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Delta yield predicts nitrogen fertilizer requirements for corn in US production systems

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Abstract

Predicting crop nitrogen (N) fertilizer needs is a major challenge in contemporary agriculture. Despite the success of current N recommendation tools,

Abbreviations: AER, agroecosystem region; dY, delta yield; dY-based N, delta yield-based nitrogen; EONR, economic optimum nitrogen rate; LP, linear plateau; LRRs, land resource regions; MAE, mean absolute error; MRTN, maximum return to nitrogen; NUE, nitrogen use efficiency; OM, organic matter; PR, price ratio; QP, quadratic plateau; QPRF, quadratic-plateau response fits; TED, technology extrapolation domains.

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environmental concerns over N pollution from agriculture, and the adoption of improved corn (*Zea mays* L.) technologies with enhanced N efficiencies highlight the need for more accurate N fertilizer recommendation systems. Here, we aimed to develop a methodology to predict corn N requirements based on delta yield (dY = maximum yield−unfertilized yield). To develop this delta yield-based nitrogen (dY-based N) tool, we selected 486 quadratic-plateau corn yield response to N curves (from 732 N rate trials across northern US) to calculate dY and N fertilizer required to reach the yield plateau (N_x). The economic optimum nitrogen rate (EONR) was calculated using different fertilizer:crop price ratios (PR). The response curve outputs were then partitioned into calibration and validation sets. The calibration set was used to select linear models to predict N_x based on dY, resulting in nine state, agroecosystem region, and irrigation-specific sub-models. These sub-models predicted N_x of the validation set with a mean absolute error (MAE) of 33.0 kg N ha^{-1}. Predicted values from the site-year quadratic-plateau response fits were used to improve further predictions' outcomes. Predictions of EONR based on dY had a lower MAE than the predictions of N_x, ranging between 19.9 and 25.4 kg N ha^{-1} depending on the PR, highlighting the system's predictive power. The exclusion of non-responsive and linear-response trials in our proposed dY-based approach enables future model refinement to improve EONR prediction accuracy across a broader range of yield responses to fertilizer-N rates. The proposed dY-based N system, which integrates both economic and agronomic inputs (including management, environmental effects on soil N supply, and maximum yields), could help to reduce N losses and provide functional benefits for N optimization.

Plain Language Summary

We developed a delta yield-based nitrogen (dY-based N) approach to predict N requirement for U.S. corn production systems. Using 486 N response trials, we modeled N rates to reach yield plateaus and found that dY effectively predicts both agronomic (N_x) and economic optimum N rate (EONR) requirements. These sub-models predicted N_x of the validation set with a mean absolute error (MAE) of 33.0 kg N ha^{-1}. Predictions of EONR based on dY had a lower MAE than the predictions of N_x, ranging between 19.9 and 25.4 kg N ha^{-1} depending on the fertilizer:grain price ratios (PR). This approach can support sustainable fertilizer use by integrating agronomic and economic factors, including soil N supply, management practices, and yield potential, offering a practical tool for improving N use efficiency and reducing environmental impact.

1 | INTRODUCTION

Quantitative data on corn (*Zea mays* L.) yield response to nitrogen (N) is a key resource for developing and refining N fertilizer recommendation systems (Morris et al., 2018; Ransom et al., 2023; Salo et al., 2015; Sawyer et al., 2006). Such data could help to simultaneously mitigate N losses and enhance functional outcomes by enabling accurate pre-season predictions of site-year yield under both zero-N input and agronomically optimal N rate fertilization scenarios. Improved N prescription technologies are increasingly necessary with adoption of enhanced corn production systems and as corn hybrids with improved nitrogen use efficiency (NUE) become more commonly commercialized (Cooper et al., 2020; Dohleman et al., 2024; Kosola et al., 2023; Ordóñez et al., 2024). Furthermore, the influence of

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preceding crops, whether under monocropping or rotational systems (Gautam et al., 2025; Ordóñez et al., 2025; Puntel et al., 2016; Sawyer et al., 2006), along with cover cropping programs (Hirsh et al., 2021; Vyn et al., 1999, 2000; White et al., 2016), can expand the complexity of soil carbon (C) and N cycling. These dynamic factors alter crop-available soil N pools, undermining the reliability of the traditional assessment methods (Morris et al., 2018; Reid et al., 2025). In response to these challenges, we propose developing a tool that relies on the delta yield (dY) metric (the yield increase associated with application of a nonlimiting N rate) to recommend N fertilizer rates (Lory & Scharf, 2003; Janovicek et al., 2021).

Despite N fertilizer being a major driver of rising crop yields in the past decades (Dobermann & Cassman, 2005; Duvick, 2005; Tilman et al., 2002), mitigating N losses from agricultural systems to protect environmental quality and enhance farmer profitability represents a global challenge (Baum et al., 2025; Cassman et al., 2002; Robertson & Vitousek, 2009). In fact, efforts are ongoing to identify the most effective methodologies that balance production and environmental outcomes, as existing tools are categorized as static or dynamic, depending on the inputs used for predictions (Mandrini, Pittelkow, et al., 2021). Applying N fertilizer at the economic optimum nitrogen rate (EONR) is well recognized to reduce N losses through various pathways (Andraski et al., 2000; Quin et al., 2018; Ransom et al., 2020; Sawyer et al., 2006), while lowering N fertilizer application rates without compromising crop productivity can also reduce nitrous oxide (N_2O) emissions (Malcolm et al., 2015). However, accurate prediction of EONR needs to be improved (Morris et al., 2018; Puntel et al., 2019; Ransom et al., 2020). Given the needs and challenges, there is increasing interest to identify new tools to determine the EONRs required by corn to maintain profitable production while improving agroecosystem services (Morris et al., 2018).

In the U.S.A., the state average corn N fertilizer application rates range from ~108 to ~196 kg N ha^{-1}, with a national average of ~167 kg N ha^{-1} (ERS-USDA, 2018). In the US Midwest, producers applied a median of 185–253 kg N ha^{-1} $year^{-1}$ to continuous corn and 157–210 kg ha^{-1} $year^{-1}$ to corn following soybean (Baum et al., 2025). About 70% of the corn production in the United States is in areas where the maximum return to nitrogen (MRTN) approach is used to determine fertilizer rates, mainly recommended by university extension services (ERS-USDA, 2018; Morris et al., 2018). The MRTN approach makes N recommendations based on a dataset of corn yield response curves for different cropping system areas and crop rotations with an adjustment based on corn grain and fertilizer price ratios. The main difference between the systems is that EONR is site-specific and highly tailored to local conditions (e.g., weather, soil, and crop), whereas MRTN is regionally derived from compiling

Core Ideas

- Delta yield (dY) can predict agronomic and economic optimum nitrogen (N) fertilizer requirements for corn.
- Prediction of agronomic optimum N rate by dY can be improved by state- and irrigation-specific calibrations.
- Predicting N fertilizer requirements by dY could serve as the basis for a new N fertilizer recommendation system.
- An efficient N recommendation tool can help to maximize crop productivity while reducing environmental issues.

EONRs across environments. While MRTN is designed to be broadly applicable using economic thresholds, it is less sensitive to field-level variability (Morris et al., 2018; Nafziger et al., 2004; Sawyer et al., 2006). The second tool widely used to make N recommendations for corn in the U.S.A. is the yield goal approach (Lory & Scharf, 2003; Morris et al., 2018) assuming

$$[N_{fer} = (N_{Crop} - N_{soil})/N_{eff}], \quad (1)$$

where N_{fer} is the N fertilizer need, N_{Crop} is the N required for the yield goal, N_{soil} is the soil-N supply, and N_{eff} is the efficiency of the fertilizer-N use (Stanford, 1973). Soil-N supply and fertilizer-N recovery efficiency cannot be accurately determined on a site-year basis before planting, and various approaches are used to estimate these factors when using yield goal N recommendations (Morris et al., 2018).

An alternative approach is to make N recommendations based on the dY concept (Kachanoski, 2009; Lory & Scharf, 2003; Janovicek et al., 2021). The dY approach was first introduced by Kachanoski et al. (1996) after evaluating over 300 field trials in Ontario, Canada. Its low adoption in US croplands might be related to the rapid expansion of the MRTN approach launched about the same time (Nafziger et al., 2004; Sawyer et al., 2006). Despite an initial lag in adoption, it is worth reconsidering the predictive power of the dY approach, particularly as agricultural N use becomes an increasingly significant environmental and societal challenge (Baum et al., 2025). The dY metric is defined as the difference between the corn yield achieved with no N limitations (Y_x) and the corn yield achieved without fertilizer N added (Y_0):

$$dY = Y_x - Y_0, \quad (2)$$

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Because corn N uptake typically scales with yield, the Y_x and Y_0 components of dY are analogs to the crop N demand and soil N supply components of the Stanford (1973) equation. Lory and Scharf (2003) demonstrated that dY explained more variation in corn EONR than the yield goal approach across several of the major corn-producing states in the United States, principally because dY accounts for soil N supply. Recently, Janovicek et al. (2021) revisited the dY approach and used a dataset of corn yield response curves to calibrate linear models that integrate dY to predict the N fertilizer required to reach the yield plateau (Y_x), often referred to as the agronomic optimum N rate (N_x). This highlights how dY, and N_x predicted by dY, could be used to calculate the EONR at any specific fertilizer:crop price ratio (PR). The dY approach is potentially superior in calculating N fertilizer recommendations because it is a hybrid of both the yield goal and MRTN recommendation methods. In fact, this approach accounts for the yield-based N demands of corn and soil N supply while also predicting EONR under a given fertilizer:crop PR based on calibration to an empirical dataset of yield response curves.

A key distinction of the dY-based method for predicting N fertilizer rates is the explicit inclusion of the unfertilized corn yield (Y_0), which is related to soil N supply capacity. Recent research has demonstrated the ability to predict unfertilized corn yield from easily measured soil and cover crop residue properties that control soil N supply, in addition to weather performance, particularly during the grain fill period (Arrington et al., 2024; White et al., 2020), or by using biochemical soil health indicators or diffuse reflectance infrared Fourier transformation spectroscopy data (Deiss et al., 2023). Others have demonstrated the success of machine-learning approaches or process-based soil and crop models at predicting fertilized and unfertilized corn yields, incorporating factors such as soil properties, management, weather variables, and crop-specific data (Baum et al., 2023; Correndo et al., 2021; Puntel et al., 2016; Shahhosseini et al., 2020; Stecker et al., 1995; Wang et al., 2021). These previous studies suggest that dY could be estimated in advance from one or more methods of making site-specific predictions of unfertilized corn yield along with estimates of a corn yield goal at the site.

Given the potential suitability of the dY-based approach to estimate fertilizer-N rates, we hypothesize that dY can be used to predict N_x across different states, agroecosystem regions (AERs), and irrigation practices through specific model calibrations. These calibrations can be further used to predict EONR given different fertilizer:crop PRs, thereby providing valuable guidance for N fertilizer decisions in individual corn fields. Here we employed the mathematical quadratic-plateau (QP) model to evaluate yield responses to N across 732 N rate trials and used the N_x, Y_x, and Y_0 to develop new N fertilizer recommendation formulas for corn based on dY. Because this unique dataset includes yield responses to N from numerous on-farm and research station trials, we anticipate this research will provide a foundation for delta yield-based nitrogen (dY-based N) recommendations for corn in a globally important AER. Additionally, it will provide a rationale and framework for future research efforts to further explain and predict the components that influence dY variations.

2 | MATERIALS AND METHODS

2.1 | Experimental sites

To calibrate equations to predict N_x and EONR in a dY-based N recommendation system, we compiled a dataset of corn yield response to N fertilizer from field experiments conducted at research stations or on-farm for corn production in the U.S.A. (Figure 1). The dataset included 732 response curves encompassing over 3500 individual N rate treatments populated from both new experimental data and data from previously published works in our AER of interest (Hirsh et al., 2021; Norris et al., 2020; Puntel et al., 2016; Quinn et al., 2023; Spargo et al., 2009; Zhao et al., 2017). The compiled dataset represents a variety of agroecological factors such as soil types, crop cultivars, crop rotations, and climatic gradients from states surrounding the Chesapeake Bay: Pennsylvania (PA), Virginia (VA), Maryland (MD), and Delaware (DE); the transitional Eastern to Midwestern environment: Kentucky (KY); and major corn-producing states in the US Midwest: Illinois (IL), Wisconsin (WI), Iowa (IA), and Nebraska (NE), as depicted in Figure 1.

Additionally, this dataset included experiments with innovative management practices that are increasingly being adopted by farmers in each AER. For example, KY, PA, and MD primarily use no-tillage soil management, while NE and DE employ irrigation systems. In contrast, IA and IL routinely employ tile drainage, whereas WI has dual-purpose grain and livestock production systems. In the Eastern states, in addition to no-till systems and the typical corn-soybean rotation, rotation systems with small grains and cover crops are more intensively implemented by farmers and are represented in the dataset (Figure 1). While the dataset includes a wide variety of management and environment combinations that could be used to test further hypothesis-driven questions, the focus of the current study is to determine whether including state or regional sub-models improves the accuracy of predicting N_x and EONR. We include irrigation level as the only management factor in the calibration process because of its dramatic effect on yield potential in AERs where it is commonly used.

Three AERs were defined by merging land resource regions (LRRs) to reflect broader regional agroecological patterns. The US Midwest AER combined the LRRs corresponding to the Lake State Fruit, Truck Crop, and Dairy; Central Feed Grains and Livestock; and East and Central Farming and For-

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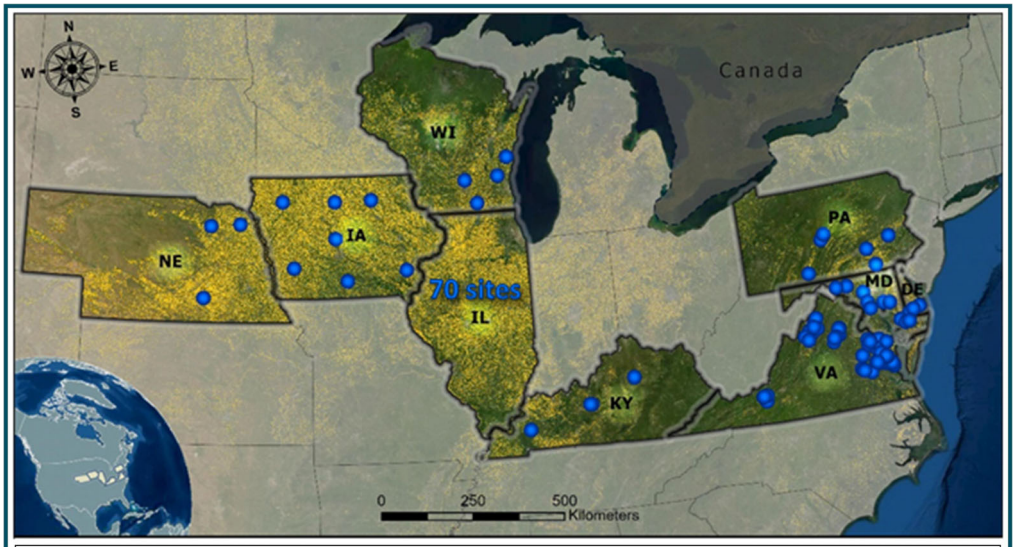

State	Previous crop			Environment		Cover crop		Manure		# Exps.
	Corn	Soybean	Others	Rainfed	Irrigated	No	Yes	No	Yes	
DE	42	0	0	34	8	42	0	26	16	42
IL	0	70	0	70	0	70	0	70	0	70
IA	50	42	0	92	0	92	0	92	0	92
KY	20	22	23	53	12	51	14	65	0	65
MD	48	0	1	49	0	41	8	41	8	49
NE	75	54	6	123	12	135	0	135	0	135
PA	31	1	6	38	0	7	31	31	7	38
VA	42	3	74	118	1	54	65	114	5	119
WI	122	0	0	122	0	31	91	49	73	122
Total	***430***	***192***	***110***	***699***	***33***	***523***	***209***	***623***	***109***	***732***

FIGURE 1 Locations of corn yield response studies used to develop models related to delta yield (dY) to fertilizer-N needed with management information provided in table. The blue points represent experimental sites, many of which had experiments over multiple years with individual response curves determined for site-years. The IL dataset was extracted from a research publication, and experimental sites could not be accurately geo-referenced. Yellow pixels in the background map represent corn production areas. Manure indicates a history of manure application but not in the year of experimentation.

est Region. This region included response curves from IL, IA, KY, NE, and WI. The Eastern Mountain AER was formed by merging the South Atlantic and Gulf Slope cash crops, forest and livestock with Northern Atlantic Slope diversified farming region, and included response curves from PA, MD, and VA. The Coastal Plain AER consisted of the Atlantic and Gulf Coast Lowland Forest and Crop Region and included response curves from DE, MD, and VA.

2.2 | Brief experimental dataset description

Within the 732 N response curve dataset from unique experimental site years, 430 were corn planted after corn, while the remainder had a previous crop other than corn (table in Figure 1). Thirty-three sites were irrigated, while the remainder were rainfed. A winter cover crop was grown immediately prior to the corn crop in 209 of the sites, and 109 of the sites had a recent history of organic N inputs (e.g., manure or compost). The fertilizer-N rates varied widely with 4–15 levels in an experiment, commonly in a randomized complete block design with 2–5 replications. The experimental units were 40–156 m^2. Plant population ranged from 6.2 to 9.9 plants per m^2 at 0.76 m row spacing. Weeds and pests were managed with agronomic practices recommended for each agroecosystem.

2.3 | Nitrogen fertilizer management and application rates and grain yield determination

Nitrogen applications were made with researcher- or farmer-preferred equipment and with commonly used N fertilizers. In some experiments, 20–50 kg N ha^{-1} of N were applied pre-plant to the whole field together with phosphorus and/or

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sulfur, such as in monoammonium phosphate, diammonium phosphate, or ammonium sulfate, or because urea ammonium nitrate solution was used as a carrier for herbicide applications. In such cases, this N rate was the lowest N rate value in the site's response curve and Y_0 parameter (yield with zero N applied) was estimated by extrapolation using the fitted curve. The N fertilizer product, timing, and method of N application varied across experiments, but for any given response curve, N rates had to be applied at the same time with the same N source and application method (except for the minimum rate in each response curve, which was either zero or the low-rate N application made to the entire field prior to or at planting).

Grain yield was generally determined with a combine harvester of two, four, six, or eight rows of each plot, depending on equipment size and plot width. A few experiments had a single central row hand-harvested from 1.5 to 2.25 m^2 within individual experimental units. Grain moisture measured at the time of harvest was considered during yield calculations. Yields (Mg ha^{-1}) were adjusted to 155 g per kg^{-1} moisture content.

2.4 | Statistical analysis, dY-based N calibration, and validation procedures

For each yield response to N rate field trial, after testing QP, quadratic (Q), linear plateau (LP), and linear response (LR) functions for each experiment, the QP emerged as the best-fit model, accounting for approximately two-thirds of all experiments. A total of 486 of the 732 experimental N response curves (Figure 2a) were best fit by a three-parameter QP yield response model (as in Baum et al., 2025; Miguez & Poffenbarger, 2022) determined by the NLMIXED procedure in SAS 9.4 (SAS Institute Inc.). In a three-parameter QP model, the joining point between the quadratic portion of the curve, where yield responds to increasing N rates, and the plateau, where yield is unresponsive, occurs at the vertex of the quadratic parabola. Differences between LP and the three- and four-parameter QP models, including their equations, are described in detail by Miguez and Poffenbarger (2022).

We selected the QP model to characterize the yield response to N fertilizer because it generally exhibited a lower AIC statistic than LP models, which is consistent with others who have reported the QP model to be a suitable function best describing results from corn yield responses to N (Bullock & Bullock, 1994; Cerrato & Blackmer, 1990; Janovicek et al., 2021). The quadratic response below the plateau points facilitates the use of formulas to calculate EONR given inputs of dY, N_x, and the fertilizer:crop PR (Janovicek et al., 2021). Response curves that did not conform to the QP model, either because they were non-responsive or did not reach a yield plateau, were not included in the subsequent analyses. Data

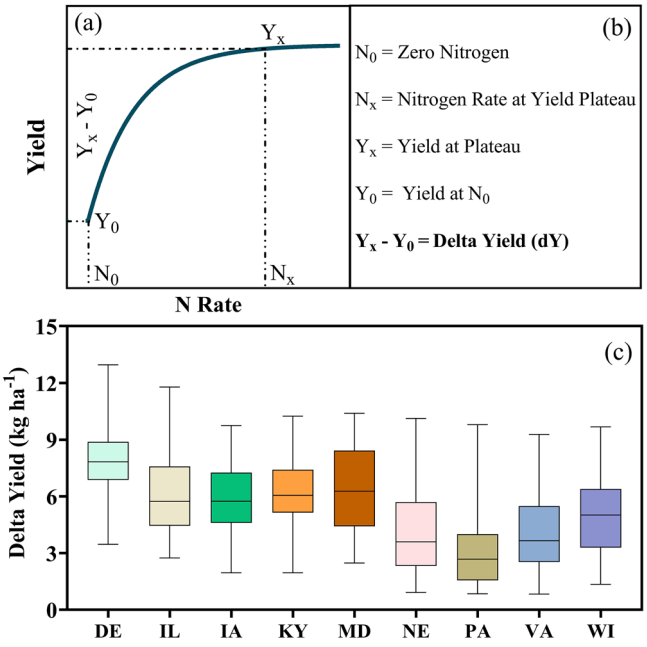

FIGURE 2 Typical quadratic-plateau yield response to N and calculated delta yield (dY). Panels (a) and (b) display the quadratic function and the variables extracted from the yield response curves used in the study. Details of the quadratic function can be found in Miguez and Poffenbarger (2022). Panel (c) shows the dY values calculated for each studied state.

visualization of the calibration and validation results was done in SAS 9.4 and R 3.6.1 (R core team, 2021). Additional figures were built through GraphPad Prism 10.0.0.

2.5 | Procedure for dY and N_x estimation across states, AERs, and irrigated areas

Our criteria for selecting sample data from the 732 response curves was that the quadratic-plateau response fits (QPRF) junction point should occur after the second N rate and before the maximum N rate value. When the join point occurred at or above the maximum N rate, it indicates the highest N rate was not sufficiently high to demonstrate that the site's maximum yield potential had been reached, which prevents an accurate calculation of dY. When the join point occurred between the first and second N rate, the shape of the response below the join point could not be accurately characterized, nor could the exact N rate where the plateau starts be determined, compromising the accuracy of the N_x estimate. Finally, several sites were unresponsive to N, where the first- and second-order coefficients of the quadratic response function were zero, preventing the calculation of a join point. From the 486 response curves that fit the QP function according to these criteria, yield with no N fertilizer addition (Y_0), maximum yield at the plateau (Y_x), and the N rate required to reach the yield plateau

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(N_x) were determined (Figure 2a,b). For experiments where the minimum N rate was greater than zero, Y_0 was estimated by extrapolating the regression line to the y-intercept. From these parameter estimates, we calculated dY as the difference between Y_x and Y_0. The distribution of dY values calculated using the QP models is displayed by state in Figure 2 (panel c).

Each selected QPRF was categorized by state, AER, and irrigation level. This categorization was based on acknowledging the range of environmental variation within the dataset, where a single model to predict N_x from dY may not represent all conditions properly. States represented in the dataset were DE (n = 30), IL (n = 55), IA (n = 72), KY (n = 56), MD (n = 39), NE (n = 98), PA (n = 19), VA (n = 43), and WI (n = 74). To test for AER-level effects, response curves from different states were categorized into AERs conforming to land resource regions (LRR) defined by the Natural Resources Conservation Service (USDA-NRCS, 2022). To prevent confounding state and regional effects, LRRs that contained response curves from only one state were merged with the closest neighboring LRR. The US Midwest AER dataset encompassed the response curves from IL, IA, KY, NE, and WI. The eastern mountain AER contained all the responses curves from PA, MD (n = 8), and VA (n = 15). The coastal plain AER contained all the response curves from DE and MD (n = 31) and 28 response curves from VA. Irrigation levels were either irrigated or rainfed, based on the management at the site, with irrigated sites only present in DE, KY, MD, NE, and VA.

2.6 | Step-by-step calibration and validation procedures

Eight experiments were the minimum for calibration and validation for each combination of AER, state and irrigation level. This resulted in the removal of sites in the coastal plain-DE-irrigated (five experiments) and coastal plain-VA-irrigated (one experiment) levels, leaving a total of 480 QPRF for calibration and validation. Next, we randomly divided the N response curve dataset into a calibration set and validation set using the SURVEYSELECT procedure in SAS 9.4. One half of the response curves (n = 240) were selected to be in the calibration set, while the other half (n = 240) were assigned to the validation set, with selection stratified by the intersection of state, AER, and irrigation level, and controlling for dY such that both calibration and validation sets had a similar range in dY in each category. Although partitioning between calibration and validation sets within the stratification levels was through random selection, the two sets do contain some dependencies, as both sets contained response curves derived from the same geographic location (e.g., a university research station, which had experiments in multiple fields and years), which may share similar soil and climatic properties.

The calibration set of QPRF was used to develop linear regression models to predict N_x as a function of dY. First, we developed a single linear regression model fitting the entire calibration dataset without regard to state, AER, or irrigation level using the REG procedure in SAS 9.4. Then, to determine if the calibration could be improved by including AER, state, or irrigation-specific effects, we used the GLMSELECT procedure in SAS 9.4. The GLMSELECT procedure has a robust framework of effect selection methods for determining a general linear model, such as the ability to include both continuous and categorical variables and their interactions and both significance-level and validation-based selection and stopping criteria. The power and validity of GLMSELECT procedure have been demonstrated in previous agricultural research (Fae et al., 2020; White et al., 2019, 2023). We allowed GLMSELECT to use AER, state, and irrigation level as categorical effects on the intercept term of the model; dY as a continuous variable affecting the slope of the model independently; and the interaction of dY with all one-way, two-way, and three-way crossings of AER by state by irrigation level to also affect the slope of the model. The categorical variables were allowed to be split, such that only specific levels of each category that affected the slope or intercept were selected.

We used a bidirectional stepwise selection method to add or remove terms in the model, using the AER, state, and irrigation categorical effects; dY as a continuous variable; and all possible interactions of dY with the categorical effects as potential candidates. The term added to the model at each iteration was the one that resulted in the lowest Akaike's information criterion (AIC) statistic. Selection of new terms was also constrained by statistical significance level; terms were required to have a p value ≤ 0.15 to be selected and retained in the model, which was the default setting. The stepwise selection routine terminated when no new terms could decrease the AIC statistic while also meeting the statistical significance threshold. Each iteration of the stepwise selection was also subjected to a fivefold cross-validation process, where observations were randomly assigned to one of five groups to serve as a validation set in each fold of the cross-validation.

The cross-validation predicted residual error sum of squares (CVPRESS) was calculated for the model in each step of the selection process, and we selected the model with the lowest CVPRESS to serve as the final model to move forward into the validation phase. Model fit and accuracy for the calibration data were evaluated based on the r^2, mean absolute error (MAE), root mean square error (RMSE), and relative root mean square error (RRMSE). In GLMSELECT, the categorical effects of AER, state, and irrigation level selected for inclusion in the model are represented as deviations from a global intercept or slope term. Based on the various effects

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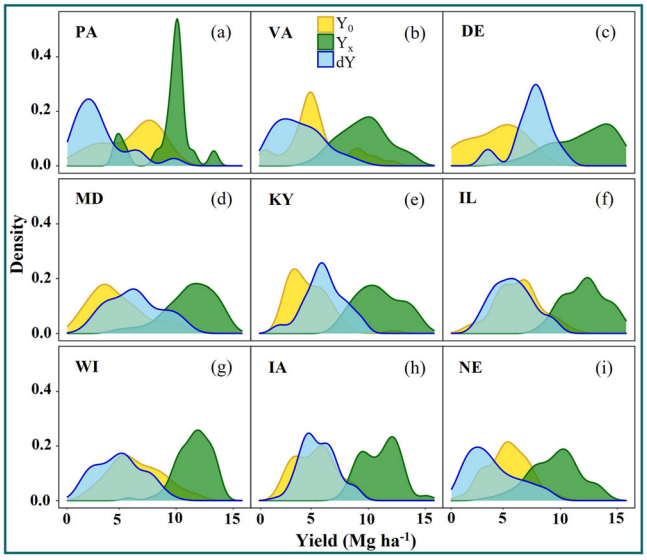

FIGURE 3 Yield density plots. The yellow histogram represents the distribution of yield at zero N (Y_0), the green histogram the maximum yield plateau (Y_x), and the blue histogram the delta yield ($dY = Y_x - Y_0$) extracted from the quadratic-plateau response fits (QPRF) for each site-year.

on the slope and intercept terms, we identified and reported the unique linear equations that predict N_x in each appropriate intersection of state, AER, and irrigation level, which we refer to as sub-models.

Next, we used the validation set of response curves to test the accuracy of the model calibrated by the GLMSELECT procedure. We used the actual dY calculated in each response curve, as well as the AER, state, and irrigation level assigned to each curve, as inputs to predict N_x based on the calibrated model. We assessed the accuracy of the model by regressing predicted N_x against observed N_x for all response curves in the validation set using the REG procedure in SAS 9.4. Fit and accuracy of the N_x predictions in the validation set were assessed based on the slope and intercept of the regression and the MAE and RMSE.

2.7 | EONR calculation and predictions

We calculated a predicted EONR for each site in the validation set using the actual dY, the predicted N_x, and the specified PR, according to Equation (3), adapted from Janovicek et al. (2021).

$$\text{EONR} = \frac{N_x \times \left(\text{PR} \times N_x - 2\text{dY}\right)}{-2\text{dY}} \quad (3)$$

In Equation (3), EONR is the EONR (kg ha^{-1} N), N_x is the agronomic optimum N rate (kg ha^{-1} N), and dY is the delta yield (Mg ha^{-1}). EONR is often calculated by setting the first derivative of the quadratic yield response equal to the PR. Equation (3) is a reformulation that results in an equivalent EONR calculation based on direct inputs of N_x and dY, simplifying the calculations for dY-based EONR recommendations. We predicted EONR at four different fertilizer:crop PRs: 9.8, 8.4, 7.0, and 5.6 kg grain kg^{-1} N. These PR values were selected for purposes of comparing results to Janovicek et al. (2021) and because they represent a range of PRs that can occur within typical fluctuations of U.S. commodity markets. Observed EONRs at each PR were also calculated for each response curve with Equation (3), but using the experimentally observed N_x from the response curve, rather than the N_x predicted by dY from the calibrated model. The fit and accuracy of the predicted EONR were assessed by regressing the predicted EONR against the observed EONR using the REG procedure in SAS 9.4 to determine slope and intercept, and by calculating MAE, RMSE, and RRMSE.

3 | RESULTS

3.1 | Grain yield production and dY

Four different yield responses to N functions were identified across the 732 field experiments included in the dataset (QP = 486; responsive until the second lowest N rate = 47; responsive but plateau point not reached = 85; and flat-unresponsive = 114). Within the 486 QPRF, there was a wide range in values for Y_x, Y_0, and dY (Figure 3). The average Y_x across all observations was 10.8 ± 2.2 Mg ha^{-1}, while the average Y_0 was 5.5 ± 2.2 Mg ha^{-1}. The highest Y_x, 15.77 Mg ha^{-1}, was in IL, and the lowest Y_x, 3.53 Mg ha^{-1} was in NE. The highest Y_0 of 12.27 Mg ha^{-1} was in KY, and the lowest Y_0 of 0.47 Mg ha^{-1} was in DE.

The distribution in dY varied widely across the nine states included in this study. The measured dY across all the environments ranged from 0.83 to 10.61 Mg ha^{-1} (Figure 3). The largest dY was in the state of DE, and the smallest dY was in the state of VA. The state of PA had the greatest density of response curves with a small dY, followed by NE and VA, while DE had the greatest density of response curves with a large dY (Figure 3). The effect of cover cropping on dY was much more evenly distributed in continuous corn than in rotational systems, with strong density peak centered between 5 to 7 Mg ha^{-1} (Figure 4a,b). Across rotation systems, dY was 14.5% higher in rotated corn compared to monocropping. Within rotational systems, cover cropping increased dY by 25.4%, whereas in monocropping systems, dY was 17.8% higher under no-cover crop conditions (Figure 4a,b). The overall coefficient of variation values were relatively close between systems (Figure 4a,b). Clearly, these results demonstrate that cover cropping influences soil-N status,

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TABLE 1 Model fit and accuracy statistics for the prediction of agronomic optimum N rate (N_x) and economic optimum nitrogen rate (EONR) for the calibration and validation datasets using the model with region, state, and irrigation level effects.

	N_x		EONR validation Price ratio, kg grain kg^{-1} N			
	Calibration	Validation	9.8	8.4	7.0	5.6
r^2	0.55	0.54	–	–	–	–
MAE, kg N ha^{-1}	32.6	33.0	19.9	21.7	23.6	25.4
RMSE, kg N ha^{-1}	41.0	40.2	26.3	28.2	30.1	32.1
RRMSE, %	21%	21%	17%	18%	18%	19%

Abbreviations: MAE, mean absolute error; RMSE, root mean square error; RRMSE, relative root mean square error.

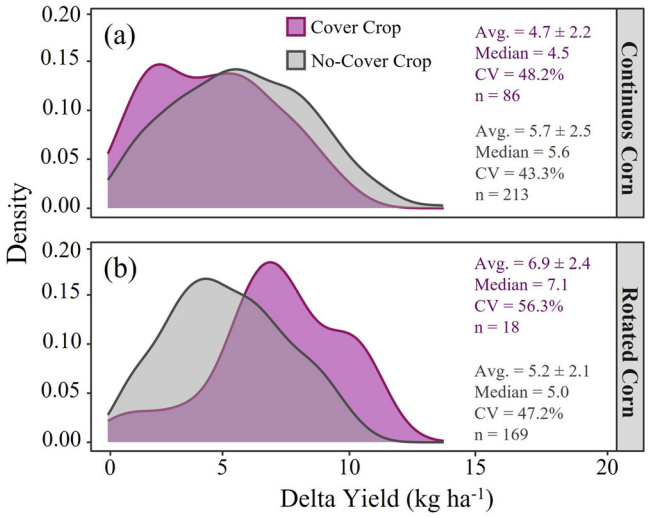

FIGURE 4 Continuous and rotated corn delta yield density plots. The purple histogram represents the distribution of yield under cover crops, while the gray histogram represents the no-cover cropping system. Delta yield, median (Mg ha^{-1}), and coefficient of variation (CV) values were extracted from predicted site-year quadratic-plateau response fits (QPRF) rather than plot data.

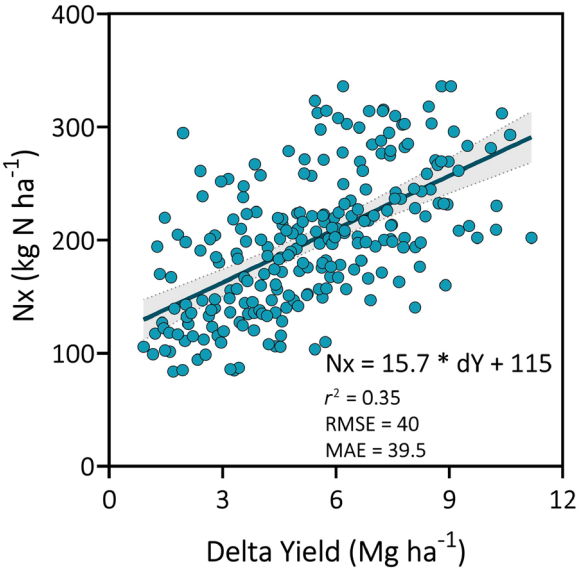

FIGURE 5 Regression to predict N_x from dY using a single linear equation fit to the entire calibration dataset. Slope and intercept of the model are both significant ($p < 0.001$). The confidence interval (CI) band, set at 95%, is also presented. The N_x associated with delta yield (dY; Mg ha^{-1}) values were predicted from the site-year quadratic-plateau response fits (QPRF) rather than plot data, so root mean square error (RMSE) and mean absolute error (MAE) are much less compared with using plot data.

with crop rotation systems amplifying its effects, whereas monocropping tended to constrain them.

3.2 | Calibrating equations to predict N_x from dY

A single linear regression model was fit to the entire calibration dataset ($n = 240$), resulting in a model fit of $r^2 = 0.35$, MAE = 39.5 kg N ha^{-1}, RMSE = 49.0 kg N ha^{-1}, and RRMSE = 25% (Figure 5). When AER, state, and irrigation effects were introduced into the model through stepwise selection, and fivefold cross-validation was used to select the most accurate predictive model, the final model had effects that differentiated the intercept and slope terms according to AER, state, and irrigation level. This model had a fit and accuracy of $r^2 = 0.55$, MAE = 32.6 kg N ha^{-1}, RMSE = 41.0 kg N ha^{-1}, and RRMSE = 21% (Table 1), which is an improvement over the model without AER, state, and irrigation level effects.

The global intercept term of the final model was 139 (± 9.0, $p < 0.001$) kg N ha^{-1}, with the intercept deviating from the global estimate for effects of certain states. These deviations were added (positive values) to or subtracted (negative values) from the global intercept, depending on the situation, for states including DE (25 ± 14.4 kg N ha^{-1} deviation, $p = 0.08$), KY (104 ± 29.5 kg N ha^{-1} deviation, $p < 0.001$), and NE (−79 ± 15.7 kg N ha^{-1} deviation, $p < 0.001$) (Figure 6a,d,f). The global slope coefficient for the model was 12.8 (± 1.7, $p < 0.001$) kg N Mg^{-1} grain dY (Figure 6a). Once again, the slope deviated from the global value for certain effects of AER, state, and irrigation level, including state-level effects for Kentucky (−11.7 ± 4.6 kg N Mg^{-1} grain dY deviation, $p = 0.01$), NE (13.4 ± 3.2 kg N Mg^{-1} grain dY deviation, $p < 0.001$), VA (−5.7 ± 2.3 kg N Mg^{-1} grain dY deviation,

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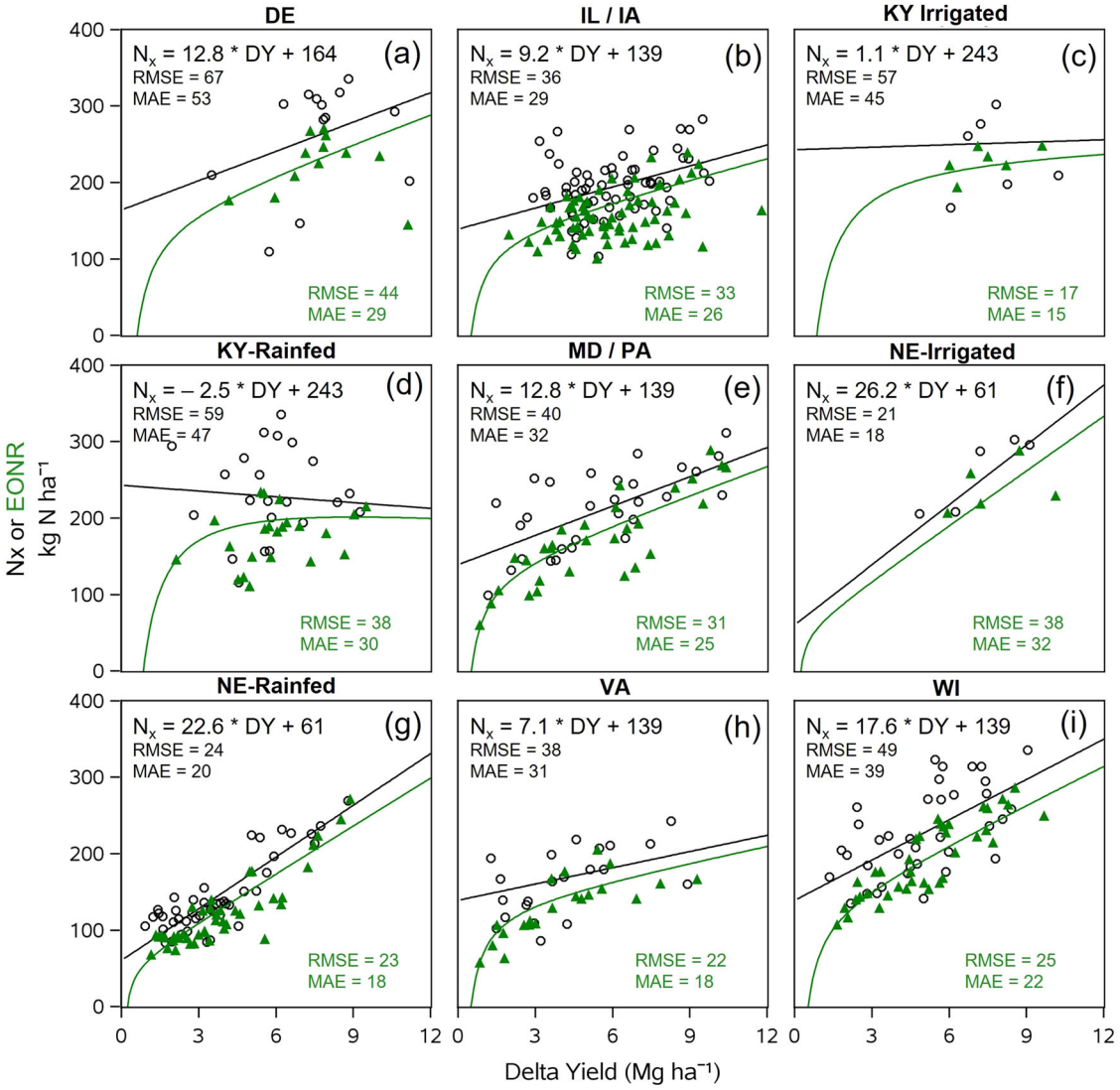

FIGURE 6 Sub-models derived from the stepwise selection and cross-validation process to identify state, agroecosystem region (AER), and irrigation effects on the intercept and slope parameters for the prediction of agronomic optimum N rate (N_x, black circles) and economic optimum nitrogen rate (EONR, green triangles) based on delta yield (dY). Black circles represent the observed N_x and dY of the calibration dataset, and the black line is the fitted sub-model indicated by the equations in each panel. Within each sub-model, the root mean square error (RMSE) and mean absolute error (MAE) of N_x for the calibration dataset are listed in black in the upper left. Green triangles represent the observed EONR and dY of the validation dataset at a price ratio (PR) of 7 kg grain kg^{-1} N, while the green line represents the predicted EONR of the validation dataset using Equation (3) with inputs of the observed dY, N_x predicted by dY, and a PR of 7 kg grain kg^{-1} N. The RMSE and MAE of the EONR prediction for each sub-model are listed in green in the lower right. The N_x associated with dY (Mg ha^{-1}) values were predicted from the site-year quadratic-plateau response fits (QPRF) rather than plot data, so RMSE and MAE are much less compared with using plot data.

$p = 0.01$), and WI (8.4 ± 1.5 kg N Mg^{-1} grain dY deviation, $p < 0.001$), and a US Midwest rainfed effect (−3.6 ± 1.2 kg N Mg^{-1} grain dY deviation, $p < 0.001$) (Figure 6). In cases when no effect of a specific level of AER, state, or irrigation level was selected for inclusion as a differentiator in the model, the global intercept and/or slope coefficients were used.

When interpreting the combination of effects on the slope and intercept of the linear model to determine sub-models based on state, AER, and irrigation level, 9 separate sub-models emerged for predicting N_x from dY (Figure 6). Two instances occurred where geographically adjoining states were contained in the same sub-model; specifically, IL and IA shared an equation, as did MD and PA (Figure 6a,e). In the KY irrigated and rainfed equations, the deviation of the slope based on the state and irrigation level led to sub-models with slopes that were close to zero (Figure 6c,d). In summary, the overall predicted N_x RMSE of the calibration set ranged from 21 to 67 kg ha^{-1} with the MAE ranging from 18 to 53 kg ha^{-1}. The predicted EONR based on dY of the validation set had an RMSE ranging from 17 to 44 kg ha^{-1} and an MAE

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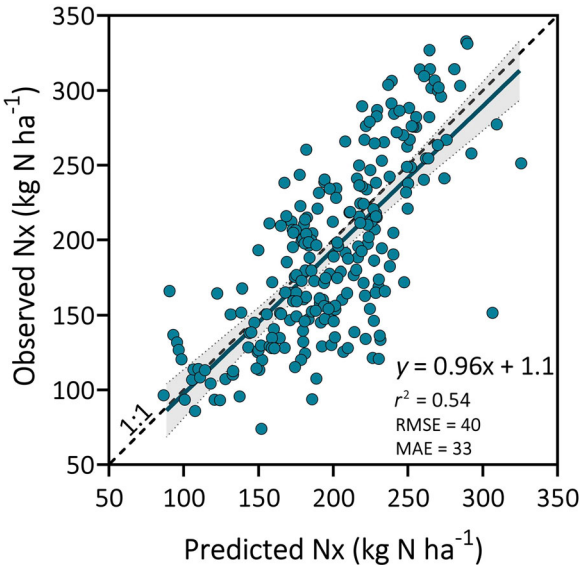

FIGURE 7 Prediction of N_x (kg N ha^{-1}) based on dY (Mg ha^{-1}) using the sub-models in Figure 6 compared to the observed N_x for the validation dataset. The relationship between predicted and observed is indicated by the solid regression line, and a 1:1 relationship is indicated by the dashed line. The N_x predicted associated with observed values were extracted from the site-year quadratic-plateau response fits (QPRF) rather than plot data, so root mean square error (RMSE) and mean absolute error (MAE) are much less compared with using plot data.

ranging from 15 to 32 kg ha^{-1} (Figure 6). For the KY sub-model calibrations, a post hoc regression analysis of these specific data were conducted, and for both the irrigated and rainfed sub-models, the slope was non-significant ($p > 0.05$). The interpretation of these results for KY is that dY does not affect N_x; rather, N_x is a constant that can be approximated by the intercept of the sub-model, which was 243 kg N ha^{-1} for both irrigated and rainfed conditions.

3.3 | Validation of the model to predict N_x and EONR from dY

To validate the accuracy of the 9 sub-models developed in the calibration process, N_x of the validation dataset was predicted based on the observed dY using the equations in Figure 6. The predicted N_x of the validation dataset had a close 1:1 correspondence with the observed N_x, with a prediction accuracy of MAE = 33.0 kg N ha^{-1}, RMSE = 40.0 kg N ha^{-1}, and RRMSE = 21% (Figure 7). The relationship between predicted N_x and observed N_x had a slope not significantly different than 1 and an intercept not significantly different than 0 according to the 95% confidence intervals of the estimates ($y = 0.96x + 1.1$).

When EONR was calculated from the predicted N_x and observed dY using Equation (3), accuracy of the predicted EONR was greater than for the predictions of N_x (Table 1). At all PRs, there was a 1:1 correspondence between predicted and observed EONR, based on intercept coefficients that were not significantly different than zero and slope coefficients not significantly different than 1 according to the 95% confidence intervals. Furthermore, the accuracy improved as the PR increased, ranging from MAE = 25.4 kg N ha^{-1} at a PR of 5.6 kg grain kg^{-1} N to MAE = 19.9 kg N ha^{-1} at a PR of 9.8 kg grain kg^{-1} N (Table 1). At higher PRs, fertilizer is relatively expensive compared to the grain price, leading to a lower EONR. The predicted EONR using Equation (3) also leads to N application rates that decline toward zero as dY approaches zero (Figure 6). As dY increases, EONR initially increases with a steep slope, which then moderates to a steady rate of increase that is approximately equal to the slope of the N_x prediction but is offset below N_x.

4 | DISCUSSION

4.1 | Importance of the new dY-based N recommendations

By systematically analyzing a large dataset of N fertilizer response trials in corn, we calibrated a model to predict N_x and EONR based on dY according to state, AER, and irrigation levels, providing a foundation for a new N fertilizer recommendation approach. Our results showed that predictions of EONR were more accurate (MAE = 20–25 kg ha^{-1} N) than the prediction of N_x (MAE = 33 kg ha^{-1} N) and that EONR also declined toward zero as dY became small (Figure 6). Furthermore, the EONR predictions became more accurate as the PR increased (Table 1). Few researchers have addressed the ability of dY to predict EONR in corn production systems (Kachanoski, 2009; Janovicek et al., 2021). Despite integrating both economic and agronomic inputs, the potential of the dY approach to recommend N rates has been less explored compared to the yield goal and MRTN approaches (Lory & Scharf, 2003; Nafziger et al., 2004; Sawyer et al., 2006). Although predicting N_x is a necessary intermediate step of the process, this work suggested that using the N_x prediction as an application recommendation will lead to greater than necessary N rates that have both poor economic and environmental outcomes. While our dY framework shows potential to inform N recommendations, we acknowledge that accurately predicting site-year optimal yield and dY prior to planting remains a significant challenge. Beyond providing a foundation for informed decision-making to improve cropping system N management, this work also serves as a call for the development of more precise and responsive N fertilizer decision-support tools.

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4.2 | Estimation and prediction of the dY-based N recommendation components

Predicting N fertilizer rates based on dY requires accurate estimation of its components, such as Y_x and Y_0. Theoretically, yields of corn without fertilizer applied (Y_0) rely exclusively on N supply from indigenous N and the N mineralization of previous crop residues (Carciochi et al., 2021; White et al., 2020). We observed that Y_0 varied across the study regions and growing seasons encompassed within our dataset (Figures 3 and 4). This could be related to the myriad factors that affect soil N supply, such as soil texture (Tremblay et al., 2012), initial soil N availability (Puntel et al., 2019), the distribution of soil organic carbon in the soil profile due to historical management (Poffenbarger et al., 2018; Paustian et al., 2019), cover cropping systems (Kaye et al., 2019; Quinn et al., 2023; Vyn et al., 1999, 2000; White et al., 2016), and root growth performance and distribution across soil profiles (Ordóñez et al., 2020, 2021).

Crop rotation and cover cropping are widely acknowledged components of N recommendation frameworks. Our results confirm their effects, although these effects are integrated within the broader context of dY predictions (Figures 4 and 6). For example, previous studies suggested that rotating corn with soybean not only enhances yield potential but also consistently reduces fertilizer N requirements relative to continuous corn system. This reduction, approximately 40 kg N ha^{-1}, is largely attributed to increased soil N mineralization driven by the quantity and biochemical characteristics of soybean residues (Baum et al., 2023, 2025; Sawyer et al., 2006). Similarly, cover cropping has emerged as a complementary strategy, particularly for reducing residual soil nitrate (NO_3-N) following cash crop harvest (Vyn et al., 2000). Cover crop N uptake is primarily determined by species selection and termination timing, both of which critically shape N accumulation and subsequent release dynamics. For instance, cereal rye (*Secale cereale* L.) has the potential to take up 60 kg N ha^{-1}, whereas leguminous cover crops such as hairy vetch (*Vicia villosa Roth*), either in monoculture or mixture species system, can accumulate up to 160 kg N ha^{-1}. Yet, N accumulation may decline significantly with earlier termination (Arrington et al., 2024; Carciochi et al., 2021; Quinn et al., 2023; White et al., 2016), influencing available N for the preceding crop. Our successful calibration of models to predict N_x based on dY was likely facilitated by the wide range in dY across the dataset of N response trials we curated, meaning that our dataset contained a sampling of fields across a spectrum from highly responsive to N fertilizer (large dY) to minimally responsive to N fertilizer (small dY). The further development of dY-based N recommendations will depend on accurately predicting dY, or its components, so understanding the factors that control dY is an important area for future study.

While concerns may arise regarding how to estimate dY without pre-existing data, predicting final corn yields over short- or long-term periods using computational models is now more feasible today than in the past (Baum et al., 2025; Elazab et al., 2016; Li et al., 2025; Martinez-Feria et al., 2019; Shahhosseini et al., 2020), even under extreme weather conditions (Gaboldón-Leal et al., 2016). In fact, recent research has also demonstrated the ability to predict the Y_0 and Y_x components of dY with site- and season-specific resolution, addressing potential concerns regarding the adoption and implementation of this N calculator tool in real-world corn production system. For example, earlier studies have predicted Y_0 and dY across a range of farms and cropping system histories based on measurements of cover crop biomass N and C:N ratio, soil carbon and nitrogen concentrations, soil texture, and infrared spectroscopy (Arrington et al., 2024; Deiss et al., 2023; White et al., 2020). In addition, previous research has identified key factors, such as previous crop, irrigation, and soil organic matter (OM) that cause variation in unfertilized corn yields using a random forest machine learning method with a dataset from multiple environments within the United States (Correndo et al., 2021). Well-calibrated biophysical models can also be used to predict both fertilized and unfertilized yields (Puntel et al., 2016) across a broad range of growing conditions. While biophysical models can be used to predict a full yield response curve to N fertilizer additions, allowing estimation of EONRs (Baum et al., 2023, 2025), a simplified approach may involve using models to only predict Y_o and Y_x for the purposes of determining dY. This growing volume of research using diverse methodologies to predict dY will serve as an advantage, making the dY-based approach a suitable candidate to calculate N fertilizer rates in the future.

We also acknowledge that predicting maximum yields under changing climate scenarios is a challenge, as seasonal weather variability impacts crop growth and final yields (Ortez et al., 2023). In this context, Niemeyer et al. (2021) reported that historical maximum economical yield was strongly correlated with EONR ($r^2 = 0.65$), and the variability of EONR was explained ($r^2 = 0.84$) by rainfall during the plant-elongation phase transition from slow to high speed (V5–V12). Therefore, future research should attempt to elucidate avenues or continue to develop technologies to accurately forecast maximum yield potential based on in-season data (Archontoulis et al., 2020), which is an important component of dY.

The prediction of N_x, and ultimately the calculation of EONR, was often improved by selecting state-specific slope and intercept terms in the linear regression model (Figure 6), although there were cases when adjoining states shared the same sub-model. The outcome of adjoining states sharing similar sub-models but relatively few parameter selections based on our categorization of AER (US Midwest, eastern

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mountains, and coastal plain) may indicate that a different method of categorizing AER is necessary. We assembled these AERs from adjoining LRRs to create regional groups that encompassed multiple states, but the results suggest that calibrations of finer resolution may produce better results. Recent research has proposed the idea of Technology Extrapolation Domains (TED) for corn production, which are spatially explicit intersections of growing degree days, aridity index, annual temperature seasonality, and plant-available water holding capacity (Rattalino-Edreira et al., 2018). In that work, 620 TEDs were identified for the corn production regions of the United States, with just 50 of those TEDs accounting for 75% of the corn production area. Future research could determine whether appropriately delineated TEDs can improve the calibration of dY-based N recommendation equations. Testing whether more specific soil properties, geographic traits, or agricultural management practices can explain additional variation in the relationship between N_x and dY within states or AER is also a worthwhile objective for future research but is beyond the scope of the current regional scale analysis. Because calibration of sub-models at higher geographic resolution than we did here may be required, and because N recommendations for corn are often developed by state-level specialists at Land Grant Universities, we suggest that future work to develop dY-based N recommendations take place through more focused, localized research initiatives, rather than at nationwide scales.

4.3 | Enhanced characteristics of dY-based N recommendations

Another important distinction between our study and that of Lory and Scharf (2003), is that their models directly predicted EONR at a single fertilizer:crop PR, whereas we used dY to predict N_x, with a subsequent step to calculate a corresponding EONR at any chosen PR using Equation (3). This gives an N recommendation system greater flexibility in adapting to fluctuating commodity and fertilizer markets. Using dY to predict N_x (according to the equations in Figure 6) and then EONR (Equation 3) also overcomes the problem pointed out by Lory and Scharf (2003), where a dY at or approaching zero still gives an EONR recommendation close to the intercept of the linear regression model, which was 66.4 kg N ha^{-1} in their study. Nel and Bloem (2006) overcame this problem by calibrating a power function (EONR = dY$^{\alpha}$ where $\alpha < 1$) to predict EONR, which ensures that the EONR declines to zero as dY becomes small. In their analysis, sites with a large dY begin to follow a linear trend that fell along a similar line as the function developed by Lory and Scharf (2003), while EONR declined toward zero as dY approached zero. This function may be a closer approximation to the EONR when the dY is small but is still limited by being developed under a single PR.

4.4 | Application and adaptation of dY-based N recommendations to a range of fields with different N responses

Our overall dataset of corn N response trials included 732 sites; however, we were only able to utilize 66% (486 experiments) that could be fit to a QPRF. This percentage was lower than 88% reported by Baum et al. (2025), but in absolute terms, it is higher than the 334 curves used in that study. This does not mean that the characteristics of one-third of sites, which could not be fit to a QPRF, render them unable to use a dY-based N recommendation system. Rather, these sites could not be used for calibration and validation of the equations needed for dY-based N recommendations because important points of the response curves could not be estimated reliably, particularly N_x and Y_x, given the range and increments of N rates used in the experimental design for those sites. Earlier studies reinforce that yield response to N curves are not adequately described by a single mathematical function (Baum et al., 2025; Lory & Scharf, 2003; Miguez & Poffenbarger, 2022). In our dataset, 85 sites, or about 12% of the total, did not reach a yield plateau under the range of N rates used in the experiment. These sites tended to have large dYs between the lowest and greatest N fertilizer rates used. Sites that met the criteria for use in our calibration dataset contained a range of dY values between 1 and 11 Mg ha^{-1}. Under some of the state-specific calibrations developed in Figure 5, dYs greater than 11 Mg ha^{-1} may require >300 kg N ha^{-1} of fertilizer, on average, to reach the yield plateau. In conditions where dYs are expected to be particularly large, for instance >10 Mg ha^{-1}, N rate trials should include several levels of N rates >300 kg N ha^{-1} to increase the likelihood of realizing the yield plateau.

4.5 | Scenarios where yield plateaued at low-N, and there were no responses to added N fertilizer rates

Within the responsiveness spectrum of curves are sites that have a small dY and, therefore, a low N fertilizer requirement. We had 47 sites that were fit best by a model where the plateau point started at the second N rate. However, without additional N rates between the first and second levels, it is not possible to determine the shape of the response between these levels, nor to confirm where exactly the plateau point starts between the first two rates. For sites where dY is expected to be low, future N response trials should include relatively small increments between N rates at the lower end of the rate spectrum. These recommendations for the design of future N response trials are consistent with a recent study to assess the accuracy and precision of agronomic N response trials, which concluded that agronomic studies should include a greater number of

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N levels than have been traditionally used, as well as more experimental replications (Miguez & Poffenbarger, 2022).

Our unique dataset of N rate trials also contained 114 sites where the yields did not respond to N fertilizer additions at all, which was the largest category of sites that were unusable for calibration purposes. Unresponsive sites, by definition, have a dY of zero and an N_x and EONR of zero. Accommodating these sites is desirable, but in our dataset, there is a lack of information about how N_x responds between the theoretically correct origin point (0 dY, 0 N_x) and the portion of the relationship, which is linear. As a result of extrapolating the linear relationship to the y-intercept, N_x at a dY of zero remains relatively high. This problem is resolved when Equation 3 is used to calculate the EONR because the EONR will decline toward zero as dY becomes small (Figure 6). Equation 3 can be used to calculate the minimum dY at which it becomes profitable to start applying fertilizer. Furthermore, when dY is small, the EONR is significantly less than the calculated N_x. While using Equation 3 to convert the N_x prediction to EONR helps to prevent overfertilization when dY is small, unresponsive sites could also still be accommodated in an N recommendation system based on dY if diagnostic procedures were in place to detect scenarios where Y_o and Y_x were equivalent.

4.6 | Limitations and real-world implications of dY-based N recommendations

Modern crop genetics have better N use efficiency and biomass partitioning to the reproductive structures compared to those in the past (Mueller et al., 2019; Ordóñez et al., 2025; Saenz et al., 2025), meaning that improving existing N fertilization systems is necessary (Norris et al., 2020). Efforts are growing to identify the best approach to meet the balance between economic returns and crop productivity (Baum et al., 2025; Madrini, Bullock, et al., 2021; Ransom et al., 2023). However, to our knowledge, only two studies (aside from the conceptual introduction by Kachanoski et al, 1996) in North America have calibrated equations that integrate both economic and environmental goals which could be used in a dynamic dY-based method for N fertilizer recommendations in corn (Lory & Scharf, 2003; Janovicek et al., 2021). Therefore, despite the hopes held onto the widely adopted N recommendation tools, such as MRTN and yield goal methods (Lory & Scharf, 2003; Sawyer et al., 2006), the proposed dY-based N approach could help enhance N prescriptions for US corn farmlands. It also has the potential to contribute to reducing agricultural N pollution by adjusting N rates, aligning with global agendas, such as the United Nations (2015) sustainable development goals by 2030, aimed at addressing N management under climate change scenarios and harnessing the momentum of improved crop varieties.

While one criticism of dY-based N recommendations is that it appears to depend on pre-N application information for a targeted field, to our knowledge, current N recommendation systems were initially developed based on historically collected field data (Vanotti & Bundy, 1994; Sawyer et al., 2006) and subsequently applied to future growing seasons. We also acknowledge that corn yields under zero N input can vary substantially from year to year, even within the same field with high soil OM, due to interannual weather variability (Puntel et al., 2019) and the effect of tillage system (Correndo et al., 2021). We also suggest that dY-based N recommendations could provide an efficient platform for farmers and their crop advisors to be able to conduct long-term research in their own production fields to determine dY and ultimately inform N fertilizer rate decisions. For instance, farmers could leave a zero N fertilizer check strip in selected fields and use combine yield monitors to measure Y_0 and Y_x at the end of the season, assuming that a farmer's typical management practice is a reflection of Y_x in any given year. As improvements due to enhanced N fertilization methods realistically cannot occur in a single year, after a few years of measuring unfertilized check strips (Y_0) and the adjoining yields under typical management (Y_x), a farm would have its own dataset of dYs. These data could be further analyzed by crop rotation history, soil type, and weather. Our calibrated sub-models for dY-based N recommendations then provide an immediately actionable way to utilize the dY history on a farm to improve N fertilizer rate decisions. One key advantage of the dY-based N recommendation approach is that once the relationship between dY and N_x is calibrated, as we have done in this study, it only requires farmers to implement a zero N fertilizer check strip to develop a dataset of on-farm dY measurements which can be used to predict EONR, rather than needing to implement multiple strips of varying N rates to determine EONR. Thus, the development of dY-based N recommendations provides a more economical way for farmers to integrate on-farm experimentation and adaptive N management into their production systems.

5 | CONCLUSION

We curated and analyzed a large dataset of corn yield response to N fertilizer experiments to fill an important gap in the spectrum of N fertilizer recommendation methods for corn. We demonstrated that it is feasible to develop N recommendations for corn based on dY (yield at agronomic optimum N rate minus yield with no fertilizer N applied), but the accuracy may be further improved by coupling this approach with complementary tools to assess early-season soil N. Both the state and irrigation-specific sub-models to predict economically optimum N rates improved the model fit and accuracy. These results not only provide a foundation to advance dY-based

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N fertilizer recommendations across a globally important corn production AER in the northern U.S.A., but also highlight the need to continue improving N recommendation systems that balance economic returns with environmental risk. Nitrogen recommendation systems based on dY could offer a number of advantages over current N recommendation methods, warranting future research efforts to predict dY under on-farm conditions and validate the efficacy of dY-based N recommendations. However, the exclusion of nearly 30% non-responsive and linearly responsive trials highlights opportunities for further refinement of the dY-based approach, including the integration of trials with no QPRF, to reduce potential over- or under-prediction of EONR. Enhancing N fertilizer recommendations for corn through such a method will be essential to continued improvements in surface and groundwater quality, air quality, and farm economics.

AUTHOR CONTRIBUTIONS

Raziel A. Ordóñez: Conceptualization; data curation; formal analysis; investigation; methodology; software; validation; visualization; writing—original draft; writing—review and editing. **Charles M. White**: Conceptualization; formal analysis; funding acquisition; investigation; writing—original draft; writing—review and editing. **John T. Spargo**: Data curation; investigation; writing—review and editing. **Jason P. Kaye**: Investigation; writing—review and editing. **Matthew Ruark**: Data curation; investigation; writing—review and editing. **Javed Iqbal**: Data curation; investigation; writing—review and editing. **Charles A. Shapiro**: Data curation; investigation; writing—review and editing. **Wade E. Thomason**: Data curation; investigation; writing—review and editing. **Nicole M. Fiorellino**: Data curation; investigation; writing—review and editing. **Louis A. Thorne**: Data curation; writing—review and editing. **Amy Shober**: Data curation; investigation; writing—review and editing. **John H. Grove**: Data curation; investigation; writing—review and editing. **Sarah M. Hirsh**: Data curation; investigation; writing—review and editing. **Ray R. Weil**: Data curation; investigation; writing—review and editing. **Michael J. Castellano**: Data curation; investigation; writing—review and editing. **Sotirios V. Archontoulis**: Data curation; investigation; writing—review and editing. **Jerry J. Hatfield**: Investigation; writing—review and editing. **Chad D. Lee**: Data curation; investigation; writing—review and editing. **Daniel J. Quinn**: Data curation; investigation; writing—review and editing. **Zachary P. Sanders**: Data curation; writing—review and editing. **Zoelie Rivera-Ocasio**: Investigation; writing—review and editing. **Sarah Tierney**: Investigation; writing—review and editing. **Kathleen E. Arrington**: Data curation; writing—review and editing. **Andrew M. Lefever**: Writing—review and editing. **Mauricio Tejera-Nieves**: Writing—review and editing. **Gerasimos G. Danalatos**: Data curation; writing—review and editing. **Laila A. Puntel**: Data curation; investigation; writing—review and editing. **Hanna Poffenbarger**: Data curation; investigation; writing—review and editing. **Sam Leuthold**: Data curation; writing—review and editing. **Jarrod Miller**: Data curation; writing—review and editing. **Gurpal S. Toor**: Investigation; writing—review and editing. **Tony J. Vyn**: Writing—review and editing.

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REFERENCES

Andraski, T. W., Bundy, L. G., & Brye, K. R. (2000). Crop management and corn nitrogen rate effects nitrate leaching. *Journal of Environmental Quality*, *29*, 1095–1103. https://doi.org/10.2134/jeq2000.00472425002900040009x

Archontoulis, S. V., Castellano, M. J., Licht, M. A., Nichols, V., Baum, M., Huber, I., Martinez-Feria, R., Puntel, L., Ordóñez, R. A., Iqbal, J., Wright, E. E., Dietzel, R. N., Helmers, M., Vanloocke, A., Liebman, M., Hatfield, J. L., Herzmann, D., Córdova, S. C., Edmonds, P., … Lamkey, K. R. (2020). Predicting crop yields and soil-plant nitrogen dynamics in the US Corn Belt. *Crop Science*, *60*, 721–738. https://doi.org/10.1002/csc2.20039

Arrington, K. E., Ordóñez, R. A., Rivera-Ocasio, Z., Luthard, M., Tierney, S., Spargo, J., Finney, D., Kaye, J., & White, C. (2024).

14350645, 2025, 5, Downloaded from https://acsess.onlinelibrary.wiley.com/doi/10.1002/agj2.70150 by University Of Delaware Library, Wiley Online Library on [17/09/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

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Improving a nitrogen mineralization model for predicting unfertilized corn yield. *Soil Science Society of America Journal*, *88*, 905–920. https://doi.org/10.1002/saj2.20665

Baum, M. E., Sawyer, J. E., Nafziger, E. D., Castellano, M. J., McDaniel, M. D., Licht, M. A., Hayes, D. J., Helmers, M. J., & Archontoulis, S. V. (2025). The optimum nitrogen fertilizer rate for maize in the US Midwest is increasing. *Nature Communications*, *16*, 404. https://doi.org/10.1038/s41467-024-55314-7

Baum, M. E., Sawyer, J. E., Nafziger, E. D., Huber, I., Thorburn, P. J., Castellano, M. J., & Archontoulis, S. V. (2023). Evaluating and improving APSIM's capacity in simulating long-term corn yield response to nitrogen in continuous- and rotated-corn systems. *Agricultural Systems*, *207*, 103629. https://doi.org/10.1016/j.agsy.2023.103629

Bullock, G., & Bullock, D. S. (1994). Quadratic and quadratic-plus-plateau models for predicting optimal nitrogen rate of corn: A comparison. *Agronomy Journal*, *86*, 191–195. https://doi.org/10.2134/agronj1994.00021962008600010033x

Carciochi, W. D., Massigoge, I., Lapaz Olveira, A., Reussi Calvo, N. I., Cafaro La Menza, F., Sainz Rozas, H. R., Barbieri, P. A., Di Napoli, M., Gonzalez Montaner, J., & Ciampitti, I. A. (2021). Cover crop species can increase or decrease the fertilizer-nitrogen requirement in maize. *Agronomy Journal*, *113*, 5412–5423. https://doi.org/10.1002/agj2.20791

Cassman, K. G., Dobermann, A. R., & Walters, D. T. (2002). Agroecosystems, nitrogen-use efficiency, and nitrogen management. *Ambio*, *2*, 132–140. https://doi.org/10.1579/0044-7447-31.2.132

Cerrato, M. E., & Blackmer, A. M. (1990). Comparison of models for describing corn yield response to nitrogen fertilizer. *Agronomy Journal*, *82*, 138–143. https://doi.org/10.2134/agronj1990.00021962008200010030x

Cooper, M., Voss-Fels, K. P., Messina, C. D., Tang, T., & Hammer, G. L. (2020). Tackling G x E x M interactions pathways for crop improvements by predicting contributions of genetics and management to crop productivity. *Theoretical Applied Genetics*, *134*, 1625–1644. https://doi.org/10.1007/s00122-021-03812-3

Correndo, A. A., Rotundo, J. L., Tremblay, N., Archontoulis, S., Coulter, J. A., Ruiz-Diaz, D., Franzen, D., Franzluebbers, A. J., Nafziger, E., Schwalbert, R., Steinke, K., Williams, J., Messina, C. D., & Ciampitti, A. I. (2021). Assessing the uncertainty of maize yield without nitrogen fertilization. *Field Crops Research*, *260*, 107985. https://doi.org/10.1016/j.fcr.2020.107985

Deiss, L., Demyan, M. S., Fulford, A., Hurisso, T., & Culman, S. W. (2023). High-throughput soil heath assessment to predict corn agronomic performance. *Field Crops Research*, *297*, 108930. https://doi.org/10.1016/j.fcr.2023.108930

Dobermann, A., & Cassman, K. G. (2005). Cereal area and nitrogen use efficiency are drivers of future nitrogen fertilizer consumption. *Science China Life Science*, *2*, 745–258. https://doi.org/10.1007/BF03187115

Dohleman, F. G., Barten, Ty. J., Helland, N., Dahal, S., Arrizia, J. L., Gehlhar, S., Foresman, C., Mack, D., Gillespie, K., Archontoulis, S., & Castellano, M. J. (2024). Benefitting productivity and the environment: Current and future maize cropping systems improve yield while reducing nitrate load. *Journal of Environmental Quality*, *53*, 187–197. https://doi.org/10.1002/jeq2.20537

Duvick, D. N. (2005). Genetic progress in yield of United States maize (*Zea mays* L.). *Maydica*, *50*, 193–202.

Elazab, A., Ordóñez, R. A., Savin, R., Slafer, G. A., & Araus, J. L. (2016). Detecting interactive effects of N fertilization and heat stress on maize productivity by remote sensing techniques. *European Journal of Agronomy*, *73*, 11–24. https://doi.org/10.1016/j.eja.2015.11.010

ERS-USDA. (2018). *Fertilize use and price*. Economic Research Service. https://www.ers.usda.gov/data-products/fertilizer-use-and-price.aspx

Faé, G. S., Kemanian, A. R., Roth, G. W., White, C., & Watson, J. E. (2020). Soybean yield in relation to environmental and soil properties. *European Journal of Agronomy*, *118*, 126070.

Gabaldón-Leal, C., Webber, H., Otegui, M. E., Slafer, G. A., Ordóñez, R. A., Gaiser, T., Lorite, I. J., Ruiz-Ramos, M., & Ewert, F. (2016). Modeling the impact of heat stress on maize yield formation. *Field Crops Research*, *198*, 226–237.

Gautam, A., Anuo, C. O., Kladivko, E., Vyn, J. T., & Armstrong, S. (2025). Does 46 years of conservation tillage and crop rotations change soil carbon and nitrogen distribution and storage? *Soil & Tillage Research*, *254*, 106702. https://doi.org/10.1016/j.still.2025.106702

Hirsh, S. M., Duiker, S. W., Graybill, J., Nichols, K., & Weil, R. R. (2021). Scavenging and recycling deep soil nitrogen using cover crops on mid-Atlantic, USA farms. *Agriculture, Ecosystems & Environment*, *309*, 107274.

Janovicek, K., Banger, K., Sulik, J., Nasielski, J., & Deen, B. (2021). Delta yield based optimal nitrogen rate estimates for corn are often economically sound. *Agronomy Journal*, *113*, 1961–1973. https://doi.org/10.1002/agj2.20521

Kachanoski, R. G. (2009). Crop response to nitrogen fertilizer: The delta yield concept. *Canadian Journal of Soil Science*, *89*, 543–554. https://doi.org/10.4141/CJSS09003

Kachanoski, R. G., O'halloran, I. P., Aspinal, D., & von Bertoldi, P. (1996). Delta yield: Mapping fertilizer nitrogen requirements for crops. *Better Crops with Plant Food*, *80*, 20–23.

Kaye, J., Finney, D., White, C., Bradley, B., Schipanski, M., Alonso-Ayuso, M., Hunter, M., Burgess, M., & Mejia, C. (2019). Managing nitrogen through cover crop species selection in the U.S. mid-Atlantic. *PLoS One*, *14*, e0215448. https://doi.org/10.1371/journal.pone.0215448

Kosola, K. R., Eller, M. S., Dohleman, F. G., Olmedo-Pico, L., Bernhard, B., Winans, E., Barten, T. J., Brzostowski, L., Murphy, L. R., Gu, C., Ralston, L., Hall, M., Gillespie, K. M., Mack, D., Below, F. E., & Vyn, T. J. (2023). Short-stature and tall maize hybrids have a similar yield response to split-rate vs. pre-plant N applications, but differ in biomass and nitrogen partitioning. *Field Crops Research*, *295*, 108880. https://doi.org/10.1016/j.fcr.2023.108880

Li, X., Lyu, Y., Zhu, B., Liu, L., & Song, K. (2025). Maize yield estimation in Northeast China's black soil region using a deep learning model with attention mechanism and remote sensing. *Scientific Reports*, *15*, 12927. https://doi.org/10.1038/s41598-025-97563-6

Lory, J. A., & Scharf, P. C. (2003). Yield goal versus delta yield for predicting fertilizer nitrogen need in corn. *Agronomy Journal*, *95*, 994–999. https://doi.org/10.2134/agronj2003.9940

Malcolm, G. M., Camargo, G. G. T., Ishler, V. A., Richard, T. L., & Karsten, H. D. (2015). Energy and greenhouse gas analysis of northeast U.S. dairy cropping systems. *Agriculture, Ecosystems & Environment*, *199*, 407–417.

Mandrini, G., Bullock, D. S., & Martin, N. F. (2021). Modeling the economic and environmental effects of corn nitrogen management in

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Version of record at: https://doi.org/10.1002/agj2.70150

Illinois. *Field Crops Research*, *261*, 108000. https://doi.org/10.1016/j.fcr.2020.108000

Mandrini, G., Pittelkow, C. M., Archontoulis, S. V., Mieno, T., & Martin, N. F. (2021). Understanding differences between static and dynamics nitrogen fertilizer tools using simulation modeling. *Agricultural Systems*, *194*, 103275. https://doi.org/10.1016/j.agsy.2021.103275

Martinez-Feria, R., Licht, M. A., Ordóñez, R. A., Hatfield, F. L., Coulter, J. A., & Archontoulis, S. V. (2019). Evaluating maize and soybean grain dry-down in the field with predictive algorithms and genotype-by-environment analysis. *Scientific Reports*, *9*, 7167. https://doi.org/10.1038/s41598-019-43653-1

Miguez, F. E., & Poffenbarger, H. (2022). How can we estimate optimum fertilizer rates with accuracy and precision? *Agricultural & Environmental Letters*, *7*, 1–5.

Morris, T. F., Murrell, T. S., Beegle, D. B., Camberato, J. J., Ferguson, R. B., Grove, J., Ketterings, Q., Kyveryga, 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., … Yang, H. (2018). Strengths and limitations of nitrogen rate recommendations for corn and opportunities for improvement. *Agronomy Journal*, *110*, 1–37. https://doi.org/10.2134/agronj2017.02.0112

Mueller, S. M., Messina, C. D., & Vyn, T. J. (2019). Simultaneous gains in grain yield and nitrogen efficiency over 70 years of maize genetic improvement. *Scientific Reports*, *9*, 9095. https://doi.org/10.1038/s41598-019-45485-5

Nafziger, E. D., Sawyer, J. E., & Hoeft, R. G. (2004, November 17–18). *Formulating N recommendations for corn in the Corn Belt using recent data* [Conference presentation]. North Central Extension-Industry Soil Fertility Conference, Des Moines, IA. Iowa State University, Ames, Iowa.

Nel, A. A., & Bloem, A. (2006). The delta yield procedure for nitrogen fertilisation of maize in South Africa. *The South African Journal of Plant and Soil*, *23*, 203–208. https://doi.org/10.1080/02571862.2006.10634755

Niemeyer, C., Nasielski, J., Janovicek, K., Bruulsema, T., & Deen, B. (2021). Yield can explain interannual variation in optimum nitrogen rates in continuous corn. *Nutrient Cycling in Agroecosystems*, *121*, 115–128. https://doi.org/10.1007/s10705-021-10168-z

Norris, R., Chim, B. K., Evanylo, G., Reiter, M., & Thomason, W. (2020). Corn yield and soil nitrogen following winter annual cover crops interseeded into soybean. *Crop Science*, *60*, 2667–2682. https://doi.org/10.1002/csc2.20185

Ordóñez, R. A., Archontoulis, S. V., Martinez-Feria, R., Hatfield, J. L., Wright, E. E., & Castellano, M. J. (2020). Root to shoot and carbon to nitrogen ratios of maize and soybean crops in the US Midwest. *European Journal of Agronomy*, *120*, 126130.

Ordóñez, R. A., Casteel, S., Stevens, R., Archontoulis, S., & Vyn, T. (in press). Climate, rotation, and tillage impacts on soybean yield gains in a 50-year experiment. *Global Change Biology*.

Ordóñez, R. A., Castellano, M. J., Danalatos, G. N., Wright, E. E., Hatfield, J. L., Burras, L., & Archontoulis, S. V. (2021). Insufficient and excessive N fertilizer input reduces maize root mass across soil type. *Field Crops Research*, *267*, 108142.

Ordóñez, R. A., Olmedo-Pico, L. B., Dohleman, F. G., Fernández-Juricic, E., Verhagen, G. S., & Vyn, T. J. (2024). Short-statured maize achieved similar growth and nitrogen uptake but greater nitrogen efficiencies than conventional tall maize. *Crop Science*, *64*, 3502–3520.

Ordóñez, R. A., Olmedo-Pico, L. B., Ferela, A., Trifunovic, S., Eudy, D., Archontoulis, S., & Vyn, T. J. (2025). Modern maize hybrids have increased grain yield and efficiency tolerances to nitrogen-limited conditions. *European Journal of Agronomy*, *168*, 127621.

Ortez, O. A., Lindsey, A. J., Thomison, P. R., Coulter, J. A., Singh, M. P., Carrijo, D. R., Quinn, D. J., Licht, M. A., & Bastos, L. (2023). Corn response to long-term seasonal stressor: A review. *Crop Science*, *63*, 3210–3235. https://doi.org/10.1002/csc2.21101

Paustian, K., Collier, S., Baldock, J., Burgess, R., Creque, J., Delonge, M., Dungait, J., Ellert, B., Frank, S., Goddard, T., Govaerts, B., Grundy, M., Henning, M., Izaurralde, R. C., Madaras, M., Mcconkey, B., Porzig, E., Rice, C., Searle, R., … Jahn, M. (2019). Quantifying carbon for agricultural soil management: From the current status toward a global soil information system. *Carbon Management*, *10*, 567–587. https://doi.org/10.1080/17583004.2019.1633231

Poffenbarger, H. J., Sawyer, J. E., Barker, D. W., Olk, D. C., Six, J., & Castellano, M. J. (2018). Legacy effects of long-term nitrogen fertilizer application on the fate of nitrogen fertilizer inputs in continuous maize. *Agriculture Ecosystems & Environment*, *265*, 544–555.

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. https://doi.org/10.1016/j.eja.2019.01.003

Puntel, L. A., Sawyer, J. E., Barker, D. W., Dietzel, R., Poffenbarger, H., Castellano, M. J., Moore, K. J., Thorburn, P., & Archontoulis, S. V. (2016). Modeling long-term corn yield response to nitrogen rate and crop rotation. *Frontier in Plant Science*, *7*, 1630.

Quin, Z., Myers, D. B., Ransom, C. J., Kitchen, N. R., Liang, S. Z., Camberato, J. J., Carter, P. R., Ferguson, R. B., Fernández, F. G., Franzen, D. W., Laboski, C. A. M., Malone, B. D., Nafziger, E. D., Sawyer, J. E., Scharf, P. C., & Shanahan, J. F. (2018). Application of machine learning methodologies for predicting corn economic optimal nitrogen rate. *Agronomy Journal*, *110*, 2593–2607.

Quinn, D. J., Poffenbarger, H. J., Miguez, F. E., & Lee, C. D. (2023). Corn optimum nitrogen fertilizer rate and application timing when following a rye cover crop. *Field Crops Research*, *291*, 108794. https://doi.org/10.1016/j.fcr.2022.108794

R Core Team. (2021). *R: A language and environment for statistical computing*. R Foundation for statistical computing. https://www.R-project.org/

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. D., 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*, 902–917. https://doi.org/10.1002/saj2.20539

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., Scharf, P. C., & Shanahan, J. F. (2020). Corn nitrogen rate recommendation tools' performance across eight U.S. Midwest corn belt states. *Agronomy Journal*, *112*, 470–492. https://doi.org/10.1002/agj2.20035

Rattalino Edreira, J. I., Cassman, K. G., Hochman, Z., Van Ittersum, M. K., Van Bussel, L., Claessens, L., & Grassini, P. (2018). Beyond the plot: Technology extrapolation domains for scaling out agronomic science. *Environmental Research Letter*, *13*, 054027. https://doi.org/10.1088/1748-9326/aac092

Reid, K., Drury, C. F., Burton, D. L., & Joosse, P. (2025). Re-thinking soil nitrogen availability to crops in the context of soil organic carbon.

14350645, 2025, 5, Downloaded from https://acsess.onlinelibrary.wiley.com/doi/10.1002/agj2.70150 by University Of Delaware Library, Wiley Online Library on [17/09/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

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Canadian Journal of Soil Science, *105*, 1–7. https://doi.org/10.1139/cjss-2025-0003

Robertson, G. P., & Vitousek, P. M. (2009). Nitrogen in agriculture: Balancing the cost of an essential resource. *Annual Review of Environmental Resource*, *34*, 97–125. https://doi.org/10.1146/annurev.environ.032108.105046

Saenz, E., Ruiz, A., Sciarresi, C., King, K., Baum, M., Ferela, A., Danalatos, G. J. N., Gambin, B., Kalogeropoulos, G., Thies, A., Ordóñez, R. A., Trifunovic, S., Narvel, J., Eudy, D. M., Schnable, P. S., Topp, C., Vyn, T. J., & Archontoulis, S. V. (2025). Historical increases in plant density increased vegetative maize biomass while breeding increased reproductive biomass and allocation to ear over stem. *Field Crops Research*, *322*, 109704. https://doi.org/10.1016/j.fcr.2024.109704

Salo, T. J., Palosuo, T., Kersebaum, K. C., Nendel, C., Angulo, C., Ewert, F., Bindi, M., Calanca, P., Klein, T., Moriondo, M., Ferrise, R., Olesen, J. E., Patil, R. H., Ruget, F., Takáč, J., Hlavinka, P., Trnka, M., & Rötter, R. P. (2015). Comparing the performance of 11 crop simulation models in predicting yield response to nitrogen fertilization. *The Journal of Agricultural Science*, *154*, 1218–1240. https://doi.org/10.1017/S0021859615001124

Sawyer, J., Nafziger, E., Randall, G., Bundy, L., Rehm, G., & Joern, B. (2006). *Concepts and rationale for regional nitrogen guidelines for corn* (PM2015). Iowa State University Extension.

Shahhosseini, M., Hu, G., & Archontoulis, S. V. (2020). Forecasting corn yield with machine learning ensembles. *Frontiers in Plant Science*, *11*, 1120. https://doi.org/10.3389/fpls.2020.01120

Spargo, J. T., Alley, M., Thomason, W. E., & Nagle, S. M. (2009). Illinois soil nitrogen test for prediction of fertilizer needs of corn in Virginia. *Soil Science Society of America Journal*, *73*, 434–442. https://doi.org/10.2136/sssaj2007.0437

Stanford, G. (1973). Rationale for optimum nitrogen fertilization in corn production. *Journal of Environmental Quality*, *2*, 159–165. https://doi.org/10.2134/jeq1973.00472425000200020001x

Stecker, J. A., Buchholz, D. D., Hanson, R. G., Wollenhaupt, N. C., & McVay, K. A. (1995). Tillage and rotation effects on corn yield response to fertilizer nitrogen and aqualf soil. *Agronomy Journal*, *87*, 409–415. https://doi.org/10.2134/agronj1995.00021962008700030004x

Tilman, D., Cassman, K., Matson, P., Naylor, R., & Polasky, S. (2002). Agricultural sustainability and intensive production practices. *Nature*, *418*, 671–677. https://doi.org/10.1038/nature01014

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. https://doi.org/10.2134/agronj2012.0184

United Nations. (2015). *Transforming our world: The 2030 agenda for sustainable development, A/RES/70/1*. https://www.un.org/sustainabledevelopment/development-agenda/

USDA-NRCS. (2022). *Land resource regions and major land resource areas of the United States, the Caribbean, and the Pacific Basin*. United States Department of Agriculture.

Vanotti, M. B., & Bundy, L. G. (1994). An alternative rationale for corn nitrogen fertilizer recommendations. *Journal of Production Agriculture*, *7*, 243–249. https://doi.org/10.2134/jpa1994.0243

Vyn, T. J., Faber, J. G., Janovicek, K. J., & Beauchamp, E. G. (2000). Cover crop effects on nitrogen availability to corn following wheat. *Agronomy Journal*, *92*, 915–924. https://doi.org/10.2134/agronj2000.925915x

Vyn, T. J., Janovicek, K. J., Miller, M. H., & Beauchamp, E. G. (1999). Soil nitrate accumulation and corn response to preceding small-grain fertilization and cover crops. *Agronomy Journal*, *91*, 17–24. https://doi.org/10.2134/agronj1999.00021962009100010004x

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*, 126193. https://doi.org/10.1016/j.eja.2020.126193

White, C. M., Bradley, B., Finney, D. M., & Kaye, J. P. (2019). Predicting cover crop nitrogen content with a handheld normalized difference vegetation index meter. *Agricultural & Environmental Letters*, *4*, 1–4. https://doi.org/10.2134/ael2019.08.0031

White, C. M., Finney, D. M., Kemanian, A. R., & Kaye, J. P. (2016). A model-data fusion approach for predicting cover crop nitrogen supply to corn. *Agronomy Journal*, *108*, 1–14. https://doi.org/10.2134/agronj2016.05.0288

White, C. M., Finney, D. M., Kemanian, A. R., & Kaye, J. P. (2020). Modeling the contribution of mineralization to yield of corn. *Agronomy Journal*, *113*, 490–503. https://doi.org/10.1002/agj2.20474

White, C. M., Sigdel, S., Karsten, H. D., Meinen, R. J., & Spargo, J. T. (2023). Recalibrating the pennsylvania pre-sidedress soil nitrate test recommendations for modern corn production. *Agronomy Journal*, *15*, 2600–2613. https://doi.org/10.1002/agj2.21426

Zhao, X., Nafziger, E. D., & Pittelkow, C. M. (2017). Nitrogen rate strategies for reducing yield-scaled nitrous oxide emissions in maize. *Environmental Research Letter*, *12*, 124006. https://doi.org/10.1088/1748-9326/aa9007

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14350645, 2025, 5, Downloaded from https://acsess.onlinelibrary.wiley.com/doi/10.1002/agj2.70150 by University Of Delaware Library, Wiley Online Library on [17/09/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License