Yin, Y., & Cui, Z. (2024). Challenges of optimal crop management. *Nature Food*, 5(1), 13–14.
- Zhang, P., Lu, B., Ge, J., Wang, X., Yang, Y., Shang, J., La, H., Zhu, Z., Zang, H., & Zeng, Z. (2025). Using UAV-based multispectral and RGB imagery to monitor above-ground biomass of oat-based diversified cropping. *European Journal of Agronomy*, 162, 127422.
- Zhou, W., Guan, K., Peng, B., Shi, J., Jiang, C., Wardlow, B., Pan, M., Kimball, J. S., Franz, T. E., Gentine, P., He, M., & Zhang, J. (2020). Connections between the hydrological cycle and crop yield in the rainfed U.S. Corn Belt. *Journal of Hydrology*, 590, 125398.

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